Fuzzy Logic Toolbox™

User's Guide

MATLAB®

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MathWorks®

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Contents

1 Getting Started

2 Fuzzy Inference System Modeling

3 Fuzzy Inference System Tuning

5 Fuzzy Logic in Simulink

6 Deployment

Getting Started

Fuzzy Logic Toolbox Product Description

Design and simulate fuzzy logic systems

Fuzzy Logic Toolbox provides MATLAB® functions, apps, and a Simulink® block for analyzing, designing, and simulating systems based on fuzzy logic. The product guides you through the steps of designing fuzzy inference systems. Functions are provided for many common methods, including fuzzy clustering and adaptive neurofuzzy learning.

The toolbox lets you model complex system behaviors using simple logic rules, and then implement these rules in a fuzzy inference system. You can use it as a stand-alone fuzzy inference engine. Alternatively, you can use fuzzy inference blocks in Simulink and simulate the fuzzy systems within a comprehensive model of the entire dynamic system.

Key Features

- Fuzzy Logic Design app for building fuzzy inference systems and viewing and analyzing results
- Membership functions for creating fuzzy inference systems
- Support for AND, OR, and NOT logic in user-defined rules
- Standard Mamdani and Sugeno-type fuzzy inference systems
- Automated membership function shaping through neuroadaptive and fuzzy clustering learning techniques
- Ability to embed a fuzzy inference system in a Simulink model
- Ability to generate embeddable C code or stand-alone executable fuzzy inference engines

What Is Fuzzy Logic?

Description of Fuzzy Logic

In recent years, the number and variety of applications of fuzzy logic have increased significantly. The applications range from consumer products such as cameras, camcorders, washing machines, and microwave ovens to industrial process control, medical instrumentation, decision-support systems, and portfolio selection.

To understand why use of fuzzy logic has grown, you must first understand what is meant by fuzzy logic.

Fuzzy logic has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multivalued logic. However, in a wider sense fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with unsharp boundaries in which membership is a matter of degree. In this perspective, fuzzy logic in its narrow sense is a branch of FL. Even in its more narrow definition, fuzzy logic differs both in concept and substance from traditional multivalued logical systems.

In Fuzzy Logic Toolbox software, fuzzy logic should be interpreted as FL, that is, fuzzy logic in its wide sense. The basic ideas underlying FL are explained in “Foundations of Fuzzy Logic” on page 1-10. What might be added is that the basic concept underlying FL is that of a linguistic variable, that is, a variable whose values are words rather than numbers. In effect, much of FL may be viewed as a methodology for computing with words rather than numbers. Although words are inherently less precise than numbers, their use is closer to human intuition. Furthermore, computing with words exploits the tolerance for imprecision and thereby lowers the cost of solution.

Another basic concept in FL, which plays a central role in most of its applications, is that of a fuzzy if-then rule or, simply, fuzzy rule. Although rule-based systems have a long history of use in Artificial Intelligence (AI), what is missing in such systems is a mechanism for dealing with fuzzy consequents and fuzzy antecedents. In fuzzy logic, this mechanism is provided by the calculus of fuzzy rules. The calculus of fuzzy rules serves as a basis for what might be called the Fuzzy Dependency and Command Language (FDCL). Although FDCL is not used explicitly in the toolbox, it is effectively one of its principal constituents. In most of the applications of fuzzy logic, a fuzzy logic solution is, in reality, a translation of a human solution into FDCL.

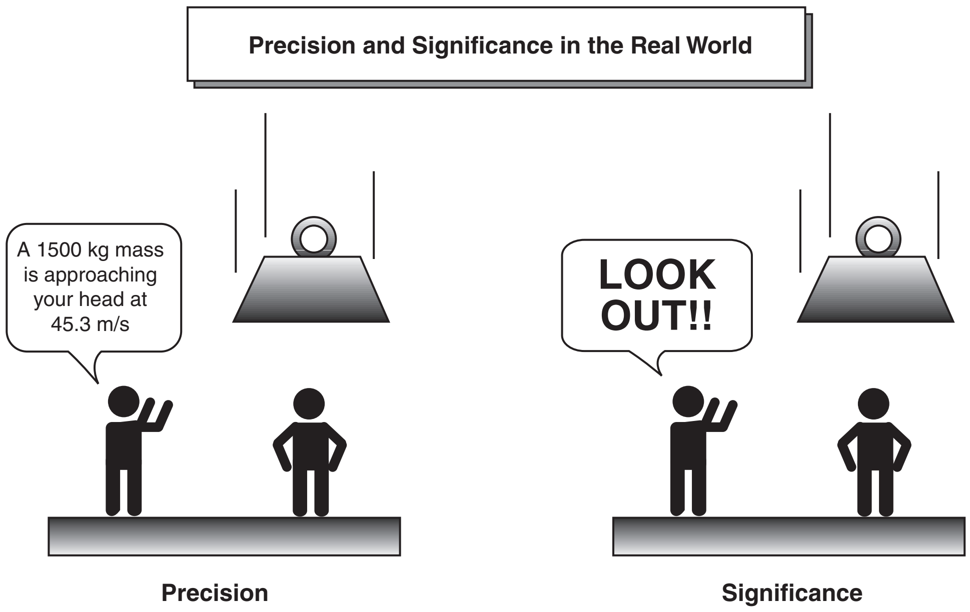
A trend that is growing in visibility relates to the use of fuzzy logic in combination with neurocomputing and genetic algorithms. More generally, fuzzy logic, neurocomputing, and genetic algorithms may be viewed as the principal constituents of what might be called soft computing. Unlike the traditional, hard computing, *soft computing* accommodates the imprecision of the real world. The guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, and low solution cost. In the future, soft computing could play an increasingly important role in the conception and design of systems whose MIQ (Machine IQ) is much higher than that of systems designed by conventional methods.

Among various combinations of methodologies in soft computing, the one that has highest visibility at this juncture is that of fuzzy logic and neurocomputing, leading to neuro-fuzzy systems. Within fuzzy logic, such systems play a particularly important role in the induction of rules from observations. An effective method developed by Dr. Roger Jang for this purpose is called ANFIS (Adaptive Neuro-Fuzzy Inference System). This method is an important component of the toolbox.

Fuzzy logic is all about the relative importance of precision: How important is it to be exactly right when a rough answer will do?

You can use Fuzzy Logic Toolbox software with MATLAB technical computing software as a tool for solving problems with fuzzy logic. Fuzzy logic is a fascinating area of research because it does a good job of trading off between significance and precision — something that humans have been managing for a very long time.

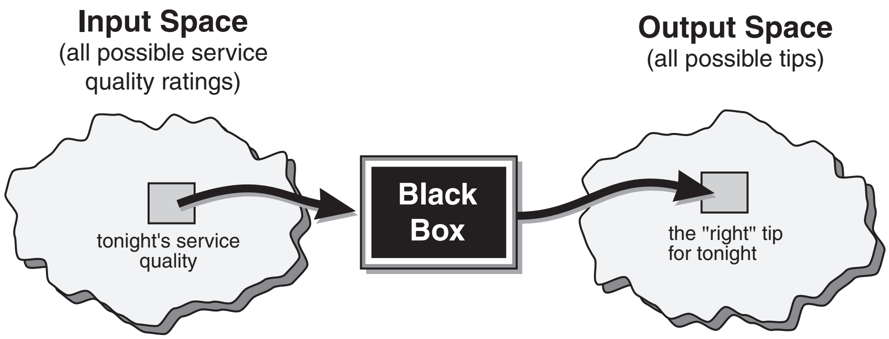
In this sense, fuzzy logic is both old and new because, although the modern and methodical science of fuzzy logic is still young, the concepts of fuzzy logic relies on age-old skills of human reasoning.


Precision and Significance in the Real World
A 1500 kg mass is approaching your head at 45.3 m/s
LOOK OUT!!
Precision
Significance

Fuzzy logic is a convenient way to map an input space to an output space. Mapping input to output is the starting point for everything. Consider the following examples:

- With information about how good your service was at a restaurant, a fuzzy logic system can tell you what the tip should be.
- With your specification of how hot you want the water, a fuzzy logic system can adjust the faucet valve to the right setting.
- With information about how far away the subject of your photograph is, a fuzzy logic system can focus the lens for you.
- With information about how fast the car is going and how hard the motor is working, a fuzzy logic system can shift gears for you.

A graphical example of an input-output map is shown in the following figure.


Input Space
(all possible service quality ratings)
tonight's service quality
Black Box
Output Space
(all possible tips)
the "right" tip for tonight

An input-output map for the tipping problem:
“Given the quality of service, how much should I tip?”

Determining the appropriate amount of tip requires mapping inputs to the appropriate outputs. Between the input and the output, the preceding figure shows a black box that can contain any number of things: fuzzy systems, linear systems, expert systems, neural networks, differential equations, interpolated multidimensional lookup tables, or even a spiritual advisor, just to name a few of the possible options. Clearly the list could go on and on.

Of the dozens of ways to make the black box work, it turns out that fuzzy is often the very best way. Why should that be? As Lotfi Zadeh, who is considered to be the father of fuzzy logic, once remarked: "In almost every case you can build the same product without fuzzy logic, but fuzzy is faster and cheaper."

Why Use Fuzzy Logic?

Here is a list of general observations about fuzzy logic:

- Fuzzy logic is conceptually easy to understand.

  The mathematical concepts behind fuzzy reasoning are very simple. Fuzzy logic is a more intuitive approach without the far-reaching complexity.
- Fuzzy logic is flexible.

  With any given system, it is easy to layer on more functionality without starting again from scratch.
- Fuzzy logic is tolerant of imprecise data.

  Everything is imprecise if you look closely enough, but more than that, most things are imprecise even on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end.

- Fuzzy logic can model nonlinear functions of arbitrary complexity.

  You can create a fuzzy system to match any set of input-output data. This process is made particularly easy by adaptive techniques like Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which are available in Fuzzy Logic Toolbox software.
- Fuzzy logic can be built on top of the experience of experts.

  In direct contrast to neural networks, which take training data and generate opaque, impenetrable models, fuzzy logic lets you rely on the experience of people who already understand your system.
- Fuzzy logic can be blended with conventional control techniques.

  Fuzzy systems don't necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.
- Fuzzy logic is based on natural language.

  The basis for fuzzy logic is the basis for human communication. This observation underpins many of the other statements about fuzzy logic. Because fuzzy logic is built on the structures of qualitative description used in everyday language, fuzzy logic is easy to use.

The last statement is perhaps the most important one and deserves more discussion. Natural language, which is used by ordinary people on a daily basis, has been shaped by thousands of years of human history to be convenient and efficient. Sentences written in ordinary language represent a triumph of efficient communication.

When Not to Use Fuzzy Logic

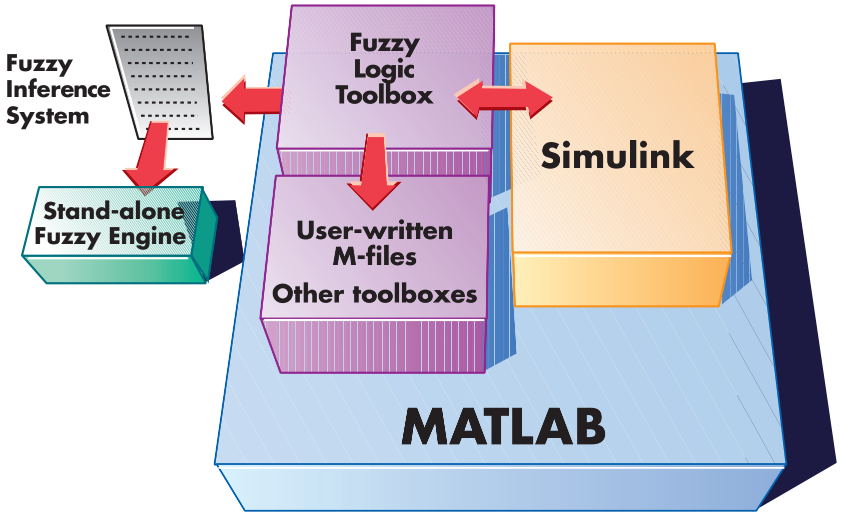
Fuzzy logic is not a cure-all. When should you not use fuzzy logic? The safest statement is the first one made in this introduction: fuzzy logic is a convenient way to map an input space to an output space. If you find it's not convenient, try something else. If a simpler solution already exists, use it. Fuzzy logic is the codification of common sense — use common sense when you implement it and you will probably make the right decision. Many controllers, for example, do a fine job without using fuzzy logic. However, if you take the time to become familiar with fuzzy logic, you'll see it can be a very powerful tool for dealing quickly and efficiently with imprecision and nonlinearity.

What Can Fuzzy Logic Toolbox Software Do?

You can create and edit fuzzy inference systems with Fuzzy Logic Toolbox software. You can create these systems using graphical tools or command-line functions, or you can generate them automatically using either clustering or adaptive neuro-fuzzy techniques.

If you have access to Simulink software, you can easily test your fuzzy system in a block diagram simulation environment.

The toolbox also lets you run your own stand-alone C programs directly. This is made possible by a stand-alone Fuzzy Inference Engine that reads the fuzzy systems saved from a MATLAB session. You can customize the stand-alone engine to build fuzzy inference into your own code. All provided code is ANSI® compliant.



Because of the integrated nature of the MATLAB environment, you can create your own tools to customize the toolbox or harness it with another toolbox, such as the Control System Toolbox™, Deep Learning Toolbox™, or Optimization Toolbox™ software.

See Also

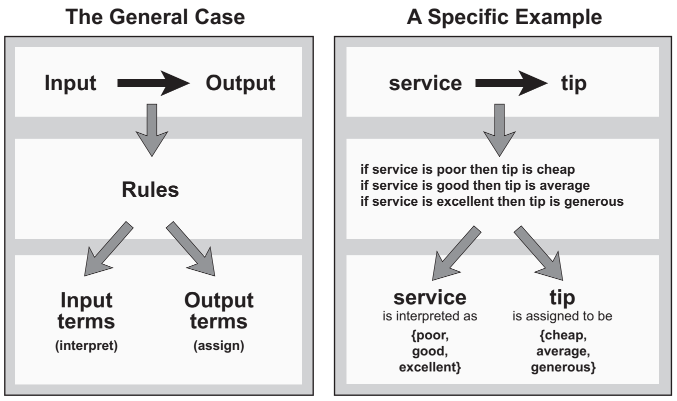
More About

- “Foundations of Fuzzy Logic” on page 1-10
- “Fuzzy vs. Nonfuzzy Logic” on page 1-47

Foundations of Fuzzy Logic

Overview

The point of fuzzy logic is to map an input space to an output space, and the primary mechanism for doing this is a list of if-then statements called rules. All rules are evaluated in parallel, and the order of the rules is unimportant. The rules themselves are useful because they refer to variables and the adjectives that describe those variables. Before you can build a system that interprets rules, you must define all the terms you plan on using and the adjectives that describe them. To say that the water is hot, you need to define the range that the water's temperature can be expected to vary as well as what we mean by the word *hot*. The following diagram provides a roadmap for the fuzzy inference process. It shows the general description of a fuzzy system on the left and a specific fuzzy system on the right.



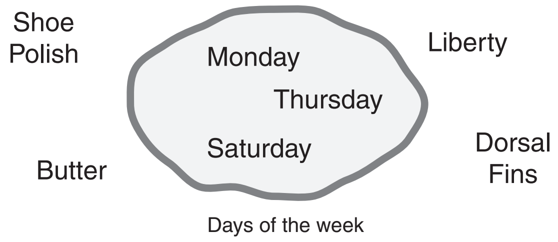
To summarize the concept of fuzzy inference depicted in this figure, *fuzzy inference is a method that interprets the values in the input vector and, based on some set of rules, assigns values to the output vector.*

This topic guides you through the fuzzy logic process step by step by providing an introduction to the theory and practice of fuzzy logic.

Fuzzy Sets

Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership.

To understand what a fuzzy set is, first consider the definition of a *classical set*. A classical set is a container that wholly includes or wholly excludes any given element. For example, the set of days of the week unquestionably includes Monday, Thursday, and Saturday. It just as unquestionably excludes butter, liberty, and dorsal fins, and so on.

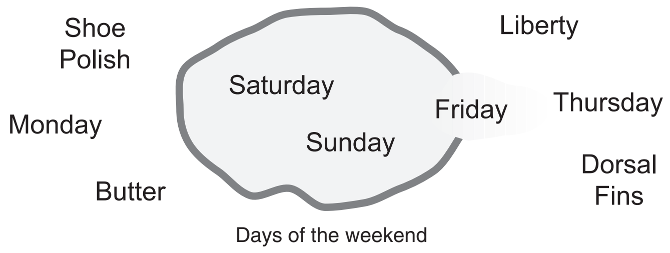


This type of set is called a classical set because it has been around for a long time. It was Aristotle who first formulated the Law of the Excluded Middle, which says X must either be in set A or in set not-A. Another version of this law is:

Of any subject, one thing must be either asserted or denied.

To restate this law with annotations: "Of any subject (say Monday), one thing (a day of the week) must be either asserted or denied (I assert that Monday is a day of the week)." This law demands that opposites, the two categories A and not-A, should between them contain the entire universe. Everything falls into either one group or the other. There is no thing that is both a day of the week and not a day of the week.

Now, consider the set of days comprising a weekend. The following diagram attempts to classify the weekend days.



Most would agree that Saturday and Sunday belong, but what about Friday? It feels like a part of the weekend, but somehow it seems like it should be technically excluded. Thus, in the preceding diagram, Friday tries its best to "straddle on the fence." Classical or normal sets would not tolerate this kind of classification. Either something is in or it is out. Human experience suggests something different, however, straddling the fence is part of life.

Of course individual perceptions and cultural background must be taken into account when you define what constitutes the weekend. Even the dictionary is imprecise, defining the weekend as the period from Friday night or Saturday to Monday morning. You are entering the realm where sharp-edged, yes-no logic stops being helpful. Fuzzy reasoning becomes valuable exactly when you work with how people really perceive the concept *weekend* as opposed to a simple-minded classification useful for accounting purposes only. More than anything else, the following statement lays the foundations for fuzzy logic.

In fuzzy logic, the truth of any statement becomes a matter of degree.

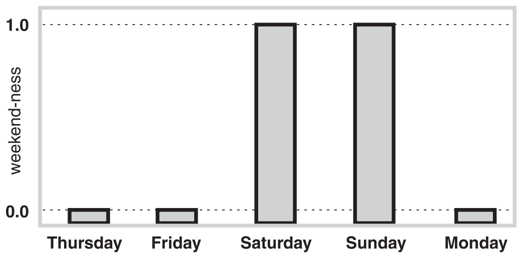
Any statement can be fuzzy. The major advantage that fuzzy reasoning offers is the ability to reply to a yes-no question with a not-quite-yes-or-no answer. Humans do this kind of thing all the time (think how rarely you get a straight answer to a seemingly simple question), but it is a rather new trick for computers.

How does it work? Reasoning in fuzzy logic is just a matter of generalizing the familiar yes-no (Boolean) logic. If you give true the numerical value of 1 and false the numerical value of 0, this value indicates that fuzzy logic also permits in-between values like 0.2 and 0.7453. For instance:

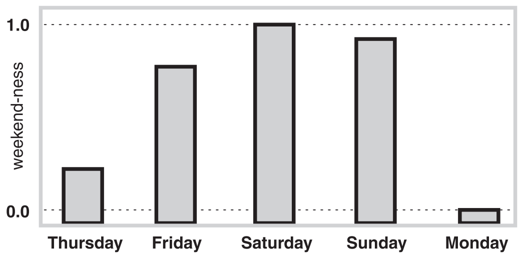
Q: Is Saturday a weekend day?
A: 1 (yes, or true)
Q: Is Tuesday a weekend day?
A: 0 (no, or false)

Q: Is Friday a weekend day?
A: 0.8 (for the most part yes, but not completely)
Q: Is Sunday a weekend day?
A: 0.95 (yes, but not quite as much as Saturday).

The following plot on the left shows the truth values for weekend-ness if you are forced to respond with an absolute yes or no response. On the right, is a plot that shows the truth value for weekend-ness if you are allowed to respond with fuzzy in-between values.



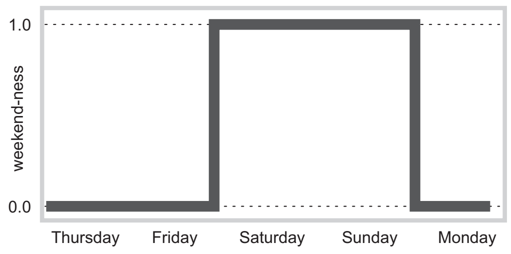
Days of the weekend two-valued membership



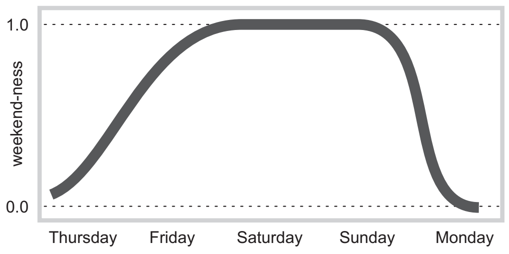
Days of the weekend multivalued membership

Technically, the representation on the right is from the domain of *multivalued logic* (or multivalent logic). If you ask the question "Is X a member of set A?" the answer might be yes, no, or any one of a thousand intermediate values in between. Thus, X might have partial membership in A. Multivalued logic stands in direct contrast to the more familiar concept of two-valued (or bivalent yes-no) logic.

To return to the example, now consider a continuous scale time plot of weekend-ness shown in the following plots.



Days of the weekend two-valued membership

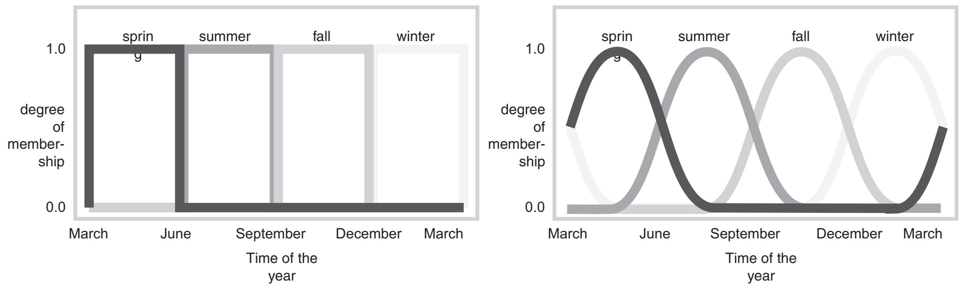


Days of the weekend multivalued membership

By making the plot continuous, you are defining the degree to which any given instant belongs in the weekend rather than an entire day. In the plot on the left, notice that at midnight on Friday, just as the second hand sweeps past 12, the weekend-ness truth value jumps discontinuously from 0 to 1. This is one way to define the weekend, and while it may be useful to an accountant, it may not really connect with your own real-world experience of weekend-ness.

The plot on the right shows a smoothly varying curve that accounts for the fact that all of Friday, and, to a small degree, parts of Thursday, partake of the quality of weekend-ness and thus deserve partial membership in the fuzzy set of weekend moments. The curve that defines the weekend-ness of any instant in time is a function that maps the input space (time of the week) to the output space (weekend-ness). Specifically it is known as a *membership function*. See “Membership Functions” on page 1-14 for a more detailed discussion.

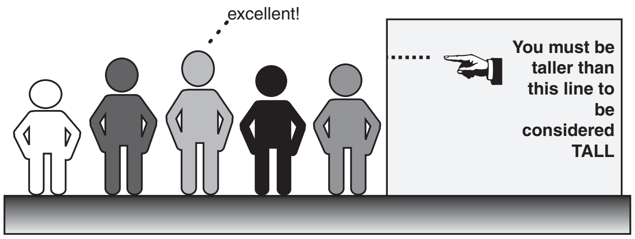
As another example of fuzzy sets, consider the question of seasons. What season is it right now? In the northern hemisphere, summer officially begins at the exact moment in the earth's orbit when the North Pole is pointed most directly toward the sun. It occurs exactly once a year, in late June. Using the astronomical definitions for the season, you get sharp boundaries as shown on the left in the figure that follows. But what you experience as the seasons vary more or less continuously as shown on the right in the following figure (in temperate northern hemisphere climates).



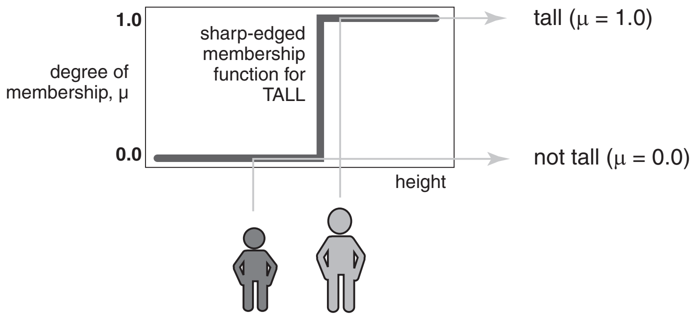
Membership Functions

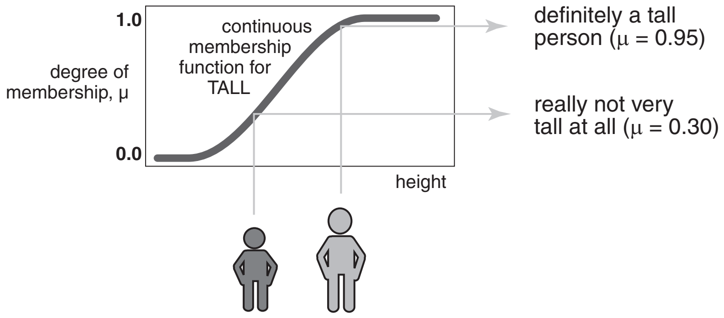
A *membership function* (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the *universe of discourse*, a fancy name for a simple concept.

One of the most commonly used examples of a fuzzy set is the set of tall people. In this case, the universe of discourse is all potential heights, say from three feet to nine feet, and the word tall would correspond to a curve that defines the degree to which any person is tall. If the set of tall people is given the well-defined (crisp) boundary of a classical set, you might say all people taller than six feet are officially considered tall. However, such a distinction is clearly absurd. It may make sense to consider the set of all real numbers greater than six because numbers belong on an abstract plane, but when we want to talk about real people, it is unreasonable to call one person short and another one tall when they differ in height by the width of a hair.



If the kind of distinction shown previously is unworkable, then what is the right way to define the set of tall people? Much as with the plot of weekend days, the figure following shows a smoothly varying curve that passes from not-tall to tall. The output-axis is a number known as the membership value between 0 and 1. The curve is known as a *membership function* and is often given the designation of µ. This curve defines the transition from not tall to tall. Both people are tall to some degree, but one is significantly less tall than the other.





1.0
0.0
degree of membership, μ
continuous membership function for TALL
height
definitely a tall person (μ = 0.95)
really not very tall at all (μ = 0.30)

Subjective interpretations and appropriate units are built right into fuzzy sets. If you say "She's tall," the membership function tall should already take into account whether you are referring to a six-year-old or a grown woman. Similarly, the units are included in the curve. Certainly it makes no sense to say "Is she tall in inches or in meters?"

Membership Functions in Fuzzy Logic Toolbox Software

The only condition a membership function must really satisfy is that it must vary between 0 and 1. The function itself can be an arbitrary curve whose shape we can define as a function that suits us from the point of view of simplicity, convenience, speed, and efficiency.

A classical set might be expressed as

$$A = \{x | x > 6\}$$

A fuzzy set is an extension of a classical set. If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs.

$$A\{x, \mu_A(x) | x \in X\}$$

A = {x, $\mu_A(x)$ | $x \in X$}

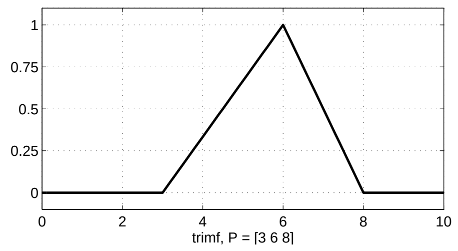
$\mu_A(x)$ is called the membership function (or MF) of x in A. The membership function maps each element of X to a membership value between 0 and 1.

The toolbox includes 11 built-in membership function types. These 11 functions are, in turn, built from several basic functions:

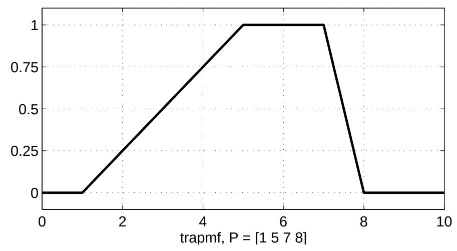
- Piece-wise linear functions
- Gaussian distribution function
- Sigmoid curve
- Quadratic and cubic polynomial curves

For detailed information on any of the membership functions mentioned next, see the corresponding reference page.

The simplest membership functions are formed using straight lines. Of these, the simplest is the *triangular* membership function, and it has the function name `trimf`. This function is nothing more than a collection of three points forming a triangle. The *trapezoidal* membership function, `trapmf`, has a flat top and really is just a truncated triangle curve. These straight line membership functions have the advantage of simplicity.



trimf

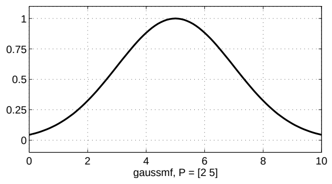


trapmf

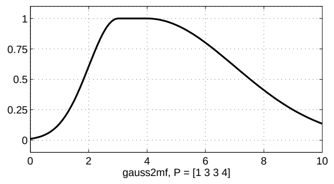
Two membership functions are built on the *Gaussian* distribution curve: a simple Gaussian curve and a two-sided composite of two different Gaussian curves. The two functions are `gaussmf` and `gauss2mf`.

The *generalized bell* membership function is specified by three parameters and has the function name `gbellmf`. The bell membership function has one more parameter than the

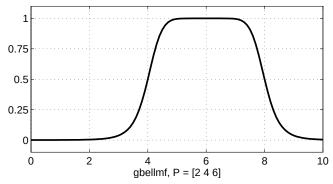
Gaussian membership function, so it can approach a non-fuzzy set if the free parameter is tuned. Because of their smoothness and concise notation, Gaussian and bell membership functions are popular methods for specifying fuzzy sets. Both of these curves have the advantage of being smooth and nonzero at all points.



gaussmf

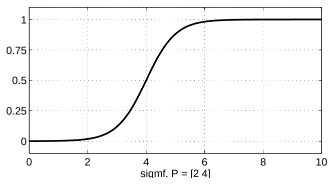


gauss2mf

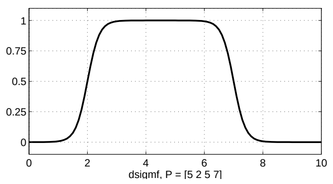


gbellmf

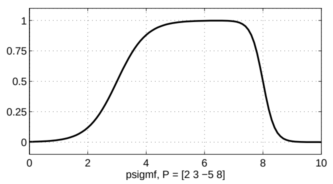
Although the Gaussian membership functions and bell membership functions achieve smoothness, they are unable to specify asymmetric membership functions, which are important in certain applications. Next, you define the *sigmoidal* membership function, which is either open left or right. Asymmetric and closed (i.e. not open to the left or right) membership functions can be synthesized using two sigmoidal functions, so in addition to the basic `sigmf`, you also have the difference between two sigmoidal functions, `dsigmf`, and the product of two sigmoidal functions `psigmf`.



sigmf

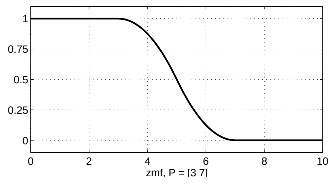


dsigmf

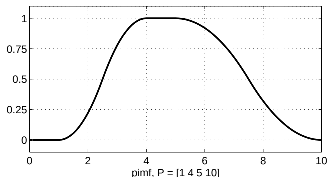


psigmf

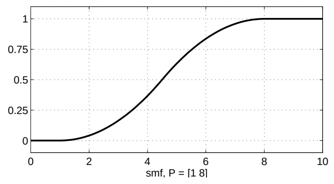
Polynomial based curves account for several of the membership functions in the toolbox. Three related membership functions are the *Z*, *S*, and*Pi* curves, all named because of their shape. The function `zmf` is the asymmetrical polynomial curve open to the left, `smf` is the mirror-image function that opens to the right, and `pimf` is zero on both extremes with a rise in the middle.



zmf



pimf



smf

There is a very wide selection to choose from when you're selecting a membership function. You can also create your own membership functions with the toolbox. However, if a list based on expanded membership functions seems too complicated, just remember that you could probably get along very well with just one or two types of membership functions, for example the triangle and trapezoid functions. The selection is wide for those who want to explore the possibilities, but expansive membership functions are not necessary for good fuzzy inference systems. Finally, remember that more details are available on all these functions in the reference section.

Summary of Membership Functions

- Fuzzy sets describe vague concepts (e.g., fast runner, hot weather, weekend days).
- A fuzzy set admits the possibility of partial membership in it. (e.g., Friday is sort of a weekend day, the weather is rather hot).
- The degree an object belongs to a fuzzy set is denoted by a membership value between 0 and 1. (e.g., Friday is a weekend day to the degree 0.8).
- A membership function associated with a given fuzzy set maps an input value to its appropriate membership value.

Logical Operations

Now that you understand the fuzzy inference, you need to see how fuzzy inference connects with logical operations.

The most important thing to realize about fuzzy logical reasoning is the fact that it is a superset of standard Boolean logic. In other words, if you keep the fuzzy values at their extremes of 1 (completely true), and 0 (completely false), standard logical operations will hold. As an example, consider the following standard truth tables.

A	B	A and B
0	0	0
0	1	0
1	0	0
1	1	1

AND

A	B	A or B
0	0	0
0	1	1
1	0	1
1	1	1

OR

A	not A
0	1
1	0

NOT

Now, because in fuzzy logic the truth of any statement is a matter of degree, can these truth tables be altered? The input values can be real numbers between 0 and 1. What function preserves the results of the AND truth table (for example) and also extend to all real numbers between 0 and 1?

One answer is the *min* operation. That is, resolve the statement A AND B, where A and B are limited to the range (0,1), by using the function *min*(A,B). Using the same reasoning, you can replace the OR operation with the *max* function, so that A OR B becomes equivalent to *max*(A,B). Finally, the operation NOT A becomes equivalent to the operation $1 - A$. Notice how the previous truth table is completely unchanged by this substitution.

A	B	min(A,B)
0	0	0
0	1	0
1	0	0
1	1	1

AND

A	B	max(A,B)
0	0	0
0	1	1
1	0	1
1	1	1

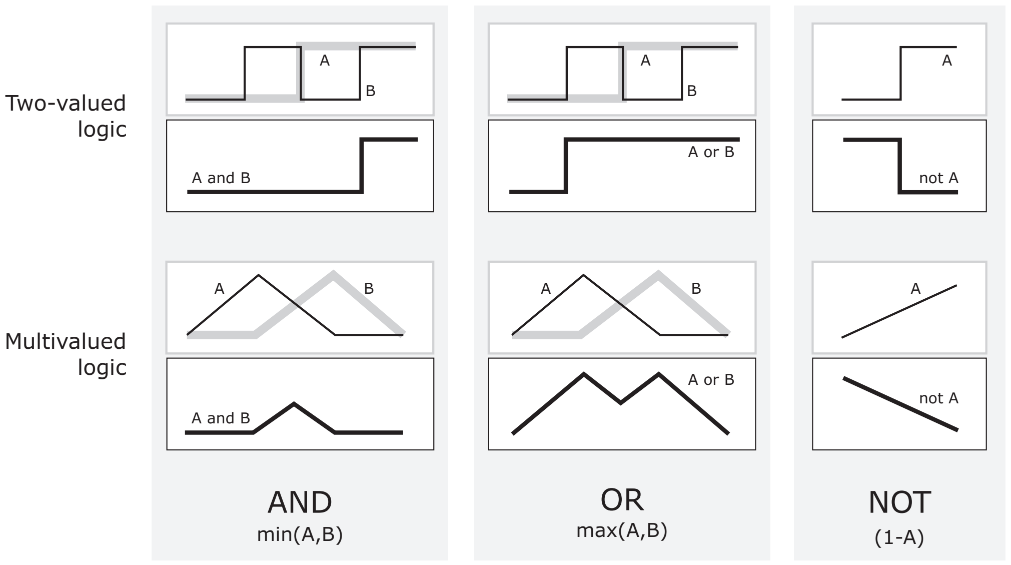
OR

A	1 - A
0	1
1	0

NOT

Moreover, because there is a function behind the truth table rather than just the truth table itself, you can now consider values other than 1 and 0.

The next figure uses a graph to show the same information. In this figure, the truth table is converted to a plot of two fuzzy sets applied together to create one fuzzy set. The upper part of the figure displays plots corresponding to the preceding two-valued truth tables, while the lower part of the figure displays how the operations work over a continuously varying range of truth values A and B according to the fuzzy operations you have defined.



Given these three functions, you can resolve any construction using fuzzy sets and the fuzzy logical operation AND, OR, and NOT.

Additional Fuzzy Operators

In this case, you defined only one particular correspondence between two-valued and multivalued logical operations for AND, OR, and NOT. This correspondence is by no means unique.

In more general terms, you are defining what are known as the fuzzy intersection or conjunction (AND), fuzzy union or disjunction (OR), and fuzzy complement (NOT). The classical operators for these functions are: AND = *min*, OR = *max*, and NOT = additive complement. Typically, most fuzzy logic applications make use of these operations and leave it at that. In general, however, these functions are arbitrary to a surprising degree. Fuzzy Logic Toolbox software uses the classical operator for the fuzzy complement as shown in the previous figure, but also enables you to customize the AND and OR operators.

The intersection of two fuzzy sets A and B is specified in general by a binary mapping T, which aggregates two membership functions as follows:

$$\mu_{A \cap B}(x) = T(\mu_A(x), \mu_B(x))$$

For example, the binary operator T may represent the multiplication of $\mu_A(x)$ and $\mu_B(x)$. These fuzzy intersection operators, which are usually referred to as T-norm (Triangular norm) operators, meet the following basic requirements:

A T-norm operator is a binary mapping $T(.,.)$ with the following properties:

- Boundary — $T(0,0) = 0,\ T(a,1) = T(1,a) = a$
- Monotonicity — $T(a,b) \leq T(c,d)$ if $a \leq c$ and $b \leq d$
- Commutativity — $T(a,b) = T(b,a)$
- Associativity — $T(a,T(b,c)) = T(T(a,b),c)$

The first requirement imposes the correct generalization to crisp sets. The second requirement implies that a decrease in the membership values in A or B cannot produce an increase in the membership value in A intersection B. The third requirement indicates that the operator is indifferent to the order of the fuzzy sets to be combined. Finally, the fourth requirement allows us to take the intersection of any number of sets in any order of pair-wise groupings.

Like fuzzy intersection, the fuzzy union operator is specified in general by a binary mapping S:

$$\mu_{A \cup B}(x) = S(\mu_A(x), \mu_B(x))$$

For example, the binary operator S can represent the addition of $\mu_A(x)$ and $\mu_B(x)$. These fuzzy union operators, which are often referred to as T-conorm (or S-norm) operators, must satisfy the following basic requirements:

A T-conorm (or S-norm) operator is a binary mapping $S(.,.)$ with the following properties:

- Boundary — $S(1,1) = 1,\ S(a,0) = S(0,a) = a$
- Monotonicity — $S(a,b) \leq S(c,d)$ if $a \leq c$ and $b \leq d$
- Commutativity — $S(a,b) = S(b,a)$
- Associativity — $S(a,S(b,c)) = S(S(a,b),c)$

Several parameterized T-norms and dual T-conorms have been proposed in the past, such as those of Yager [10], Dubois and Prade [1], Schweizer and Sklar [7], and Sugeno [8]. Each of these provides a way to vary the gain on the function so that it can be very restrictive or very permissive.

If-Then Rules

Fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. These if-then rule statements are used to formulate the conditional statements that comprise fuzzy logic.

A single fuzzy if-then rule assumes the form

If *x* is *A*, then *y* is *B*

where *A* and *B* are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively. The if-part of the rule "*x* is *A*" is called the *antecedent* or premise, while the then-part of the rule "*y* is *B*" is called the *consequent* or conclusion. An example of such a rule might be
If service is good then tip is average

The concept *good* is represented as a number between 0 and 1, and so the antecedent is an interpretation that returns a single number between 0 and 1. Conversely, *average* is represented as a fuzzy set, and so the consequent is an assignment that assigns the entire fuzzy set B to the output variable *y*. In the if-then rule, the word *is* gets used in two entirely different ways depending on whether it appears in the antecedent or the consequent. In MATLAB terms, this usage is the distinction between a relational test using "==" and a variable assignment using the "=" symbol. A less confusing way of writing the rule would be

If service == good, then tip = average

In general, the input to an if-then rule is the current value for the input variable (in this case, *service*) and the output is an entire fuzzy set (in this case, *average*). This set will later be *defuzzified,* assigning one value to the output. The concept of defuzzification is described in the next section.

Interpreting an if-then rule involves two steps:

- Evaluation of the antecedent — *Fuzzifying* the inputs and applying any necessary *fuzzy operators*.
- Application of the result to the consequent.

The second step is known as *implication*. For an if-then rule, the antecedent, *p*, *implies* the consequent, *q*. In binary logic, if *p* is true, then *q* is also true ($p \rightarrow q$). In fuzzy logic, if *p* is true to some degree of membership, then *q* is also true to the same degree ($0.5p \rightarrow 0.5q$). In both cases, if *p* is false, then the value of *q* is undetermined.

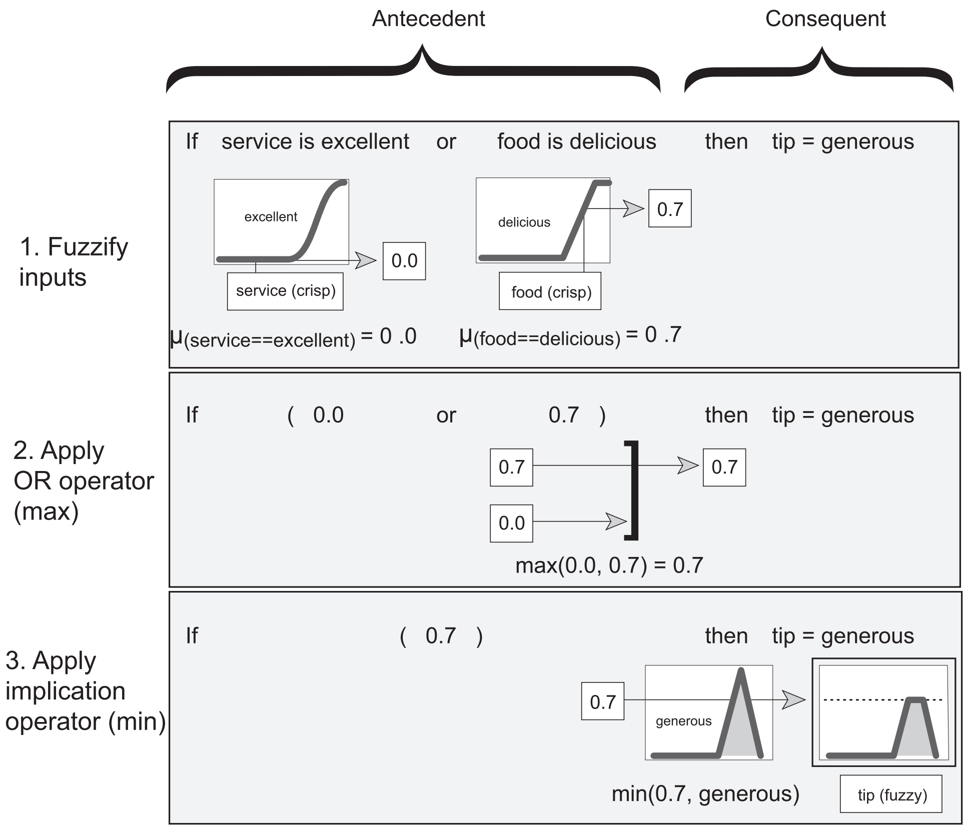
The antecedent of a rule can have multiple parts.

If sky is gray and wind is strong and barometer is falling, then ...

In this case all parts of the antecedent are calculated simultaneously and resolved to a single number using the logical operators described in the preceding section. The consequent of a rule can also have multiple parts.

If temperature is cold, then hot water valve is open and cold water valve is shut

In this case, all consequents are affected equally by the result of the antecedent. How is the consequent affected by the antecedent? The consequent specifies a fuzzy set be assigned to the output. The *implication function* then modifies that fuzzy set to the degree specified by the antecedent. The most common ways to modify the output fuzzy set are truncation using the `min` function (where the fuzzy set is truncated as shown in the following figure) or scaling using the `prod` function (where the output fuzzy set is squashed). Both are supported by the toolbox, but you use truncation for the examples in this section.


Antecedent
Consequent
If service is excellent or food is delicious then tip = generous
1. Fuzzify inputs
excellent
service (crisp)
0.0
delicious
food (crisp)
0.7
μ(service==excellent) = 0 .0
μ(food==delicious) = 0 .7
If (0.0 or 0.7) then tip = generous
2. Apply OR operator (max)
0.7
0.0
0.7
max(0.0, 0.7) = 0.7
If (0.7) then tip = generous
3. Apply implication operator (min)
0.7
generous
min(0.7, generous)
tip (fuzzy)

Summary of If-Then Rules

Interpreting if-then rules is a three-part process. This process is explained in detail in the next section:

1. **Fuzzify inputs**: Resolve all fuzzy statements in the antecedent to a degree of membership between 0 and 1. If there is only one part to the antecedent, then this is the degree of support for the rule.
2. **Apply fuzzy operator to multiple part antecedents**: If there are multiple parts to the antecedent, apply fuzzy logic operators and resolve the antecedent to a single number between 0 and 1. This is the degree of support for the rule.
3. **Apply implication method**: Use the degree of support for the entire rule to shape the output fuzzy set. The consequent of a fuzzy rule assigns an entire fuzzy set to the

output. This fuzzy set is represented by a membership function that is chosen to indicate the qualities of the consequent. If the antecedent is only partially true, (i.e., is assigned a value less than 1), then the output fuzzy set is truncated according to the implication method.

In general, one rule alone is not effective. Two or more rules that can play off one another are needed. The output of each rule is a fuzzy set. The output fuzzy sets for each rule are then aggregated into a single output fuzzy set. Finally the resulting set is defuzzified, or resolved to a single number. “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14 shows how the whole process works from beginning to end for a particular type of fuzzy inference system called a *Mamdani type*.

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[9] Sugeno, M., *Industrial applications of fuzzy control*, Elsevier Science Pub. Co., 1985.

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See Also

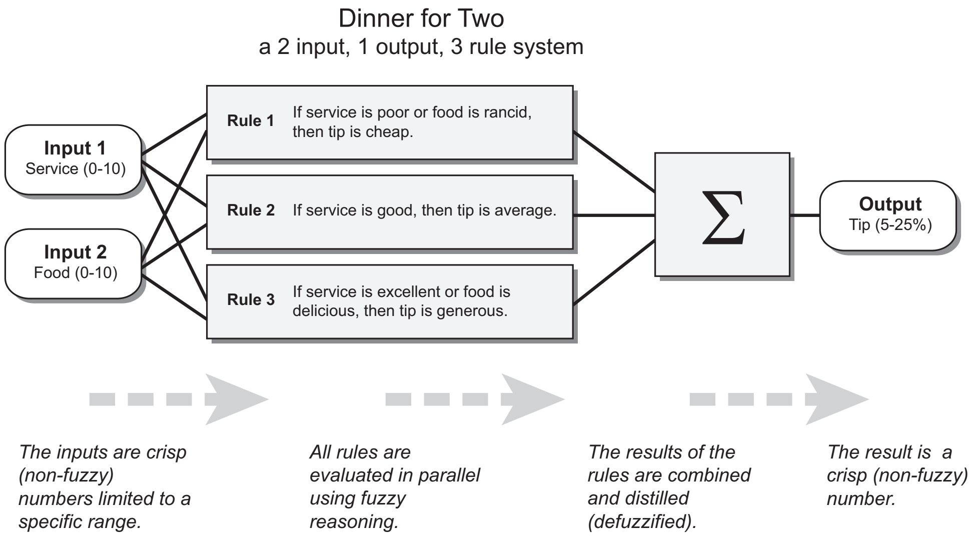
More About

- “What Is Fuzzy Logic?” on page 1-3
- “Fuzzy Inference Process” on page 1-28
- “Fuzzy vs. Nonfuzzy Logic” on page 1-47

Fuzzy Inference Process

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all the pieces that are described in “Membership Functions” on page 1-14, “Logical Operations” on page 1-19, and “If-Then Rules” on page 1-23.

This section describes the fuzzy inference process and uses the example of the two-input, one-output, three-rule tipping problem from “The Basic Tipping Problem” on page 2-16. The basic structure of this example is shown in the following diagram:


Dinner for Two
a 2 input, 1 output, 3 rule system
Input 1
Service (0-10)
Input 2
Food (0-10)
Rule 1
If service is poor or food is rancid, then tip is cheap.
Rule 2
If service is good, then tip is average.
Rule 3
If service is excellent or food is delicious, then tip is generous.
Σ
Output
Tip (5-25%)
The inputs are crisp (non-fuzzy) numbers limited to a specific range.
All rules are evaluated in parallel using fuzzy reasoning.
The results of the rules are combined and distilled (defuzzified).
The result is a crisp (non-fuzzy) number.

Information flows from left to right, from two inputs to a single output. The parallel nature of the rules is an important aspect of fuzzy logic systems. Instead of sharp switching between modes based on breakpoints, logic flows smoothly from regions where one rule or another dominates.

Fuzzy inference process comprises of five parts:

- Fuzzification of the input variables on page 1-29
- Application of the fuzzy operator (AND or OR) in the antecedent on page 1-30
- Implication from the antecedent to the consequent on page 1-31

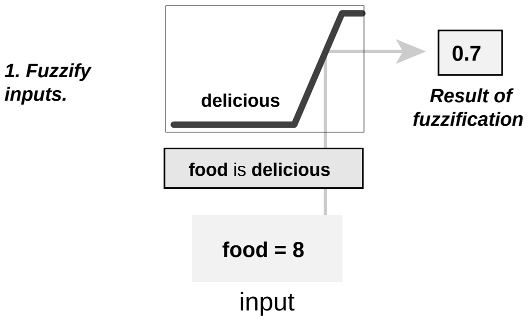
- Aggregation of the consequents across the rules on page 1-31
- Defuzzification on page 1-33

A fuzzy inference diagram on page 1-34 displays all parts of the fuzzy inference process — from fuzzification through defuzzification.

Fuzzify Inputs

The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. In Fuzzy Logic Toolbox software, the input is always a crisp numerical value limited to the universe of discourse of the input variable (in this case, the interval from 0 through 10) . The output is a fuzzy degree of membership in the qualifying linguistic set (always the interval from 0 through 1). Fuzzification of the input amounts to either a table lookup or a function evaluation.

This example is built on three rules, and each of the rules depends on resolving the inputs into several different fuzzy linguistic sets: service is poor, service is good, food is rancid, food is delicious, and so on. Before the rules can be evaluated, the inputs must be fuzzified according to each of these linguistic sets. For example, to what extent is the food delicious? The following figure shows how well the food at the hypothetical restaurant (rated on a scale from 0 through 10) qualifies as the linguistic variable delicious using a membership function. In this case, we rate the food as an 8, which, given the graphical definition of delicious, corresponds to $\mu = 0.7$ for the delicious membership function.



In this manner, each input is fuzzified over all the qualifying membership functions required by the rules.

Apply Fuzzy Operator

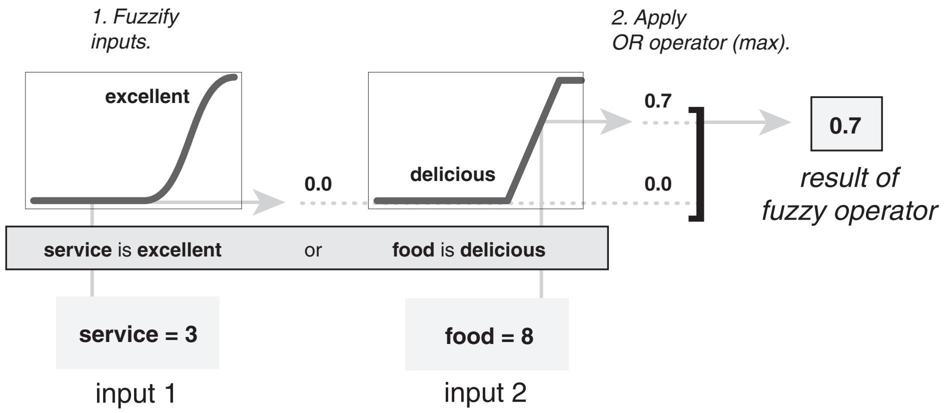
After the inputs are fuzzified, you know the degree to which each part of the antecedent is satisfied for each rule. If the antecedent of a rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the rule antecedent. This number is then applied to the output function. The input to the fuzzy operator is two or more membership values from fuzzified input variables. The output is a single truth value.

As is described in "Logical Operations" on page 1-19 section, any number of well-defined methods can fill in for the AND operation or the OR operation. In the toolbox, two built-in AND methods are supported: *min* (minimum) and *prod* (product). Two built-in OR methods are also supported: *max* (maximum), and the probabilistic OR method *probor*. The probabilistic OR method (also known as the algebraic sum) is calculated according to the equation:

$probor(a,b) = a + b - ab$

In addition to these built-in methods, you can create your own methods for AND and OR by writing any function and setting that to be your method of choice.

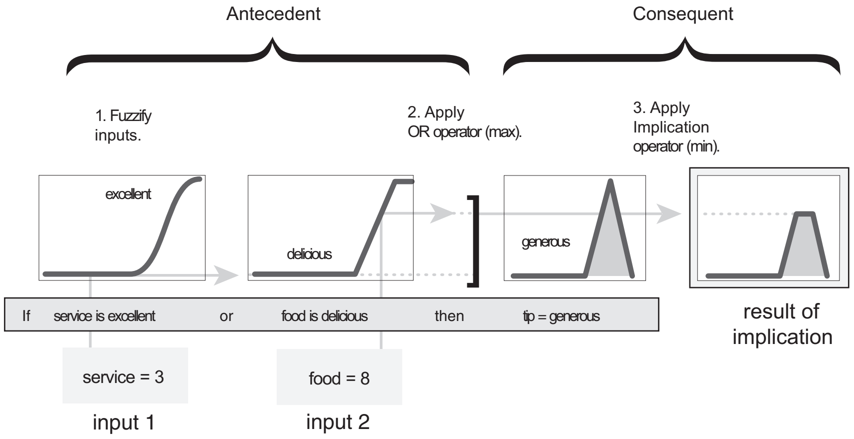
The following figure shows the OR operator *max* at work, evaluating the antecedent of the rule 3 for the tipping calculation. The two different pieces of the antecedent (service is excellent and food is delicious) yielded the fuzzy membership values 0.0 and 0.7 respectively. The fuzzy OR operator simply selects the maximum of the two values, 0.7, and the fuzzy operation for rule 3 is complete. The probabilistic OR method would still result in 0.7.



Apply Implication Method

Before applying the implication method, you must determine the rule weight. Every rule has a *weight* (a number from 0 through 1), which is applied to the number given by the antecedent. Generally, this weight is 1 (as it is for this example) and thus has no effect on the implication process. However, you can decrease the effect of one rule relative to the others by changing its weight value to something other than 1.

After proper weighting has been assigned to each rule, the implication method is implemented. A consequent is a fuzzy set represented by a membership function, which weights appropriately the linguistic characteristics that are attributed to it. The consequent is reshaped using a function associated with the antecedent (a single number). The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Implication is implemented for each rule. Two built-in methods are supported, and they are the same functions that are used by the AND method: *min* (minimum), which truncates the output fuzzy set, and *prod* (product), which scales the output fuzzy set.


Antecedent
Consequent
1. Fuzzify inputs.
2. Apply OR operator (max).
3. Apply Implication operator (min).
excellent
delicious
generous
If service is excellent or food is delicious then tip = generous
result of implication
service = 3
food = 8
input 1
input 2

Note Sugeno systems always use the product implication method.

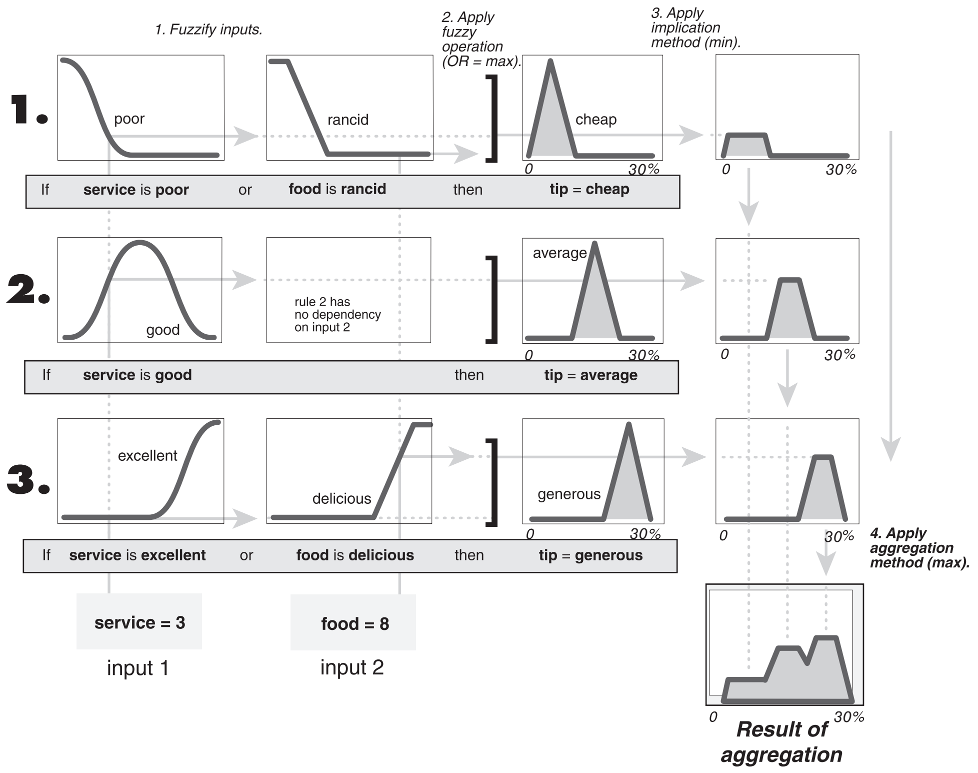
Aggregate All Outputs

Since decisions are based on testing all the rules in a FIS, the rule outputs must be combined in some manner. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Aggregation only occurs once for each output variable, which is before the final defuzzification step. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable.

As long as the aggregation method is commutative, then the order in which the rules are executed is unimportant. Three built-in methods are supported:

- `max` (maximum)
- `probor` (probabilistic OR)
- `sum` (sum of the rule output sets)

In the following diagram, all three rules are displayed to show how the rule outputs are aggregated into a single fuzzy set whose membership function assigns a weighting for every output (tip) value.

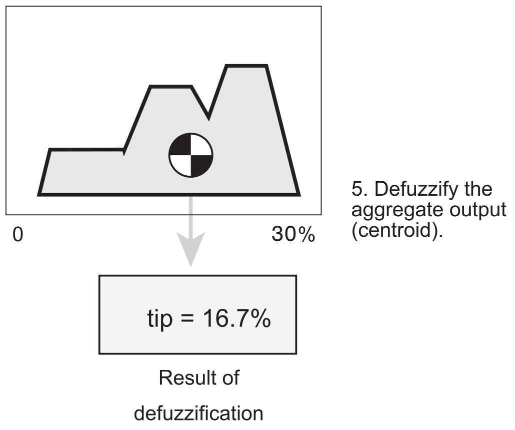

1. Fuzzify inputs.
2. Apply fuzzy operation (OR = max).
3. Apply implication method (min).
1.
poor
rancid
cheap
0
30%
If service is poor or food is rancid then tip = cheap
2.
good
rule 2 has no dependency on input 2
average
If service is good then tip = average
3.
excellent
delicious
generous
If service is excellent or food is delicious then tip = generous
4. Apply aggregation method (max).
service = 3
input 1
food = 8
input 2
Result of aggregation

Note Sugeno systems always use the `sum` aggregation method.

Defuzzify

The input for the defuzzification process is a fuzzy set (the aggregate output fuzzy set) and the output is a single number. As much as fuzziness helps the rule evaluation during the intermediate steps, the final desired output for each variable is generally a single number. However, the aggregate of a fuzzy set encompasses a range of output values, and so must be defuzzified to obtain a single output value from the set.

There are five built-in defuzzification methods supported: centroid, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum, and smallest of maximum. Perhaps the most popular defuzzification method is the centroid calculation, which returns the center of area under the curve, as shown in the following:

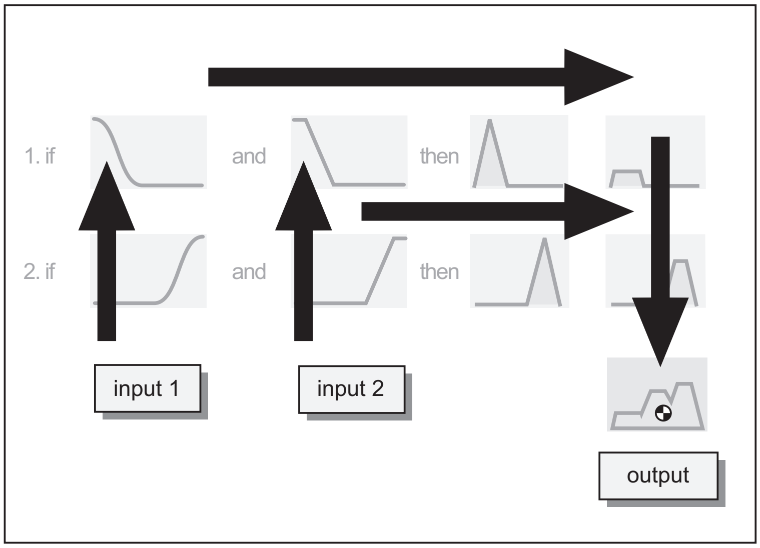

0
30%
5. Defuzzify the aggregate output (centroid).
tip = 16.7%
Result of defuzzification

While the aggregate output fuzzy set covers a range from 0% though 30%, the defuzzified value is between 5% and 25%. These limits correspond to the centroids of the `cheap` and `generous` membership functions, respectively.

Fuzzy Inference Diagram

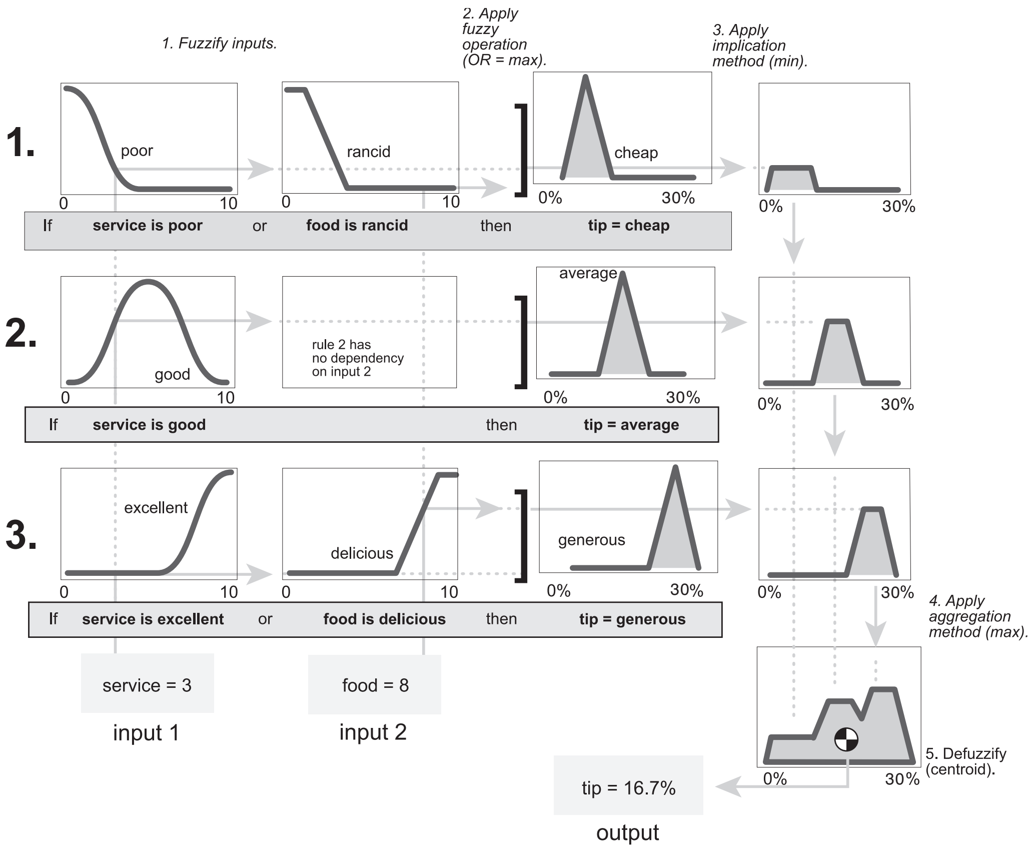
The fuzzy inference diagram is the composite of all the smaller diagrams presented so far in this section. It simultaneously displays all parts of the fuzzy inference process you have examined. Information flows through the fuzzy inference diagram as shown in the following figure.

Interpreting the fuzzy inference diagram



In this figure, the flow proceeds up from the inputs in the lower left, across each row, and then down the rule outputs in the lower right. This compact flow shows everything at once, from linguistic variable fuzzification all the way through defuzzification of the aggregate output.

The following figure shows the actual full-size fuzzy inference diagram. Using a fuzzy inference diagram, you can learn a lot about how the system operates. For instance, for the particular inputs in this diagram, you can see that the implication method is truncation with the *min* function. The *max* function is used for the fuzzy OR operation. Rule 3 (the bottom-most row in the diagram shown previously) has the strongest influence on the output. The Rule Viewer described in “The Rule Viewer” on page 2-33 is an implementation of the fuzzy inference diagram.


1. Fuzzify inputs.
2. Apply fuzzy operation (OR = max).
3. Apply implication method (min).
1.
poor
0
10
rancid
0
10
cheap
0%
30%
0%
30%
If service is poor or food is rancid then tip = cheap
2.
good
0
10
rule 2 has no dependency on input 2
average
0%
30%
0%
30%
If service is good then tip = average
3.
excellent
0
10
delicious
0
10
generous
0%
30%
0%
30%
4. Apply aggregation method (max).
If service is excellent or food is delicious then tip = generous
service = 3
input 1
food = 8
input 2
0%
30%
5. Defuzzify (centroid).
tip = 16.7%
output

See Also

More About

- "Foundations of Fuzzy Logic" on page 1-10

Membership Function Gallery

This example shows how to display 11 membership functions supported in the Fuzzy Logic Toolbox�.

Define membership functions.

```
mf = [...
    fismf('trapmf',[-19 -17 -12 -7]) ...
    fismf('gbellmf',[3 4 -8]) ...
    fismf('trimf',[-9 -1 2]) ...
    fismf('gaussmf',[3 5]) ...
    fismf('gauss2mf',[3 10 5 13]) ...
    fismf('smf',[11 17]) ...
    fismf('zmf',[-18 -10]) ...
    fismf('psigmf',[2 -11 -5 -4]) ...
    fismf('dsigmf',[5 -3 1 5]) ...
    fismf('pimf',[0 7 11 15]) ...
    fismf('sigmf',[2 15]) ...
    ];
```

For more information on the different membership functions and their parameters, see their respective function reference pages.

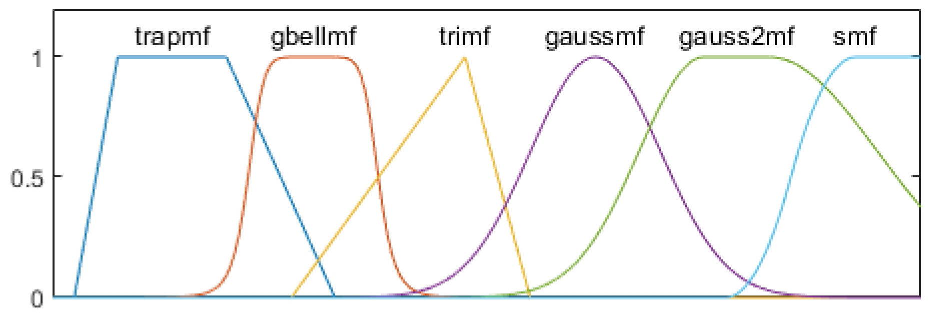
Evaluate the membership functions.

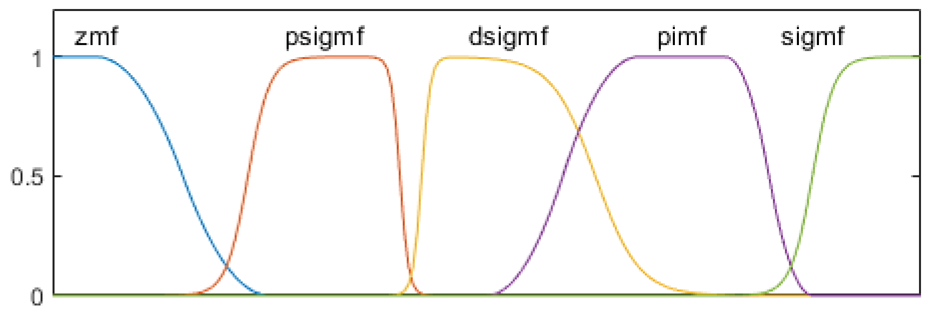
```
x = linspace(-20,20,201);
y = evalmf(mf,x);
```

Plot the evaluated membership functions with labels.

```
subplot(2,1,1);
plot(x,y(1:6,:)');
axis([min(x) max(x) 0 1.2]);
text((mf(1).Parameters(2)+mf(1).Parameters(3))/2,1.1,mf(1).Type,...
    'horizon','center');
text(mf(2).Parameters(3),1.1,mf(2).Type,...
    'horizon','center');
text(mf(3).Parameters(2),1.1,mf(3).Type,...
    'horizon','center');
text(mf(4).Parameters(2),1.1,mf(4).Type,...
    'horizon','center');
text((mf(5).Parameters(2)+mf(5).Parameters(4))/2,1.1,mf(5).Type,...
    'horizon','center');
```

```
text(mf(6).Parameters(2), 1.1,mf(6).Type,...
    'horizon','center');
h_gca = gca;
h_gca.XTick = [];

subplot(2,1,2);
plot(x,y(7:11,:)');
axis([min(x) max(x) 0 1.2]);
text(mf(7).Parameters(1),1.1,mf(7).Type,...
    'horizon','center');
text((mf(8).Parameters(2)+mf(8).Parameters(4))/2,1.1,mf(8).Type,...
    'horizon','center');
text((mf(9).Parameters(2)+mf(9).Parameters(4))/2,1.1,mf(9).Type,...
    'horizon','center');
text((mf(10).Parameters(2)+mf(10).Parameters(3))/2,1.1,mf(10).Type,...
    'horizon','center');
text(mf(11).Parameters(2),1.1,mf(11).Type,...
    'horizon','center');
h_gca =  gca;
h_gca.XTick = [];
```





See Also

More About

- “Foundations of Fuzzy Logic” on page 1-10
- “Fuzzy Inference Process” on page 1-28

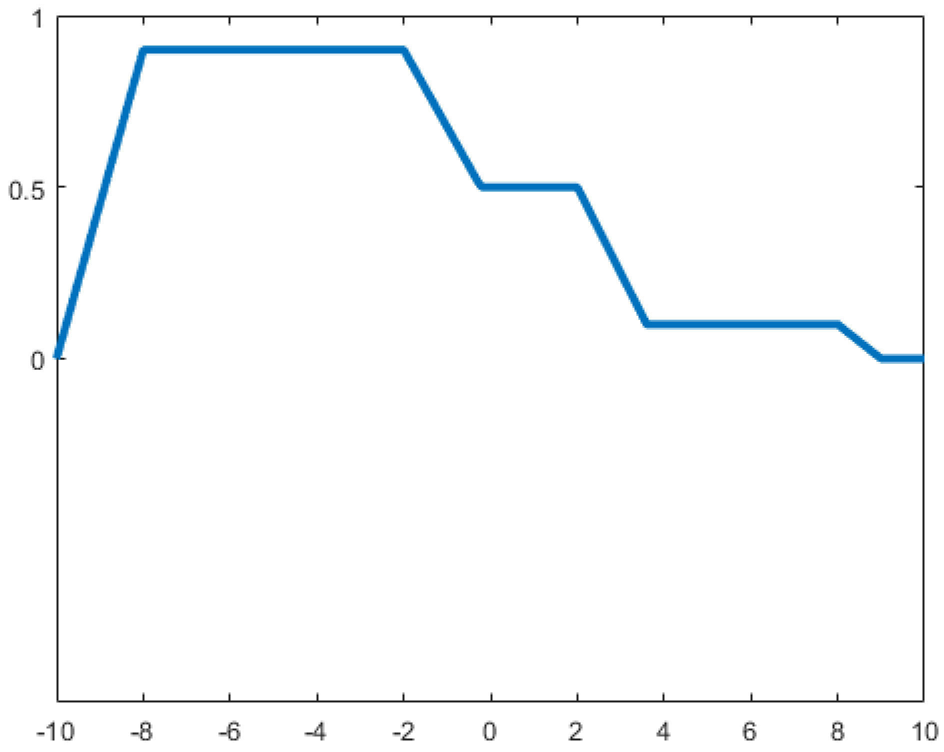
Defuzzification Methods

This example shows how to display five defuzzification methods supported in the Fuzzy Logic Toolbox™.

Problem Setup

Suppose you have the following region to be defuzzified. What are some of the methods you might choose?

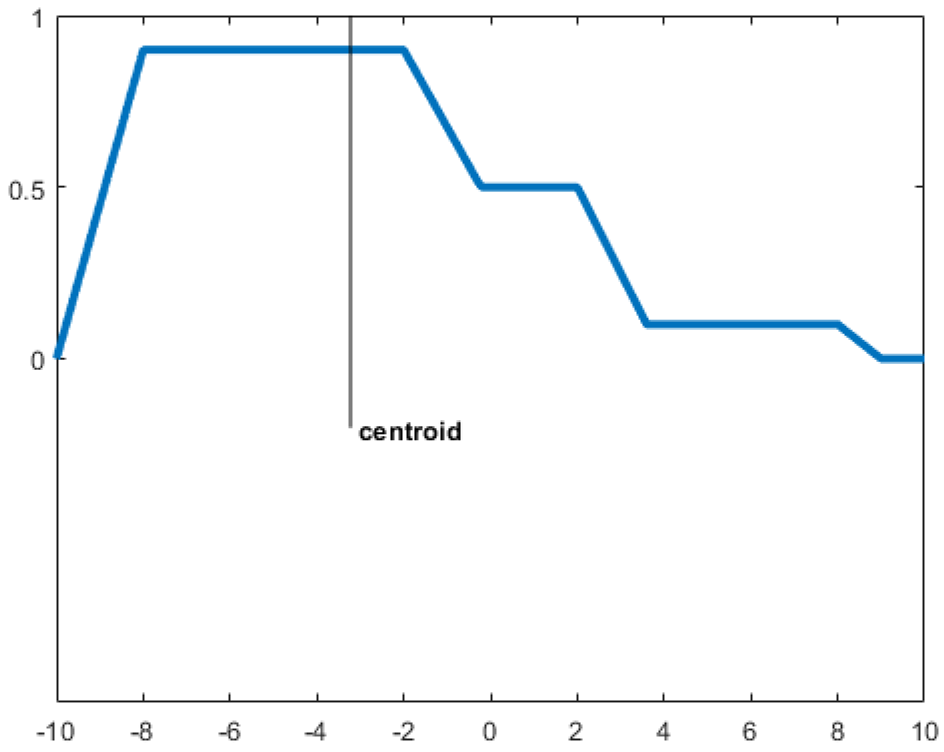
```
x = -10:0.1:10;

mf1 = trapmf(x,[-10 -8 -2 2]);
mf2 = trapmf(x,[-5 -3 2 4]);
mf3 = trapmf(x,[2 3 8 9]);
mf1 = max(0.5*mf2,max(0.9*mf1,0.1*mf3));

figure('Tag','defuzz');
plot(x,mf1,'LineWidth',3);
h_gca = gca;
h_gca.YTick = [0 .5 1] ;
ylim([-1 1]);
```



Centroid

Centroid defuzzification returns the center of area under the curve. If you think of the area as a plate of equal density, the centroid is the point along the x axis about which this shape would balance.

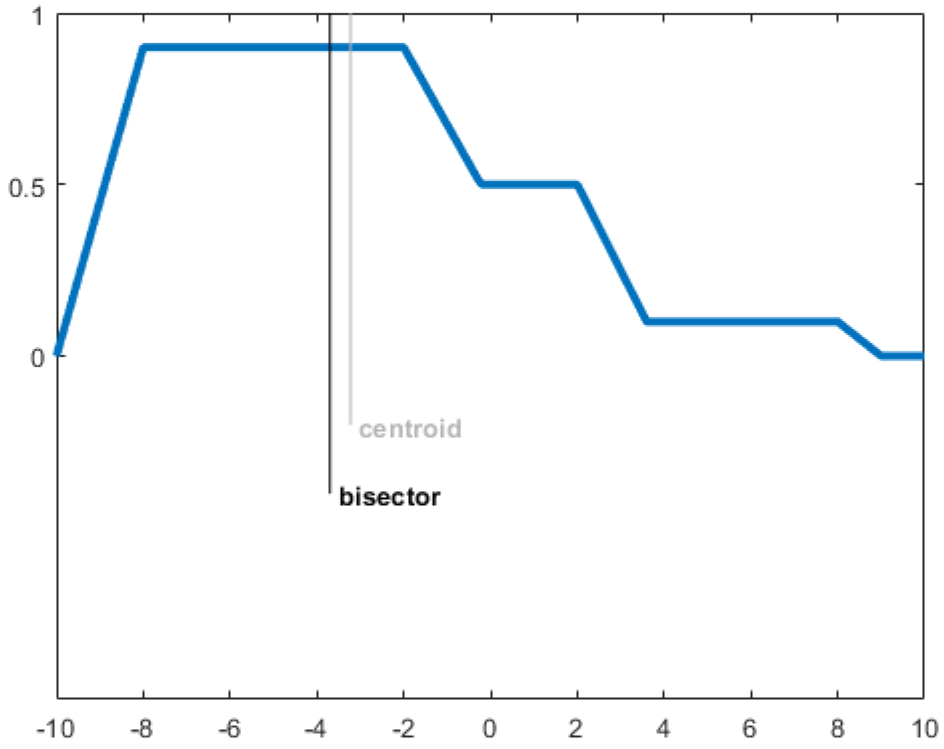
```
x1 = defuzz(x,mf1,'centroid'); % #ok<*NOPTS>

h1 = line([x1 x1],[-0.2 1.2],'Color','k');
t1 = text(x1,-0.2,' centroid','FontWeight','bold');
```



Bisector

The bisector is the vertical line that will divide the region into two sub-regions of equal area. It is sometimes, but not always coincident with the centroid line.

```
x2 =  defuzz(x,mf1,'bisector');

gray = 0.7*[1 1 1];
h1.Color = gray;
t1.Color = gray;
h2 = line([x2 x2],[-0.4 1.2],'Color','k');
t2 = text(x2,-0.4,' bisector','FontWeight','bold');
```



Middle, Smallest, and Largest of Maximum

MOM, SOM, and LOM stand for Middle, Smallest, and Largest of Maximum, respectively. These three methods key off the maximum value assumed by the aggregate membership function. In this example, because there is a plateau at the maximum value, they are distinct. If the aggregate membership function has a unique maximum, then MOM, SOM, and LOM all take on the same value.

```
x3 = defuzz(x,mf1,'mom')
```

```
x3 = -5
```

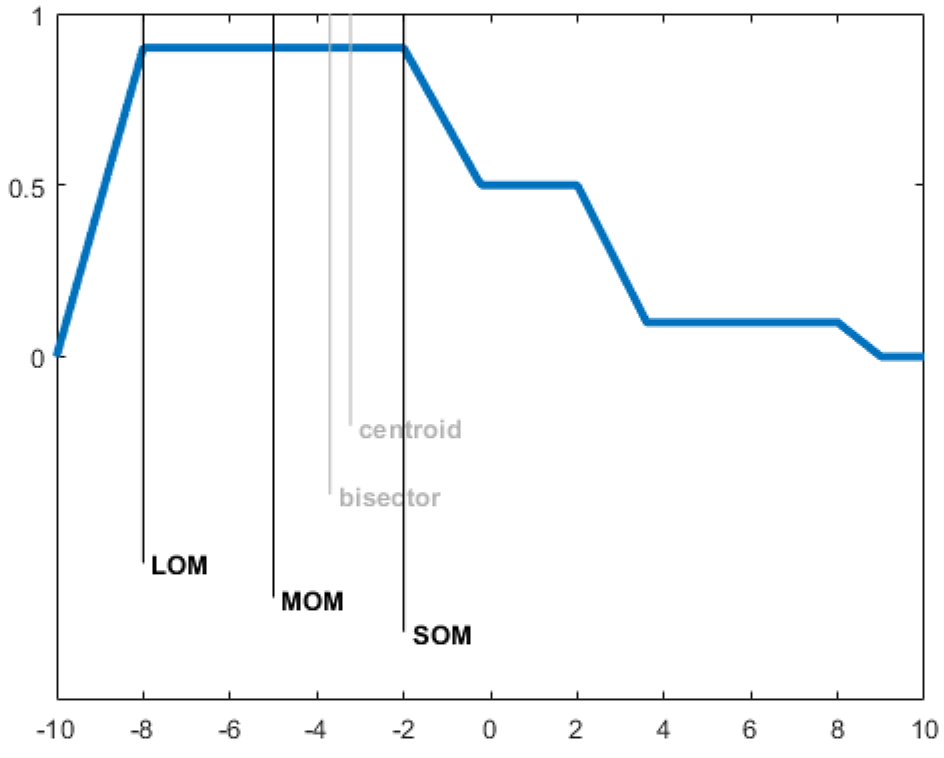
```
x4 = defuzz(x,mf1,'som')
```

```
x4 = -2
```

```
x5 = defuzz(x,mf1,'lom')
```

```
x5 = -8
```

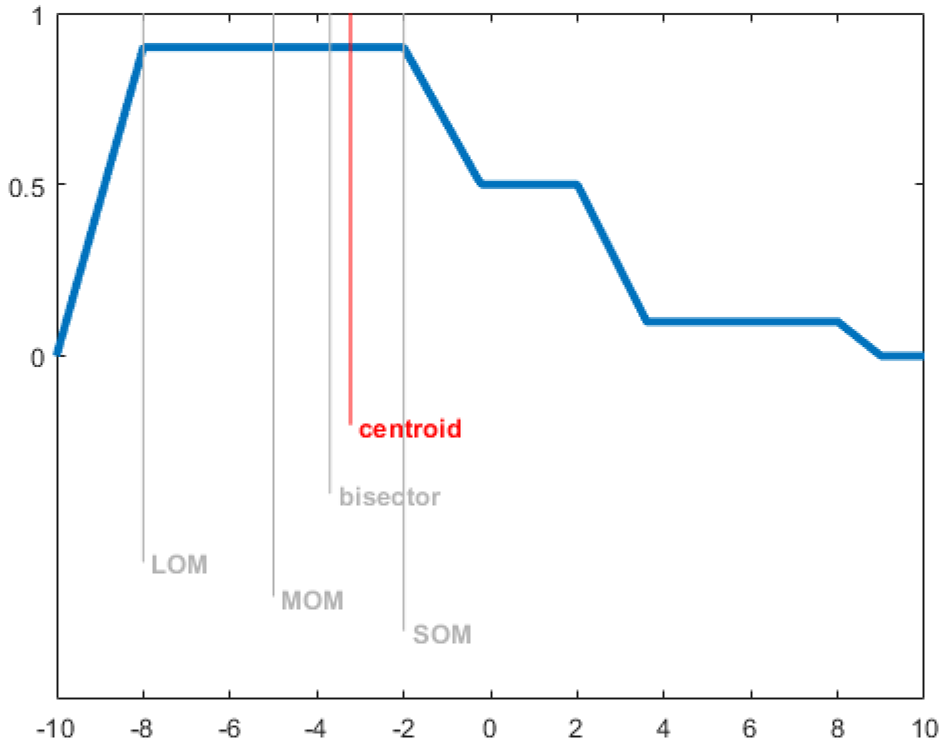
```
h2.Color = gray;
t2.Color = gray;

h3 = line([x3 x3],[-0.7 1.2],'Color','k');
t3 = text(x3,-0.7,' MOM','FontWeight','bold');
h4 = line([x4 x4],[-0.8 1.2],'Color','k');
t4 = text(x4,-0.8,' SOM','FontWeight','bold');
h5 = line([x5 x5],[-0.6 1.2],'Color','k');
t5 = text(x5,-0.6,' LOM','FontWeight','bold');
```



Picking a Method

Which of these methods is the right one? There's no simple answer. But if you want to get started quickly, generally the centroid method is good enough. Later you can always change your defuzzification method to see if another method works better.

```
h3.Color = gray;
t3.Color = gray;
h4.Color = gray;
t4.Color = gray;
h5.Color = gray;
t5.Color = gray;
h1.Color = 'red';
t1.Color = 'red';
```



See Also

More About

- “Foundations of Fuzzy Logic” on page 1-10
- “Fuzzy Inference Process” on page 1-28

Fuzzy vs. Nonfuzzy Logic

Basic Tipping Problem

To illustrate the value of fuzzy logic, examine both linear and fuzzy approaches to the following problem:

What is the right amount to tip your waitperson?

First, work through this problem the conventional (nonfuzzy) way, writing MATLAB® commands that spell out linear and piecewise-linear relations. Then, look at the same system using fuzzy logic.

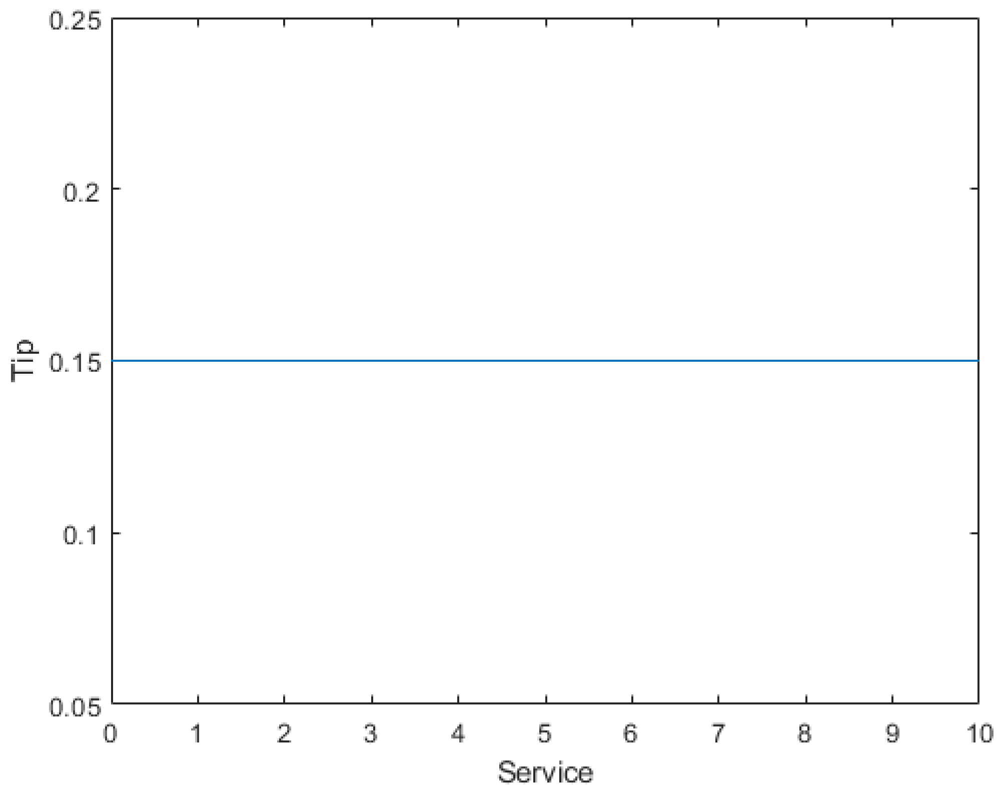
Basic Tipping Problem. Given a number from 0 through 10 that represents the quality of service at a restaurant (where 10 is excellent), what should the tip be?

This problem is based on tipping as it is typically practiced in the United States. An average tip for a meal in the US is 15%, though the actual amount can vary depending on the quality of the service provided.

Nonfuzzy Approach

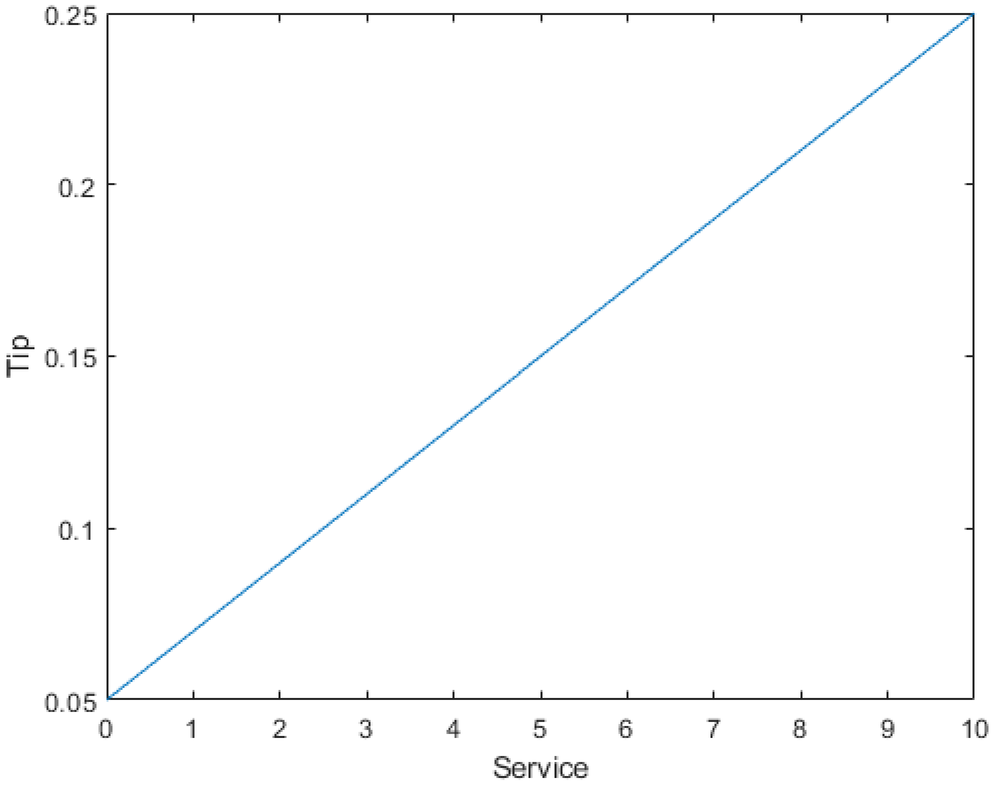
Begin with the simplest possible relationship. Suppose that the tip always equals 15% of the total bill.

```
service = 0:.5:10;
tip = 0.15*ones(size(service));
plot(service,tip)
xlabel('Service')
ylabel('Tip')
ylim([0.05 0.25])
```



This relationship does not account for the quality of the service, so you must add a term to the equation. Since service is rated on a scale from 0 through 10, you the tip increase linearly from 5% if the service is bad to 25% if the service is excellent. Now the relation looks like the following plot:

```
tip = (.20/10)*service+0.05;
plot(service,tip)
xlabel('Service')
ylabel('Tip')
ylim([0.05 0.25])
```



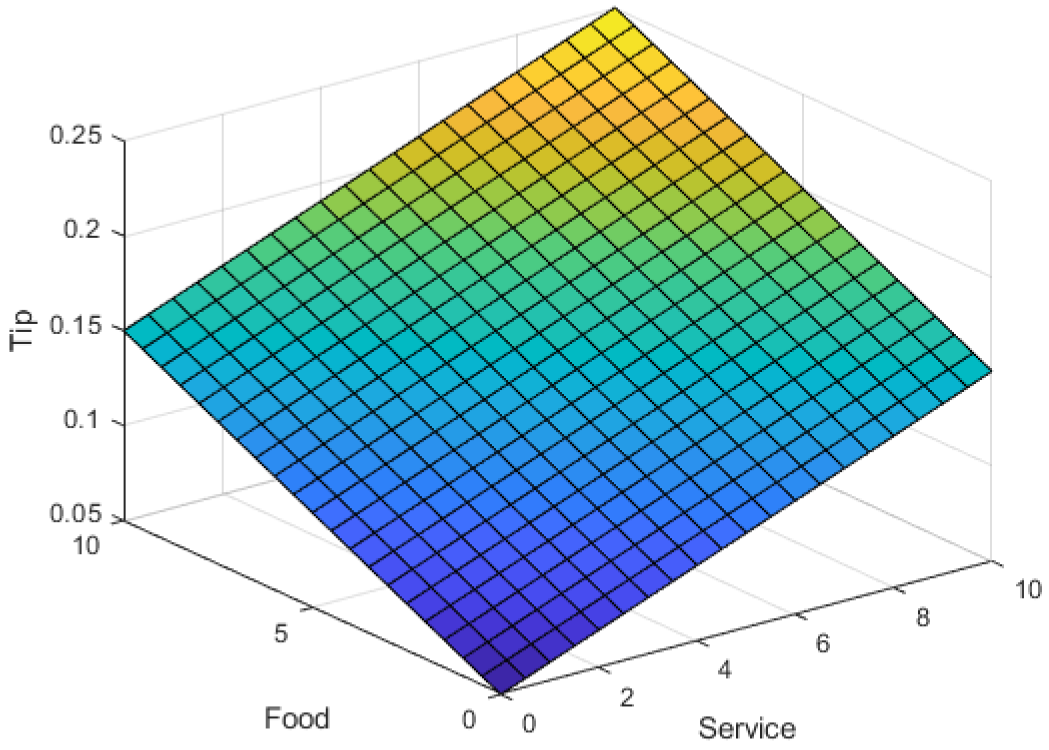
The formula does what you want it to do, and is straight forward. However, you may want the tip to reflect the quality of the food as well. This extension of the problem is defined as follows.

Extended Tipping Problem. Given two sets of numbers from 0 through 10 (where 10 is excellent) that respectively represent the quality of the service and the quality of the food at a restaurant, what should the tip be?

See how the formula is affected now that you have added another variable.

```
food = 0:.5:10;
[F,S] = meshgrid(food,service);
tip = (0.20/20).*(S+F)+0.05;
surf(S,F,tip)
```

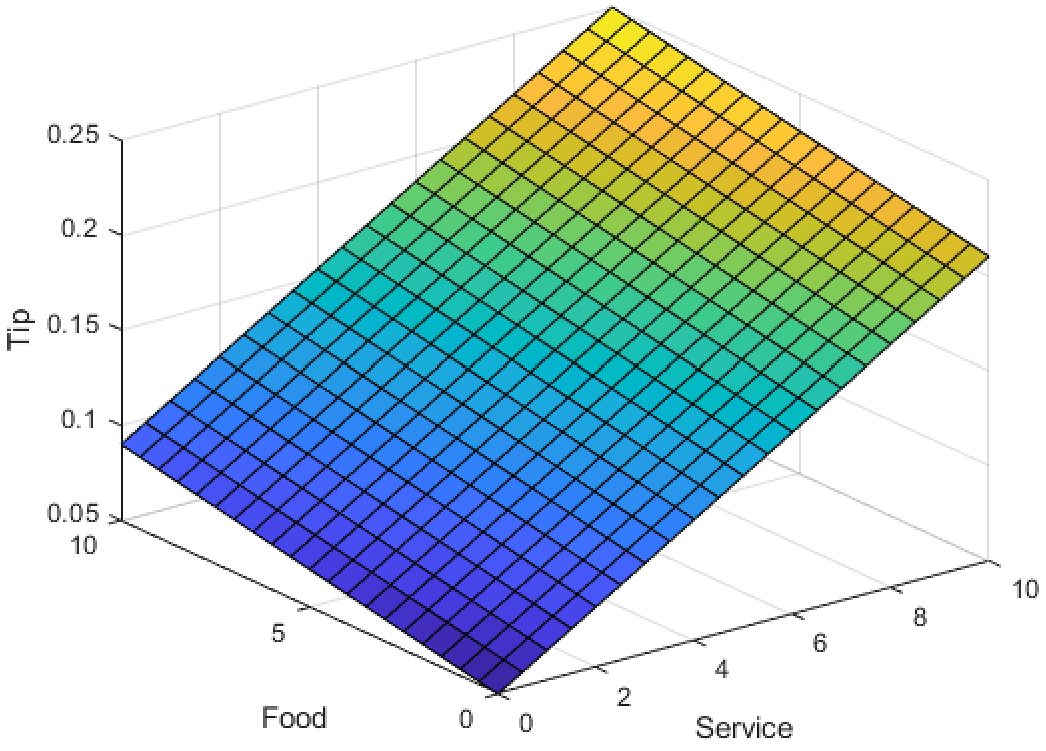
```
xlabel('Service')
ylabel('Food')
zlabel('Tip')
```



In this case, the results look satisfactory, but when you look at them closely, they do not seem right. Suppose that you want the service to be a more important factor than the food quality. Specify that service accounts for 80% of the overall tipping grade and the food makes up the other 20%.

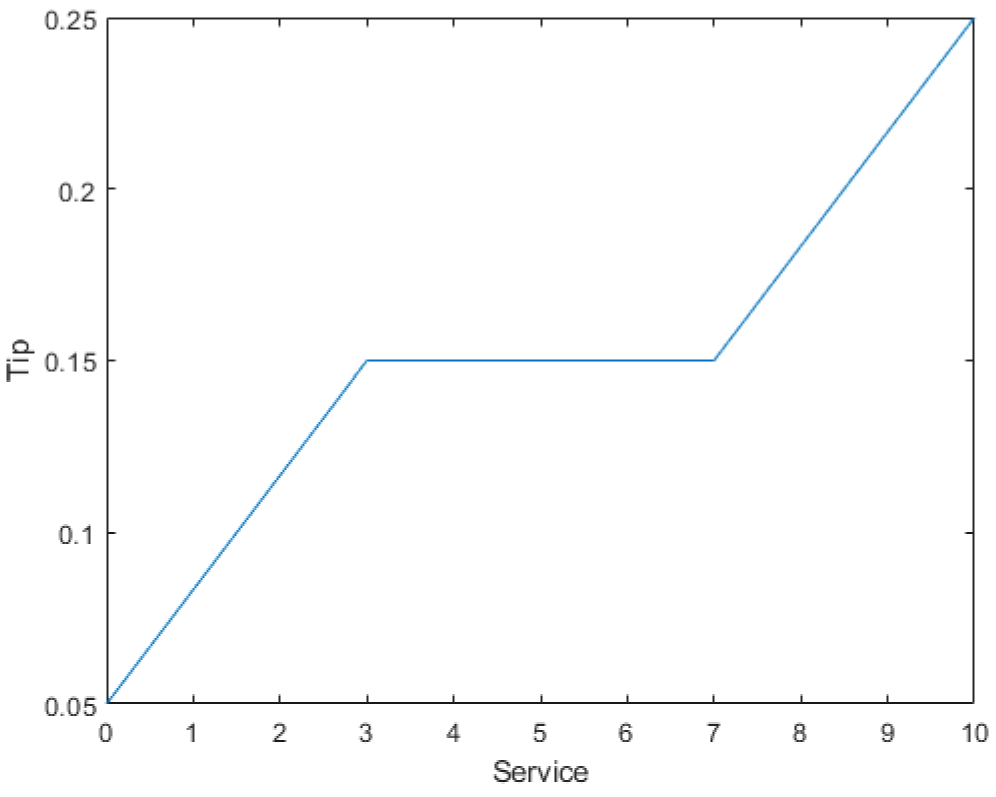
```
servRatio = 0.8;
tip = servRatio*(0.20/10*S+0.05) + ...
    (1-servRatio)*(0.20/10*F+0.05);
surf(S,F,tip)
xlabel('Service')
```

```
ylabel('Food')
zlabel('Tip')
```



The response is still some how too uniformly linear. Suppose that you want more of a flat response in the middle, that is, you want to give a 15% tip in general, but want to also specify a variation if the service is exceptionally good or bad. This factor, in turn, means that the previous linear mappings no longer apply. You can still use the linear calculation with a piecewise linear construction. Now, return to the one-dimensional problem of just considering the service. You can create a simple conditional tip assignment using logical indexing.

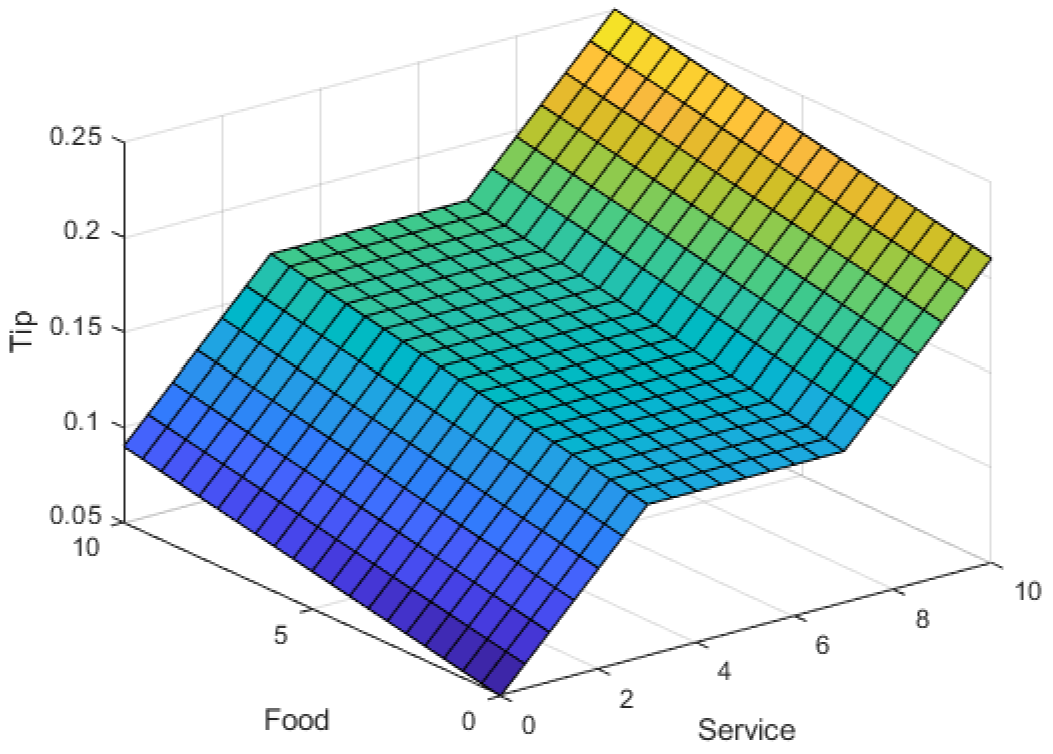
```
tip = zeros(size(service));
tip(service<3) = (0.10/3)*service(service<3)+0.05;
tip(service>=3 & service<7) = 0.15;
tip(service>=7 & service<=10) = ...
    (0.10/3)*(service(service>=7 & service<=10)-7)+0.15;
plot(service,tip)
xlabel('Service')
ylabel('Tip')
ylim([0.05 0.25])
```



Suppose that you extend this approach to two dimensions, where you account for food quality again.

```
servRatio = 0.8;
tip = zeros(size(S));
tip(S<3) = ((0.10/3)*S(S<3)+0.05)*servRatio + ...
    (1-servRatio)*(0.20/10*F(S<3)+0.05);
```

```
tip(S>=3 & S<7) = (0.15)*servRatio + ...
    (1-servRatio)*(0.20/10*F(S>=3 & S<7)+0.05);
tip(S>=7 & S<=10) = ((0.10/3)*(S(S>=7 & S<=10)-7)+0.15)*servRatio + ...
    (1-servRatio)*(0.20/10*F(S>=7 & S<=10)+0.05);
surf(S,F,tip)
xlabel('Service')
ylabel('Food')
zlabel('Tip')
```



The plot looks good, but the function is surprisingly complicated. It is even not apparent how the algorithm works to someone who did not see the original design process.

Fuzzy Logic Approach

In general, you want to capture the essentials of this problem, leaving aside all the factors that could be arbitrary. If you make a list of what really matters in this problem, you could end up with the following rule descriptions.

Tipping Problem Rules - Service Factor

- If service is poor, then tip is cheap
- If service is good, then tip is average
- If service is excellent, then tip is generous

The order in which the rules are presented here is arbitrary. It does not matter which rules come first. To include the effect of food quality on the tip, add the following two rules.

Tipping Problem Rules - Food Factor

- If food is rancid, then tip is cheap
- If food is delicious, then tip is generous

You can combine the two different lists of rules into one list of three rules like so.

Tipping Problem Rules - Both Service and Food Factors

- If service is poor or the food is rancid, then tip is cheap
- If service is good, then tip is average
- If service is excellent or food is delicious, then tip is generous

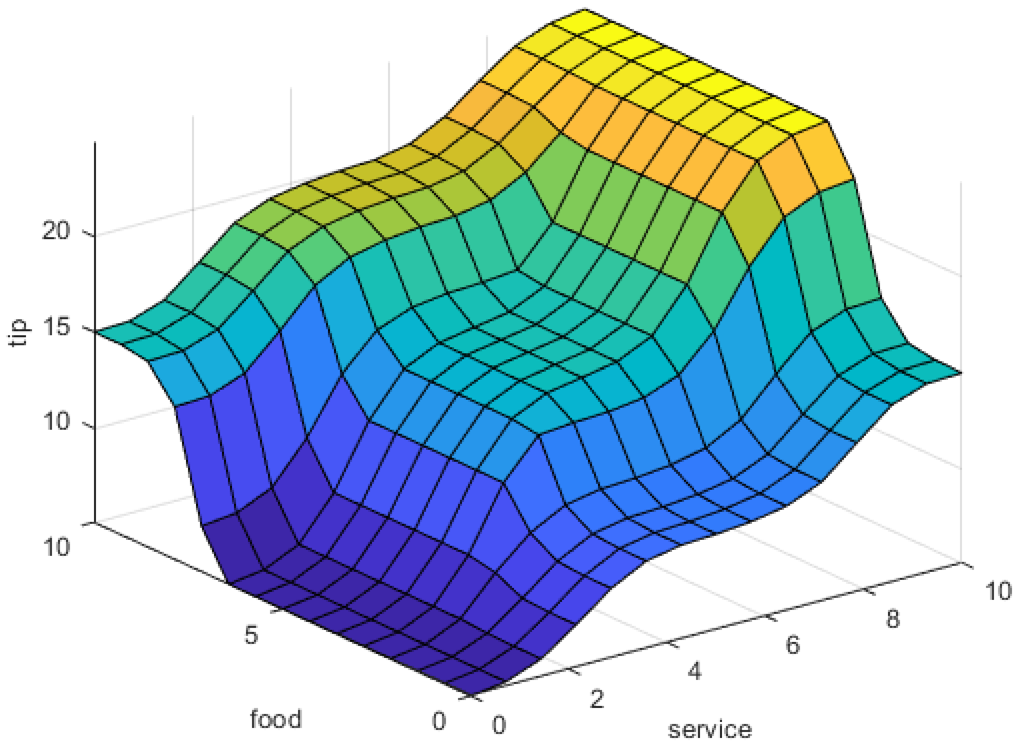
These three rules are the core of your solution and they correspond to the rules for a fuzzy logic system. When you give mathematical meaning to the linguistic variables (what is an average tip, for example) you have a complete fuzzy inference system. The methodology of fuzzy logic must also consider:

- How are the rules all combined?
- How do I define mathematically what an average tip is?

Problem Solution

The following plot represents the fuzzy logic system that solves the tipping problem.

```
gensurf(readfis('tipper'))
```



This plot was generated by the three rules that accounted for both service and food factors.

Observations Consider some observations about the example so far. You found a piecewise linear relation that solved the problem. It worked, but it was problematic to derive, and when you wrote it down as code, it was not easy to interpret. Conversely, the fuzzy logic system is based on some common sense statements. Also, you were able to add two more rules to the list that influenced the shape of the overall output without needing to undo what had already been done.

Moreover, by using fuzzy logic rules, the maintenance of the structure of the algorithm decouples along fairly clean lines. The notion of an average tip can change from day to day, city to city, country to country. However, the underlying logic is the same: if the service is good, the tip should be average.

Recalibrating the Method You can recalibrate the method quickly by simply shifting the fuzzy set that defines average without rewriting the fuzzy logic rules.

You can shift lists of piecewise linear functions, but there is a greater likelihood for difficult recalibration.

In the following example, the piecewise linear tipping problem is rewritten to make it more generic. It performs the same function as before, only now the constants can be easily changed.

```
lowTip = 0.05;
averTip = 0.15;
highTip = 0.25;
tipRange = highTip-lowTip;
badService = 0;
okayService = 3;
goodService = 7;
greatService = 10;
serviceRange = greatService-badService;
badFood = 0;
greatFood = 10;
foodRange = greatFood-badFood;

% If service is poor or food is rancid, tip is cheap
if service<okayService
    tip = (((averTip-lowTip)/(okayService-badService)) ...
        *service+lowTip)*servRatio + ...
        (1-servRatio)*(tipRange/foodRange*food+lowTip);

% If service is good, tip is average
elseif service<goodService
    tip = averTip*servRatio + (1-servRatio)* ...
        (tipRange/foodRange*food+lowTip);

% If service is excellent or food is delicious, tip is generous
else
    tip = (((highTip-averTip)/ ...
        (greatService-goodService))* ...
        (service-goodService)+averTip)*servRatio + ...
        (1-servRatio)*(tipRange/foodRange*food+lowTip);
end
```

As with all code, the more generality that is introduced, the less precise the algorithm becomes. You can improve clarity by adding more comments, or perhaps rewriting the algorithm in slightly more self-evident ways. But, the piecewise linear methodology is not the optimal way to resolve this issue.

If you remove everything from the algorithm except for three comments, what remain are exactly the fuzzy logic rules you previously wrote down.

- If service is poor or food is rancid, tip is cheap
- If service is good, tip is average
- If service is excellent or food is delicious, tip is generous

Fuzzy logic uses language that is clear to you and that also has meaning to the computer, which is why it is a successful technique for bridging the gap between people and machines.

By making the equations as simple as possible (linear) you make things simpler for the machine, but more complicated for you. However, the limitation is no longer the computer - it is your mental model of what the computer is doing. Fuzzy logic lets the machine work with your preferences rather than the other way around.

See Also

Related Examples

- "Build Fuzzy Systems at the Command Line" on page 2-38
- "Build Fuzzy Systems Using Fuzzy Logic Designer" on page 2-14

Fuzzy Inference System Modeling

Types of Fuzzy Inference Systems

You can implement two types of fuzzy inference systems in the toolbox:

- Mamdani
- Sugeno

These two types of inference systems vary somewhat in the way outputs are determined.

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani [1] as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes [2]. Although the inference process described in the next few sections differs somewhat from the methods described in the original paper, the basic idea is much the same.

Mamdani-type inference, as defined for the toolbox, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It is possible, and in many cases much more efficient, to use a single spike as the output membership function rather than a distributed fuzzy set. This type of output is sometimes known as a *singleton* output membership function, and it can be thought of as a pre-defuzzified fuzzy set. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function. Rather than integrating across the two-dimensional function to find the centroid, you use the weighted average of a few data points. Sugeno-type systems support this type of model. In general, Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant.

For descriptions of these two types of fuzzy inference systems, see [3], [1], and [4].

Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Because of its multidisciplinary nature, fuzzy inference systems are associated with a number of names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers, and simply (and ambiguously) fuzzy systems.

References

[1] Mamdani, E.H. and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," *International Journal of Man-Machine Studies*, Vol. 7, No. 1, pp. 1-13, 1975.

[2] Zadeh, L.A., "Outline of a new approach to the analysis of complex systems and decision processes," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 3, No. 1, pp. 28-44, Jan. 1973.

[3] Jang, J.-S. R. and C.-T. Sun, *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Prentice Hall, 1997.

[4] Sugeno, M., *Industrial applications of fuzzy control*, Elsevier Science Pub. Co., 1985.

See Also

More About

- “Fuzzy Inference Process” on page 1-28
- “What Is Mamdani-Type Fuzzy Inference?” on page 2-4
- “What Is Sugeno-Type Fuzzy Inference?” on page 2-5
- “Comparison of Sugeno and Mamdani Systems” on page 2-12

What Is Mamdani-Type Fuzzy Inference?

Mamdani fuzzy inference is the most commonly seen fuzzy methodology and was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani [1] as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes [2]. Although the inference process described in the next few sections differs somewhat from the methods described in the original paper, the basic idea is much the same.

Mamdani-type inference, as defined for the toolbox, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification.

References

[1] Mamdani, E.H. and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," *International Journal of Man-Machine Studies*, Vol. 7, No. 1, pp. 1-13, 1975.

[2] Zadeh, L.A., "Outline of a new approach to the analysis of complex systems and decision processes," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 3, No. 1, pp. 28-44, Jan. 1973.

See Also

More About

- “Comparison of Sugeno and Mamdani Systems” on page 2-12
- “What Is Sugeno-Type Fuzzy Inference?” on page 2-5
- “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14
- “Build Fuzzy Systems at the Command Line” on page 2-38
- “Build Fuzzy Systems Using Custom Functions” on page 2-50

What Is Sugeno-Type Fuzzy Inference?

This topic discusses the Sugeno, or Takagi-Sugeno-Kang, method of fuzzy inference. Introduced in 1985 [1], this method is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

A typical rule in a Sugeno fuzzy model has the form:
If Input 1 is x and Input 2 is y, then Output is $z = ax + by + c$

For a zero-order Sugeno model, the output level z is a constant ($a = b = 0$).

Each rule weights its output level, z_i, by the firing strength of the rule, w_i. For example, for an AND rule with Input 1 = x and Input 2 = y, the firing strength is

$$w_i = AndMethod(F_1(x), F_2(y))$$

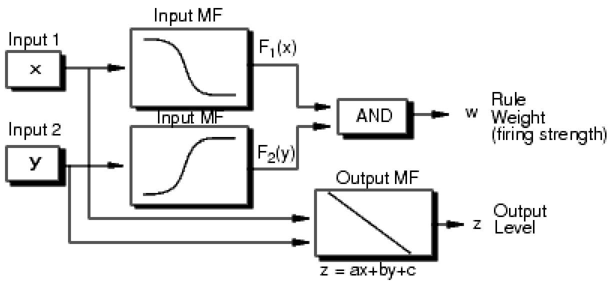
where $F_{1,2}(.)$ are the membership functions for Inputs 1 and 2.

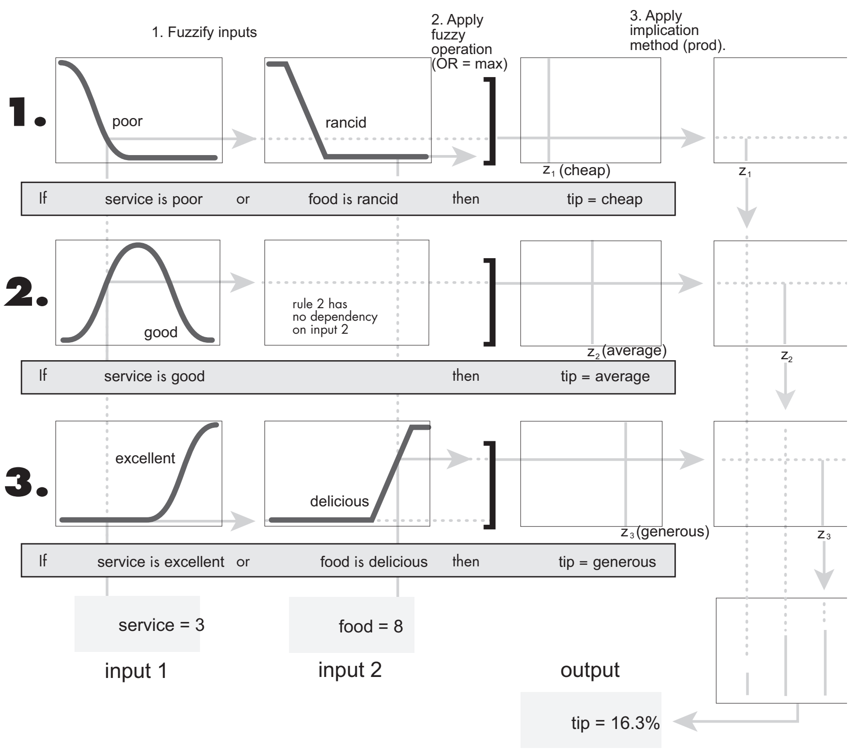
The final output of the system is the weighted average of all rule outputs, computed as

$$\text{Final Output} = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$$

where N is the number of rules.

A Sugeno rule operates as shown in the following diagram.

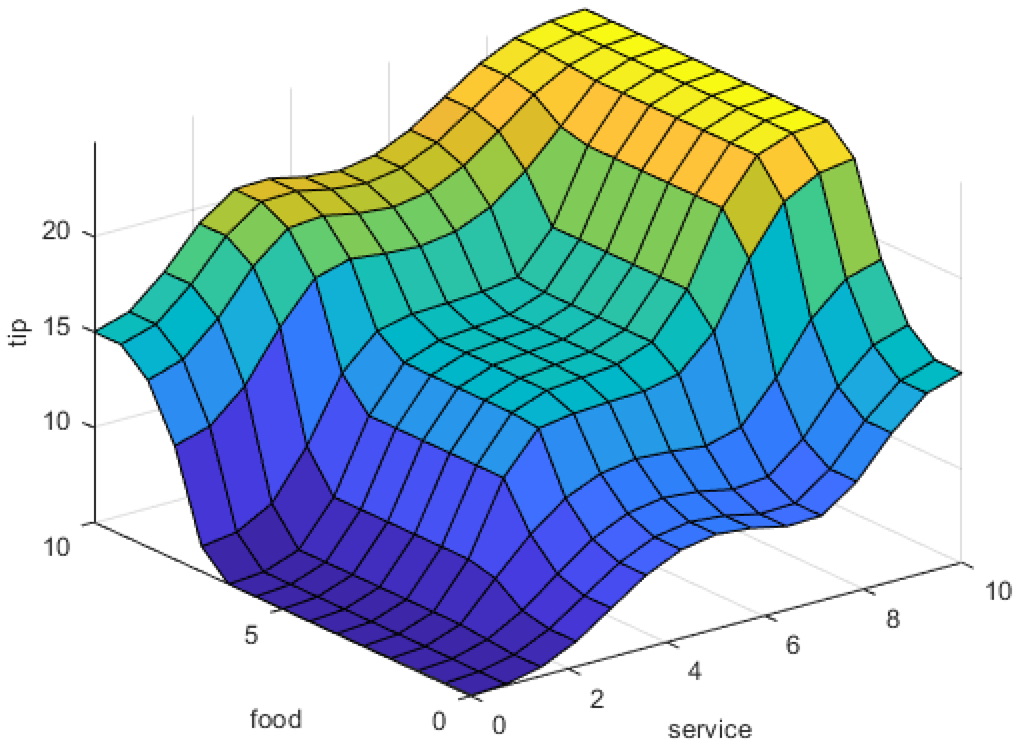



1. Fuzzify inputs
2. Apply fuzzy operation (OR = max)
3. Apply implication method (prod).
1.
poor
rancid
z_1 (cheap)
z_1
If service is poor or food is rancid then tip = cheap
2.
good
rule 2 has no dependency on input 2
z_2 (average)
z_2
If service is good then tip = average
3.
excellent
delicious
z_3 (generous)
z_3
If service is excellent or food is delicious then tip = generous
service = 3
input 1
food = 8
input 2
output
tip = 16.3%

Note Sugeno systems always use product implication and sum aggregation.

The preceding figure shows the fuzzy tipping model developed in “Fuzzy Inference Process” on page 1-28 adapted for use as a Sugeno system. Fortunately, it is frequently the case that singleton output functions are sufficient for the needs of a given problem. As an example, the system `tippersg.fis` is the Sugeno-type representation of the now-familiar tipping model. If you load the system and plot its output surface, you see that it is almost the same as the Mamdani system you have previously seen.

```
fis = readfis('tippersg');
gensurf(fis)
```



The easiest way to visualize first-order Sugeno systems is to think of each rule as defining the location of a moving singleton. That is, the singleton output spikes can move around in a linear fashion in the output space, depending on what the input is. This also tends to make the system notation compact and efficient. Higher-order Sugeno fuzzy models are possible, but they introduce significant complexity with little obvious merit. Sugeno fuzzy models whose output membership functions are greater than first order are not supported by Fuzzy Logic Toolbox software.

Because of the linear dependence of each rule on the input variables, the Sugeno method is ideal for acting as an interpolating supervisor of multiple linear controllers that are to be applied, respectively, to different operating conditions of a dynamic nonlinear system. For example, the performance of an aircraft may change dramatically with altitude and Mach number. Linear controllers, though easy to compute and suited to any given flight condition, must be updated regularly and smoothly to keep up with the changing state of the flight vehicle. A Sugeno fuzzy inference system is suited to the task of smoothly interpolating the linear gains that would be applied across the input space; it is a natural and efficient gain scheduler. Similarly, a Sugeno system is suited for modeling nonlinear systems by interpolating between multiple linear models.

To see a specific example of a system with linear output membership functions, consider the one-input, one-output system stored in `sugeno1.fis`. Load the system and view the properties of its output variable.

```
fis = readfis('sugeno1');
fis.Outputs(1)
```

```
ans = 
  fisvar with properties:

                   Name: "output"
                  Range: [0 1]
    MembershipFunctions: [1x2 fismf]
```

The output variable has two membership functions. View the properties of the first membership function.

```
fis.Outputs(1).MembershipFunctions(1)
```

```
ans = 
  fismf with properties:

          Name: "line1"
          Type: "linear"
    Parameters: [-1 -1]
```

View the properties of the second membership function.

```
fis.Outputs(1).MembershipFunctions(2)
```

```
ans = 
  fismf with properties:

          Name: "line2"
          Type: "linear"
    Parameters: [1 -1]
```

Further, these membership functions are linear functions of the input variable. The membership function `line1` is defined by the equation:

$$output = (-1) \times input + (-1)$$

and the membership function `line2` is:

$$output = (1) \times input + (-1)$$

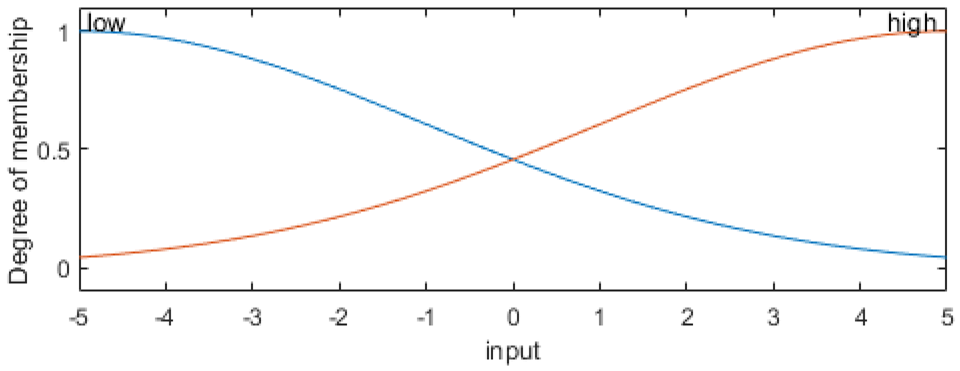
The input membership functions and rules define which of these output functions are expressed and when:

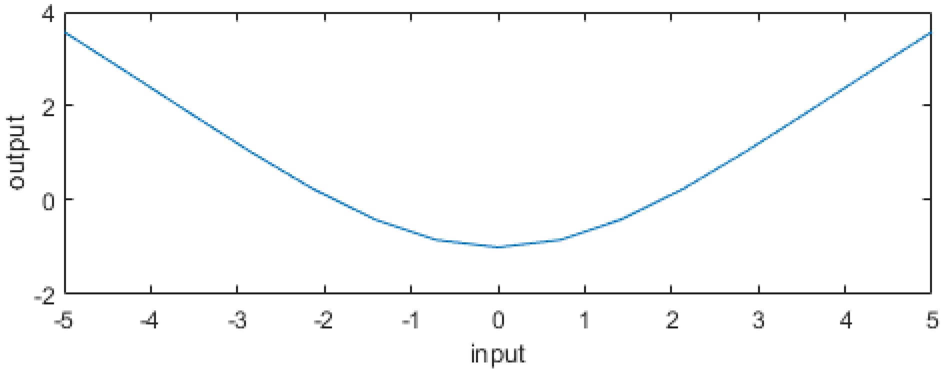
```
fis.Rules
```

```
ans = 
  1x2 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                   Description                
         _________________________________

    1    "input==low => output=line1 (1)" 
    2    "input==high => output=line2 (1)"
```

The function `plotmf` shows us that the membership function `low` generally refers to input values less than zero, while `high` refers to values greater than zero. The function `gensurf` shows how the overall fuzzy system output switches smoothly from the line called `line1` to the line called `line2`.

```
subplot(2,1,1)
plotmf(fis,'input',1)
subplot(2,1,2)
gensurf(fis)
```





As this example shows, Sugeno-type system gives you the freedom to incorporate linear systems into your fuzzy systems. By extension, you could build a fuzzy system that switches between several optimal linear controllers as a highly nonlinear system moves around in its operating space.

References

[1] Sugeno, M., *Industrial applications of fuzzy control*, Elsevier Science Pub. Co., 1985.

See Also

`gensurf` | `readfis`

More About

- “Comparison of Sugeno and Mamdani Systems” on page 2-12
- “What Is Mamdani-Type Fuzzy Inference?” on page 2-4

Comparison of Sugeno and Mamdani Systems

Because it is a more compact and computationally efficient representation than a Mamdani system, a Sugeno system lends itself to the use of adaptive techniques for constructing fuzzy models. These adaptive techniques can be used to customize the membership functions so that the fuzzy system best models the data.

You can convert a Mamdani system into a Sugeno system using the `convertToSugeno` function. The resulting Sugeno system has constant output membership functions that correspond to the centroids of the Mamdani output membership functions.

Advantages of the Sugeno Systems

Sugeno systems:

- Are computationally efficient.
- Work well with linear techniques, such as PID control.
- Work well with optimization and adaptive techniques.
- Guarantee continuity of the output surface.
- Well-suited to mathematical analysis.

Advantages of the Mamdani Systems

Mamdani systems:

- Are intuitive.
- Have widespread acceptance.
- Are well-suited to human input.

See Also

`convertToSugeno`

More About

- "What Is Mamdani-Type Fuzzy Inference?" on page 2-4

- “What Is Sugeno-Type Fuzzy Inference?” on page 2-5

Build Fuzzy Systems Using Fuzzy Logic Designer

Fuzzy Logic Toolbox Graphical User Interface Tools

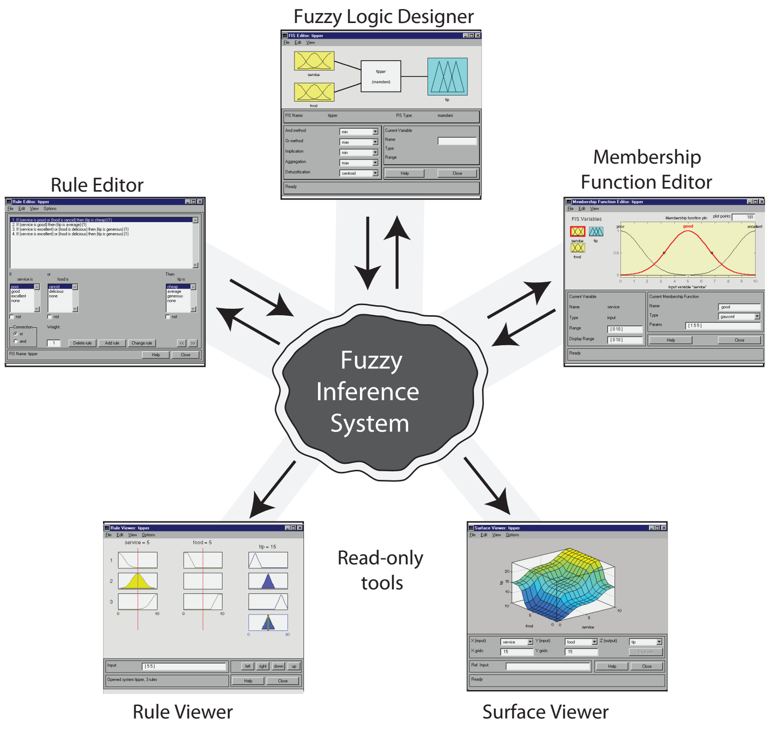
This example shows how to build a fuzzy inference system (FIS) for the tipping example, described in “The Basic Tipping Problem” on page 2-16, using the Fuzzy Logic Toolbox UI tools.

You use the following tools to build, edit, and view fuzzy inference systems:

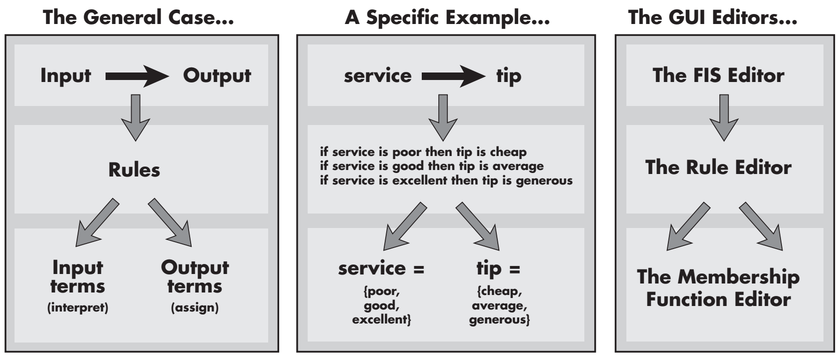
- **Fuzzy Logic Designer** to handle the high-level issues for the system — How many input and output variables? What are their names?

  Fuzzy Logic Toolbox software does not limit the number of inputs. However, the number of inputs may be limited by the available memory of your machine. If the number of inputs is too large, or the number of membership functions is too big, then it may also be difficult to analyze the FIS using the other tools.
- **Membership Function Editor** on page 2-22 to define the shapes of all the membership functions associated with each variable
- **Rule Editor** on page 2-30 to edit the list of rules that defines the behavior of the system.
- **Rule Viewer** on page 2-33 to view the fuzzy inference diagram. Use this viewer as a diagnostic to see, for example, which rules are active, or how individual membership function shapes influence the results
- **Surface Viewer** on page 2-35 to view the dependency of one of the outputs on any one or two of the inputs; that is, it generates and plots an output surface map for the system.

These UIs are dynamically linked, in that changes you make to the FIS using one of them, affect what you see on any of the other open UIs. For example, if you change the names of the membership functions in the Membership Function Editor, the changes are reflected in the rules shown in the Rule Editor. You can use the UIs to read and write variables both to the MATLAB workspace and to a file (the read-only viewers can still exchange plots with the workspace and save them to a file). You can have any or all of them open for any given system or have multiple editors open for any number of fuzzy systems.



The following figure shows how the main components of a FIS and the three editors fit together. The two viewers examine the behavior of the entire system.


The General Case...
Input
Output
Rules
Input terms (interpret)
Output terms (assign)
A Specific Example...
service
tip
if service is poor then tip is cheap
if service is good then tip is average
if service is excellent then tip is generous
service = {poor, good, excellent}
tip = {cheap, average, generous}
The GUI Editors...
The FIS Editor
The Rule Editor
The Membership Function Editor

In addition to these five primary UIs, the toolbox includes the graphical **Neuro-Fuzzy Designer**, which you use to build and analyze Sugeno-type adaptive neuro-fuzzy inference systems.

The Fuzzy Logic Toolbox UIs do not support building a FIS using data. If you want to use data to build a FIS, use one of the following techniques:

- `genfis` to generate a Sugeno-type FIS. Then, select **File** > **Import** in the **Fuzzy Logic Designer** to import the FIS and perform fuzzy inference, as described in "The Fuzzy Logic Designer" on page 2-17.
- Neuro-adaptive learning techniques to model the FIS, as described in "Neuro-Adaptive Learning and ANFIS" on page 3-86.

If you want to use MATLAB workspace variables, use the command-line interface instead of the **Fuzzy Logic Designer**. For an example, see "Build Fuzzy Systems at the Command Line" on page 2-38.

The Basic Tipping Problem

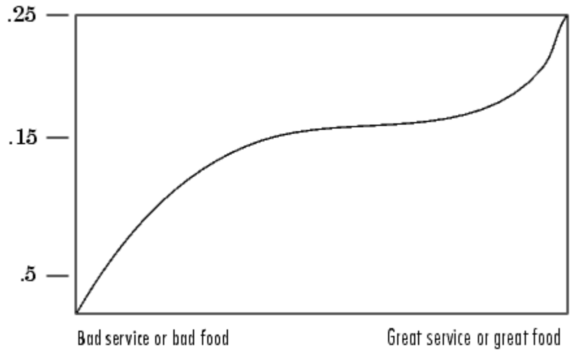
This example creates a Mamdani fuzzy inference system using on a two-input, one-output tipping problem based on tipping practices in the U.S. While the example creates a Mamdani FIS, the methods used apply to creating Sugeno systems as well.

Given a number between 0 and 10 that represents the quality of service at a restaurant (where 10 is excellent), and another number between 0 and 10 that represents the quality of the food at that restaurant (again, 10 is excellent), what should the tip be?

The starting point is to write down the three golden rules of tipping:

1. *If the service is poor or the food is rancid, then tip is cheap.*
2. *If the service is good, then tip is average.*
3. *If the service is excellent or the food is delicious, then tip is generous.*

Assume that an average tip is 15%, a generous tip is 25%, and a cheap tip is 5%.



The numbers and the shape of the curve are subject to local traditions, cultural bias, and so on, but the three rules are generally universal.

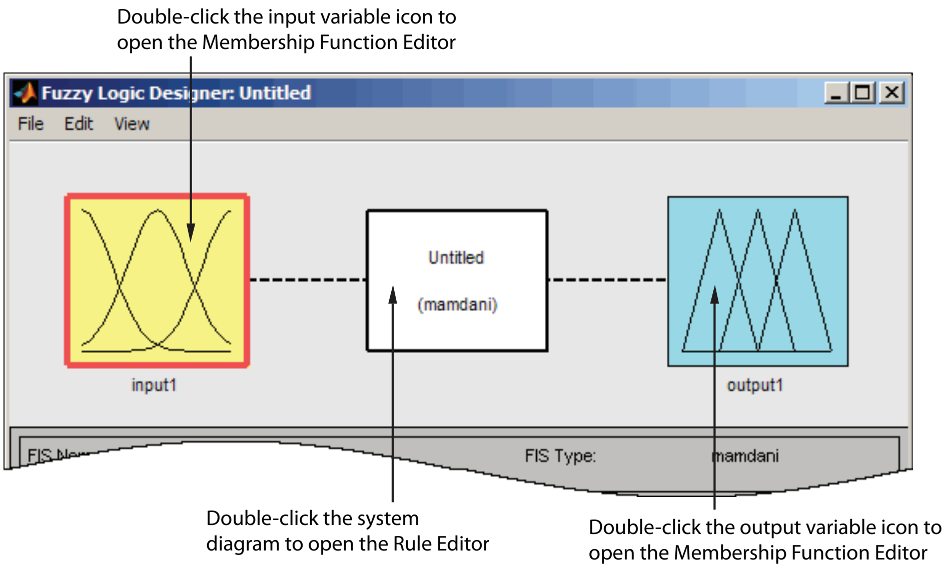
Now that you know the rules and have an idea of what the output should look like, use the UI tools to construct a fuzzy inference system for this decision process.

The Fuzzy Logic Designer

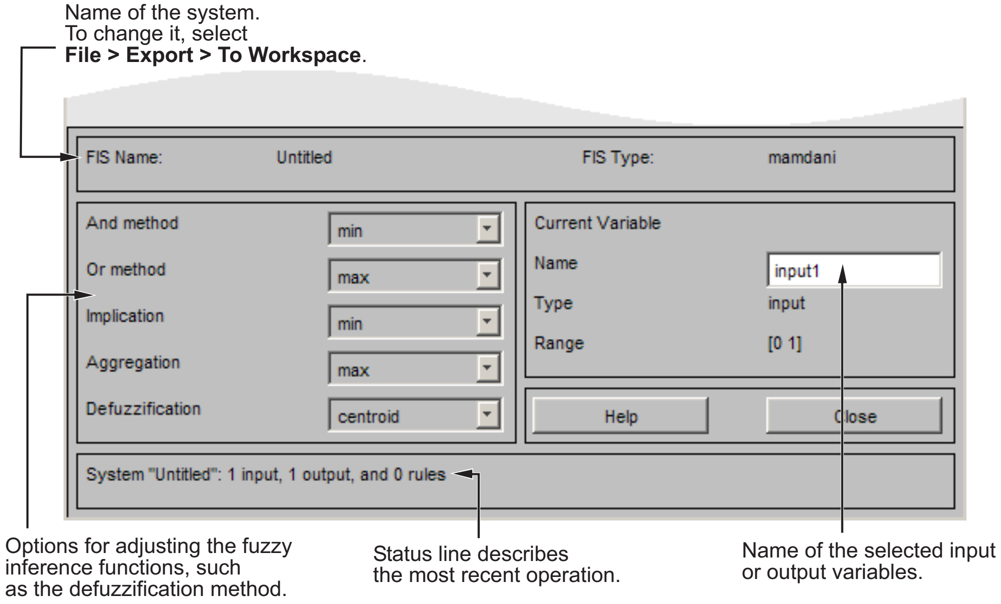
The **Fuzzy Logic Designer** displays information about a fuzzy inference system. To open the **Fuzzy Logic Designer**, type the following command at the MATLAB prompt:

```
fuzzyLogicDesigner
```

The **Fuzzy Logic Designer** opens and displays a diagram of the fuzzy inference system with the names of each input variable on the left, and those of each output variable on the right, as shown in the next figure. The sample membership functions shown in the boxes are just icons and do not depict the actual shapes of the membership functions.


Double-click the input variable icon to open the Membership Function Editor
Fuzzy Logic Designer: Untitled
File
Edit
View
input1
Untitled
(mamdani)
output1
FIS Type:
mamdani
Double-click the system diagram to open the Rule Editor
Double-click the output variable icon to open the Membership Function Editor

Below the diagram is the name of the system and the type of inference used.


Name of the system.
To change it, select
File > Export > To Workspace.
Options for adjusting the fuzzy inference functions, such as the defuzzification method.
Status line describes the most recent operation.
Name of the selected input or output variables.
Help
Close

FIS Name: Untitled
FIS Type: mamdani

And method: min
Or method: max
Implication: min
Aggregation: max
Defuzzification: centroid

Current Variable
Name: input1
Type: input
Range: [0 1]

System "Untitled": 1 input, 1 output, and 0 rules

In this example, you use the default Mamdani-type inference. Another type of inference, called Sugeno-type inference, is also available. See “What Is Sugeno-Type Fuzzy Inference?” on page 2-5.

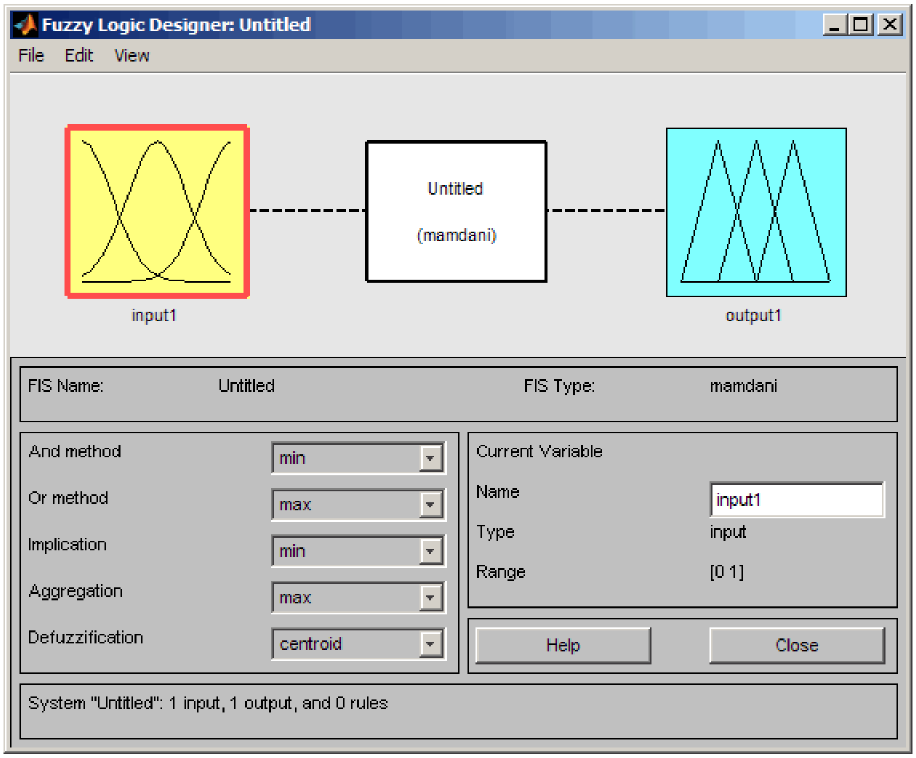
In the **Fuzzy Logic Designer**:

- The drop-down lists let you modify the fuzzy inference functions.
- The **Current Variable** area displays the name of either an input or output variable, its type, and default range.
- A status line at the bottom displays information about the most recent operation.

To build the fuzzy inference system described in “The Basic Tipping Problem” on page 2-16 from scratch, type the following command at the MATLAB prompt:

```
fuzzyLogicDesigner
```

The generic untitled **Fuzzy Logic Designer** opens, with one input **input1**, and one output **output1**.



FIS Name: Untitled FIS Type: mamdani

And method: min
Or method: max
Implication: min
Aggregation: max
Defuzzification: centroid

Current Variable
Name: input1
Type: input
Range: [0 1]

System "Untitled": 1 input, 1 output, and 0 rules

Tip To open the **Fuzzy Logic Designer** with the prebuilt fuzzy inference system stored in `tipper.fis`, enter

```
fuzzyLogicDesigner('tipper.fis')
```

However, if you load the prebuilt system, you will not build rules or construct membership functions.

In this example, you construct a two-input, one output system. The two inputs are **service** and **food**. The one output is **tip**.

To add a second input variable and change the variable names to reflect these designations:

1. Select **Edit > Add variable > Input**.

A second yellow box labeled **input2** appears.

2 Click the yellow box **input1**. This box is highlighted with a red outline.

3 Edit the **Name** field from `input1` to `service`, and press **Enter**.

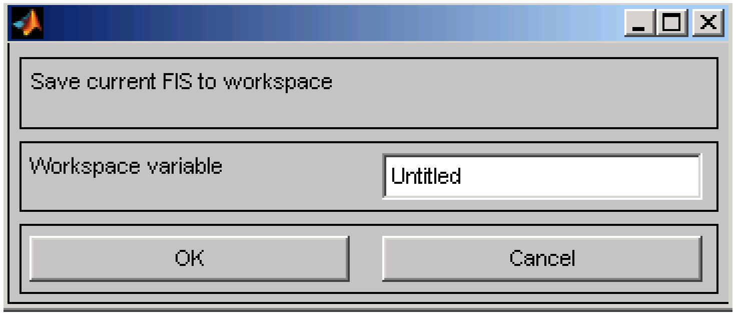
4 Click the yellow box **input2**. This box is highlighted with a red outline.

5 Edit the **Name** field from `input2` to `food`, and press **Enter**.

6 Click the blue box **output1**.

7 Edit the **Name** field from `output1` to `tip`, and press **Enter**.

8 Select **File > Export > To Workspace**.

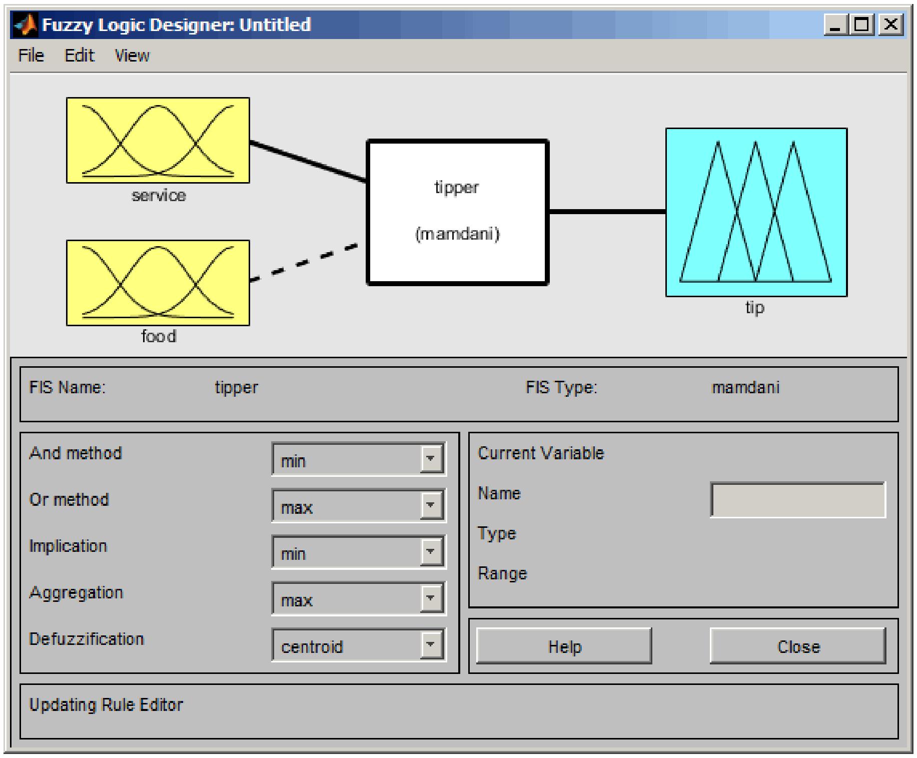


Save current FIS to workspace

Workspace variable Untitled

9 Enter the **Workspace variable** name `tipper`, and click **OK**.

The diagram is updated to reflect the new names of the input and output variables. There is now a new variable in the workspace called `tipper` that contains all the information about this system. By saving to the workspace with a new name, you also rename the entire system. Your window looks something like the following diagram.



FIS Name: tipper

FIS Type: mamdani

And method: min

Or method: max

Implication: min

Aggregation: max

Defuzzification: centroid

Current Variable

Name

Type

Range

Updating Rule Editor

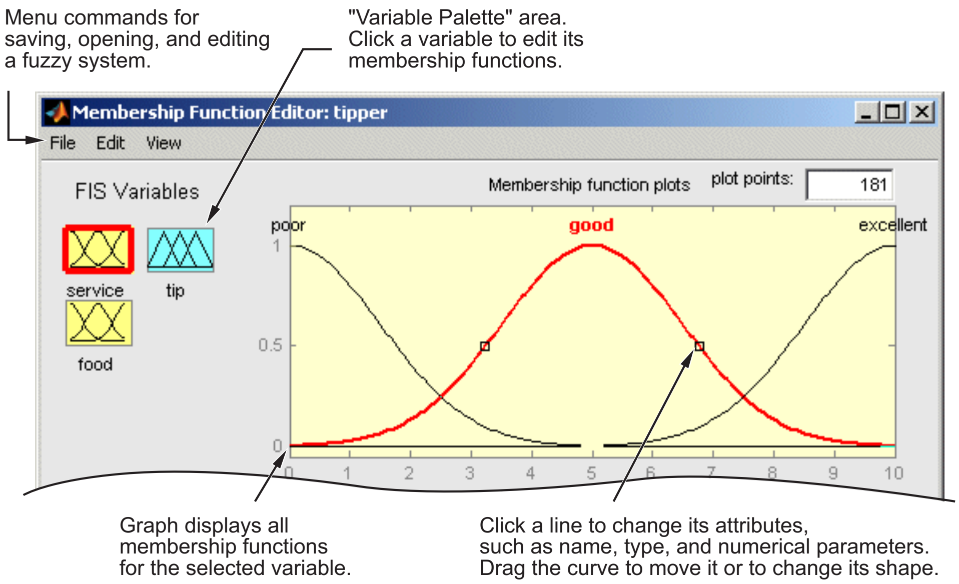
Leave the inference options in the lower left in their default positions for now. You have entered all the information you need for this particular UI. Next, define the membership functions associated with each of the variables. To do this, open the Membership Function Editor.

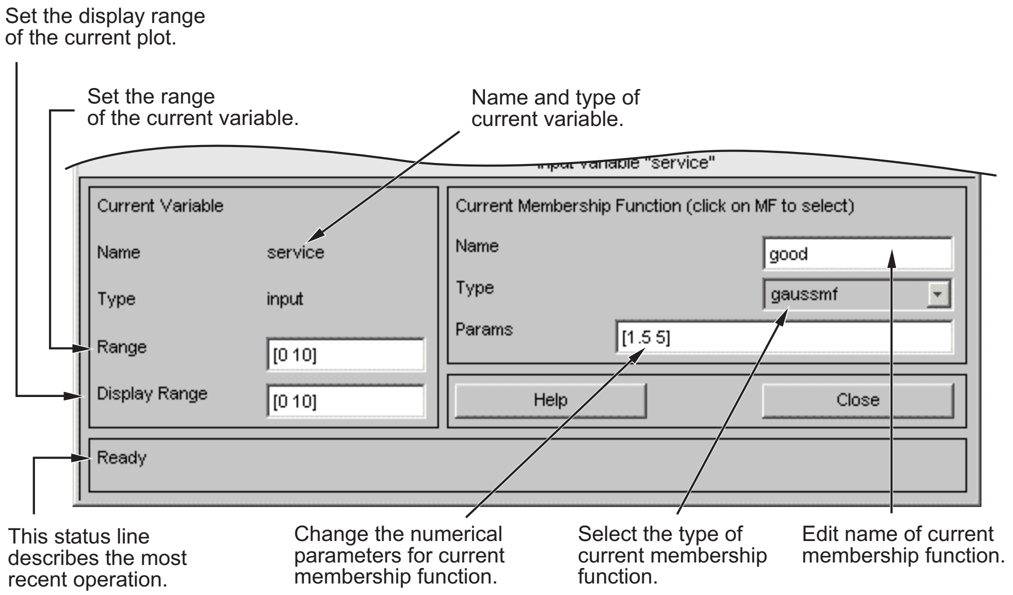
You can open the Membership Function Editor in one of three ways:

- Within the **Fuzzy Logic Designer** window, select **Edit > Membership Functions**.
- Within the **Fuzzy Logic Designer** window, double-click the blue icon called **tip**.
- At the command line, type `mfedit`.

The Membership Function Editor

The Membership Function Editor is the tool that lets you display and edit all of the membership functions associated with all of the input and output variables for the entire fuzzy inference system. The Membership Function Editor shares some features with the **Fuzzy Logic Designer**, as shown in the next figure. In fact, all of the five basic UI tools have similar menu options, status lines, and **Help** and **Close** buttons.


Menu commands for saving, opening, and editing a fuzzy system.
"Variable Palette" area. Click a variable to edit its membership functions.
Membership Function Editor: tipper
File
Edit
View
FIS Variables
service
tip
food
Membership function plots
plot points:
181
poor
good
excellent
Graph displays all membership functions for the selected variable.
Click a line to change its attributes, such as name, type, and numerical parameters. Drag the curve to move it or to change its shape.


Set the display range of the current plot.
Set the range of the current variable.
Name and type of current variable.
Input variable "service"
Current Variable
Name
service
Type
input
Range
[0 10]
Display Range
[0 10]
Current Membership Function (click on MF to select)
Name
good
Type
gaussmf
Params
[1.5 5]
Help
Close
Ready
This status line describes the most recent operation.
Change the numerical parameters for current membership function.
Select the type of current membership function.
Edit name of current membership function.

When you open the Membership Function Editor to work on a fuzzy inference system that does not already exist in the workspace, there are no membership functions associated with the variables that you defined with the **Fuzzy Logic Designer**.

On the upper-left side of the graph area in the Membership Function Editor is a "Variable Palette" that lets you set the membership functions for a given variable.

To set up the membership functions associated with an input or an output variable for the FIS, select a FIS variable in this region by clicking it.

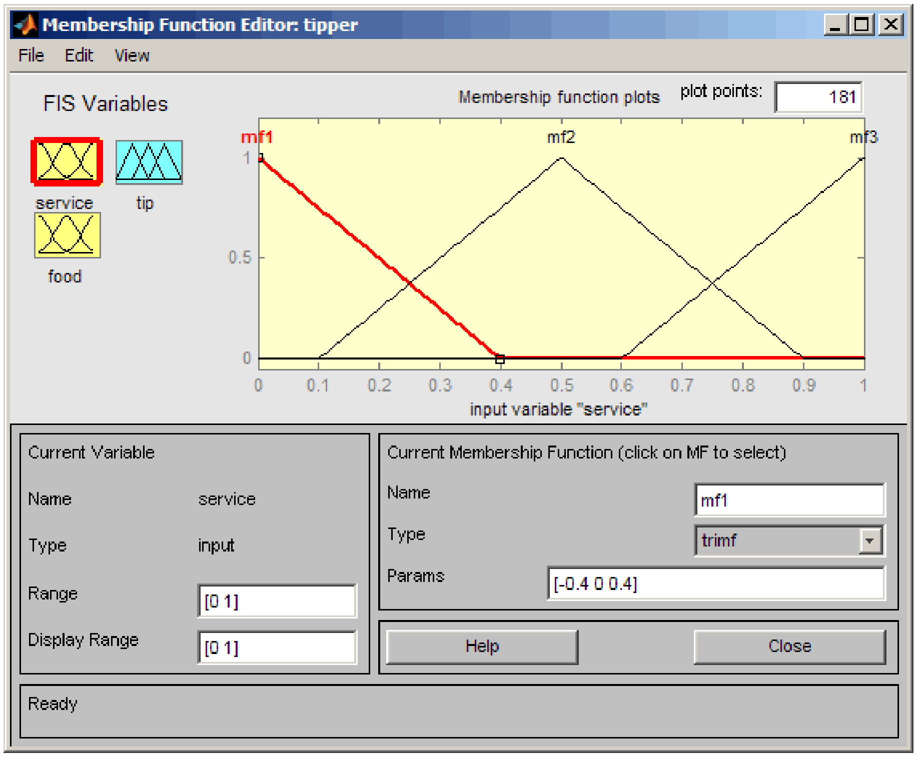
Next select the **Edit** pull-down menu, and choose **Add MFs ..**. A new window appears, which allows you to select both the membership function type and the number of membership functions associated with the selected variable. In the lower-right corner of the window are the controls that let you change the name, type, and parameters (shape), of the membership function, after it is selected.

The membership functions from the current variable are displayed in the main graph. These membership functions can be manipulated in two ways. You can first use the mouse to select a particular membership function associated with a given variable quality, (such as poor, for the variable, service), and then drag the membership function from side to side. This action affects the mathematical description of the quality associated with that membership function for a given variable. The selected membership function can also be tagged for dilation or contraction by clicking on the small square drag points on the membership function, and then dragging the function with the mouse toward the *outside*, for dilation, or toward the *inside*, for contraction. This action changes the parameters associated with that membership function.

Below the Variable Palette is some information about the type and name of the current variable. There is a text field in this region that lets you change the limits of the current variable's range (universe of discourse) and another that lets you set the limits of the current plot (which has no real effect on the system).

The process of specifying the membership functions for the two-input tipping example, `tipper`, is as follows:

1 Double-click the input variable `service` to open the Membership Function Editor.



plot points: 181

Current Variable

Name	service
Type	input
Range	[0 1]
Display Range	[0 1]

Current Membership Function (click on MF to select)

Name	mf1
Type	trimf
Params	[-0.4 0 0.4]

Ready

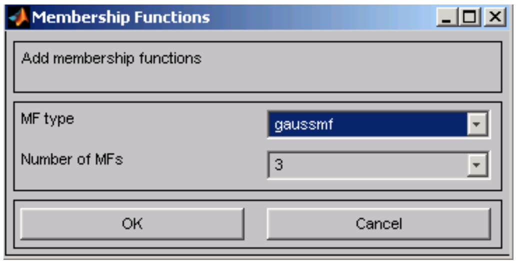
2 In the Membership Function Editor, enter `[0 10]` in the **Range** and the **Display Range** fields.

3 Create membership functions for the input variable `service`.

   a Select **Edit > Remove All MFs** to remove the default membership functions for the input variable `service`.

   b Select **Edit > Add MFs** to open the Membership Functions dialog box.

   c In the Membership Functions dialog box, select `gaussmf` as the **MF Type**.



MF type: gaussmf
Number of MFs: 3

   d Verify that 3 is selected as the **Number of MFs**.

   e Click **OK** to add three Gaussian curves to the input variable `service`.

4 Rename the membership functions for the input variable `service`, and specify their parameters.

   a Click on the curve named `mf1` to select it, and specify the following fields in the **Current Membership Function (click on MF to select)** area:

   - In the **Name** field, enter `poor`.
   - In the **Params** field, enter `[1.5 0]`.

     The two inputs of **Params** represent the standard deviation and center for the Gaussian curve.

Tip To adjust the shape of the membership function, type in the desired parameters or use the mouse, as described previously.

   b Click on the curve named `mf2` to select it, and specify the following fields in the **Current Membership Function (click on MF to select)** area:

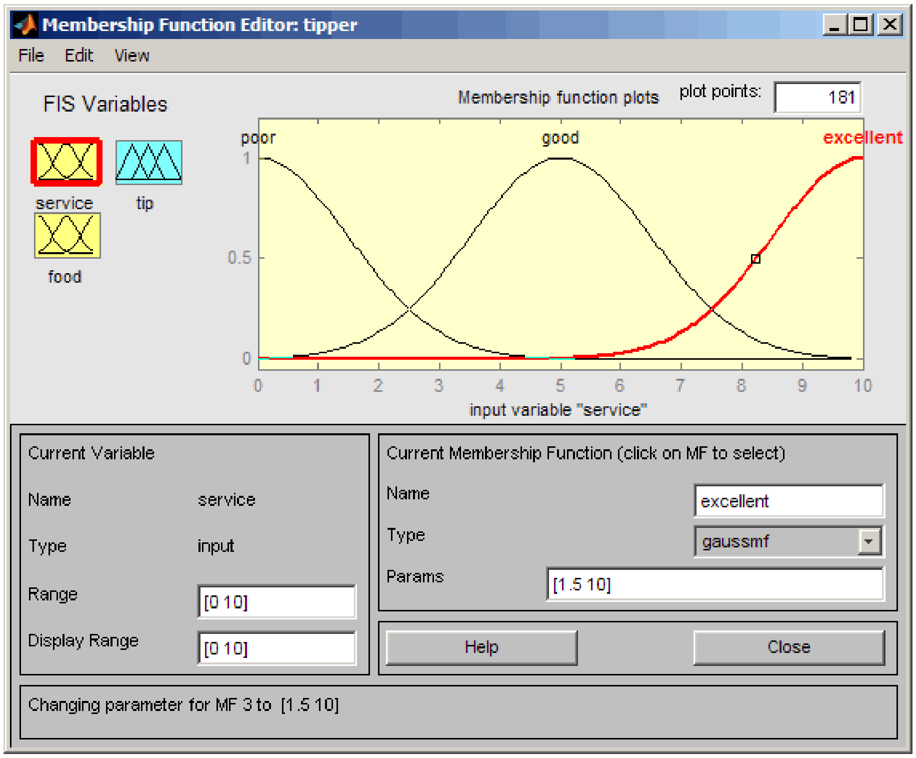
   - In the **Name** field, enter `good`.

- In the **Params** field, enter `[1.5 5]`.

c Click on the curve named `mf3`, and specify the following fields in the **Current Membership Function (click on MF to select)** area:

- In the **Name** field, enter `excellent`.
- In the **Params** field, enter `[1.5 10]`.

The Membership Function Editor window looks similar to the following figure.



Current Variable

Name service

Type input

Range [0 10]

Display Range [0 10]

Current Membership Function (click on MF to select)

Name excellent

Type gaussmf

Params [1.5 10]

Changing parameter for MF 3 to [1.5 10]

5 In the **FIS Variables** area, click the input variable `food` to select it.

6 Enter `[0 10]` in the **Range** and the **Display Range** fields.

7 Create the membership functions for the input variable `food`.

a Select **Edit > Remove All MFs** to remove the default Membership Functions for the input variable `food`.

- **b** Select **Edit > Add MFs** to open the Membership Functions dialog box.
- **c** In the Membership Functions dialog box, select `trapmf` as the **MF Type**.
- **d** Select 2 in the **Number of MFs** drop-down list.
- **e** Click **OK** to add two trapezoidal curves to the input variable `food`.

8 Rename the membership functions for the input variable `food`, and specify their parameters:

- **a** In the **FIS Variables** area, click the input variable `food` to select it.
- **b** Click on the curve named `mf1`, and specify the following fields in the **Current Membership Function (click on MF to select)** area:
  - In the **Name** field, enter `rancid`.
  - In the **Params** field, enter `[0 0 1 3]`.
- **c** Click on the curve named `mf2` to select it, and enter `delicious` in the **Name** field.

  Reset the associated parameters if desired.

9 Click on the output variable `tip` to select it.

10 Enter `[0 30]` in the **Range** and the **Display Range** fields to cover the output range.

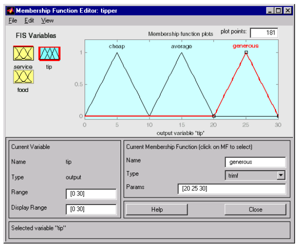
The inputs ranges from 0 to 10, but the output is a tip between 5% and 25%.

11 Rename the default triangular membership functions for the output variable `tip`, and specify their parameters.

- **a** Click the curve named `mf1` to select it, and specify the following fields in the **Current Membership Function (click on MF to select)** area:
  - In the **Name** field, enter `cheap`.
  - In the **Params** field, enter `[0 5 10]`.
- **b** Click the curve named `mf2` to select it, and specify the following fields in the **Current Membership Function (click on MF to select)** area:
  - In the **Name** field, enter `average`.
  - In the **Params** field, enter `[10 15 20]`.
- **c** Click the curve named `mf3` to select it, and specify the following:
  - In the **Name** field, enter `generous`.

- In the **Params** field, enter `[20 25 30]`.

The Membership Function Editor looks similar to the following figure.



plot points: 181

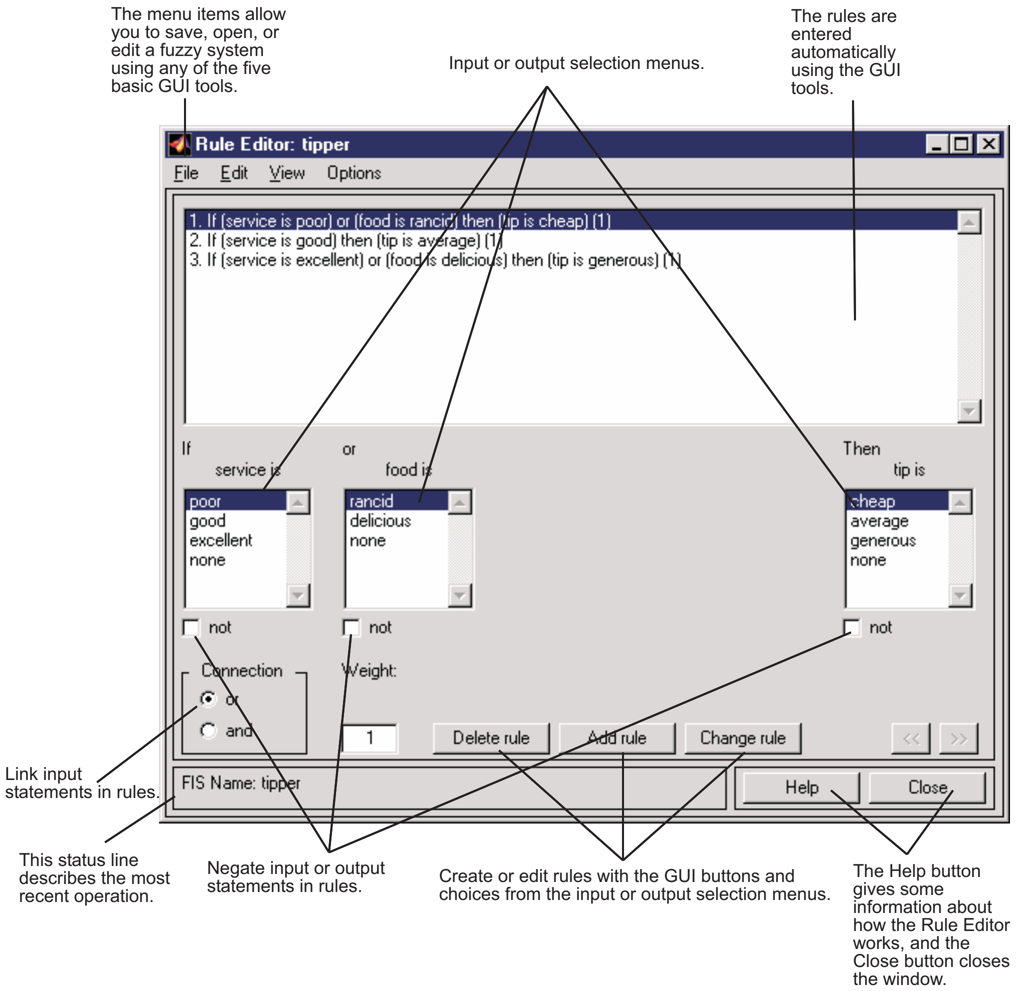
Current Variable
Name tip
Type output
Range [0 30]
Display Range [0 30]

Current Membership Function (click on MF to select)
Name generous
Type trimf
Params [20 25 30]

Selected variable "tip"

Now that the variables have been named and the membership functions have appropriate shapes and names, you can enter the rules. To call up the Rule Editor, go to the **Edit** menu and select **Rules**, or type `ruleedit` at the command line.

The Rule Editor



The menu items allow you to save, open, or edit a fuzzy system using any of the five basic GUI tools.

Input or output selection menus.

The rules are entered automatically using the GUI tools.

1. If (service is poor) or (food is rancid) then (tip is cheap) (1)
2. If (service is good) then (tip is average) (1)
3. If (service is excellent) or (food is delicious) then (tip is generous) (1)

FIS Name: tipper

Link input statements in rules.

This status line describes the most recent operation.

Negate input or output statements in rules.

Create or edit rules with the GUI buttons and choices from the input or output selection menus.

The Help button gives some information about how the Rule Editor works, and the Close button closes the window.

Constructing rules using the graphical Rule Editor interface is fairly self evident. Based on the descriptions of the input and output variables defined with the **Fuzzy Logic Designer**, the Rule Editor allows you to construct the rule statements automatically. You can:

- Create rules by selecting an item in each input and output variable box, selecting one **Connection** item, and clicking **Add Rule**. You can choose `none` as one of the variable qualities to exclude that variable from a given rule and choose `not` under any variable name to negate the associated quality.
- Delete a rule by selecting the rule and clicking **Delete Rule**.
- Edit a rule by changing the selection in the variable box and clicking **Change Rule**.
- Specify weight to a rule by typing in a desired number between `0` and `1` in **Weight**. If you do not specify the weight, it is assumed to be unity `(1)`.

Similar to those in the **Fuzzy Logic Designer** and the Membership Function Editor, the Rule Editor has the menu bar and the status line. The menu items allow you to open, close, save and edit a fuzzy system using the five basic UI tools. From the menu, you can also:

- Set the format for the display by selecting **Options** > **Format**.
- Set the language by selecting **Options** > **Language**.

You can access information about the Rule Editor by clicking **Help** and close the UI using **Close**.

To insert the first rule in the Rule Editor, select the following:

- `poor` under the variable **service**
- `rancid` under the variable **food**
- The **or** radio button, in the **Connection** block
- `cheap`, under the output variable, **tip**.

Then, click **Add rule**.

The resulting rule is
1. If (service is poor) or (food is rancid) then (tip is cheap) (1)

The numbers in the parentheses represent weights.

Follow a similar procedure to insert the second and third rules in the Rule Editor to get

1. *If (service is poor) or (food is rancid) then (tip is cheap) (1)*
2. *If (service is good) then (tip is average) (1)*
3. *If (service is excellent) or (food is delicious) then (tip is generous) (1)*

Tip To change a rule, first click on the rule to be changed. Next make the desired changes to that rule, and then click **Change rule**. For example, to change the first rule to
1. If (service not poor) or (food not rancid) then (tip is not cheap) (1)

Select the **not** check box under each variable, and then click **Change rule**.

The **Format** pop-up menu from the **Options** menu indicates that you are looking at the verbose form of the rules. Try changing it to `symbolic`. You will see
1. (service==poor) | (food==rancid) => (tip=cheap) (1)
2. (service==good) => (tip=average) (1)
3. (service==excellent) | (food==delicious) => (tip=generous) (1)

There is not much difference in the display really, but it is slightly more language neutral, because it does not depend on terms like *if* and *then*. If you change the format to indexed, you see an extremely compressed version of the rules.
1 1, 1 (1) : 2
2 0, 2 (1) : 1
3 2, 3 (1) : 2

This is the version of the rules that the machine deals with.

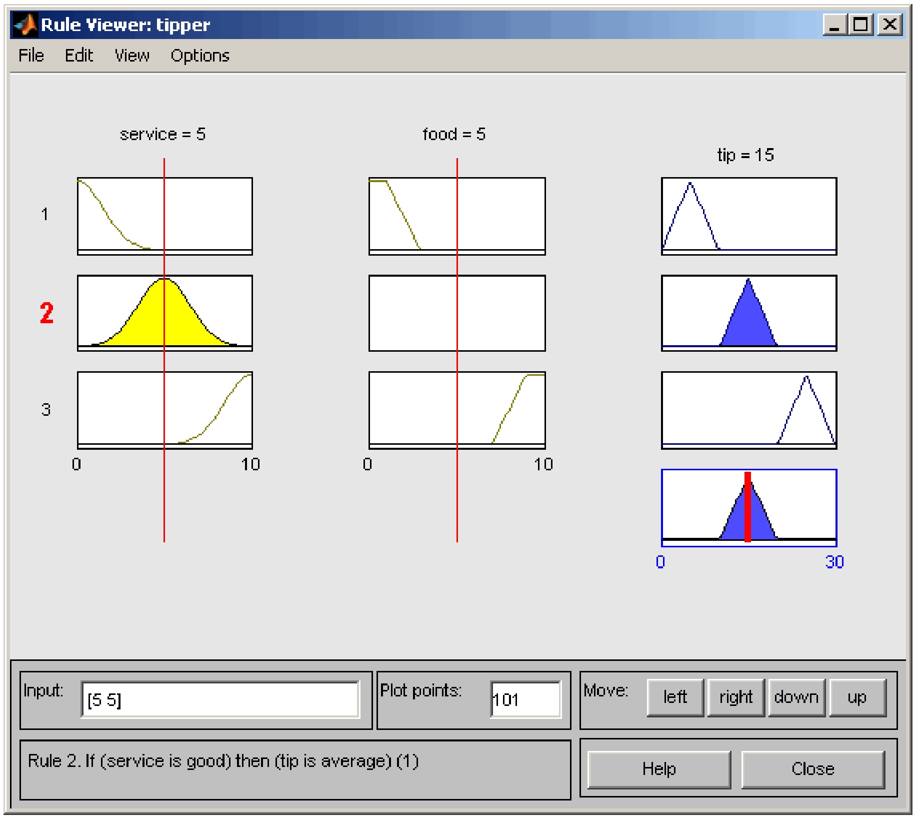
- The first column in this structure corresponds to the input variables.
- The second column corresponds to the output variable.
- The third column displays the weight applied to each rule.
- The fourth column is shorthand that indicates whether this is an OR (2) rule or an AND (1) rule.
- The numbers in the first two columns refer to the index number of the membership function.

A literal interpretation of rule 1 is "If input 1 is MF1 (the first membership function associated with input 1) or if input 2 is MF1, then output 1 should be MF1 (the first membership function associated with output 1) with the weight 1."

The symbolic format does not consider the terms, *if*, *then*, and so on. The indexed format doesn't even bother with the names of your variables. Obviously the functionality of your system doesn't depend on how well you have named your variables and membership functions. The whole point of naming variables descriptively is, as always, making the system easier for you to interpret. Thus, unless you have some special purpose in mind, it is probably be easier for you to continue with the **verbose** format.

At this point, the fuzzy inference system has been completely defined, in that the variables, membership functions, and the rules necessary to calculate tips are in place. Now, look at the fuzzy inference diagram presented at the end of the previous section and verify that everything is behaving the way you think it should. You can use the Rule Viewer, the next of the UI tools we'll look at. From the **View** menu, select **Rules**.

The Rule Viewer



Input: [5 5]

Plot points: 101

Rule 2. If (service is good) then (tip is average) (1)

The Rule Viewer displays a roadmap of the whole fuzzy inference process. It is based on the fuzzy inference diagram described in the previous section. You see a single figure window with 10 plots nested in it. The three plots across the top of the figure represent the antecedent and consequent of the first rule. Each rule is a row of plots, and each column is a variable. The rule numbers are displayed on the left of each row. You can click on a rule number to view the rule in the status line.

- The first two columns of plots (the six yellow plots) show the membership functions referenced by the antecedent, or the if-part of each rule.
- The third column of plots (the three blue plots) shows the membership functions referenced by the consequent, or the then-part of each rule.

  Notice that under **food**, there is a plot which is blank. This corresponds to the characterization of `none` for the variable **food** in the second rule.
- The fourth plot in the third column of plots represents the aggregate weighted decision for the given inference system.

  This decision will depend on the input values for the system. The defuzzified output is displayed as a bold vertical line on this plot.

The variables and their current values are displayed on top of the columns. In the lower left, there is a text field **Input** in which you can enter specific input values. For the two-input system, you will enter an input vector, `[9 8]`, for example, and then press **Enter**. You can also adjust these input values by clicking on any of the three plots for each input. This will move the red index line horizontally, to the point where you have clicked. Alternatively, you can also click and drag this line in order to change the input values. When you release the line, (or after manually specifying the input), a new calculation is performed, and you can see the whole fuzzy inference process take place:

- Where the index line representing service crosses the membership function line "service is poor" in the upper-left plot determines the degree to which rule one is activated.
- A yellow patch of color under the actual membership function curve is used to make the fuzzy membership value visually apparent.

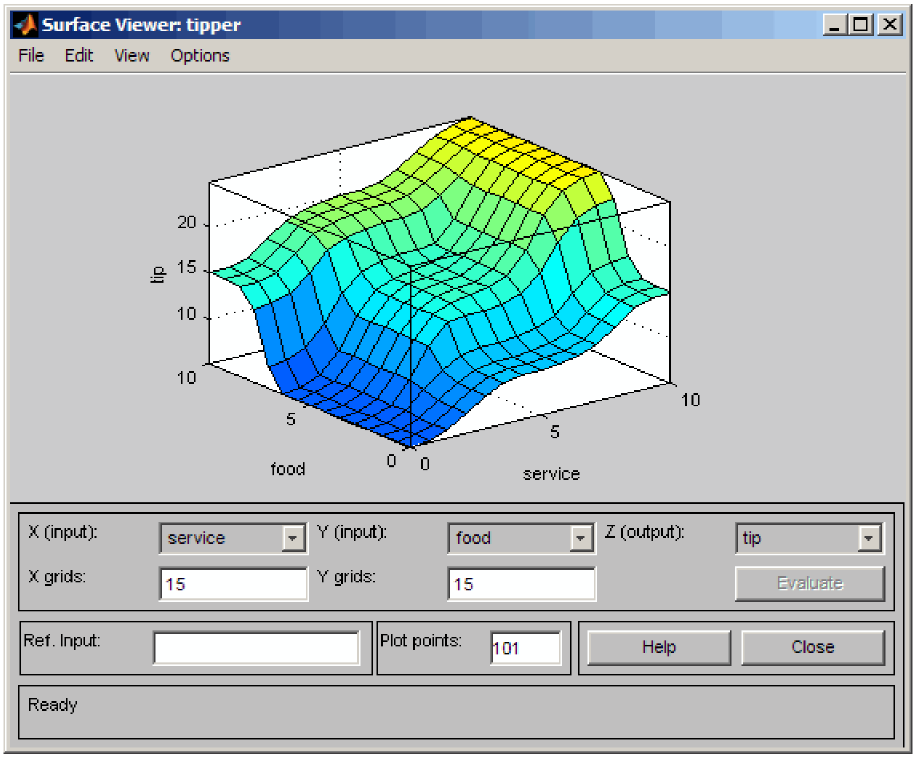
Each of the characterizations of each of the variables is specified with respect to the input index line in this manner. If you follow rule 1 across the top of the diagram, you can see the consequent "tip is cheap" has been truncated to exactly the same degree as the (composite) antecedent — this is the implication process in action. The aggregation occurs down the third column, and the resultant aggregate plot is shown in the single plot appearing in the lower right corner of the plot field. The defuzzified output value is shown by the thick line passing through the aggregate fuzzy set.

You can shift the plots using **left**, **right**, **down**, and **up**. The menu items allow you to save, open, or edit a fuzzy system using any of the five basic UI tools.

The Rule Viewer allows you to interpret the entire fuzzy inference process at once. The Rule Viewer also shows how the shape of certain membership functions influences the overall result. Because it plots every part of every rule, it can become unwieldy for particularly large systems, but, for a relatively small number of inputs and outputs, it performs well (depending on how much screen space you devote to it) with up to 30 rules and as many as 6 or 7 variables.

The Rule Viewer shows one calculation at a time and in great detail. In this sense, it presents a sort of micro view of the fuzzy inference system. If you want to see the entire output surface of your system — the entire span of the output set based on the entire span of the input set — you need to open up the Surface Viewer. This viewer is the last of the five basic Fuzzy Logic Toolbox UI tools. To open the Surface Viewer, select **Surface** from the **View** menu.

The Surface Viewer



X (input): service
Y (input): food
Z (output): tip
X grids: 15
Y grids: 15
Ref. Input:
Plot points: 101
Ready

Upon opening the Surface Viewer, you see a three-dimensional curve that represents the mapping from food and service quality to tip amount. Because this curve represents a two-input one-output case, you can see the entire mapping in one plot. When we move beyond three dimensions overall, we start to encounter trouble displaying the results.

Accordingly, the Surface Viewer is equipped with drop-down menus **X (input)**, **Y (input)** and **Z (output)** that let you select any two inputs and any one output for plotting. Below these menus are two input fields **X grids** and **Y grids** that let you specify how many x-axis and y-axis grid lines you want to include. This capability allows you to keep the calculation time reasonable for complex problems.

By default, the surface plot updates automatically when you change the input or output variable selections or the number of grid points. To disable automatic plot updates, in the **Options** menu, clear the **Always evaluate** option. When this option is disabled, to update the plot, click **Evaluate**.

If you want to create a smoother plot, use the **Plot points** field to specify the number of points on which the membership functions are evaluated in the input or output range. This field defaults to the minimum number of plot plots, `101`. If you specify fewer plot points, the field value automatically resets to `101`. When you specify the number of plot points, the surface plot automatically updates.

By clicking on the plot axes and dragging the mouse, you can manipulate the surface so that you can view it from different angles.

The **Ref. Input** field is used in situations when there are more inputs required by the system than the surface is mapping. You can edit this field to explicitly set inputs not specified in the surface plot.

Suppose you have a four-input one-output system and would like to see the output surface. The Surface Viewer can generate a three-dimensional output surface where any two of the inputs vary, but two of the inputs must be held constant because computer monitors cannot display a five-dimensional shape. In such a case, the input is a four-dimensional vector with `NaN`s holding the place of the varying inputs while numerical values indicates those values that remain fixed.

The menu items allow you to open, close, save and edit a fuzzy system using the five basic UI tools. You can access information about the Surface Viewer by clicking **Help** and close the UI using **Close**.

Importing and Exporting Fuzzy Inference Systems

When you save a fuzzy system to a file, you are saving an ASCII text FIS file representation of that system with the file suffix `.fis`. Do not manually edit the contents of a `.fis` file. Doing so can produce unexpected results when loading the file. When you save your fuzzy system to the MATLAB workspace, you are creating a variable that acts as a MATLAB object for the fuzzy system.

Note If you do not save your FIS to a file, but only save it to the MATLAB workspace, you cannot recover it for use in a new MATLAB session.

See Also

Fuzzy Logic Designer

More About

- “What Is Mamdani-Type Fuzzy Inference?” on page 2-4
- “Build Fuzzy Systems at the Command Line” on page 2-38
- “Simulate Fuzzy Inference Systems in Simulink” on page 5-2

Build Fuzzy Systems at the Command Line

You can construct a fuzzy inference system (FIS) at the MATLAB® command line. This method is an alternative to interactively designing your FIS using Fuzzy Logic Designer.

This example shows you how to create a Mamdani fuzzy inference system. While you create a Mamdani FIS, the methods used apply to creating Sugeno systems as well.

Tipping Problem at the Command Line

To demonstrate the command-line functionality for creating and viewing fuzzy inference systems, this example uses the tipper FIS.

```
fis = readfis('tipper.fis');
```

This command returns a `mamfis` object that contains the properties of the fuzzy system. For a Sugeno system, this command returns a `sugfis` object.

You can access the FIS properties using dot notation. For example, view the inputs of the fuzzy system.

```
fis.Inputs
```

```
ans = 

  1x2 fisvar array with properties:

    Name
    Range
    MembershipFunctions

  Details:
             Name         Range      MembershipFunctions
           _________    _______    ___________________

    1    "service"    0    10        [1x3 fismf]
    2    "food"       0    10        [1x2 fismf]
```

To set the properties of your fuzzy system, use dot notation. For example, set the name of the FIS.

```
fis.Name = "gratuity";
```

FIS Object

You represent fuzzy inference systems using `mamfis` and `sugfis` objects. These objects contain all the fuzzy inference system information, including the variable names, membership function definitions, and fuzzy inference methods. Each FIS is itself a hierarchy of objects. The following objects are used within a fuzzy system:

- `fisvar` objects represent both input and output variables.
- `fismf` objects represent membership functions within each input and output variable.
- `fisrule` objects represent fuzzy rules that map inputs to outputs.

View all the information for a FIS by directly listing its properties.

```
fis
```

```
fis = 

  mamfis with properties:

                       Name: "gratuity"
                  AndMethod: "min"
                   OrMethod: "max"
          ImplicationMethod: "min"
          AggregationMethod: "max"
      DefuzzificationMethod: "centroid"
                     Inputs: [1x2 fisvar]
                    Outputs: [1x1 fisvar]
                      Rules: [1x3 fisrule]
    DisableStructuralChecks: 0

    See 'getTunableSettings' method for parameter optimization.
```

You can view the properties of the objects within a FIS object using dot notation. For example, view the `fisvar` object for first input variable.

```
fis.Inputs(1)
```

```
ans = 

  fisvar with properties:
```

```
                   Name: "service"
                  Range: [0 10]
    MembershipFunctions: [1x3 fismf]
```

Also, view the membership functions for this variable.

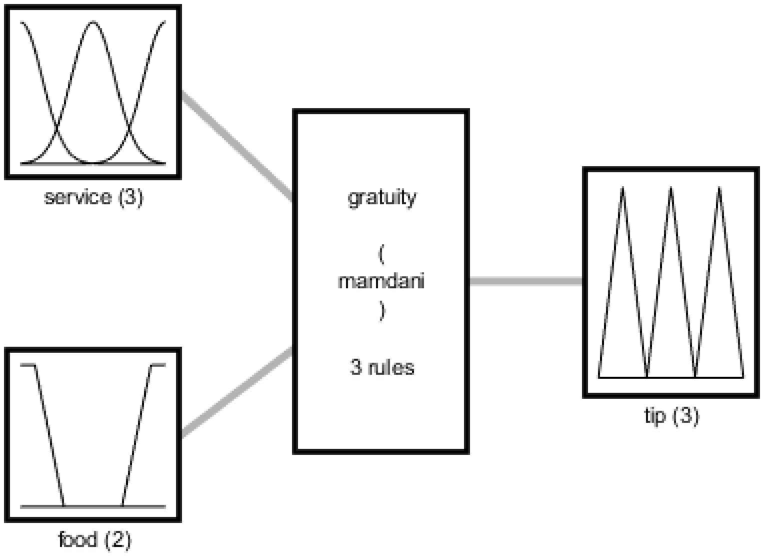
```
fis.Inputs(1).MembershipFunctions
```

```
ans = 

  1x3 fismf array with properties:

    Name
    Type
    Parameters

  Details:
             Name          Type       Parameters
          ___________    _________    __________

    1    "poor"         "gaussmf"    1.5      0
    2    "good"         "gaussmf"    1.5      5
    3    "excellent"    "gaussmf"    1.5     10
```

System Display Functions

To get a high-level view of your fuzzy system from the command line, use the `plotfis`, `plotmf`, and `gensurf` functions. `plotfis` displays the whole system as a block diagram, as shown in the **Fuzzy Logic Designer**.

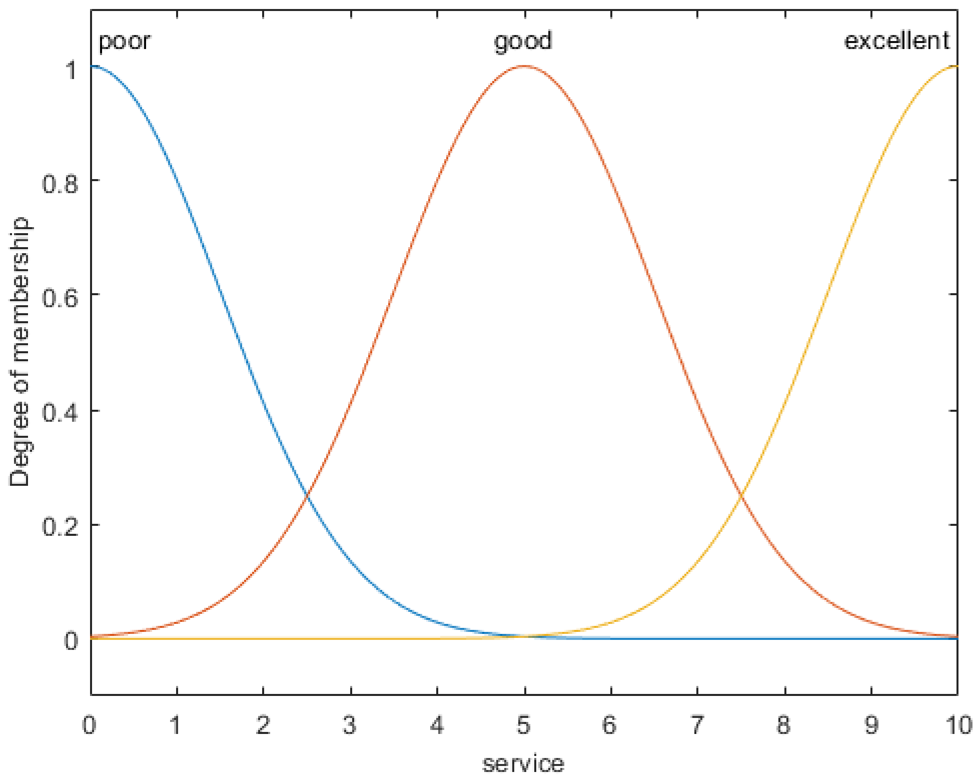
```
plotfis(fis)
```



System gratuity: 2 inputs, 1 outputs, 3 rules

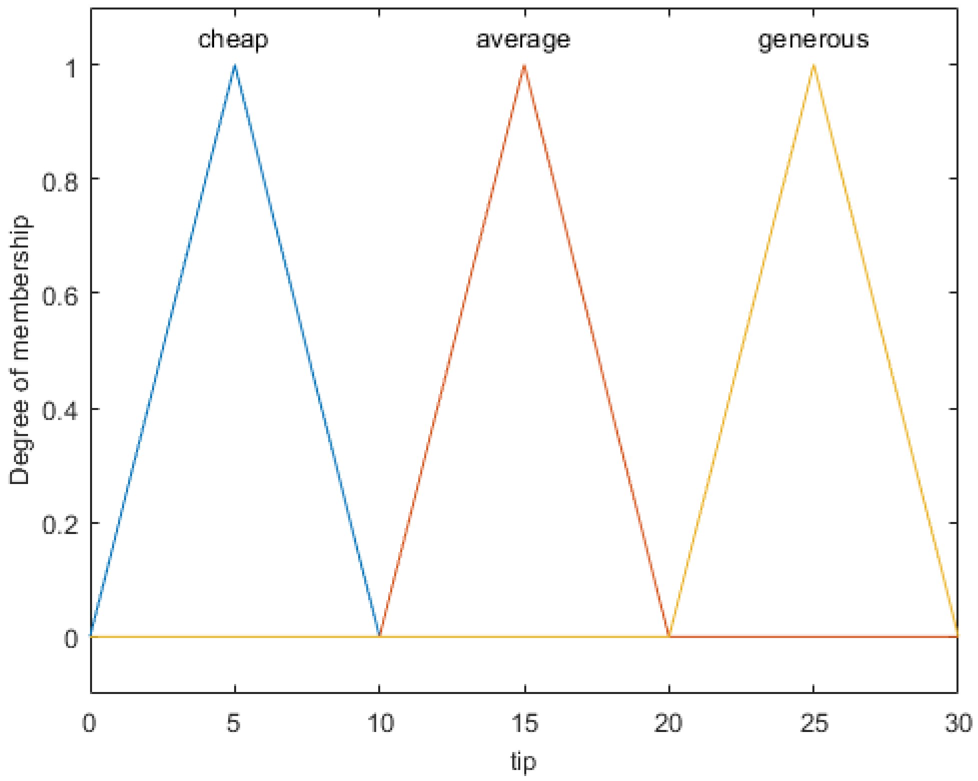
The `plotmf` function plots all the membership functions associated with a given variable. For example, view the membership functions for the first input variable.

```
plotmf(fis,'input',1)
```



Similarly, to view the membership functions for the first output, type:

```
plotmf(fis,'output',1)
```



`plotmf` does not support viewing the output membership functions for Sugeno systems.

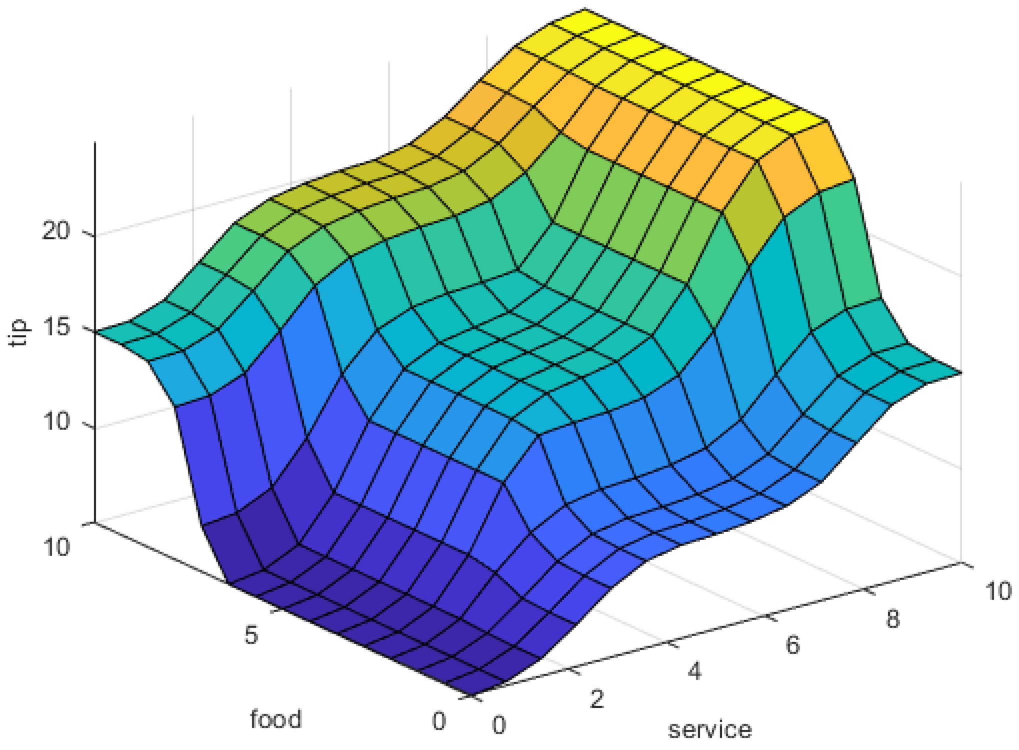
To view the rules of the fuzzy system, type:

```
fis.Rules
```

```
ans = 

  1x3 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                                Description
         ___________________________________________________________

    1    "service==poor | food==rancid => tip=cheap (1)"
    2    "service==good => tip=average (1)"
    3    "service==excellent | food==delicious => tip=generous (1)"
```

The `gensurf` function plots the output of the FIS for any one or two input variables.

```
gensurf(fis)
```



Build Fuzzy Inference System

As an alternative to using the **Fuzzy Logic Designer** app, you can construct a FIS entirely from the command line.

First, create a Mamdani FIS, specifying its name.

```
fis = mamfis('Name',"tipper");
```

Add the first input variable for the service quality using `addInput`.

```
fis = addInput(fis,[0 10],'Name',"service");
```

Add membership functions for each of the service quality levels using `addMF`. In this case, use Gaussian membership functions. For more information on Gaussian membership function properties, see `gaussmf`.

```
fis = addMF(fis,"service","gaussmf",[1.5 0],'Name',"poor");
fis = addMF(fis,"service","gaussmf",[1.5 5],'Name',"good");
fis = addMF(fis,"service","gaussmf",[1.5 10],'Name',"excellent");
```

Add the second input variable for the food quality, and add two trapezoidal membership functions. For information on trapezoidal membership functions, see `trapmf`.

```
fis = addInput(fis,[0 10],'Name',"food");
fis = addMF(fis,"food","trapmf",[-2 0 1 3],'Name',"rancid");
fis = addMF(fis,"food","trapmf",[7 9 10 12],'Name',"delicious");
```

Add the output variable for the tip, and add three triangular membership functions. For more information on the triangular membership function, see `trimf`.

```
fis = addOutput(fis,[0 30],'Name',"tip");
fis = addMF(fis,"tip","trimf",[0 5 10],'Name',"cheap");
fis = addMF(fis,"tip","trimf",[10 15 20],'Name',"average");
fis = addMF(fis,"tip","trimf",[20 25 30],'Name',"generous");
```

Specify the following three rules for the FIS as a numeric array:

1. If (service is poor) or (food is rancid), then (tip is cheap).
2. If (service is good), then (tip is average).
3. If (service is excellent) or (food is delicious), then (tip is generous).

Each row of the array contains one rule in the following format.

- Column 1 - Index of membership function for first input
- Column 2 - Index of membership function for second input
- Column 3 - Index of membership function for output
- Column 4 - Rule weight (from `0` to `1`)
- Column 5 - Fuzzy operator (`1` for AND, `2` for OR)

For the membership function indices, indicate a NOT condition using a negative value. For more information on fuzzy rule specification, see `addRule`.

```
ruleList = [1 1 1 1 2;
            2 0 2 1 1;
            3 2 3 1 2];
```

Add the rules to the FIS.

```
fis = addRule(fis,ruleList);
```

Alternatively, you can create the fuzzy inference system using a combination of dot notation and `fisvar`, `fismf`, and `fisrule` objects. This method is not a good practice for most applications. However, you can use this approach when your application requires greater flexibility in constructing and modifying your FIS.

Create the fuzzy inference system.

```
fis = mamfis('Name','tipper');
```

Add and configure the first input variable. In this case, create a default `fisvar` object and specify its properties using dot notation.

```
fis.Inputs(1) = fisvar;
fis.Inputs(1).Name = "service";
fis.Inputs(1).Range = [0 10];
```

Define the membership functions for the first input variable. For each MF, create a `fismf` object, and set the properties using dot notation.

```
fis.Inputs(1).MembershipFunctions(1) = fismf;
fis.Inputs(1).MembershipFunctions(1).Name = "poor";
fis.Inputs(1).MembershipFunctions(1).Type = "gaussmf";
fis.Inputs(1).MembershipFunctions(1).Parameters = [1.5 0];
fis.Inputs(1).MembershipFunctions(2) = fismf;
fis.Inputs(1).MembershipFunctions(2).Name = "good";
fis.Inputs(1).MembershipFunctions(2).Type = "gaussmf";
fis.Inputs(1).MembershipFunctions(2).Parameters = [1.5 5];
fis.Inputs(1).MembershipFunctions(3) = fismf;
fis.Inputs(1).MembershipFunctions(3).Name = "excellent";
fis.Inputs(1).MembershipFunctions(3).Type = "gaussmf";
fis.Inputs(1).MembershipFunctions(3).Parameters = [1.5 10];
```

Add and configure the second input variable. For this variable, specify the name and range when you create the `fisvar` object.

```
fis.Inputs(2) = fisvar([0 10],'Name',"food");
```

Specify the membership functions for the second input. For each MF, specify the name, type, and parameters when you create the `fismf` object.

```
fis.Inputs(2).MembershipFunctions(1) = fismf("trapmf",[-2 0 1 3],...
                                             'Name',"rancid");
fis.Inputs(2).MembershipFunctions(2) = fismf("trapmf",[7 9 10 12],...
                                             'Name',"delicious");
```

Similarly, add and configure the output variable and its membership functions.

```
fis.Outputs(1) = fisvar([0 30],'Name',"tip");
```

In this case, specify the output membership functions using a vector of `fismf` objects.

```
mf1 = fismf("trimf",[0 5 10],'Name',"cheap");
mf2 = fismf("trimf",[10 15 20],'Name',"average");
mf3 = fismf("trimf",[20 25 30],'Name',"generous");
fis.Outputs(1).MembershipFunctions = [mf1 mf2 mf3];
```

Create the rules for the fuzzy system. For each rule create a `fisrule` object. Then, specify the rules using a vector of these objects. When creating a `fisrule` object using numeric values, you must specify the number of inputs variables.

```
rule1 = fisrule([1 1 1 1 2],2);
rule2 = fisrule([2 0 2 1 1],2);
rule3 = fisrule([3 2 3 1 2],2);
rules = [rule1 rule2 rule3];
```

Before adding your rules to your fuzzy system, you must update them using the data in the FIS object. Update the rules using the `update` function, and add them the fuzzy system.

```
rules = update(rules,fis);
fis.Rules = rules;
```

When constructing your fuzzy system, you can also specify custom membership functions and inference functions. For more information, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

Evaluate Fuzzy Inference System

To evaluate the output of a fuzzy system for a given input combination, use the `evalfis` command. For example, evaluate `fis` using input variable values of `1` and `2`.

```
evalfis(fis,[1 2])
```

```
ans =

    5.5586
```

You can also evaluate multiple input combinations using an array where each row represents one input combination.

```
inputs = [3 5;
          2 7;
          3 1];
evalfis(fis,inputs)
```

```
ans =

   12.2184
    7.7885
    8.9547
```

See Also

`evalfis` | `gensurf` | `mamfis` | `plotfis` | `plotmf` | `sugfis`

More About

- “What Is Mamdani-Type Fuzzy Inference?” on page 2-4
- “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14

Build Fuzzy Systems Using Custom Functions

Build Fuzzy Inference Systems Using Custom Functions in Fuzzy Logic Designer

When you build a fuzzy inference system, as described in “Fuzzy Inference Process” on page 1-28, you can replace the built-in membership functions, inference functions, or both with custom functions. In this section, you learn how to build a fuzzy inference system using custom functions in the **Fuzzy Logic Designer** app.

To build a fuzzy inference system using custom functions in the **Fuzzy Logic Designer** app:

1. Open **Fuzzy Logic Designer**. At the MATLAB command line, type:

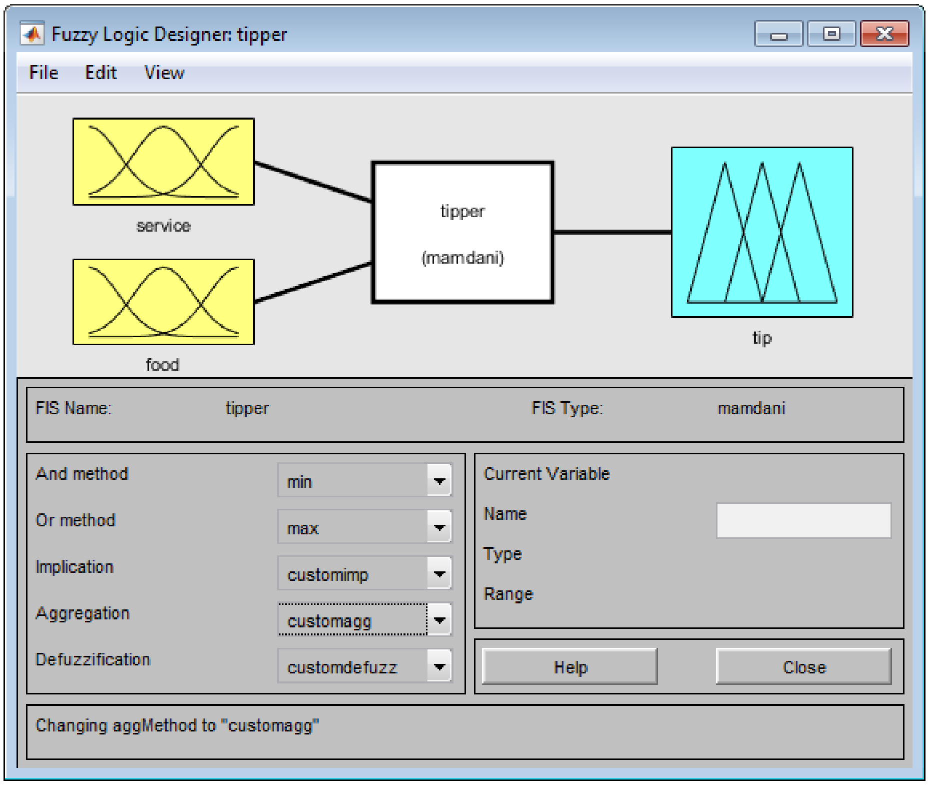
   ```
   fuzzyLogicDesigner
   ```
2. Specify the number of inputs and outputs of the fuzzy system, as described in “The Fuzzy Logic Designer” on page 2-17.
3. Create custom membership functions, and replace the built-in membership functions with them, as described in “Specify Custom Membership Functions” on page 2-51.

   Membership functions define how each point in the input space is mapped to a membership value between 0 and 1.
4. Create rules using the Rule Editor, as described in “The Rule Editor” on page 2-30.

   Rules define the logical relationship between the inputs and the outputs.
5. Create custom inference functions, and replace the built-in inference functions with them, as described in “Specify Custom Inference Functions” on page 2-57.

   Inference methods include the AND, OR, implication, aggregation, and defuzzification methods. This action generates the output values for the fuzzy system.

   The next figure shows the tipping problem example where the built-in **Implication**, **Aggregation** and **Defuzzification** functions are replaced with the custom functions, `customimp`, `customagg`, and `customdefuzz`, respectively.



FIS Name: tipper
FIS Type: mamdani
And method: min
Or method: max
Implication: customimp
Aggregation: customagg
Defuzzification: customdefuzz
Current Variable
Name
Type
Range
Changing aggMethod to "customagg"

6 Select **View** > **Surface** to view the output of the fuzzy inference system in the Surface Viewer, as described in “The Surface Viewer” on page 2-35.

Specify Custom Membership Functions

You can create custom membership functions and use them in the fuzzy inference process. The values of these functions must lie between 0 and 1. For more information on the properties of membership functions, see “Membership Functions” on page 1-14.

To create a custom membership function, and replace the built-in membership function:

1 Create a MATLAB function, and save it in your current working folder.

To learn how to create MATLAB functions, see “Scripts vs. Functions” (MATLAB).

The following code is an example of a multistep custom membership function, `custmf1`, that depends on eight parameters between `0` and `10`.

```
% Function to generate a multi-step custom membership function
% using 8 parameters for the input argument x
function out = custmf1(x,params)

for i = 1:length(x)
    if x(i) < params(1)
        y(i) = params(1);
    elseif x(i) < params(2)
        y(i) = params(2);
    elseif x(i) < params(3)
        y(i) = params(3);
    elseif x(i) < params(4)
        y(i) = params(4);
    elseif x(i) < params(5)
        y(i) = params(5);
    elseif x(i) < params(6)
        y(i) = params(6);
    elseif x(i) < params(7)
        y(i) = params(7);
    elseif x(i) < params(8)
        y(i) = params(8);
    else
        y(i) = 0;
    end
end

out = 0.1*y'; % Scale the output to lie between 0 and 1.
```

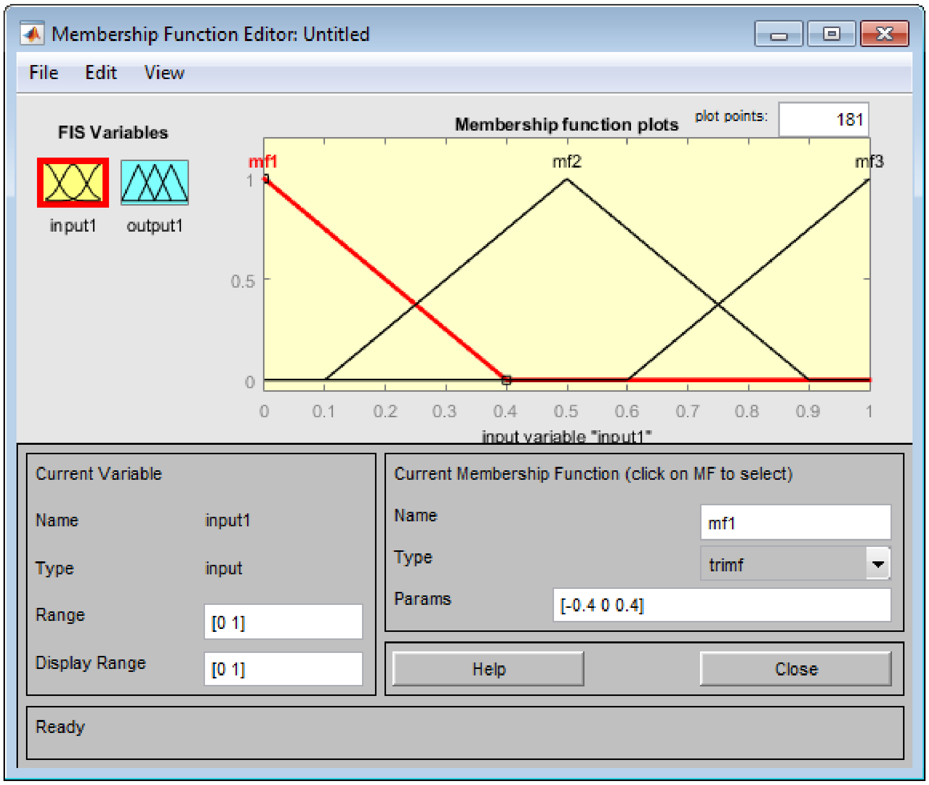
2 Open the **Fuzzy Logic Designer** app.

```
fuzzyLogicDesigner
```

The **Fuzzy Logic Designer** opens with the default FIS name, `Untitled`, and contains one input, **input1**, and one output, **output1**.

3 In the **Fuzzy Logic Designer**, select **Edit > Membership Functions** to open the Membership Function Editor.

Three triangular-shaped membership functions for **input1** are displayed by default.



Current Variable

Name input1

Type input

Range [0 1]

Display Range [0 1]

Current Membership Function (click on MF to select)

Name mf1

Type trimf

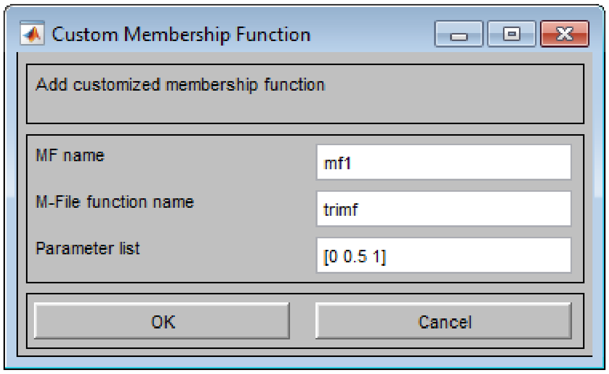
Params [-0.4 0 0.4]

Ready

4 To replace the default membership function with a custom function in the Membership Function Editor:

a Select **Edit > Remove All MFs** to remove the default membership functions for **input1**.

b Select **Edit > Add Custom MF** to open the Custom Membership Function dialog box.


Custom Membership Function

Add customized membership function

MF name: mf1

M-File function name: trimf

Parameter list: [0 0.5 1]

5 To specify a custom function, in the Custom Membership Function dialog box:

   a In the **MF name** field, specify a name for the custom membership function.

   Note When adding additional custom membership functions, specify a different **MF name** for each function.

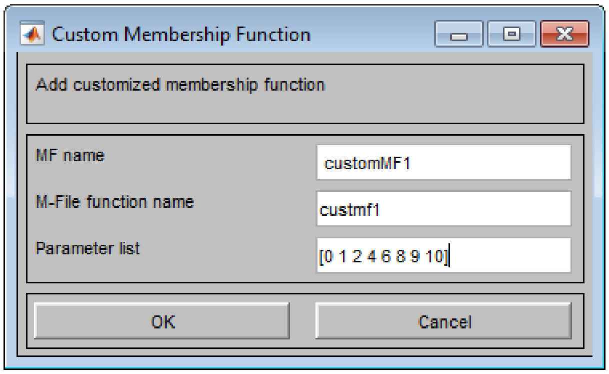
   b In the **M-file function name** field, specify the name of the custom membership function file.

   c In the **Parameter list**, specify a vector of parameters.

   These values determine the shape and position of the membership function, and the function is evaluated using these parameter values.

   Note The length of the parameter vector must be greater than or equal to the number of parameters in the custom membership function.

   Using the `custmf1` example in step 1, the Custom Membership Function dialog box looks similar to the following figure.


Custom Membership Function
Add customized membership function
OK
Cancel

MF name: customMF1

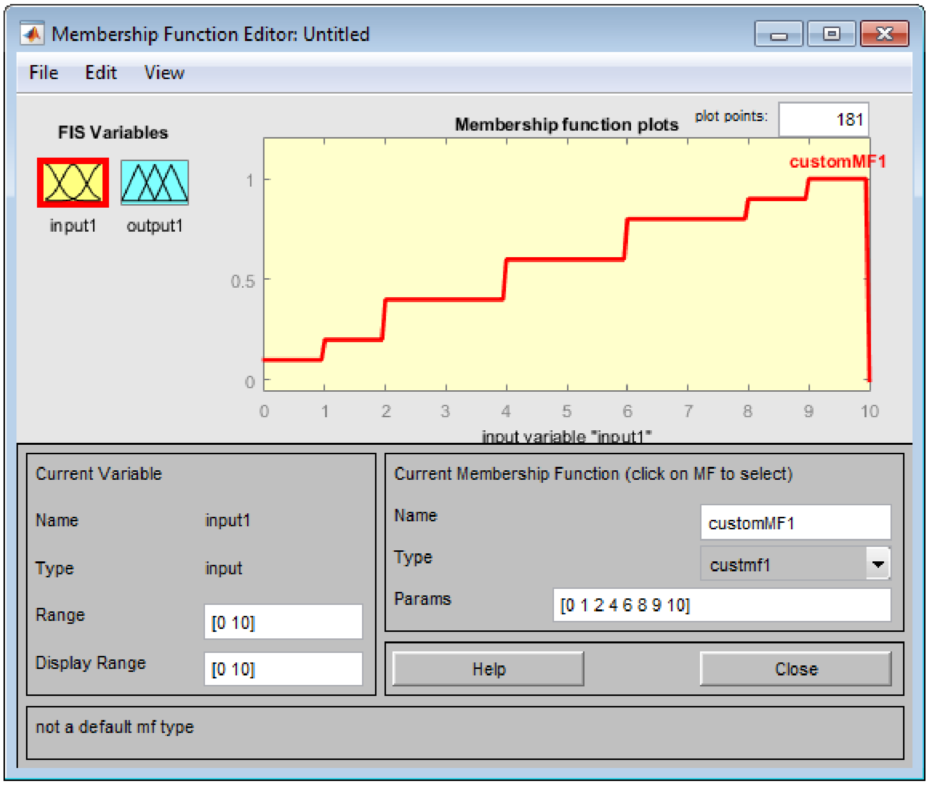
M-File function name: custmf1

Parameter list: [0 1 2 4 6 8 9 10]

d Click **OK** to add the custom membership function.

e Specify both the **Range** and **Display Range** to be `[0 10]` to match the range of the custom membership function.

The Membership Function Editor displays the custom membership function plot.



Current Variable

Name input1

Type input

Range [0 10]

Display Range [0 10]

Current Membership Function (click on MF to select)

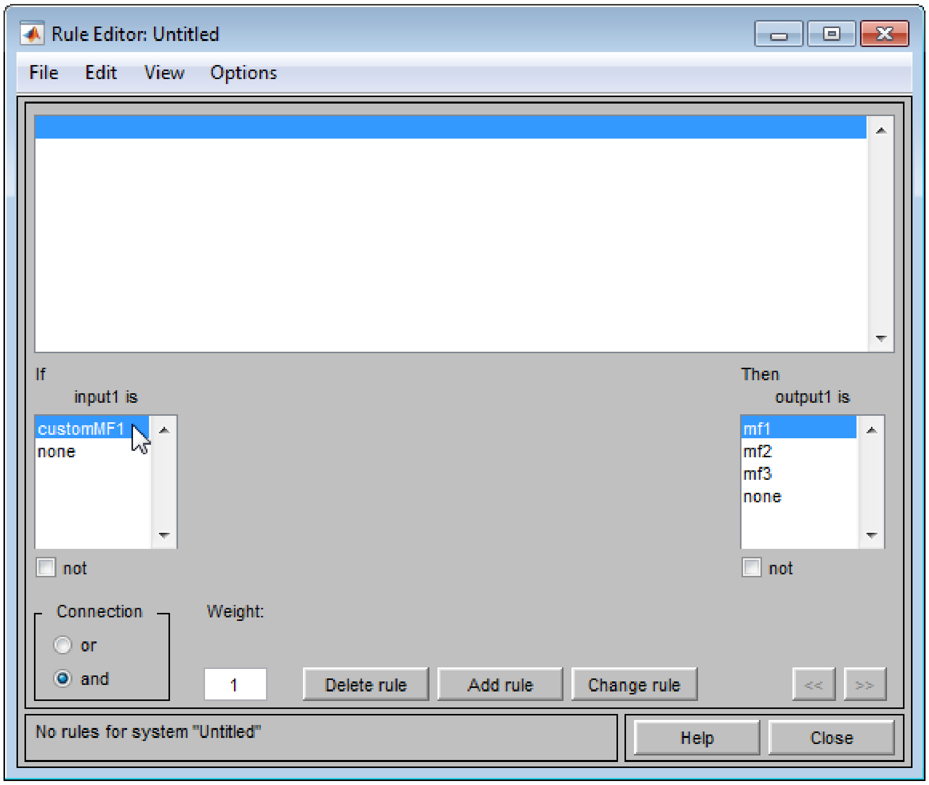
Name customMF1

Type custmf1

Params [0 1 2 4 6 8 9 10]

not a default mf type

This action also adds the custom membership function to the Rule Viewer, and makes it available for creating rules for the fuzzy inference process. To view the custom function in the Rule Viewer, select **Edit > Rules** in either the **Fuzzy Logic Designer** or the Membership Function Editor.



No rules for system "Untitled"

6 To add custom membership functions for **output1**, select it in the Membership Function Editor, and repeat steps 4 and 5.

You can also add a custom membership function to a FIS at the MATLAB command line. For example, to add `custmf1` to the first input variable, `input1` of the FIS, `myFIS`, and name it `customMF1`, type the following:

```
myFIS = addMF(myFIS,"input1","custmf1",[0 1 2 4 6 8 9 10],'Name',"customMF1");
```

Specify Custom Inference Functions

You can replace the built-in AND, OR, implication, aggregation, and defuzzification inference methods with custom functions. After you create the custom inference function, save it in your current working folder. To learn how to build fuzzy systems using custom inference functions, see the “Build Fuzzy Inference Systems Using Custom Functions in Fuzzy Logic Designer” on page 2-50 section.

The guidelines for creating and specifying the functions for building fuzzy inference systems are described in the following sections.

- "Create Custom AND and OR Functions" on page 2-58
- "Create Custom Implication Functions" on page 2-59
- "Create Custom Aggregation Functions" on page 2-60
- "Create Custom Defuzzification Functions" on page 2-61
- "Steps for Specifying Custom Inference Functions" on page 2-61

Create Custom AND and OR Functions

The custom AND and OR inference functions must operate column-wise on a matrix, in the same way as the MATLAB functions `max`, `min`, or `prod`.

For a row or column vector `x`, `min(x)` returns the minimum element.

```
x = [1 2 3 4];
min(x)

ans =
     1
```

For a matrix `x`, `min(x)` returns a row vector containing the minimum element from each column.

```
x = [1 2 3 4;5 6 7 8;9 10 11 12];
min(x)

ans =
     1     2     3     4
```

For N-D arrays, `min(x)` operates along the first non-singleton dimension.

The function `min(x,y)` returns an array that is same size as `x` and `y` with the minimum elements from `x` or `y`. Either of the input arguments can be a scalar. Functions such as `max`, and `prod` operate in a similar manner.

In the toolbox, the AND implication methods perform an element by element matrix operation, similar to the MATLAB function `min(x,y)`.

```
a = [1 2; 3 4];
b = [2 2; 2 2];
min(a,b)
```

```
ans =
     1     2
     2     2
```

The OR implication methods perform an element by element matrix operation, similar to the MATLAB function `max(x,y)`.

Create Custom Implication Functions

Custom implication functions must operate in the same way as the MATLAB functions `max`, `min`, or `prod`. Your custom implication function must be a *T*-norm fuzzy intersection operation. For more information, see “Additional Fuzzy Operators” on page 1-21.

An implication function must support either one or two inputs because the software calls the function in two ways:

- To calculate the output fuzzy set values using the firing strength of all the rules and the corresponding output membership functions. In this case, the software calls the implication function using two inputs, similar to the following example:

  ```
  impvals = customimp(w,outputmf)
  ```

  - `w` — Firing strength of multiple rules, specified as an *nr*-by-*ns* matrix. Here, *nr* is the number of rules and *ns* is the number of samples of the output membership functions.

    `w(:,j) = w(:,1)` for all *j*. `w(i,1)` is the firing strength of the *i*th rule.
  - `outputmf` — Output membership function values, specified as an *nr*-by-*ns* matrix. Here, *nr* is the number of rules and *ns* is the number of samples of the output membership functions.

    `outputmf(i,:)` contains the data of the *i*th output membership function.
- To calculate the output fuzzy value using the firing strength of a single rule and the corresponding output membership function, for a given sample. In this case, the software calls the implication function using one input, similar to the following example:

  ```
  impval = customimp([w outputmf])
  ```

  `w` and `outputmf` are scalar values representing the firing strength of a rule and the corresponding output membership function value, for a given sample.

The following is an example of a bounded product custom implication function with binary mapping $T(a, b) = \max\{0, a + b - 1\}$. [1]

```
function y = customimp(x1,x2)

if nargin == 1
    % x1 assumed to be non-empty column vector or matrix.
    minVal = zeros(1,size(x1,2));
    y = ones(1,size(x1,2));

    for i = 1:size(x1,1)
        y = max(minVal,sum([y;x1(i,:)])-1);
    end
else
    % x1 and x2 assumed to be non-empty matrices.
    minVal = zeros(1,size(x1,2));
    y = zeros(size(x1));

    for i = 1:size(x1,1)
        y(i,:) = max(minVal,sum([x1(i,:);x2(i,:)])-1);
    end
end
```

Note Custom implication functions are not supported for Sugeno-type systems.

Create Custom Aggregation Functions

The custom aggregation functions must operate in the same way as the MATLAB functions `max`, `min`, or `prod` and must be of the form `y = customagg(x)`. Your custom implication function must be a *T*-conorm (*S*-norm) fuzzy intersection operation. For more information, see “Additional Fuzzy Operators” on page 1-21.

x is an *nv*-by-*nr* matrix, which is the list of truncated output functions returned by the implication method for each rule. *nv* is the number of output variables, and *nr* is the number of rules. The output of the aggregation method is one fuzzy set for each output variable.

The following is an example of a bounded sum custom aggregation function with binary mapping $S(a, b) = \min\{a + b, 1\}$. [1]

```
function y = customagg(x)
```

```
maxVal = ones(1,size(x,2));
y = zeros(1,size(x,2));

for i = 1:size(x,1)
    y = min(maxVal,sum([y;x(i,:)]));
end
```

Note Custom aggregation functions are not supported for Sugeno-type systems.

Create Custom Defuzzification Functions

The custom defuzzification functions must be of the form `y = customdefuzz(xmf,ymf)`, where *(xmf,ymf)* is a finite set of membership function values. *xmf* is the vector of values in the membership function input range. *ymf* is the value of the membership function at *xmf*.

The following is an example of a custom defuzzification function:

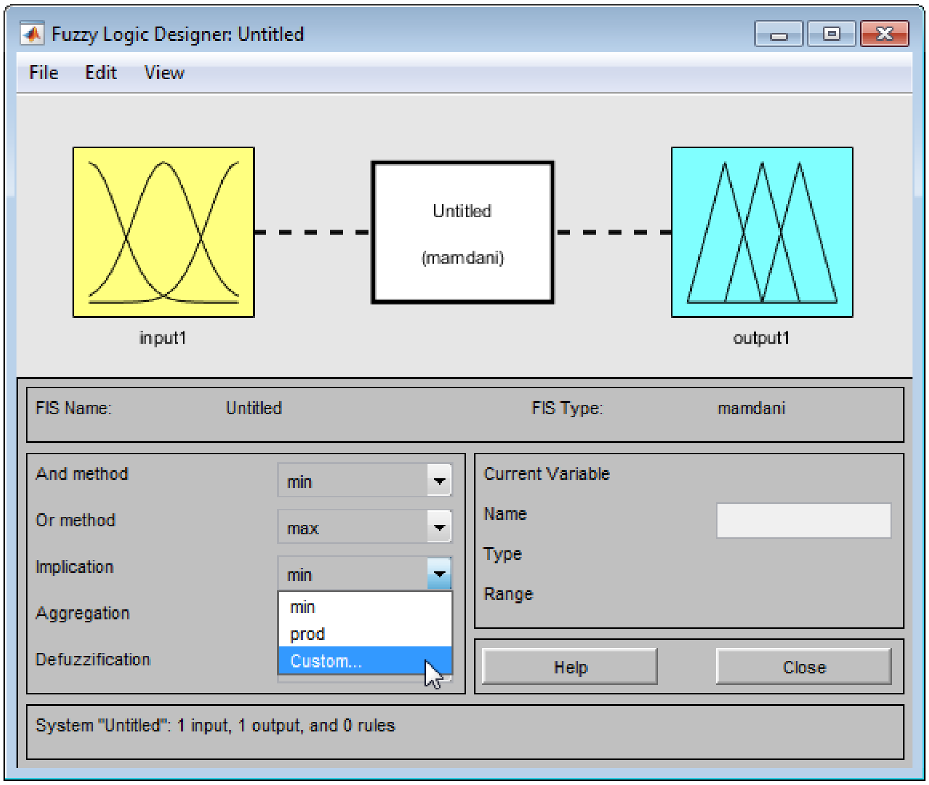
```
function defuzzfun = customdefuzz(xmf,ymf)

total_area = sum(ymf);
defuzzfun = sum(ymf.*xmf)/total_area;
```

Note Custom defuzzification functions are not supported for Sugeno-type systems.

Steps for Specifying Custom Inference Functions

After you create and save a custom inference function, specify the function in the fuzzy inference system using the following steps:

1 In the lower-left panel of the **Fuzzy Logic Designer**, select `Custom` from the drop-down menu corresponding to the inference method for which you want to specify the custom function.



FIS Name: Untitled

FIS Type: mamdani

And method: min

Or method: max

Implication: min

Aggregation

Defuzzification

Current Variable

Name

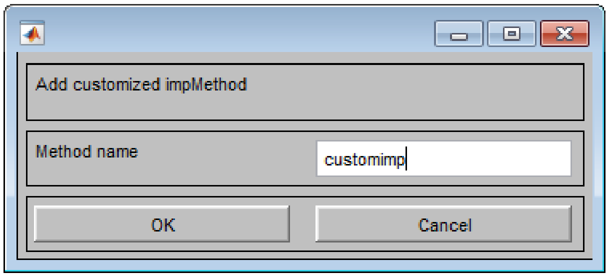
Type

Range

System "Untitled": 1 input, 1 output, and 0 rules

Doing so opens a dialog box where you specify the name of the custom inference function.

2 In the **Method name** field, specify the name of the custom inference function, and click **OK**.



Add customized impMethod

Method name: customimp

The custom function replaces the built-in function when building the fuzzy inference system.

Note In order to specify a custom inference function, you must first add at least one rule to your FIS.

---

3 To specify custom functions for other inference methods, repeat steps 1 and 2.

You can also specify custom inference functions for a FIS at the MATLAB command line. For example, to add a custom:

- Defuzzification method, type

  ```
  myFIS.DefuzzificationMethod = "customdefuzz";
  ```

  where `customdefuzz` is the name of the custom defuzzification function.
- Implication method, type

  ```
  myFIS.ImplicationMethod = "customimp";
  ```

  where `customimp` is the name of the custom implication function.
- Aggregation method, type

  ```
  myFIS.AggregationMethod = "customagg";
  ```

  where `customagg` is the name of the custom aggregation function.

Use Custom Functions in Code Generation

You can use custom functions in fuzzy inference systems for which you generate code. For more information on code generation for fuzzy systems, see “Deploy Fuzzy Inference Systems” on page 6-2.

If you use a nondouble data type for your generated code, you must propagate the data type from the input arguments of your custom function to the output argument. For example, the following custom aggregation function maintains the data type of `x` in `y` using the `ones` and `zeros` with the `'like'` argument.

```
function y = customagg(x)

maxVal = ones(1,size(x,2),'like',x);
y = zeros(1,size(x,2),'like',x);
```

```
for i = 1:size(x,1)
    y = min(maxVal,sum([y;x(i,:)]));
end
```

For more information on writing functions that support C/C++ code generation, see “MATLAB Programming for Code Generation” (MATLAB Coder).

References

[1] Mizumoto, M. "Pictorial Representations of Fuzzy Connectives, Part II: Cases of Compensatory Operators and Self-Dual Operators." *Fuzzy Sets and Systems*. Vol. 32, Number 1., 1989, pp. 45-79.

See Also

Fuzzy Logic Designer

Related Examples

- “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14
- “Build Fuzzy Systems at the Command Line” on page 2-38

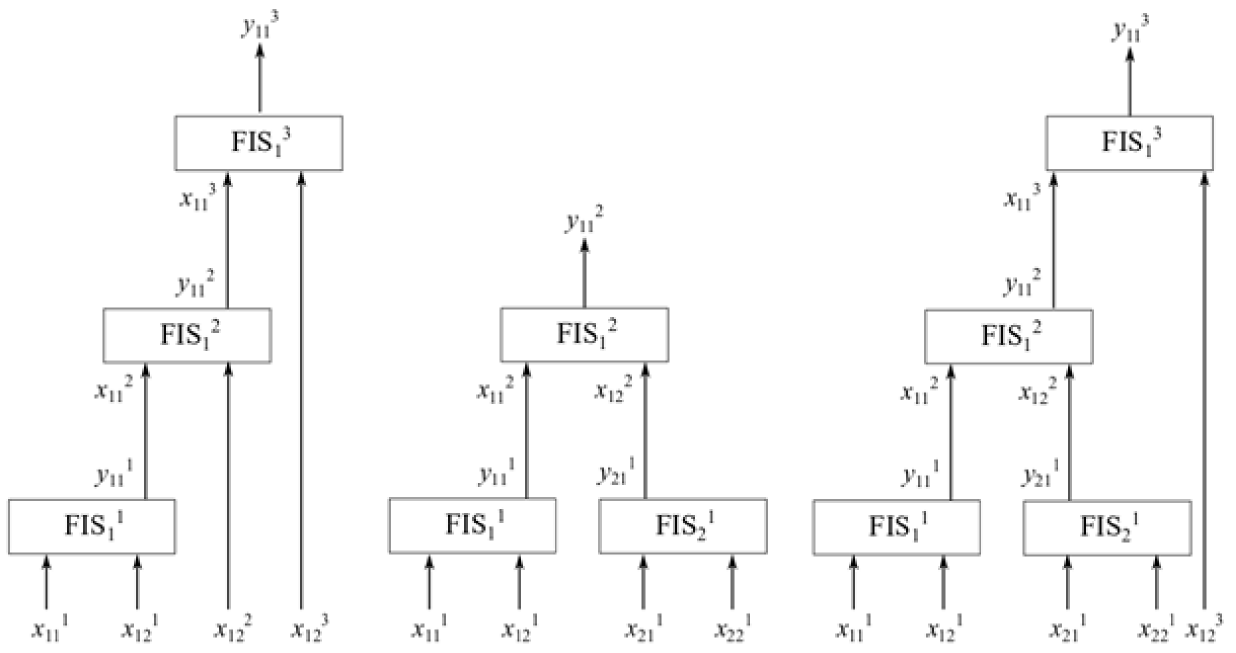
Fuzzy Trees

As the number of inputs to a fuzzy system increases, the number of rules increases exponentially. This large rule base reduces the computational efficiency of the fuzzy system. It also makes the operation of the fuzzy system harder to understand, and it makes the tuning of rule and membership function parameters more difficult. Because many applications have a limited amounts of training data, a large rule base reduces the generalizability of tuned fuzzy systems.

To overcome this issue, you can implement a fuzzy inference system (FIS) as a tree of smaller interconnected FIS objects rather than as a single monolithic FIS. These fuzzy trees are also known as hierarchical fuzzy systems because the fuzzy systems are arranged in hierarchical tree structures. In a tree structure, the outputs of the low-level fuzzy systems are used in high-level fuzzy systems. A fuzzy tree is more computationally efficient and easier to understand than a single FIS with the same number of inputs.

Types of Hierarchical Structures

There are several fuzzy tree structures that you can use for your application. The following figure shows commonly used fuzzy tree structures: an incremental, aggregated, or cascaded structure.

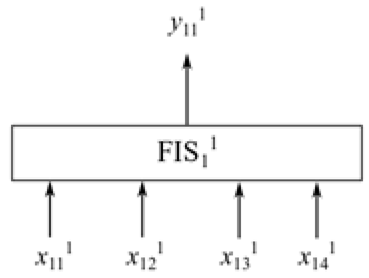


(a) Incremental (b) Aggregated (c) Cascaded (combined)

Incremental Structure

In an incremental structure, input values are incorporated in multiple stages to refine the output values in several levels. For example, the previous figure shows a three-level incremental fuzzy tree having fuzzy inference systems FIS_i^n, where i indicates the index of a FIS in the nth level. In an incremental fuzzy tree, i = 1, meaning that each level has only one fuzzy inference system. In the previous figure, the jth input of the ith FIS in the nth level is shown as input $x_{ij}{}^n$, whereas the kth output of the ith FIS in the nth level is shown as input $x_{ik}{}^n$. In the figure, n = 3, j = 1 or 2, and k = 1. If each input has m membership functions (MFs), each FIS has a complete set of m^2 rules. Hence, the total number of rules is nm^2 = 3 □ 3^2 = 27.

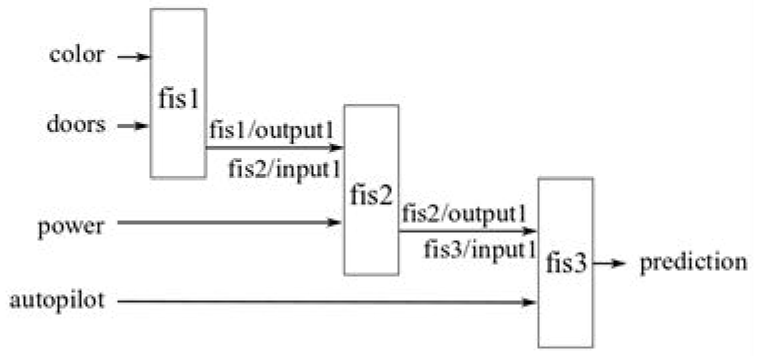
The following figure shows a monolithic (n = 1) FIS with four inputs (j=1, 2, 3, 4) and three MFs (m = 3).



In the FIS of this figure, the total number of rules is $nm^4 = 1 \square 3^4 = 81$. Hence, the total number of rules in an incremental fuzzy tree is linear with the number of input pairs.

Input selection at different levels in an incremental fuzzy tree uses input rankings based on their contributions to the final output values. The input values that contribute the most are generally used at the lowest level, while the least influential ones are used at the highest level. In other words, low-rank input values are dependent on high-rank input values.

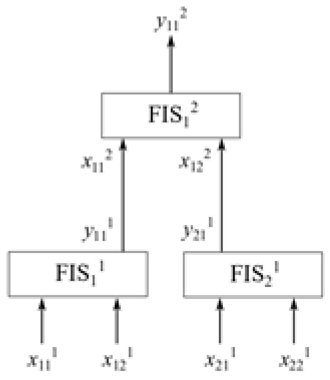
In an incremental fuzzy tree, each input value usually contributes to the inference process to a certain extent, without being significantly correlated with the other inputs. For example, a fuzzy system forecasts the possibility of buying an automobile using four inputs: color, number of doors, horse power, and autopilot. The inputs are four distinct automobile features, which can independently influence a buyer’s decision. Hence, the inputs can be ranked using the existing data to construct a fuzzy tree, as shown in the following figure.



For an example that illustrates creating an incremental fuzzy tree in MATLAB, see the example Create Incremental FIS Tree on the `fistree` reference page.

Aggregated Structure

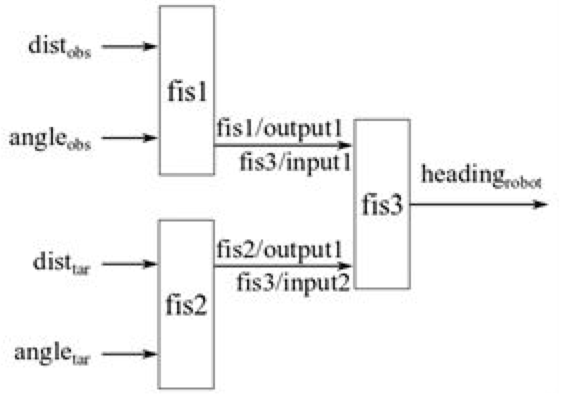
In an aggregated structure, input values are incorporated as groups at the lowest level, where each input group is fed into a FIS. The outputs of the lower level fuzzy systems are combined (aggregated) using the higher level fuzzy systems. For example, the following shows a two-level aggregated fuzzy tree having fuzzy inference systems $FIS_{i_n}^n$, where i_n indicates the index of a FIS in the nth level.



Aggregated

In this aggregated fuzzy tree, $i_1 = 1,2$ and $i_2 = 1$. Hence, each level includes a different number of FIS. The jth input of the i_nth FIS is shown in the figure as input $x_{i_n j}$, and the kth output of the i_nth FIS is shown as output $y_{i_n k}$. In the figure, $j = 1,2$ and $k = 1$. In other words, each FIS has two inputs and one output. If each input has m MFs, then each FIS has a complete set of m^2 rules. Hence, the total number of rules for the three fuzzy systems is 3 m^2 = 3 □ 32 = 27, which is the same as an incremental FIS for a similar configuration.

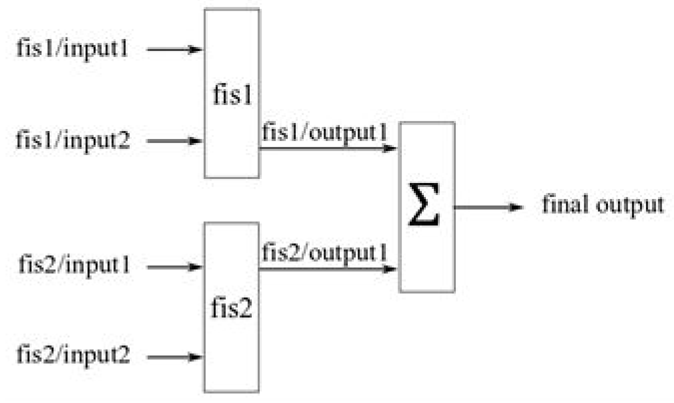
In an aggregated fuzzy tree, input values are naturally grouped together for specific decision-making. For example, an autonomous robot navigation task combines obstacle avoidance and target reaching subtasks for collision-free navigation. To achieve the navigation task, the fuzzy tree can use four inputs: distance to the closest obstacle, angle of the closest obstacle, distance to the target, and angle of the target. Distances and angles are measured with respect to the current position and heading direction of the robot. In this case, at the lowest level, the inputs naturally group as shown in the following figure: obstacle distance and obstacle angle (group 1) and target distance and target angle (group 2). Two fuzzy systems separately process individual group inputs and then another fuzzy system combines their outputs to produce a collision-free heading for the robot.



For an example that illustrates creating an aggregated fuzzy tree in MATLAB, see the example Create Aggregated FIS Tree on the `fistree` reference page.

Variation on Aggregated Structure

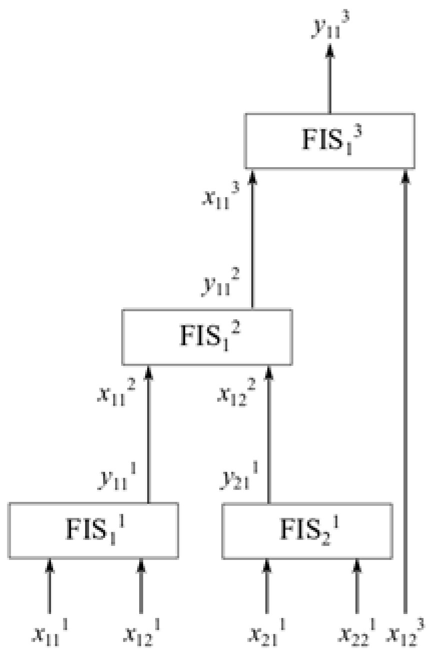
In a variation of the aggregated structure known as parallel structure [1], the outputs of the lowest-level fuzzy systems are directly summed to generate the final output value. The following figure shows an example of a parallel fuzzy tree, where outputs of fis1 and fis2 are summed to produce the final output.



The `fistree` object does not provide the summing node Σ. Therefore, you must add a custom aggregation method to evaluate a parallel fuzzy tree. For an example, see Create and Evaluate Parallel FIS Tree on the `fistree` reference page.

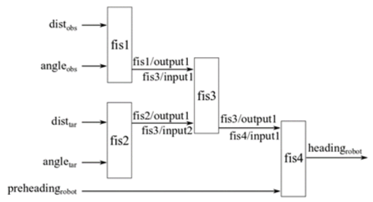
Cascaded or Combined Structure

A cascaded structure, also known as combined structure, combines both incremental and aggregated structures to construct a fuzzy tree. This structure is suitable for a system that includes both correlated and uncorrelated inputs. The tree groups the correlated inputs in an aggregated structure, and adds uncorrelated inputs in an incremental structure. The following figure shows an example of a cascaded tree structure, where the first four inputs are grouped pairwise in an aggregated structure and the fifth input is added in an incremental structure.



Cascaded (combined)

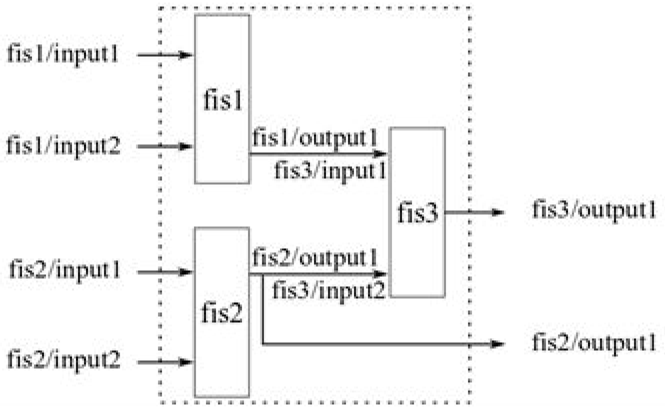
For example, consider the robot navigation task discussed in “Aggregated Structure” on page 2-68. Suppose that tasks includes another input, the previous heading direction of the robot, taken into account to prevent large changes in the robot’s heading direction. You can add this input using the incremental structure of the following diagram.


$\mathrm{dist}_{\mathrm{obs}}$
$\mathrm{angle}_{\mathrm{obs}}$
$\mathrm{dist}_{\mathrm{tar}}$
$\mathrm{angle}_{\mathrm{tar}}$
$\mathrm{preheading}_{\mathrm{robot}}$
fis1
fis2
fis3
fis4
fis1/output1
fis3/input1
fis2/output1
fis3/input2
fis3/output1
fis4/input1
$\mathrm{heading}_{\mathrm{robot}}$

For an example that illustrates creating an aggregated fuzzy tree in MATLAB, see the example Create Cascaded FIS Tree on the `fistree` reference page.

Add or Remove FIS Tree Outputs

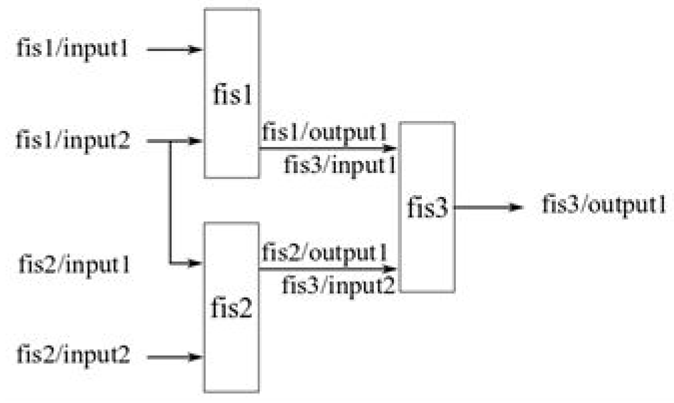
When you evaluate a `fistree` object, it returns results for only the open outputs, which are not connected to any FIS inputs in the fuzzy tree. You can optionally access other outputs in the tree. For instance, in the following diagram of an aggregated fuzzy tree, you might want to obtain the output of fis2 when you evaluate the tree.



You can add such outputs to a `fistree` object. You can also remove outputs, provided that the fuzzy tree always has at least one output. For an example, see Update FIS Tree Outputs on the `fistree` reference page.

Use the Same Value for Multiple inputs of FIS Tree

A `fistree` object allows using the same value for multiple inputs. For instance, in the following figure, input2 of fis1 and input 1 of fis2 use the same value during evaluation.



For an example showing how to construct a FIS tree in this way, see the example Use Same Value for Multiple Inputs of a FIS Tree on the `fistree` reference page.

Update Fuzzy Inference Systems in FIS Tree

You can add or remove individual FIS elements from a `fistree` object. When you do so, the software automatically updates the `Connections`, `Inputs`, and `Outputs` properties of the `fistree` object. For an example, see Update Fuzzy Inference Systems in a FIS Tree in the `fistree` reference page.

Tune a Fuzzy Tree

Once you have configured the internal connections in your fuzzy tree as you want them, the next step is to tune the parameters of the tree. For an example, see “Tune FIS Tree for Gas Mileage Prediction” on page 3-47.

References

[1] Siddique, N., and H. Adeli. *Computational Intelligence: Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing*. Hoboken, NJ: Wiley, 2013.

See Also

`fistree`

More About

- "Tuning Fuzzy Inference Systems" on page 3-2
- "Tune FIS Tree for Gas Mileage Prediction" on page 3-47

Fuzzy Logic Image Processing

This example shows how to use fuzzy logic for image processing. Specifically, this example shows how to detect edges in an image.

An edge is a boundary between two uniform regions. You can detect an edge by comparing the intensity of neighboring pixels. However, because uniform regions are not crisply defined, small intensity differences between two neighboring pixels do not always represent an edge. Instead, the intensity difference might represent a shading effect.

The fuzzy logic approach for image processing allows you to use membership functions to define the degree to which a pixel belongs to an edge or a uniform region.

Import RGB Image and Convert to Grayscale

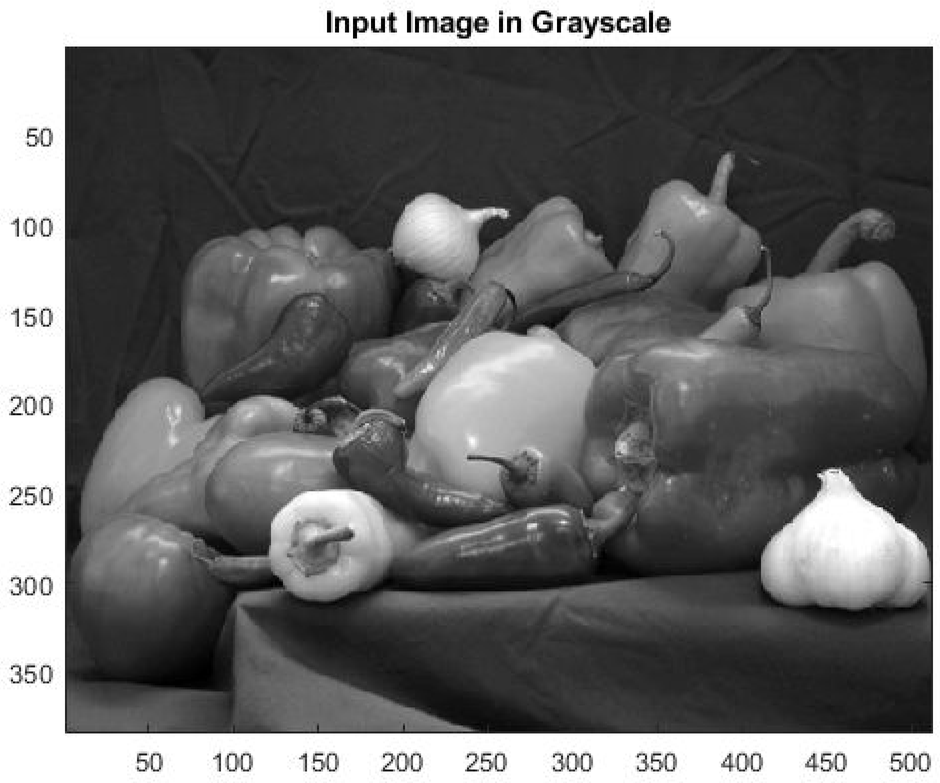
Import the image.

```
Irgb = imread('peppers.png');
```

`Irgb` is a 384 x 512 x 3 `uint8` array. The three channels of `Irgb` (third array dimension) represent the red, green, and blue intensities of the image.

Convert `Irgb` to grayscale so that you can work with a 2-D array instead of a 3-D array. To do so, use the `rgb2gray` function.

```
Igray = rgb2gray(Irgb);

figure
image(Igray,'CDataMapping','scaled')
colormap('gray')
title('Input Image in Grayscale')
```



Convert Image to Double-Precision Data

The `evalfis` function for evaluating fuzzy inference systems supports only single-precision and double-precision data. Therefore, convert `Igray` to a `double` array using the `im2double` function.

```
I = im2double(Igray);
```

Obtain Image Gradient

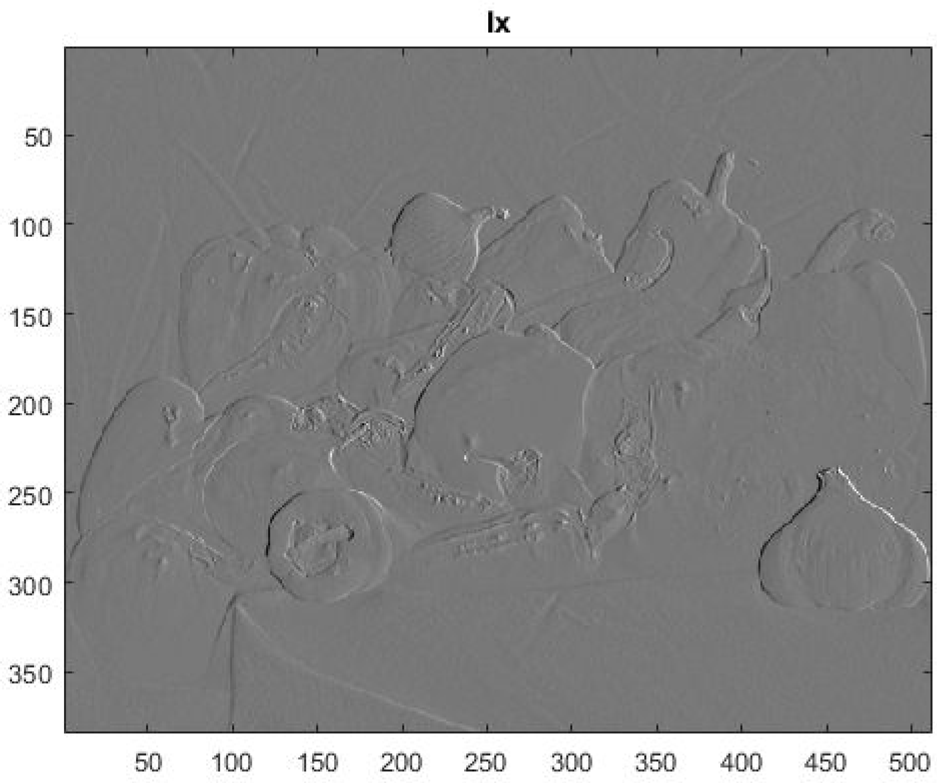
The fuzzy logic edge-detection algorithm for this example relies on the image gradient to locate breaks in uniform regions. Calculate the image gradient along the *x*-axis and *y*-axis.

`Gx` and `Gy` are simple gradient filters. To obtain a matrix containing the *x*-axis gradients of `I`, you convolve `I` with `Gx` using the `conv2` function. The gradient values are in the [-1 1] range. Similarly, to obtain the *y*-axis gradients of `I`, convolve `I` with `Gy`.

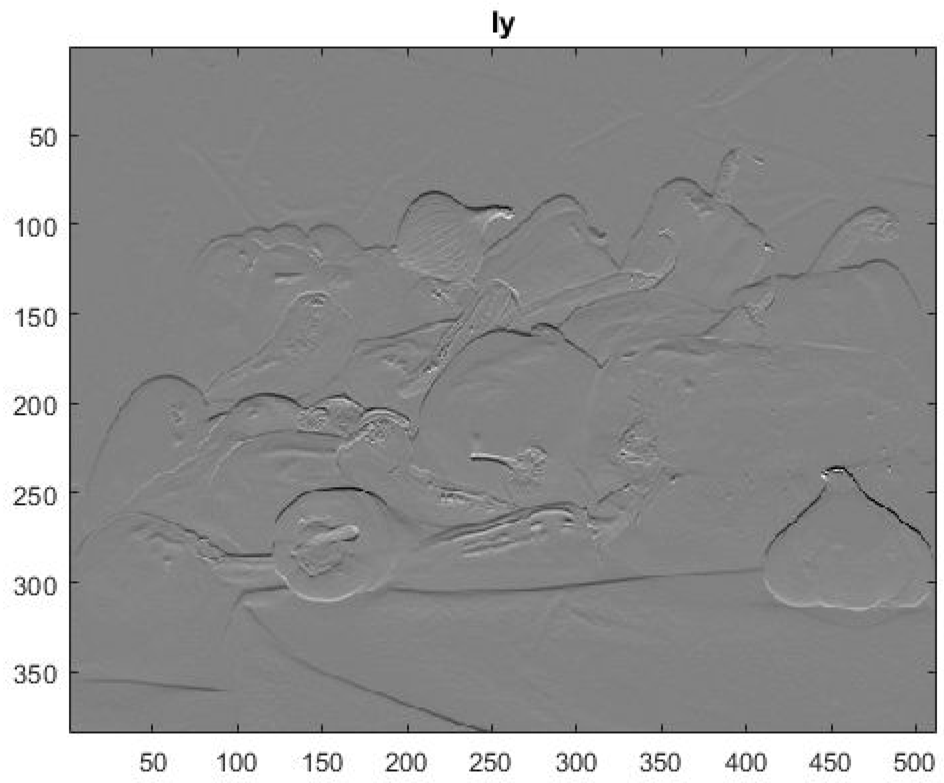
```
Gx = [-1 1];
Gy = Gx';
Ix = conv2(I,Gx,'same');
Iy = conv2(I,Gy,'same');
```

Plot the image gradients.

```
figure
image(Ix,'CDataMapping','scaled')
colormap('gray')
title('Ix')
```



```
figure
image(Iy,'CDataMapping','scaled')
colormap('gray')
title('Iy')
```



You can use other filters to obtain the image gradients, such as the Sobel operator or the Prewitt operator. For information about how you can filter an image using convolution, see “What Is Image Filtering in the Spatial Domain?” (Image Processing Toolbox)

Alternatively, if you have the Image Processing Toolbox software, you can use the `imfilter`, `imgradientxy`, or `imgradient` functions to obtain the image gradients.

Define Fuzzy Inference System (FIS) for Edge Detection

Create a fuzzy inference system (FIS) for edge detection, `edgeFIS`.

```
edgeFIS = mamfis('Name','edgeDetection');
```

Specify the image gradients, `Ix` and `Iy`, as the inputs of `edgeFIS`.

```
edgeFIS = addInput(edgeFIS,[-1 1],'Name','Ix');
edgeFIS = addInput(edgeFIS,[-1 1],'Name','Iy');
```

Specify a zero-mean Gaussian membership function for each input. If the gradient value for a pixel is `0`, then it belongs to the zero membership function with a degree of `1`.

```
sx = 0.1;
sy = 0.1;
edgeFIS = addMF(edgeFIS,'Ix','gaussmf',[sx 0],'Name','zero');
edgeFIS = addMF(edgeFIS,'Iy','gaussmf',[sy 0],'Name','zero');
```

`sx` and `sy` specify the standard deviation for the zero membership function for the `Ix` and `Iy` inputs. To adjust the edge detector performance, you can change the values of `sx` and `sy`. Increasing the values makes the algorithm less sensitive to the edges in the image and decreases the intensity of the detected edges.

Specify the intensity of the edge-detected image as an output of `edgeFIS`.

```
edgeFIS = addOutput(edgeFIS,[0 1],'Name','Iout');
```

Specify the triangular membership functions, white and black, for `Iout`.

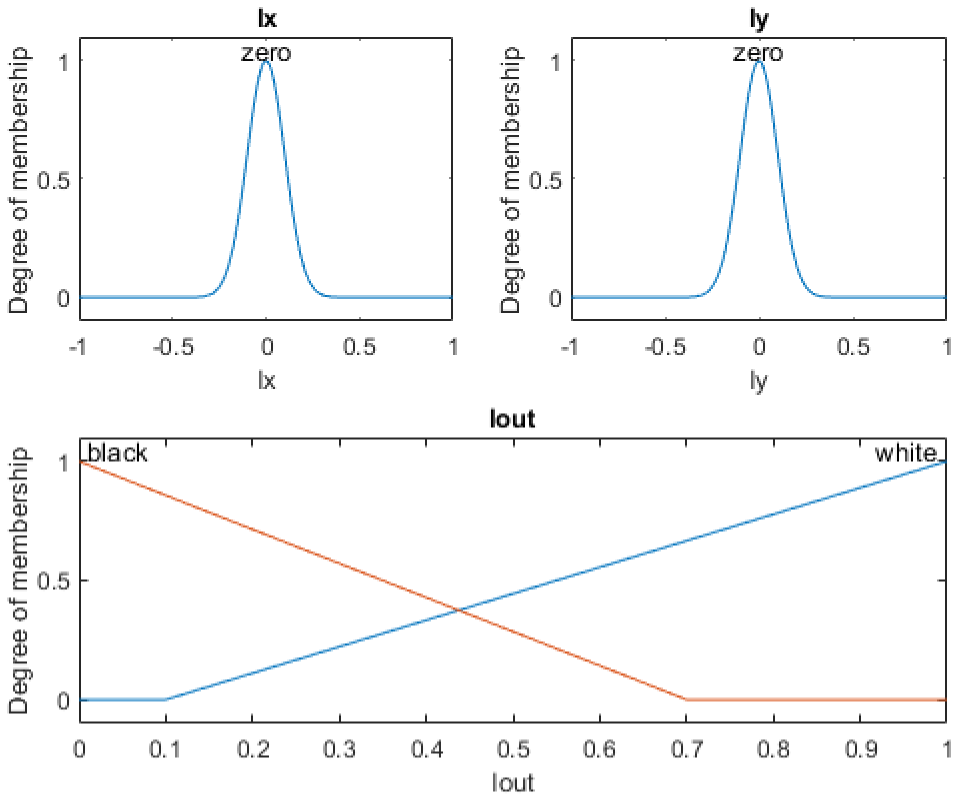
```
wa = 0.1;
wb = 1;
wc = 1;
ba = 0;
bb = 0;
bc = 0.7;
edgeFIS = addMF(edgeFIS,'Iout','trimf',[wa wb wc],'Name','white');
edgeFIS = addMF(edgeFIS,'Iout','trimf',[ba bb bc],'Name','black');
```

As you can with `sx` and `sy`, you can change the values of `wa`, `wb`, `wc`, `ba`, `bb`, and `bc` to adjust the edge detector performance. The triplets specify the start, peak, and end of the triangles of the membership functions. These parameters influence the intensity of the detected edges.

Plot the membership functions of the inputs and outputs of `edgeFIS`.

```
figure
subplot(2,2,1)
plotmf(edgeFIS,'input',1)
title('Ix')
subplot(2,2,2)
plotmf(edgeFIS,'input',2)
```

```
title('Iy')
subplot(2,2,[3 4])
plotmf(edgeFIS,'output',1)
title('Iout')
```



Specify FIS Rules

Add rules to make a pixel white if it belongs to a uniform region and black otherwise. A pixel is in a uniform region when the image gradient is zero in both directions. If either direction has a nonzero gradient, then the pixel is on an edge.

```
r1 = "If Ix is zero and Iy is zero then Iout is white";
r2 = "If Ix is not zero or Iy is not zero then Iout is black";
```

```
edgeFIS = addRule(edgeFIS,[r1 r2]);
edgeFIS.Rules

ans = 
  1x2 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                         Description
         _______________________________________

    1    "Ix==zero & Iy==zero => Iout=white (1)"
    2    "Ix~=zero | Iy~=zero => Iout=black (1)"
```

Evaluate FIS

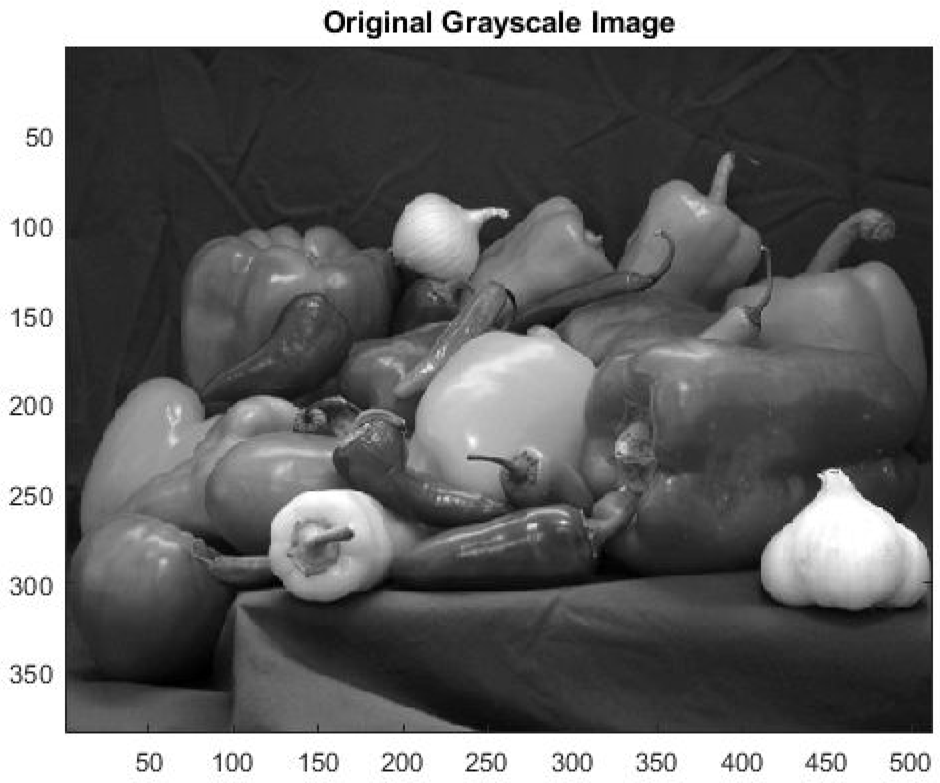
Evaluate the output of the edge detector for each row of pixels in `I` using corresponding rows of `Ix` and `Iy` as inputs.

```
Ieval = zeros(size(I));
for ii = 1:size(I,1)
    Ieval(ii,:) = evalfis(edgeFIS,[(Ix(ii,:));(Iy(ii,:))]');
end
```

Plot Results

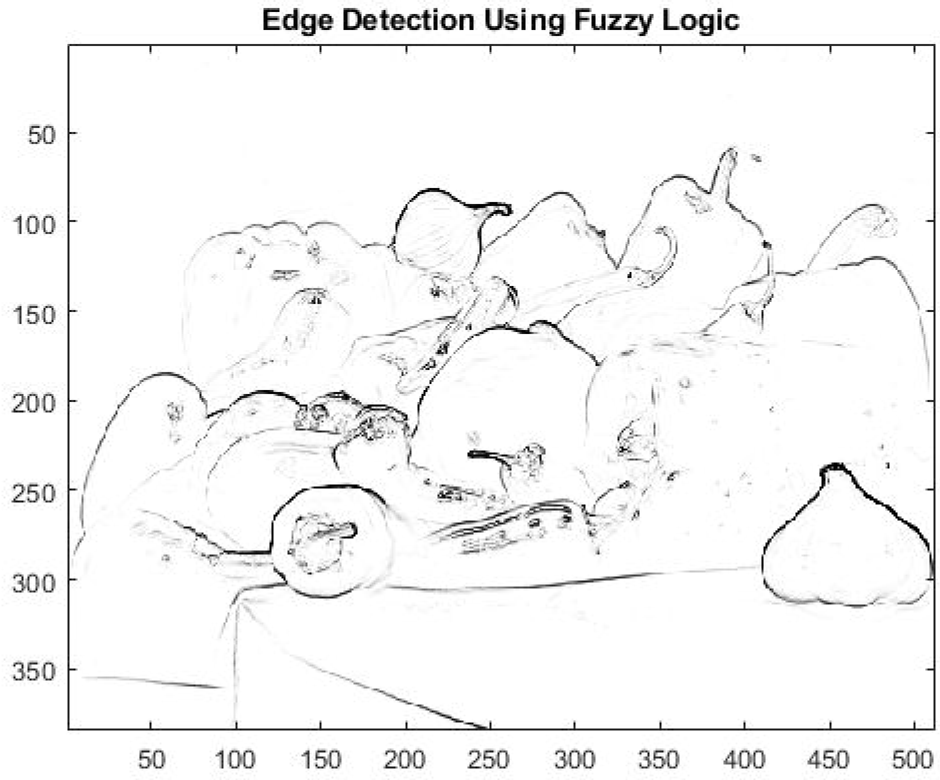
Plot the original grayscale image.

```
figure
image(I,'CDataMapping','scaled')
colormap('gray')
title('Original Grayscale Image')
```



Plot the detected edges.

```
figure
image(Ieval,'CDataMapping','scaled')
colormap('gray')
title('Edge Detection Using Fuzzy Logic')
```



See Also

`evalfis`

More About

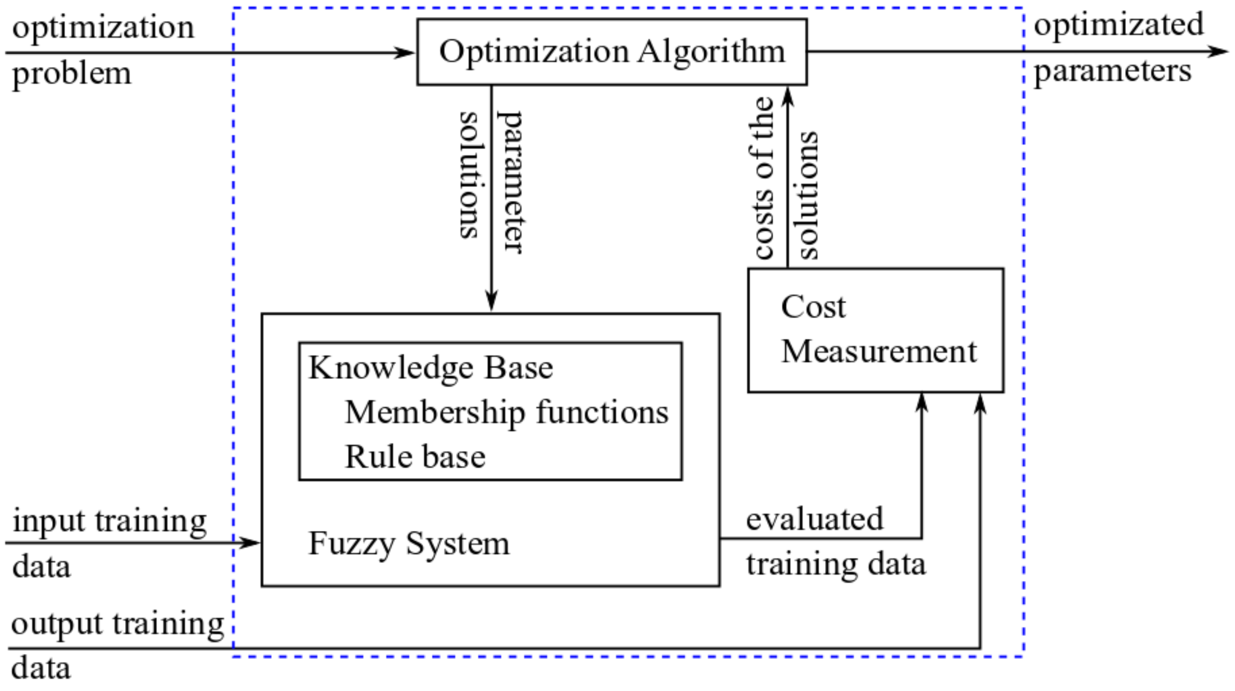
- "Build Fuzzy Systems at the Command Line" on page 2-38

Fuzzy Inference System Tuning

Tuning Fuzzy Inference Systems

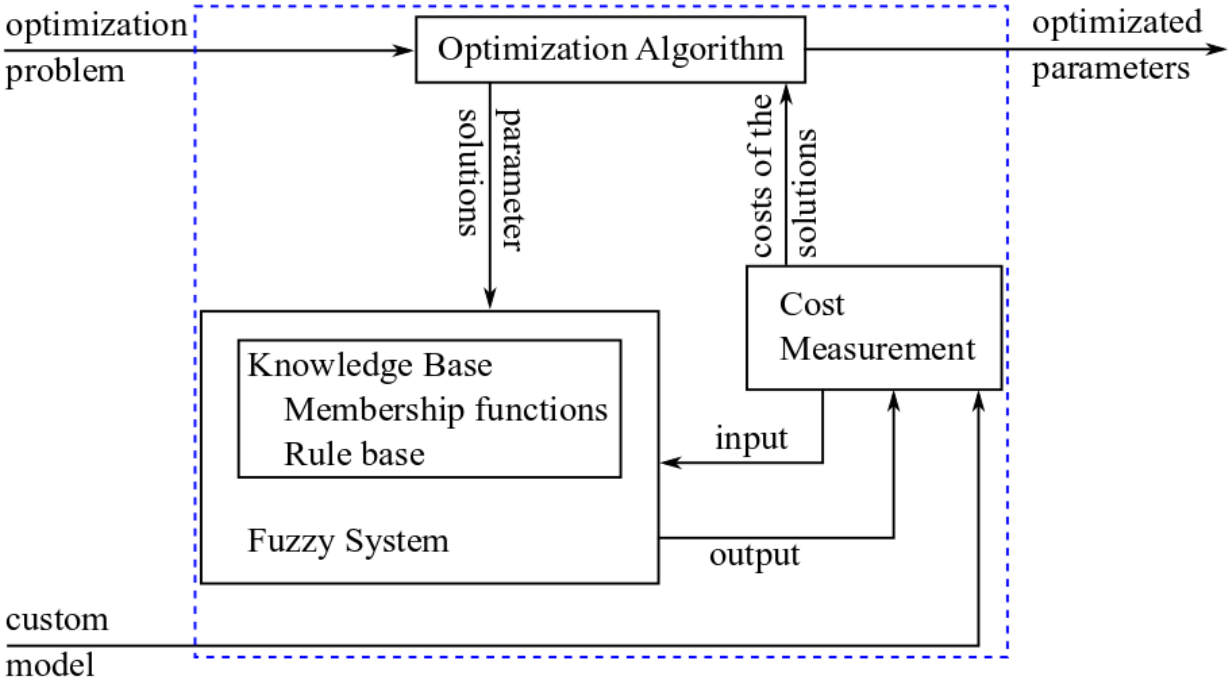
Designing a complex fuzzy inference system (FIS) with large number of inputs and membership functions (MFs) is a challenging problem due to large number of MF parameters and increasing number of rules. A promising solution to this problem is to design FIS trees, which include hierarchically connected modular FISs having small number of inputs. Designing a FIS tree with appropriate MF parameters and rules, however, is a difficult task when adequate expert knowledge is not available for a complex system. Hence, the data-driven approach of tuning and optimizing MF and rule parameters offers an elegant solution to this problem.

You can tune a fuzzy system using the `tunefis` command. The following figure shows how a fuzzy system is tuned with input/output training data. The tuning process uses an optimization method on an optimization problem created from a fuzzy system.



In each iteration, the optimization method generates multiple sets of solutions, which are values for the selected parameters of the fuzzy system. The fuzzy system is updated with each solution and then evaluated using the input training data. The evaluated output is compared with the output training data to generate costs of the solutions. This process continues for multiple iterations until the stop condition is met, and then it returns the minimum cost solution with the optimized fuzzy system parameters. For an example that uses this approach, see “Tune Mamdani Fuzzy Inference System” on page 3-33.

If input/output training data is not available, you can use a custom model in place of the training data to evaluate a fuzzy system for cost measurement. This approach is shown in the following figure.



In this case, the custom model uses the fuzzy system to minimize the cost of achieving specific performance goals. The parameter solution that produces the best performance of the custom model is returned as the optimization result. For example, in a robot navigation model, the performance goal is to minimize the travelled distances to target positions without colliding with any of the obstacles. Hence, the navigation model uses the fuzzy system to control the robot’s heading direction to achieve the goal. For an example that uses this approach, see “Tune Fuzzy Systems using Custom Cost Function” on page 3-70.

You can select individual MF and rule parameters of a fuzzy system for optimization.

Tune Membership Function Parameters

This example shows how to specify parameter settings for each input and output MF of a FIS and tune it.

Create a FIS.

```
fis = mamfis;
fis = addInput(fis,[0 10],'NumMFs',3);
fis = addOutput(fis,[0 1],'NumMFs',3);
fis = addRule(fis,[1 1 1 1;1 1 1 1;1 1 1 1]);
```

Extract input and output parameter settings from the FIS.

```
[in,out] = getTunableSettings(fis)
```

```
in = 
  VariableSettings with properties:

                   Type: "input"
           VariableName: "input1"
    MembershipFunctions: [1x3 fuzzy.tuning.MembershipFunctionSettings]
                FISName: "fis"


out = 
  VariableSettings with properties:

                   Type: "output"
           VariableName: "output1"
    MembershipFunctions: [1x3 fuzzy.tuning.MembershipFunctionSettings]
                FISName: "fis"
```

The parameter settings are represented by `VariableSettings` objects that include the FIS name, variable type, variable name, and MF parameter settings. Examine the parameter settings of MF 1 of input 1.

```
in(1).MembershipFunctions(1).Parameters
```

```
ans = 
  NumericParameters with properties:

    Minimum: [-Inf -Inf -Inf]
    Maximum: [Inf Inf Inf]
       Free: [1 1 1]
```

For each parameter value of an input/output MF, you can specify whether it is available for tuning and its minimum and maximum values. By default, all MF parameters are free for tuning and their ranges are set to `[-Inf,Inf]. Make` MF 1 of input 1 nontunable.

```
in(1).MembershipFunctions(1) = setTunable(in(1).MembershipFunctions(1),false);
```

Similarly, make the first parameter of MF 2 of input 1 nontunable.

```
in(1).MembershipFunctions(2).Parameters.Free(1) = false;
```

Set minimum ranges for second and third parameters of MF 3 of input 1 to 0.

```
in(1).MembershipFunctions(3).Parameters.Minimum(2:3) = 0;
```

Set maximum ranges for second and third parameters of MF 3 of input 1 to 15.

```
in(1).MembershipFunctions(3).Parameters.Maximum(2:3) = 15;
```

Note that the default minimum and maximum range values of tunable MF parameters are set to corresponding input/output ranges in the tuning process.

Finally, make the output nontunable.

```
out = setTunable(out,false);
```

Now that you have configured the parameters, specify input and output training data. Generate some data for this example.

```
x = (0:0.1:10)';
y = abs(sin(2*x)./exp(x/5));
```

Specify options for `tunefis`. Use genetic algorithm for optimization.

```
options = tunefisOptions("Method","ga");
```

Specify maximum 5 generations for optimization.

```
options.MethodOptions.MaxGenerations = 5;
```

If you have Parallel Computing Toolbox™ software, you can improve the speed of the tuning process by setting `options.UseParallel` to `true`. If you do not have Parallel Computing Toolbox software, set `options.UseParallel` to `false`.

By default, `tunefis` uses root mean squared error (RMSE) for cost calculation. You can change the cost function to `norm1` or `norm2` by setting `options.DistanceMetric`.

```
options.DistanceMetric = "norm1";
```

Tune `fis` using the parameter settings, training data, and tuning options.

```
rng('default')  % for reproducibility
[fisout,optimout] = tunefis(fis,[in;out],x,y,options);
```

```
                                  Best            Mean      Stall
Generation      Func-count         f(x)            f(x)    Generations
    1              100            32.84           32.84        0
    2              150            32.84           32.84        1
    3              200            32.84           32.84        2
    4              250            32.84           32.84        3
    5              300            32.84           32.84        4
Optimization terminated: maximum number of generations exceeded.
```

`fisout` includes the updated parameter values. `optimout` provides additional outputs of the optimization method and any error message that are returned during the update process of the input fuzzy system using the optimized parameter values.

```
optimout
```

```
optimout = struct with fields:
    tuningOutputs: [1x1 struct]
     errorMessage: []
```

```
optimout.tuningOutputs
```

```
ans = struct with fields:
             x: [5 9.1667 5.8333 10 14.1667]
          fval: 32.8363
      exitflag: 0
        output: [1x1 struct]
    population: [50x5 double]
        scores: [50x1 double]
```

You can optionally tune `fis` using either input or output parameter settings. In this example, output parameter settings are set to nontunable. Therefore, tuning `fis` with only input parameter settings produces the same results.

```
rng('default')
tunefis(fis,in,x,y,options);
```

```
                                  Best            Mean      Stall
Generation      Func-count         f(x)            f(x)    Generations
    1              100           32.84           32.84        0
    2              150           32.84           32.84        1
    3              200           32.84           32.84        2
    4              250           32.84           32.84        3
    5              300           32.84           32.84        4
Optimization terminated: maximum number of generations exceeded.
```

Note that the best optimization costs shown in column 3 of both tuning results are the same, which indicates that the optimization results are the same in both cases.

Tune Fuzzy Rules

You can specify only rule parameters of a fuzzy system for tuning.

Use `getTunableSettings` to get rule parameter settings from a fuzzy system. Rule parameter settings are returned as the third output argument.

```
[~,~,rule] = getTunableSettings(fis)
```

```
rule = 
  3x1 RuleSettings array with properties:

    Index
    Antecedent
    Consequent
    FISName
```

Each rule parameter settings include FIS name, index of the rule in the FIS, and parameter settings for the rule antecedent and consequent (the *rule clause*).

The parameter settings for a rule clause include three options:

- Whether the input/output MF indices are available for tuning. By default, clause parameters are free for tuning.

- Whether the clause allows use of NOT logic, in other words, whether it allows negative MF indices. By default, rules do not allow NOT logic.
- Whether the cluase allows absence of input/output variables, in other words, if it allows zero MF indices. By default, absence of a variable is allowed.

```
rule(1).Antecedent(1)
```

```
ans = 
  ClauseParameters with properties:

      AllowNot: 0
    AllowEmpty: 1
          Free: 1
```

Allow NOT logic in the antecedent of rule 1.

```
rule(1).Antecedent.AllowNot = true;
```

Make the consequent of rule 1 not available for tuning.

```
rule(1).Consequent.Free = 0;
```

Do not allow absence of a variable in the consequent of rule 2.

```
rule(2).Consequent.AllowEmpty = false;
```

Set rule 3 nontunable.

```
rule(3) = setTunable(rule(3),false);
```

Set `options.DistanceMetric` to `norm2`.

```
options.DistanceMetric = "norm2";
```

Tune `fis` with the rule parameter settings.

```
rng('default')  % for reproducibility
fisout = tunefis(fis,rule,x,y,options);
```

```
                                  Best            Mean      Stall
Generation      Func-count        f(x)            f(x)    Generations
    1              100           1.648           2.575        0
    2              150           1.648           2.448        1
    3              200           1.648           2.212        2
    4              250           1.648            2.052        3
    5              300           1.648            1.874        4
Optimization terminated: maximum number of generations exceeded.
```

Because you made rule 3 nontunable, you can exclude rule 3 when you tune `fis`.

```
rng('default')  % for reproducibility
tunefis(fis,rule(1:2),x,y,options);
```

```
                                 Best             Mean      Stall
Generation      Func-count        f(x)             f(x)    Generations
    1              100           1.648            2.575        0
    2              150           1.648            2.448        1
    3              200           1.648            2.212        2
    4              250           1.648            2.052        3
    5              300           1.648            1.874        4
Optimization terminated: maximum number of generations exceeded.
```

Note that the best optimization costs shown in column 3 of both tuning results are the same, which indicates the optimization results are the same in both cases.

Learn Fuzzy Rules

You can tune a fuzzy system without any rules in `tunefis`. In this case, set the `OptimizationType` option of `tunefisOptions`to `learning` so that `tunefis` learns rules for the FIS.

```
fisin = fis;
fisin.Rules = [];
options.OptimizationType = 'learning';
```

Specify maximum size of the rule base to 3. This value specifies the maximum number of rules in the tuned FIS.

```
options.NumMaxRules = 3;
```

Note that the size of the tuned rule base may be less than `NumMaxRules`, because `tunefis` removes duplicate rules from the tuned FIS. If you do not specify `NumMaxRules`, then `tunefis` adds the maximum number of rules determined by the combinations of input MFs. The default input MF combinations include zero MF indices, which allow absence of variables. The default combinations exclude negative MF indices, so that NOT logic is not allowed.

Set `options.DistanceMetric` to `rmse` and tune the FIS.

```
options.DistanceMetric = "rmse";
rng('default')  % for reproducibility
fisout = tunefis(fisin,[],x,y,options);
```

```
                                 Best            Mean      Stall
Generation      Func-count        f(x)            f(x)    Generations
    1              400           0.165           0.2973        0
    2              600           0.165           0.2891        1
    3              800           0.165           0.2685        2
    4             1000           0.165           0.2548        3
    5             1200           0.165           0.2378        4
Optimization terminated: maximum number of generations exceeded.
```

During the tuning process, the FIS automatically learns rules after cost optimization with the training data. Examine the tuned rules.

```
fisout.Rules
```

```
ans = 
  1x3 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                   Description
         ________________________________

    1    "input1==mf3 => output1=mf1 (1)"
    2    "input1==mf1 => output1=mf2 (1)"
    3    "input1==mf2 => output1=mf1 (1)"
```

You can remove some of the existing rules and learn additional rules.

```
fisout.Rules(2:end) = [];
rng('default')  % for reproducibility
fisout = tunefis(fisin,[],x,y,options);
```

```
                                 Best            Mean      Stall
Generation      Func-count        f(x)            f(x)    Generations
    1              400           0.165           0.2973        0
    2              600           0.165          0.2891        1
    3              800           0.165          0.2685        2
    4             1000           0.165          0.2548        3
    5             1200           0.165          0.2378        4
Optimization terminated: maximum number of generations exceeded.
```

```
fisout.Rules
```

```
ans = 
  1x3 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                   Description                
         ________________________________

    1    "input1==mf3 => output1=mf1 (1)"
    2    "input1==mf1 => output1=mf2 (1)"
    3    "input1==mf2 => output1=mf1 (1)"
```

You can also tune existing rules and learn new rules.

```
fisout.Rules(2:end) = [];
fisout.Rules(1).Antecedent = 1;
fisout.Rules(1).Consequent = 1;
[~,~,rule] = getTunableSettings(fisout);
rng('default')
fisout = tunefis(fisin,rule,x,y,options);
```

```
                                 Best            Mean      Stall
Generation      Func-count        f(x)            f(x)    Generations
    1              400           0.165          0.3075        0
    2              600           0.165          0.2738        1
    3              800           0.165          0.2545        2
    4             1000           0.165          0.2271        3
    5             1200           0.165          0.2083        4
Optimization terminated: maximum number of generations exceeded.
```

```
fisout.Rules
```

```
ans = 
  1x3 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                       Description
         ________________________________

    1    "input1==mf1 => output1=mf2 (1)"
    2    "input1==mf2 => output1=mf1 (1)"
    3    "input1==mf3 => output1=mf1 (1)"
```

Tune MF and Rule Parameters

You can tune all FIS parameters together.

```
[in,out,rule] = getTunableSettings(fis);
options = tunefisOptions('Method','ga');
options.MethodOptions.MaxGenerations = 5;
rng('default')  % for reproducibility
fisout = tunefis(fis,[in;out;rule],x,y,options);
```

```
                                  Best           Mean      Stall
Generation      Func-count        f(x)           f(x)    Generations
    1              400           0.1624         0.2997        0
    2              600           0.1624         0.2776        1
    3              800           0.1624         0.2653        2
    4             1000           0.1592         0.2486        0
    5             1200           0.1592         0.2342        1
Optimization terminated: maximum number of generations exceeded.
```

For a large fuzzy system, tuning all FIS parameters in the same tuning process may take several iterations to obtain the expected results. Hence, you can tune parameters in two steps:

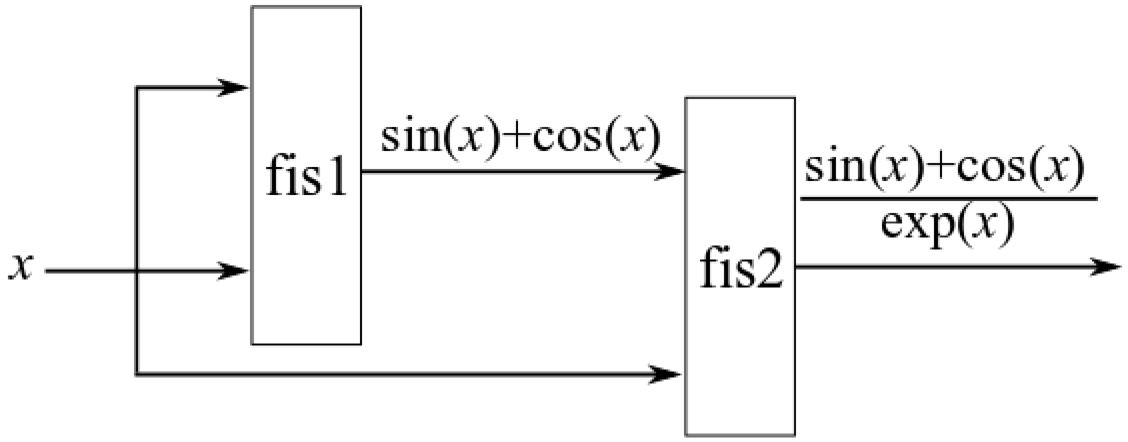
1. Tune or learn rule parameters only.
2. Tune both MF and rule parameters.

The first step is less computationally expensive due to the small number of rule parameters. It quickly converges to a fuzzy rule base during training. In the second step, using the rule base from the first step as an initial condition provides fast convergence of the parameter tuning process.

Tune FIS Tree Parameters

You can tune the parameters of a FIS tree using a similar two-step process to the one described above for tuning a FIS.

Create a FIS tree to model $\frac{\sin(x) + \cos(x)}{\exp(x)}$ as shown in the following figure.



Create `fis1` as a Sugeno type FIS, which results in faster tuning process due to computationally efficient defuzzification method. Add two inputs with range [0 10] having three MFs each. Use a smooth differentiable MF, such as `gaussmf`, to match characteristics of the data type you are modeling.

```
fis1 = sugfis('Name','fis1');
fis1 = addInput(fis1,[0 10],'NumMFs',3,'MFType','gaussmf');
fis1 = addInput(fis1,[0 10],'NumMFs',3,'MFType','gaussmf');
```

Add an output with range [–1.5 1.5] having nine MFs to provide maximum granularity corresponding to each combination of the input MFs. The output range is set according to the values of $\sin(x) + \cos(x)$.

```
fis1 = addOutput(fis1,[-1.5 1.5],'NumMFs',9);
```

Create `fis2` as a Sugeno type FIS as well. Add two inputs. Use [-1.5 1.5] as the range of the first input, which is the output of `fis1`. The second input is the same as the inputs of `fis1`, so it also uses range [0 10]. Add three MFs for each of the inputs.

```
fis2 = sugfis('Name','fis2');
fis2 = addInput(fis2,[-1.5 1.5],'NumMFs',3,'MFType','gaussmf');
fis2 = addInput(fis2,[0 10],'NumMFs',3,'MFType','gaussmf');
```

Add an output with range [0 1] having nine MFs to provide maximum granularity corresponding to each combination of the input MFs. The output range is set according to the values of $\frac{\sin(x) + \cos(x)}{\exp(x)}$.

```
fis2 = addOutput(fis2,[0 1],'NumMFs',9);
```

Connect the inputs and the outputs as shown in the diagram. Output 1 of `fis1` connects to input 1 of `fis2`, inputs 1 and 2 of `fis1` connect to each other, and input 2 of `fis1` connects to input 2 of `fis2`.

```
con1 = ["fis1/output1" "fis2/input1"];
con2 = ["fis1/input1" "fis1/input2"];
con3 = ["fis1/input2" "fis2/input2"];
```

Finally, create a FIS tree using `fis1`, `fis2`, `con1`, `con2`, and `con3`.

```
fisT = fistree([fis1 fis2],[con1;con2;con3]);
```

Specify an additional output to the FIS tree to access the output of `fis1`.

```
fisT.Outputs = ["fis1/output1";fisT.Outputs];
```

Generate input and output training data.

```
x = (0:0.1:10)';
y1 = sin(x)+cos(x);
y2 = y1./exp(x);
y = [y1 y2];
```

Tune the FIS tree parameters in two steps. First, use a global optimization method such as particle swarm or genetic algorithm to learn the rules of the FIS tree. Create `tunefis` options for learning with the `particleswarm` method.

```
options = tunefisOptions('Method','particleswarm','OptimizationType','learning');
```

This tuning step uses small number of iterations to learn a rule base without overfitting the training data. The rule base provides an educated initial condition for the second step to optimize all the FIS tree parameters together. Set the maximum iteration number to 5, and learn the rule base.

```
options.MethodOptions.MaxIterations = 5;
rng('default')  % for reproducibility
fisTout1 = tunefis(fisT,[],x,y,options);
```

```
                                 Best            Mean     Stall
Iteration     f-count            f(x)            f(x)    Iterations
    0            100            0.6682          0.9395        0
    1            200            0.6682           1.023        0
    2            300            0.6652          0.9308        0
    3            400            0.6259           0.958        0
    4            500            0.6259           0.918        1
    5            600            0.5969          0.9179        0
Optimization ended: number of iterations exceeded OPTIONS.MaxIterations.
```

To tune all the FIS tree parameters, the second step uses a local optimization method such as pattern search or simulation annealing method. Local optimization is generally faster than global optimization and can produce better results when the input fuzzy system parameters are already consistent with the training data.

Use the `patternsearch` method for optimization. Set the number of iterations to 25.

```
options.Method = 'patternsearch';
options.MethodOptions.MaxIterations = 25;
```

Use `getTunableSettings` to get input, output, and rule parameter settings from `fisTout1`.

```
[in,out,rule] = getTunableSettings(fisTout1);
```

Tune all FIS tree parameters.

```
rng('default') % for reproducibility
fisTout2 = tunefis(fisTout1,[in;out;rule],x,y,options);
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1      0.596926             1      
    1           3      0.551284             2     Successful Poll
    2          13      0.548551             4     Successful Poll
    3          20      0.546331             8     Successful Poll
    4          33      0.527482            16     Successful Poll
    5          33      0.527482             8     Refine Mesh
    6          61      0.511532            16     Successful Poll
    7          61       0.511532             8     Refine Mesh
    8          92       0.505355            16     Successful Poll
    9          92       0.505355             8     Refine Mesh
   10         128       0.505355             4     Refine Mesh
   11         175       0.487734             8     Successful Poll
   12         212       0.487734             4     Refine Mesh
   13         265       0.487734             2     Refine Mesh
   14         275       0.486926             4     Successful Poll
   15         328       0.486926             2     Refine Mesh
   16         339       0.483683             4     Successful Poll
   17         391       0.483683             2     Refine Mesh
   18         410       0.442624             4     Successful Poll
   19         462       0.442624             2     Refine Mesh
   20         469        0.44051             4     Successful Poll
   21         521        0.44051             2     Refine Mesh
   22         542       0.435381             4     Successful Poll
   23         594       0.435381             2     Refine Mesh
   24         614       0.398872             4     Successful Poll
   25         662       0.398385             8     Successful Poll
   26         698       0.398385             4     Refine Mesh
Maximum number of iterations exceeded: increase options.MaxIterations.
```

The optimization cost reduces from 0.59 to 0.39 in the second step.

Tune FIS Tree with Selected Fuzzy Systems

You can tune specific fuzzy systems in a FIS tree. To get parameter settings of the specific fuzzy systems, use `getTunableSettings`. For example, after learning the rule base of the previous FIS tree, separately tune `fis1` and `fis2` parameters. First, get the parameter settings for `fis1`.

```
[in,out,rule] = getTunableSettings(fisTout1,"FIS","fis1");
```

Tune `fis1` parameters of the tree.

```
rng('default')
fisTout2 = tunefis(fisTout1,[in;out;rule],x,y,options);
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1       0.596926             1
    1           3       0.551284             2     Successful Poll
    2          18       0.510362             4     Successful Poll
    3          28       0.494804             8     Successful Poll
    4          56       0.494804             4     Refine Mesh
    5          84       0.493422             8     Successful Poll
    6         107      0.492883           16     Successful Poll
    7         107      0.492883            8     Refine Mesh
    8         136      0.492883            4     Refine Mesh
    9         171      0.492883            2     Refine Mesh
   10         178      0.491534            4     Successful Poll
   11         213      0.491534            2     Refine Mesh
   12         229      0.482682            4     Successful Poll
   13         264      0.482682            2     Refine Mesh
   14         279      0.446645            4     Successful Poll
   15         313      0.446645            2     Refine Mesh
   16         330       0.44657            4     Successful Poll
   17         364       0.44657            2     Refine Mesh
   18         384      0.446495            4     Successful Poll
   19         418      0.446495            2     Refine Mesh
   20         461      0.445938            4     Successful Poll
   21         495      0.445938            2     Refine Mesh
   22         560      0.422421            4     Successful Poll
   23         594      0.422421            2     Refine Mesh
   24         597      0.397265            4     Successful Poll
   25         630      0.397265            2     Refine Mesh
   26         701      0.390338            4     Successful Poll
Maximum number of iterations exceeded: increase options.MaxIterations.
```

In this case, the optimization cost is improved by tuning only `fis1` parameter values.

Next, get the paramter settings for `fis2` and tune the `fis2` parameters.

```
[in,out,rule] = getTunableSettings(fisTout2,"FIS","fis2");
rng('default')
fisTout3 = tunefis(fisTout2,[in;out;rule],x,y,options);
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1      0.390338            1
    1           2      0.374103            2     Successful Poll
    2           5      0.373855            4     Successful Poll
    3          10      0.356619            8     Successful Poll
    4          33      0.356619            4     Refine Mesh
    5          43      0.350715            8     Successful Poll
    6          65      0.349417           16     Successful Poll
    7          65      0.349417            8     Refine Mesh
    8          87      0.349417            4     Refine Mesh
    9          91      0.349356            8     Successful Poll
   10         112      0.349356            4     Refine Mesh
   11         138      0.346102            8     Successful Poll
   12         159      0.346102            4     Refine Mesh
   13         172       0.345938            8     Successful Poll
   14         193       0.345938            4     Refine Mesh
   15         222       0.342721            8     Successful Poll
   16         244       0.342721            4     Refine Mesh
   17         275       0.342721            2     Refine Mesh
   18         283       0.340727            4     Successful Poll
   19         312       0.340554            8     Successful Poll
   20         335       0.340554            4     Refine Mesh
   21         366       0.340554            2     Refine Mesh
   22         427       0.337873            4     Successful Poll
   23         457       0.337873            2     Refine Mesh
   24         521        0.33706            4     Successful Poll
   25         551        0.33706            2     Refine Mesh
   26         624       0.333193            4     Successful Poll
Maximum number of iterations exceeded: increase options.MaxIterations.
```

The optimization cost is further reduced by tuning `fis2` parameter values. To avoid overfitting of individual FIS parameter values, you can further tune both `fis1` and `fis2` parameters together.

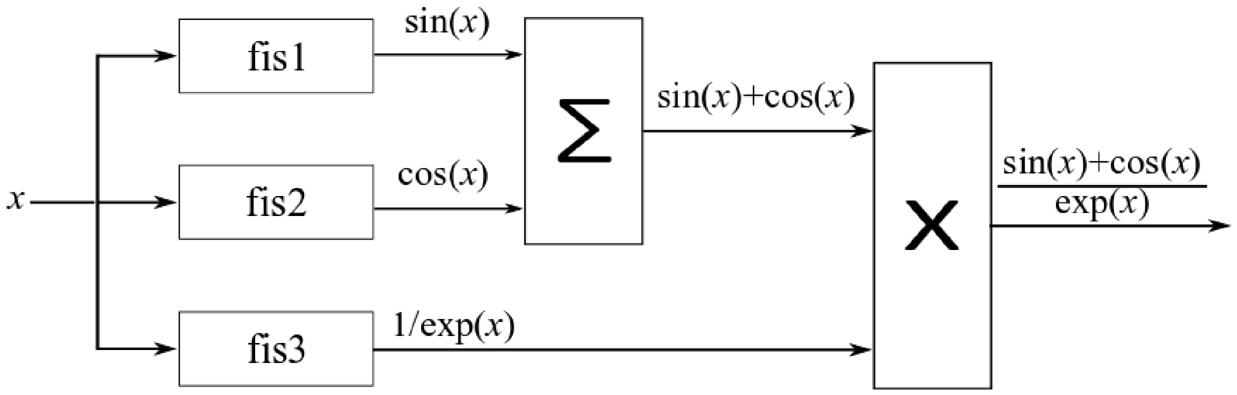
```
[in,out,rule] = getTunableSettings(fisTout3);
rng('default')
fisTout4 = tunefis(fisTout3,[in;out;rule],x,y,options);
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1       0.333193            1     
    1           8       0.326804            2     Successful Poll
    2          91       0.326432            4     Successful Poll
    3         116       0.326261            8     Successful Poll
    4         154       0.326261            4     Refine Mesh
    5         205       0.326261            2     Refine Mesh
    6         302       0.326092            4     Successful Poll
    7         352       0.326092            2     Refine Mesh
    8         391       0.325964            4     Successful Poll
    9         441       0.325964            2     Refine Mesh
   10         478        0.32578            4     Successful Poll
   11         528        0.32578            2     Refine Mesh
   12         562       0.325691            4     Successful Poll
   13         612       0.325691            2     Refine Mesh
   14         713       0.229273            4     Successful Poll
   15         763       0.229273            2     Refine Mesh
   16         867        0.22891            4     Successful Poll
   17         917        0.22891            2     Refine Mesh
   18        1036       0.228688            4     Successful Poll
   19        1086       0.228688            2     Refine Mesh
   20         1212         0.228688             1     Refine Mesh
   21         1266         0.228445             2     Successful Poll
   22         1369         0.228441             4     Successful Poll
   23         1381         0.227645             8     Successful Poll
   24         1407         0.226125            16     Successful Poll
   25         1407         0.226125             8     Refine Mesh
   26         1447         0.226125             4     Refine Mesh
Maximum number of iterations exceeded: increase options.MaxIterations.
```

Overall, the optimization cost reduces from 0.59 to 0.22 in three steps.

Tune with Custom Cost Function

Suppose you want to modify the previous FIS tree as shown in the following diagram.



Create the FIS tree.

```
fis1 = sugfis('Name','fis1');
fis1 = addInput(fis1,[0 10],'NumMFs',3,'MFType','gaussmf');
fis1 = addOutput(fis1,[-1 1],'NumMFs',3);

fis2 = sugfis('Name','fis2');
fis2 = addInput(fis2,[0 10],'NumMFs',3,'MFType','gaussmf');
fis2 = addOutput(fis2,[-1 1],'NumMFs',3);

fis3 = sugfis('Name','fis3');
fis3 = addInput(fis3,[0 10],'NumMFs',3,'MFType','gaussmf');
fis3 = addOutput(fis3,[0 1],'NumMFs',3);
```

```
con = ["fis1/input1" "fis2/input1";"fis2/input1" "fis3/input1"];

fisT = fistree([fis1 fis2 fis3],con);
```

To implement the addition and multiplication operations, use a custom cost function. For this example, use the function `customcostfcn`, included at the end of the example. Learn a rule base with this cost function.

```
options.Method = 'particleswarm';
options.MethodOptions.MaxIterations = 5;
rng('default')
fisTout1 = tunefis(fisT,[],@(fis)customcostfcn(fis,x,y),options);
```

```
                                Best            Mean     Stall
Iteration     f-count           f(x)            f(x)    Iterations
    0             100          0.746           1.318        0
    1             200         0.5787           1.236        0
    2             300         0.5787           1.104        1
    3             400         0.5787           1.097        0
    4             500         0.5171           1.155        0
    5             600         0.5171           1.067        1
Optimization ended: number of iterations exceeded OPTIONS.MaxIterations.
```

Tune all parameters of the FIS tree.

```
options.Method = 'patternsearch';
options.MethodOptions.MaxIterations = 25;
[in,out,rule] = getTunableSettings(fisTout1);
rng('default')
fisTout2 = tunefis(fisTout1,[in;out;rule],@(fis)customcostfcn(fis,x,y),options);
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1       0.51705            1
    1          11      0.514884            2     Successful Poll
    2          21      0.512873            4     Successful Poll
    3          43      0.512873            8     Successful Poll
    4          56      0.512873            4     Refine Mesh
    5          79      0.512873            2     Refine Mesh
    6         106      0.512869            4     Successful Poll
    7         129      0.512869            2     Refine Mesh
    8         174      0.512869            1     Refine Mesh
    9         197      0.512862            2     Successful Poll
   10         242      0.512862            1     Refine Mesh
   11         314      0.512862          0.5     Refine Mesh
   12         388       0.512862          0.25     Refine Mesh
   13         422       0.510163           0.5     Successful Poll
   14         429       0.509153             1     Successful Poll
   15         439       0.509034             2     Successful Poll
   16         460       0.509034             4     Successful Poll
   17         483       0.507555             8     Successful Poll
   18         495       0.507555             4     Refine Mesh
   19         519       0.507555             2     Refine Mesh
   20         565       0.507555             1     Refine Mesh
   21         636       0.507555             2     Successful Poll
   22         682       0.507555             1     Refine Mesh
   23         755       0.507555           0.5     Refine Mesh
   24         799       0.507554             1     Successful Poll
   25         872       0.507554           0.5     Refine Mesh
   26         947       0.507554          0.25     Refine Mesh
Maximum number of iterations exceeded: increase options.MaxIterations.
```

You can add more input/output MFs and specify additional FIS tree outputs to improve the tuning performance. Using additional MF parameters and more training data for additional FIS tree outputs can further fine tune the outputs of `fis1`, `fis2`, and `fis3`.

Custom Optimization Method

You can implement your own FIS parameter optimization method using `getTunableSettings`, `getTunableValues`, and `setTunableValues`. This example uses these functions to tune a rule base of a fuzzy system.

Create a FIS to approximate $\sin(\theta)$, where θ varies from 0 to 2π.

```
fisin = mamfis;
```

Add an input with range [0 2π] having five MFs of Gaussian type, and an output with range [–1 1] having five MFs of Gaussian type.

```
fisin = addInput(fisin,[0 2*pi],'NumMFs',5,'MFType','gaussmf');
fisin = addOutput(fisin,[-1 1],'NumMFs',5,'MFType','gaussmf');
```

Add 5 rules.

```
fisin = addRule(fisin,[1 1 1 1;2 2 1 1;3 3 1 1;4 4 1 1;5 5 1 1]);
fisin.Rules
```

```
ans = 
  1x5 fisrule array with properties:
    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                   Description
         ________________________________

    1    "input1==mf1 => output1=mf1 (1)"
    2    "input1==mf2 => output1=mf2 (1)"
    3    "input1==mf3 => output1=mf3 (1)"
    4    "input1==mf4 => output1=mf4 (1)"
    5    "input1==mf5 => output1=mf5 (1)"
```

Set `DisableStructuralChecks` to true for faster FIS update.

```
fisin.DisableStructuralChecks = true;
```

Get the rule parameter settings.

```
[~,~,rule] = getTunableSettings(fisin);
```

Make the antecedent nontunable. In the consequent, do not allow NOT logic (negative MF indices) or empty variables (zero MF indices) in the rules.

```
for i = 1:numel(rule)
    rule(i).Antecedent.Free = false;
    rule(i).Consequent.AllowNot = false;
    rule(i).Consequent.AllowEmpty = false;
end
```

Generate data for tuning.

```
x = (0:0.1:2*pi)';
y = sin(x);
```

To tune the rule parameters, use the `customtunefis` function defined at the end of this example. Set the number of iterations to 2, and do not allow invalid parameter values when updating the FIS using `setTunableValues`.

```
numite = 2;
ignoreinvp = false;
fisout = customtunefis(fisin,rule,x,y,numite,ignoreinvp);
```

```
Initial cost = 1.170519
Iteration 1: Cost = 0.241121
Iteration 2: Cost = 0.241121
```

Display tuned rules.

```
fisout.Rules
```

```
ans = 
  1x5 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                 Description          
         _________________________________

    1    "input1==mf1 => output1=mf4 (1)"
    2    "input1==mf2 => output1=mf5 (1)"
    3    "input1==mf3 => output1=mf3 (1)"
    4    "input1==mf4 => output1=mf1 (1)"
    5    "input1==mf5 => output1=mf2 (1)"
```

Allow NOT logic in the rules, and optimize the FIS again.

```
for i = 1:numel(rule)
    rule(i).Consequent.AllowNot = true;
end
fisout = customtunefis(fisin,rule,x,y,numite,ignoreinvp);
```

```
Initial cost = 1.170519
Iteration 1: Cost = 0.357052
Iteration 2: Cost = 0.241121
```

```
fisout.Rules
```

```
ans = 
  1x5 fisrule array with properties:
    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                   Description
         ________________________________

    1    "input1==mf1 => output1=mf4 (1)"
    2    "input1==mf2 => output1=mf5 (1)"
    3    "input1==mf3 => output1=mf3 (1)"
    4    "input1==mf4 => output1=mf1 (1)"
    5    "input1==mf5 => output1=mf2 (1)"
```

With NOT logic, there are more combinations of rule parameters, and it generally takes more iterations to tune a FIS.

Next, reset `AllowNot` to `false` and set `AllowEmpty` to `true`, in other words, allow absence of variables (zero output MF indices) in the consequent. Tune the FIS with the updated rule parameter settings.

```
for i = 1:numel(rule)
    rule(i).Consequent.AllowNot = false;
    rule(i).Consequent.AllowEmpty = true;
end

try
    fisout = customtunefis(fisin,rule,x,y,numite,ignoreinvp);
catch me
    disp("Error: "+me.message)
end
```

```
Initial cost = 1.170519
Error: Rule consequent must have at least one nonzero membership function index.
```

The tuning process fails since the FIS only contains one output, which must be nonzero (nonempty) in the rule consequent. To ignore invalid parameter values, specify `IgnoreInvalidParameters` with `setTunableValues`.

Set `ignoreinvp` to `true`, which specifies `IgnoreInvalidParameters` value in the call to `setTunableValues` used in `customtunefis`.

```
ignoreinvp = true;
fisout = customtunefis(fisin,rule,x,y,numite,ignoreinvp);

Initial cost = 1.170519
Iteration 1: Cost = 0.241121
Iteration 2: Cost = 0.241121

fisout.Rules

ans = 
  1x5 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                   Description
         ________________________________

    1    "input1==mf1 => output1=mf4 (1)"
    2    "input1==mf2 => output1=mf5 (1)"
    3    "input1==mf3 => output1=mf3 (1)"
    4    "input1==mf4 => output1=mf1 (1)"
    5    "input1==mf5 => output1=mf2 (1)"
```

In this case, the tuning process bypasses the invalid values and uses only valid parameter values for optimization.

By default, `tunefis` ignores invalid values when updating fuzzy system parameters. You can change this behavior by setting `tunefisOptions.IgnoreInvalidParameters` to `false`.

Generate FIS from Data and Tune

You can generate a FIS from the training data using `genfis` and then optimize the FIS with `tunefis`. In this approach, the tuning process can employ a local optimization method because the rule base is derived from the training data.

This example describes the tuning steps to approximate the function

$$\frac{\sin(2x)}{\exp\left(\frac{x}{5}\right)},$$

where the input x varies from 0 to 10.

Generate training data.

```
x = (0:0.1:10)';
y = sin(2*x)./exp(x/5);
```

Create options for `genfis` that specify five MFs, a Gaussian MF for the input, and a constant MF for the output.

```
goptions = genfisOptions('GridPartition','NumMembershipFunctions',5, ...
    'InputMembershipFunctionType','gaussmf', ...
    'OutputMembershipFunctionType','constant');
```

Generate the initial FIS, and get its parameter settings.

```
fisin = genfis(x,y,goptions);
[in,out,rule] = getTunableSettings(fisin);
```

Use pattern search method for optimization, setting the maximum number of iterations to 25, and tune the FIS.

```
toptions = tunefisOptions('Method','patternsearch');
toptions.MethodOptions.MaxIterations = 25;
rng('default')
fisout = tunefis(fisin,[in;out],x,y,toptions);
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1       0.346649           1
    1          19       0.346649         0.5     Refine Mesh
    2          28       0.295219           1     Successful Poll
    3          34       0.295069           2     Successful Poll
    4          48       0.295069           1     Refine Mesh
    5          56       0.295064           2     Successful Poll
    6          71       0.294986           4     Successful Poll
    7          82       0.294986           2     Refine Mesh
    8          98       0.294986           1     Refine Mesh
    9         112       0.293922           2     Successful Poll
   10         128       0.293922           1     Refine Mesh
   11         131        0.29151           2     Successful Poll
   12         144       0.290141           4     Successful Poll
   13          156       0.290141              2     Refine Mesh
   14          171       0.290006              4     Successful Poll
   15          184       0.290006              2     Refine Mesh
   16          200       0.290006              1     Refine Mesh
   17          207       0.289743              2     Successful Poll
   18          223       0.289743              1     Refine Mesh
   19          243       0.289743            0.5     Refine Mesh
   20          257       0.286935              1     Successful Poll
   21          260       0.282278              2     Successful Poll
   22          263       0.281878              4     Successful Poll
   23          267       0.280144              8     Successful Poll
   24          272       0.280144              4     Refine Mesh
   25          278       0.275167              8     Successful Poll
   26          284       0.275167              4     Refine Mesh
Maximum number of iterations exceeded: increase options.MaxIterations.
```

You can increase the number of iterations to further optimize the cost.

Validate Training Results

To avoid overfitting of training data sets, check the performance of a trained fuzzy system with validation data. One common approach is to divide available data into training and validation data sets so that both data sets include similar characteristics.

If training and validation performances differ significantly, you can:

- Change the maximum number of tuning iterations. For example, if the training performance is better than validation performance, you can reduce the number of tuning iterations.
- Resample the training and validation data sets to maintain homogeneity.

To see how the validation performance can vary based on nonhomogenous sampling, create a single-input-single-output fuzzy inference system to model the function

$$\frac{\sin(2x)}{\exp\left(\frac{x}{5}\right)},$$

where the input varies from 0 to 10 and the output range is [0 1]. Add five default MFs to the input and output. Get the input and output parameter settings.

```
fisin = sugfis;
fisin = addInput(fisin,[0 10],'NumMFs',5,'MFType','gaussmf');
fisin = addOutput(fisin,[0 1],'NumMFs',5);
[in,out] = getTunableSettings(fisin);
```

Create `tunefis` options for `learning` with the `particleswarm` optimization method, and set the maximum number of iterations to 5.

```
options = tunefisOptions('Method','particleswarm','OptimizationType','learning');
options.MethodOptions.MaxIterations = 5;
```

Divide the available data into two sets without maintaining homogeneity in the data sets.

```
x = (0:0.1:10)';
n = numel(x);
midn = floor(n/2);
trnX = x(1:midn);
vldX = x(midn+1:end);
f = @(x)(sin(2*x)./exp(x/5));
trnY = f(trnX);
vldY = f(vldX);
```

Tune the FIS parameters.

```
rng('default')
fisout = tunefis(fisin,[in;out],trnX,trnY,options);
```

```
                                 Best            Mean     Stall
Iteration     f-count            f(x)            f(x)    Iterations
    0            100           0.4279          0.5932        0
    1            200           0.3846          0.6183        0
    2            300           0.3751          0.5675        0
    3            400           0.3606           0.568        0
    4            500           0.3606          0.5596        1
    5            600           0.3598          0.5307        0
Optimization ended: number of iterations exceeded OPTIONS.MaxIterations.
```

Find the optimization cost for validation data using the `findcost` function defined at the end of this example.

```
vldCost = findcost(fisout,vldX,vldY)
```

```
vldCost = 0.1780
```

Note that the validation cost differs from the best training cost shown in column 3 of the tuning result.

Next, resample the available data, and create two homogenous data sets for training and validation.

```
trnX = x(1:2:end);
vldX = x(2:2:end);
f = @(x)(sin(2*x)./exp(x/5));
trnY = f(trnX);
vldY = f(vldX);
```

Tune the FIS with the new training data.

```
rng('default')
fisout = tunefis(fisin,[in;out],trnX,trnY,options);
```

```
                                 Best            Mean     Stall
Iteration     f-count            f(x)            f(x)    Iterations
    0             100          0.3445          0.5852        0
    1             200          0.2996          0.5616        0
    2             300          0.2907          0.5381        0
    3             400          0.2878          0.5334        0
    4             500          0.2878          0.5624        1
    5             600          0.2877             Inf        0
Optimization ended: number of iterations exceeded OPTIONS.MaxIterations.
```

Find the optimization cost for the new validation data.

```
vldCost = findcost(fisout,vldX,vldY)
```

```
vldCost = 0.2803
```

In this case, homogenous sampling reduces the difference between the training and validation costs.

Ways to Improve Tuning Results

You can improve the training error of a tuned fuzzy systems by following these guidelines.

- **Use multiple steps in a tuning process.** For example, first learn the rules of a fuzzy system, and then tune input/output MF parameters using the learned rule base. You can also separately tune individual FIS parameters in a FIS tree and then tune all the fuzzy systems together to generalize the parameter values.
- **Increase the number of iterations in both the rule-learning and parameter-tuning phases.** Doing so increases the duration of the optimization process. It can also increase validation error due to overtuned system parameters with the training data.
- **Use global optimization methods, such as `ga` and `particleswarm`, in both rule-learning and parameter-tuning phases**. Global optimizers `ga` and `particleswarm`

perform better for large parameter tuning ranges than local optimizers. The local optimizers `patternsearch` and `simulannealbnd` perform better for small parameter ranges. If rules are already added to a FIS tree using training data, then `patternsearch` and `simulannealbnd` can produce faster convergence compared to `ga` and `particleswarm`. For more information on these optimization methods and their options, see `ga`, `particleswarm`, `patternsearch`, and `simulannealbnd`.

- **Change the clustering technique used by `genfis`.** Depending on the clustering technique, the generated rules can differ in their representation of the training data. Hence, the use of different clustering techniques can affect the performance of `tunefis`.
- **Change FIS properties.** Try changing properties such as the type of FIS, number of inputs, number of input/output MFs, MF types, and number of rules. A Sugeno system has fewer output MF parameters (assuming constant MFs) and faster defuzzification. Therefore, for fuzzy systems with a large number of inputs, a Sugeno FIS generally converges faster than a Mamdani FIS. Small numbers of MFs and rules reduce the number of parameters to tune, producing a faster tuning process. Furthermore, a large number of rules might overfit the training data.
- **Modify tunable parameter settings for MFs and rules.** For example, you can tune the support of a triangular MF without changing its peak location. Doing so reduces the number of tunable parameters and can produce a faster tuning process for specific applications. For rules, you can exclude zero MF indices by setting the `AllowEmpty` tunable setting to `false`, which reduces the overall number of rules during the learning phase.
- **Change FIS tree properties**, such as the number of fuzzy systems and the connections between the fuzzy systems.
- **Use different ranking and grouping of the inputs to the FIS tree.** For more information about creating FIS trees, see “Fuzzy Trees” on page 2-65.

Local functions

```
function cost = customcostfcn(fis,x,y)

tY = evalfis(fis,x);
sincosx = tY(:,1)+tY(:,2);
sincosexpx = sincosx.*tY(:,3);
actY = [sincosx;sincosexpx];
d = y(:)-actY;
cost = sqrt(mean(d.*d));

end
```

```
function fis = customtunefis(fis,rule,x,y,n,ignore)

% Show initial cost.
cost = findcost(fis,x,y);
fprintf('Initial cost = %f\n',cost);

% Optimize rule parameters.
numMFs = numel(fis.Outputs.MembershipFunctions);
for ite = 1:n
    for i = 1:numel(rule)
        % Get consequent value.
        pval = getTunableValues(fis,rule(i));
        % Loop through output MF indices to minimize the cost.
        % Use output indices according to AllowNot and AllowEmpty.
        allowNot = rule(i).Consequent.AllowNot;
        allowEmpty = rule(i).Consequent.AllowEmpty;
        if allowNot && allowEmpty
            mfID = -numMFs:numMFs;
        elseif allowNot && ~allowEmpty
            mfID = [-numMFs:-1 1:numMFs];
        elseif ~allowNot && allowEmpty
            mfID = 0:numMFs;
        else
            mfID = 1:numMFs;
        end
        cost = 1000;
        minCostFIS = fis;
        for j = 1:length(mfID)
            % Update consequent value.
            pval(1) = mfID(j);
            % Set updated consequent value to the FIS.
            fis = setTunableValues(fis,rule(i),pval,'IgnoreInvalidParameters',ignore);
            % Evaluate cost.
            rmse = findcost(fis,x,y);
            % Update FIS with the minimum cost.
            if rmse<cost
                cost = rmse;
                minCostFIS = fis;
            end
        end
        fis = minCostFIS;
    end
    fprintf('Iteration %d: Cost = %f\n',ite,cost);
```

```
end

end

function cost = findcost(fis,x,y)

actY = evalfis(fis,x);
d = y - actY;
cost = sqrt(mean(d.*d));

end
```

See Also

genfis | getTunableSettings | tunefis

More About

- “Tune Mamdani Fuzzy Inference System” on page 3-33
- “Tune FIS Tree for Gas Mileage Prediction” on page 3-47

Tune Mamdani Fuzzy Inference System

This example shows how to tune membership function (MF) and rule parameters of a Mamdani fuzzy inference system (FIS). This example uses particle swarm and pattern search optimization, which require Global Optimization Toolbox™ software.

Automobile fuel consumption prediction in miles per gallon (MPG) is a typical nonlinear regression problem. It uses several automobile profile attributes to predict fuel consumption. The training data is available in the University of California at Irvine Machine Learning Repository and contains data collected from automobiles of various makes and models.

This example uses the following six input data attributes to predict the output data attribute MPG with a FIS:

1. Number of cylinders
2. Displacement
3. Horsepower
4. Weight
5. Acceleration
6. Model year

Prepare Data

Load the data. Each row of the dataset obtained from the repository represents a different automobile profile.

```
[data,name] = loadgas;
```

Remove leading and trailing whitespace from the attribute names.

```
name = strtrim(string(name));
```

`data` contains 7 columns, where the first six columns contain the following input attributes.

- Number of cylinders
- Displacement
- Horsepower

- Weight
- Acceleration
- Model year

The seventh column contains the output attribute, MPG.

Create separate input and output data sets, X and Y, respectively.

```
X = data(:,1:6);
Y = data(:,7);
```

Partition the input and output data sets into training data (odd-indexed samples) and validation data (even-indexed samples).

```
trnX = X(1:2:end,:); % Training input data set
trnY = Y(1:2:end,:); % Training output data set
vldX = X(2:2:end,:); % Validation input data set
vldY = Y(2:2:end,:); % Validation output data set
```

Extract the range of each data attribute, which you will use for input/output range definition during FIS construction.

```
dataRange = [min(data)' max(data)'];
```

Construct FIS using Data Attribute Ranges

Create a Mamdani FIS for tuning.

```
fisin = mamfis;
```

Add input and output variables to the FIS, where each variable represents one of the data attributes. For each variable, use the corresponding attribute name and range.

To reduce the number of rules, use two MFs for each input variable, which results in $2^6 = 64$ input MF combinations. Therefore, the FIS uses a maximum of 64 rules corresponding to the input MF combinations.

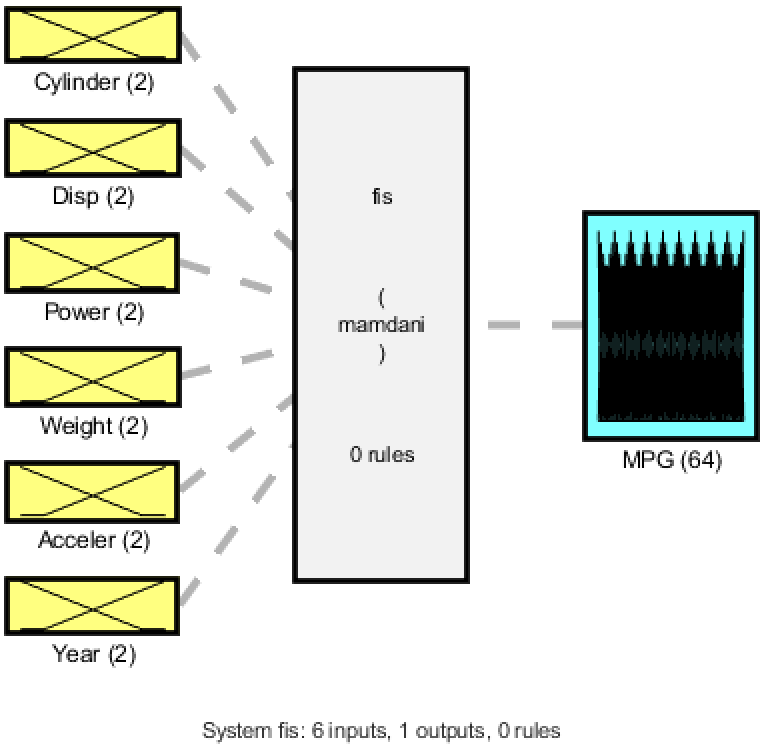
To improve data generalization beyond the training data, use 64 MFs for the output variable. Doing so allows the FIS to use a different output MF for each rule.

Both input and output variables use default triangular MFs, which are uniformly distributed over the variable ranges.

```
for i = 1:6
    fisin = addInput(fisin,dataRange(i,:),'Name',name(i),'NumMFs',2);
end
fisin = addOutput(fisin,dataRange(7,:),'Name',name(7),'NumMFs',64);
```

View the FIS structure. Initially, the FIS has zero rules. The rules of the system are found during the tuning process.

```
figure
plotfis(fisin)
```



Tune FIS with Training Data

Tuning is performed in two steps.

1. Learn the rule base while keeping the input and output MF parameters constant.
2. Tune the parameters of the input/output MFs and rules.

The first step is less computationally expensive due to the small number of rule parameters, and it quickly converges to a fuzzy rule base during training. In the second step, using the rule base from the first step as an initial condition provides fast convergence of the parameter tuning process.

Learn Rules

To learn a rule base, first specify tuning options using a `tunefisOptions` object. Since the FIS allows a large number of output MFs (used in rule consequents), use a global optimization method (genetic algorithm or particle swarm). Such methods perform better in large parameter tuning ranges as compared to local optimization methods (pattern search and simulation annealing). For this example, tune the FIS using the particle swarm optimization method (`'particleswarm'`).

To learn new rules, set the `OptimizationType` to `'learning'`. Restrict the maximum number of rules to 64. The number of tuned rules can be less than this limit, since the tuning process removes duplicate rules.

```
options = tunefisOptions('Method','particleswarm',...
    'OptimizationType','learning', ...
    'NumMaxRules',64);
```

If you have Parallel Computing Toolbox™ software, you can improve the speed of the tuning process by setting `options.UseParallel` to `true`. If you do not have Parallel Computing Toolbox software, set `options.UseParallel` to `false`.

Set the maximum number of iterations to 20. To reduce training error in the rule learning process, you can increase the number of iterations. However, using too many iterations can overtune the FIS to the training data, increasing the validation errors.

```
options.MethodOptions.MaxIterations = 20;
```

Since particle swarm optimization uses random search, to obtain reproducible results, initialize the random number generator to its default configuration.

```
rng('default')
```

Tune the FIS using the specified tuning data and options.

Learning rules using the `tunefis` function takes approximately 5 minutes. For this example, enable tuning by setting `runtunefis` to `true`. To load pretrained results without running `tunefis`, you can set `runtunefis` to `false`.

```
runtunefis = true;
```

Parameter settings can be empty when learning new rules. For more information, see `tunefis`.

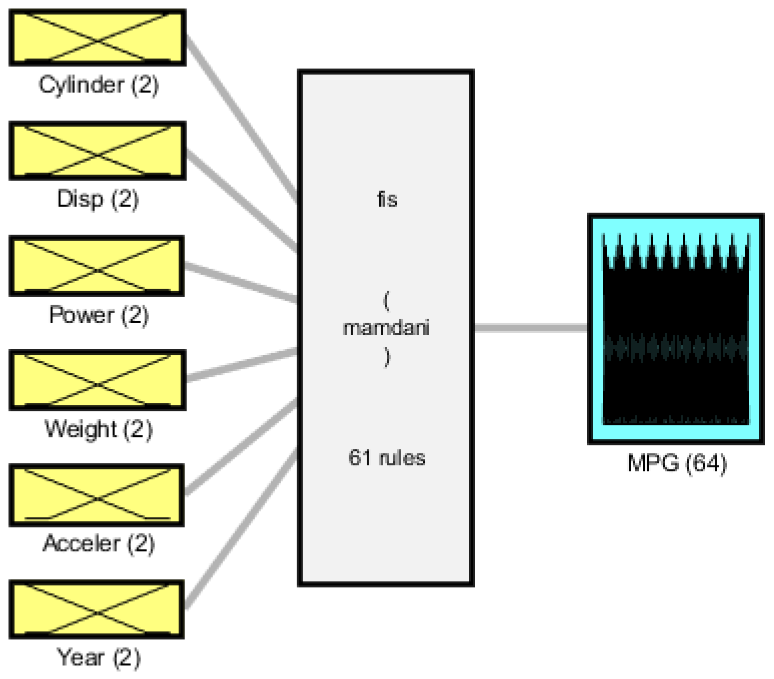
```
if runtunefis
    fisout1 = tunefis(fisin,[],trnX,trnY,options);
else
    tunedfis = load('tunedfismpgprediction.mat'); %#ok<UNRCH>
    fisout1 = tunedfis.fisout1;
    fprintf('Training RMSE = %.3f MPG\n',calculateRMSE(fisout1,trnX,trnY));
end
```

```
                                 Best            Mean     Stall
Iteration     f-count            f(x)            f(x)    Iterations
    0            100            7.008           9.256        0
    1            200            6.515           9.432        0
    2            300            6.515           9.214        1
    3            400            6.496            9.02        0
    4            500            6.495           9.008        0
    5            600            6.084           8.783        0
    6            700            5.889           8.795        0
    7            800            5.889           8.794        1
    8            900            5.134           8.463        0
    9           1000            5.134           8.676        1
   10           1100            5.134           8.609        2
   11           1200            5.134           8.244        3
   12           1300            5.134           8.365        4
   13           1400            5.134           8.054        5
   14           1500            5.134           8.112        6
   15           1600            5.134           7.703        7
   16           1700            4.932           7.326        0
   17           1800            4.554           7.113        0
   18           1900            4.554           6.702        1
   19           2000            4.452           6.377        0
   20           2100            4.452           6.235        1
Optimization ended: number of iterations exceeded OPTIONS.MaxIterations.
```

The `Best f(x)` column shows the training root-mean-squared-error (RMSE).

View the structure of the tuned FIS, `fisout1`.

```
plotfis(fisout1)
```



System fis: 6 inputs, 1 outputs, 61 rules

The learning process produces a set of new rules for the FIS. For example, view the descriptions of the first three rules.

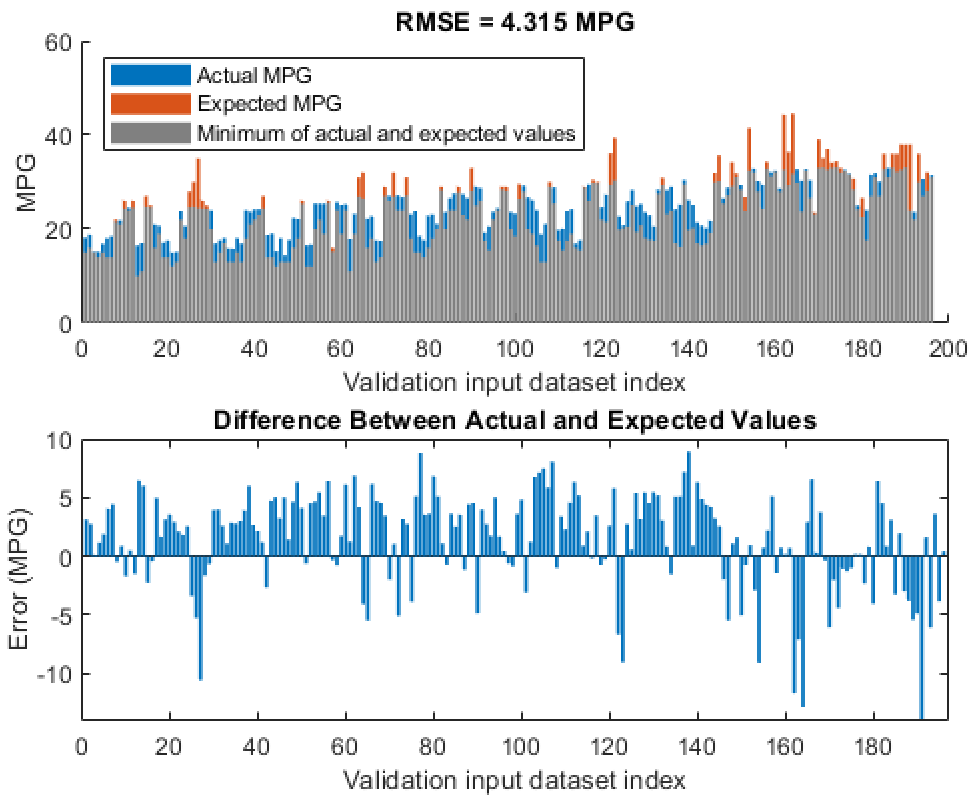
```
[fisout1.Rules(1:3).Description]'
```

```
ans = 3×1 string array
    "Cylinder==mf2 & Disp==mf2 & Power==mf2 & Weight==mf2 & Year==mf2 => MPG=mf5 (1)"
    "Cylinder==mf1 & Power==mf2 & Weight==mf2 & Acceler==mf2 & Year==mf1 => MPG=mf63 (1
    "Cylinder==mf2 & Disp==mf1 & Acceler==mf2 => MPG=mf28 (1)"
```

The learned system should have similar RMSE performance for both the training and validation data sets. To calculate the RMSE for the validation data set, evaluate `fisout1` using validation input data set `vldX`. To hide run-time warnings during evaluation, set all the warning options to `none`.

Calculate the RMSE between the generated output data and the validation output data set `vldY`.

```
plotActualAndExpectedResultsWithRMSE(fisout1,vldX,vldY)
```



Since the training and validation errors are similar, the learned system does not overfit the training data.

Tune All Parameters

After learning the new rules, tune the input/output MF parameters along with the parameters of the learned rules. To obtain the tunable parameters of the FIS, use the `getTunableSettings` function.

```
[in,out,rule] = getTunableSettings(fisout1);
```

To tune the existing FIS parameter settings without learning new rules, set the `OptimizationType` to `'tuning'`.

```
options.OptimizationType = 'tuning';
```

Since the FIS already learned rules using the training data, use a local optimization method for fast convergence of the parameter values. For this example, use the pattern search optimization method (`'patternsearch'`).

```
options.Method = 'patternsearch';
```

Tuning the FIS parameters takes more iterations than the previous rule-learning step. Therefore, increase the maximum number of iterations of the tuning process to 60. As in the first tuning stage, you can reduce training errors by increasing the number of iterations. However, using too many iterations can overtune the parameters to the training data, increasing the validation errors.

```
options.MethodOptions.MaxIterations = 60;
```

Tune the FIS parameters using the specified tunable settings, training data, and tuning options.

Tuning parameter values with `tunefis` function takes approximately 5 minutes. To load pretrained results without running `tunefis`, you can set `runtunefis` to `false`.

```
if runtunefis
    rng('default')
    fisout = tunefis(fisout1,[in;out;rule],trnX,trnY,options);
else
    fisout = tunedfis.fisout; %#ok<UNRCH>
    fprintf('Training RMSE = %.3f MPG\n',calculateRMSE(fisout,trnX,trnY));
end
```

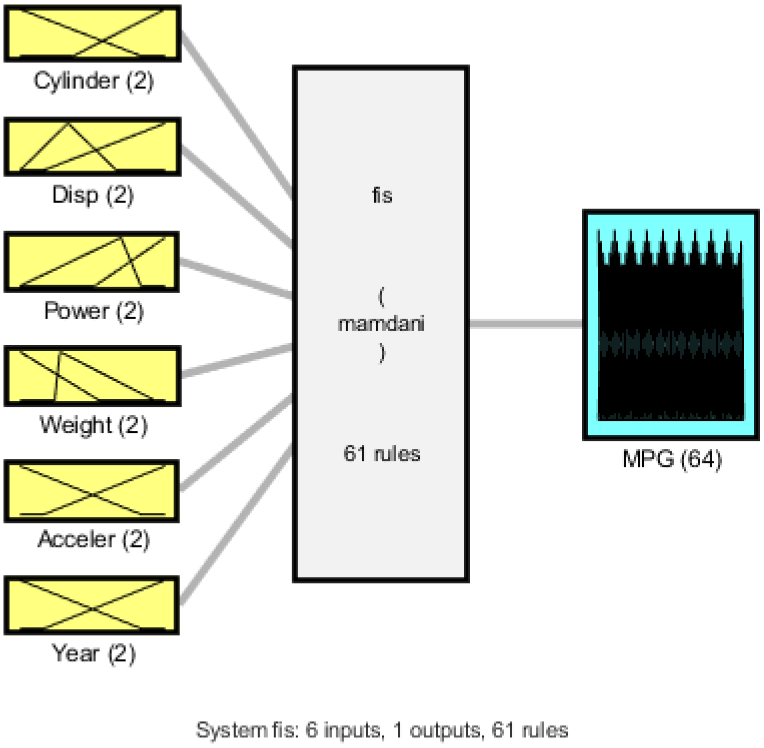
```
Iter     Func-count       f(x)      MeshSize     Method
    0           1       4.25857             1
    1           2       4.23578             2     Successful Poll
    2           4       4.23562             4     Successful Poll
    3           5       4.23525             8     Successful Poll
```

```
      4           6         4.23473            16      Successful Poll
      5           7         4.23324            32      Successful Poll
      6           8         4.23129            64      Successful Poll
      7          10         4.17603           128      Successful Poll
      8          14         4.16089           256      Successful Poll
      9          19         4.02839           512      Successful Poll
     10          22          3.8461          1024      Successful Poll
     11          28          3.7905          2048      Successful Poll
     12          34          3.7905          1024      Refine Mesh
     13          39         3.73343          2048      Successful Poll
     14          45         3.73343          1024      Refine Mesh
     15          53         3.73343           512      Refine Mesh
     16          57         3.72264          1024      Successful Poll
     17          65         3.72264           512      Refine Mesh
     18          73         3.71039          1024      Successful Poll
     19          81         3.71039           512      Refine Mesh
     20          91         3.70128          1024      Successful Poll
     21          99         3.70128           512      Refine Mesh
     22         110         3.70128           256      Refine Mesh
     23         114         3.69992           512      Successful Poll
     24         120         3.68807          1024      Successful Poll
     25         128         3.68807           512      Refine Mesh
     26         135          3.6867          1024      Successful Poll
     27         142          3.6867           512      Refine Mesh
     28         152         3.67888          1024      Successful Poll
     29         159         3.67888           512      Refine Mesh
     30         170         3.67888           256      Refine Mesh

Iter     Func-count       f(x)        MeshSize      Method
     31         176         3.67859           512      Successful Poll
     32         186         3.67859           256      Refine Mesh
     33         194          3.6466           512      Successful Poll
     34         203          3.6466           256      Refine Mesh
     35         206         3.64121           512      Successful Poll
     36         215         3.64121           256      Refine Mesh
     37         228          3.6412           512      Successful Poll
     38         237          3.6412           256      Refine Mesh
     39         254          3.6412           128      Refine Mesh
     40         273         3.47202           256      Successful Poll
     41         280         3.47067           512      Successful Poll
     42         289         3.47067           256      Refine Mesh
     43         303         3.38247           512      Successful Poll
     44         308         3.34678          1024      Successful Poll
     45         315         3.34678           512      Refine Mesh
```

```
   46         324        3.34678          256     Refine Mesh
   47         330        3.34482          512     Successful Poll
   48         339        3.34482          256     Refine Mesh
   49         347        3.32178          512     Successful Poll
   50         348        3.32027         1024     Successful Poll
   51         355        3.32027          512     Refine Mesh
   52         364        3.32027          256     Refine Mesh
   53         371        3.30488          512     Successful Poll
   54         380        3.30488          256     Refine Mesh
   55         395        3.30488          128     Refine Mesh
   56         402        3.28894          256     Successful Poll
   57         405        3.27455          512     Successful Poll
   58         414        3.27455          256     Refine Mesh
   59         429        3.27209          512     Successful Poll
   60         438        3.27209          256     Refine Mesh
   61         454        3.27209          128     Refine Mesh
Maximum number of iterations exceeded: increase options.MaxIterations.
```

At the end of the tuning process, some of the tuned MF shapes are different than the original ones.

```
figure
plotfis(fisout)
```

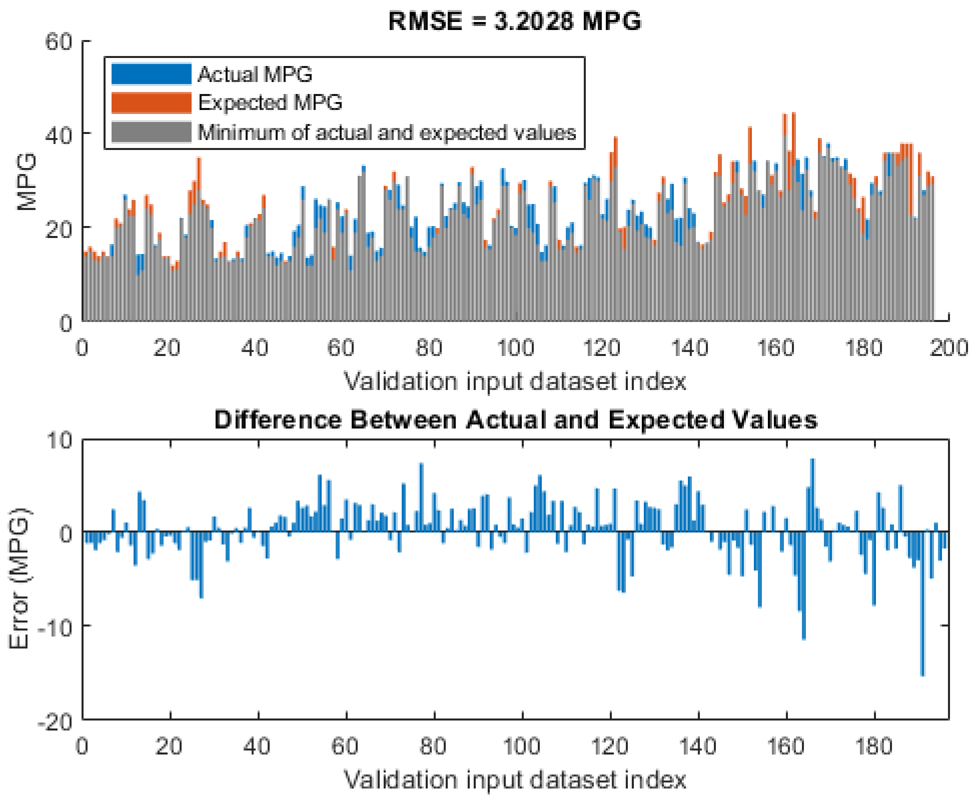


Check Performance

Validate the performance of the tuned FIS, `fisout`, using the validation input data set `vldX`.

Compare the expected MPG obtained from the validation output data set `vldY` and actual MPG generated using `fisout`. Compute the RMSE between these results.

```
plotActualAndExpectedResultsWithRMSE(fisout,vldX,vldY);
```



Tuning the FIS parameters improves the RMSE compared to the results from the initial learned rule base. Since the training and validation errors are similar, the parameters values are not overtuned.

Conclusion

You can further improve the training error of the tuned FIS by:

- Increasing number of iterations in both the rule-learning and parameter-tuning phases. Doing so increases the duration of the optimization process and can also increase validation error due to overtuned system parameters with the training data.
- Using global optimization methods, such as `ga` and `particleswarm`, in both rule-learning and parameter-tuning phases. `ga` and `particleswarm` perform better for

large parameter tuning ranges since they are global optimizers. On the other hand, `patternsearch` and `simulannealbnd` perform better for small parameter ranges since they are local optimizers. If a FIS is generated from training data with `genfis` or a rule base is already added to a FIS using training data, then `patternsearch` and `simulannealbnd` may produce faster convergence as compared to `ga` and `particleswarm`. For more information on these optimization methods and their options, see `ga`, `particleswarm`, `patternsearch`, and `simulannealbnd`.

- Changing the FIS properties, such as the type of FIS, number of inputs, number of input/output MFs, MF types, and number of rules. For fuzzy systems with a large number of inputs, a Sugeno FIS generally converges faster than a Mamdani FIS since a Sugeno system has fewer output MF parameters (if `constant` MFs are used) and faster defuzzification. Small numbers of MFs and rules reduce the number of parameters to tune, producing a faster tuning process. Furthermore, a large number of rules may overfit the training data. In general, for larger fuzzy systems, a FIS tree can produce similar performance with a smaller number of rules as compared to a single FIS. For an example, see "Tune FIS Tree for Gas Mileage Prediction" on page 3-47.
- Modifying tunable parameter settings for MFs and rules. For example, you can tune the support of a triangular MF without changing its peak location. Doing so reduces the number of tunable parameters and can produce a faster tuning process for specific applications. For rules, you can exclude zero MF indices by setting the `AllowEmpty` tunable setting to `false`, which reduces the overall number of rules during the learning phase.

Local Functions

```
function plotActualAndExpectedResultsWithRMSE(fis,x,y)

% Calculate RMSE bewteen actual and expected results
[rmse,actY] = calculateRMSE(fis,x,y);

% Plot results
figure
subplot(2,1,1)
hold on
bar(actY)
bar(y)
bar(min(actY,y),'FaceColor',[0.5 0.5 0.5])
hold off
axis([0 200 0 60])
xlabel("Validation input dataset index"),ylabel("MPG")
```

```
legend(["Actual MPG" "Expected MPG" "Minimum of actual and expected values"],...
        'Location','NorthWest')
title("RMSE = " + num2str(rmse) + " MPG")

subplot(2,1,2)
bar(actY-y)
xlabel("Validation input dataset index"),ylabel("Error (MPG)")
title("Difference Between Actual and Expected Values")

end

function [rmse,actY] = calculateRMSE(fis,x,y)

% Specify options for FIS evaluation
persistent evalOptions
if isempty(evalOptions)
    evalOptions = evalfisOptions("EmptyOutputFuzzySetMessage","none", ...
        "NoRuleFiredMessage","none","OutOfRangeInputValueMessage","none");
end

% Evaluate FIS
actY = evalfis(fis,x,evalOptions);

% Calculate RMSE
del = actY - y;
rmse = sqrt(mean(del.^2));

end
```

See Also
getTunableSettings | mamfis | tunefis

More About
- “Tuning Fuzzy Inference Systems” on page 3-2
- “Tune FIS Tree for Gas Mileage Prediction” on page 3-47

Tune FIS Tree for Gas Mileage Prediction

This example shows how to tune parameters of a FIS tree, which is a collection of connected fuzzy inference systems. This example uses particle swarm and pattern search optimization, which require Global Optimization Toolbox™ software.

Automobile fuel consumption prediction in miles per gallon (MPG) is a typical nonlinear regression problem. It uses several automobile profile attributes to predict fuel consumption. The training data is available in the University of California at Irvine Machine Learning Repository and contains data collected from automobiles of various makes and models.

This example uses the following six input data attributes to predict the output data attribute MPG with a FIS tree:

1. Number of cylinders
2. Displacement
3. Horsepower
4. Weight
5. Acceleration
6. Model year

Prepare Data

Load the data. Each row of the dataset obtained from the repository represents a different automobile profile.

```
data = loadgas;
```

`data` contains 7 columns, where the first six columns contain the following input attributes.

- Number of cylinders
- Displacement
- Horsepower
- Weight
- Acceleration
- Model year

The seventh column contains the output attribute, MPG.

Create separate input and output data sets, X and Y, respectively.

```
X = data(:,1:6);
Y = data(:,7);
```

Partition the input and output data sets into training data (odd-indexed samples) and validation data (even-indexed samples).

```
trnX = X(1:2:end,:); % Training input data set
trnY = Y(1:2:end,:); % Training output data set
vldX = X(2:2:end,:); % Validation input data set
vldY = Y(2:2:end,:); % Validation output data set
```

Extract the range of each data attribute, which you will use for input/output range definition during FIS construction.

```
dataRange = [min(data)' max(data)'];
```

Construct a FIS Tree

For this example, construct a FIS tree using the following steps:

1. Rank the input attributes based on their correlations with the output attribute.
2. Create multiple FIS objects using the ranked input attributes.
3. Construct a FIS tree from the FIS objects.

Rank Inputs According to Correlation Coefficients

Calculate the correlation coefficients for the training data. In the final row of the correlation matrix, the first six elements show the correlation coefficients between the six put data attributes and the output attribute.

```
c1 = corrcoef(data);
c1(end,:)
```

```
ans = 1×7

   -0.7776   -0.8051   -0.7784   -0.8322    0.4233    0.5805    1.0000
```

The first four input attributes have negative values, and the last two input attributes have positive values.

Rank the input attributes that have negative correlations in descending order by the absolute value of their correlation coefficients.

1. Weight
2. Displacement
3. Horsepower
4. Number of cylinders

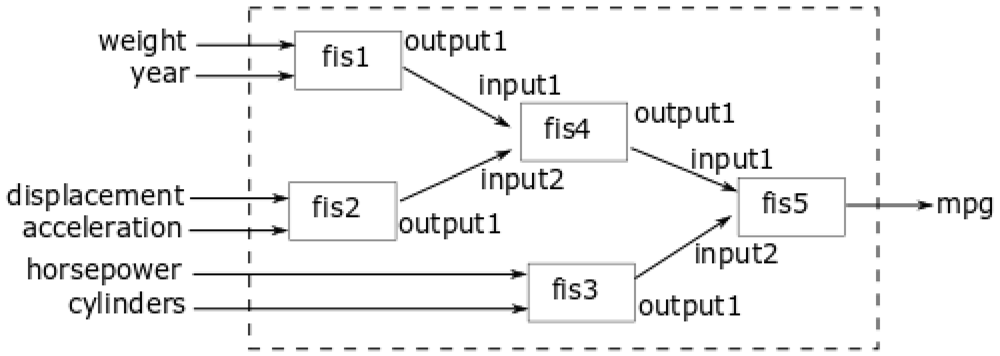
Rank the input attributes that have positive correlations in descending order by the absolute value of their correlation coefficients.

1. Model year
2. Acceleration

These rankings show that the weight and model year have the highest negative and positive correlations with MPG, respectively.

Create Fuzzy Inference Systems

For this example, implement a FIS tree with the following structure.



The FIS tree uses multiple two-input-one-output FIS objects to reduce the total number of rules used In the inference process. `fis1`, `fis2`, and `fis3` directly take the input values and generate intermediate `MPG` values, which are further combined using `fis4` and `fis5`.

Input attributes with negative and positive correlation values are paired up to combine both positive and negative effects on the output for prediction. The inputs are grouped according to their ranks as follows:

- Weight and model year
- Displacement and acceleration
- Horsepower and number of cylinders

The last group includes only inputs with negative correlation values since there are only two inputs with positive correlation values.

This example uses Sugeno-type FIS objects for faster evaluation during the tuning process as compared to Mamdani systems. Each FIS includes two inputs and one output, where each input contains two default triangular membership functions (MFs), and the output includes 4 default constant MFs. Specify the input and output ranges using the corresponding data attribute ranges.

The first FIS combines the weight and model year attributes.

```
fis1 = sugfis('Name','fis1');
fis1 = addInput(fis1,dataRange(4,:),'NumMFs',2,'Name',"weight");
fis1 = addInput(fis1,dataRange(6,:),'NumMFs',2,'Name',"year");
fis1 = addOutput(fis1,dataRange(7,:),'NumMFs',4);
```

The second FIS combines the displacement and acceleration attributes.

```
fis2 = sugfis('Name','fis2');
fis2 = addInput(fis2,dataRange(2,:),'NumMFs',2,'Name',"displacement");
fis2 = addInput(fis2,dataRange(5,:),'NumMFs',2,'Name',"acceleration");
fis2 = addOutput(fis2,dataRange(7,:),'NumMFs',4);
```

The third FIS combines the horsepower and number of cylinder attributes.

```
fis3 = sugfis('Name','fis3');
fis3 = addInput(fis3,dataRange(3,:),'NumMFs',2,'Name',"horsepower");
fis3 = addInput(fis3,dataRange(1,:),'NumMFs',2,'Name',"cylinders");
fis3 = addOutput(fis3,dataRange(7,:),'NumMFs',4);
```

The fourth FIS combines the outputs of the first and second FIS.

```
fis4 = sugfis('Name','fis4');
fis4 = addInput(fis4,dataRange(7,:),'NumMFs',2);
fis4 = addInput(fis4,dataRange(7,:),'NumMFs',2);
fis4 = addOutput(fis4,dataRange(7,:),'NumMFs',4);
```

The final FIS combines the outputs of third and fourth FIS and generates the estimated MPG. This FIS has the same input and output ranges as the fourth FIS.

```
fis5 = fis4;
fis5.Name = 'fis5';
fis5.Outputs(1).Name = "mpg";
```

Construct FIS Tree

Connect the fuzzy systems (`fis1`, `fis2`, `fis3`, `fis4`, and `fis5`) according to the FIS tree diagram.

```
fisTin = fistree([fis1 fis2 fis3 fis4 fis5],[ ...
    "fis1/output1" "fis4/input1"; ...
    "fis2/output1" "fis4/input2"; ...
    "fis3/output1" "fis5/input2"; ...
    "fis4/output1" "fis5/input1"])
```

```
fisTin = 
  fistree with properties:

                        FIS: [1×5 sugfis]
                Connections: [4×2 string]
                     Inputs: [6×1 string]
                    Outputs: "fis5/mpg"
    DisableStructuralChecks: 0

    See 'getTunableSettings' method for parameter optimization.
```

Tune FIS Tree with Training Data

Tuning is performed in two steps.

1. Learn the rule base while keeping the input and output MF parameters constant.
2. Tune the parameters of the input/output MFs and rules.

The first step is less computationally expensive due to the small number of rule parameters, and it quickly converges to a fuzzy rule base during training. In the second step, using the rule base from the first step as an initial condition provides fast convergence of the parameter tuning process.

Learn Rules

To learn a rule base, first specify tuning options using a `tunefisOptions` object. Global optimization methods (genetic algorithm or particle swarm) are suitable for initial training when all the parameters of a fuzzy system are untuned. For this example, tune the FIS tree using the particle swarm optimization method (`'particleswarm'`).

To learn new rules, set the `OptimizationType` to `'learning'`. Restrict the maximum number of rules to 4. The number of tuned rules of each FIS can be less than this limit, since the tuning process removes duplicate rules.

```
options = tunefisOptions('Method','particleswarm',...
    'OptimizationType','learning', ...
    'NumMaxRules',4);
```

If you have Parallel Computing Toolbox™ software, you can improve the speed of the tuning process by setting `options.UseParallel` to `true`. If you do not have Parallel Computing Toolbox software, set `options.UseParallel` to `false`.

Set the maximum number of iterations to 50. To reduce training error in the rule learning process, you can increase the number of iterations. However, using too many iterations can overtune the FIS tree to the training data, increasing the validation errors.

```
options.MethodOptions.MaxIterations = 50;
```

Since particle swarm optimization uses random search, to obtain reproducible results, initialize the random number generator to its default configuration.

```
rng('default')
```

Tune the FIS tree using the specified tuning data and options. Set the input order of the training data according to the FIS tree connections as follows: `weight`, `year`, `displacement`, `acceleration`, `horsepower`, and `cylinders`.

```
inputOrders1 = [4 6 2 5 3 1];
orderedTrnX1 = trnX(:,inputOrders1);
```

Learning rules with `tunefis` function takes approximately 4 minutes. For this example, enable tuning by setting `runtunefis` to `true`. To load pretrained results without running `tunefis`, you can set `runtunefis` to `false`.

```
runtunefis = true;
```

Parameter settings can be empty when learning new rules. For more information, see `tunefis`.

```
if runtunefis
    fisTout1 = tunefis(fisTin,[],orderedTrnX1,trnY,options);
```

```
else
    tunedfis = load('tunedfistreempgprediction.mat'); %#ok<UNRCH>
    fisTout1 = tunedfis.fisTout1;
    fprintf('Training RMSE = %.3f MPG\n',calculateRMSE(fisTout1,orderedTrnX1,trnY));
end

                                 Best                Mean      Stall
Iteration        f-count           f(x)                f(x)    Iterations
    0              100           5.697               12.63        0
    1              200           5.697               14.45        0
    2              300           5.222               12.26        0
    3              400           5.222               13.44        1
    4              500           5.222                12.9        2
    5              600           4.944               12.19        0
    6              700           4.944                12.2        1
    7              800           4.563               13.31        0
    8              900           4.563               12.92        1
    9             1000           4.563               12.06        2
   10             1100           4.563               13.32        3
   11             1200           4.563               11.82        4
   12             1300           4.563               13.04        5
   13             1400           4.563                12.2        6
   14             1500           4.563               11.94        7
   15             1600           4.563               11.33        8
   16             1700           4.563               10.71        9
   17             1800           4.538               11.39        0
   18             1900           4.538               11.27        1
   19             2000           4.538               11.32        2
   20             2100           4.538               11.26        3
   21             2200           4.538               11.07        4
   22             2300           4.538               10.53        5
   23             2400           4.538               10.15        6
   24             2500           4.538               10.66        7
   25             2600           4.452               10.28        0
   26             2700           4.408               10.42        0
   27             2800           4.243               9.661        0
   28             2900           4.061               9.153        0
   29             3000           4.061               9.849        1
   30             3100           4.024               9.029        0

                                 Best                Mean      Stall
Iteration        f-count           f(x)                f(x)    Iterations
   31             3200           4.024                9.91        1
   32             3300           4.024               8.847        2
   33             3400           3.996               8.684        0
   34         3500         3.991         8.674      0
   35         3600         3.569         9.125      0
   36         3700         3.569         8.942      1
   37         3800         3.512          8.21      0
   38         3900         3.512         8.262      1
   39         4000         3.512         8.452      2
   40         4100         3.485         8.343      0
   41         4200         3.485         8.451      1
   42         4300         3.437          8.52      0
   43         4400         3.425         8.136      0
   44         4500         3.425         8.254      1
   45         4600         3.423         8.065      0
   46         4700         3.423           7.6      1
   47         4800         3.417         7.586      0
   48         4900         3.399         7.546      0
   49         5000         3.399         7.335      1
   50         5100         3.399         7.816      2
Optimization ended: number of iterations exceeded OPTIONS.MaxIterations.
```

The `Best f(x)` column shows the training root-mean-squared-error (RMSE).

The learning process produces a set of new rules for the FIS tree.

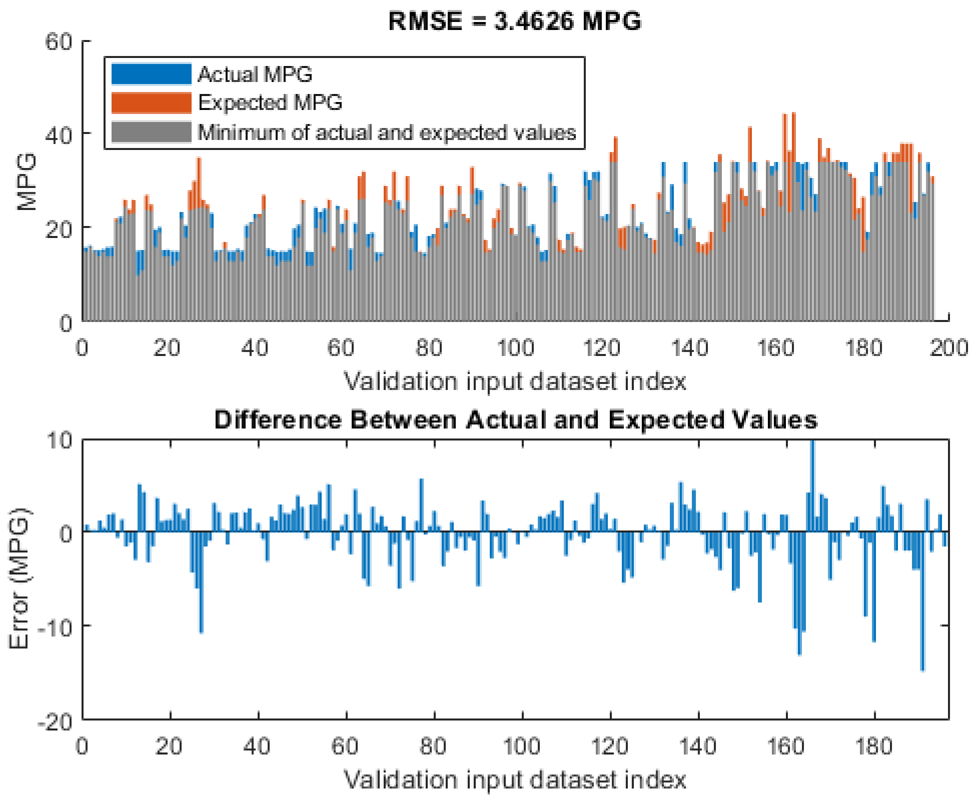
```
fprintf("Total number of rules = %d\n",numel([fisTout1.FIS.Rules]));
```

```
Total number of rules = 17
```

The learned system should have similar RMSE performance for both the training and validation data sets. To calculate the RMSE for the validation data set, evaluate `fisout1` using validation input data set `vldX`. To hide run-time warnings during evaluation, set all the warning options to `none`.

Calculate the RMSE between the generated output data and the validation output data set `vldY`. Since the training and validation errors are similar, the learned system does not overfit the training data.

```
orderedVldX1 = vldX(:,inputOrders1);
plotActualAndExpectedResultsWithRMSE(fisTout1,orderedVldX1,vldY)
```



Tune All Parameters

After learning the new rules, tune the input/output MF parameters along with the parameters of the learned rules. To obtain the tunable parameters of the FIS tree, use the `getTunableSettings` function.

```
[in,out,rule] = getTunableSettings(fisTout1);
```

To tune the existing FIS tree parameter settings without learning new rules, set the `OptimizationType` to `'tuning'`.

```
options.OptimizationType = 'tuning';
```

Since the FIS tree already learned rules using the training data, use a local optimization method for fast convergence of the parameter values. For this example, use the pattern search optimization method (`'patternsearch'`).

```
options.Method = 'patternsearch';
```

Tuning the FIS tree parameters takes more iterations than the previous rule-learning step. Therefore, increase the maximum number of iterations of the tuning process to 75. As in the first tuning stage, you can reduce training errors by increasing the number of iterations. However, using too many iterations can overtune the parameters to the training data, increasing the validation errors.

```
options.MethodOptions.MaxIterations = 75;
```

Tune the FIS tree parameters using the specified tunable settings, training data, and tuning options.

Tuning parameter values with `tunefis` function takes several minutes. To load pretrained results without running `tunefis`, you can set `runtunefis` to `false`.

```
rng('default')
if runtunefis
    fisTout2 = tunefis(fisTout1,[in;out;rule],orderedTrnX1,trnY,options);
else
    fisTout2 = tunedfis.fisTout2; %#ok<UNRCH>
    fprintf('Training RMSE = %.3f MPG\n',calculateRMSE(fisTout2,orderedTrnX1,trnY));
end
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1      3.56396             1      
    1           2      3.56389             2     Successful Poll
    2           3      3.56374             4     Successful Poll
    3           4      3.56344             8     Successful Poll
    4           5      3.56285            16     Successful Poll
    5           6      3.56172            32     Successful Poll
    6           7       3.5596            64     Successful Poll
    7           8        3.556           128     Successful Poll
    8           9      3.55073           256     Successful Poll
    9          10       3.5431           512     Successful Poll
   10          17       3.5431           256     Refine Mesh
   11          27         3.54           512     Successful Poll
   12          34         3.54           256     Refine Mesh
   13          48         3.54           128     Refine Mesh
   14          50      3.53968           256     Successful Poll
```

```
      15          55         3.53961          512     Successful Poll
      16          62         3.53961          256     Refine Mesh
      17          76         3.53961          128     Refine Mesh
      18          84         3.35952          256     Successful Poll
      19          86         3.35153          512     Successful Poll
      20          93         3.35078         1024     Successful Poll
      21          99         3.35078          512     Refine Mesh
      22         107         3.35078          256     Refine Mesh
      23         120         3.35078          128     Refine Mesh
      24         141         3.34063          256     Successful Poll
      25         150         3.33599          512     Successful Poll
      26         158         3.33599          256     Refine Mesh
      27         172         3.33599          128     Refine Mesh
      28         181         3.33546          256     Successful Poll
      29         194         3.33546          128     Refine Mesh
      30         217          3.3198          256     Successful Poll

Iter     Func-count       f(x)       MeshSize      Method
      31         230          3.3198          128     Refine Mesh
      32         240         3.31883          256     Successful Poll
      33         253         3.31883          128     Refine Mesh
      34         275         3.31883           64     Refine Mesh
      35         276           3.316          128     Successful Poll
      36         298           3.316           64     Refine Mesh
      37         321           3.316           32     Refine Mesh
      38         329         3.31085           64     Successful Poll
      39         347         3.30905          128     Successful Poll
      40         348         3.30398          256     Successful Poll
      41         361         3.30398          128     Refine Mesh
      42         383         3.30398           64     Refine Mesh
      43         408         3.30398           32     Refine Mesh
      44         460         3.30398           16     Refine Mesh
      45         467         3.30375           32     Successful Poll
      46         519         3.30375           16     Refine Mesh
      47         532         3.30329           32     Successful Poll
      48         584         3.30329           16     Refine Mesh
      49         598         3.28079           32     Successful Poll
      50         608         3.28036           64     Successful Poll
      51         630         3.27888          128     Successful Poll
      52         639         3.27672          256     Successful Poll
      53         652         3.27672          128     Refine Mesh
      54         672         3.27672           64     Refine Mesh
      55         697         3.27672           32     Refine Mesh
      56         750         3.27672           16     Refine Mesh
```

```
   57         779       3.27535            32     Successful Poll
   58         832       3.27535            16     Refine Mesh
   59         863       3.27182            32     Successful Poll
   60         910       3.26985            64     Successful Poll

Iter     Func-count       f(x)       MeshSize      Method
   61         935       3.26985            32     Refine Mesh
   62         988       3.26985            16     Refine Mesh
   63        1064       3.26985             8     Refine Mesh
   64        1066       3.26957            16     Successful Poll
   65        1142       3.26957             8     Refine Mesh
   66        1155       3.26792            16     Successful Poll
   67        1231       3.26792             8     Refine Mesh
   68        1247       3.26139            16     Successful Poll
   69        1323       3.26139             8     Refine Mesh
   70        1421       3.26139             4     Refine Mesh
   71        1422       3.26118             8     Successful Poll
   72        1520       3.26118             4     Refine Mesh
   73        1522       3.26095             8     Successful Poll
   74        1620       3.26095             4     Refine Mesh
   75        1633       3.26094             8     Successful Poll
   76        1731       3.26094             4     Refine Mesh
Maximum number of iterations exceeded: increase options.MaxIterations.
```

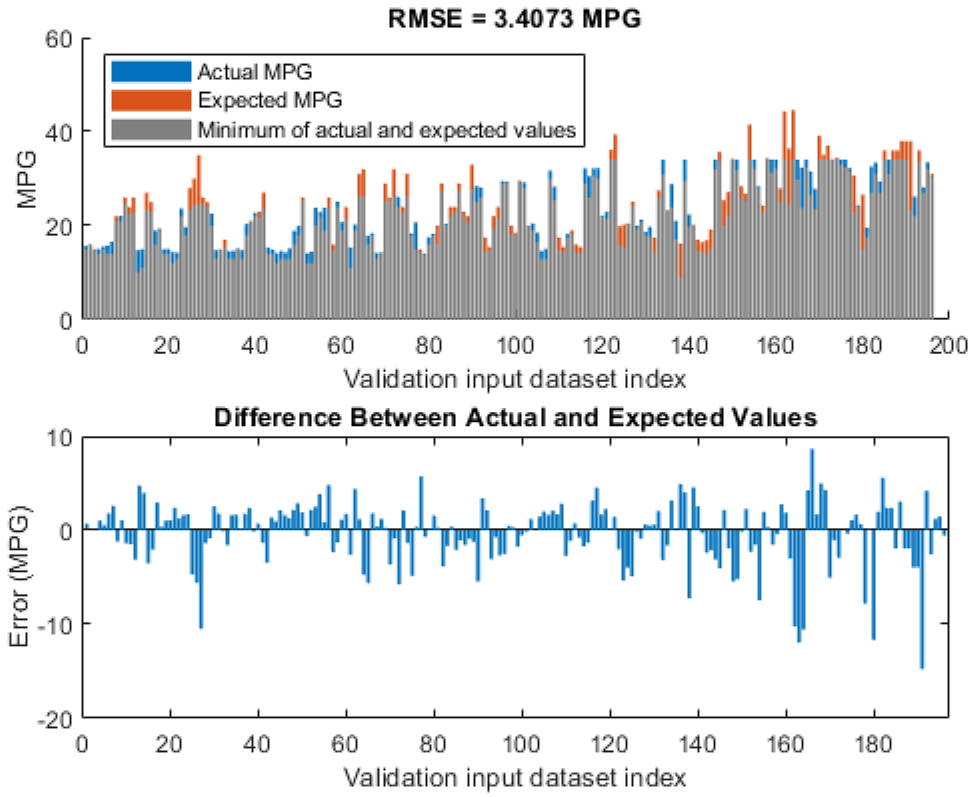
At the end of the tuning process, the training error reduces compared to the previous step.

Check Performance

Validate the performance of the tuned FIS tree, `fisout2`, using the validation input data set `vldX`.

Compare the expected MPG obtained from the validation output data set `vldY` and actual MPG generated using `fisout2`. Compute the RMSE between these results.

```
plotActualAndExpectedResultsWithRMSE(fisTout2,orderedVldX1,vldY)
```



Tuning the FIS tree parameters improves the RMSE compared to the results from the initial learned rule base. Since the training and validation errors are similar, the parameters values are not overtuned.

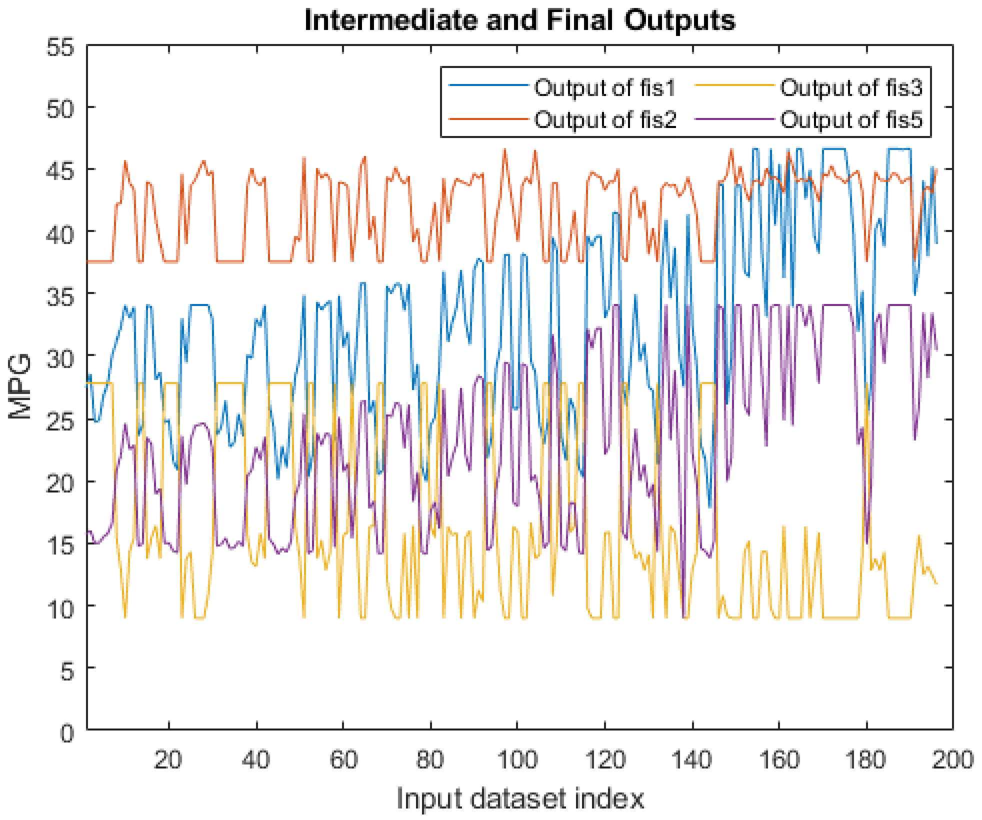
Analyze Intermediate Data

To gain insight into the operation of your fuzzy tree, you can add the outputs of the component fuzzy systems as outputs of your FIS tree. For this example, to access the intermediate FIS outputs, add three additional outputs to the tuned FIS tree.

```
fisTout3 = fisTout2;
fisTout3.Outputs(end+1) = "fis1/output1";
fisTout3.Outputs(end+1) = "fis2/output1";
fisTout3.Outputs(end+1) = "fis3/output1";
```

To generate the additional outputs, evaluate the augmented FIS tree, `fisTout3`.

```
actY = evaluateFIS(fisTout3,orderedVldX1);
figure,plot(actY(:,[2 3 4 1])),xlabel("Input dataset index"),ylabel("MPG"),axis([1 200
legend(["Output of fis1" "Output of fis2" "Output of fis3" "Output of fis5"],...
    'Location','NorthEast','NumColumns',2)
title("Intermediate and Final Outputs")
```



The final output of the FIS tree (`fis5` output) appears to be highly correlated with the outputs of `fis1` and `fis3`. To validate this assessment, check the correlation coefficients of the FIS outputs.

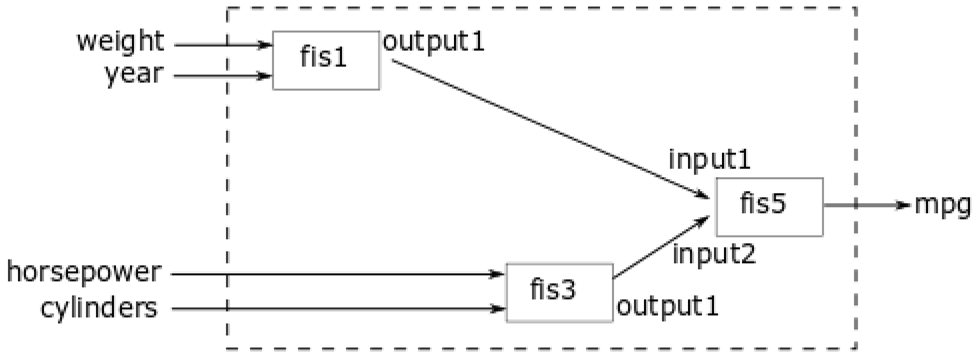
```
c2 = corrcoef(actY(:,[2 3 4 1]));
c2(end,:)
```

```
ans = 1×4

    0.9724    0.7935   -0.8156    1.0000
```

The last row of the correlation matrix shows that the outputs of `fis1` and `fis3` (first and third column, respectively) have higher correlations with the final output as compared to the output of `fis2` (second column). This result indicates that simplifying the FIS tree by removing `fis2` and `fis4` and can potentially produce similar training results compared to the original tree structure.

Simplify and Retrain FIS Tree

Remove `fis2` and `fis4` from the FIS tree and connect the output of `fis1` to the first input of `fis5`. When you remove a FIS from a FIS tree, any existing connections to that FIS are also removed.



```
fisTout3.FIS([2 4]) = [];
fisTout3.Connections(end+1,:) = ["fis1/output1" "fis5/input1"];
fis5.Inputs(1).Name = "fis1out";
```

To make the number of FIS tree outputs match the number of outputs in the training data, remove the FIS tree outputs from `fis1` and `fis3`.

```
fisTout3.Outputs(2:end) = [];
```

Update the input training data order according to the new FIS tree input configuration.

```
inputOrders2 = [4 6 3 1];
orderedTrnX2 = trnX(:,inputOrders2);
```

Since the FIS tree configuration is changed, you must rerun both the learning and tuning steps. In the learning phase, the existing rule parameters are also tuned to fit the new configuration of the FIS tree.

```
options.Method = "particleswarm";
options.OptimizationType = "learning";
options.MethodOptions.MaxIterations = 50;

[~,~,rule] = getTunableSettings(fisTout3);

rng('default')
if runtunefis
    fisTout4 = tunefis(fisTout3,rule,orderedTrnX2,trnY,options);
else
    fisTout4 = tunedfis.fisTout4; %#ok<UNRCH>
    fprintf('Training RMSE = %.3f MPG\n',calculateRMSE(fisTout4,orderedTrnX2,trnY));
end
```

```
                                 Best            Mean     Stall
Iteration     f-count            f(x)            f(x)    Iterations
    0             100           5.592           11.74        0
    1             200           5.592           13.89        0
    2             300           5.278           12.52        0
    3             400            4.84           11.89        0
    4             500            4.84           12.98        1
    5             600           3.803           11.59        0
    6             700           3.803           12.25        1
    7             800           3.803           11.88        2
    8             900           3.803           12.28        3
    9            1000            3.17           11.53        0
   10            1100            3.17           12.09        1
   11            1200            3.17           11.92        2
   12            1300            3.17           11.38        3
   13            1400            3.17           11.89        4
   14            1500            3.17           10.51        5
   15            1600            3.17           9.628        6
   16            1700            3.17           9.383        7
   17            1800            3.17           8.849        8
   18            1900            3.17            8.35        9
   19            2000            3.17           8.374       10
   20            2100           3.163           7.869        0
   21            2200           3.163           7.388        1
   22            2300           3.163            7.35        2
   23            2400           3.163           7.067        3
   24            2500           3.163           7.111        4
   25           2600          3.163          6.967        5
   26           2700          3.085          6.565        0
   27           2800          3.004          6.608        0
   28           2900          3.004          6.321        1
   29           3000          2.983          6.008        0
   30           3100          2.983          5.986        1

                               Best           Mean     Stall
Iteration     f-count          f(x)           f(x)    Iterations
   31           3200          2.983          6.467        2
   32           3300          2.983          5.947        3
   33           3400          2.977          5.921        0
   34           3500          2.977           5.44        1
   35           3600          2.977          5.796        2
   36           3700          2.977          5.591        3
   37           3800          2.977          5.492        4
   38           3900          2.977          5.521        5
   39           4000          2.977          5.628        6
   40           4100          2.977          5.931        7
   41           4200          2.943          5.258        0
   42           4300          2.943          5.904        1
   43           4400          2.943          6.198        2
   44           4500          2.929          5.612        0
   45           4600          2.929          5.587        1
   46           4700          2.929          5.715        2
   47           4800          2.929          5.525        3
   48           4900          2.929          5.506        4
   49           5000          2.929          5.336        5
   50           5100          2.929          5.493        6
Optimization ended: number of iterations exceeded OPTIONS.MaxIterations.
```

In the training phase, the parameters of the membership function and rules are tuned.

```
options.Method = "patternsearch";
options.OptimizationType = "tuning";
options.MethodOptions.MaxIterations = 75;
[in,out,rule] = getTunableSettings(fisTout4);
rng('default')
if runtunefis
    fisTout5 = tunefis(fisTout4,[in;out;rule],orderedTrnX2,trnY,options);
else
    fisTout5 = tunedfis.fisTout5; %#ok<UNRCH>
    fprintf('Training RMSE = %.3f MPG\n',calculateRMSE(fisTout5,orderedTrnX2,trnY));
end
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1       2.92888             1     
    1           2       2.92888             2     Successful Poll
    2           3       2.92887             4     Successful Poll
    3           4       2.92884             8     Successful Poll
    4           5       2.92881            16     Successful Poll
    5           6       2.92879            32     Successful Poll
    6          14        2.9117            64     Successful Poll
    7          15       2.91093           128     Successful Poll
    8          22       2.90552           256     Successful Poll
    9          23       2.88691           512     Successful Poll
   10          29       2.88691           256     Refine Mesh
   11          37       2.88691           128     Refine Mesh
   12          38       2.88549           256     Successful Poll
   13          46       2.88549           128     Refine Mesh
   14          59       2.88549            64     Refine Mesh
   15          65       2.88521           128     Successful Poll
   16          78       2.88521            64     Refine Mesh
   17          80        2.8825           128     Successful Poll
   18          85       2.87991           256     Successful Poll
   19          93       2.87991           128     Refine Mesh
   20         106       2.87991            64     Refine Mesh
   21         119       2.87526           128     Successful Poll
   22         131       2.87526            64     Refine Mesh
   23         147       2.87526            32     Refine Mesh
   24         154       2.87514            64     Successful Poll
   25         170       2.87514            32     Refine Mesh
   26         180       2.86842            64     Successful Poll
   27         187       2.86722           128     Successful Poll
   28         200       2.86722            64     Refine Mesh
   29         207       2.86719           128     Successful Poll
   30         220       2.86719            64     Refine Mesh

Iter     Func-count        f(x)       MeshSize      Method
   31         235       2.86719            32     Refine Mesh
   32         236       2.86708            64     Successful Poll
   33         251       2.86708            32     Refine Mesh
   34         260       2.86638            64     Successful Poll
   35         261       2.86515           128     Successful Poll
   36         274       2.86515            64     Refine Mesh
   37         289       2.86515            32     Refine Mesh
   38         290       2.86501            64     Successful Poll
   39         305       2.86501            32     Refine Mesh
   40         336       2.86501            16     Refine Mesh
   41         339        2.85839            32     Successful Poll
   42         370        2.85839            16     Refine Mesh
   43         374        2.85824            32     Successful Poll
   44         405        2.85824            16     Refine Mesh
   45         417        2.85823            32     Successful Poll
   46         448        2.85823            16     Refine Mesh
   47         490        2.85823             8     Refine Mesh
   48         491        2.85822            16     Successful Poll
   49         533        2.85822             8     Refine Mesh
   50         535        2.85806            16     Successful Poll
   51         547        2.85797            32     Successful Poll
   52         578        2.85797            16     Refine Mesh
   53         590        2.85796            32     Successful Poll
   54         621        2.85796            16     Refine Mesh
   55         663        2.85796             8     Refine Mesh
   56         664        2.85795            16     Successful Poll
   57         706        2.85795             8     Refine Mesh
   58         711         2.8579            16     Successful Poll
   59         753         2.8579             8     Refine Mesh
   60         759        2.85743            16     Successful Poll

Iter     Func-count       f(x)       MeshSize      Method
   61         771        2.85698            32     Successful Poll
   62         778        2.85633            64     Successful Poll
   63         785        2.85584           128     Successful Poll
   64         797        2.85584            64     Refine Mesh
   65         813        2.85584            32     Refine Mesh
   66         844        2.85584            16     Refine Mesh
   67         886        2.85584             8     Refine Mesh
   68         904        2.85548            16     Successful Poll
   69         905        2.85539            32     Successful Poll
   70         936        2.85539            16     Refine Mesh
   71         937        2.85538            32     Successful Poll
   72         968        2.85538            16     Refine Mesh
   73        1010        2.85538             8     Refine Mesh
   74        1026        2.85537            16     Successful Poll
   75        1068        2.85537             8     Refine Mesh
   76        1090        2.82832            16     Successful Poll
Maximum number of iterations exceeded: increase options.MaxIterations.
```

At the end of the tuning process, the FIS tree contains updated MF and rule parameter values. The rule base size of the new FIS tree configuration is smaller than the previous configuration.

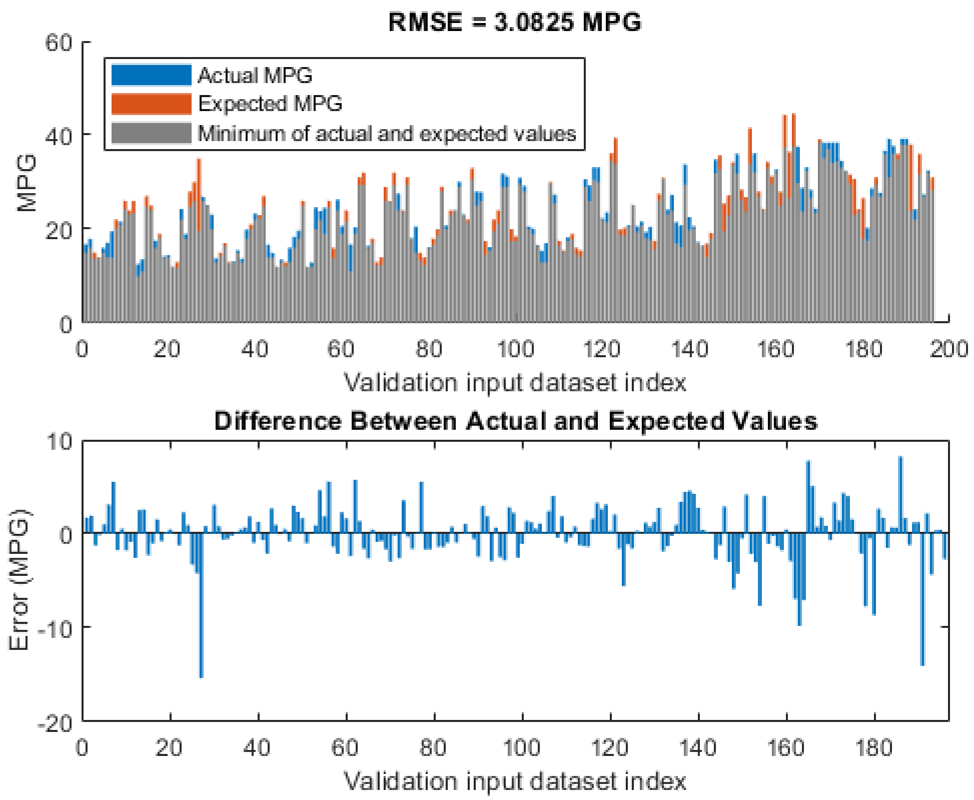
```
fprintf("Total number of rules = %d\n",numel([fisTout5.FIS.Rules]));
```

```
Total number of rules = 11
```

Check Performance of the Simplified FIS Tree

Evaluate the updated FIS tree using the four input attributes of the checking dataset.

```
orderedVldX2 = vldX(:,inputOrders2);
plotActualAndExpectedResultsWithRMSE(fisTout5,orderedVldX2,vldY)
```



The simplified FIS tree with four input attributes produces better results in terms of RMSE as compared to the first configuration, which uses six input attributes. Therefore, it shows that a FIS tree can be represented with fewer number of inputs and rules to generalize the training data.

Conclusion

You can further improve the training error of the tuned FIS tree by:

- Increasing number of iterations in both the rule-learning and parameter-tuning phases. Doing so increases the duration of the optimization process and can also increase validation error due to overtuned system parameters with the training data.
- Using global optimization methods, such as `ga` and `particleswarm`, in both rule-learning and parameter-tuning phases. `ga` and `particleswarm` perform better for large parameter tuning ranges since they are global optimizers. On the other hand, `patternsearch` and `simulannealbnd` perform better for small parameter ranges since they are local optimizers. If rules are already added to a FIS tree using training data, then `patternsearch` and `simulannealbnd` may produce faster convergence as compared to `ga` and `particleswarm`. For more information on these optimization methods and their options, see `ga`, `particleswarm`, `patternsearch`, and `simulannealbnd`.
- Changing the FIS properties, such as the type of FIS, number of inputs, number of input/output MFs, MF types, and number of rules. For fuzzy systems with a large number of inputs, a Sugeno FIS generally converges faster than a Mamdani FIS since a Sugeno system has fewer output MF parameters (if `constant` MFs are used) and faster defuzzification. Small numbers of MFs and rules reduce the number of parameters to tune, producing a faster tuning process. Furthermore, a large number of rules may overfit the training data.
- Modifying tunable parameter settings for MFs and rules. For example, you can tune the support of a triangular MF without changing its peak location. Doing so reduces the number of tunable parameters and can produce a faster tuning process for specific applications. For rules, you can exclude zero MF indices by setting the `AllowEmpty` tunable setting to `false`, which reduces the overall number of rules during the learning phase.
- Changing FIS tree properties, such as number of fuzzy systems and connections between the fuzzy systems.
- Using different ranking and grouping of the inputs to the FIS tree.

Local Functions

```
function plotActualAndExpectedResultsWithRMSE(fis,x,y)

% Calculate RMSE bewteen actual and expected results
[rmse,actY] = calculateRMSE(fis,x,y);
```

```
% Plot results
figure
subplot(2,1,1)
hold on
bar(actY)
bar(y)
bar(min(actY,y),'FaceColor',[0.5 0.5 0.5])
hold off
axis([0 200 0 60])
xlabel("Validation input dataset index"),ylabel("MPG")
legend(["Actual MPG" "Expected MPG" "Minimum of actual and expected values"],...
    'Location','NorthWest')
title("RMSE = " + num2str(rmse) + " MPG")

subplot(2,1,2)
bar(actY-y)
xlabel("Validation input dataset index"),ylabel("Error (MPG)")
title("Difference Between Actual and Expected Values")

end

function [rmse,actY] = calculateRMSE(fis,x,y)

% Evaluate FIS
actY = evaluateFIS(fis,x);

% Calculate RMSE
del = actY - y;
rmse = sqrt(mean(del.^2));

end

function y = evaluateFIS(fis,x)

% Specify options for FIS evaluation
persistent evalOptions
if isempty(evalOptions)
    evalOptions = evalfisOptions("EmptyOutputFuzzySetMessage","none", ...
        "NoRuleFiredMessage","none","OutOfRangeInputValueMessage","none");
end

% Evaluate FIS
y = evalfis(fis,x,evalOptions);
```

```
end
```

See Also

`fistree` | `getTunableSettings` | `sugfis` | `tunefis`

More About

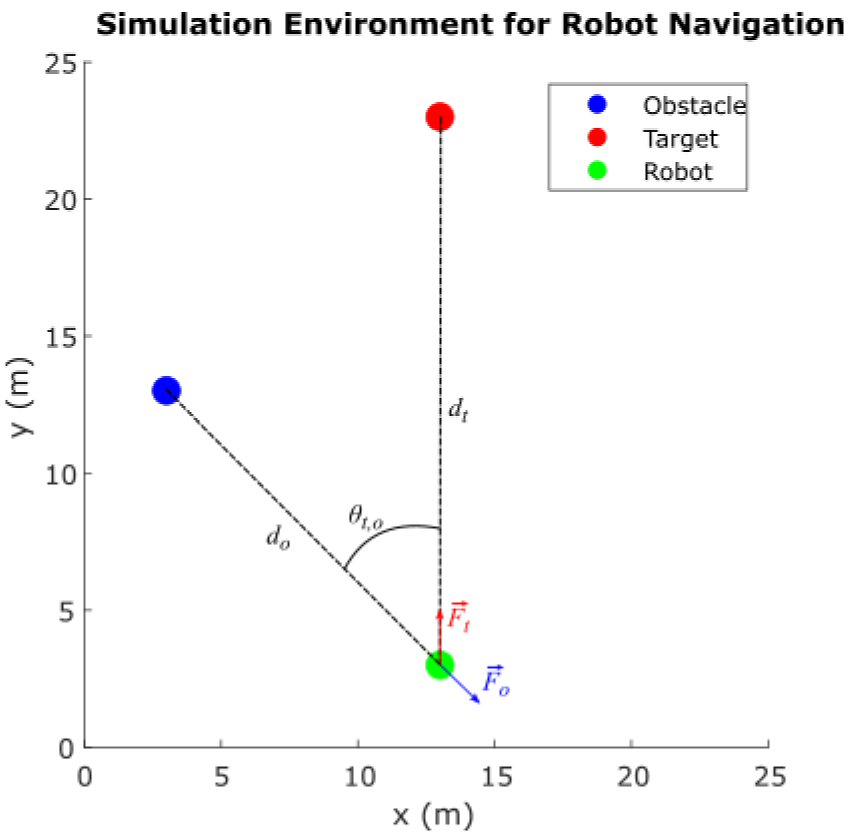
- “Tuning Fuzzy Inference Systems” on page 3-2
- “Tune Mamdani Fuzzy Inference System” on page 3-33

Tune Fuzzy Systems using Custom Cost Function

This example shows how to tune a fuzzy inference system (FIS) using a custom cost function. The example requires Global Optimization Toolbox™ software.

Problem Description

You use a custom cost function to learn robot navigation in a simulation environment. The goal of the navigation task is to reach a specified target while avoiding obstacles. The direction to the target is represented as a unit force vector ($\overrightarrow{F_t}$) directed from the robot to a target location. The obstacle avoidance direction is represented by a unit force vector ($\overrightarrow{F_o}$) directed towards the robot from the closest obstacle location.



The robot, target, and obstacle are shown as circles with 0.5 m radius in the 25 m x 25 m simulation environment. The navigation task is to combine the force vectors such that the direction θ of the resultant force vector $\overrightarrow{F}$ provides a collision-free direction for the robot.

$\overrightarrow{F} = w\overrightarrow{F_o} + (1 - w)\overrightarrow{F_t}$, where $0 \le w \le 1$

$$\theta = \angle\overrightarrow{F}$$

This example assumes a robot with differential kinematics for the simulation. In other words, the robot can rotate on its center without any constraints. However, to avoid sharp turns, the change per time step in the robot direction is limited to $\left[-\frac{\pi}{4}, \frac{\pi}{4}\right]$. Therefore, if the current robot heading direction is $\theta_r(k)$, the next heading direction is calculated as:

$$\theta_r(k+1) = \theta_r(k) + \min\left(\max\left(\theta - \theta_r(k), \frac{\pi}{4}\right), -\frac{\pi}{4}\right).$$

The weight w of the force vector $\overrightarrow{F_o}$ is calculated using function f_w:

$$w = f_w(\alpha, \theta_{t,o})$$

where

- $\alpha = \frac{d_o}{d_t}$ is the ratio of the robot-to-obstacle distance (d_o) and the robot-to-target-distance (d_t)
- $\theta_{t,o}$ is the absolute difference between the target and obstacle directions with respect to the robot

To achieve the navigation task, the function f_w must generate high w values, that is, focus on avoiding the obstacle when:

- Both the target and obstacle directions from the robot are similar ($\theta_{t,o}$ is low)
- The obstacle is closer to the robot than the target (α is low).

Otherwise, f_w must generate low w values, that is, focus on reaching the target.

The goal of this example is to design a FIS that learns fuzzy rules and optimizes the FIS parameters to model the function f_w for collision-free robot navigation in the simulation environment.

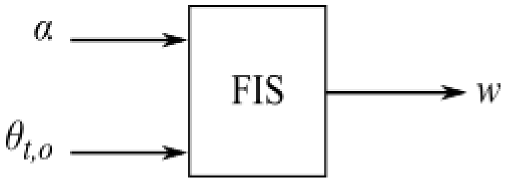
Assumptions

The following assumptions apply for the robot simulation:

- The robot can perfectly localize in the simulation environment; that is, the robot knows its current position in the simulation environment.
- The robot is equipped with perfect sensors to identify the obstacle and determine its location.
- The robot has no dynamic constraints; that is, the robot can rotate and move as commanded without any mechanical constraints. To avoid sharp turns, a soft constraint is imposed on rotation, which limits the change per time step in the robot heading to $\left[-\frac{\pi}{4}, \frac{\pi}{4}\right]$.
- The robot runs with a fixed speed. You can include additional fuzzy systems to control the robot speed. For simplicity, this example uses a fixed speed for the robot.

Construct Fuzzy Systems

To model function f_w, construct a FIS as shown in the following figure. For this example, use a Mamdani FIS.



```
fisin = mamfis;
```

Add the following two inputs as shown in the previous figure.

- α — Ratio of distances, robot-to-obstacle / robot-to-target
- $\theta_{t,o}$ — Difference between target and obstacle directions

Set the range of the first input to `[0,2]`, which indicates that α contributes to obstacle avoidance when the obstacle distance is less than or equal to twice the target distance.

Set the range of the second input to `[0,pi/2]`, which indicates that $\theta_{t,o}$ contributes to obstacle avoidance when the difference between the target and obstacle directions is less than or equal to `pi/2`.

```
fisin = addInput(fisin,[0 2],'Name','alpha');
fisin = addInput(fisin,[0 pi/2],'Name','theta_t_o');
```

To minimize the number of rules, which corresponds to the number of combinations of input membership functions, add two membership functions (MFs) to each input. To generate similar membership values beyond the input ranges, use `zmf` (Z-shaped curve membership function) and `smf` (S-shaped curve membership function) MFs. The tuning process optimizes the input MF parameter values.

Add membership functions to the first input.

```
fisin = addMF(fisin,'alpha','zmf',[0 2],'Name','low');
fisin = addMF(fisin,'alpha','smf',[0 2],'Name','high');
```

Add membership functions to the second input.

```
fisin = addMF(fisin,'theta_t_o','zmf',[0 pi/2],'Name','low');
fisin = addMF(fisin,'theta_t_o','smf',[0 pi/2],'Name','high');
```

Add an output to the FIS or the obstacle force vector weight, restricting the weight values to the range `[0,1]`.

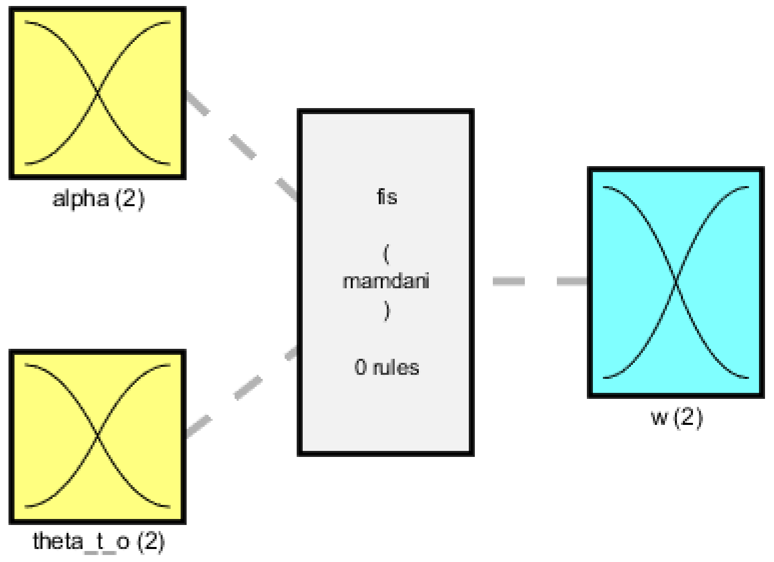
```
fisin = addOutput(fisin,[0 1],'Name','w');
```

Add two MFs to the output. You can add more MFs to the output for finer granularity of output values. However, doing so increases the number of tuning parameters. The output MFs also use `zmf` and `smf` to generate similar membership values beyond the input ranges. The tuning process optimizes the output MF parameter values.

```
fisin = addMF(fisin,'w','zmf',[0 1],'Name','low');
fisin = addMF(fisin,'w','smf',[0 1],'Name','high');
```

View the FIS structure. Initially, the FIS has zero rules. The tuning process finds rules for the fuzzy system.

```
figure
plotfis(fisin)
```



System fis: 2 inputs, 1 outputs, 0 rules

Learn Rules and Optimize FIS Parameters

Since you do not have training data for this example, you simulate the robot navigation using a custom cost function. The tuning process uses this custom cost function when optimizing the FIS parameters.

For parameter optimization, obtain the parameter settings from the FIS.

```
[in,out] = getTunableSettings(fisin);
```

Next, create tuning options with `OptimizationType` set to `learning`. This example uses the genetic algorithm (`ga`) optimization method for the tuning process. To improve the speed of the tuning process, set the `UseParallel` option to `true`, which requires

Parallel Computing Toolbox™ software. If you do not have Parallel Computing Toolbox software, set `UseParallel` to `false`.

```
options = tunefisOptions('Method','ga','OptimizationType','learning');
```

Set the population size of the genetic algorithm to 200. The larger population size increases the probability of generating a better solution in fewer generations.

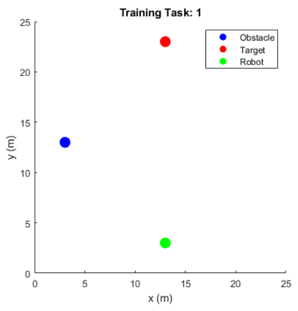
```
options.MethodOptions.PopulationSize = 200;
```

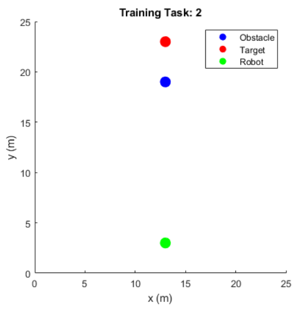
Set the maximum number of generations to 25. To tune the parameters further, you can set a higher number of generations. However, doing so increases the duration of the tuning process and can overtune the parameter values.

```
options.MethodOptions.MaxGenerations = 25;
```

Set the locations of the obstacle, target, and robot for the training environments. Set the initial heading of the robot to `pi/2` for the training environment. To learn navigation both with and without obstacle avoidance on the way to the target location, use two training tasks with different obstacle locations.

```
trnObstacle = [3 12;13 18];
trnTarget = [13 22;13 22];
trnRobot = [13 2 pi/2;13 2 pi/2;];

showSimulationEnvironmentsForTraining(trnObstacle,trnTarget,trnRobot)
```





Specify the custom cost function using a function handle.

```
costFunction = @(fis)navigationCostFcn(fis,trnObstacle,trnTarget,trnRobot);
```

In the cost function, the robot navigation is simulated in the training environments using each FIS from the population. Each navigation task is run for 100 iterations, where each iteration is equivalent to a decision cycle of length 1 s. The robot uses a fixed speed of 0.5 m/s throughout the navigation task. For more simulation details, see the `getNavigationResults` function.

```
function cost = navigationCostFcn(fis,obstacle,target,robot)

cost = 0;

for i = 1:size(obstacle,1)

results =
getNavigationResults(fis,obstacle(i,:),target(i,:),robot(i,:));

cost = cost + getNavigationCost(results);

end

end
```

The cost of each navigation task is the total distance traveled by the robot. If the robot does not reach the target or collides with the obstacle, a high cost value (200) is assigned for the simulation.

```
function cost = getNavigationCost(results)

if results.notSafe || ~results.reachedTarget

cost = 200;

else

cost = results.travelledDistance;

end

end
```

Since genetic algorithm optimization uses random search, to obtain reproducible results, initialize the random number generator to its default configuration.

```
rng('default')
```

Learning rules using the `tunefis` function takes approximately 10 minutes. For this example, enable tuning by setting `runtunefis` to `true`. To load pretrained results without running `tunefis`, you can set `runtunefis` to `false`.

```
runtunefis = true;
```

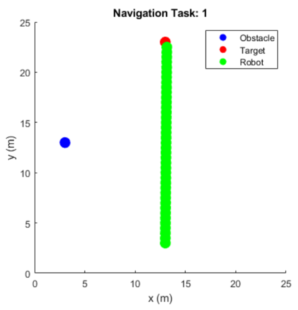
Tune the FIS using the specified training environments and tuning options.

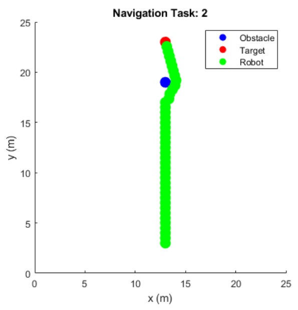
```
if runtunefis
    fisout = tunefis(fisin,[in;out],costFunction,options);
else
   tunedfis = load('tunedfisnavigation.mat');  %#ok<UNRCH>
   fisout = tunedfis.fisout;
end
```

```
                                  Best            Mean      Stall
Generation       Func-count        f(x)            f(x)    Generations
    1              400            219.5           389.5        0
    2              600            219.5           368.4        1
    3              800             49.5           350.3        0
    4             1000             48.5           322.7        0
    5             1200             48.5             289        1
    6             1400             45.5           259.8        0
    7             1600             40.5           243.1        0
    8             1800             40.5           224.3        1
    9             2000               40           205.5        0
   10             2200               40             187        1
   11             2400               40           176.1        2
   12             2600               40           180.8        0
   13             2800               40           189.3        1
   14             3000               40           167.5        2
   15             3200             39.5             167        0
   16             3400             39.5           137.4        1
   17             3600             39.5           125.5        2
   18             3800             39.5           109.9        3
   19             4000             39.5           92.45        0
   20             4200             39.5           95.89        1
   21             4400             39.5           96.73        0
   22             4600             39.5           95.67        1
   23             4800             39.5             110        2
   24             5000             39.5           107.4        3
   25             5200             39.5           100.2        0
Optimization terminated: maximum number of generations exceeded.
```

The tuned FIS produces the following robot trajectories in the simulation environments.

```
showNavigationTrajectories(fisout,trnObstacle,trnTarget,trnRobot)
```

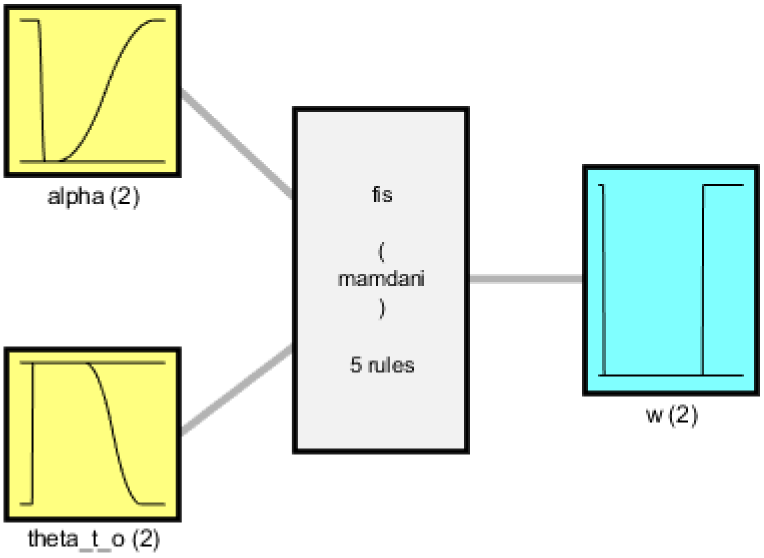




In the first case, the robot reaches the target with minimum distance since the obstacle is not on the path to the target. In the second case, the robot successfully avoids the obstacle and reaches the target.

View the structure of the tuned FIS, `fisout`.

```
figure,plotfis(fisout)
```



System fis: 2 inputs, 1 outputs, 5 rules

The tuning process produces a set of new rules for the FIS.

```
fisout.Rules
```

```
ans = 
  1×5 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
```

```
                        Description
                ____________________________________________

    1    "alpha==low & theta_t_o==high => w=low (1)"
    2    "alpha==low & theta_t_o==low => w=high (1)"
    3    "theta_t_o==high => w=low (1)"
    4    "alpha==high & theta_t_o==high => w=low (1)"
    5    "alpha==low => w=low (1)"
```

The rules are described as follows with respect to the expected behaviors of f_w:

- Rule 1 is consistent with the expected behavior of f_w. When the obstacle is not located in front of the robot on the way to the target ($\theta_{t,o}$ is high) and the obstacle is close (α is low), this rule produces low weight values.
- Rule 4 is also consistent with the expected behavior of f_w. When the obstacle is not located in front of the robot on the way to the target ($\theta_{t,o}$ is high) and the obstacle is farther away (α is high), this rule produces low weight values.
- Rule 3 generates low weight values when the obstacle is not located in front of the robot ($\theta_{t,o}$ is high), irrespective of the obstacle distance. This rule covers the conditions for both rule 1 and rule 4. Therefore, rules 1 and 4 are redundant and can be removed.
- Rule 2 is also consistent with the expected behavior of f_w. When the obstacle is close to the robot (α is low) and is located in front of the robot on the way to the target ($\theta_{t,o}$ is low), this rule produces high weight values for the obstacle avoidance task.
- Rule 5 generates low weight values when the obstacle distance is low. This rule contradicts rule 2 when $\theta_{t,o}$ is low. In this case, the output of rule 5 does not contribute to the final output due to the high output values of rule 2. Therefore, rule 5 can also be removed.

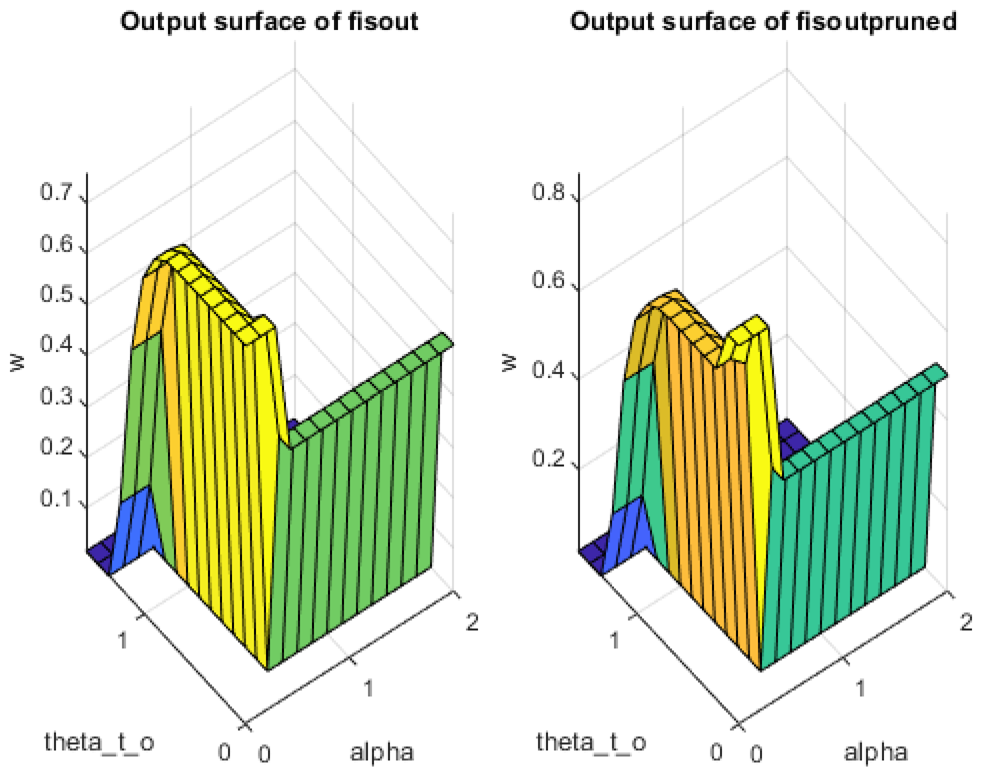
Remove the redundant rules.

```
fisoutpruned = fisout;
fisoutpruned.Rules([1 4 5]) = [];
fisoutpruned.Rules
```

```
ans = 
  1×2 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                         Description
         ___________________________________________

    1    "alpha==low & theta_t_o==low => w=high (1)"
    2    "theta_t_o==high => w=low (1)"
```

`fisout` and `fisoutpruned` generate similar control surfaces. Therefore, only two rules are necessary for obstacle avoidance in the simulation environment.

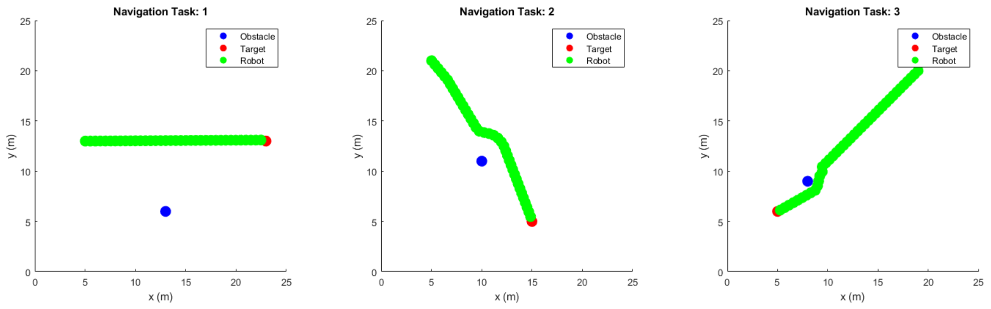
```
figure
subplot(1,2,1)
gensurf(fisout)
title('Output surface of fisout')
subplot(1,2,2)
gensurf(fisoutpruned)
title('Output surface of fisoutpruned')
```



Check Performance

Validate the performance of the tuned FIS with different positions of the obstacle, robot, and target. In the following validation cases, the robot successfully avoids the obstacle to reach the target position using the tuned FIS.

```
vldObstacle = [13 5;10 10;8 8];
vldRobot = [5 12 0;5 20 -pi/2;19 19 -pi];
vldTarget = [23 12;15 4;5 5];

showNavigationTrajectories(fisoutpruned,vldObstacle,vldTarget,vldRobot)
```



Conclusion

This example uses a custom cost function that simulates robot navigation in different training environments to learn fuzzy rules and optimize the FIS parameter values for collision-free navigation. You can Include more training environments to learn obstacle avoidance in other scenarios, for example narrow corridor and U-shape obstacles. In these scenarios, the robot may need additional navigation subtasks, such as wall following and subtarget (intermediate landmark) reaching, for successful collision-free navigation to the target. Complex environments also require additional terms in the cost calculation for safe navigation. For example, in a narrow corridor the robot should stay in the middle; that is, the distances to the obstacles on the left and right should be the same.

Using a custom cost function with `tunefis` provides the flexibility of simulating a custom system with custom cost calculation. However, the tradeoff is a lengthy tuning process due to the number of simulations required (for each set of optimized parameter values). Therefore, if possible, to expedite the tuning process, use training data. For instance, the tuning process in this example would run faster if input/output decision data of a human operator was available for tuning the FIS.

Local Functions

```
function showSimulationEnvironment(obstacle,target,robot,navigationResults)

% Show the robot trajectory in the simulation environment.

% Radius of the robot, target, and obstacle.
radius = 1; % 1m

% Use 25mx25m simulation environment.
axis([0 25 0 25]);
```

```
% Set equal aspect ratio.
pbaspect([1 1 1])

% Temporary plots to enable legends.
hold on
plot(robot(1),robot(2)+radius,'ob','LineWidth',radius*1,'MarkerFaceColor','b')
plot(robot(1),robot(2)+radius,'or','LineWidth',radius*1,'MarkerFaceColor','r')
plot(robot(1),robot(2)+radius,'og','LineWidth',radius*1,'MarkerFaceColor','g')
hold off

% Draw obstacle.
rectangle('Position',[obstacle(1)-0.5*radius obstacle(2)+0.5*radius radius radius],'Cu
    'FaceColor','b','EdgeColor','b')

% Draw target.
rectangle('Position',[target(1)-0.5*radius target(2)+0.5*radius radius radius],'Curvatu
    'FaceColor','r','EdgeColor','r')

% Draw robot.
rectangle('Position',[robot(1)-0.5*radius robot(2)+0.5*radius radius radius],'Curvature
    'FaceColor','g','EdgeColor','g')

% Add labels, title, and legends.
xlabel('x (m)'),ylabel('y (m)')
title('Simulation Environment for Robot Navigation')
legend(["Obstacle" "Target" "Robot"])

% Plot the robot trajectory if specified.
if nargin == 4
    x = navigationResults.x;
    y = navigationResults.y;
    for i = 1:numel(x)
        rectangle('Position',[x(i)-0.5*radius y(i)+0.5*radius radius radius], ...
            'Curvature',[1 1],'FaceColor','g','EdgeColor','g')
    end
end

end

function showSimulationEnvironmentsForTraining(obstacle,target,robot)

% Show simulation environments for training.
drawEnvironmentAndShowTrajectory(obstacle,target,robot,'Training Task')
```

```
end

function showNavigationTrajectories(fis,obstacle,target,robot)

% Show robot trajectories in the simulation environments.
drawEnvironmentAndShowTrajectory(obstacle,target,robot,'Navigation Task',fis)

end

function drawEnvironmentAndShowTrajectory(obstacle,target,robot,plotTitle,varargin)

% Expand figure horizontally to tile the simulation environments.
h = figure;
h.Position = [h.Position(1:2) 3*h.Position(3) h.Position(4)];
numTasks = size(target,1);

% Draw each simulation environment.
for i = 1:numTasks
    o = obstacle(i,:);
    t = target(i,:);
    r = robot(i,:);
    subplot(1,numTasks,i)
    if ~isempty(varargin)
        results = getNavigationResults(varargin{1},o,t,r);
        showSimulationEnvironment(o,t,r,results)
    else
        showSimulationEnvironment(o,t,r)
    end
    title([plotTitle ': ' num2str(i)])
end

end
```

See Also

`getTunableSettings` | `mamfis` | `tunefis`

More About

- “Tuning Fuzzy Inference Systems” on page 3-2
- “Tune Mamdani Fuzzy Inference System” on page 3-33

Neuro-Adaptive Learning and ANFIS

When to Use Neuro-Adaptive Learning

The basic structure of Mamdani fuzzy inference system is a model that maps input characteristics to input membership functions, input membership functions to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership functions to a single-valued output or a decision associated with the output. Such a system uses fixed membership functions that are chosen arbitrarily and a rule structure that is essentially predetermined by the user's interpretation of the characteristics of the variables in the model.

`anfis` and the **Neuro-Fuzzy Designer** apply fuzzy inference techniques to data modeling. As you have seen from the other fuzzy inference GUIs, the shape of the membership functions depends on parameters, and changing these parameters change the shape of the membership function. Instead of just looking at the data to choose the membership function parameters, you choose membership function parameters automatically using these Fuzzy Logic Toolbox applications.

Suppose you want to apply fuzzy inference to a system for which you already have a collection of input/output data that you would like to use for modeling, model-following, or some similar scenario. You do not necessarily have a predetermined model structure based on characteristics of variables in your system.

In some modeling situations, you cannot discern what the membership functions should look like simply from looking at data. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. In such cases, you can use the Fuzzy Logic Toolbox *neuro-adaptive* learning techniques incorporated in the `anfis` command.

Model Learning and Inference Through ANFIS

The neuro-adaptive learning method works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to *learn* information about a data set. Fuzzy Logic Toolbox software computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. The Fuzzy Logic Toolbox function that accomplishes this membership function parameter adjustment is called `anfis`. The `anfis` function can be accessed either from the command line or through the **Neuro-Fuzzy Designer**. Because the functionality of the command line function `anfis` and the **Neuro-Fuzzy Designer** is similar, they are used somewhat interchangeably in this discussion, except when specifically describing the **Neuro-Fuzzy Designer** app.

What Is ANFIS?

The acronym ANFIS derives its name from *adaptive neuro-fuzzy inference system*. Using a given input/output data set, the toolbox function `anfis` constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows your fuzzy systems to learn from the data they are modeling.

FIS Structure and Parameter Adjustment

A network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map.

The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs. `anfis` uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation.

Know Your Data

The modeling approach used by `anfis` is similar to many system identification techniques. First, you hypothesize a parameterized model structure (relating inputs to membership functions to rules to outputs to membership functions, and so on). Next, you collect input/output data in a form that will be usable by `anfis` for training. You can then use `anfis` to *train* the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion.

In general, this type of modeling works well if the training data presented to `anfis` for training (estimating) membership function parameters is fully representative of the features of the data that the trained FIS is intended to model. In some cases however, data is collected using noisy measurements, and the training data cannot be representative of all the features of the data that will be presented to the model. In such situations, model validation is helpful.

Model Validation Using Testing and Checking Data Sets

Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values.

One problem with model validation for models constructed using adaptive techniques is selecting a data set that is both representative of the data the trained model is intended to emulate, yet sufficiently distinct from the training data set so as not to render the validation process trivial.

If you have collected a large amount of data, hopefully this data contains all the necessary representative features, so the process of selecting a data set for checking or testing purposes is made easier. However, if you expect to be presenting noisy measurements to your model, it is possible the training data set does not include all of the representative features you want to model.

The testing data set lets you check the generalization capability of the resulting fuzzy inference system. The idea behind using a checking data set for model validation is that after a certain point in the training, the model begins overfitting the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that overfitting begins, and then the model error for the checking data suddenly increases. Overfitting is accounted for by testing the FIS trained on the training data against the checking data, and choosing the membership function parameters to be those associated with the minimum checking error if these errors indicate model overfitting.

Usually, these training and checking data sets are collected based on observations of the target system and are then stored in separate files.

In the first example, two similar data sets are used for checking and training, but the checking data set is corrupted by a small amount of noise. This example illustrates of the use of the **Neuro-Fuzzy Designer** with checking data to reduce the effect of model overfitting. In the second example, a training data set that is presented to `anfis` is sufficiently different than the applied checking data set. By examining the checking error sequence over the training period, it is clear that the checking data set is not good for model validation purposes. This example illustrates the use of the **Neuro-Fuzzy Designer** to compare data sets.

References

[1] Jang, J.-S. R., "Fuzzy Modeling Using Generalized Neural Networks and Kalman Filter Algorithm," *Proc. of the Ninth National Conf. on Artificial Intelligence (AAAI-91)*, pp. 762-767, July 1991.

[2] Jang, J.-S. R., "ANFIS: Adaptive-Network-based Fuzzy Inference Systems," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 23, No. 3, pp. 665-685, May 1993.

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[4] Jang, J.-S. R. and C.-T. Sun, "Neuro-fuzzy modeling and control," *Proceedings of the IEEE*, March 1995.

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[6] Wang, L.-X., *Adaptive fuzzy systems and control: design and stability analysis*, Prentice Hall, 1994.

[7] Widrow, B. and D. Stearns, *Adaptive Signal Processing*, Prentice Hall, 1985.

See Also

Apps
Neuro-Fuzzy Designer

Functions
`anfis`

More About

- “Comparison of anfis and Neuro-Fuzzy Designer Functionality” on page 3-91
- “Train Adaptive Neuro-Fuzzy Inference Systems” on page 3-97

- “Test Data Against Trained System” on page 3-102
- “Save Training Error Data to MATLAB Workspace” on page 3-119
- “Predict Chaotic Time-Series using ANFIS” on page 3-127

Comparison of anfis and Neuro-Fuzzy Designer Functionality

This topic discusses the arguments and range components of the command-line function `anfis` and the analogous functionality of the **Neuro-Fuzzy Designer**.

You can configure the training options for the `anfis` command using an `anfisOptions` option set.

```
opt = anfisOptions;
[fismat1,trnError,ss,fismat2,chkError] = anfis(trnData,opt);
```

where `trnData` is the training data. To use default training options, omit `opt`. You can modify the default option set using dot notation. For more information on the available options and their default values, see the `anfisOptions` reference page. All output arguments other than `fismat1`, the tuned fuzzy system, are optional.

When you open the **Neuro-Fuzzy Designer**, only the training data set must exist before implementing `anfis`. In addition, the step-size is fixed when the adaptive neuro-fuzzy system is trained using this app.

Training Data

The training data, `trnData`, is a required argument to `anfis`, and to the **Neuro-Fuzzy Designer**. Each row of `trnData` is a desired input/output pair of the target system you want to model. Each row starts with an input vector and is followed by an output value. Therefore, the number of rows of `trnData` is equal to the number of training data pairs. Since there is only one output, the number of columns of `trnData` is equal to the number of inputs plus one.

Input FIS Object

You can define the FIS object to tune using the `opt.InitialFIS` training option. You can create this object using:

- The **Fuzzy Logic Designer**
- The Membership Function Editor
- The Rule Editor from the **Neuro-Fuzzy Designer** (which allows an FIS object to be loaded from a file or the MATLAB workspace)

- The command-line function, `genfis` (for which you only specify numbers and types of membership functions)

The FIS object contains both the model structure (which specifies such items as the number of rules in the FIS and the number of membership functions for each input) and the parameters (which specify the shapes of membership functions).

There are two *methods* that `anfis` learning employs for updating membership function parameters, which you can select using the `opt.OptimizationMethod` training option:

- Backpropagation for all parameters (a steepest descent method)
- A hybrid method consisting of backpropagation for the parameters associated with the input membership functions, and least squares estimation for the parameters associated with the output membership functions

As a result, the training error decreases, at least locally, throughout the learning process. Therefore, the more the initial membership functions resemble the optimal ones, the easier it is for the model parameter training to converge. Human expertise about the target system to be modeled can aid in setting up these initial membership function parameters in the FIS object.

The `genfis` function, when used with grid partitioning, produces an FIS object based on a fixed number of membership functions. This object can cause an excessive number of rules when the number of inputs is moderately large; that is, more than four or five. Fuzzy Logic Toolbox software offers a method that provides for some dimension reduction in the fuzzy inference system: you can generate an FIS object using the clustering algorithm discussed in “Subtractive Clustering” on page 4-3. To use the clustering algorithm, you must select the **Sub. Clustering** option in the **Generate FIS** portion of the **Neuro-Fuzzy Designer** before the FIS is generated. This subtractive clustering method partitions the data into clusters, and generates an FIS with the minimum number of rules required to distinguish the fuzzy qualities associated with each clusters.

Training Options

The **Neuro-Fuzzy Designer** allows you to choose your desired error tolerance and number of training epochs.

For `anfis` command, you can specify training the training termination condition and gradient descent step size. To specify the following options, first create a default `anfisOptions` option set, `opt`. You can then modify the options using dot notation.

- `opt.EpochNumber` — Number of training epochs (default = `10`)
- `opt.ErrorGoal` — Training error goal (default = `0`)
- `opt.InitialStepSize` — Initial step-size (default = `0.01`)
- `opt.StepSizeDecreaseRate` — Step-size decrease rate (default = `0.9`)
- `opt.StepSizeIncreaseRate` — Step-size increase rate (default = `1.1`)

If you do not modify an option in `opt`, the default value is used. The training process stops if the designated epoch number is reached or the error goal is achieved, whichever comes first.

Usually, the step-size profile is a curve that increases initially, reaches some maximum, and then decreases for the remainder of the training. You achieve this ideal step-size profile by adjusting the initial step-size and the increase and decrease rates (`opt.InitialStepSize`, `opt.StepSizeDecreaseRate`, `opt.StepSizeIncreaseRate`). The default values are configured to cover a wide range of learning tasks. For any specific application, you can modify these step-size options to optimize the training. However, there are no user-specified step-size options for training the adaptive neuro-fuzzy inference system generated using the **Neuro-Fuzzy Designer**.

Display Options

Display options apply only to the command-line function `anfis`. You can specify what training progress information to display in the MATLAB Command Window. As with the training options, you specify the display options using the `anfisOptions` option set, `opt` . For each display option, if you specify a value of `1` (the default value), the corresponding data is displayed. Specifying a value of `0` suppresses the display:

- `opt.DisplayANFISInformation` — Display ANFIS information at the start of training
- `opt.DisplayErrorValues` — Display the training error at each epoch
- `opt.DisplayStepSize` — Display the step-size each time it changes.
- `opt.DisplayFinalResults` — Display the final training error and validation error

Method

Both the **Neuro-Fuzzy Designer** and the command-line `anfis` apply either a backpropagation form of the steepest descent method for membership function parameter estimation, or a hybrid combination of backpropagation and the least-squares methods. The choices for this argument are `hybrid` or `backpropagation`. To specify the training method for the `anfis` function, use the `opt.OptimizationMethod` training option as either `1` (`hybrid`) or `0` (`backpropagation`).

Output FIS Object for Training Data

`fismat1` is the output FIS object corresponding to the minimum training error. This FIS object is the one that you use to represent the fuzzy system when there is no checking data used for model cross-validation. `fismat1` corresponds to the FIS object that the **Neuro-Fuzzy Designer** saves when the checking data option is not used. For more information on cross-validation using checking data, see “Checking Data” on page 3-95.

Training Error

The training error is the difference between the training data output value, and the output of the fuzzy inference system corresponding to the same training data input value (the one associated with that training data output value). The training error `trnError` records the root mean squared error (RMSE) of the training data set at each epoch. `fismat1` is the snapshot of the FIS object when the training error measure is at its minimum.

The **Neuro-Fuzzy Designer** plots the training error versus epochs curve as the system is trained.

Step-Size

You cannot control the step-size options with the **Neuro-Fuzzy Designer**. Using the command-line `anfis`, the step-size array `ss` records the step-size during the training. Plotting `ss` gives the step-size profile, which serves as a reference for adjusting the initial step-size (`opt.InitialStepSize`) and the corresponding decrease and increase rates. The step-size for the command-line function `anfis` is updated according to the following guidelines:

- If the error undergoes four consecutive reductions, increase the step-size by multiplying it by a constant (`opt.StepSizeIncreaseRate`) greater than one.
- If the error undergoes two consecutive combinations of one increase and one reduction, decrease the step-size by multiplying it by a constant (`opt.StepSizeDecreaseRate`) less than one.

The default value for the initial step-size is `0.01`; the default values for `opt.StepSizeIncreaseRate` and `opt.StepSizeDecreaserate` are `1.1` and `0.9`, respectively.

Checking Data

The checking data, `opt.ValidationData`, is used for testing the generalization capability of the fuzzy inference system at each epoch. The checking data has the same format as the training data, and its elements are distinct from those of the training data.

The checking data is important for learning tasks for which the input number is large or the data itself is noisy. A fuzzy inference system should track a given input/output data set well. Because the model structure used for `anfis` is fixed with a large number of parameters, there is a tendency for the model to overfit the data on which it is trained, especially for many training epochs. If overfitting does occur, the fuzzy inference system may not respond well to other independent data sets, especially if they are noisy. A validation or checking data set can be useful for these situations. This data set is used to cross-validate the fuzzy inference model. This cross-validation requires applying the checking data to the model and then seeing how well the model responds to this data.

When the checking data option is used with `anfis`, either via the command line, or using the **Neuro-Fuzzy Designer**, the checking data is applied to the model at each training epoch. When the command-line `anfis` is invoked, the model parameters that correspond to the minimum checking error are returned via the output argument `fismat2`. When both training and checking data are loaded, the FIS membership function parameters computed using the **Neuro-Fuzzy Designer** are associated with the training epoch that has a minimum checking error.

The use of the minimum checking data error epoch to set the membership function parameters assumes the checking data:

- Is similar enough to the training data that the checking data error decreases as the training begins.
- Increases at some point in the training after the data overfitting occurs.

For information on using checking data, see “Checking Data Does Not Validate Model” on page 3-113.

Output FIS Object for Checking Data

The output of the command-line `anfis`, `fismat2`, is the output FIS object with the minimum checking error. This FIS object is the one that you should use for further calculation if checking data is used for cross-validation. `fismat2` is only returned if you specify validation data using `opt.ValidationData`.

`fismat2` corresponds to the FIS object that the **Neuro-Fuzzy Designer** saves when the checking data option is used.

Checking Error

The checking error is the difference between the checking data output value, and the output of the fuzzy inference system corresponding to the same checking data input value, which is the one associated with that checking data output value. The checking error `chkError` records the RMSE for the checking data at each epoch. `fismat2` is the snapshot of the FIS object when the checking error is at its minimum. `chkError` is only returned if you specify validation data using `opt.ValidationData`.

The **Neuro-Fuzzy Designer** plots the checking error versus epochs curve as the system is trained.

See Also

Apps
Neuro-Fuzzy Designer

Functions
`anfis`

More About

- "Neuro-Adaptive Learning and ANFIS" on page 3-86
- "Train Adaptive Neuro-Fuzzy Inference Systems" on page 3-97
- "Test Data Against Trained System" on page 3-102
- "Save Training Error Data to MATLAB Workspace" on page 3-119
- "Predict Chaotic Time-Series using ANFIS" on page 3-127

Train Adaptive Neuro-Fuzzy Inference Systems

This example shows how to create, train, and test Sugeno-type fuzzy systems using the **Neuro-Fuzzy Designer**.

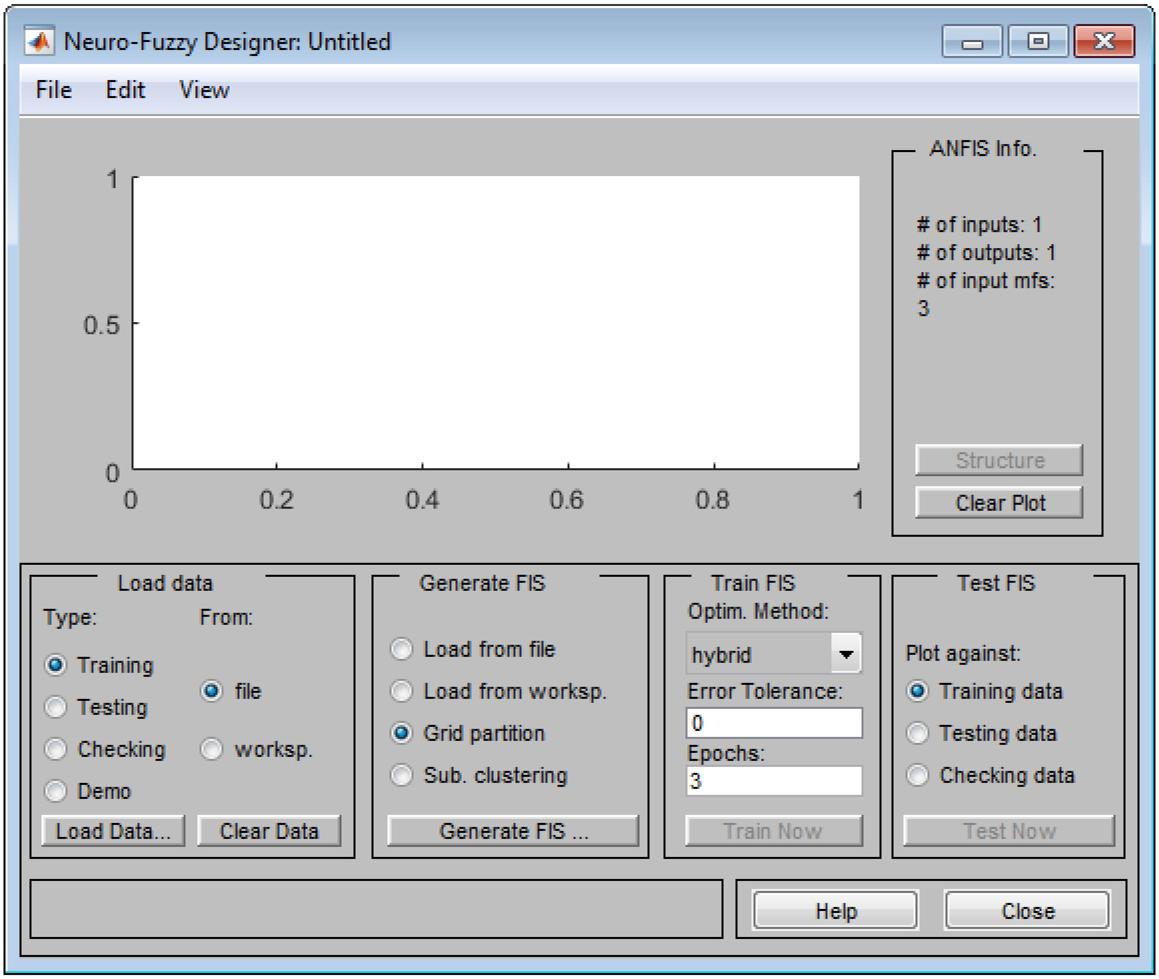
To start the app, type the following command at the MATLAB prompt:

```
neuroFuzzyDesigner
```

The **Neuro-Fuzzy Designer** includes four distinct areas to support a typical workflow. The app lets you perform the following tasks:

1. “Loading, Plotting, and Clearing the Data” on page 3-98
2. “Generating or Loading the Initial FIS Structure” on page 3-99
3. “Training the FIS” on page 3-100
4. “Validating the Trained FIS” on page 3-100

Access the online help topics by clicking **Help** in the **Neuro-Fuzzy Designer**.



# of inputs: 1
# of outputs: 1
# of input mfs:
3

Type: [✓ Training] Testing Checking Demo

From: [✓ file] worksp.

Generate FIS: Load from file, Load from worksp., [✓ Grid partition], Sub. clustering

Optim. Method: hybrid

Error Tolerance: 0

Epochs: 3

Plot against: [✓ Training data] Testing data Checking data

Loading, Plotting, and Clearing the Data

To train an FIS, you must begin by loading a **Training** data set that contains the desired input/output data of the system to be modeled. Any data set you load must be an array with the data arranged as column vectors, and the output data in the last column.

You can also load **Testing** and **Checking** data in the designer. For more information on testing and checking data sets, see “Model Validation Using Testing and Checking Data Sets” on page 3-88.

To load a data set using the **Load data** portion of the designer:

1. Specify the data **Type**.
2. Select the data from a **file** or the MATLAB **worksp**.
3. Click **Load Data**.

After you load the data, it displays in the plot. The training, testing and checking data are annotated in blue as *circles*, *diamonds*, and *pluses* respectively.

To clear a specific data set from the designer:

1. In the **Load data** area, select the data **Type**.
2. Click **Clear Data**.

This action also removes the corresponding data from the plot.

Generating or Loading the Initial FIS Structure

Before you start the FIS training, you must specify an initial FIS model structure. To specify the model structure, perform one of the following tasks:

- Load a previously saved Sugeno-type FIS structure from a file or the MATLAB workspace.
- Generate the initial FIS model by choosing one of the following partitioning techniques:
  - **Grid partition**— Generates a single-output Sugeno-type FIS by using grid partitioning on the data.
  - **Sub. clustering** — Generates an initial model for ANFIS training by first applying subtractive clustering on the data.

To view a graphical representation of the initial FIS model structure, click **Structure**.

Training the FIS

After loading the training data and generating the initial FIS structure, you can start training the FIS.

Tip If you want to save the training error generated during ANFIS training to the MATLAB workspace, see “Save Training Error Data to MATLAB Workspace” on page 3-119.

The following steps show you how to train the FIS.

1. In **Optim. Method**, choose **hybrid** or **backpropaga** as the optimization method.

   The optimization methods train the membership function parameters to emulate the training data.

   Note The **hybrid** optimization method is a combination of least-squares and backpropagation gradient descent method.
2. Enter the number of training **Epochs** and the training **Error Tolerance** to set the stopping criteria for training.

   The training process stops whenever the maximum epoch number is reached or the training error goal is achieved.
3. Click **Train Now** to train the FIS.

   This action adjusts the membership function parameters and displays the error plots.

Examine the error plots to determine overfitting during the training. If you notice the checking error increasing over iterations, it indicates model overfitting. For examples on model overfitting, see “Checking Data Helps Model Validation” on page 3-102 and “Checking Data Does Not Validate Model” on page 3-113.

Validating the Trained FIS

After the FIS is trained, validate the model using a **Testing** or **Checking** data that differs from the one you used to train the FIS. To validate the trained FIS:

1. Select the validation data set and click **Load Data**.

2. Click **Test Now**.

   This action plots the test data against the FIS output (shown in red) in the plot.

For more information on the use of testing data and checking data for model validation, see “Model Validation Using Testing and Checking Data Sets” on page 3-88.

See Also

Neuro-Fuzzy Designer

More About

- “Neuro-Adaptive Learning and ANFIS” on page 3-86
- “Comparison of anfis and Neuro-Fuzzy Designer Functionality” on page 3-91
- “Test Data Against Trained System” on page 3-102
- “Save Training Error Data to MATLAB Workspace” on page 3-119

Test Data Against Trained System

Checking Data Helps Model Validation

In this section, we look at an example that loads similar training and checking data sets. The checking data set is corrupted by noise.

1. "Loading Data" on page 3-102
2. "Initializing and Generating Your FIS" on page 3-106
3. "Viewing Your FIS Structure" on page 3-108
4. "ANFIS Training" on page 3-110
5. "Testing Your Data Against the Trained FIS" on page 3-112

Loading Data

To work both of the following examples, you load the training data sets (`fuzex1trnData` and `fuzex2trnData`) and the checking data sets (`fuzex1chkData` and `fuzex2chkData`), into the **Neuro-Fuzzy Designer** from the workspace. You may also substitute your own data sets.

To load the data sets from the workspace into the **Neuro-Fuzzy Designer**:

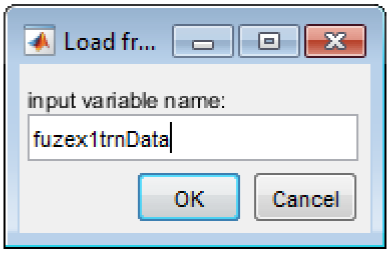
1. Type the following commands at the MATLAB command line to load the data sets into the MATLAB workspace:

   ```
   load fuzex1trnData.dat
   load fuzex2trnData.dat
   load fuzex1chkData.dat
   load fuzex2chkData.dat
   ```
2. Open the **Neuro-Fuzzy Designer** by typing `neuroFuzzyDesigner` in the MATLAB command line.
3. To load the training data set from the workspace:

   a. In the **Load data** portion of the designer, select the following options:

      - **Type: Training**
      - **From: worksp**

   b. Click **Load Data** to open the Load from workspace dialog box.

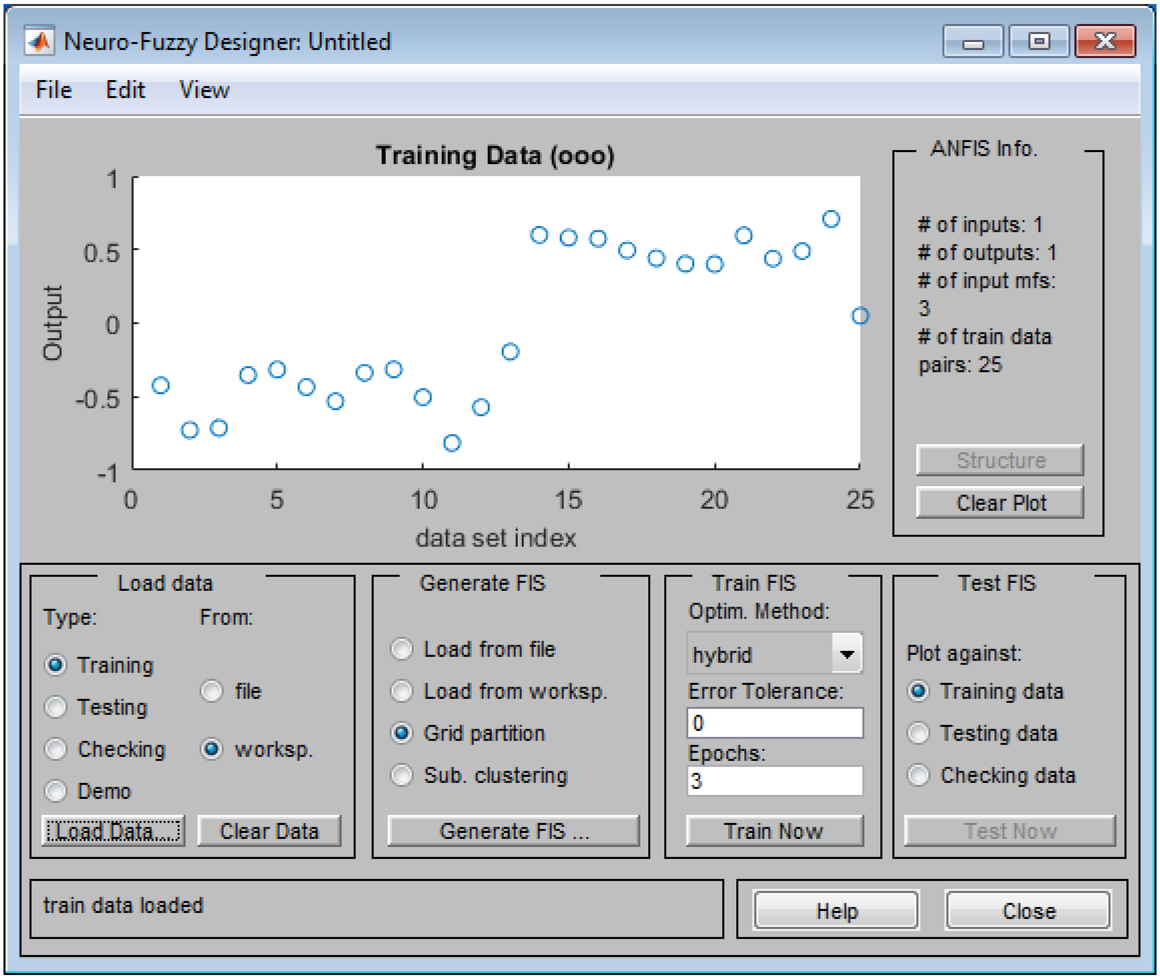

Load fr...

input variable name:

fuzex1trnData

c Type `fuzex1trnData` as shown in the following figure, and click **OK**.

The training data set is used to train a fuzzy system by adjusting the membership function parameters that best model this data, and appears in the plot in the center of the app as a set of *circles*.



ANFIS Info.: # of inputs: 1, # of outputs: 1, # of input mfs: 3, # of train data pairs: 25

Load data — Type: [✓ Training] Testing Checking Demo; From: file [✓ worksp.]

Generate FIS: Load from file, Load from worksp., [✓ Grid partition], Sub. clustering

Train FIS — Optim. Method: hybrid; Error Tolerance: 0; Epochs: 3

Test FIS — Plot against: [✓ Training data] Testing data Checking data

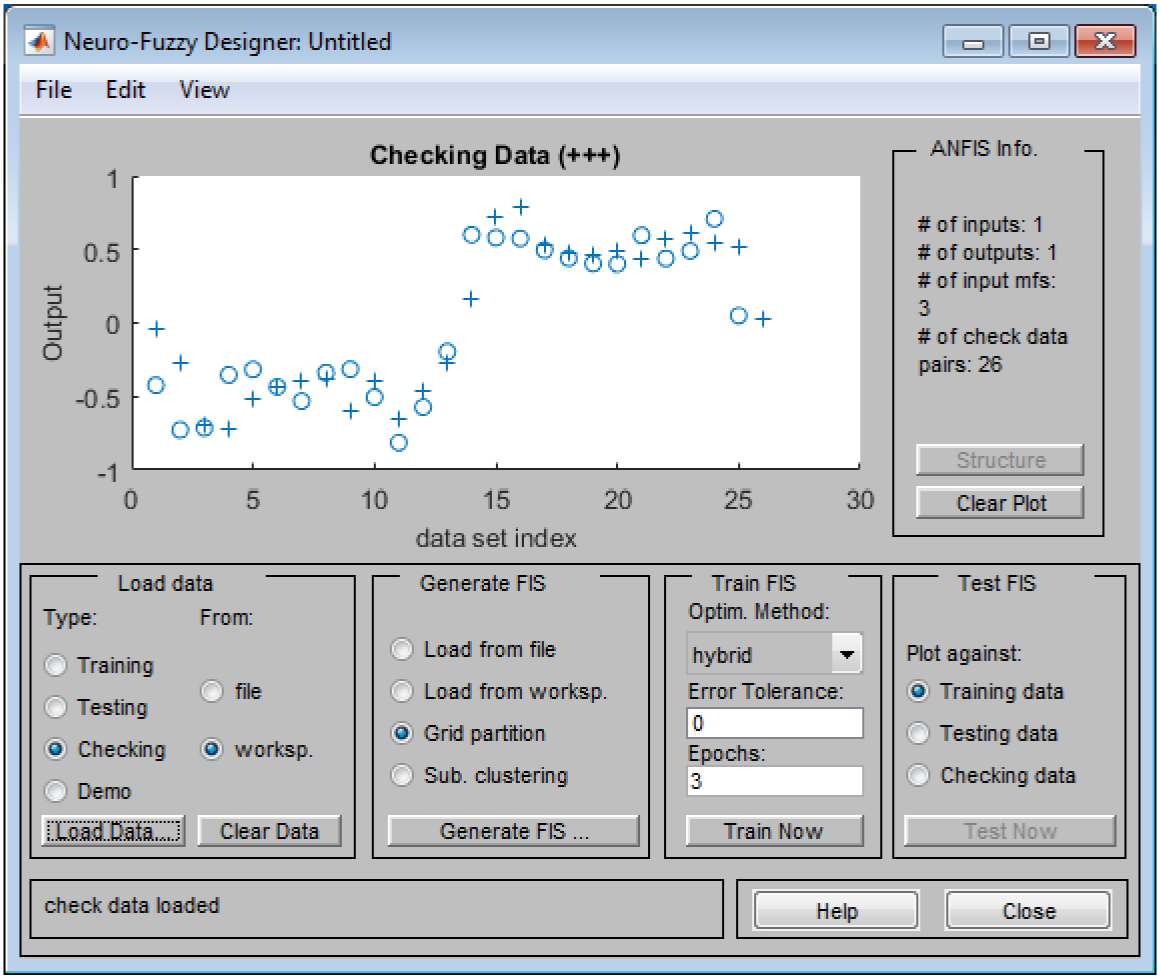
train data loaded

The horizontal axis is marked **data set index**. This index indicates the row from which that input data value was obtained (whether or not the input is a vector or a scalar).

4 To load the checking data set from the workspace:

- **a** In the **Load data** section, select **Checking** in the **Type** column.
- **b** Click **Load Data** to open the Load from workspace dialog box.
- **c** Type `fuzex1chkData` as the variable name and click **OK**.

The checking data appears in the plot as *pluses* superimposed on the training data.



ANFIS Info.

# of inputs: 1
# of outputs: 1
# of input mfs: 3
# of check data pairs: 26

Load data

Type: Training, Testing, [✓ Checking], Demo

From: file, [✓ worksp.]

Generate FIS

Load from file, Load from worksp., [✓ Grid partition], Sub. clustering

Train FIS

Optim. Method: hybrid

Error Tolerance: 0

Epochs: 3

Test FIS

Plot against: [✓ Training data], Testing data, Checking data

check data loaded

The next step is to specify an initial fuzzy inference system for `anfis` to train.

Initializing and Generating Your FIS

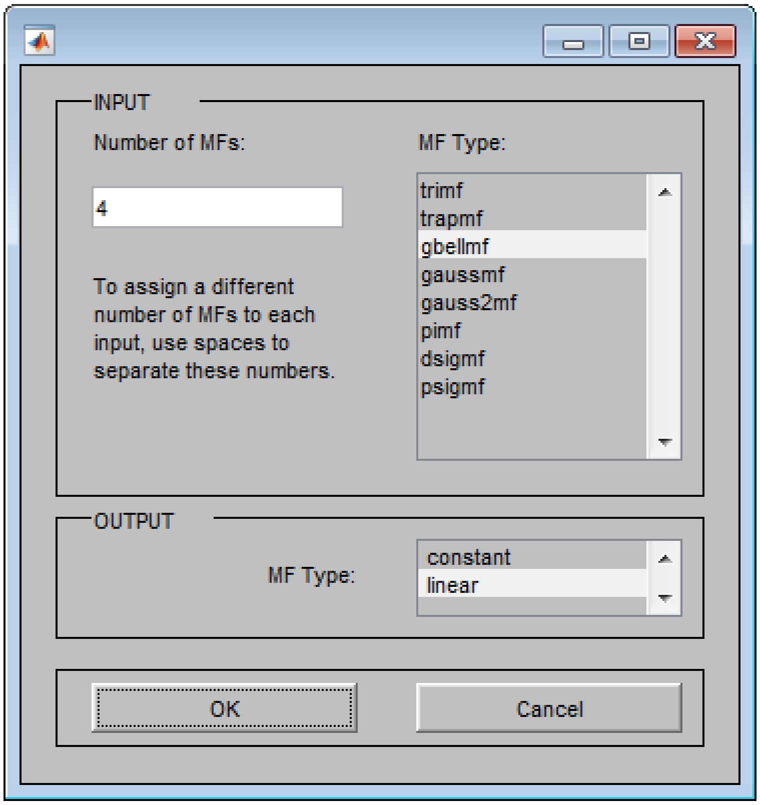
You can either initialize the FIS parameters to your own preference, or if you do not have any preference for how you want the initial membership functions to be parameterized, you can let `anfis` initialize the parameters for you, as described in the following sections:

- "Automatic FIS Structure Generation" on page 3-106
- "Specifying Your Own Membership Functions for ANFIS" on page 3-107

Automatic FIS Structure Generation

To initialize your FIS using `anfis`:

1. Choose **Grid partition**, the default partitioning method. The two partition methods, grid partitioning and subtractive clustering, are described in `genfis`.
2. Click **Generate FIS** . Clicking this button displays a menu from which you can choose the number of membership functions, **MFs**, and the type of input and output membership functions. There are only two choices for the output membership function: `constant` and `linear`. This limitation of output membership function choices is because `anfis` only operates on Sugeno-type systems.
3. Fill in the entries as shown in the following figure, and click **OK.**



You can also implement this FIS generation from the command line using `genfis`.

Specifying Your Own Membership Functions for ANFIS

You can choose your own preferred membership functions with specific parameters to be used by `anfis` as an initial FIS for training.

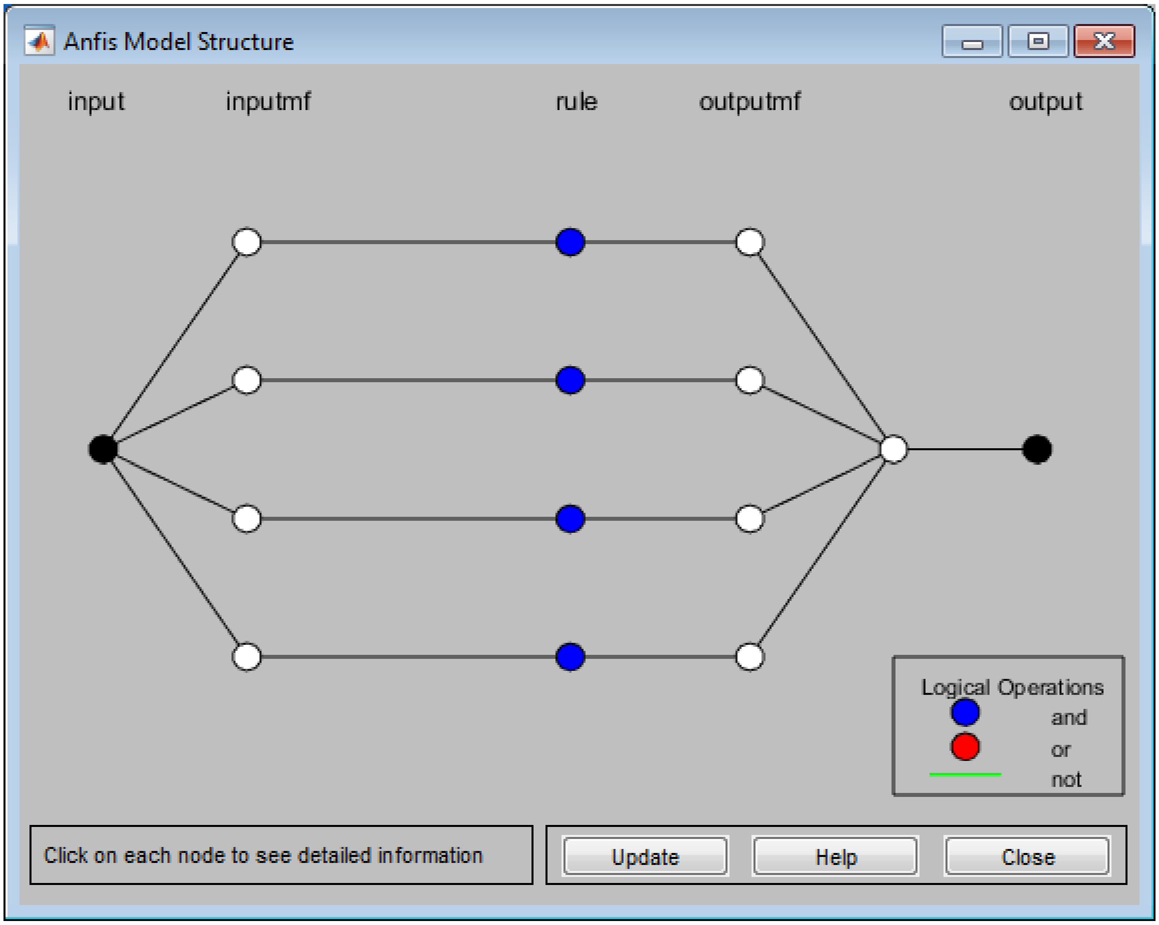
To define your own FIS structure and parameters:

1. Open the **Membership functions** menu item from the **Edit** menu.
2. Add your desired membership functions (the custom membership option will be disabled for `anfis`). The output membership functions must either be all constant or all linear. For carrying out this and the following step, see “The Fuzzy Logic Designer” on page 2-17 and “The Membership Function Editor” on page 2-22.

3. Select the **Rules** menu item in the **Edit** menu, and use the Rule Editor to generate the rules (see “The Rule Editor” on page 2-30).
4. Select the **FIS Properties** menu item from the **Edit** menu. Name your FIS, and save it to either the workspace or to file.
5. Click the **Close** button to return to the **Neuro-Fuzzy Designer** to train the FIS.
6. To load an existing FIS for ANFIS initialization, in the **Generate FIS** portion of the designer, click **Load from worksp** or **Load from file**. You load your FIS from a file if you have saved an FIS previously that you would like to use. Otherwise you load your FIS from the workspace.

Viewing Your FIS Structure

After you generate the FIS, you can view the model structure by clicking the **Structure** button in the middle of the right side of the editor. A new editor appears, as follows.



The branches in this graph are color coded. Color coding of branches characterize the rules and indicate whether or not *and*, *not*, or *or* are used in the rules. The input is represented by the left-most node and the output by the right-most node. The node represents a normalization factor for the rules. Clicking on the nodes indicates information about the structure.

You can view the membership functions or the rules by opening either the Membership Function Editor, or the Rule Editor from the **Edit** menu.

ANFIS Training

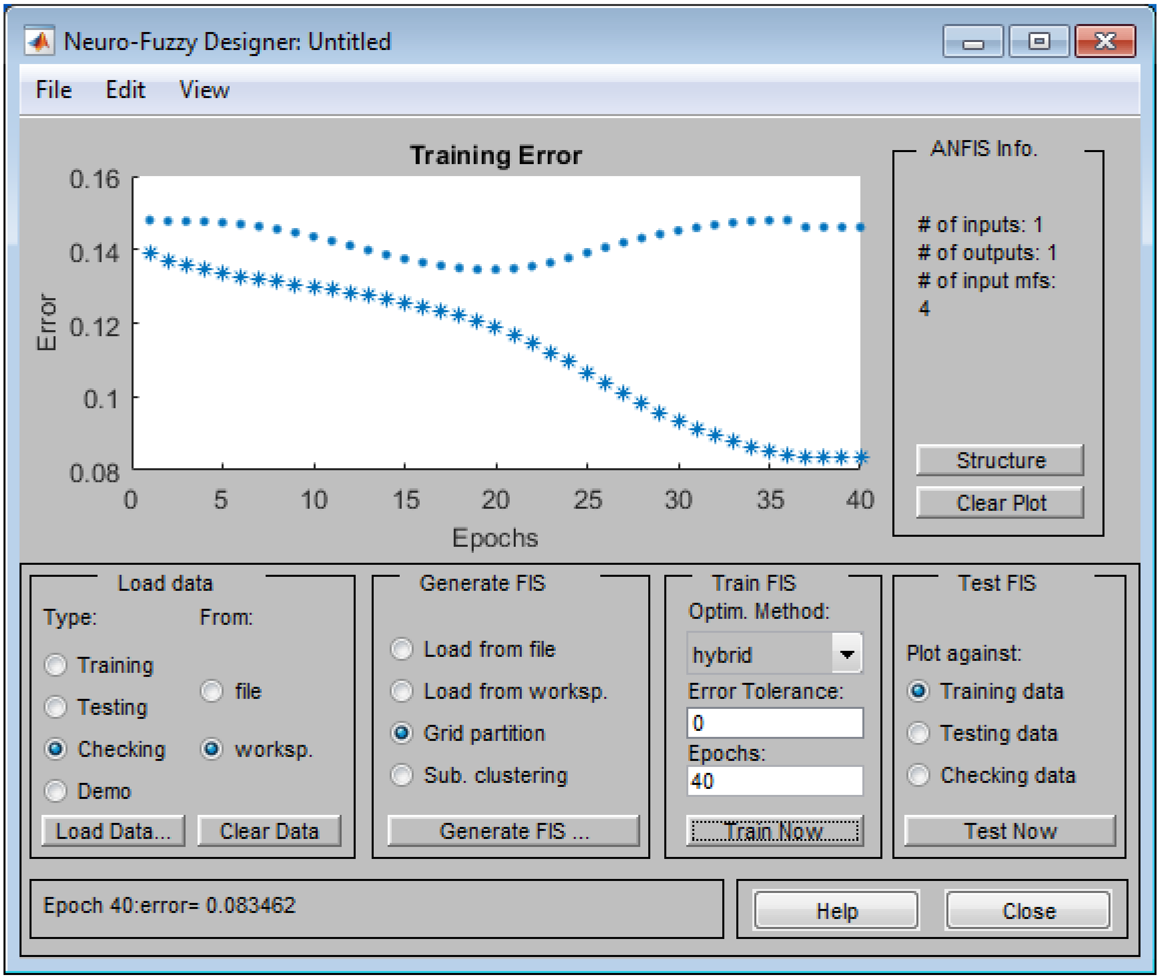
The two `anfis` parameter optimization method options available for FIS training are `hybrid` (the default, mixed least squares and backpropagation) and `backpropa` (backpropagation). **Error Tolerance** is used to create a training stopping criterion, which is related to the error size. The training will stop after the training data error remains within this tolerance. This is best left set to 0 if you are unsure how your training error may behave.

Note If you want to save the training error data generated during ANFIS training to the MATLAB workspace, you must train the FIS at the command line. For an example, "Save Training Error Data to MATLAB Workspace" on page 3-119.

To start the training:

1. Leave the optimization method at `hybrid`.
2. Set the number of training **Epochs** to 40 (the default value is 3).
3. Select **Train Now**.

   The following window appears on your screen.



# of inputs: 1
# of outputs: 1
# of input mfs:
4

Load data — Type: Training, Testing, [✓ Checking], Demo. From: file, [✓ worksp.]

Generate FIS: Load from file, Load from worksp., [✓ Grid partition], Sub. clustering

Train FIS — Optim. Method: hybrid; Error Tolerance: 0; Epochs: 40

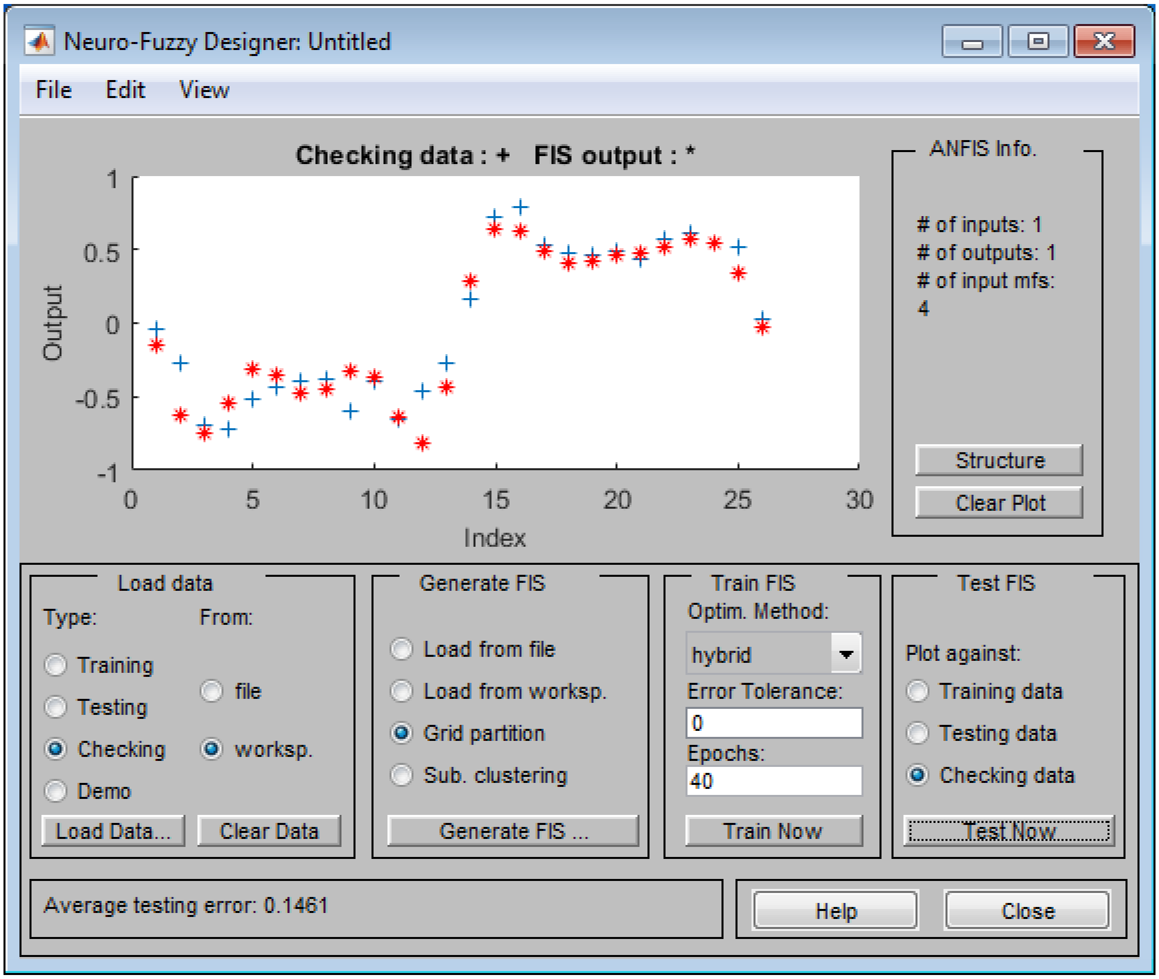
Test FIS — Plot against: [✓ Training data], Testing data, Checking data

Epoch 40:error= 0.083462

The plot shows the checking error as ♦ ♦ on the top . The training error appears as * * on the bottom. The checking error decreases up to a certain point in the training, and then it increases. This increase represents the point of model overfitting. `anfis` chooses the model parameters associated with the minimum checking error (just prior to this jump point). This example shows why the checking data option of `anfis` is useful.

Testing Your Data Against the Trained FIS

To test your FIS against the checking data, select **Checking data** in the **Test FIS** portion of the **Neuro-Fuzzy Designer**, and click **Test Now**. When you test the checking data against the FIS, it looks satisfactory.



ANFIS Info.
# of inputs: 1
# of outputs: 1
# of input mfs:
4

Load data — Type: [✓ Checking] (Training, Testing, Demo); From: [✓ worksp.] (file)

Generate FIS: [✓ Grid partition] (Load from file, Load from worksp., Sub. clustering)

Train FIS — Optim. Method: hybrid; Error Tolerance: 0; Epochs: 40

Test FIS — Plot against: [✓ Checking data] (Training data, Testing data)

Average testing error: 0.1461

Loading More Data with anfis

If you load data into `anfis` after clearing previously loaded data, you must make sure that the newly loaded data sets have the same number of inputs as the previously loaded ones did. Otherwise, you must start a new **Neuro-Fuzzy Designer** session from the command line.

Checking Data Option and Clearing Data

If you do not want to use the checking data option of `anfis`, then do not load any checking data before you train the FIS. If you decide to retrain your FIS with no checking data, you can unload the checking data in one of two ways:

- Select the **Checking** option button in the **Load data** portion of the **Neuro-Fuzzy Designer**, and then click **Clear Data** to unload the checking data.
- Close the **Neuro-Fuzzy Designer**, and go to the MATLAB command line, and retype `neuroFuzzyDesigner`. In this case you must reload the training data.

After clearing the data, you must regenerate your FIS. After the FIS is generated, you can use your first training experience to decide on the number of training epochs you want for the second round of training.

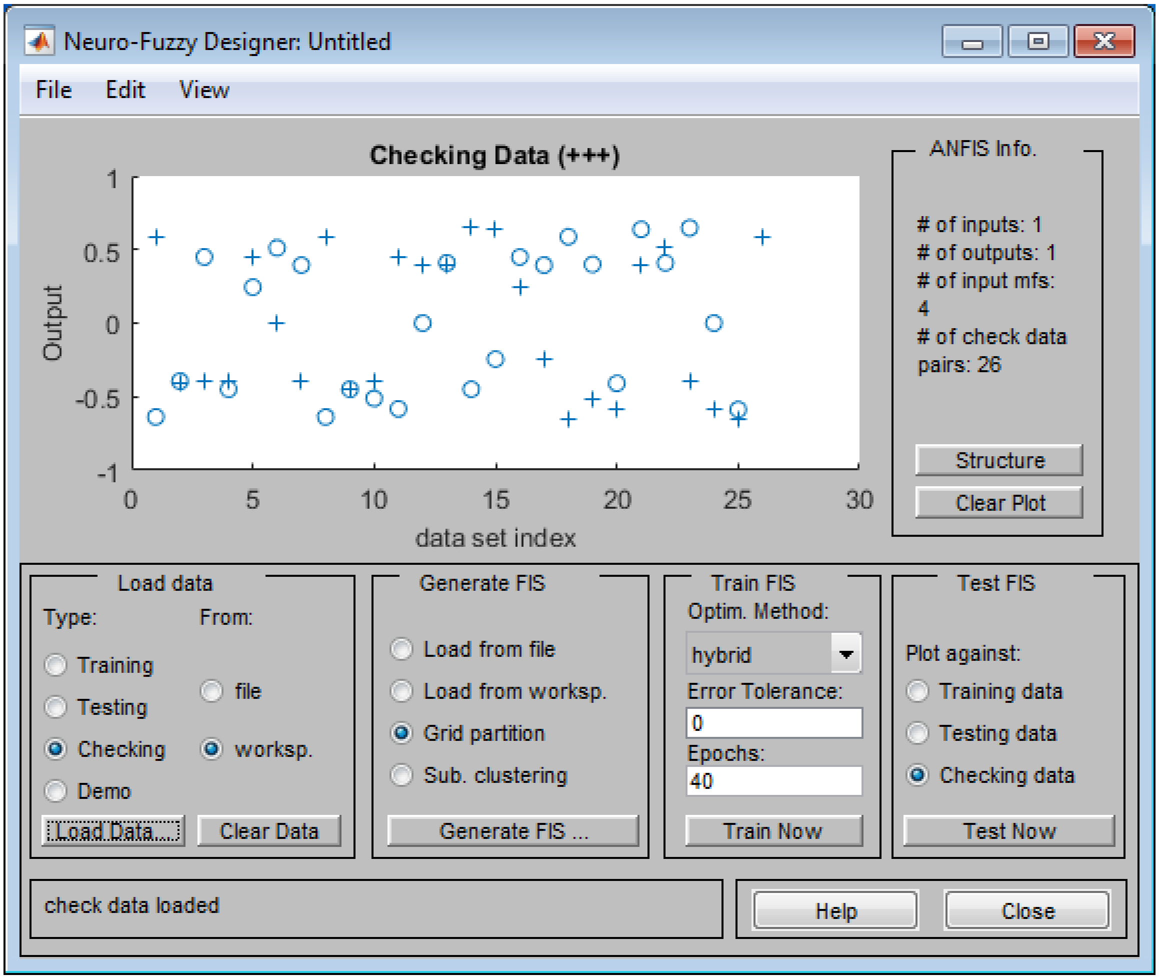
Checking Data Does Not Validate Model

This example examines what happens when the training and checking data sets are sufficiently different. To see how the **Neuro-Fuzzy Designer** can be used to learn something about data sets and how they differ:

1. Clear the **Neuro-Fuzzy Designer**:

   - Clear both the training and checking data.
   - (optional) Click the **Clear Plot** button on the right.
2. Load `fuzex2trnData` and `fuzex2chkData` (respectively, the training data and checking data) from the MATLAB workspace just as you did in the previous example.

You should see a plot similar to the one in the following figure. The training data appears as *circles* superimposed with the checking data, appearing as *pluses*.



# of inputs: 1
# of outputs: 1
# of input mfs:
4
# of check data
pairs: 26

Type: Training Testing [✓ Checking] Demo

From: file [✓ worksp.]

Load from file / Load from worksp. / [✓ Grid partition] / Sub. clustering

Optim. Method: hybrid

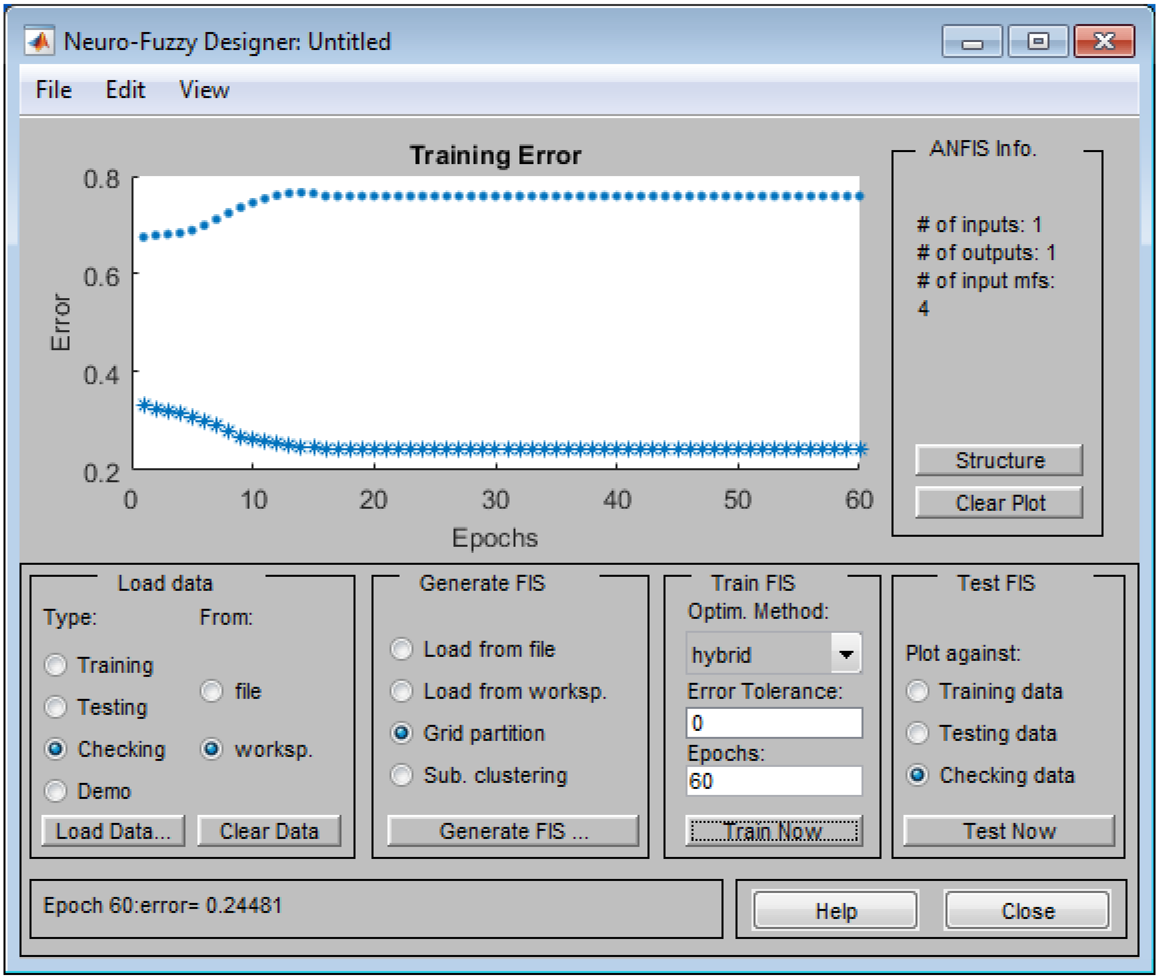
Error Tolerance: 0

Epochs: 40

Plot against: Training data / Testing data / [✓ Checking data]

check data loaded

Train the FIS for this system exactly as you did in the previous example, except now choose `60` **Epochs** before training. You should get the following plot, showing the checking error as ♦ ♦ on top and the training error as * * on the bottom.



# of inputs: 1
# of outputs: 1
# of input mfs:
4

Load data — Type: Training / Testing / [✓ Checking] / Demo; From: file / [✓ worksp.]

Generate FIS — Load from file / Load from worksp. / [✓ Grid partition] / Sub. clustering

Train FIS — Optim. Method: hybrid; Error Tolerance: 0; Epochs: 60

Test FIS — Plot against: Training data / Testing data / [✓ Checking data]

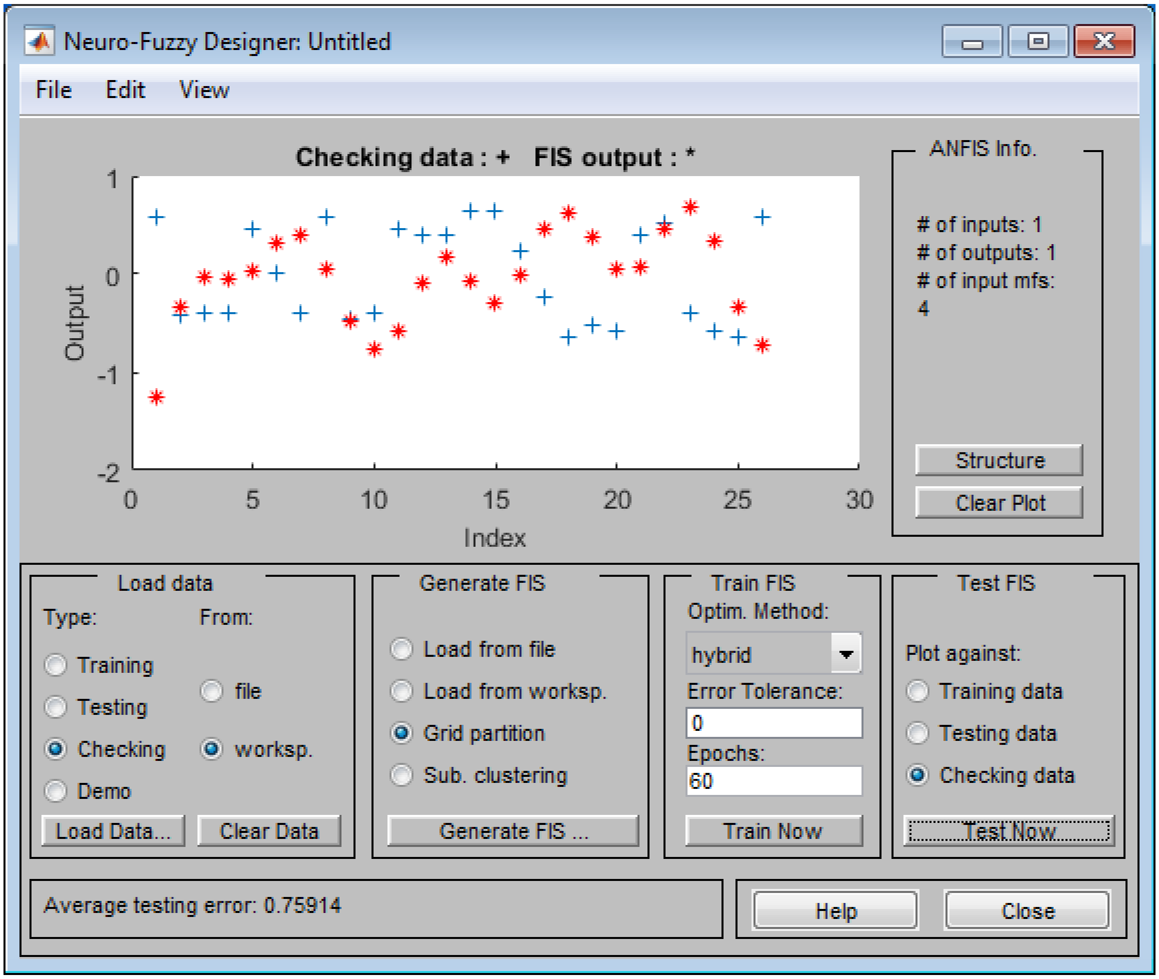
Epoch 60:error= 0.24481

In this case, the checking error is quite large. It appears that the minimum checking error occurs within the first epoch. Using the checking data option with `anfis` automatically sets the FIS parameters to be those associated with the minimum checking error. Clearly this set of membership functions is not the best choice for modeling the training data.

This example illustrates the problem discussed earlier wherein the checking data set presented to `anfis` for training was sufficiently different from the training data set. As a result, the trained FIS did not capture the features of this data set very well. It is important to know the features of your data set well when you select your training and checking data. When you do not know the features of your data, you can analyze the checking error plots to see whether or not the checking data performed sufficiently well with the trained model.

In this example, the checking error is sufficiently large to indicate that either you need to select more data for training or modify your membership function choices (both the number of membership functions and the type). Otherwise, the system can be retrained without the checking data, if you think the training data sufficiently captures the features you are trying to represent.

To complete this example, test the trained FIS model against the checking data. To do so, select **Checking data** in the **Test FIS** portion of the app, and click **Test Now**. The following plot in the app indicates that there is quite a discrepancy between the checking data output and the FIS output.



# of inputs: 1
# of outputs: 1
# of input mfs:
4

Type: [✓ Checking]
From: [✓ worksp.]

Generate FIS: [✓ Grid partition]

Optim. Method: hybrid
Error Tolerance: 0
Epochs: 60

Plot against: [✓ Checking data]

Average testing error: 0.75914

See Also

Neuro-Fuzzy Designer

More About

- "Neuro-Adaptive Learning and ANFIS" on page 3-86

- “Comparison of anfis and Neuro-Fuzzy Designer Functionality” on page 3-91
- “Train Adaptive Neuro-Fuzzy Inference Systems” on page 3-97
- “Save Training Error Data to MATLAB Workspace” on page 3-119

Save Training Error Data to MATLAB Workspace

When using **Neuro-Fuzzy Designer**, you can export your initial FIS structure to the MATLAB workspace and then save the ANFIS training error values in the workspace.

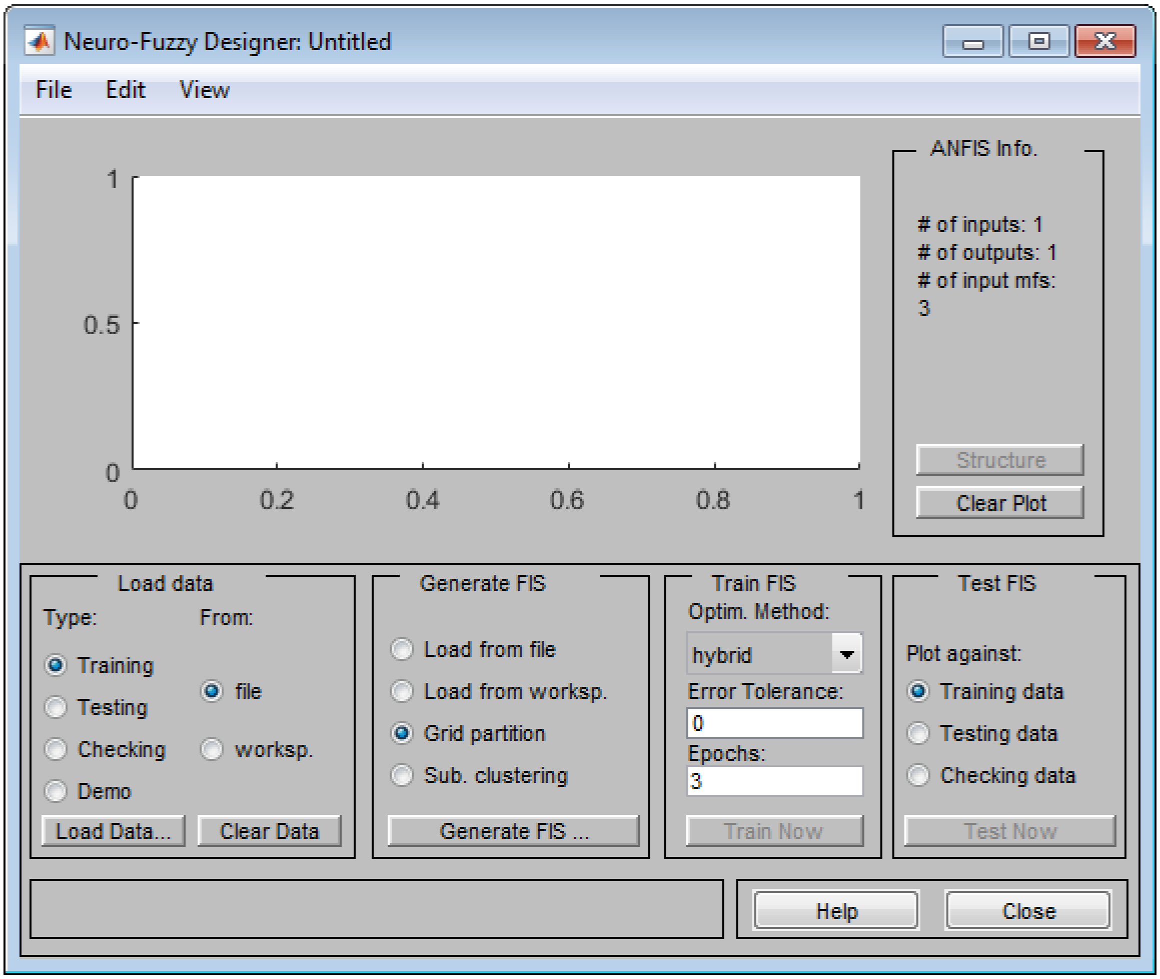
The following example shows how to save the training error generated during ANFIS training to the MATLAB workspace:

1. Load the training and checking data in the MATLAB workspace by typing the following commands at the MATLAB prompt:

   ```
   load fuzex1trnData.dat
   load fuzex1chkData.dat
   ```

2. Open the **Neuro-Fuzzy Designer** by typing the following command:

   ```
   neuroFuzzyDesigner
   ```



# of inputs: 1
# of outputs: 1
# of input mfs:
3

Type: [✓ Training] Testing Checking Demo
From: [✓ file] worksp.

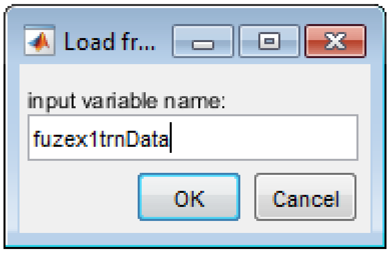
Load from file
Load from worksp.
[✓ Grid partition]
Sub. clustering

Optim. Method: hybrid
Error Tolerance: 0
Epochs: 3

Plot against: [✓ Training data] Testing data Checking data

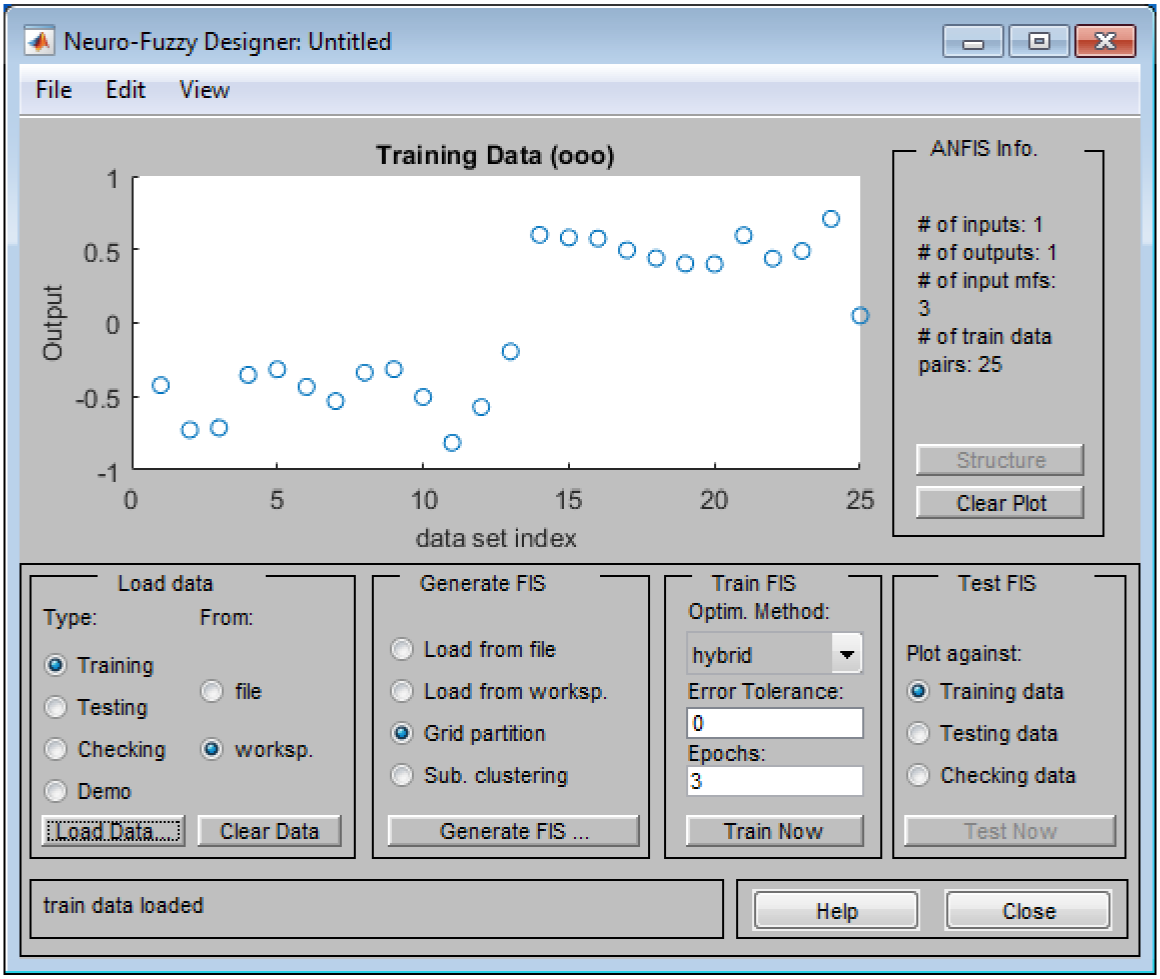
3 Load the training data from the MATLAB workspace into the **Neuro-Fuzzy Designer**:

- **a** In the **Load data** panel of the **Neuro-Fuzzy Designer**, verify that **Training** is selected in the **Type** column.
- **b** Select **worksp** in the **From** column.
- **c** Click **Load Data** to open the Load from workspace dialog box.



d Type `fuzex1trnData`, and click **OK**.

The **Neuro-Fuzzy Designer** displays the training data in the plot as a set of circles (○).



ANFIS Info.: # of inputs: 1; # of outputs: 1; # of input mfs: 3; # of train data pairs: 25

Load data — Type: [✓ Training] Testing Checking Demo; From: file [✓ worksp.]

Generate FIS — Load from file, Load from worksp., [✓ Grid partition], Sub. clustering

Train FIS — Optim. Method: hybrid; Error Tolerance: 0; Epochs: 3

Test FIS — Plot against: [✓ Training data] Testing data Checking data

train data loaded

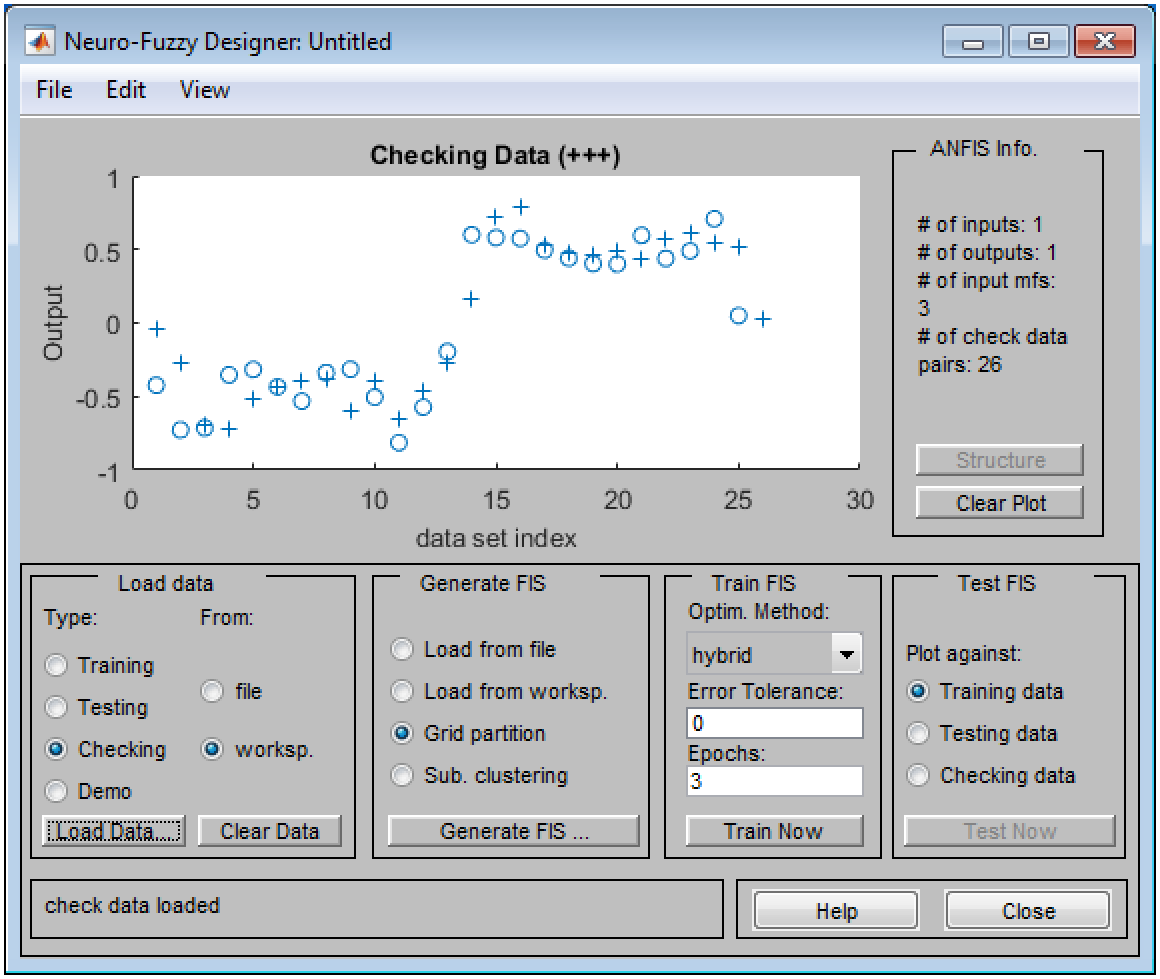
4 Load the checking data from the MATLAB workspace into the **Neuro-Fuzzy Designer**:

a In the **Load data** panel of the **Neuro-Fuzzy Designer**, select **Checking** in the **Type** column.

b Click **Load Data** to open the Load from workspace dialog box.

c Type `fuzex1chkData` as the variable name, and click **OK**.

The **Neuro-Fuzzy Designer** displays the checking data as plus signs (+) superimposed on the training data.



# of inputs: 1
# of outputs: 1
# of input mfs: 3
# of check data pairs: 26

Type: Checking
From: worksp.
Grid partition
Optim. Method: hybrid
Error Tolerance: 0
Epochs: 3
Plot against: Training data

check data loaded

5 Generate an initial FIS:

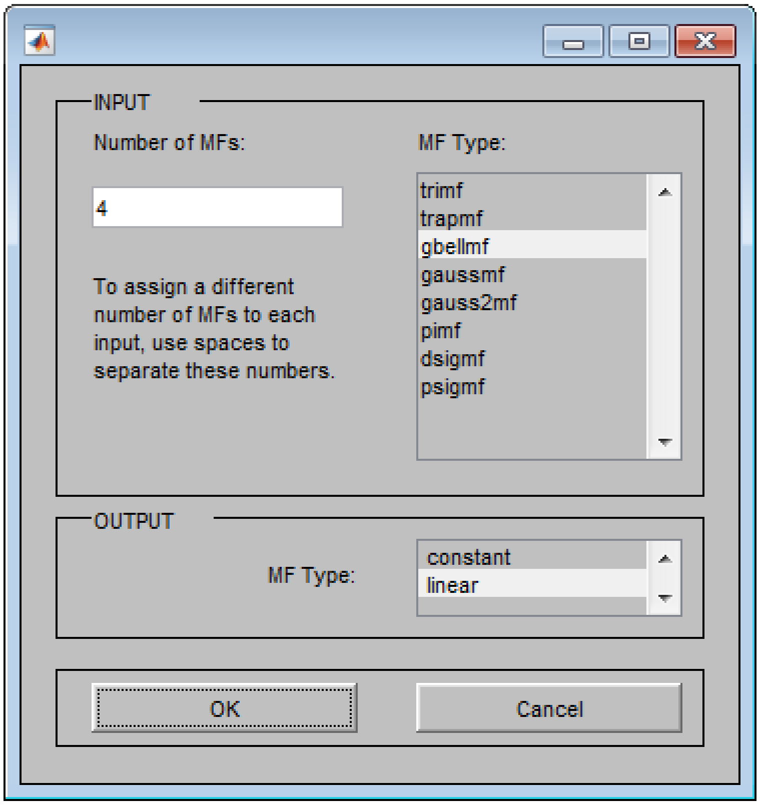
a In the **Generate FIS** panel, verify that **Grid partition** option is selected.

b Click **Generate FIS**.

This action opens a dialog box where you specify the structure of the FIS.

c In the dialog box, specify the following:

- Enter 4 in the **Number of MFs** field.
- Select `gbellmf` as the **Membership Type** for the input.
- Select `linear` as the **Membership Type** for the output.


INPUT

Number of MFs: 4

To assign a different number of MFs to each input, use spaces to separate these numbers.

MF Type: trimf, trapmf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, psigmf

OUTPUT

MF Type: constant, linear

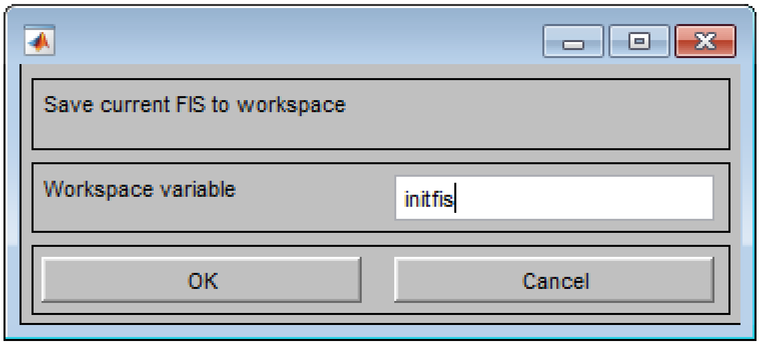
d Click **OK** to generate the FIS and close the dialog box.

6 Export the initial FIS to the MATLAB workspace:

a In the **Neuro-Fuzzy Designer**, select **File > Export > To Workspace**.

This action opens a dialog box where you specify the MATLAB variable name.

b In the dialog box, in the **Workspace variable** text box, enter `initfis`.


Save current FIS to workspace

Workspace variable initfis

c Click **OK** to close the dialog box.

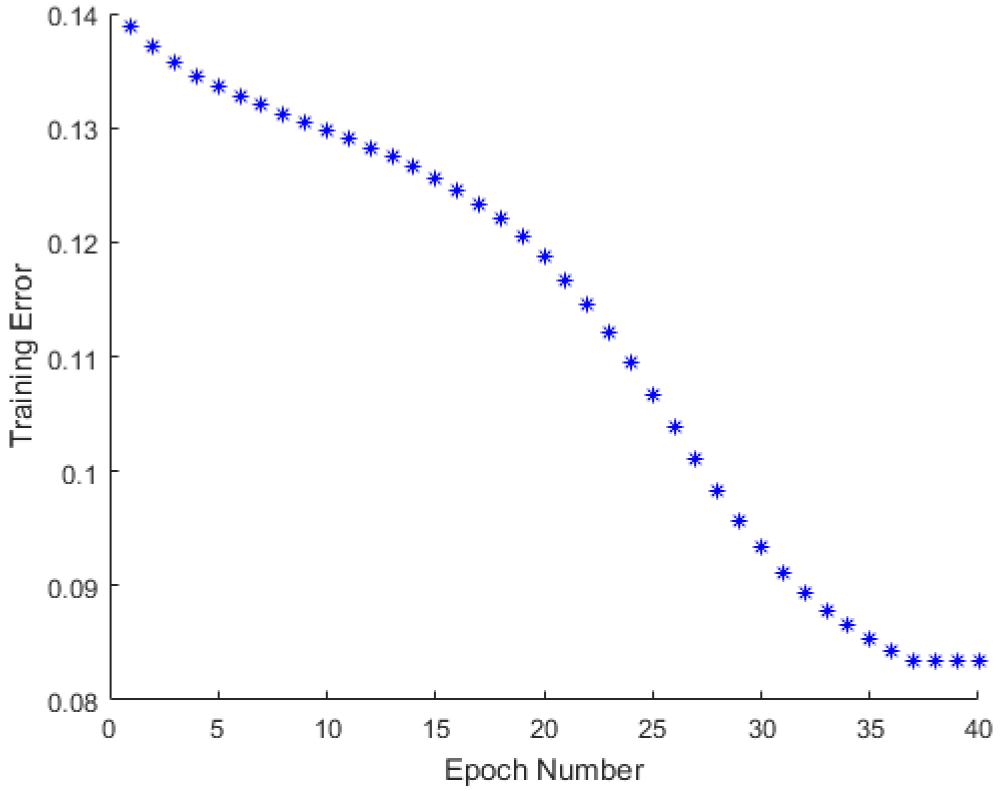
A variable named `initfis` now appears in the MATLAB workspace.

7 Train the FIS for `40` epochs by typing the following command at the MATLAB prompt:

```
figure
hold on
fismat = initfis;
opt = anfisOptions('EpochNumber',2,'ValidationData',fuzex1chkData);
for ct = 1:40
    opt.InitialFIS = fismat;
    [fismat,error] = anfis(fuzex1trnData,opt);
    plot(ct,error(1),'b*');
end
```

To improve accuracy when you train the FIS, the code uses the results of the current iteration returned by the `anfis` command as the initial conditions for the next iteration. The output argument `error` contains the root mean squared errors representing the training data error. For more information, see the `anfis` reference page.

The plot of the training error versus the number of epochs appears in the next figure.



See Also

Neuro-Fuzzy Designer

More About

- “Neuro-Adaptive Learning and ANFIS” on page 3-86
- “Comparison of anfis and Neuro-Fuzzy Designer Functionality” on page 3-91
- “Train Adaptive Neuro-Fuzzy Inference Systems” on page 3-97
- “Test Data Against Trained System” on page 3-102

Predict Chaotic Time-Series using ANFIS

This example shows how to do chaotic time-series prediction using ANFIS.

Time Series Data

This example uses `anfis` to predict a time series generated by the following Mackey-Glass (MG) time-delay differential equation.

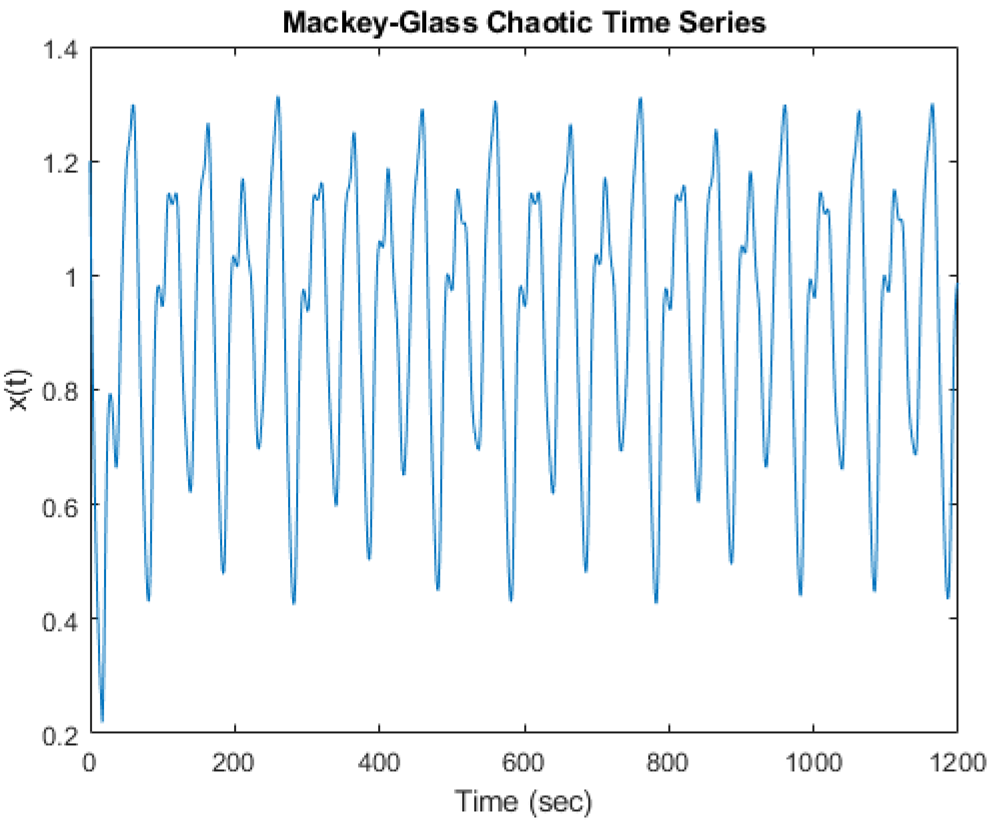
$$\dot{x}(t) = \frac{0.2x(t-\tau)}{1 + x^{10}(t-\tau)} = 0.1x(t)$$

This time series is chaotic with no clearly defined period. The series does not converge or diverge, and the trajectory is highly sensitive to initial conditions. This benchmark problem is used in the neural network and fuzzy modeling research communities.

To obtain the time series value at integer points, the fourth-order Runge-Kutta method was used to find the numerical solution to the previous MG equation. It was assumed that $x(0) = 1.2$, $\tau = 17$, and $x(t) = 0$ for $t < 0$. The result was saved in the file `mgdata.dat`.

Load and plot the MG time series.

```
load mgdata.dat
time = mgdata(:,1);
x = mgdata(:, 2);
figure(1)
plot(time,x)
title('Mackey-Glass Chaotic Time Series')
xlabel('Time (sec)')
ylabel('x(t)')
```



Preprocess Data

In time-series prediction, you use known values of the time series up to point in time, t, to predict the value at some point in the future, $t + P$. The standard method for this type of prediction is to create a mapping from D sample data points, sampled every Δ units in time $(x(t - (D - 1)\Delta), \ldots, x(t - \Delta), x(t))$ to a predicted future value $x = (t + P)$. Following the conventional settings for predicting the MG time series, set $D = 4$ and $\Delta = P = 6$. For each t, the input training data for `anfis` is a four-column vector of the following form.

$$w(t) = [x(t - 19), x(t - 12), x(t - 6), x(t)]$$

The output training data corresponds to the trajectory prediction.

$$s(t) = x(t + 6)$$

For each *t*, ranging in values from 118 to 1117, there are 1000 input/output training samples. For this example, use the first 500 samples as training data (`trnData`) and the second 500 values as checking data for validation (`chkData`). Each row of the training and checking data arrays contains one sample point where the first four columns contain the four-dimensional input *w* and the fifth column contains the output *s*.

Construct the training and checking data arrays.

```
for t = 118:1117
    Data(t-117,:) = [x(t-18) x(t-12) x(t-6) x(t) x(t+6)];
end
trnData = Data(1:500,:);
chkData = Data(501:end,:);
```

Build Initial Fuzzy System

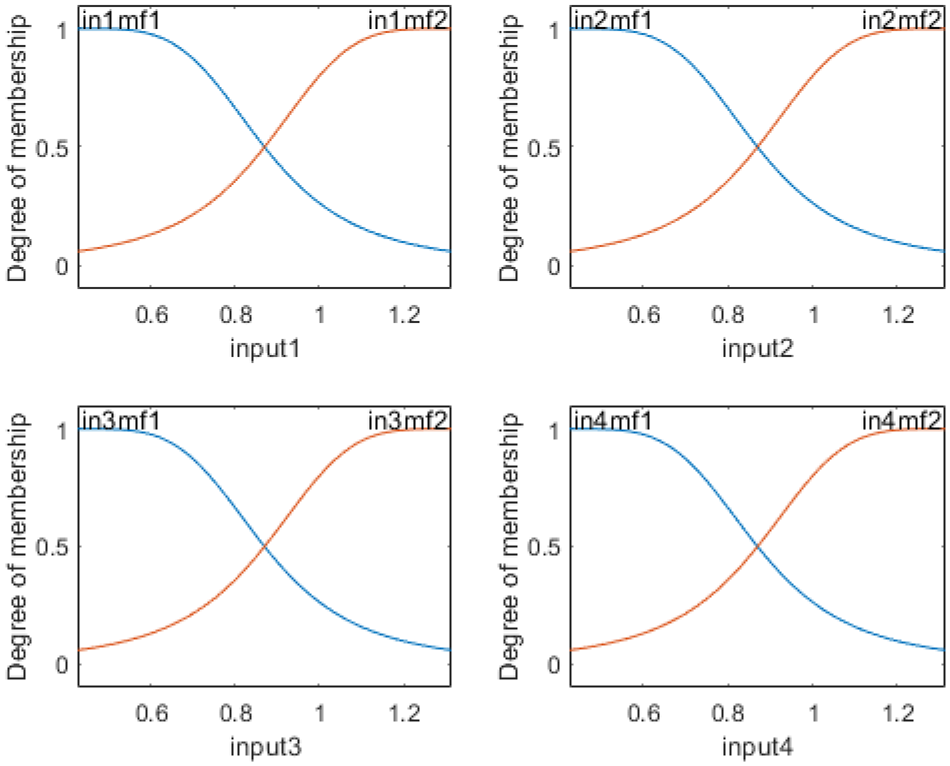
Create an initial Sugeno FIS object for training using the `genfis` function with grid partitioning.

```
fis = genfis(trnData(:,1:end-1),trnData(:,end),...
    genfisOptions('GridPartition'));
```

The number of FIS inputs and outputs corresponds to the number of columns in the input and output training data, four and one, respectively.

By default, `genfis` creates two generalized bell membership functions for each of the four inputs. The initial membership functions for each variable are equally spaced and cover the whole input space.

```
figure
subplot(2,2,1)
plotmf(fis,'input',1)
subplot(2,2,2)
plotmf(fis,'input',2)
subplot(2,2,3)
plotmf(fis,'input',3)
subplot(2,2,4)
plotmf(fis,'input',4)
```



The generated FIS object contains $2^4 = 16$ fuzzy rules with 104 parameters (24 nonlinear parameters and 80 linear parameters). To achieve good generalization capability, it is important that the number of training data points be several times larger than the number parameters being estimated. In this case, the ratio between data and parameters is approximately five (500/104), which is a good balance between fitting parameters and training sample points.

Train ANFIS Model

To configure training options, create an `anfisOptions` option set, specifying the initial FIS and validation data.

```
options = anfisOptions('InitialFIS',fis,'ValidationData',chkData);
```

Train the FIS using the specified training data and options.

```
[fis1,error1,ss,fis2,error2] = anfis(trnData,options);
```

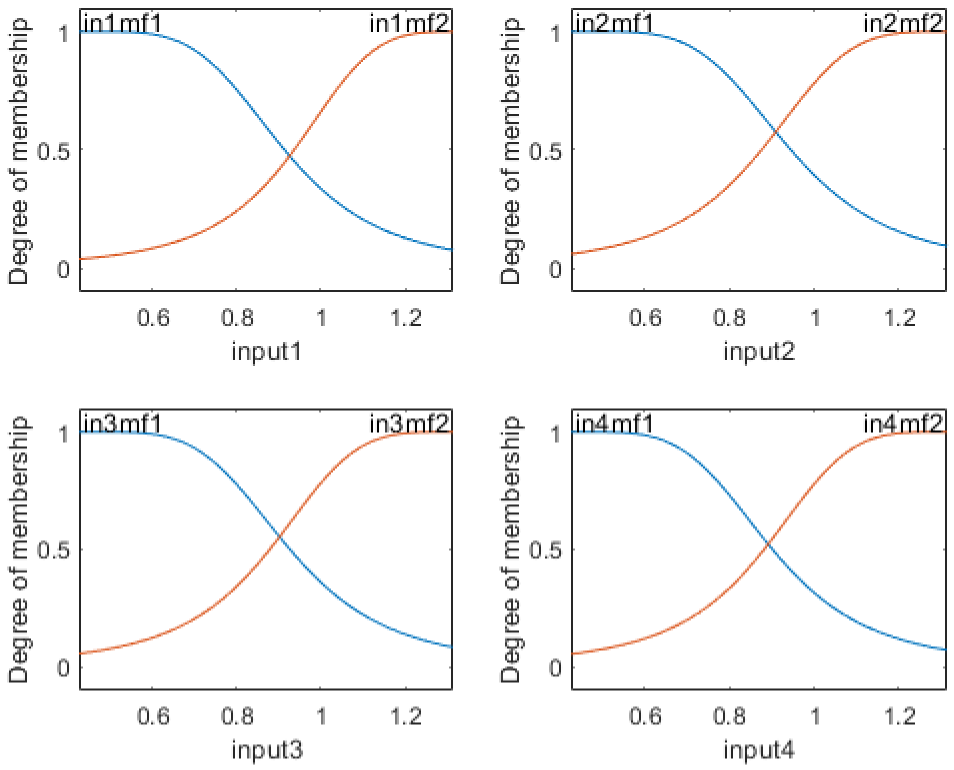
```
ANFIS info:
    Number of nodes: 55
    Number of linear parameters: 80
    Number of nonlinear parameters: 24
    Total number of parameters: 104
    Number of training data pairs: 500
    Number of checking data pairs: 500
    Number of fuzzy rules: 16


Start training ANFIS ...

   1      0.00296046      0.00292488
   2      0.00290346      0.0028684
   3      0.00285048      0.00281544
   4      0.00280117      0.00276566
   5      0.00275517      0.00271874
Step size increases to 0.011000 after epoch 5.
   6      0.00271214      0.00267438
   7      0.00266783      0.00262818
   8      0.00262626      0.00258435
   9      0.00258702      0.00254254
Step size increases to 0.012100 after epoch 9.
  10      0.00254972      0.00250247

Designated epoch number reached --> ANFIS training completed at epoch 10.

Minimal training RMSE = 0.002550
Minimal checking RMSE = 0.00250247
```

`fis1` is the trained fuzzy inference system for the training epoch where the training error is smallest. Since you specified validation data, the fuzzy system with the minimum checking error, `fis2`, is also returned. The FIS with the smallest checking error shows the best generalization beyond the training data.

Plots the membership functions for the trained system.

```
figure
subplot(2,2,1)
plotmf(fis2,'input',1)
subplot(2,2,2)
```

```
plotmf(fis2,'input',2)
subplot(2,2,3)
plotmf(fis2,'input',3)
subplot(2,2,4)
plotmf(fis2,'input',4)
```

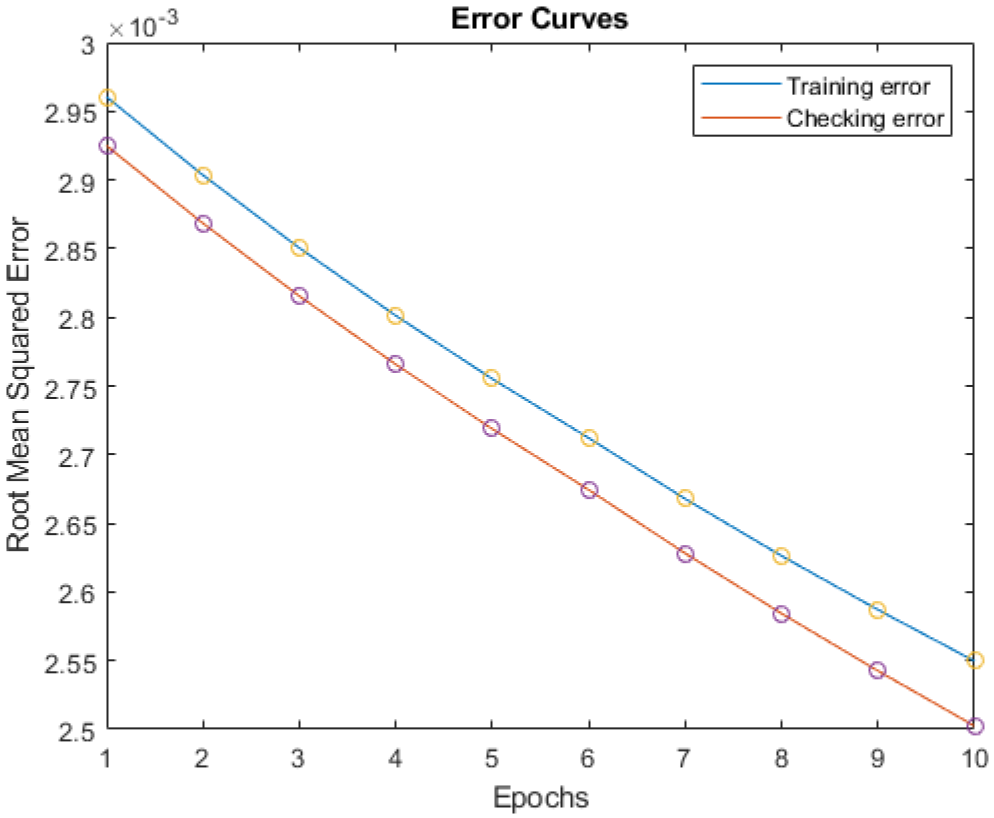


Plot Errors Curves

Plot the training and checking error signals.

```
figure
plot([error1 error2])
hold on
plot([error1 error2],'o')
```

```
legend('Training error','Checking error')
xlabel('Epochs')
ylabel('Root Mean Squared Error')
title('Error Curves')
```

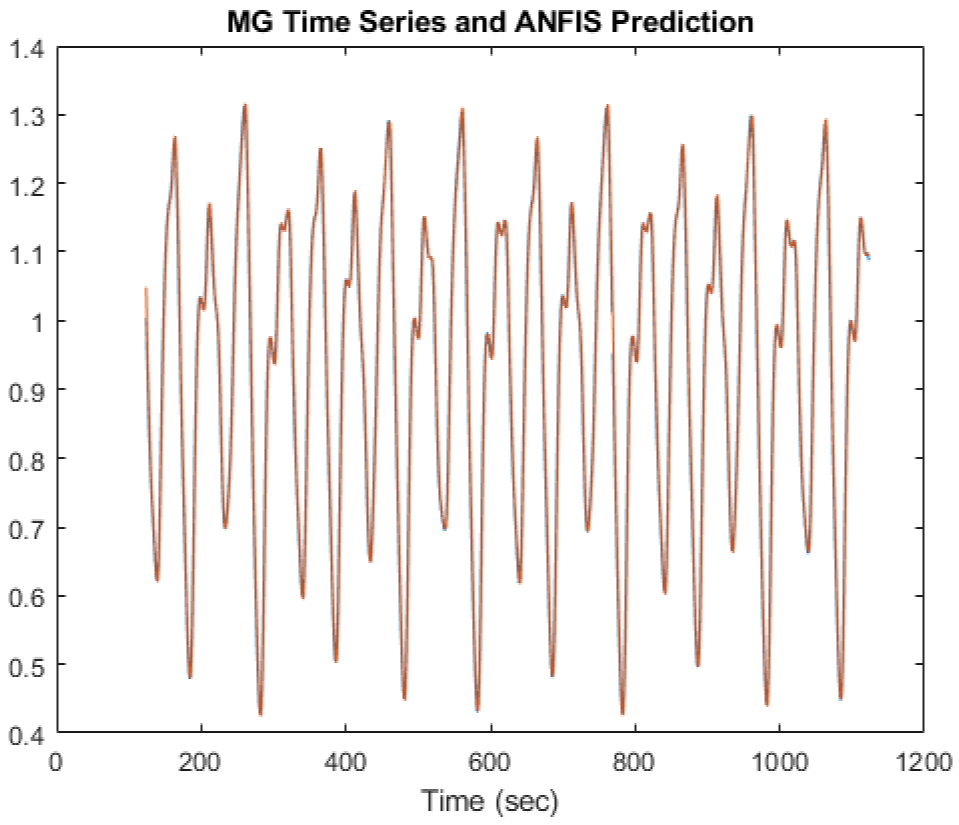


The training error is higher than the checking error in all epochs. This phenomenon is not uncommon in ANFIS learning or nonlinear regression in general; it could indicate that additional training could produce better training results.

Compare Original and Predicted Series

To check prediction capability of the trained system, evaluate the fuzzy system using the training and checking data, and plot the result alongside the original

```
anfis_output = evalfis(fis2,[trnData(:,1:4); chkData(:,1:4)]);

figure
index = 125:1124;
plot(time(index),[x(index) anfis_output])
xlabel('Time (sec)')
title('MG Time Series and ANFIS Prediction')
```

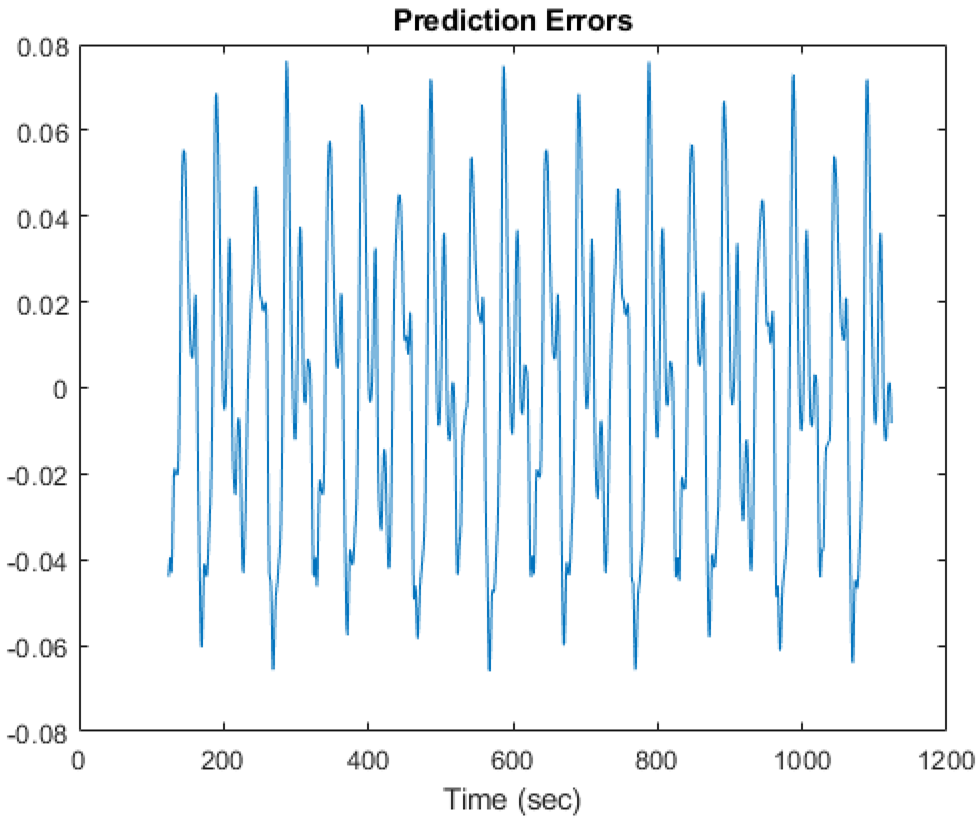


The predicted series is similar to the original series.

Calculate and plot the prediction error.

```
diff = x(index) - anfis_output;
plot(time(index),diff)
```

```
xlabel('Time (sec)')
title('Prediction Errors')
```



The scale of the prediction error plot is about one-hundredth of the scale of the time-series plot. In this example, you trained the system for only 10 epoch. Training for additional epochs can improve the training results.

See Also

`anfis` | `evalfis` | `genfis`

More About

- “Neuro-Adaptive Learning and ANFIS” on page 3-86
- “Comparison of anfis and Neuro-Fuzzy Designer Functionality” on page 3-91

Modeling Inverse Kinematics in a Robotic Arm

This example shows how to use a fuzzy system to model the inverse kinematics in a two-joint robotic arm.

What Is Inverse Kinematics?

Kinematics is the science of motion. In a two-joint robotic arm, given the angles of the joints, the kinematics equations give the location of the tip of the arm. Inverse kinematics refers to the reverse process. Given a desired location for the tip of the robotic arm, what should the angles of the joints be so as to locate the tip of the arm at the desired location. There is usually more than one solution and can at times be a difficult problem to solve.

This is a typical problem in robotics that needs to be solved to control a robotic arm to perform tasks it is designated to do. In a 2-dimensional input space, with a two-joint robotic arm and given the desired coordinate, the problem reduces to finding the two angles involved. The first angle is between the first arm and the ground (or whatever it is attached to). The second angle is between the first arm and the second arm.

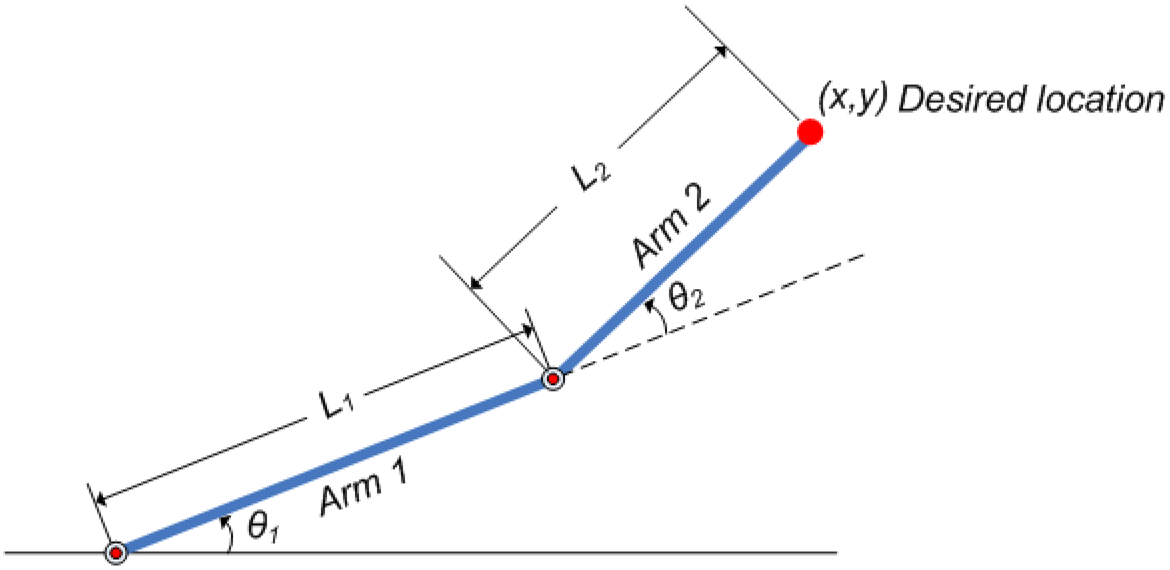


Figure 1: Illustration showing the two-joint robotic arm with the two angles, `theta1` and `theta2`

Why Use Fuzzy Logic?

For simple structures like the two-joint robotic arm, it is possible to mathematically deduce the angles at the joints given the desired location of the tip of the arm. However with more complex structures (eg: n-joint robotic arms operating in a 3-dimensional input space) deducing a mathematical solution for the inverse kinematics may prove challenging.

Using fuzzy logic, we can construct a fuzzy inference system that deduces the inverse kinematics if the forward kinematics of the problem is known, hence sidestepping the need to develop an analytical solution. Also, the fuzzy solution is easily understandable and does not require special background knowledge to comprehend and evaluate it.

In the following section, a broad outline for developing such a solution is described, and later, the detailed steps are elaborated.

Overview of Fuzzy Solution

Since the forward kinematics formulae for the two-joint robotic arm are known, x and y coordinates of the tip of the arm are deduced for the entire range of angles of rotation of the two joints. The coordinates and the angles are saved to be used as training data to train an ANFIS (adaptive neuro-fuzzy inference system) network.

During training, the ANFIS network learns to map the coordinates (`x`, `y`) to the angles (`theta1`, `theta2`). The trained ANFIS network is then used as a part of a larger control system to control the robotic arm. Knowing the desired location of the robotic arm, the control system uses the trained ANFIS network to deduce the angular positions of the joints and applies force to the joints of the robotic arm accordingly to move it to the desired location.

What Is ANFIS?

ANFIS stands for adaptive neuro-fuzzy inference system. It is a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference systems. The learning algorithm tunes the membership functions of a Sugeno-type fuzzy inference system using the training input/output data.

In this case, the input/output data refers to the "coordinates/angles" dataset. The coordinates act as input to the ANFIS and the angles act as the output. The learning algorithm teaches the ANFIS to map the coordinates to the angles through a process called training. At the end of training, the trained ANFIS network would have learned the input-output map and be ready to be deployed into the larger control system solution.

Data Generation

Let `theta1` be the angle between the first arm and the ground. Let `theta2` be the angle between the second arm and the first arm (Refer to Figure 1 for illustration). Let the length of the first arm be `l1` and that of the second arm be `l2`.

Assume that the first joint has limited freedom to rotate and it can rotate between 0 and 90 degrees. Similarly, assume that the second joint has limited freedom to rotate and can rotate between 0 and 180 degrees. (This assumption takes away the need to handle some special cases which will confuse the discourse.) Hence, `0<=theta1<=pi/2` and `0<=theta2<=pi`.

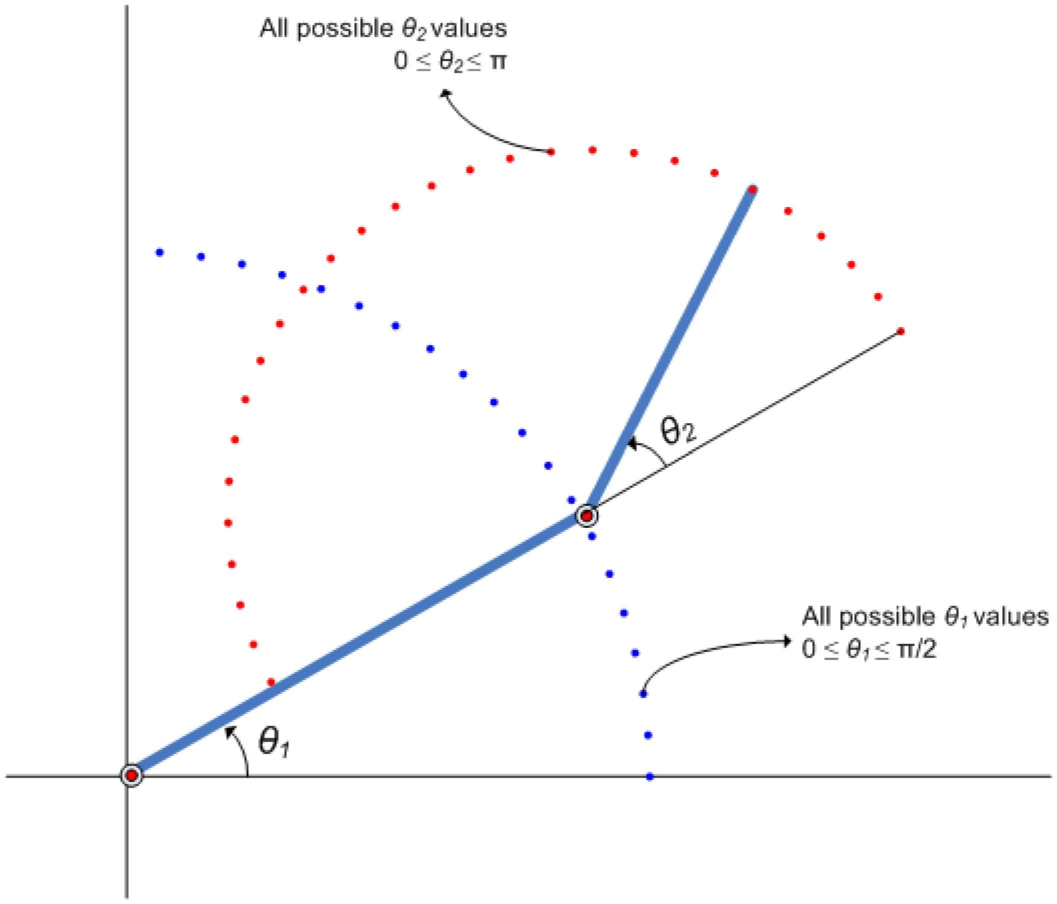

All possible θ_2 values
$0 \leq \theta_2 \leq \pi$
θ_2
All possible θ_1 values
$0 \leq \theta_1 \leq \pi/2$
θ_1

Figure 2: Illustration showing all possible `theta1` and `theta2` values.

Now, for every combination of `theta1` and `theta2` values the x and y coordinates are deduced using forward kinematics formulae.

The following code snippet shows how data is generated for all combination of `theta1` and `theta2` values and saved into a matrix to be used as training data. The reason for saving the data in two matrices is explained in the following section.

```
l1 = 10; % length of first arm
l2 = 7; % length of second arm

theta1 = 0:0.1:pi/2; % all possible theta1 values
theta2 = 0:0.1:pi; % all possible theta2 values

[THETA1,THETA2] = meshgrid(theta1,theta2); % generate a grid of theta1 and theta2 value

X = l1 * cos(THETA1) + l2 * cos(THETA1 + THETA2); % compute x coordinates
Y = l1 * sin(THETA1) + l2 * sin(THETA1 + THETA2); % compute y coordinates

data1 = [X(:) Y(:) THETA1(:)]; % create x-y-theta1 dataset
data2 = [X(:) Y(:) THETA2(:)]; % create x-y-theta2 dataset
```

Click here for unvectorized code

The following plot shows all the X-Y data points generated by cycling through different combinations of `theta1` and `theta2` and deducing x and y coordinates for each. The plot can be generated by using the code-snippet shown below. The plot is illustrated further for easier understanding.

```
  plot(X(:),Y(:),'r.');
  axis equal;
  xlabel('X','fontsize',10)
  ylabel('Y','fontsize',10)
  title('X-Y coordinates generated for all theta1 and theta2 combinations using forward
```

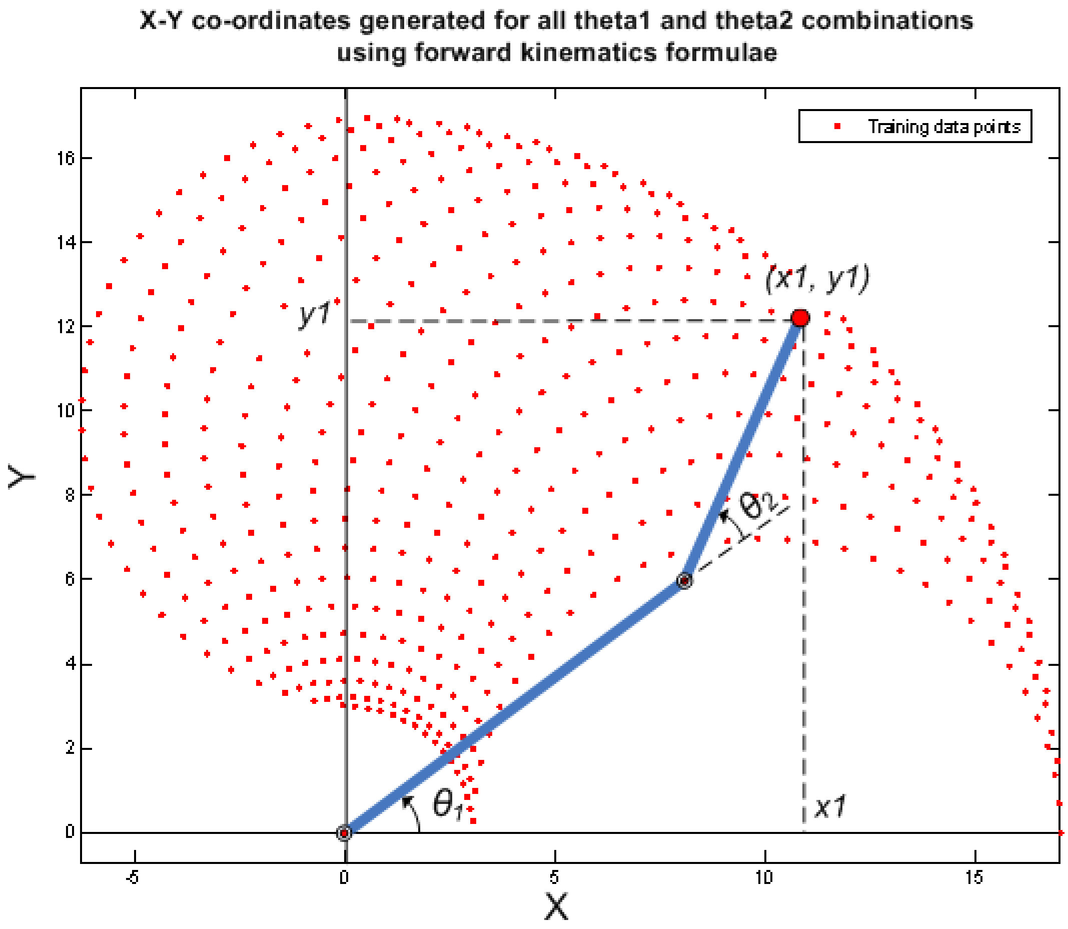


Figure 3: X-Y coordinates generated for all `theta1` and `theta2` combinations using forward kinematics formulae

Building ANFIS Networks

One approach to building an ANFIS solution for this problem, is to build two ANFIS networks, one to predict `theta1` and the other to predict `theta2`.

In order for the ANFIS networks to be able to predict the angles they have to be trained with sample input-output data. The first ANFIS network will be trained with X and Y coordinates as input and corresponding `theta1` values as output. The matrix `data1` contains the `x-y-theta1` dataset required to train the first ANFIS network. Therefore `data1` will be used as the dataset to train the first ANFIS network.

Similarly, the second ANFIS network will be trained with X and Y coordinates as input and corresponding `theta2` values as output. The matrix `data2` contains the `x-y-theta2` dataset required to train the second ANFIS network. Therefore `data2` will be used as the dataset to train the second ANFIS network.

To train an ANFIS network, first specify the training options using the `anfisOptions` command. For this example, specify an FIS object with `7` membership functions for each input variable. Train the system for `150` epochs and suppress the Command Window display of training information.

```
opt = anfisOptions;
opt.InitialFIS = 7;
opt.EpochNumber = 150;
opt.DisplayANFISInformation = 0;
opt.DisplayErrorValues = 0;
opt.DisplayStepSize = 0;
opt.DisplayFinalResults = 0;
```

Train an ANFIS system using the first set of training data, `data1`.

```
disp('--> Training first ANFIS network.')
```

```
--> Training first ANFIS network.
```

```
anfis1 = anfis(data1,opt);
```

Change the number of input membership functions and train an ANFIS system using the second set of training data, `data2`.

```
disp('--> Training second ANFIS network.')
```

```
--> Training second ANFIS network.
```

```
opt.InitialFIS = 6;
anfis2 = anfis(data2,opt);
```

For this example, the number of input membership functions and training epochs were selected based on experimentation with different potential values.

`anfis1` and `anfis2` represent the two trained ANFIS networks that will be deployed in the larger control system.

Once the training is complete, the two ANFIS networks have learned to approximate the angles (`theta1`, `theta2`) as a function of the coordinates (`x`, `y`). One advantage of using the fuzzy approach is that the ANFIS network can now approximate the angles for coordinates that are similar but not exactly the same as it was trained with. For example, the trained ANFIS networks are now capable of approximating the angles for coordinates that lie between two points that were included in the training dataset. This will allow the final controller to move the arm smoothly in the input space.

We now have two trained ANFIS networks which are ready to be deployed into the larger system that will utilize these networks to control the robotic arms.

Validating ANFIS Networks

Having trained the networks, an important follow up step is to validate the networks to determine how well the ANFIS networks would perform inside the larger control system.

Since this example problem deals with a two-joint robotic arm whose inverse kinematics formulae can be derived, it is possible to test the answers that the ANFIS networks produce with the answers from the derived formulae.

Let's assume that it is important for the ANFIS networks to have low errors within the operating range `0<x<2` and `8<y<10`.

```
x = 0:0.1:2; % x coordinates for validation
y = 8:0.1:10; % y coordinates for validation
```

The `theta1` and `theta2` values are deduced mathematically from the x and y coordinates using inverse kinematics formulae.

```
[X,Y] = meshgrid(x,y);

c2 = (X.^2 + Y.^2 - l1^2 - l2^2)/(2*l1*l2);
s2 = sqrt(1 - c2.^2);
THETA2D = atan2(s2,c2); % theta2 is deduced

k1 = l1 + l2.*c2;
k2 = l2*s2;
THETA1D = atan2(Y,X) - atan2(k2,k1); % theta1 is deduced
```

Click here for unvectorized code

`THETA1D` and `THETA2D` are the variables that hold the values of `theta1` and `theta2` deduced using the inverse kinematics formulae.

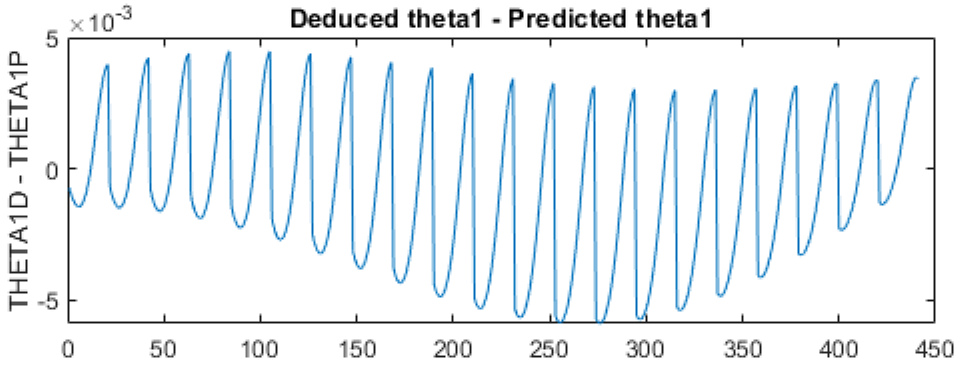
`theta1` and `theta2` values predicted by the trained anfis networks are obtained by using the command `evalfis` which evaluates a FIS for the given inputs.

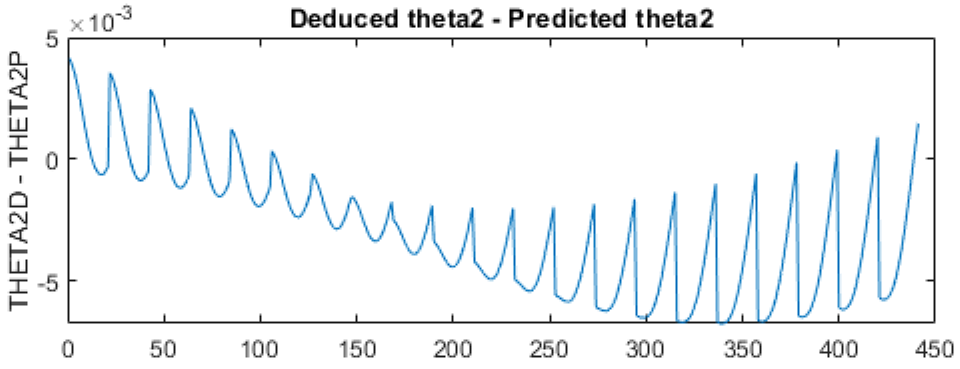
Here, `evalfis` is used to find out the FIS outputs for the same x-y values used earlier in the inverse kinematics formulae.

```
XY = [X(:) Y(:)];
THETA1P = evalfis(anfis1,XY); % theta1 predicted by anfis1
THETA2P = evalfis(anfis2,XY); % theta2 predicted by anfis2
```

Now, we can see how close the FIS outputs are with respect to the deduced values.

```
theta1diff = THETA1D(:) - THETA1P;
theta2diff = THETA2D(:) - THETA2P;

subplot(2,1,1);
plot(theta1diff);
ylabel('THETA1D - THETA1P','fontsize',10)
title('Deduced theta1 - Predicted theta1','fontsize',10)

subplot(2,1,2);
plot(theta2diff);
ylabel('THETA2D - THETA2P','fontsize',10)
title('Deduced theta2 - Predicted theta2','fontsize',10)
```



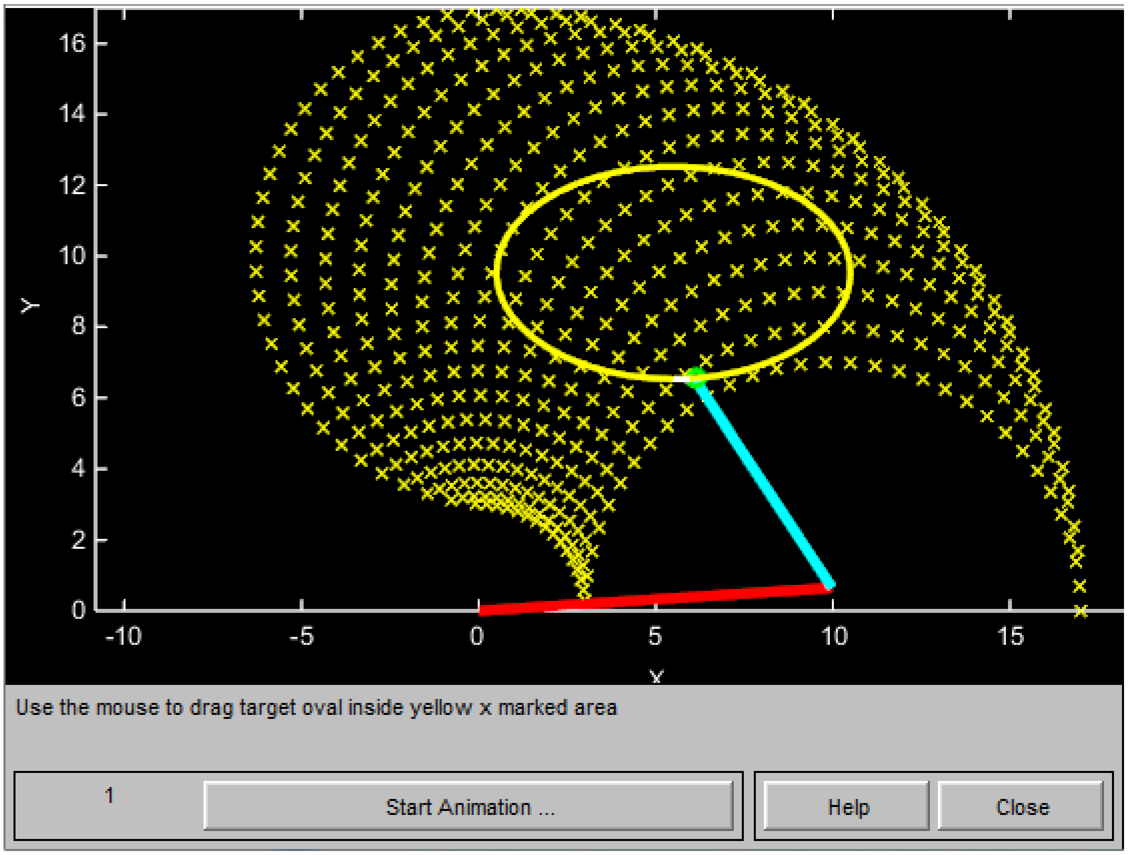


The errors are in the `1e-3` range which is a fairly good number for the application it is being used in. However this may not be acceptable for another application, in which case the parameters to the `anfis` function may be tweaked until an acceptable solution is arrived at. Also, other techniques like input selection and alternate ways to model the problem may be explored.

Building a Solution Around the Trained ANFIS Networks

Now given a specific task, such as robots picking up an object in an assembly line, the larger control system will use the trained ANFIS networks as a reference, much like a lookup table, to determine what the angles of the arms must be, given a desired location for the tip of the arm. Knowing the desired angles and the current angles of the joints, the system will apply force appropriately on the joints of the arms to move them towards the desired location.

The invkine command launches a GUI that shows how the two trained ANFIS networks perform when asked to trace an ellipse.



Use the mouse to drag target oval inside yellow x marked area

Figure 4: GUI for Inverse Kinematics Modeling.

The two ANFIS networks used in the example have been pretrained and are deployed into a larger system that controls the tip of the two-joint robot arm to trace an ellipse in the input space.

The ellipse to be traced can be moved around. Move the ellipse to a slightly different location and observe how the system responds by moving the tip of the robotic arm from its current location to the closest point on the new location of the ellipse. Also observe that the system responds smoothly as long as the ellipse to be traced lies within the 'x' marked spots which represent the data grid that was used to train the networks. Once the ellipse is moved outside the range of data it was trained with, the ANFIS networks respond unpredictably. This emphasizes the importance of having relevant and representative data for training. Data must be generated based on the expected range of operation to avoid such unpredictability and instability issues.

See Also

`anfis` | `evalfis`

More About

- “Neuro-Adaptive Learning and ANFIS” on page 3-86
- “Comparison of anfis and Neuro-Fuzzy Designer Functionality” on page 3-91

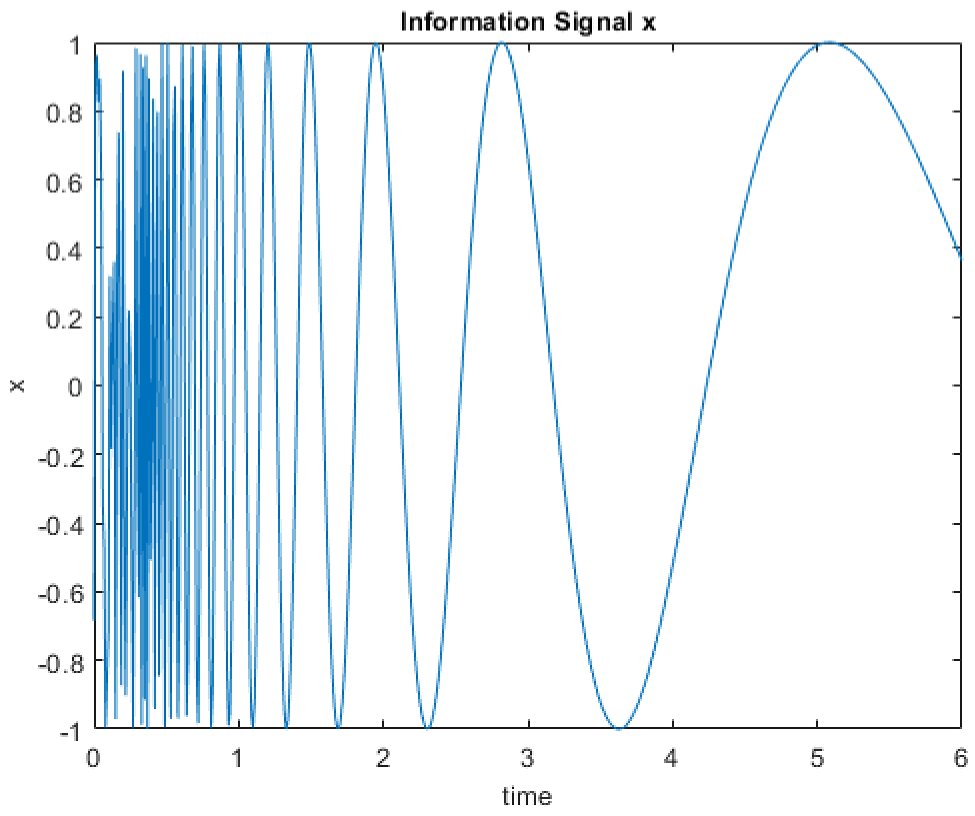
Adaptive Noise Cancellation Using ANFIS

This example shows how to do adaptive nonlinear noise cancellation using the `anfis` and `genfis` commands.

Signal and Noise

Define a hypothetical information signal, `x`, sampled at 100Hz over 6 seconds.

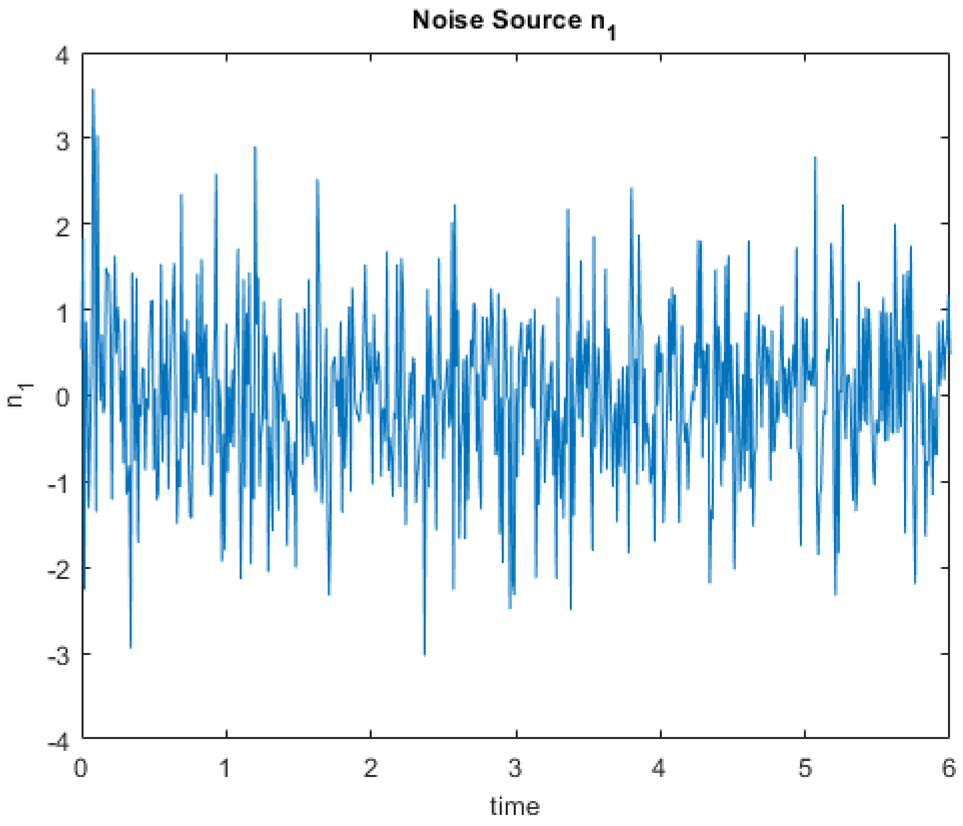
```
time = (0:0.01:6)';
x = sin(40./(time+0.01));
plot(time,x)
title('Information Signal x','fontsize',10)
xlabel('time','fontsize',10)
ylabel('x','fontsize',10)
```



Assume that x cannot be measured without an interference signal, n_2, which is generated from another noise source, n_1, via a certain unknown nonlinear process.

The plot below shows noise source n_1.

```
n1 = randn(size(time));
plot(time,n1)
title('Noise Source n_1','fontsize',10)
xlabel('time','fontsize',10)
ylabel('n_1','fontsize',10)
```



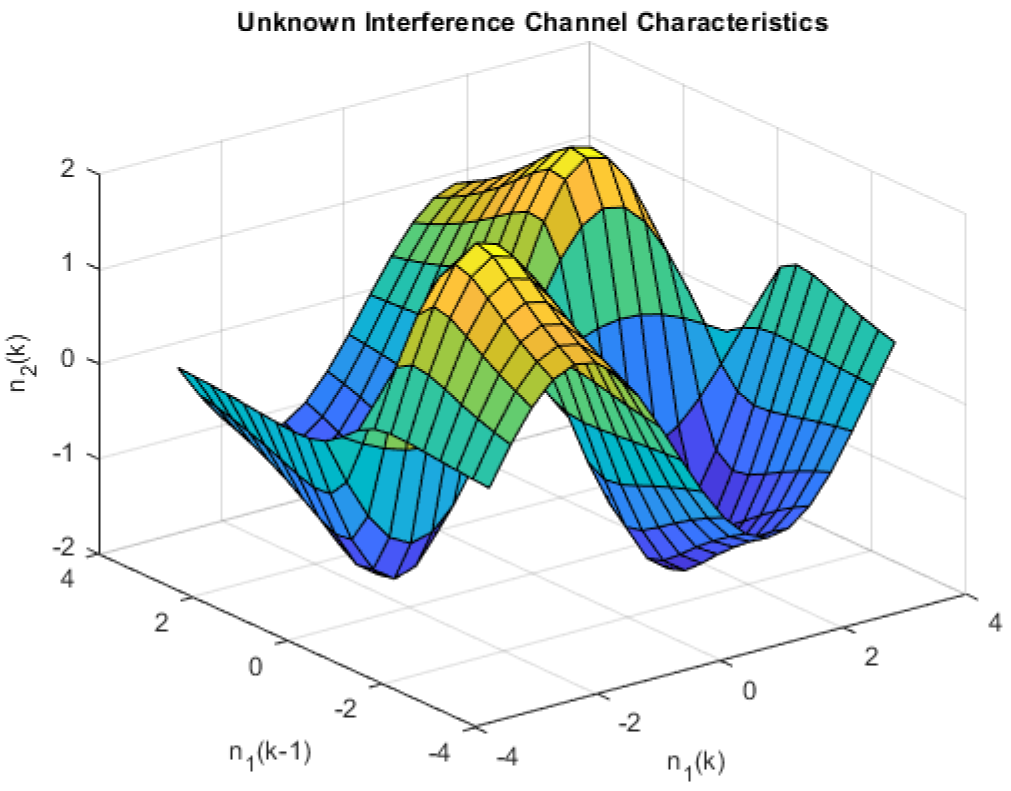
Assume that the interference signal, n_2, that appears in the measured signal is generated via an unknown nonlinear equation:

$$n_2(k) = \frac{4\sin(n_1(k)) \cdot n_1(k-1)}{1 + n_1(k-1)^2}$$

Plot this nonlinear characteristic as a surface.

```
domain = linspace(min(n1),max(n1),20);
[xx,yy] = meshgrid(domain,domain);
zz = 4*sin(xx).*yy./(1+yy.^2);

surf(xx,yy,zz);
```

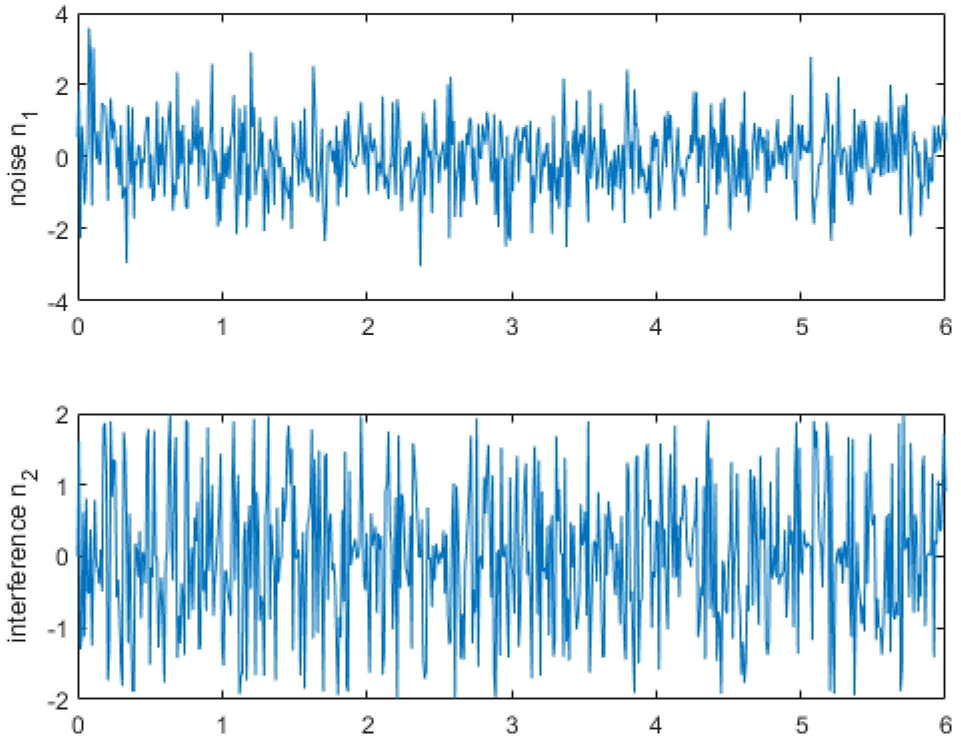
```
xlabel('n_1(k)','fontsize',10);
ylabel('n_1(k-1)','fontsize',10);
zlabel('n_2(k)','fontsize',10);
title('Unknown Interference Channel Characteristics','fontsize',10);
```



Compute the interference signal, n_2, from the noise source, n_1, and plot both signals.

```
n1d0 = n1;                            % n1 with delay 0
n1d1 = [0; n1d0(1:length(n1d0)-1)];   % n1 with delay 1
n2 = 4*sin(n1d0).*n1d1./(1+n1d1.^2);  % interference

subplot(2,1,1)
plot(time,n1);
ylabel('noise n_1','fontsize',10);
```

```
subplot(2,1,2)
plot(time,n2);
ylabel('interference n_2','fontsize',10);
```

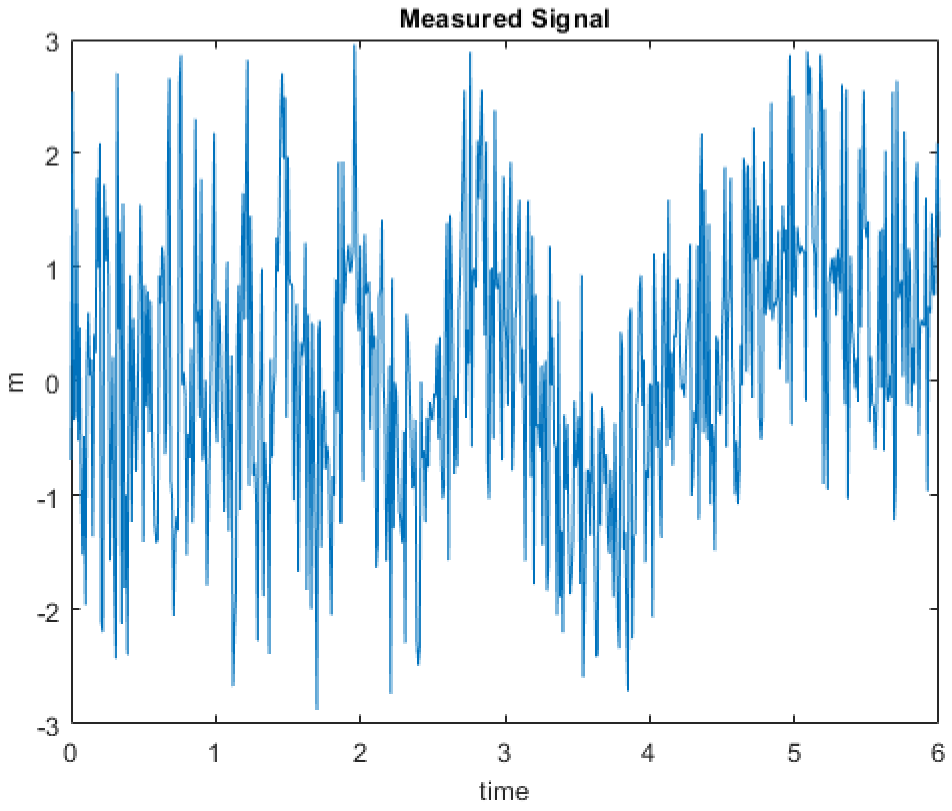


n_2 is related to n_1 via the highly nonlinear process shown previously; from the plots, it is hard to see if these two signals are correlated in any way.

The measured signal, `m`, is the sum of the original information signal, `x`, and the interference, n_2. However, we do not know n_2. The only signals available to us are the noise signal, n_1, and the measured signal `m`.

```
m = x + n2;              % measured signal
subplot(1,1,1)
plot(time, m)
```

```
title('Measured Signal','fontsize',10)
xlabel('time','fontsize',10)
ylabel('m','fontsize',10)
```



You can recover the original information signal, x, using adaptive noise cancellation via ANFIS training.

Build the ANFIS Model

Use the `anfis` command to identify the nonlinear relationship between n_1 and n_2. While n_2 is not directly available, you can assume that m is a "contaminated" version of n_2 for training. This assumption treats x as "noise" in this kind of nonlinear fitting.

Assume the order of the nonlinear channel is known (in this case, 2), so you can use a 2-input ANFIS model for training.

Define the training data. The first two columns of `data` are the inputs to the ANFIS model, n_1 and a delayed version of n_1. The final column of `data` is the measured signal, `m`.

```
delayed_n1 = [0; n1(1:length(n1)-1)];
data = [delayed_n1 n1 m];
```

Generate the initial FIS object. By default, the grid partitioning algorithm uses two membership functions for each input variable, which produces four fuzzy rules for learning.

```
genOpt = genfisOptions('GridPartition');
inFIS = genfis(data(:,1:end-1),data(:,end),genOpt);
```

Tune the FIS using the `anfis` command with an initial training step size of `0.2`.

```
trainOpt = anfisOptions('InitialFIS',inFIS,'InitialStepSize',0.2);
outFIS = anfis(data,trainOpt);
```

```
ANFIS info:
    Number of nodes: 21
    Number of linear parameters: 12
    Number of nonlinear parameters: 12
    Total number of parameters: 24
    Number of training data pairs: 601
    Number of checking data pairs: 0
    Number of fuzzy rules: 4


Start training ANFIS ...

   1      0.761817
   2      0.748426
   3      0.739315
   4      0.733993
   5      0.729492
Step size increases to 0.220000 after epoch 5.
   6      0.725382
   7      0.721269
   8      0.717621
   9      0.714474
Step size increases to 0.242000 after epoch 9.
  10      0.71207
```

```
Designated epoch number reached --> ANFIS training completed at epoch 10.

Minimal training RMSE = 0.712070
```

The tuned FIS, `outFIS`, models the second-order relationship between n_1 and n_2.

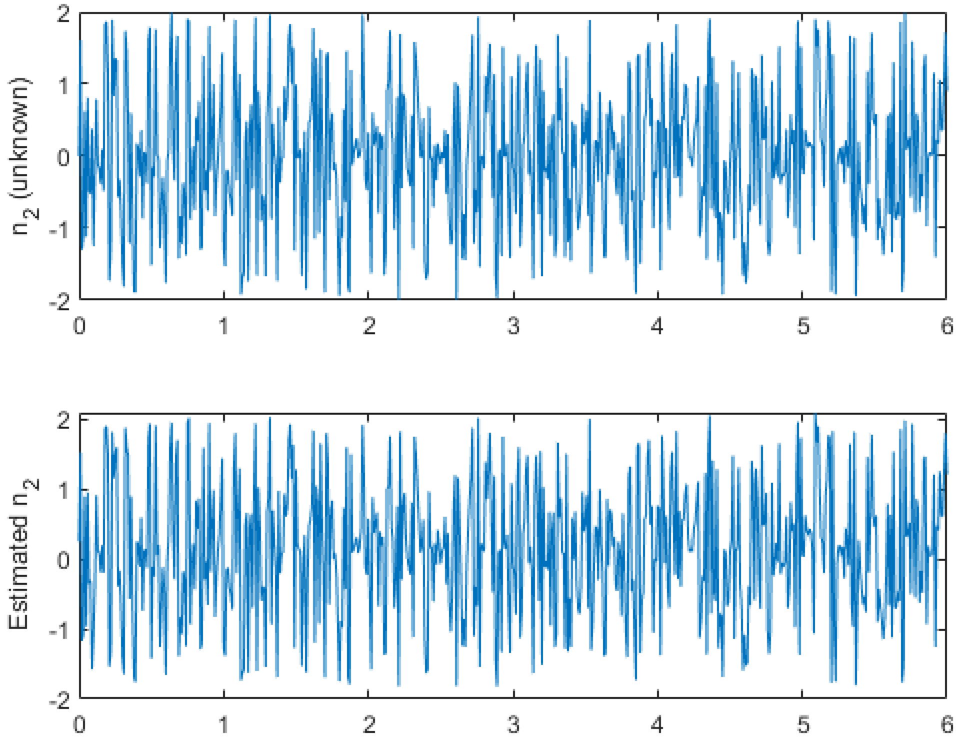
Evaluate Model

Calculate the estimated interference signal, `estimated_n2`, by evaluating the tuned FIS using the original training data.

```
estimated_n2 = evalfis(outFIS,data(:,1:2));
```

Plot the and actual n_2 signal and the estimated version from the ANFIS output.

```
subplot(2,1,1)
plot(time, n2)
ylabel('n_2 (unknown)');

subplot(2,1,2)
plot(time, estimated_n2)
ylabel('Estimated n_2');
```

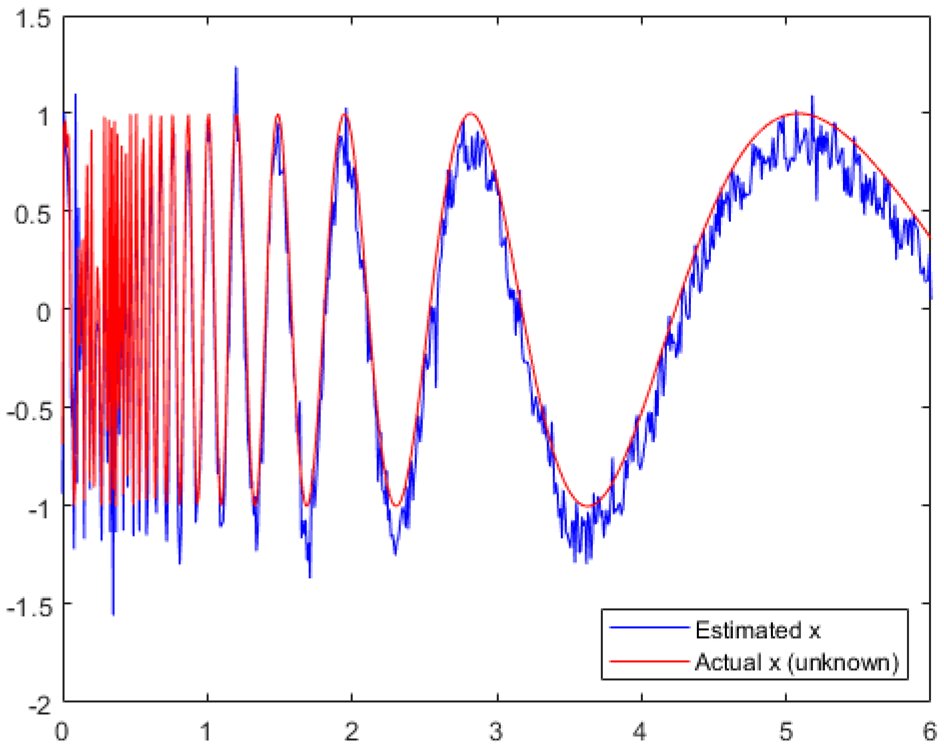


The estimated information signal is equal to the difference between the measured signal, `m`, and the estimated interference (ANFIS output).

```
estimated_x = m - estimated_n2;
```

Compare the original information signal, `x`, and the estimate, `estimated_x`.

```
figure
plot(time,estimated_x,'b',time,x,'r')
legend('Estimated x','Actual x (unknown)','Location','SouthEast')
```



Without extensive training, the ANFIS produces a good estimate of the information signal.

See Also

`anfis` | `evalfis` | `genfis`

More About

- "Neuro-Adaptive Learning and ANFIS" on page 3-86
- "Comparison of anfis and Neuro-Fuzzy Designer Functionality" on page 3-91

Nonlinear System Identification

This example shows how to use `anfis` command for nonlinear dynamic system identification.

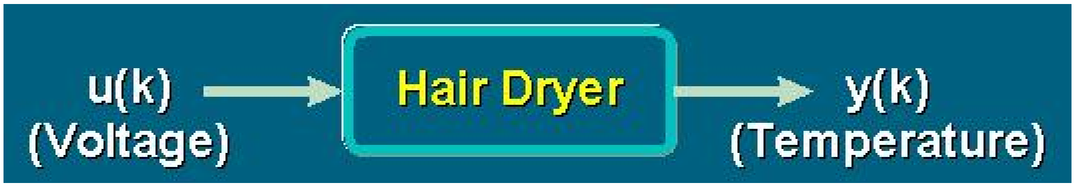
This example requires System Identification Toolbox™, as a comparison is made between a nonlinear ANFIS and a linear ARX model.

Problem Setup

Exit if System Identification Toolbox is not available.

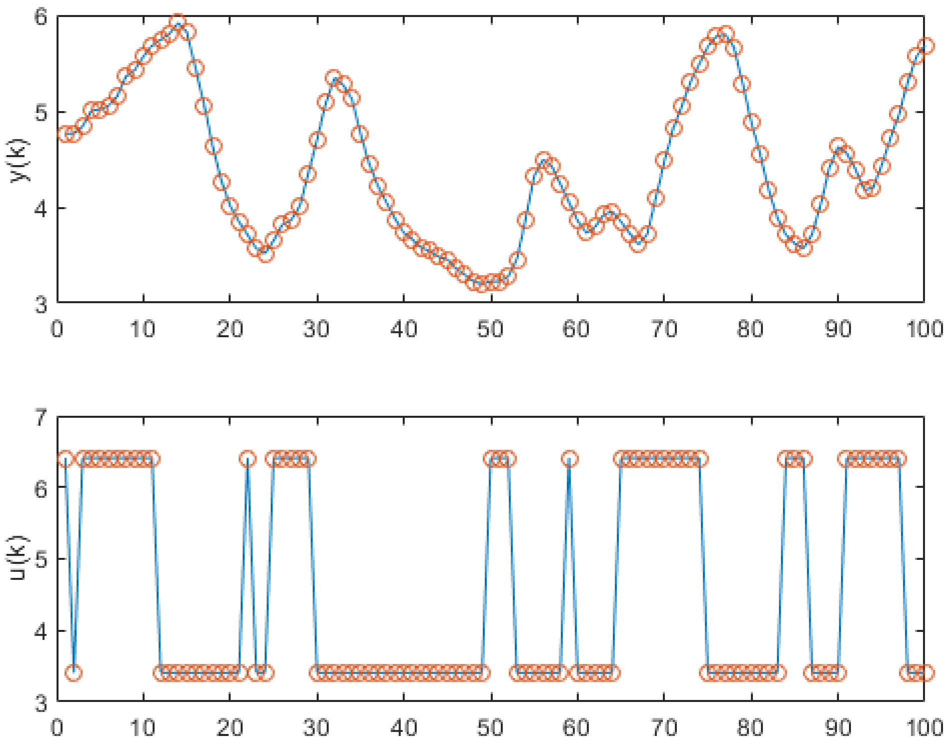
```
if ~fuzzychecktoolboxinstalled('ident')
    errordlg('DRYDEMO needs the System Identification Toolbox.');
    return;
end
```

The data set for ANFIS and ARX modeling was obtained from a laboratory device called Feedback's Process Trainer PT 326, as described in Chapter 17 of Prof. Lennart Ljung's book "System Identification, Theory for the User", Prentice-Hall, 1987. The device functions like a hair dryer: air is fanned through a tube and heated at the inlet. The air temperature is measured by a thermocouple at the outlet. The input u(k) is the voltage over a mesh of resistor wires to heat incoming air; the output y(k) is the outlet air temperature.



Here are the results of the test.

```
load drydemodata
data_n = length(y2);
output = y2;
input = [[0; y2(1:data_n-1)] ...
        [0; 0; y2(1:data_n-2)] ...
        [0; 0; 0; y2(1:data_n-3)] ...
        [0; 0; 0; 0; y2(1:data_n-4)] ...
        [0; u2(1:data_n-1)] ...
        [0; 0; u2(1:data_n-2)] ...
        [0; 0; 0; u2(1:data_n-3)] ...
        [0; 0; 0; 0; u2(1:data_n-4)] ...
        [0; 0; 0; 0; 0; u2(1:data_n-5)] ...
        [0; 0; 0; 0; 0; 0; u2(1:data_n-6)]];
data = [input output];
data(1:6, :) = [];
input_name = char('y(k-1)','y(k-2)','y(k-3)','y(k-4)','u(k-1)','u(k-2)','u(k-3)','u(k-4
index = 1:100;
subplot(2,1,1)
plot(index,y2(index),'-',index,y2(index),'o')
ylabel('y(k)','fontsize',10)
subplot(2,1,2)
plot(index,u2(index),'-',index,u2(index),'o')
ylabel('u(k)','fontsize',10)
```



The data points were collected at a sampling time of 0.08 seconds. One thousand input-output data points were collected from the process as the input u(k) was chosen to be a binary random signal shifting between 3.41 and 6.41 V. The probability of shifting the input at each sample was 0.2. The data set is available from the System Identification Toolbox, and the above plots show the output temperature y(k) and input voltage u(t) for the first 100 time steps.

ARX Model Identification

A conventional method is to remove the means from the data and assume a linear model of the form:

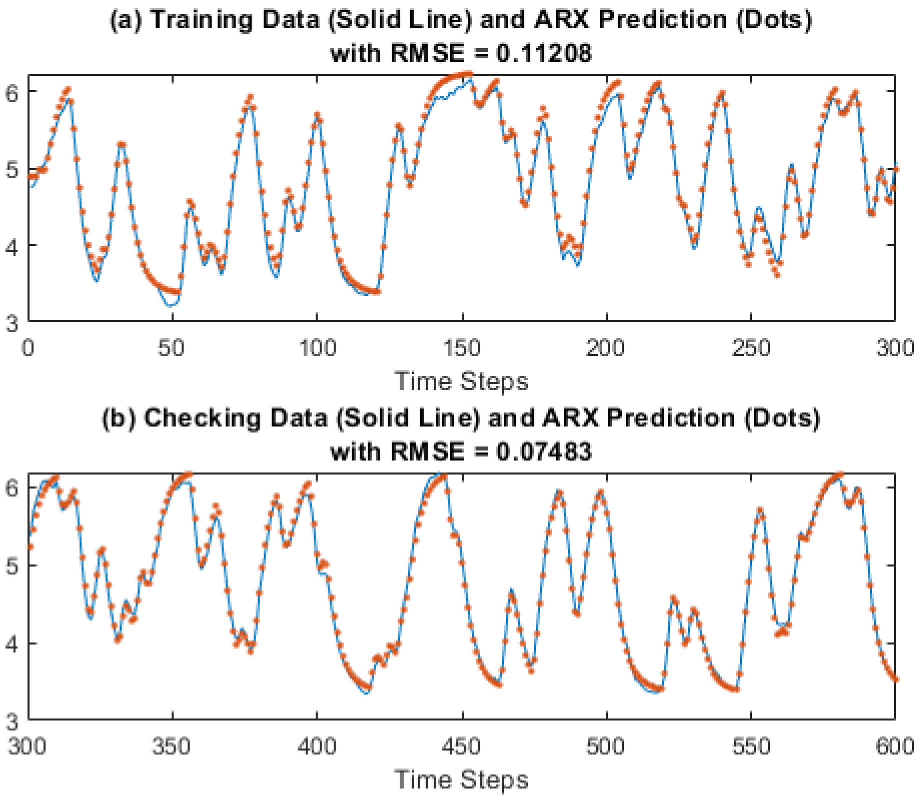
y(k)+a1*y(k-1)+...+am*y(k-m)=b1*u(k-d)+...+bn*u(k-d-n+1)

where ai (i = 1 to m) and bj (j = 1 to n) are linear parameters to be determined by least-squares methods. This structure is called the ARX model and it is exactly specified by three integers [m, n, d]. To find an ARX model for the dryer device, the data set was divided into a training (k = 1 to 300) and a checking (k = 301 to 600) set. An exhaustive search was performed to find the best combination of [m, n, d], where each of the integer is allowed to changed from 1 to 10 independently. The best ARX model thus found is specified by [m, n, d] = [5, 10, 2], with a training RMSE of 0.1122 and a checking RMSE of 0.0749. The above figure shows the fitting results of the best ARX model.

```
trn_data_n = 300;
total_data_n = 600;
z = [y2 u2];
z = dtrend(z);
ave = mean(y2);
ze = z(1:trn_data_n,:);
zv = z(trn_data_n+1:total_data_n,:);
T = 0.08;

% Run through all different models
V = arxstruc(ze,zv,struc(1:10,1:10,1:10));
% Find the best model
nn = selstruc(V,0);
% Time domain plot
th = arx(ze,nn);
th.Ts = 0.08;
u = z(:,2);
y = z(:,1)+ave;
yp = sim(u,th)+ave;
```

```
xlbl = 'Time Steps';

subplot(2,1,1)
index = 1:trn_data_n;
plot(index, y(index), index, yp(index), '.')
rmse = norm(y(index)-yp(index))/sqrt(length(index));
title(sprintf(['(a) Training Data (Solid Line) and ARX Prediction (Dots)\nwith RMSE =
disp(['[na nb d] = ' num2str(nn)])
xlabel(xlbl,'fontsize',10)

subplot(2,1,2)
index = (trn_data_n+1):(total_data_n);
plot(index,y(index),index,yp(index),'.')
rmse = norm(y(index)-yp(index))/sqrt(length(index));
title(sprintf(['(b) Checking Data (Solid Line) and ARX Prediction (Dots)\nwith RMSE =
xlabel(xlbl,'fontsize',10)
```

```
[na nb d] = 5  10   2
```



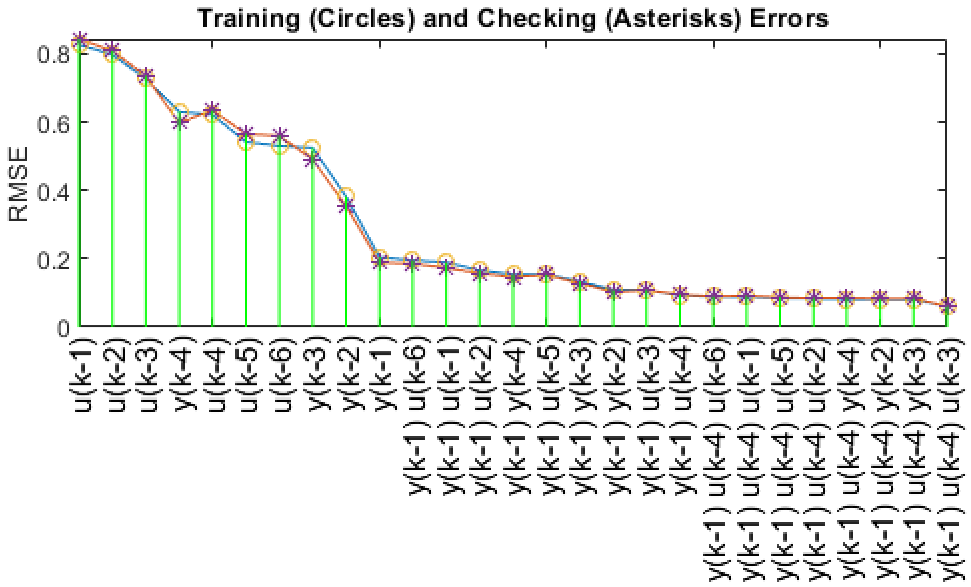
ANFIS Model Identification

The ARX model is inherently linear and the most significant advantage is that we can perform model structure and parameter identification rapidly. The performance in the above plots appears to be satisfactory. However, if a better performance level is desired, we might want to resort to a nonlinear model. In particular, we are going to use a neuro-fuzzy modeling approach, ANFIS, to see if we can push the performance level with a fuzzy inference system.

To use ANFIS for system identification, the first thing we need to do is select the input. That is, to determine which variables should be the input arguments to an ANFIS model. For simplicity, we suppose that there are 10 input candidates (y(k-1), y(k-2), y(k-3), y(k-4), u(k-1), u(k-2), u(k-3), u(k-4), u(k-5), u(k-6)), and the output to be predicted is y(k). A heuristic approach to input selection is called sequential forward search, in which each input is selected sequentially to optimize the total squared error. This can be done by the function seqsrch; the result is shown in the above plot, where 3 inputs (y(k-1), u(k-3), and u(k-4)) are selected with a training RMSE of 0.0609 and checking RMSE of 0.0604.

```
trn_data_n = 300;
trn_data = data(1:trn_data_n,:);
chk_data = data(trn_data_n+1:trn_data_n+300,:);
[~,elapsed_time] = seqsrch(3,trn_data,chk_data,input_name); % #ok<*ASGLU>
fprintf('\nElapsed time = %f\n',elapsed_time);
winH1 = gcf;
```

```
Selecting input 1 ...
ANFIS model 1: y(k-1) --> trn=0.2043, chk=0.1888
ANFIS model 2: y(k-2) --> trn=0.3819, chk=0.3541
ANFIS model 3: y(k-3) --> trn=0.5245, chk=0.4903
ANFIS model 4: y(k-4) --> trn=0.6308, chk=0.5977
ANFIS model 5: u(k-1) --> trn=0.8271, chk=0.8434
ANFIS model 6: u(k-2) --> trn=0.7976, chk=0.8087
ANFIS model 7: u(k-3) --> trn=0.7266, chk=0.7349
ANFIS model 8: u(k-4) --> trn=0.6215, chk=0.6346
ANFIS model 9: u(k-5) --> trn=0.5419, chk=0.5650
ANFIS model 10: u(k-6) --> trn=0.5304, chk=0.5601
Currently selected inputs: y(k-1)

Selecting input 2 ...
ANFIS model 11: y(k-1) y(k-2) --> trn=0.1085, chk=0.1024
ANFIS model 12: y(k-1) y(k-3) --> trn=0.1339, chk=0.1283
ANFIS model 13: y(k-1) y(k-4) --> trn=0.1542, chk=0.1461
ANFIS model 14: y(k-1) u(k-1) --> trn=0.1892, chk=0.1734
ANFIS model 15: y(k-1) u(k-2) --> trn=0.1663, chk=0.1574
ANFIS model 16: y(k-1) u(k-3) --> trn=0.1082, chk=0.1077
ANFIS model 17: y(k-1) u(k-4) --> trn=0.0925, chk=0.0948
ANFIS model 18: y(k-1) u(k-5) --> trn=0.1533, chk=0.1531
ANFIS model 19: y(k-1) u(k-6) --> trn=0.1952, chk=0.1853
Currently selected inputs: y(k-1) u(k-4)

Selecting input 3 ...
ANFIS model 20: y(k-1) u(k-4) y(k-2) --> trn=0.0808, chk=0.0822
ANFIS model 21: y(k-1) u(k-4) y(k-3) --> trn=0.0806, chk=0.0836
ANFIS model 22: y(k-1) u(k-4) y(k-4) --> trn=0.0817, chk=0.0855
ANFIS model 23: y(k-1) u(k-4) u(k-1) --> trn=0.0886, chk=0.0912
ANFIS model 24: y(k-1) u(k-4) u(k-2) --> trn=0.0835, chk=0.0843
ANFIS model 25: y(k-1) u(k-4) u(k-3) --> trn=0.0609, chk=0.0604
ANFIS model 26: y(k-1) u(k-4) u(k-5) --> trn=0.0848, chk=0.0867
ANFIS model 27: y(k-1) u(k-4) u(k-6) --> trn=0.0890, chk=0.0894
Currently selected inputs: y(k-1) u(k-3) u(k-4)

Elapsed time = 25.675000
```



For input selection, another more computationally intensive approach is to do an exhaustive search on all possible combinations of the input candidates. The function that performs exhaustive search is exhsrch, which selects 3 inputs from 10 candidates. However, exhsrch usually involves a significant amount of computation if all combinations are tried. For instance, if 3 is selected out of 10, the total number of ANFIS models is C(10, 3) = 120.

Fortunately, for dynamic system identification, we do know that the inputs should not come from either of the following two sets of input candidates exclusively:

Y = {y(k-1), y(k-2), y(k-3), y(k-4)}

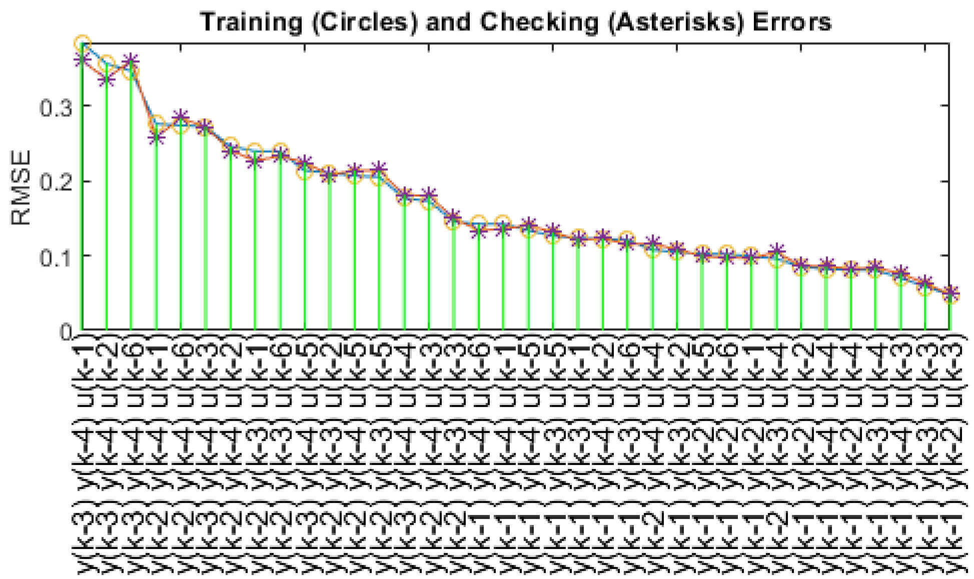
U = {u(k-1), u(k-2), u(k-3), u(k-4), u(k-5), u(k-6)}

A reasonable guess would be to take two inputs from Y and one from U to form the inputs to ANFIS; the total number of ANFIS models is then C(4,2)*6=36, which is much less. The above plot shows that the selected inputs are y(k-1), y(k-2) and u(k-3), with a training RMSE of 0.0474 and checking RMSE of 0.0485, which are better than ARX models and ANFIS via sequential forward search.

```
group1 = [1 2 3 4];    % y(k-1), y(k-2), y(k-3), y(k-4)
group2 = [1 2 3 4];    % y(k-1), y(k-2), y(k-3), y(k-4)
group3 = [5 6 7 8 9 10];    % u(k-1) through y(k-6)

anfis_n = 6*length(group3);
index = zeros(anfis_n,3);
trn_error = zeros(anfis_n,1);
chk_error = zeros(anfis_n,1);
% ======= Training options
% Create option set for generating initial FIS.
genOpt = genfisOptions('GridPartition','NumMembershipFunctions',2, ...
                       'InputMembershipFunctionType','gbellmf');
% Create option set for |anfis| command and set options that remain constant
% for different training scenarios.
anfisOpt = anfisOptions('EpochNumber',1,...
                        'InitialStepSize',0.1,...
                        'StepSizeDecreaseRate',0.5,...
                        'StepSizeIncreaseRate',1.5,...
                        'DisplayANFISInformation',0,...
                        'DisplayErrorValues',0,...
                        'DisplayStepSize',0,...
                        'DisplayFinalResults',0);
% ====== Train ANFIS with different input variables
fprintf('\nTrain %d ANFIS models, each with 3 inputs selected from 10 candidates...\n\
    anfis_n);
model = 1;
for i = 1:length(group1)
    for j = i+1:length(group2)
        for k = 1:length(group3)
            in1 = deblank(input_name(group1(i),:));
            in2 = deblank(input_name(group2(j),:));
            in3 = deblank(input_name(group3(k),:));
            index(model, :) = [group1(i) group2(j) group3(k)];
            trn_data = data(1:trn_data_n, [group1(i) group2(j) group3(k) size(data,2)]
            chk_data = data(trn_data_n+1:trn_data_n+300, [group1(i) group2(j) group3(k
            in_fismat = genfis(trn_data(:,1:end-1),trn_data(:,end),genOpt);
            % Set initial FIS and validation data in option set for ANFIS training.
            anfisOpt.InitialFIS = in_fismat;
            anfisOpt.ValidationData = chk_data;
            [~, t_err, ~, ~, c_err] = anfis(trn_data,anfisOpt);
            trn_error(model) = min(t_err);
            chk_error(model) = min(c_err);
            fprintf('ANFIS model = %d: %s %s %s',model,in1,in2,in3);
            fprintf(' --> trn=%.4f,',trn_error(model));
            fprintf(' chk=%.4f',chk_error(model));
            fprintf('\n');
            model = model+1;
        end
    end
end

% ====== Reordering according to training error
[~, b] = sort(trn_error);
b = flipud(b);        % List according to decreasing trn error
trn_error = trn_error(b);
chk_error = chk_error(b);
index = index(b,:);

% ====== Display training and checking errors
x = (1:anfis_n)';
subplot(2,1,1)
plot(x, trn_error,'-',x,chk_error,'-', ...
     x,trn_error,'o',x,chk_error,'*')
tmp = x(:, ones(1,3))';
X = tmp(:);
tmp = [zeros(anfis_n,1) max(trn_error,chk_error) nan*ones(anfis_n,1)]';
Y = tmp(:);
hold on
plot(X,Y,'g')
hold off
axis([1 anfis_n -inf inf])
h_gca = gca;
h_gca.XTickLabel = [];

% ====== Add text of input variables
```

```
for k = 1:anfis_n
    text(x(k), 0, ...
        [input_name(index(k,1),:) ' ' ...
         input_name(index(k,2),:) ' ' ...
         input_name(index(k,3),:)]);
end
h = findobj(gcf,'type','text');
set(h,'rot',90,'fontsize',11,'hori','right');

drawnow

% ====== Generate input_index for bjtrain.m
[a, b] = min(trn_error);
input_index = index(b,:);
title('Training (Circles) and Checking (Asterisks) Errors','fontsize',10)
ylabel('RMSE','fontsize',10)
```

```
Train 36 ANFIS models, each with 3 inputs selected from 10 candidates...

ANFIS model = 1: y(k-1) y(k-2) u(k-1) --> trn=0.0990, chk=0.0962
ANFIS model = 2: y(k-1) y(k-2) u(k-2) --> trn=0.0852, chk=0.0862
ANFIS model = 3: y(k-1) y(k-2) u(k-3) --> trn=0.0474, chk=0.0485
ANFIS model = 4: y(k-1) y(k-2) u(k-4) --> trn=0.0808, chk=0.0822
ANFIS model = 5: y(k-1) y(k-2) u(k-5) --> trn=0.1023, chk=0.0991
ANFIS model = 6: y(k-1) y(k-2) u(k-6) --> trn=0.1021, chk=0.0974
ANFIS model = 7: y(k-1) y(k-3) u(k-1) --> trn=0.1231, chk=0.1206
ANFIS model = 8: y(k-1) y(k-3) u(k-2) --> trn=0.1047, chk=0.1085
ANFIS model = 9: y(k-1) y(k-3) u(k-3) --> trn=0.0587, chk=0.0626
ANFIS model = 10: y(k-1) y(k-3) u(k-4) --> trn=0.0806, chk=0.0836
ANFIS model = 11: y(k-1) y(k-3) u(k-5) --> trn=0.1261, chk=0.1311
ANFIS model = 12: y(k-1) y(k-3) u(k-6) --> trn=0.1210, chk=0.1151
ANFIS model = 13: y(k-1) y(k-4) u(k-1) --> trn=0.1420, chk=0.1353
ANFIS model = 14: y(k-1) y(k-4) u(k-2) --> trn=0.1224, chk=0.1229
ANFIS model = 15: y(k-1) y(k-4) u(k-3) --> trn=0.0700, chk=0.0765
ANFIS model = 16: y(k-1) y(k-4) u(k-4) --> trn=0.0817, chk=0.0855
ANFIS model = 17: y(k-1) y(k-4) u(k-5) --> trn=0.1337, chk=0.1405
ANFIS model = 18: y(k-1) y(k-4) u(k-6) --> trn=0.1421, chk=0.1333
ANFIS model = 19: y(k-2) y(k-3) u(k-1) --> trn=0.2393, chk=0.2264
ANFIS model = 20: y(k-2) y(k-3) u(k-2) --> trn=0.2104, chk=0.2077
ANFIS model = 21: y(k-2) y(k-3) u(k-3) --> trn=0.1452, chk=0.1497
ANFIS model = 22: y(k-2) y(k-3) u(k-4) --> trn=0.0958, chk=0.1047
ANFIS model = 23: y(k-2) y(k-3) u(k-5) --> trn=0.2048, chk=0.2135
ANFIS model = 24: y(k-2) y(k-3) u(k-6) --> trn=0.2388, chk=0.2326
ANFIS model = 25: y(k-2) y(k-4) u(k-1) --> trn=0.2756, chk=0.2574
ANFIS model = 26: y(k-2) y(k-4) u(k-2) --> trn=0.2455, chk=0.2400
ANFIS model = 27: y(k-2) y(k-4) u(k-3) --> trn=0.1726, chk=0.1797
ANFIS model = 28: y(k-2) y(k-4) u(k-4) --> trn=0.1074, chk=0.1157
ANFIS model = 29: y(k-2) y(k-4) u(k-5) --> trn=0.2061, chk=0.2133
ANFIS model = 30: y(k-2) y(k-4) u(k-6) --> trn=0.2737, chk=0.2836
ANFIS model = 31: y(k-3) y(k-4) u(k-1) --> trn=0.3842, chk=0.3605
ANFIS model = 32: y(k-3) y(k-4) u(k-2) --> trn=0.3561, chk=0.3358
ANFIS model = 33: y(k-3) y(k-4) u(k-3) --> trn=0.2719, chk=0.2714
ANFIS model = 34: y(k-3) y(k-4) u(k-4) --> trn=0.1763, chk=0.1808
ANFIS model = 35: y(k-3) y(k-4) u(k-5) --> trn=0.2132, chk=0.2240
ANFIS model = 36: y(k-3) y(k-4) u(k-6) --> trn=0.3460, chk=0.3601
```

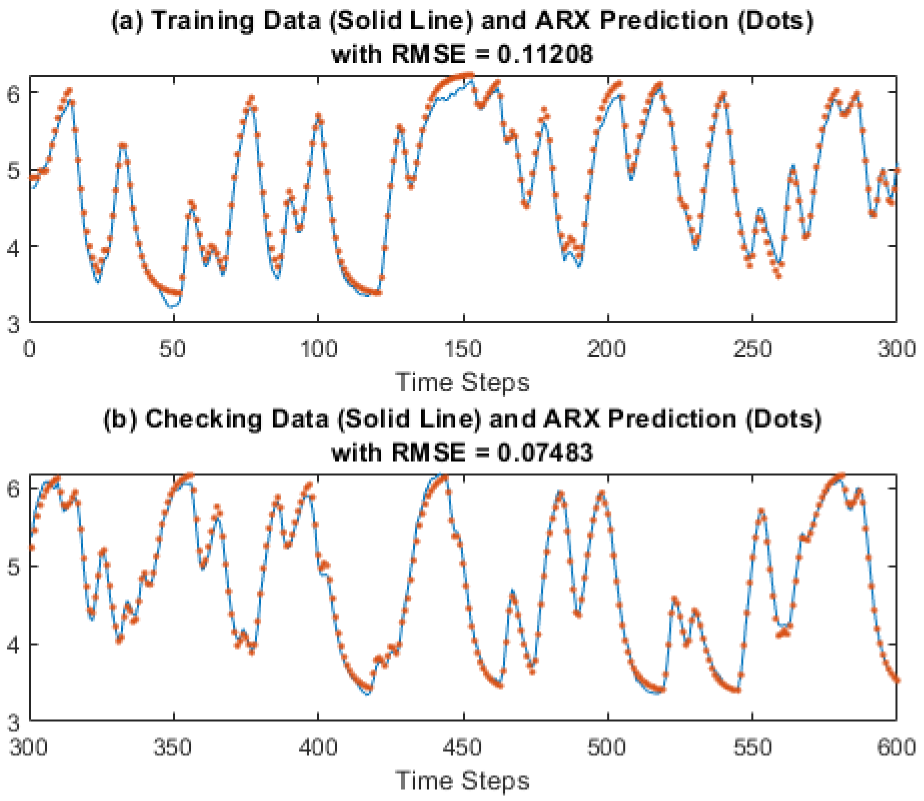


This window shows ANFIS predictions on both training and checking data sets. Obviously the performance is better than those of the ARX model.

```
if ishghandle(winH1),delete(winH1);
end

trn_data = data(1:trn_data_n,[input_index, size(data,2)]);
chk_data = data(trn_data_n+1:600,[input_index, size(data,2)]);

% generate FIS matrix
in_fismat = genfis(trn_data(:,1:end-1),trn_data(:,end));
anfisOpt = anfisOptions('InitialFIS',in_fismat,...
                        'EpochNumber',1,...
                        'InitialStepSize',0.01,...
                        'StepSizeDecreaseRate',0.5,...
                        'StepSizeIncreaseRate',1.5,...
                        'ValidationData',chk_data);
[trn_out_fismat,trn_error,step_size,chk_out_fismat,chk_error] = ...
    anfis(trn_data,anfisOpt);

subplot(2,1,1)
index = 1:trn_data_n;
plot(index,y(index),index,yp(index),'.')
rmse = norm(y(index)-yp(index))/sqrt(length(index));
title(sprintf(['(a) Training Data (Solid Line) and ARX Prediction (Dots)\nwith RMSE =
disp(['[na nb d] = ' num2str(nn)])
xlabel('Time Steps','fontsize',10)
subplot(2,1,2)
index = (trn_data_n+1):(total_data_n);
plot(index, y(index),index,yp(index),'.')
rmse = norm(y(index)-yp(index))/sqrt(length(index));
title(sprintf(['(b) Checking Data (Solid Line) and ARX Prediction (Dots)\nwith RMSE =
xlabel('Time Steps','fontsize',10)
```

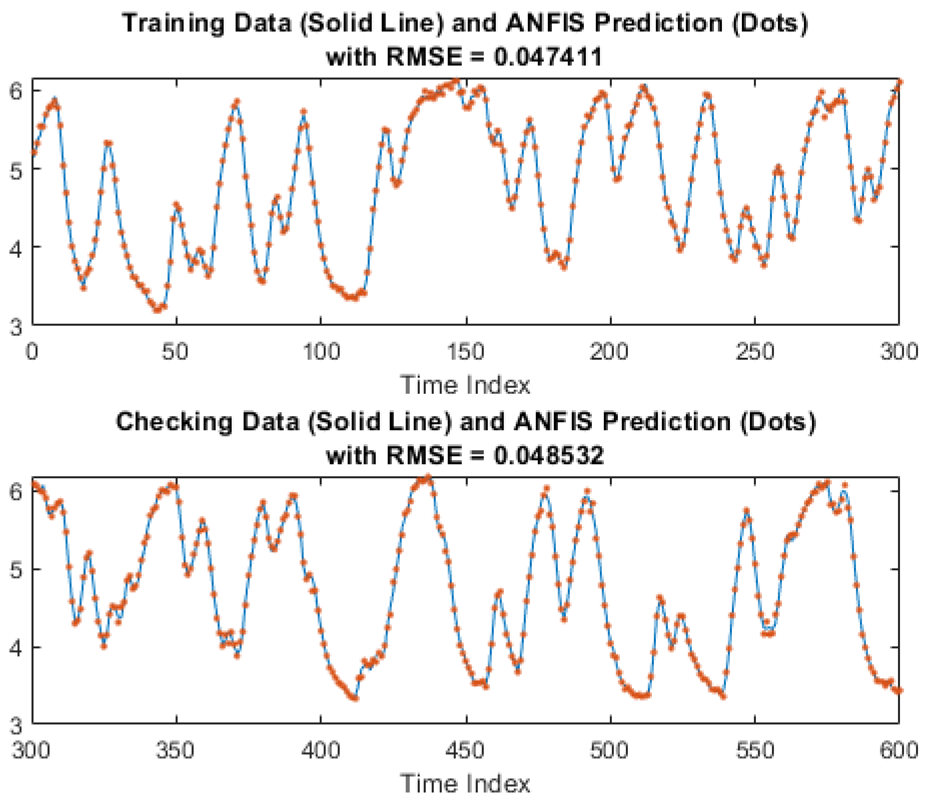
```
ANFIS info:
    Number of nodes: 34
    Number of linear parameters: 32
    Number of nonlinear parameters: 18
    Total number of parameters: 50
    Number of training data pairs: 300
    Number of checking data pairs: 300
    Number of fuzzy rules: 8


Start training ANFIS ...

   1      0.0474113      0.0485325
```

```
Designated epoch number reached --> ANFIS training completed at epoch 1.

Minimal training RMSE = 0.047411
Minimal checking RMSE = 0.0485325
[na nb d] = 5  10   2
```



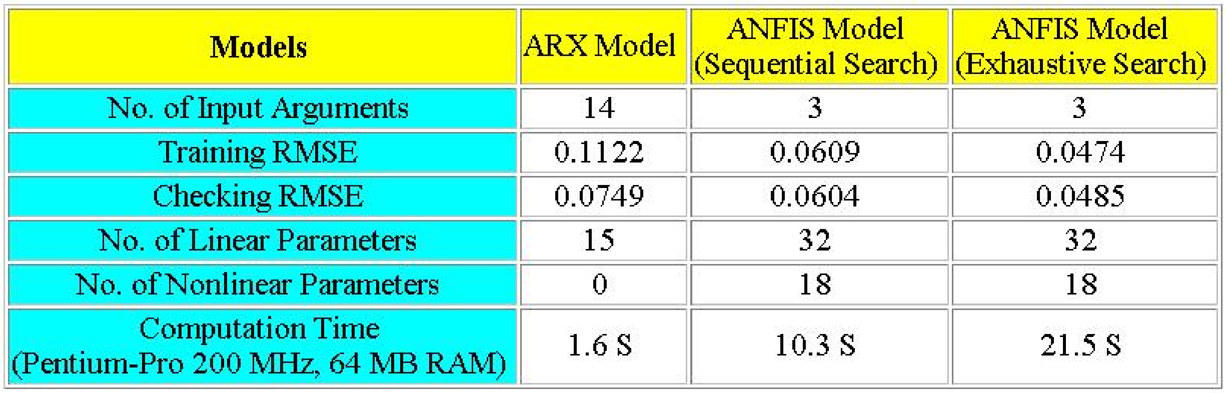
```
y_hat = evalfis(chk_out_fismat,data(1:600,input_index));

subplot(2,1,1)
index = 1:trn_data_n;
plot(index,data(index,size(data,2)),'-', ...
     index,y_hat(index),'.')
rmse = norm(y_hat(index)-data(index,size(data,2)))/sqrt(length(index));
```

```
title(sprintf(['Training Data (Solid Line) and ANFIS Prediction (Dots)\nwith RMSE = ' r
xlabel('Time Index','fontsize',10)
ylabel('')

subplot(2,1,2)
index = trn_data_n+1:600;
plot(index,data(index,size(data,2)),'-',index,y_hat(index),'.')
rmse = norm(y_hat(index)-data(index,size(data,2)))/sqrt(length(index));
title(sprintf(['Checking Data (Solid Line) and ANFIS Prediction (Dots)\nwith RMSE = ' r
xlabel('Time Index','fontsize',10)
ylabel('')
```



Conclusion

The table above is a comparison among various modeling approaches. The ARX modeling spends the least amount of time to reach the worst precision, and the ANFIS modeling via exhaustive search takes the most amount of time to reach the best precision. In other words, if fast modeling is the goal, then ARX is the right choice. But if precision is the utmost concern, then we should go with ANFIS, which is designed for nonlinear modeling and higher precision.



Models	ARX Model	ANFIS Model (Sequential Search)	ANFIS Model (Exhaustive Search)
No. of Input Arguments	14	3	3
Training RMSE	0.1122	0.0609	0.0474
Checking RMSE	0.0749	0.0604	0.0485
No. of Linear Parameters	15	32	32
No. of Nonlinear Parameters	0	18	18
Computation Time (Pentium-Pro 200 MHz, 64 MB RAM)	1.6 S	10.3 S	21.5 S

See Also

`anfis` | `evalfis` | `genfis`

More About

- "Neuro-Adaptive Learning and ANFIS" on page 3-86

Gas Mileage Prediction

This example shows how to predict of fuel consumption (miles per gallon) for automobiles, using data from previously recorded observations.

Introduction

Automobile MPG (miles per gallon) prediction is a typical nonlinear regression problem, in which several attributes of an automobile's profile information are used to predict another continuous attribute, the fuel consumption in MPG. The training data is available in the UCI (Univ. of California at Irvine) Machine Learning Repository and contains data collected from automobiles of various makes and models.

The table shown above is several observations or samples from the MPG data set. The six input attributes are no. of cylinders, displacement, horsepower, weight, acceleration, and model year. The output variable to be predicted is the fuel consumption in MPG. (The automobile's manufacturers and models in the first column of the table are not used for prediction).

Partitioning Data

The data set is obtained from the original data file 'auto-gas.dat'. The dataset is then partitioned into a training set (odd-indexed samples) and a checking set (even-indexed samples).

```
[data,input_name] = loadgas;
trn_data = data(1:2:end,:);
chk_data = data(2:2:end,:);
```

Input Selection

The function `exhsrch` performs an exhaustive search within the available inputs to select the set of inputs that most influence the fuel consumption. The first parameter to the function specifies the number of input combinations to be tried during the search. Essentially, `exhsrch` builds an ANFIS model for each combination and trains it for one epoch and reports the performance achieved. In the following example, `exhsrch` is used to determine the one most influential input attribute in predicting the output.

```
exhsrch(1,trn_data,chk_data,input_name);
```

```
Train 6 ANFIS models, each with 1 inputs selected from 6 candidates...

ANFIS model 1: Cylinder --> trn=4.6400, chk=4.7255
ANFIS model 2: Disp --> trn=4.3106, chk=4.4316
ANFIS model 3: Power --> trn=4.5399, chk=4.1713
ANFIS model 4: Weight --> trn=4.2577, chk=4.0863
ANFIS model 5: Acceler --> trn=6.9789, chk=6.9317
ANFIS model 6: Year --> trn=6.2255, chk=6.1693
```

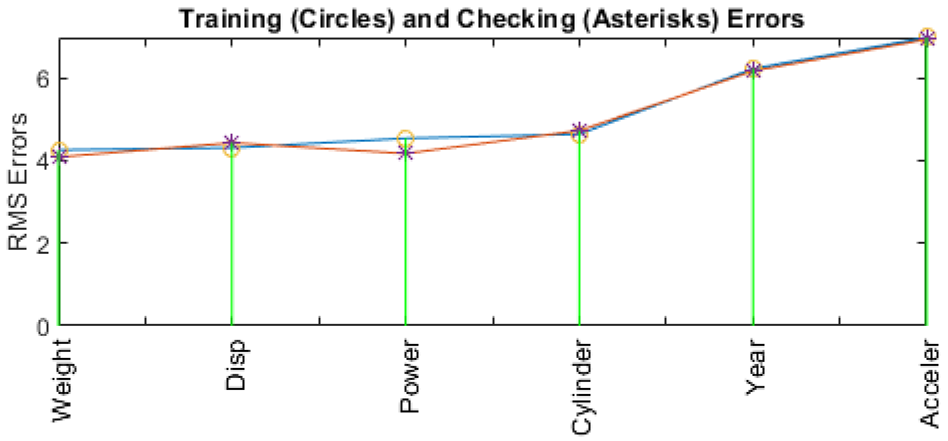


Figure 1: Every input variable's influence on fuel consumption

The left-most input variable in Figure 1 has the least error or in other words the most relevance with respect to the output.

The plot and results from the function clearly indicate that the input attribute 'Weight' is the most influential. The training and checking errors are comparable, which implies that there is no overfitting. This means we can push a little further and explore if we can select more than one input attribute to build the ANFIS model.

Intuitively, we can simply select `Weight` and `Disp` directly since they have the least errors as shown in the plot. However, this will not necessarily be the optimal combination of two inputs that result in the minimal training error. To verify this, we can use `exhsrch` to search for the optimal combination of 2 input attributes.

```
input_index = exhsrch(2,trn_data,chk_data,input_name);
```

```
Train 15 ANFIS models, each with 2 inputs selected from 6 candidates...

ANFIS model 1: Cylinder Disp --> trn=3.9320, chk=4.7920
ANFIS model 2: Cylinder Power --> trn=3.7364, chk=4.8683
ANFIS model 3: Cylinder Weight --> trn=3.8741, chk=4.6763
ANFIS model 4: Cylinder Acceler --> trn=4.3287, chk=5.9625
ANFIS model 5: Cylinder Year --> trn=3.7129, chk=4.5946
ANFIS model 6: Disp Power --> trn=3.8087, chk=3.8594
ANFIS model 7: Disp Weight --> trn=4.0271, chk=4.6350
ANFIS model 8: Disp Acceler --> trn=4.0782, chk=4.4890
ANFIS model 9: Disp Year --> trn=2.9565, chk=3.3905
ANFIS model 10: Power Weight --> trn=3.9310, chk=4.2976
ANFIS model 11: Power Acceler --> trn=4.2740, chk=3.8738
ANFIS model 12: Power Year --> trn=3.3796, chk=3.3505
ANFIS model 13: Weight Acceler --> trn=4.0875, chk=4.0095
ANFIS model 14: Weight Year --> trn=2.7657, chk=2.9953
ANFIS model 15: Acceler Year --> trn=5.6242, chk=5.6481
```

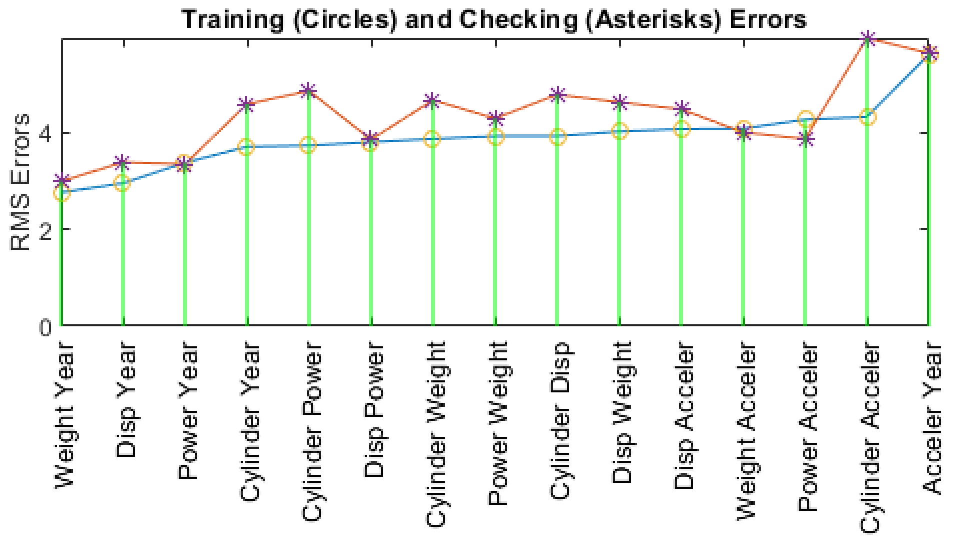


Figure 2: All two input variable combinations and their influence on fuel consumption

The results from `exhsrch` indicate that `Weight` and `Year` form the optimal combination of two input attributes. The training and checking errors are getting distinguished, indicating the outset of overfitting. It may not be prudent to use more than two inputs for building the ANFIS model. We can test this premise to verify it's validity.

```
exhsrch(3,trn_data,chk_data,input_name);
```

```
Train 20 ANFIS models, each with 3 inputs selected from 6 candidates...

ANFIS model 1: Cylinder Disp Power --> trn=3.4446, chk=11.5329
ANFIS model 2: Cylinder Disp Weight --> trn=3.6686, chk=4.8922
ANFIS model 3: Cylinder Disp Acceler --> trn=3.6610, chk=5.2384
ANFIS model 4: Cylinder Disp Year --> trn=2.5463, chk=4.9001
ANFIS model 5: Cylinder Power Weight --> trn=3.4797, chk=9.3761
ANFIS model 6: Cylinder Power Acceler --> trn=3.5432, chk=4.4804
ANFIS model 7: Cylinder Power Year --> trn=2.6300, chk=3.6300
ANFIS model 8: Cylinder Weight Acceler --> trn=3.5708, chk=4.8379
ANFIS model 9: Cylinder Weight Year --> trn=2.4951, chk=4.0435
ANFIS model 10: Cylinder Acceler Year --> trn=3.2698, chk=6.2616
ANFIS model 11: Disp Power Weight --> trn=3.5879, chk=7.4942
ANFIS model 12: Disp Power Acceler --> trn=3.5395, chk=3.9953
ANFIS model 13: Disp Power Year --> trn=2.4607, chk=3.3563
ANFIS model 14: Disp Weight Acceler --> trn=3.6075, chk=4.2318
ANFIS model 15: Disp Weight Year --> trn=2.5617, chk=3.7866
ANFIS model 16: Disp Acceler Year --> trn=2.4149, chk=3.2480
ANFIS model 17: Power Weight Acceler --> trn=3.7884, chk=4.0480
ANFIS model 18: Power Weight Year --> trn=2.4371, chk=3.2852
ANFIS model 19: Power Acceler Year --> trn=2.7276, chk=3.2580
ANFIS model 20: Weight Acceler Year --> trn=2.3603, chk=2.9152
```

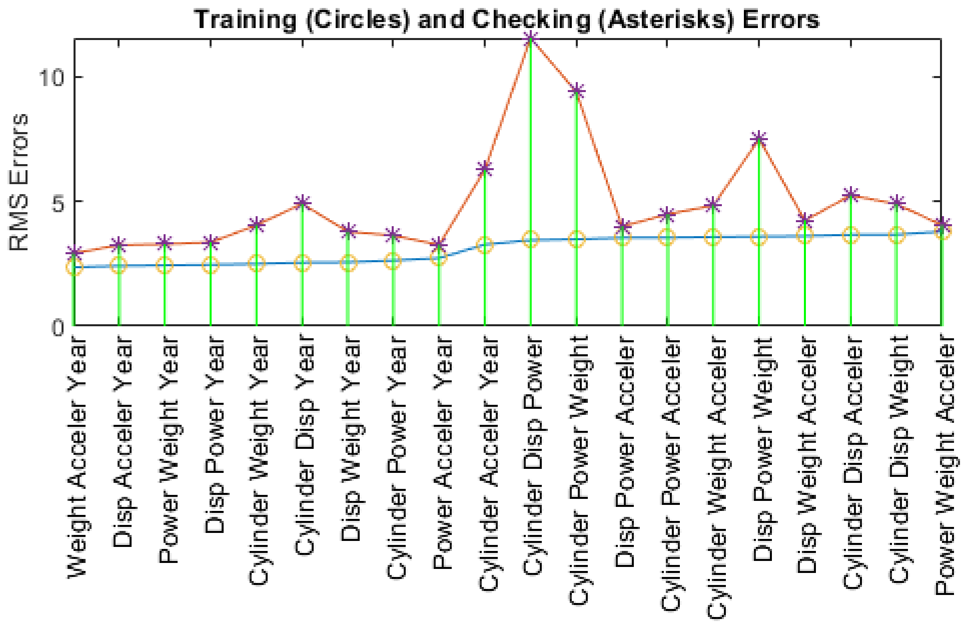


Figure 3: All three input variable combinations and their influence on fuel consumption

The plot shows the result of selecting three inputs, in which `Weight`, `Year`, and `Acceler` are selected as the best combination of three input variables. However, the minimal training (and checking) error do not reduce significantly from that of the best two-input model, which indicates that the newly added attribute `Acceler` does not improve the prediction much. For better generalization, we always prefer a model with a simple structure. Therefore we will stick to the two-input ANFIS for further exploration.

We then extract the selected input attributes from the original training and checking datasets.

```
close all;
new_trn_data = trn_data(:,[input_index, size(trn_data,2)]);
new_chk_data = chk_data(:,[input_index, size(chk_data,2)]);
```

Training ANFIS Model

The function `exhsrch` only trains each ANFIS for a single epoch in order to be able to quickly find the right inputs. Now that the inputs are fixed, we can spend more time on ANFIS training (100 epochs).

The `genfis` function generates a initial FIS from the training data, which is then fine-tuned by ANFIS to generate the final model.

```
in_fismat = genfis(new_trn_data(:,1:end-1),new_trn_data(:,end));
anfisOpt = anfisOptions('InitialFIS',in_fismat,'EpochNumber',100,...
                        'StepSizeDecreaseRate',0.5,...
                        'StepSizeIncreaseRate',1.5,...
                        'ValidationData',new_chk_data,...
                        'DisplayANFISInformation',0,...
                        'DisplayErrorValues',0,...
                        'DisplayStepSize',0,...
                        'DisplayFinalResults',0);
[trn_out_fismat,trn_error,step_size,chk_out_fismat,chk_error] = ...
    anfis(new_trn_data,anfisOpt);
```

ANFIS returns the error with respect to training data and checking data in the list of its output parameters. The plot of the errors provides useful information about the training process.

```
[a,b] = min(chk_error);
plot(1:100,trn_error,'g-',1:100,chk_error,'r-',b,a,'ko')
title('Training (green) and checking (red) error curve','fontsize',10)
xlabel('Epoch numbers','fontsize',10)
ylabel('RMS errors','fontsize',10)
```

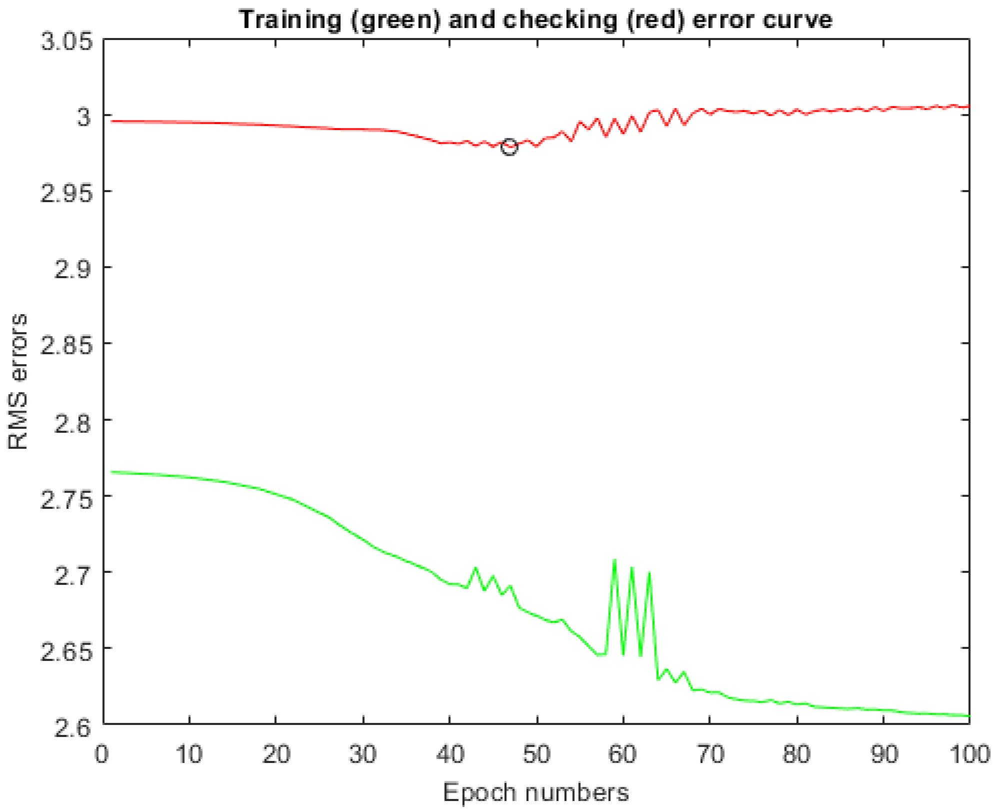


Figure 4: ANFIS training and checking errors

The plot above shows the error curves for 100 epochs of ANFIS training. The green curve gives the training errors and the red curve gives the checking errors. The minimal checking error occurs at about epoch 45, which is indicated by a circle. Notice that the checking error curve goes up after 50 epochs, indicating that further training over fits the data and produces worse generalization

ANFIS vs Linear Regression

A good exercise at this point would be to check the performance of the ANFIS model with a linear regression model.

The ANFIS prediction can be compared against a linear regression model by comparing their respective RMSE (Root mean square) values against checking data.

```
% Performing Linear Regression
N = size(trn_data,1);
A = [trn_data(:,1:6) ones(N,1)];
B = trn_data(:,7);
coef = A\B; % Solving for regression parameters from training data

Nc = size(chk_data,1);
A_ck = [chk_data(:,1:6) ones(Nc,1)];
B_ck = chk_data(:,7);
lr_rmse = norm(A_ck*coef-B_ck)/sqrt(Nc);
% Printing results
fprintf('\nRMSE against checking data\nANFIS : %1.3f\tLinear Regression : %1.3f\n',a,l
```

```
RMSE against checking data
ANFIS : 2.978    Linear Regression : 3.444
```

It can be seen that the ANFIS model outperforms the linear regression model.

Analyzing ANFIS Model

The variable `chk_out_fismat` represents the snapshot of the ANFIS model at the minimal checking error during the training process. The input-output surface of the model is shown in the plot below.

```
chk_out_fismat.Inputs(1).Name = "Weight";
chk_out_fismat.Inputs(2).Name = "Year";
chk_out_fismat.Outputs(1).Name = "MPG";

% Generating the FIS output surface plot
gensurf(chk_out_fismat);
```

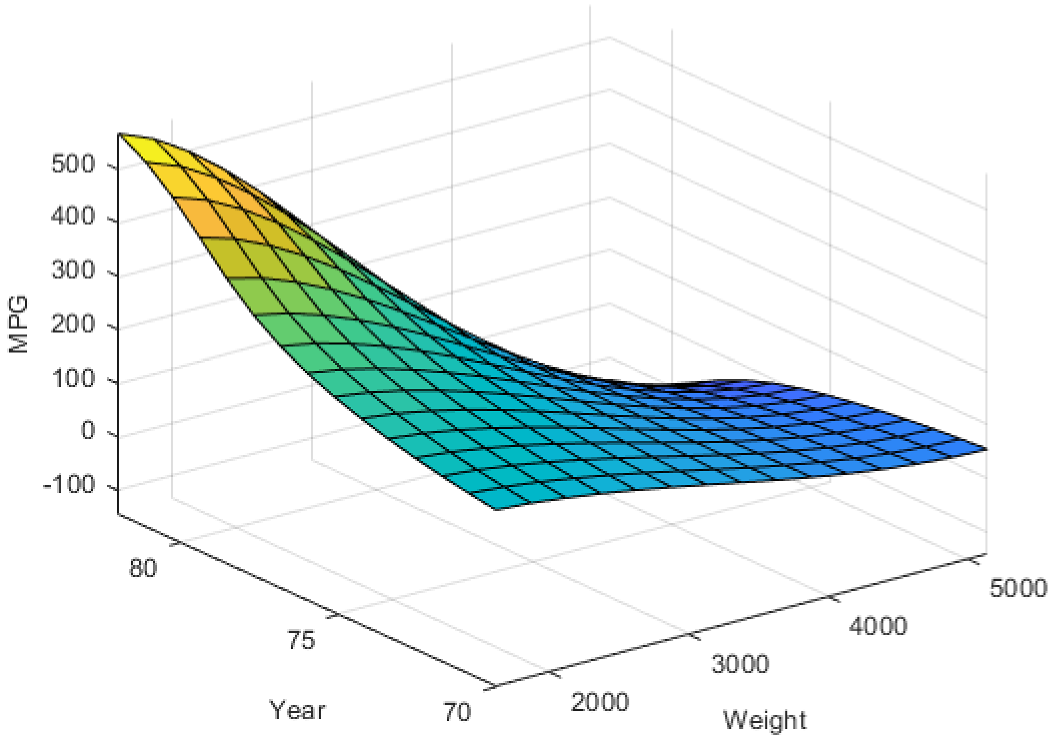


Figure 5: Input-Output surface for trained FIS

The input-output surface shown above is a nonlinear and monotonic surface and illustrates how the ANFIS model will respond to varying values of 'weight' and 'year'.

Limitations and Cautions

We can see some spurious effects at the far-end corner of the surface. The elevated corner says that the heavier an automobile is, the more gas-efficient it will be. This is totally counter-intuitive, and it is a direct result from lack of data.

```
plot(new_trn_data(:,1),new_trn_data(:, 2),'bo', ...
     new_chk_data(:,1),new_chk_data(:, 2),'rx')
xlabel('Weight','fontsize',10)
```

```
ylabel('Year','fontsize',10)
title('Training (o) and checking (x) data','fontsize',10)
```

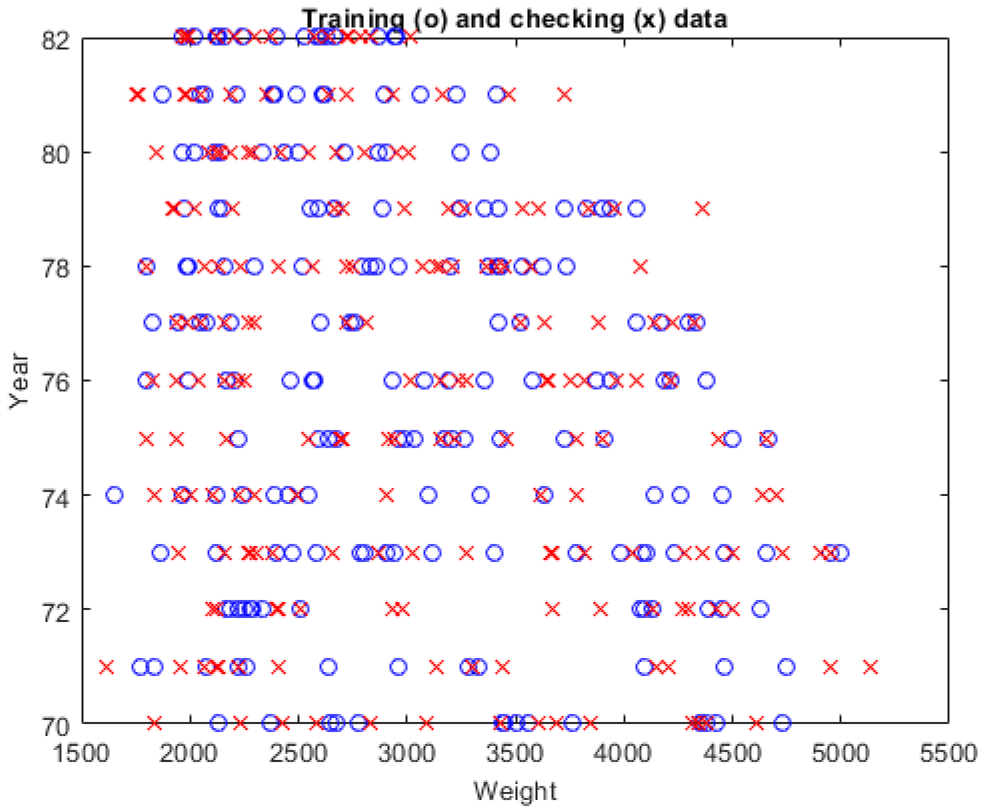


Figure 6: Weight vs Year plot showing lack of data in the upper-right corner

This plot above shows the data distribution. The lack of training data at the upper right corner causes the spurious ANFIS surface mentioned earlier. Therefore the prediction by ANFIS should always be interpreted with the data distribution in mind.

See Also

`anfis` | `evalfis` | `genfis`

More About

- "Neuro-Adaptive Learning and ANFIS" on page 3-86

Data Clustering

Fuzzy Clustering

What Is Data Clustering?

Clustering of numerical data forms the basis of many classification and system modeling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior.

Fuzzy Logic Toolbox tools allow you to find clusters in input-output training data. You can use the cluster information to generate a Sugeno-type fuzzy inference system that best models the data behavior using a minimum number of rules. The rules partition themselves according to the fuzzy qualities associated with each of the data clusters. to automatically generate this type of FIS, use the `genfis` command.

Fuzzy C-Means Clustering

Fuzzy c-means (FCM) is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. This technique was originally introduced by Jim Bezdek in 1981 [1] as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters.

The command line function `fcm` starts with an initial guess for the cluster centers, which are intended to mark the mean location of each cluster. The initial guess for these cluster centers is most likely incorrect. Additionally, `fcm` assigns every data point a membership grade for each cluster. By iteratively updating the cluster centers and the membership grades for each data point, `fcm` iteratively moves the cluster centers to the right location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point's membership grade.

The command line function `fcm` outputs a list of cluster centers and several membership grades for each data point. You can use the information returned by `fcm` to help you build a fuzzy inference system by creating membership functions to represent the fuzzy qualities of each cluster. To generate a Sugeno-type fuzzy inference system that models the behavior of input/output data, you can configure the `genfis` command to use FCM clustering.

Subtractive Clustering

If you do not have a clear idea how many clusters there should be for a given set of data, *subtractive clustering* is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers for a set of data [2]. The cluster estimates, which are obtained from the `subclust` function, can be used to initialize iterative optimization-based clustering methods (`fcm`) and model identification methods (like `anfis`). The `subclust` function finds the clusters using the subtractive clustering method.

To generate a Sugeno-type fuzzy inference system that models the behavior of input/output data, you can configure the `genfis` command to use subtractive clustering.

References

[1] Bezdek, J.C., *Pattern Recognition with Fuzzy Objective Function Algorithms*, Plenum Press, New York, 1981.

[2] Chiu, S., "Fuzzy Model Identification Based on Cluster Estimation," *Journal of Intelligent & Fuzzy Systems*, Vol. 2, No. 3, Sept. 1994.

See Also

`fcm` | `genfis` | `subclust`

More About

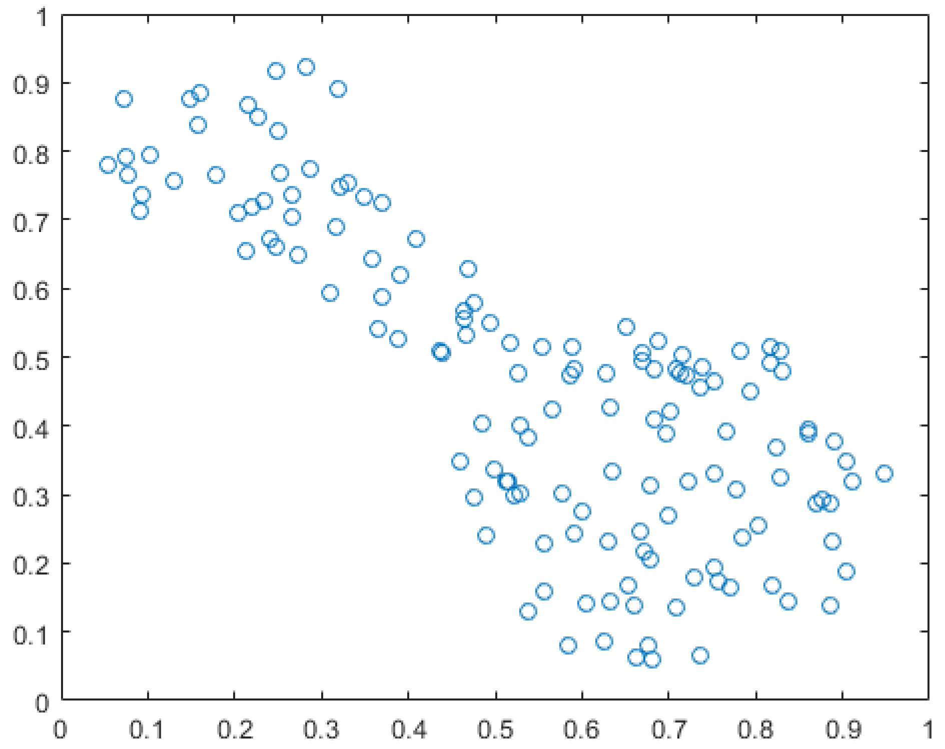
- “Cluster Quasi-Random Data Using Fuzzy C-Means Clustering” on page 4-4
- “Model Suburban Commuting Using Subtractive Clustering” on page 4-22
- “Data Clustering Using Clustering Tool” on page 4-48

Cluster Quasi-Random Data Using Fuzzy C-Means Clustering

This example shows how FCM clustering works using quasi-random two-dimensional data.

Load the data set and plot it.

```
load fcmdata.dat
plot(fcmdata(:,1),fcmdata(:,2),'o')
```



Next, invoke the command-line function, `fcm`, to find two clusters in this data set until the objective function is no longer decreasing much at all.

```
[center,U,objFcn] = fcm(fcmdata,2);
```

```
Iteration count = 1, obj. fcn = 8.970479
Iteration count = 2, obj. fcn = 7.197402
Iteration count = 3, obj. fcn = 6.325579
Iteration count = 4, obj. fcn = 4.586142
Iteration count = 5, obj. fcn = 3.893114
Iteration count = 6, obj. fcn = 3.810804
Iteration count = 7, obj. fcn = 3.799801
Iteration count = 8, obj. fcn = 3.797862
Iteration count = 9, obj. fcn = 3.797508
Iteration count = 10, obj. fcn = 3.797444
Iteration count = 11, obj. fcn = 3.797432
Iteration count = 12, obj. fcn = 3.797430
```

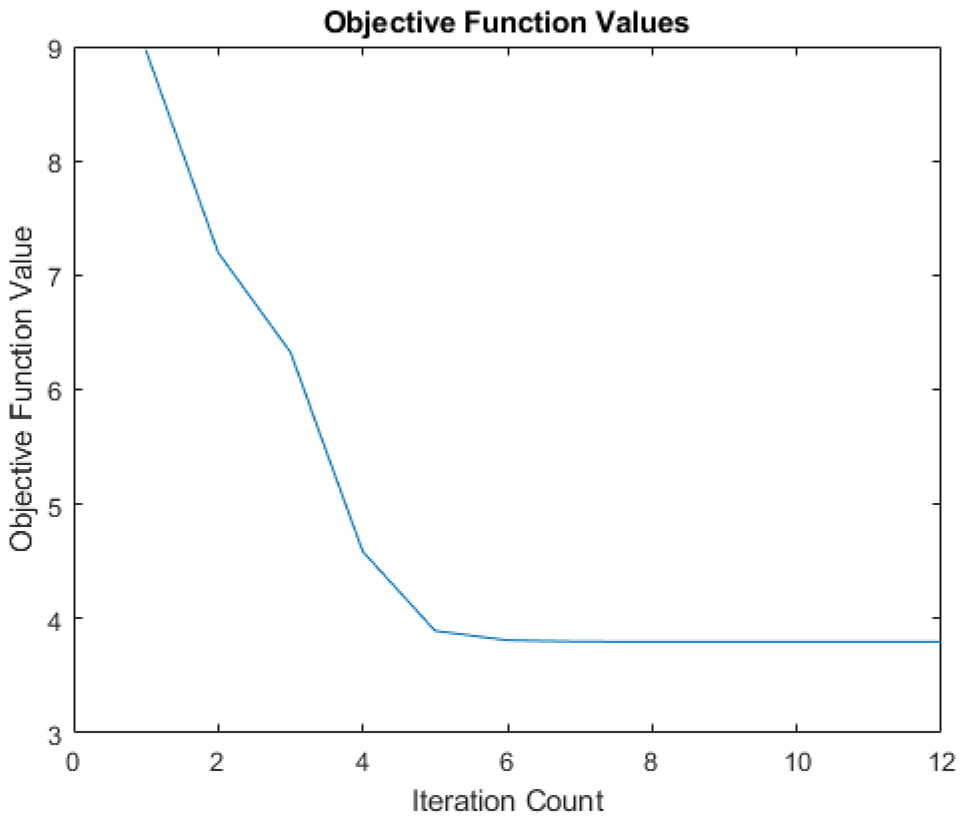
`center` contains the coordinates of the two cluster centers, `U` contains the membership grades for each of the data points, and `objFcn` contains a history of the objective function across the iterations.

The `fcm` function is an iteration loop built on top of the following routines:

- `initfcm` - initializes the problem
- `distfcm` - performs Euclidean distance calculation
- `stepfcm` - performs one iteration of clustering

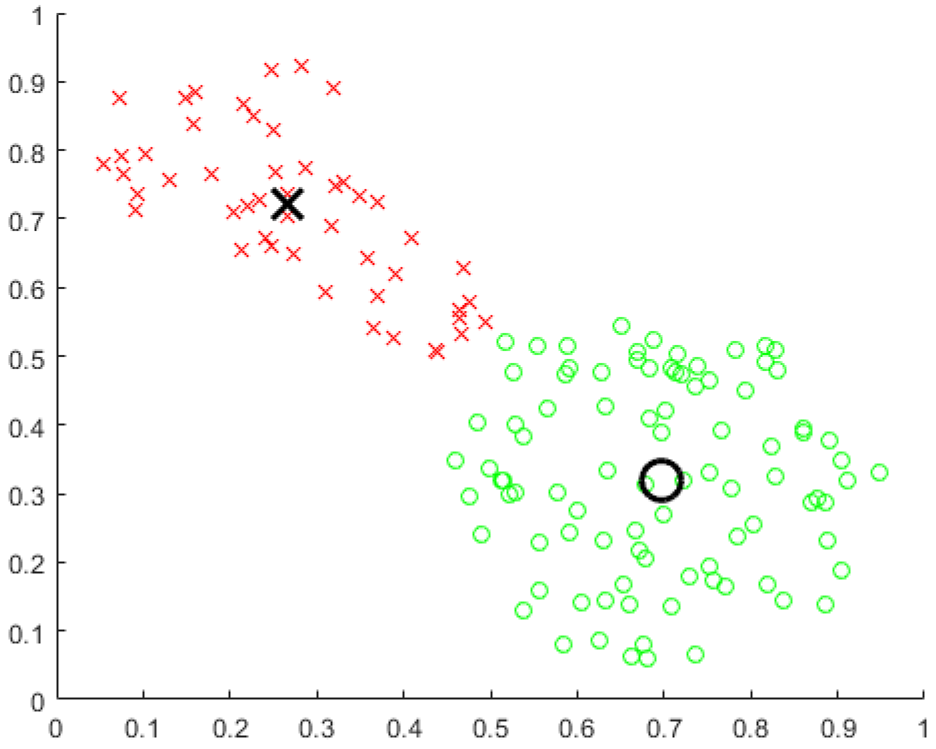
To view the progress of the clustering, plot the objective function.

```
figure
plot(objFcn)
title('Objective Function Values')
xlabel('Iteration Count')
ylabel('Objective Function Value')
```



Finally, plot the two cluster centers found by the `fcm` function. The large characters in the plot indicate cluster centers.

```
maxU = max(U);
index1 = find(U(1,:) == maxU);
index2 = find(U(2,:) == maxU);
figure
line(fcmdata(index1,1), fcmdata(index1,2), 'linestyle',...
                        'none','marker', 'o','color','g')
line(fcmdata(index2,1),fcmdata(index2,2),'linestyle',...
                        'none','marker', 'x','color','r')
hold on
plot(center(1,1),center(1,2),'ko','markersize',15,'LineWidth',2)
plot(center(2,1),center(2,2),'kx','markersize',15,'LineWidth',2)
```



Note: Every time you run this example, the `fcm` function initializes with different initial conditions. This behavior swaps the order in which the cluster centers are computed and plotted.

See Also

`fcm`

More About

- "Fuzzy Clustering" on page 4-2

Adjust Fuzzy Overlap in Fuzzy C-Means Clustering

This example shows how to adjust the amount of fuzzy overlap when performing fuzzy c-means clustering.

Create a random data set. For reproducibility, initialize the random number generator to its default value.

```
rng('default')
data = rand(100,2);
```

Specify fuzzy partition matrix exponents.

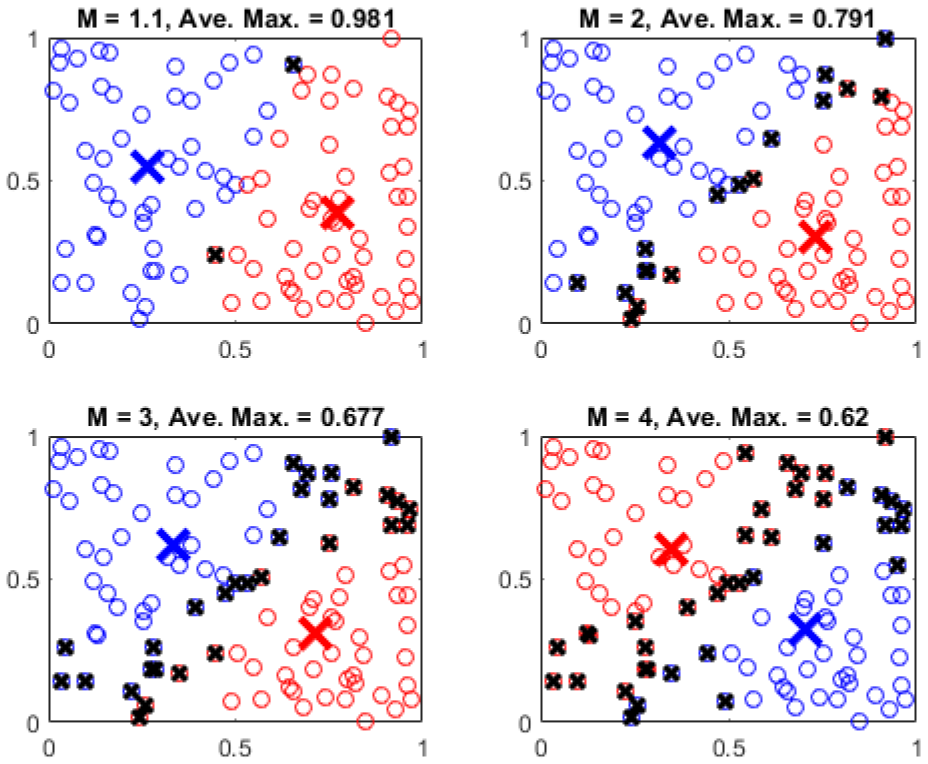
```
M = [1.1 2.0 3.0 4.0];
```

The exponent values in `M` must be greater than `1`, with smaller values specifying a lower degree of fuzzy overlap. In other words, as `M` approaches `1`, the boundaries between the clusters become more crisp.

For each overlap exponent:

- Cluster the data.
- Classify each data point into the cluster for which it has the highest degree of membership.
- Find the data points with maximum membership values below `0.6`. These points have a more fuzzy classification.
- To quantify the degree of fuzzy overlap, calculate the average maximum membership value across all data points. A higher average maximum membership value indicates that there is less fuzzy overlap.
- Plot the clustering results.

```
for i = 1:4
    % Cluster the data.
    options = [M(i) NaN NaN 0];
    [centers,U] = fcm(data,2,options);

    % Classify the data points.
    maxU = max(U);
    index1 = find(U(1,:) == maxU);
    index2 = find(U(2,:) == maxU);
    % Find data points with lower maximum membership values.
    index3 = find(maxU < 0.6);

    % Calculate the average maximum membership value.
    averageMax = mean(maxU);

    % Plot the results.
    subplot(2,2,i)
    plot(data(index1,1),data(index1,2),'ob')
    hold on
    plot(data(index2,1),data(index2,2),'or')
    plot(data(index3,1),data(index3,2),'xk','LineWidth',2)
    plot(centers(1,1),centers(1,2),'xb','MarkerSize',15,'LineWidth',3)
    plot(centers(2,1),centers(2,2),'xr','MarkerSize',15,'LineWidth',3)
    hold off
    title(['M = ' num2str(M(i)) ', Ave. Max. = ' num2str(averageMax,3)])
end
```



A given data point is classified into the cluster for which it has the highest membership value, as indicated by `maxU`. A maximum membership value of `0.5` indicates that the point belongs to both clusters equally. The data points marked with a black **x** have maximum membership values below `0.6`. These points have a greater degree of uncertainty in their cluster membership.

More data points with low maximum membership values indicate a greater degree of fuzzy overlap in the clustering result. The average maximum membership value, `averageMax`, provides a quantitative description of the overlap. An `averageMax` value of `1` indicates crisp clusters, with smaller values indicating more overlap.

See Also

`fcm`

More About

- “Fuzzy Clustering” on page 4-2
- “Cluster Quasi-Random Data Using Fuzzy C-Means Clustering” on page 4-4

Fuzzy C-Means Clustering

This example shows how to perform fuzzy c-means clustering on 2-dimensional data. For an example that clusters higher-dimensional data, see “Fuzzy C-Means Clustering for Iris Data” on page 4-17.

Fuzzy c-means (FCM) is a data clustering technique in which a data set is grouped into *N* clusters with every data point in the dataset belonging to every cluster to a certain degree. For example, a data point that lies close to the center of a cluster will have a high degree of membership in that cluster, and another datapoint that lies far away from the center of a cluster will have a low degree of membership to that cluster.

The `fcm` function performs FCM clustering. It starts with a random initial guess for the cluster centers; that is the mean location of each cluster. Next, `fcm` assigns every data point a random membership grade for each cluster. By iteratively updating the cluster centers and the membership grades for each data point, `fcm` moves the cluster centers to the correct location within a data set and, for each data point, finds the degree of membership in each cluster. This iteration minimizes an objective function that represents the distance from any given data point to a cluster center weighted by the membership of that data point in the cluster.

Load Data

Load the five sample data sets, and select a data set to cluster. These data sets have different numbers of clusters and data distributions.

```
load fcmdata
dataset = fcmdata3;
```

Specify FCM Settings

Configure the clustering algorithm settings. For more information on these settings, see `fcm`. To obtain accurate clustering results for each data set, try different clustering options.

Specify the number of clusters to compute, which must be greater than `1`.

```
N = 4;
```

Specify the exponent the fuzzy partition matrix, which controls the degree of fuzzy overlap between clusters. This value must be greater than `1`, with smaller values creating more crisp cluster boundaries. For more information, see “Adjust Fuzzy Overlap in Fuzzy C-Means Clustering” on page 4-8.

```
exponent = 2;
```

Specify the maximum number of optimization iterations.

```
maxIterations = 100;
```

Specify the minimum improvement in the objective function between successive iterations. When the objective function improves by a value below this threshold, the optimization stops. A smaller value produces more accurate clustering results, but the clustering can take longer to converge.

```
minImprovement = 0.00001;
```

Specify whether to display the objective function value after each iteration.

```
displayObjectiveFunction = false;
```

Create an option vector for the `fcm` function using these settings.

```
options = [exponent maxIterations minImprovement displayObjectiveFunction];
```

Cluster Data

Cluster the data into `N` clusters.

```
[C,U] = fcm(dataset,N,options);
```

`C` contains the computed centers for each cluster. `U` contains the computed fuzzy partition matrix, which indicates the degree of membership of each data point within each cluster.

Classify each data point into the cluster for which it has the highest degree of membership.

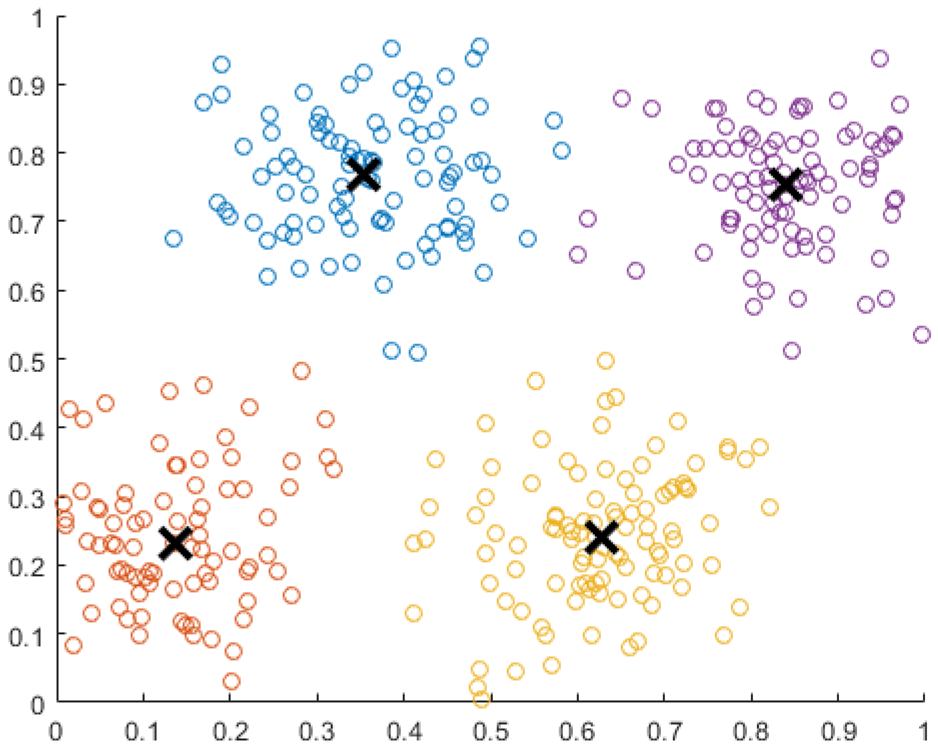
```
maxU = max(U);
index = cell(N,1);
for i=1:N
    index{i} = find(U(i,:) == maxU);
end
```

Plot Clustering Results

Plot the clustering results.

```
figure
hold on
```

```
for i=1:N
    plot(dataset(index{i},1),dataset(index{i},2),'o')
    plot(C(i,1),C(i,2),'xk','MarkerSize',15,'LineWidth',3)
end
hold off
```



The data points in each cluster are shown in a different colors. The center for each cluster is shown as a black X.

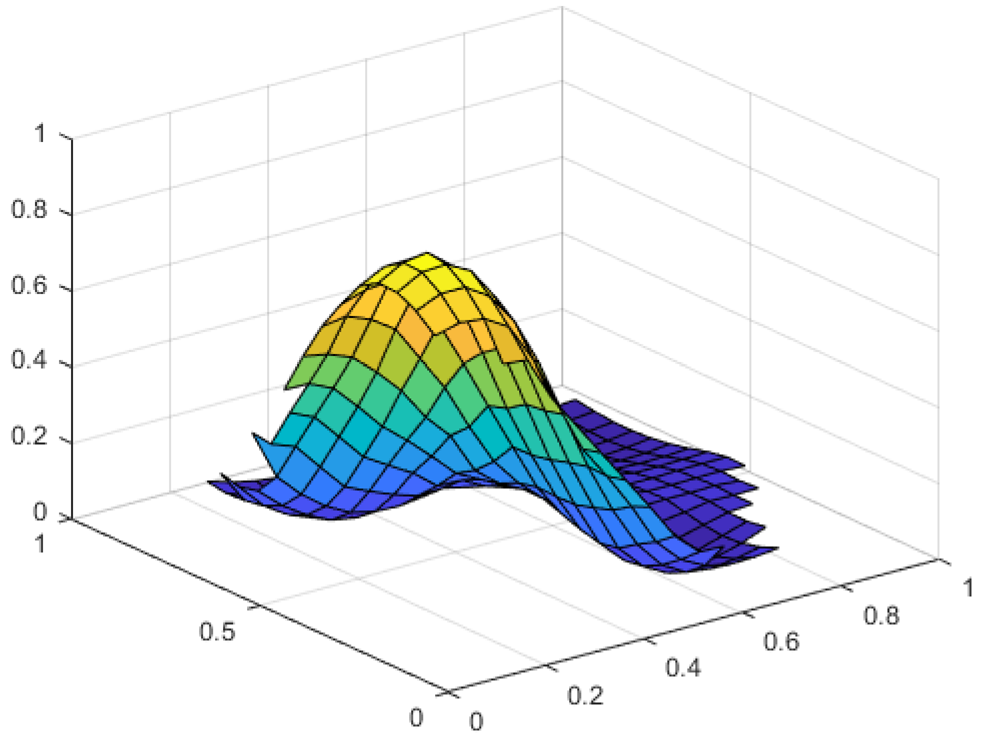
Plot Data Point Membership Values

Select a cluster for which to plot a membership function surface.

```
cluster = 2;
```

Obtain the membership function for the selected cluster by fitting a surface to the cluster membership values for all data points. For more information on interpolating scattered 3-D data, see `griddata`.

```
[X,Y] = meshgrid(0:0.05:1, 0:0.05:1);
Z = griddata(dataset(:,1),dataset(:,2),U(cluster,:),X,Y);
surf(X,Y,Z)
```



When you decrease the `exponent` value, the transition from maximum full cluster membership to zero cluster membership becomes more steep; that is, the cluster boundary becomes more crisp.

See Also

`fcm`

More About

- "Fuzzy Clustering" on page 4-2

Fuzzy C-Means Clustering for Iris Data

This example shows how to use fuzzy c-means clustering for the iris data set. This dataset was collected by botanist Edgar Anderson and contains random samples of flowers belonging to three species of iris flowers: *setosa*, *versicolor*, and *virginica*. For each of the species, the data set contains 50 observations for sepal length, sepal width, petal length, and petal width.

Load Data

Load the data set from the `iris.dat` data file.

```
load iris.dat
```

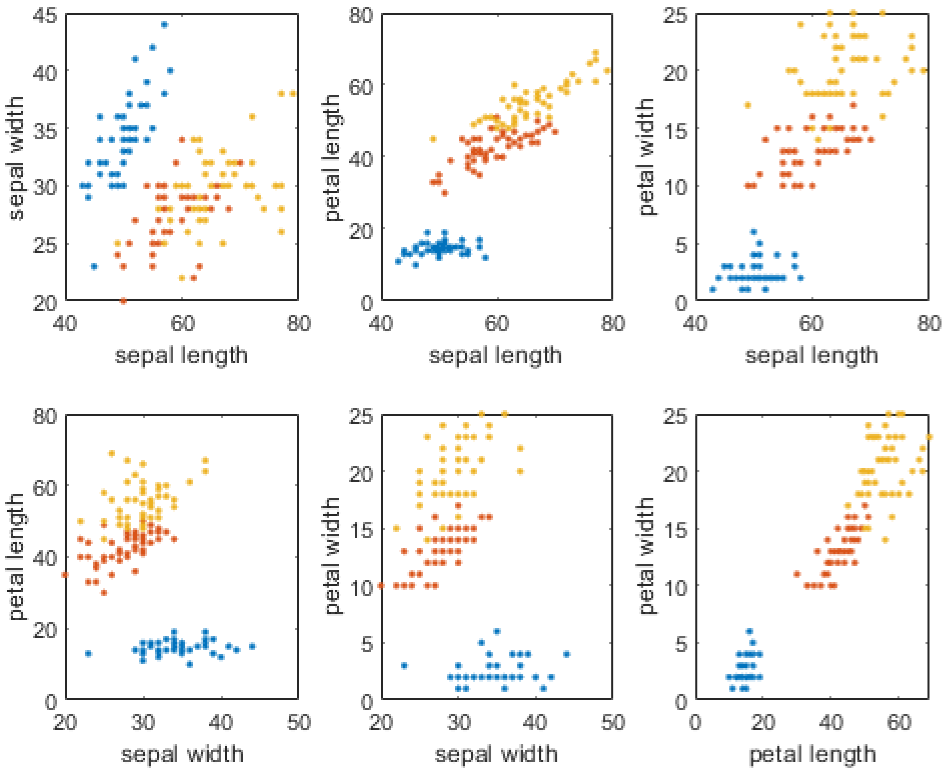
Partition the data into three groups named `setosa`, `versicolor`, and `virginica`.

```
setosaIndex = iris(:,5)==1;
versicolorIndex = iris(:,5)==2;
virginicaIndex = iris(:,5)==3;

setosa = iris(setosaIndex,:);
versicolor = iris(versicolorIndex,:);
virginica = iris(virginicaIndex,:);
```

Plot Data in 2-D

The iris data contains four dimensions representing sepal length, sepal width, petal length, and petal width. Plot the data points for each combination of two dimensions.

```
Characteristics = {'sepal length','sepal width','petal length','petal width'};
pairs = [1 2; 1 3; 1 4; 2 3; 2 4; 3 4];

for i = 1:6
    x = pairs(i,1);
    y = pairs(i,2);
    subplot(2,3,i)
    plot([setosa(:,x) versicolor(:,x) virginica(:,x)],...
         [setosa(:,y) versicolor(:,y) virginica(:,y)], '.')
    xlabel(Characteristics{x})
    ylabel(Characteristics{y})
end
```



Setup Parameters

Specify the options for clustering the data using fuzzy c-means clustering. These options are:

- `Nc` — Number of clusters
- M — Fuzzy partition matrix exponent, which indicates the degree of fuzzy overlap between clusters. For more information, see “Adjust Fuzzy Overlap in Fuzzy C-Means Clustering” on page 4-8.
- `maxIter` — Maximum number of iterations. The clustering process stops after this number of iterations.

- `minImprove` — Minimum improvement. The clustering process stops when the objective function improvement between two consecutive iterations is less than this value.

```
Nc = 3;
M = 2.0;
maxIter = 100;
minImprove = 1e-6;
```

For more information about these options and the fuzzy c-means algorithm, see `fcm`.

Compute Clusters

Fuzzy c-means clustering is an iterative process. Initially, the `fcm` function generates a random fuzzy partition matrix. This matrix indicates the degree of membership of each data point in each cluster.

In each clustering iteration, `fcm` calculates the cluster centers and updates the fuzzy partition matrix using the calculated center locations. It then computes the objective function value.

Cluster the data, displaying the objective function value after each iteration.

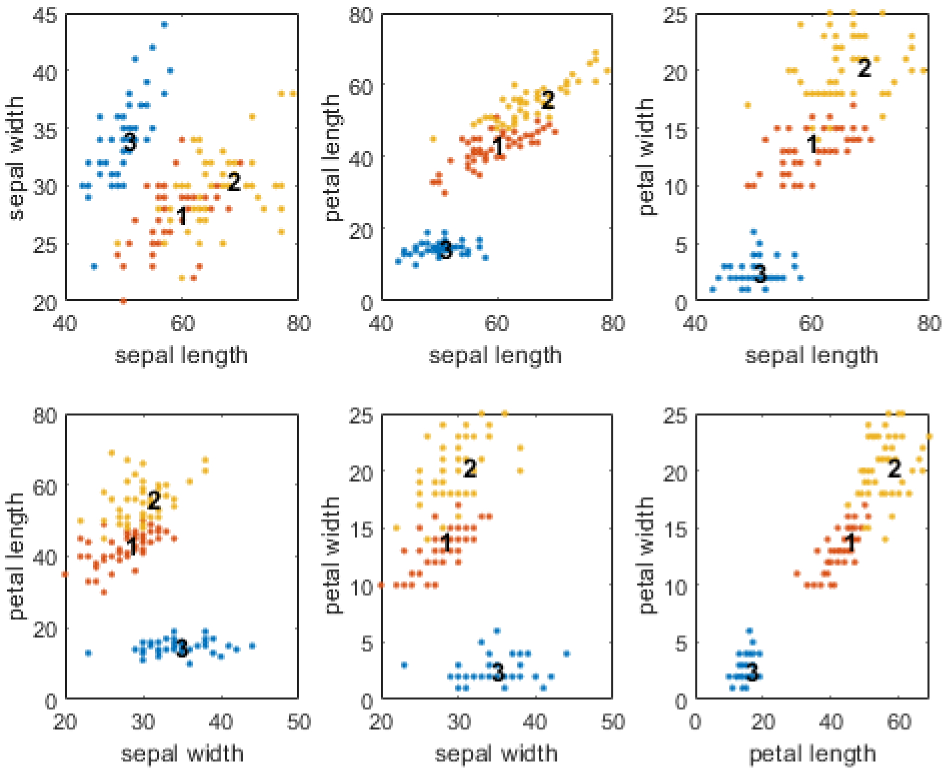
```
clusteringOptions = [M maxIter minImprove true];
[centers,U] = fcm(iris,Nc,clusteringOptions);
```

```
Iteration count = 1, obj. fcn = 28838.424340
Iteration count = 2, obj. fcn = 21010.880067
Iteration count = 3, obj. fcn = 15272.280943
Iteration count = 4, obj. fcn = 11029.756194
Iteration count = 5, obj. fcn = 10550.015503
Iteration count = 6, obj. fcn = 10301.776800
Iteration count = 7, obj. fcn = 9283.793786
Iteration count = 8, obj. fcn = 7344.379868
Iteration count = 9, obj. fcn = 6575.117093
Iteration count = 10, obj. fcn = 6295.215539
Iteration count = 11, obj. fcn = 6167.772051
Iteration count = 12, obj. fcn = 6107.998500
Iteration count = 13, obj. fcn = 6080.461019
Iteration count = 14, obj. fcn = 6068.116247
Iteration count = 15, obj. fcn = 6062.713326
Iteration count = 16, obj. fcn = 6060.390433
Iteration count = 17, obj. fcn = 6059.403978
Iteration count = 18, obj. fcn = 6058.988494
Iteration count = 19, obj. fcn = 6058.814438
Iteration count = 20, obj. fcn = 6058.741777
Iteration count = 21, obj. fcn = 6058.711512
Iteration count = 22, obj. fcn = 6058.698925
Iteration count = 23, obj. fcn = 6058.693695
Iteration count = 24, obj. fcn = 6058.691523
Iteration count = 25, obj. fcn = 6058.690622
Iteration count = 26, obj. fcn = 6058.690247
Iteration count = 27, obj. fcn = 6058.690092
Iteration count = 28, obj. fcn = 6058.690028
Iteration count = 29, obj. fcn = 6058.690001
Iteration count = 30, obj. fcn = 6058.689990
Iteration count = 31, obj. fcn = 6058.689985
Iteration count = 32, obj. fcn = 6058.689983
Iteration count = 33, obj. fcn = 6058.689983
```

The clustering stops when the objective function improvement is below the specified minimum threshold.

Plot the computed cluster centers as bold numbers.

```
for i = 1:6
    subplot(2,3,i);
    for j = 1:Nc
        x = pairs(i,1);
        y = pairs(i,2);
        text(centers(j,x),centers(j,y),int2str(j),'FontWeight','bold');
    end
end
```



See Also

`fcm`

More About

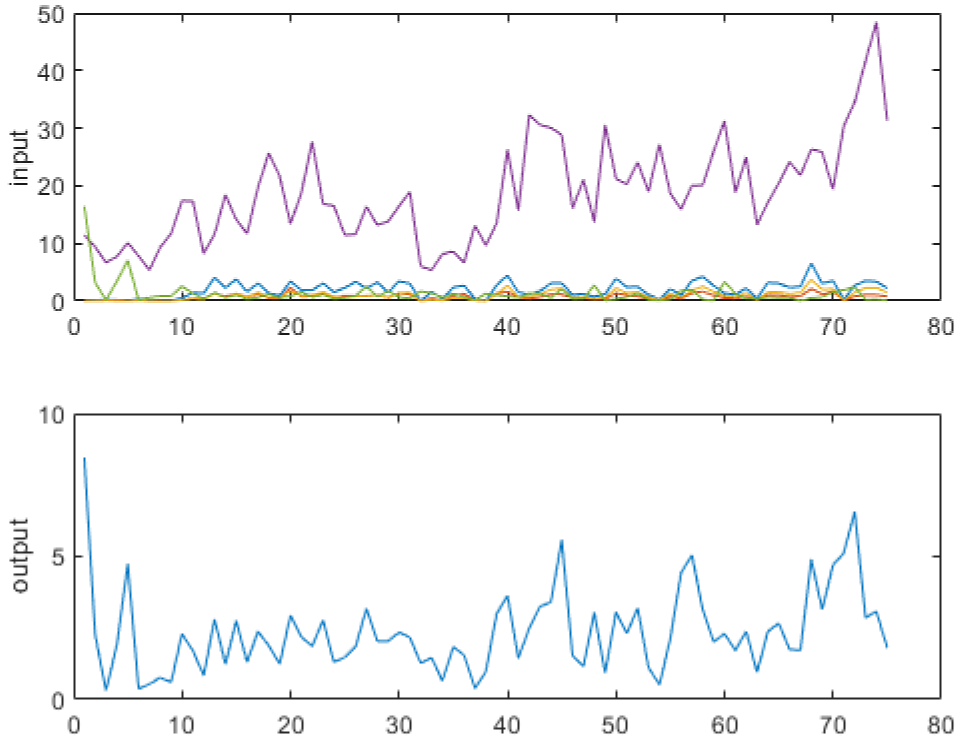
- “Fuzzy Clustering” on page 4-2

Model Suburban Commuting Using Subtractive Clustering

This example shows how to model the relationship between the number of automobile trips generated from an area and the demographics of the area using the `genfis` function. Demographic and trip data are from 100 traffic analysis zones in New Castle County, Delaware. Five demographic factors are considered: population, number of dwelling units, vehicle ownership, median household income, and total employment. Hence, the model has five input variables and one output variable.

Load and plot the data.

```
mytripdata
subplot(2,1,1)
plot(datin)
ylabel('input')
subplot(2,1,2)
plot(datout)
ylabel('output')
```



The `mytripdata` command creates several variables in the workspace. Of the original 100 data points, use 75 data points as training data (`datin` and `datout`) and 25 data points as checking data (as well as for test data to validate the model). The checking data input/output pair variables are `chkdatin` and `chkdatout`.

Generate a model from the data using subtractive clustering using the `genfis` command.

First, create a `genfisOptions` option set for subtractive clustering, specifying `ClusterInfluenceRange` range property. The `ClusterInfluenceRange` property indicates the range of influence of a cluster when you consider the data space as a unit hypercube. Specifying a small cluster radius usually yields many small clusters in the data, and results in many rules. Specifying a large cluster radius usually yields a few large clusters in the data, and results in fewer rules.

```
opt = genfisOptions('SubtractiveClustering','ClusterInfluenceRange',0.5);
```

Generate the FIS model using the training data and the specified options.

```
fismat = genfis(datin,datout,opt);
```

The `genfis` command uses a one-pass method that does not perform any iterative optimization. The model type for the generated FIS object is a first order Sugeno model with three rules.

Verify the model. Here, `trnRMSE` is the root mean squared error of the system generated by the training data.

```
fuzout = evalfis(fismat,datin);
trnRMSE = norm(fuzout-datout)/sqrt(length(fuzout))
```

```
trnRMSE = 0.5276
```

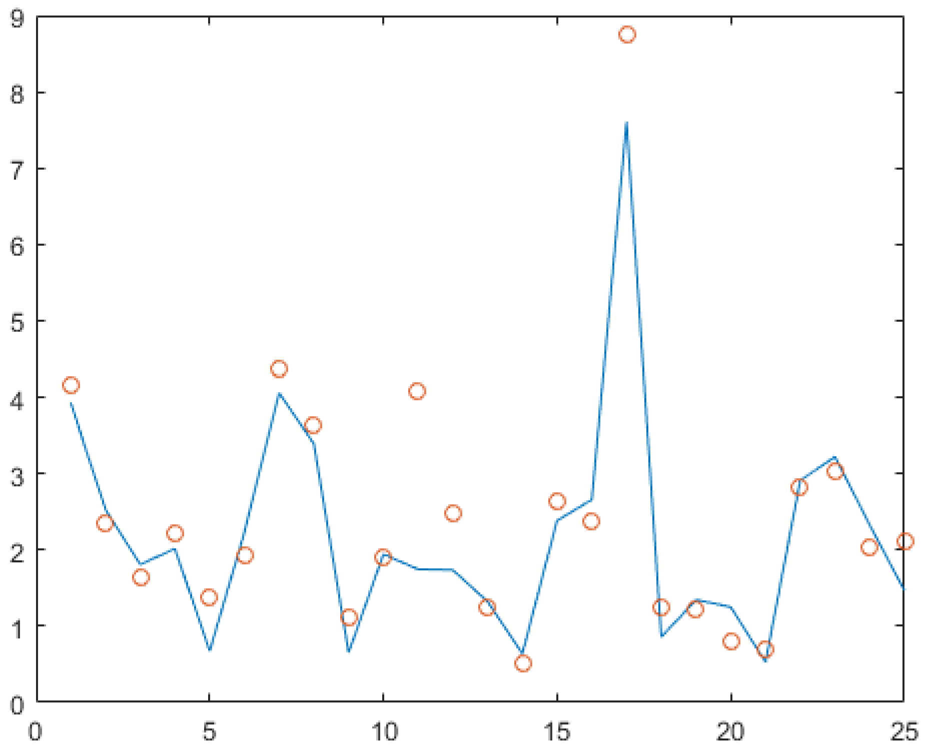
Next, apply the test data to the FIS to validate the model. In this example, the validation data is used for both checking and testing the FIS parameters. Here, `chkRMSE` is the root mean squared error of the system generated by the validation data.

```
chkfuzout = evalfis(fismat,chkdatin);
chkRMSE = norm(chkfuzout-chkdatout)/sqrt(length(chkfuzout))
```

```
chkRMSE = 0.6179
```

Plot the output of the model, `chkfuzout`, against the validation data, `chkdatout`.

```
figure
plot(chkdatout)
hold on
plot(chkfuzout,'o')
hold off
```



The model output and validation data are shown as circles and solid blue line, respectively. The plot shows that the model does not perform well on the validation data.

At this point, you can use the optimization capability of `anfis` to improve the model. First, try using a relatively short training period (20 epochs) without using validation data, and then test the resulting FIS model against the testing data.

```
anfisOpt = anfisOptions('InitialFIS',fismat,'EpochNumber',20,...
                        'InitialStepSize',0.1);
fismat2 = anfis([datin datout],anfisOpt);
```

```
ANFIS info:
    Number of nodes: 44
    Number of linear parameters: 18
    Number of nonlinear parameters: 30
    Total number of parameters: 48
    Number of training data pairs: 75
    Number of checking data pairs: 0
    Number of fuzzy rules: 3


Start training ANFIS ...

   1      0.527607
   2      0.513727
   3      0.492996
   4      0.499985
   5      0.490585
   6      0.492924
   7      0.48733
Step size decreases to 0.090000 after epoch 7.
   8      0.485036
   9      0.480813
  10      0.475097
Step size increases to 0.099000 after epoch 10.
  11      0.469759
  12      0.462516
  13      0.451177
  14      0.447856
Step size increases to 0.108900 after epoch 14.
  15      0.444357
  16      0.433904
  17      0.433739
  18      0.420408
Step size increases to 0.119790 after epoch 18.
  19      0.420512
  20      0.420275

Designated epoch number reached --> ANFIS training completed at epoch 20.

Minimal training RMSE = 0.420275
```

After the training is complete, validate the model.

```
fuzout2 = evalfis(fismat2,datin);
trnRMSE2 = norm(fuzout2-datout)/sqrt(length(fuzout2))
```

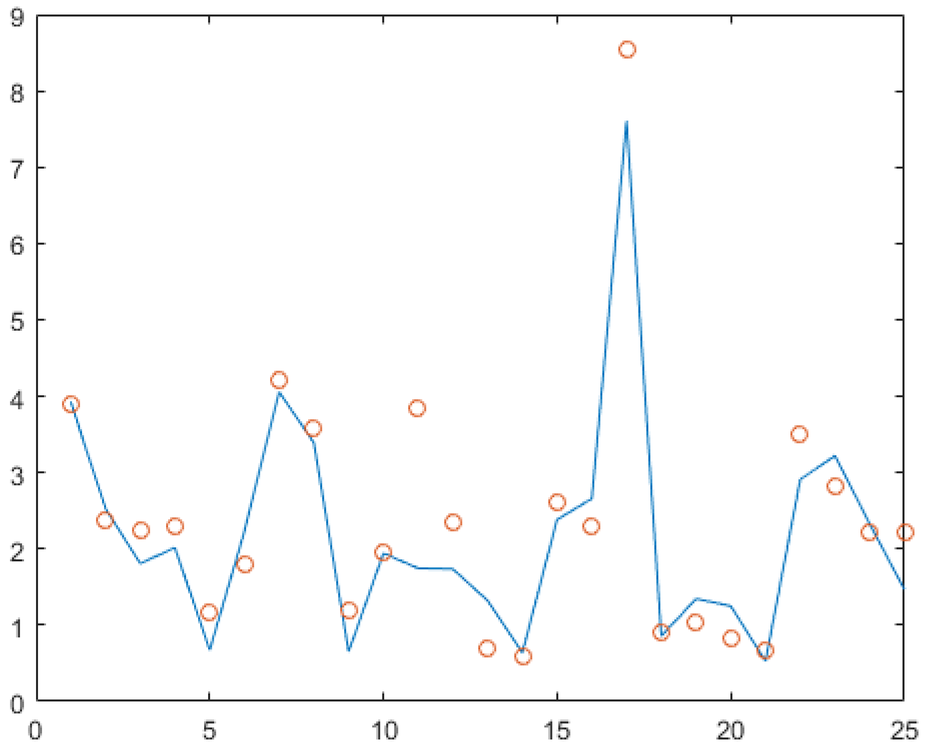
```
trnRMSE2 = 0.4203
```

```
chkfuzout2 = evalfis(fismat2,chkdatin);
chkRMSE2 = norm(chkfuzout2-chkdatout)/sqrt(length(chkfuzout2))
```

```
chkRMSE2 = 0.5894
```

The model has improved a lot with respect to the training data, but only a little with respect to the validation data. Plot the improved model output obtained using `anfis` against the testing data.

```
figure
plot(chkdatout)
hold on
plot(chkfuzout2,'o')
hold off
```



The model output and validation data are shown as circles and solid blue line, respectively. This plot shows that subtractive clustering with `genfis` can be used as a standalone, fast method for generating a fuzzy model from data, or as a preprocessor to determine the initial rules for `anfis` training. An important advantage of using a clustering method to find rules is that the resultant rules are more tailored to the input data than they are in a FIS generated without clustering. This result reduces the problem of an excessive propagation of rules when the input data has a high dimension.

Overfitting can be detected when the checking error starts to increase while the training error continues to decrease.

To check the model for overfitting, use `anfis` with validation data to train the model for 200 epochs.

First configure the ANFIS training options by modifying the existing `anfisOptions` option set. Specify the epoch number and validation data. Since the number of training epochs is larger, suppress the display of training information to the Command Window.

```
anfisOpt.EpochNumber = 200;
anfisOpt.ValidationData = [chkdatin chkdatout];
anfisOpt.DisplayANFISInformation = 0;
anfisOpt.DisplayErrorValues = 0;
anfisOpt.DisplayStepSize = 0;
anfisOpt.DisplayFinalResults = 0;
```

Train the FIS.

```
[fismat3,trnErr,stepSize,fismat4,chkErr] = anfis([datin datout],anfisOpt);
```

Here,

- `fismat3` is the FIS object when the training error reaches a minimum.
- `fismat4` is the snapshot FIS object when the validation data error reaches a minimum.
- `stepSize` is a history of the training step sizes.
- `trnErr` is the RMSE using the training data
- `chkErr` is the RMSE using the validation data for each training epoch.

After the training completes, validate the model.

```
fuzout4 = evalfis(fismat4,datin);
trnRMSE4 = norm(fuzout4-datout)/sqrt(length(fuzout4))
```

```
trnRMSE4 = 0.3393
```

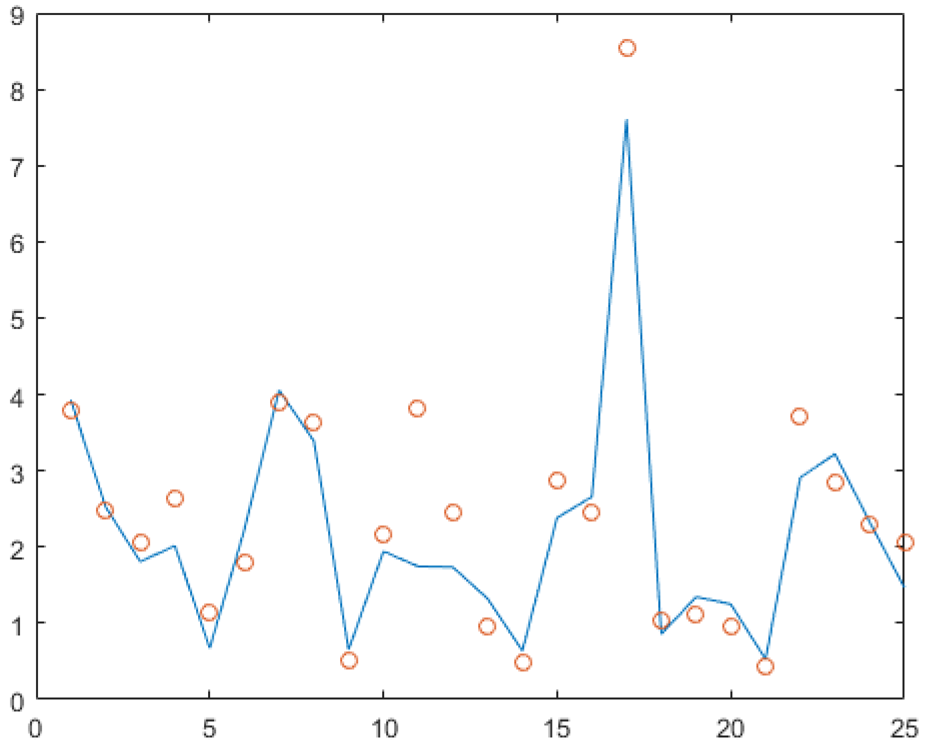
```
chkfuzout4 = evalfis(fismat4,chkdatin);
chkRMSE4 = norm(chkfuzout4-chkdatout)/sqrt(length(chkfuzout4))
```

```
chkRMSE4 = 0.5834
```

The error with the training data is the lowest thus far, and the error with the validation data is also slightly lower than before. This result suggests possible overfitting, which occurs when you fit the fuzzy system to the training data so well that it no longer does a good job of fitting the validation data. The result is a loss of generality.

View the improved model output. Plot the model output against the checking data.

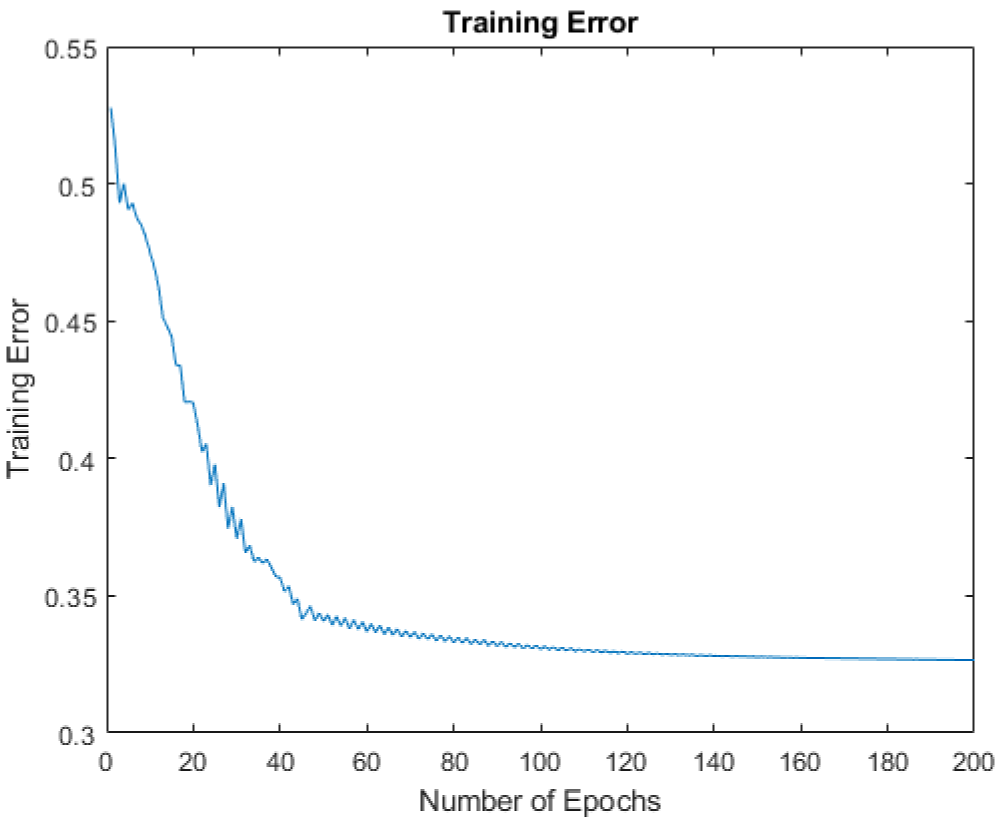
```
figure
plot(chkdatout)
hold on
plot(chkfuzout4,'o')
hold off
```



The model output and validation data are shown as circles and solid blue line, respectively.

Next, plot the training error, `trnErr`.

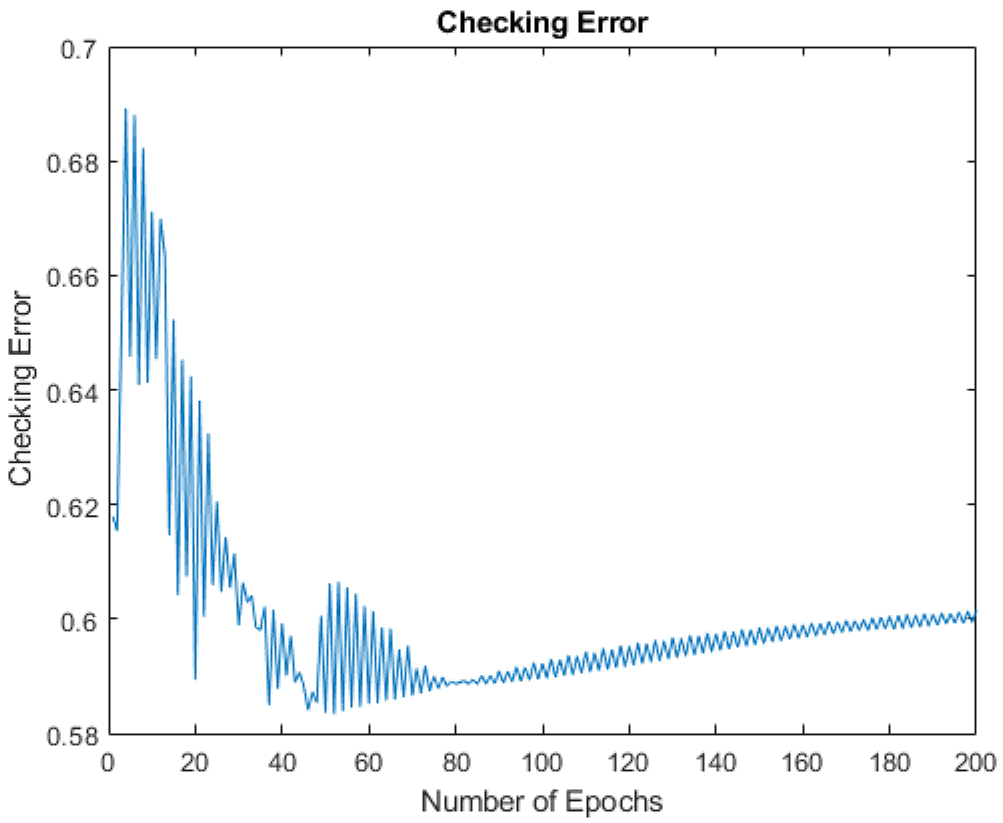
```
figure
plot(trnErr)
title('Training Error')
xlabel('Number of Epochs')
ylabel('Training Error')
```



This plot shows that the training error settles at about the 60th epoch point.

Plot the checking error, `chkErr`.

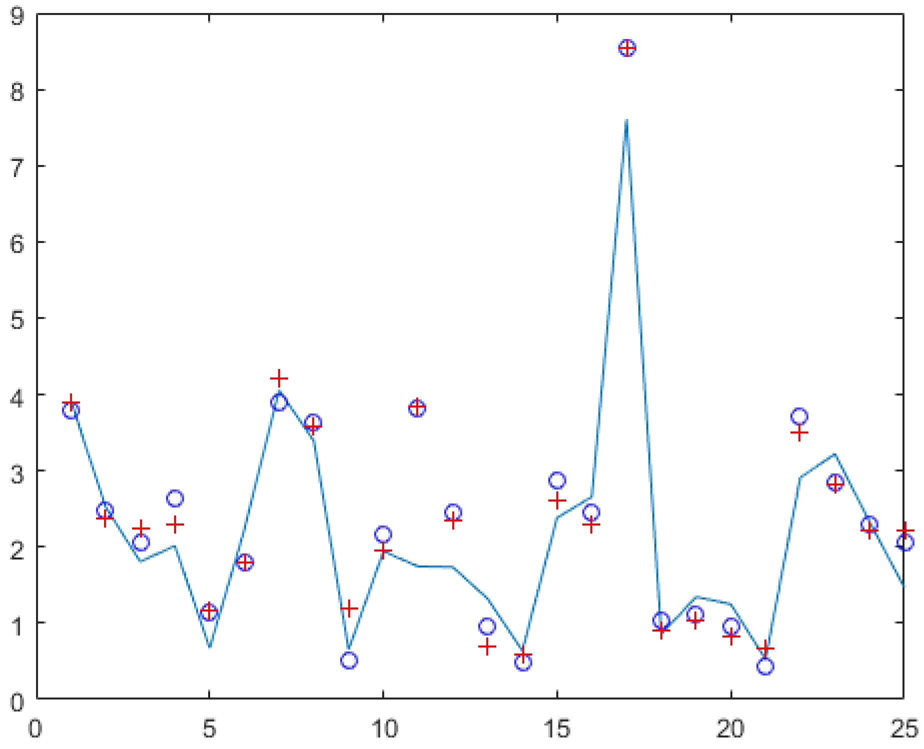
```
figure
plot(chkErr)
title('Checking Error')
xlabel('Number of Epochs')
ylabel('Checking Error')
```



The plot shows that the smallest value of the validation data error occurs at the 52nd epoch. After this point it increases slightly even as `anfis` continues to minimize the error against the training data all the way to the 200th epoch. Depending on the specified error tolerance, the plot also indicates the ability of the model to generalize the test data.

You can also compare the output of `fismat2` and `fistmat4` against the validation data, `chkdatout`.

```
figure
plot(chkdatout)
hold on
plot(chkfuzout4,'ob')
plot(chkfuzout2,'+r')
```



See Also

`anfis` | `subclust`

More About

- "Fuzzy Clustering" on page 4-2

Modeling Traffic Patterns using Subtractive Clustering

This example shows how to use subtractive clustering to model traffic patterns in an area based on the demographics of the area.

The Problem: Understanding Traffic Patterns

In this example we attempt to understand the relationship between the number of automobile trips generated from an area and the area's demographics. Demographic and trip data were collected from traffic analysis zones in New Castle County, Delaware. Five demographic factors are considered: population, number of dwelling units, vehicle ownership, median household income and total employment.

Hereon, the demographic factors will be addressed as inputs and the trips generated will be addressed as output. Hence our problem has five input variables (five demographic factors) and one output variable (number of trips generated).

The Data

Load the input and output variables used for this example into the workspace.

```
tripdata
```

Two variables are loaded in the workspace, `datin` and `datout`. `datin` has 5 columns representing the 5 input variables and `datout` has 1 column representing the 1 output variable.

```
subplot(2,1,1)
plot(datin)
legend('population', 'num. of dwelling units', 'vehicle ownership',...
    'median household income', 'total employment')
title('Input Variables','fontsize',10)

subplot(2,1,2)
plot(datout)
legend('num of trips')
title('Output Variable','fontsize',10)
```

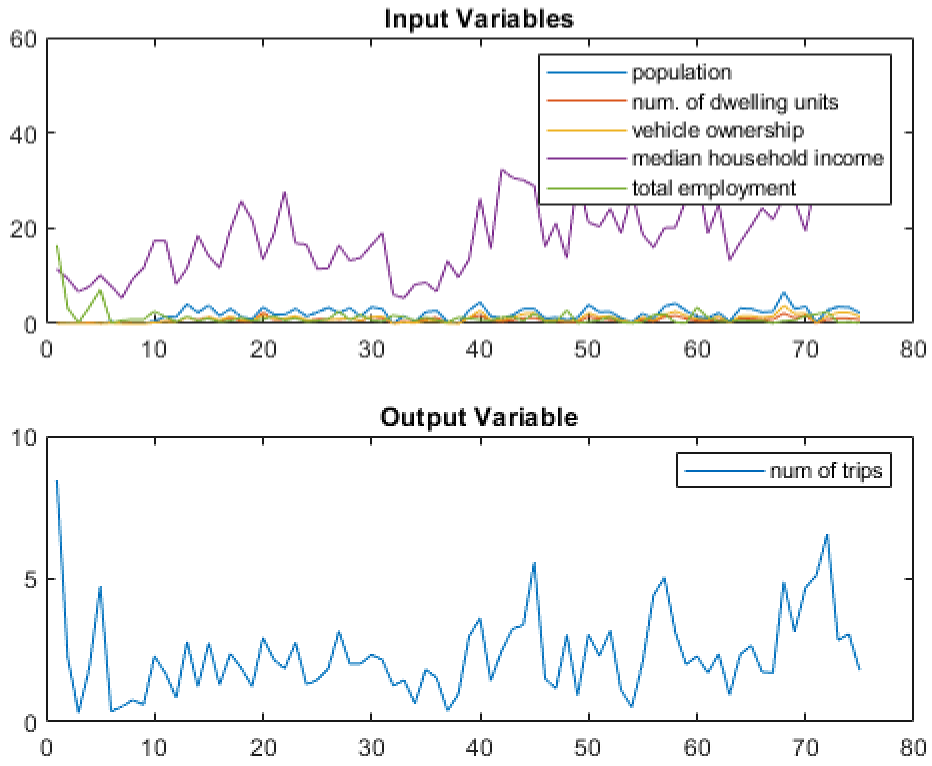


Figure 1: Input and Output variables

The number of rows in `datin` and `datout`, 75, represent the number of observations or samples or datapoints available. A row in `datin`, say row 11, constitutes a set of observed values of the 5 input variables (population, number of dwelling units, vehicle ownership, median household income and total employment) and the corresponding row, row 11, in `datout` represents the observed value for the number of trips generated given the observations made for the input variables.

We will model the relationship between the input variables (demographics) and the output variable (trips) by first clustering the data. The cluster centers will then be used as a basis to define a Fuzzy Inference System (FIS) which can then be used to explore and understand traffic patterns.

Why Clustering and Fuzzy Logic?

Clustering can be a very effective technique to identify natural groupings in data from a large data set, thereby allowing concise representation of relationships embedded in the data. In this example, clustering allows us to group traffic patterns into broad categories hence allowing for easier understandability.

Fuzzy logic is an effective paradigm to handle imprecision. It can be used to take fuzzy or imprecise observations for inputs and yet arrive at crisp and precise values for outputs. Also, the Fuzzy Inference System (FIS) is a simple and commonsensical way to build systems without using complex analytical equations.

In our example, fuzzy logic will be employed to capture the broad categories identified during clustering into a Fuzzy Inference System (FIS). The FIS will then act as a model that will reflect the relationship between demographics and auto trips.

Clustering and fuzzy logic together provide a simple yet powerful means to model the traffic relationship that we want to study.

Clustering the Data

`subclust` is the function that implements a clustering technique called subtractive clustering. Subtractive clustering, [1], is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a dataset.

In this section, we will see how subtractive clustering is performed on a dataset and in the next section we will explore independently how clustering is used to build a Fuzzy Inference System(FIS).

```
[C,S] = subclust([datin datout],0.5);
```

The first argument to the `subclust` function is the data to be clustered. The second argument to the function is the `radii` which marks a cluster's radius of influence in the input space.

The variable `C` now holds all the centers of the clusters that have been identified by `subclust`. Each row of `C` contains the position of a cluster.

```
C
```

```
C =
    1.8770    0.7630    0.9170   18.7500    1.5650    2.1830
    0.3980    0.1510    0.1320    8.1590    0.6250    0.6480
    3.1160    1.1930    1.4870   19.7330    0.6030    2.3850
```

In this case, `C` has 3 rows representing 3 clusters with 6 columns representing the positions of the clusters in each dimension.

`subclust` has hence identified 3 natural groupings in the demographic-trip dataset being considered. The following plot shows how the clusters have been identified in the 'total employment' and 'trips' dimensions of the input space.

```
clf
plot(datin(:,5),datout(:,1),'.',C(:,5),C(:,6),'r*')
legend('Data points','Cluster centers','Location','SouthEast')
xlabel('total employment','fontsize',10)
ylabel('num of trips','fontsize',10)
title('Data and Clusters in selected two dimensions of the input space','fontsize',10)
```

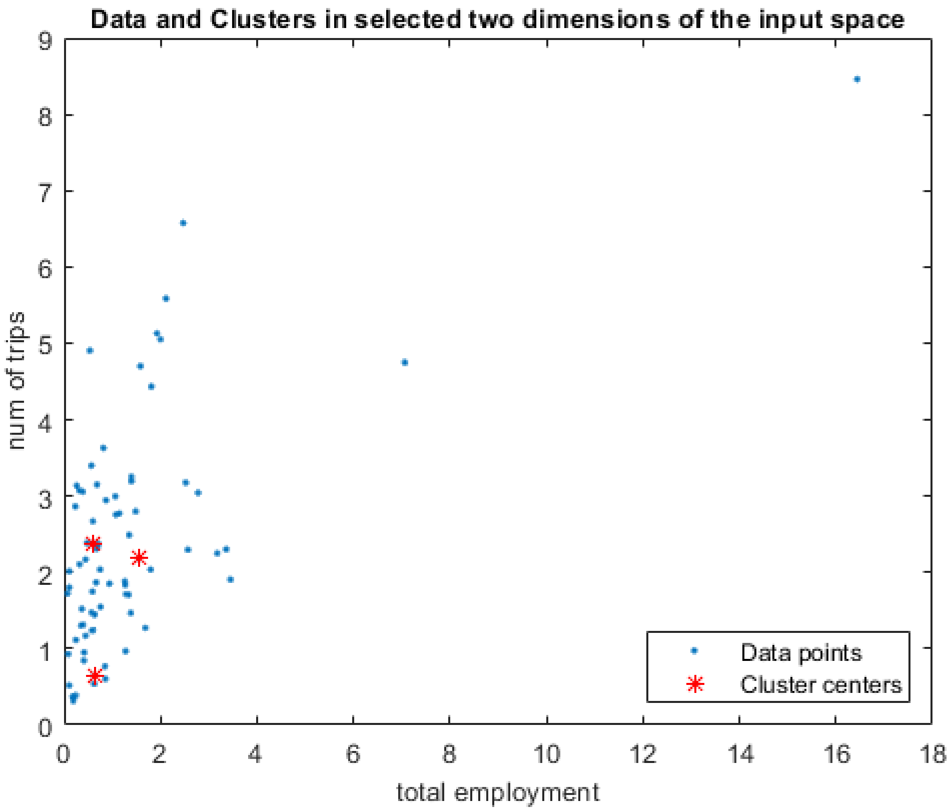


Figure 2: Cluster centers in the 'total employment' and 'trips' dimensions of the input space

The variable S contains the sigma values that specify the range of influence of a cluster center in each of the data dimensions. All cluster centers share the same set of sigma values.

```
S
```

```
S =

    1.1621    0.4117    0.6555    7.6139    2.8931    1.4395
```

S in this case has 6 columns representing the influence of the cluster centers on each of the 6 dimensions.

Generating the Fuzzy Inference System (FIS)

genfis is the function that creates a FIS using subtractive clustering. genfis employs subclust behind the scenes to cluster the data and uses the cluster centers and their range of influences to build a FIS which will then be used to explore and understand traffic patterns.

```
myfis=genfis(datin,datout, ...
    genfisOptions('SubtractiveClustering','ClusterInfluenceRange',0.5));
```

The first argument is the input variables matrix datin, the second argument is the output variables matrix datout and the third argument is the radii that should be used while using subclust.

genfis assigns default names for inputs, outputs and membership functions. For our understanding it is beneficial to rename the inputs and outputs meaningfully.

Assign names to the inputs and outputs.

```
myfis.Inputs(1).Name = "population";
myfis.Inputs(2).Name = "dwelling units";
myfis.Inputs(3).Name = "num vehicles";
myfis.Inputs(4).Name = "income";
myfis.Inputs(5).Name = "employment";
myfis.Outputs(1).Name = "num of trips";
```

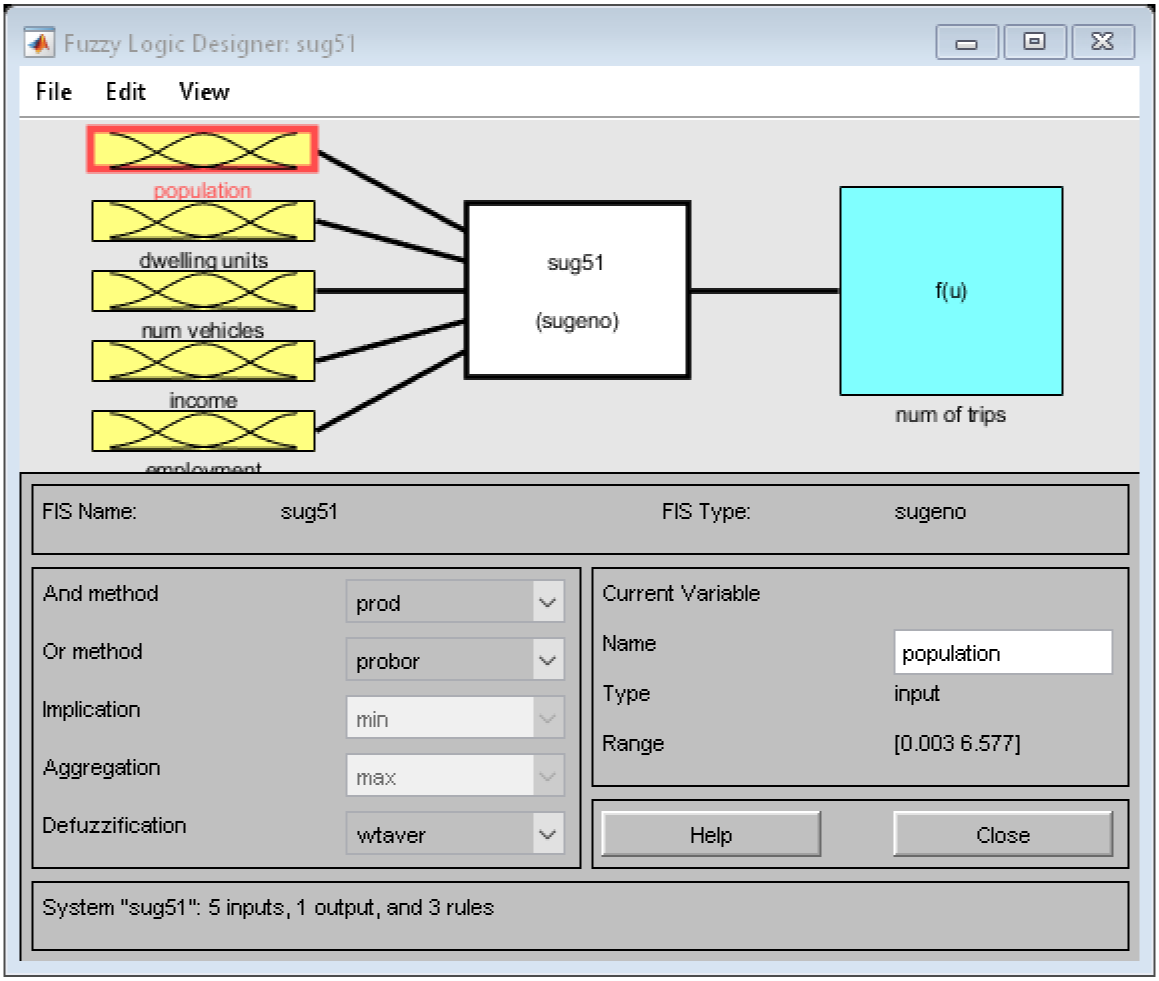
Understanding the Clusters-FIS Relationship

An FIS is composed of inputs, outputs, and rules. Each input and output can have any number of membership functions. The rules dictate the behavior of the fuzzy system based on inputs, outputs and membership functions. genfis constructs the FIS in an attempt to capture the position and influence of each cluster in the input space.

myfis is the FIS that genfis has generated. Since the dataset has 5 input variables and 1 output variable, genfis constructs a FIS with 5 inputs and 1 output. Each input and output has as many membership functions as the number of clusters that subclust has identified. As seen previously, for the current dataset subclust identified 3 clusters. Therefore each input and output will be characterized by 3 membership functions. Also, the number of rules equals the number of clusters and hence 3 rules are created.

We can now probe the FIS to understand how the clusters got converted internally into membership functions and rules using the Fuzzy Logic Designer app.

```
fuzzyLogicDesigner(myfis)
```



FIS Name: sug51
FIS Type: sugeno
And method: prod
Or method: probor
Implication: min
Aggregation: max
Defuzzification: wtaver
Current Variable
Name: population
Type: input
Range: [0.003 6.577]

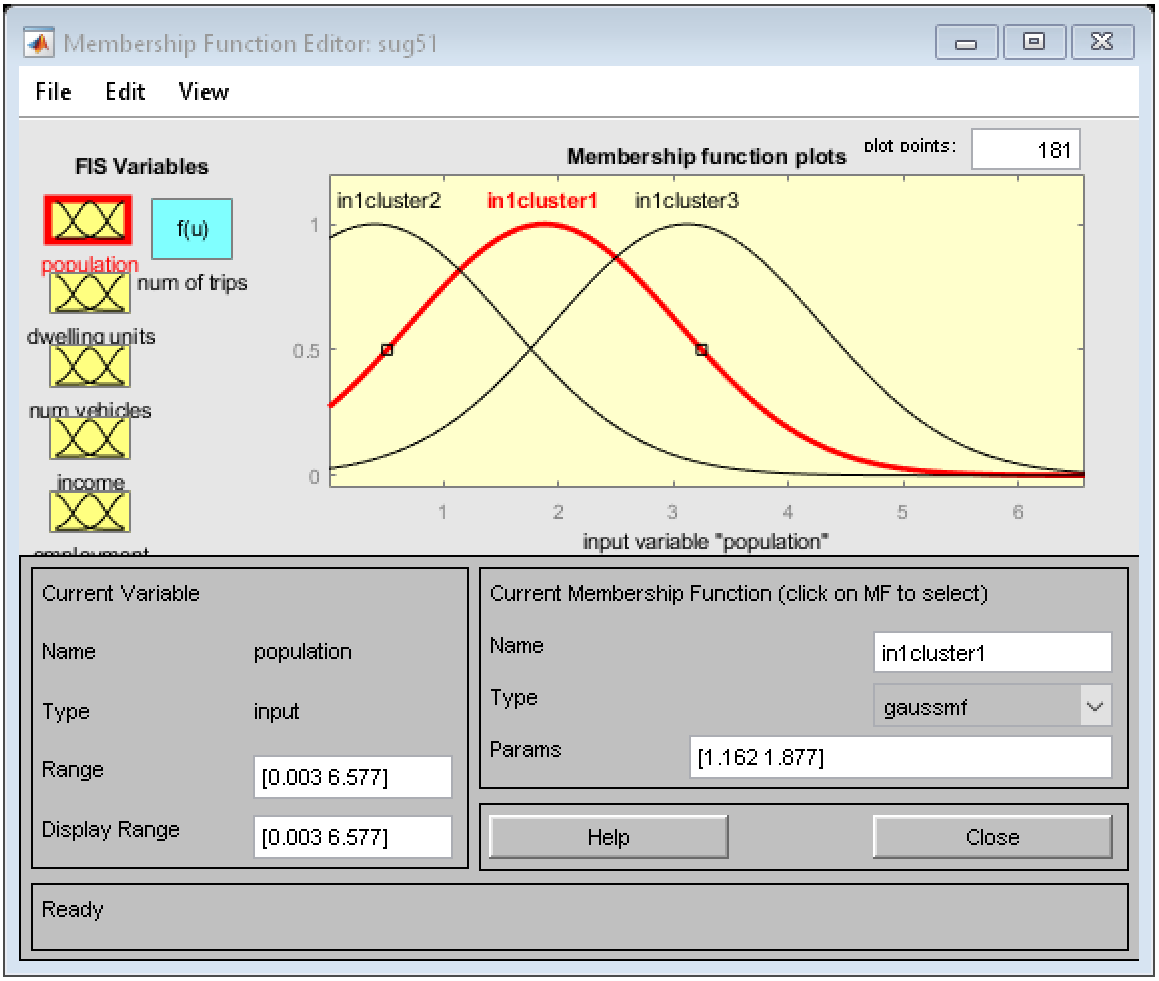
System "sug51": 5 inputs, 1 output, and 3 rules

Figure 3: The graphical editor for building Fuzzy Inference Systems (FIS)

As can be seen, the FIS has 5 inputs and 1 output with the inputs mapped to the outputs through a rule base (white box in the figure).

Let's now try to analyze how the cluster centers and the membership functions are related.

```
mfedit(myfis)
```



Current Variable

Name	population
Type	input
Range	[0.003 6.577]
Display Range	[0.003 6.577]

Current Membership Function (click on MF to select)

Name	in1cluster1
Type	gaussmf
Params	[1.162 1.877]

Figure 4: The graphical membership function editor

`mfedit(myfis)` launches the graphical membership function editor. It can also be launched by clicking on the inputs or the outputs in the FIS editor launched by `fuzzyLogicDesigner`.

Notice that all the inputs and outputs have exactly 3 membership functions. The 3 membership functions represent the 3 clusters that were identified by `subclust`.

Each input in the FIS represents an input variable in the input dataset `datin` and each output in the FIS represents an output variable in the output dataset `datout`.

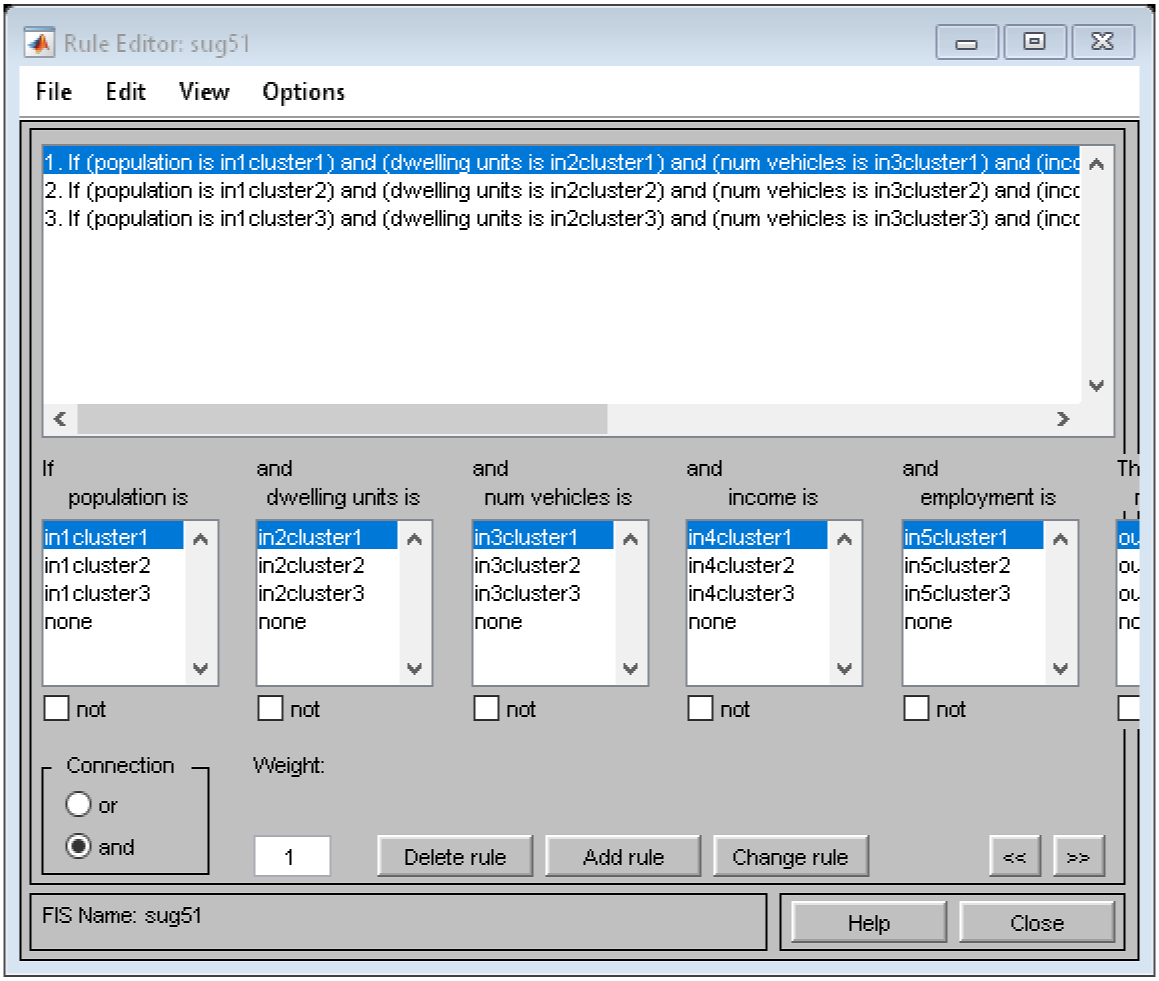
By default, the first membership function, `in1cluster1`, of the first input `population` would be selected in the membership function editor. Notice that the membership function type is `gaussmf` (Gaussian type membership function) and the parameters of the membership function are `[1.162 1.877]`, where `1.162` represents the spread coefficient of the Gaussian curve and `1.877` represents the center of the Gaussian curve. `in1cluster1` captures the position and influence of the first cluster for the input variable `population`. `(C(1,1)=1.877, S(1)=1.1621 )`

Similarly, the position and influence of the other 2 clusters for the input variable `population` are captured by the other two membership functions `in1cluster2` and `in1cluster3`.

The rest of the 4 inputs follow the exact pattern mimicking the position and influence of the 3 clusters along their respective dimensions in the dataset.

Now, let's explore how the fuzzy rules are constructed.

```
ruleedit(myfis)
```



1. If (population is in1cluster1) and (dwelling units is in2cluster1) and (num vehicles is in3cluster1) and (inco
2. If (population is in1cluster2) and (dwelling units is in2cluster2) and (num vehicles is in3cluster2) and (inco
3. If (population is in1cluster3) and (dwelling units is in2cluster3) and (num vehicles is in3cluster3) and (inco

If population is	and dwelling units is	and num vehicles is	and income is	and employment is	Th
in1cluster1	in2cluster1	in3cluster1	in4cluster1	in5cluster1	ou
in1cluster2	in2cluster2	in3cluster2	in4cluster2	in5cluster2	ou
in1cluster3	in2cluster3	in3cluster3	in4cluster3	in5cluster3	ou
none	none	none	none	none	nc
☐ not	☐ not	☐ not	☐ not	☐ not	☐

Connection: or [✓ and]

Weight: 1

FIS Name: sug51

Figure 5: The graphical rule editor

`ruleedit` is the graphical fuzzy rule editor. As you can notice, there are exactly three rules. Each rule attempts to map a cluster in the input space to a cluster in the output space.

The first rule can be explained simply as follows. If the inputs to the FIS, `population`, `dwelling units`, `num vehicles`, `income`, and `employment`, strongly belong to their respective `cluster1` membership functions then the output, `num of trips`, must strongly belong to its `cluster1` membership function. The (1) at the end of the rule is to indicate that the rule has a weight or an importance of "1". Weights can take any value between 0 and 1. Rules with lesser weights will count for less in the final output.

The significance of the rule is that it succinctly maps cluster 1 in the input space to cluster 1 in the output space. Similarly the other two rules map cluster 2 and cluster 3 in the input space to cluster 2 and cluster 3 in the output space.

If a datapoint closer to the first cluster, or in other words having strong membership to the first cluster, is fed as input to `myfis` then rule1 will fire with more firing strength than the other two rules. Similarly, an input with strong membership to the second cluster will fire the second rule will with more firing strength than the other two rules and so on.

The output of the rules (firing strengths) are then used to generate the output of the FIS through the output membership functions.

The one output of the FIS, `num of trips`, has 3 linear membership functions representing the 3 clusters identified by `subclust`. The coefficients of the linear membership functions though are not taken directly from the cluster centers. Instead, they are estimated from the dataset using least squares estimation technique.

All 3 membership functions in this case will be of the form `a*population + b*dwelling units + c*num vehicles + d*income + e*employment + f`, where `a`, `b`, `c`, `d`, `e` and `f` represent the coefficients of the linear membership function. Click on any of the `num of trips` membership functions in the membership function editor to observe the parameters of these linear membership functions.

Using the FIS for Data Exploration

You can now use the FIS that has been constructed to understand the underlying dynamics of relationship being modeled.

```
surfview(myfis)
```

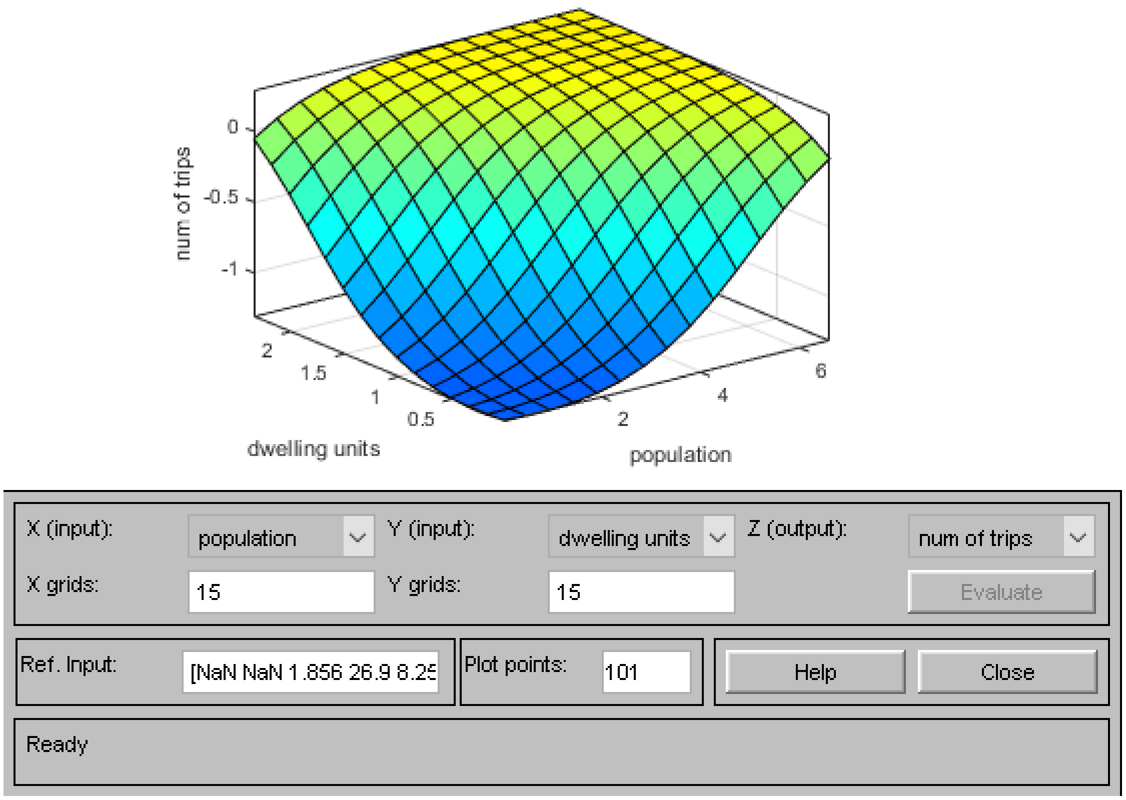
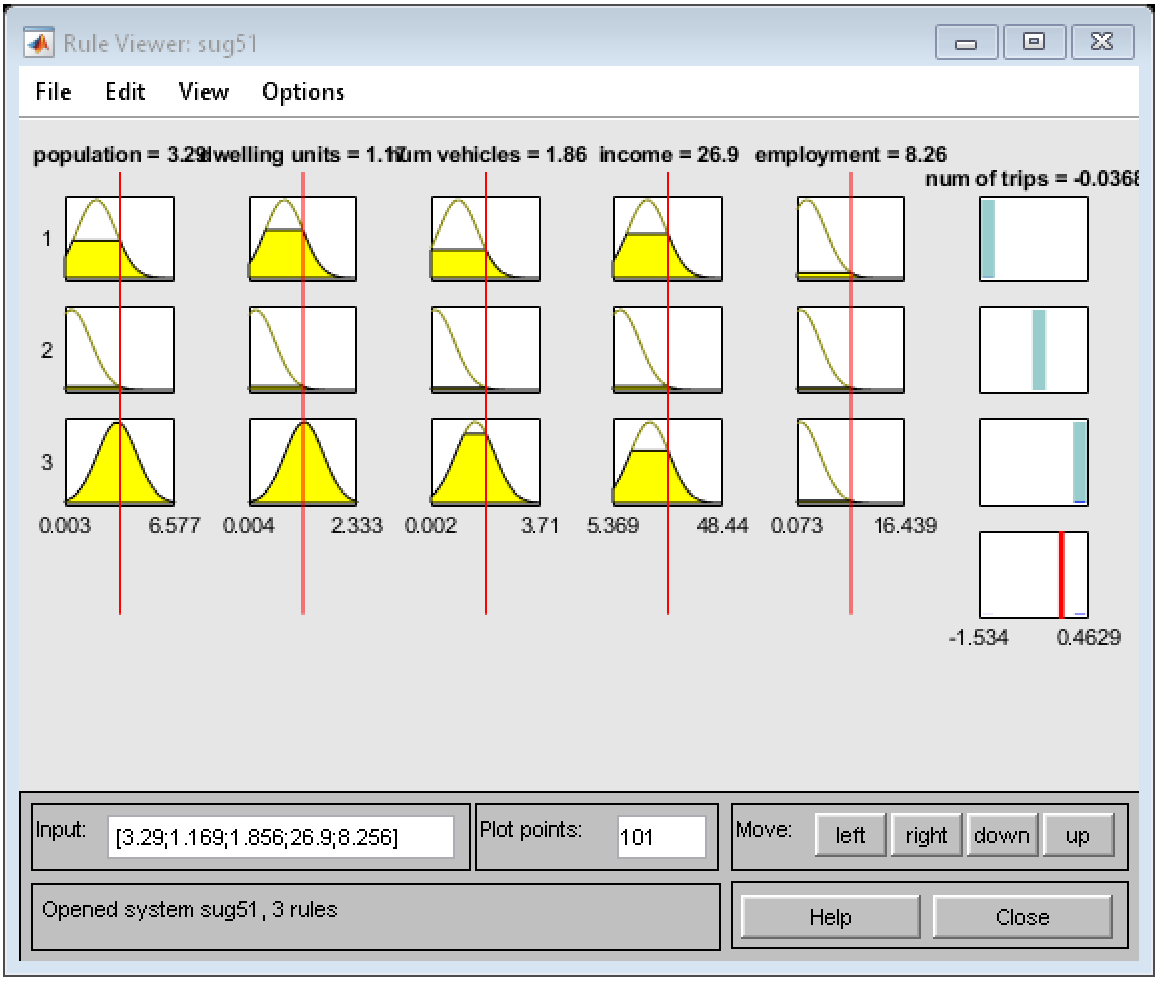


Figure 6: Input-Output Surface viewer

`surfview` is the surface viewer that helps view the input-output surface of the fuzzy system. In other words, this tool simulates the response of the fuzzy system for the entire range of inputs that the system is configured to work for. Thereafter, the output or the response of the FIS to the inputs are plotted against the inputs as a surface. This visualization is very helpful to understand how the system is going to behave for the entire range of values in the input space.

In the plot above the surface viewer shows the output surface for two inputs `population` and `num of dwelling units`. As you can see the number of auto trips increases with increase in population and dwelling units, which sounds very rational. You can change the inputs in the X and Y drop-down boxes to observe the output surface with respect to the inputs you choose.

```
ruleview(myfis)
```



Input: [3.29;1.169;1.856;26.9;8.256]

Plot points: 101

Opened system sug51 , 3 rules

Figure 7: Rule viewer that simulates the entire fuzzy inference process

`ruleview` is the graphical simulator for simulating the FIS response for specific values of the input variables. Now, having built the fuzzy system, if we want to understand how many trips will occur for a particular demographic setup, say an area with a particular population, a certain number of dwelling units and so on, this tool will help you simulate the FIS response for the input of your choice.

Another feature of this GUI tool is, it gives you a snapshot of the entire fuzzy inference process, right from how the membership functions are being satisfied in every rule to how the final output is being generated through defuzzification.

Conclusion

This example has attempted to convey how clustering and fuzzy logic can be employed as effective techniques for data modeling and analysis.

Fuzzy logic has also found various applications in other areas of technology like non-linear control, automatic control, signal processing, system identification, pattern recognition, time series prediction, data mining, financial applications etc.

Reference

[1] - S. Chiu, "Fuzzy Model Identification Based on Cluster Estimation," *J. of Intelligent & Fuzzy Systems*, Vol. 2, No. 3, 1994.

See Also

`anfis` | `subclust`

More About

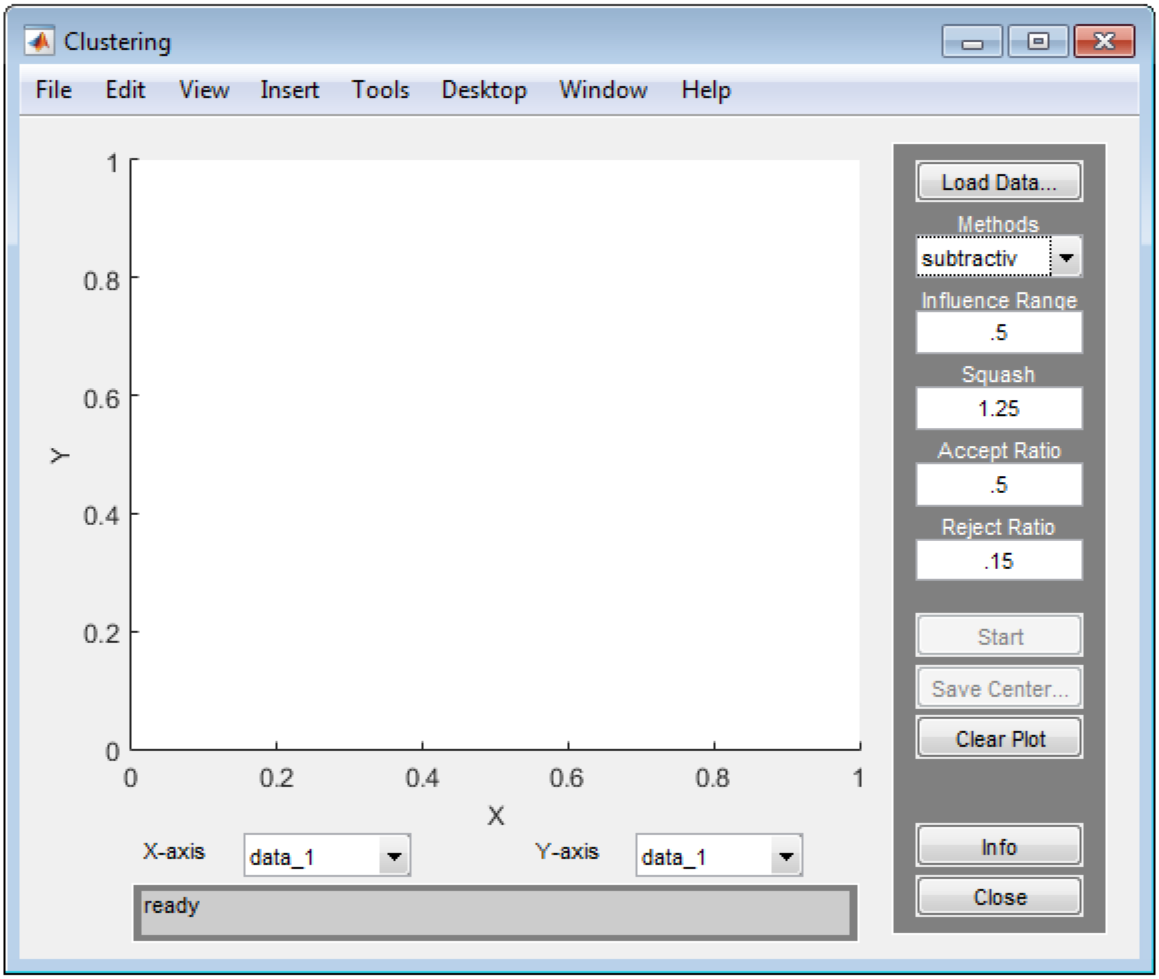
- “Fuzzy Clustering” on page 4-2

Data Clustering Using Clustering Tool

The Clustering tool implements the fuzzy data clustering functions `fcm` and `subclust`, and lets you perform clustering on data. For more information on the clustering methods, see "Fuzzy Clustering" on page 4-2.

To open the tool, at the MATLAB command line, type:

```
findcluster
```



Methods: subtractiv
Influence Range: .5
Squash: 1.25
Accept Ratio: .5
Reject Ratio: .15
X-axis: data_1
Y-axis: data_1

ready

Use the Clustering tool to perform the following tasks:

1. Load and plot the data.
2. Perform the clustering.
3. Save the cluster center.

Access the online help topics by clicking **Info** or using the **Help** menu.

Load and Plot Data

To load a data set, perform either of the following actions:

- Click **Load Data**, and select the file containing the data.
- Open the Clustering Tool with a data set directly by calling `findcluster` with the data set as an input argument.

  The data set file must have the extension `.dat`. Each line of the data set file contains one data point. For example, if you have 5-dimensional data with 100 data points, the file contains 100 lines, and each line contains five values.

  For example, enter:

  ```
  findcluster('clusterdemo.dat')
  ```

The Clustering tool works on multidimensional data sets, but displays only two of those dimensions on the plot. To select other dimensions in the data set for plotting, you can use the drop-down lists under **X-axis** and **Y-axis**.

Cluster Data

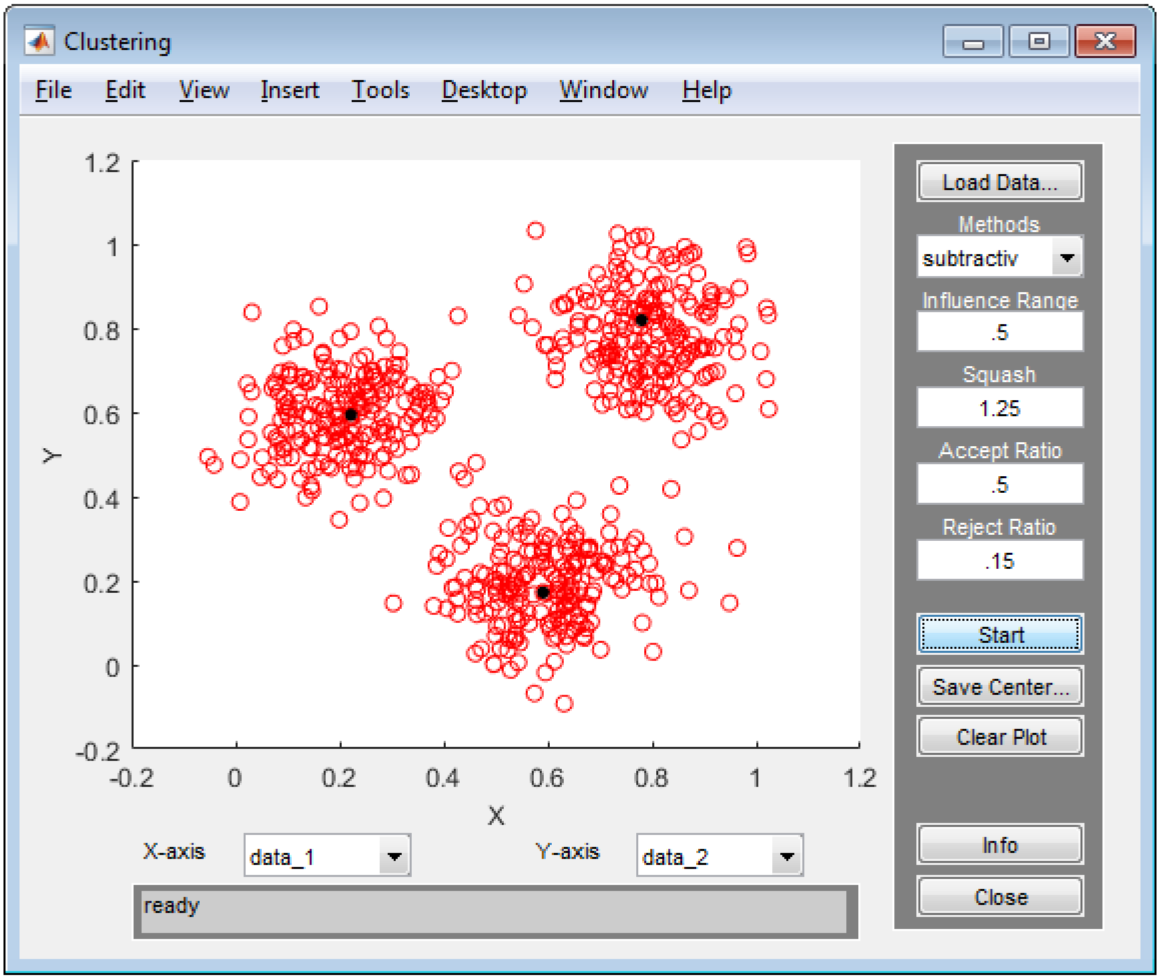
To start clustering the data:

1. Choose the clustering function `fcm` (fuzzy C-Means clustering) or `subtractiv` (subtractive clustering) from the drop-down menu under **Methods**.
2. Set options for:

   - Fuzzy c-means clustering using the **Cluster Num**, **Max Iteration**, **Min**, and **Exponent** fields. For information on these options, see `fcm`.
   - Subtractive clustering using the **Influence Range**, **Squash**, **Aspect Ratio**, and **Reject Ratio** fields. For information on these options, see `subclust`.

3 Cluster the data by clicking **Start**.

Once the clustering is complete, the cluster centers appear in black as shown in the next figure.



Methods: subtractiv

Influence Range: .5

Squash: 1.25

Accept Ratio: .5

Reject Ratio: .15

X-axis: data_1

Y-axis: data_2

ready

Tip Using the Clustering tool, you can obtain only the computed cluster centers. To obtain additional information for:

- Fuzzy c-means clustering, such as the fuzzy partition matrix, cluster the data using `fcm`.
- Subtractive clustering, such as the range of influence in each data dimension, cluster the data using `subclust`.

To use the same clustering data with either `fcm` or `subclust`, first load the data file into the MATLAB workspace. For example, at the MATLAB command line, type:

```
load clusterdemo.dat
```

Save Cluster Centers

To save the cluster centers, click **Save Center**.

See Also

`fcm` | `findcluster` | `subclust`

More About

- “Fuzzy Clustering” on page 4-2

Fuzzy Logic in Simulink

Simulate Fuzzy Inference Systems in Simulink

You can simulate a fuzzy inference system (FIS) in Simulink using either the Fuzzy Logic Controller or Fuzzy Logic Controller with Ruleviewer blocks. Alternatively, you can evaluate fuzzy systems at the command line using `evalfis`.

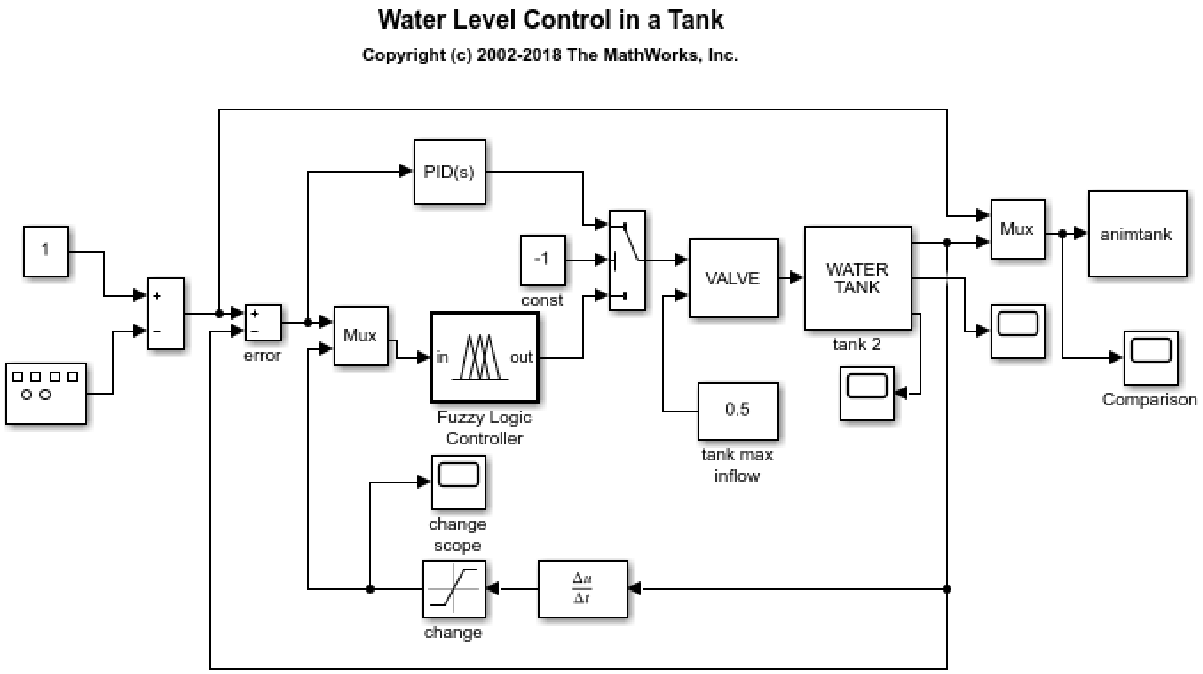
For more information on creating fuzzy inference systems, see “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14 and “Build Fuzzy Systems at the Command Line” on page 2-38.

Simulate Fuzzy Inference System

Once you have implemented a fuzzy inference system using **Fuzzy Logic Designer**, using **Neuro-Fuzzy Designer**, or at the command line, you can simulate the system in Simulink.

For this example, you control the level of water in a tank using a fuzzy inference system implemented using a Fuzzy Logic Controller block. Open the `sltank` model.

```
open_system('sltank')
```



For this system, you control the water that flows into the tank using a valve. The outflow rate depends on the diameter of the output pipe, which is constant, and the pressure in the tank, which varies with water level. Therefore, the system has nonlinear characteristics.

The two inputs to the fuzzy system are the water level error, `level`, and the rate of change of the water level, `rate`. The output of the fuzzy system is the rate at which the control valve is opening or closing, `valve`.

To implement a fuzzy inference system, specify the **FIS name** parameter of the Fuzzy Logic Controller block as the name of a FIS object in the MATLAB® workspace. In this example, the block uses the `mamfis` object `tank`.

For more information on this system, see “Water Level Control in a Tank” on page 5-15.

As a first attempt to control the water level, set the following rules in the FIS. These rules adjust the valve based on only the water level error.

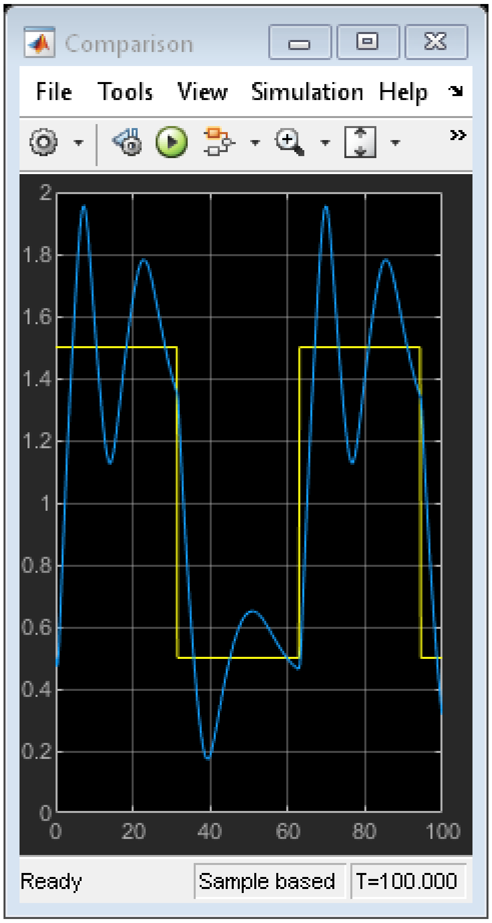
- If the water level is okay, then do not adjust the valve.
- If the water level is low, then open the valve quickly.
- If the water level is high, then close the valve quickly.

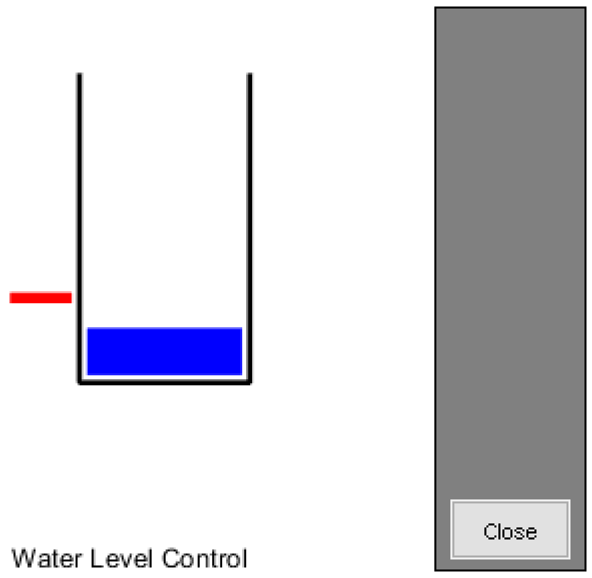
Specify the rules by creating a vector of `fisrule` objects and assigning it to the `Rules` property of the `tank` FIS object.

```
rule1 = "If level is okay then valve is no_change";
rule2 = "If level is low then valve is open_fast";
rule3 = "If level is high then valve is close_fast";
rules = [rule1 rule2 rule3];
tank.Rules = fisrule(rules);
```

Simulate the model, and view the water level.

```
open_system('sltank/Comparison')
sim('sltank',100)
```


Comparison
File Tools View Simulation Help
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0 20 40 60 80 100
Ready
Sample based
T=100.000



These rules are insufficient for controlling the system, since the water level oscillates around the setpoint.

To reduce the oscillations, add two more rules to the system. These rules adjust the valve based on the rate of change of the water level when the water level is near the setpoint.

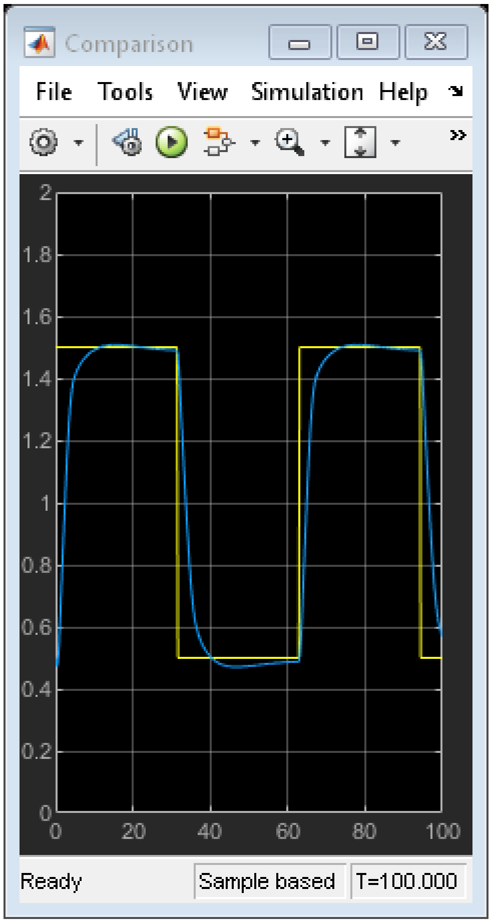
- If the water level is okay and increasing, then close the valve slowly.
- If the water level is okay and decreasing, then open the valve slowly.

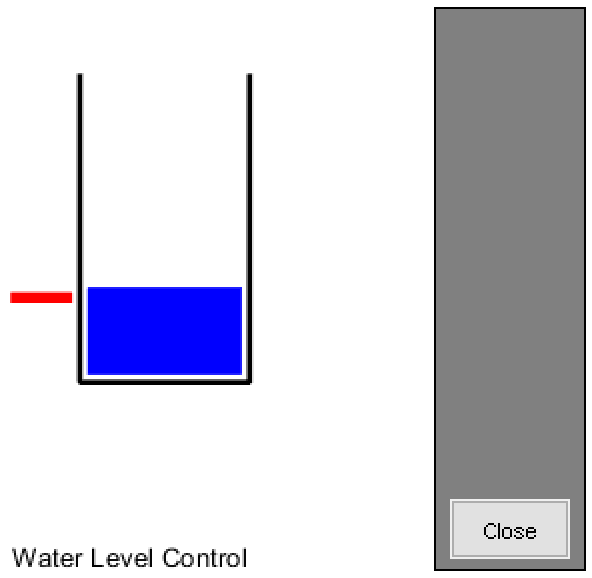
To add these rules, use the `addRule` function.

```
rule4 = "If level is okay and rate is positive then valve is close_slow";
rule5 = "If level is okay and rate is negative then valve is open_slow";
newRules = [rule4 rule5];
tank = addRule(tank,newRules);
```

Simulate the model.

```
sim('sltank',100)
```

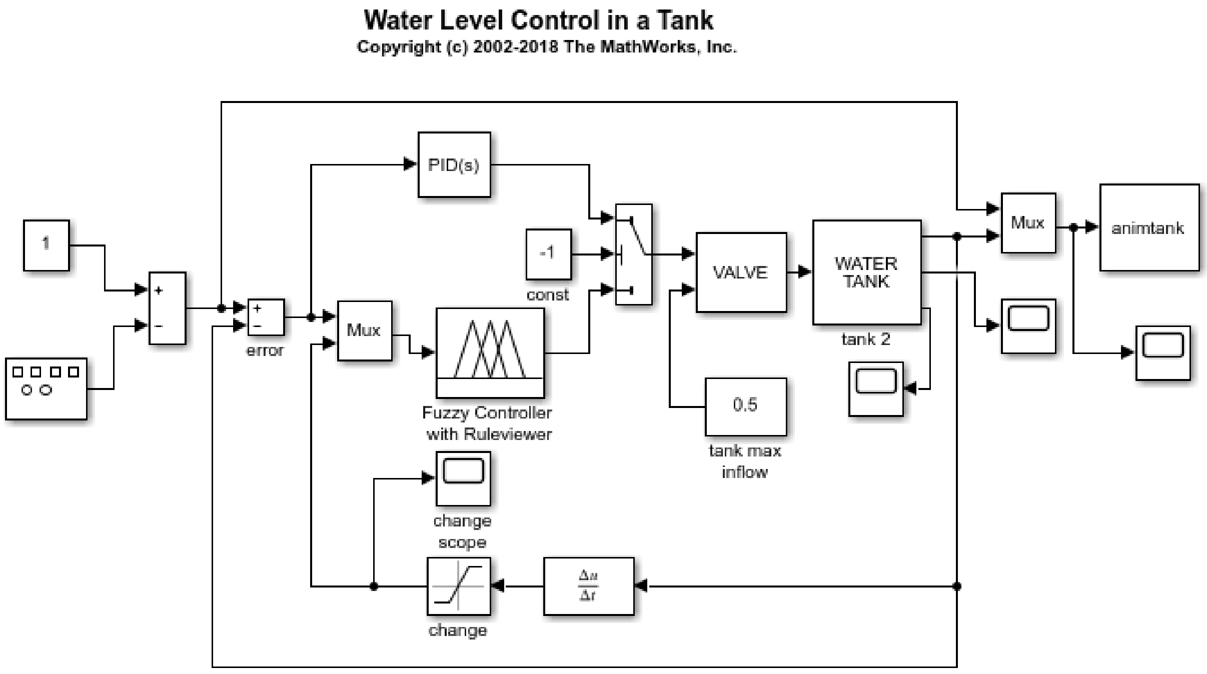

Comparison
File Tools View Simulation Help
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0 20 40 60 80 100
Ready
Sample based
T=100.000



The water level now tracks the setpoint without oscillating.

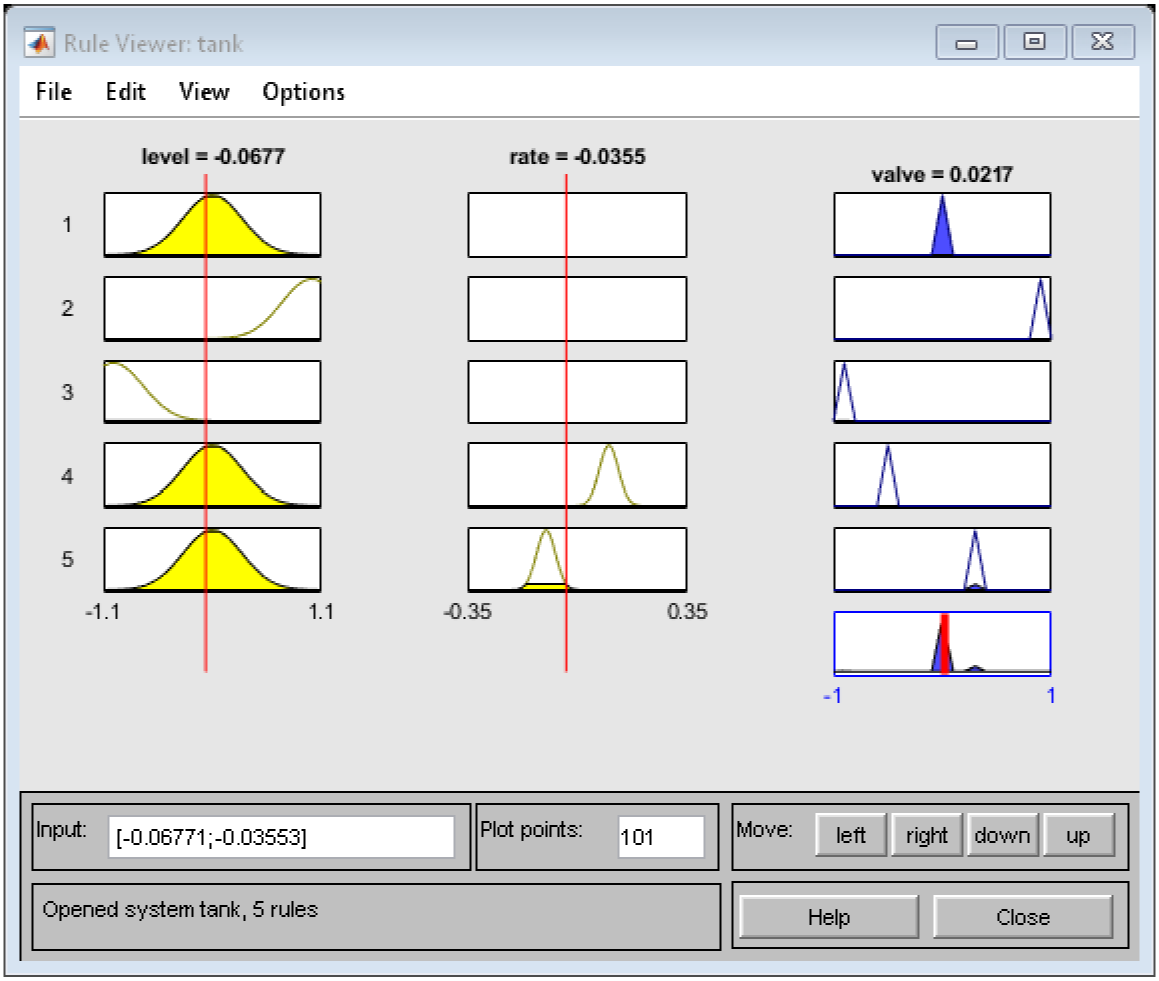
You can also simulate fuzzy systems using the Fuzzy Logic Controller with Ruleviewer block. The `sltankrule` model is the same as the `sltank` model, except that it uses the Fuzzy Logic Controller with Ruleviewer block.

```
open_system('sltankrule')
```



During simulation, this block displays the Rule Viewer from the **Fuzzy Logic Designer** app.

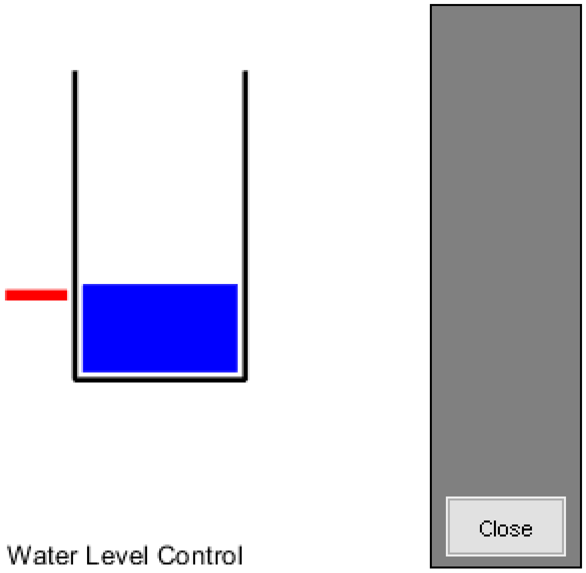
```
sim('sltankrule',100)
```



Input: [-0.06771;-0.03553]

Plot points: 101

Opened system tank, 5 rules



If you pause the simulation, you can examine the FIS behavior by manually adjusting the input variable values in the Rule Viewer, and observing the inference process and output.

You can also access the **Fuzzy Logic Designer** editors from the Rule Viewer. From the Rule Viewer, you can then adjust the parameters of your fuzzy system using these editors, and export the updated system to the MATLAB workspace. To simulate the updated FIS, restart the simulation. For more information on using these editors, see “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14.

Access Intermediate Fuzzy Inference Results

You can access intermediate fuzzy inference results using the Fuzzy Logic Controller block. You can use this data to visualize the fuzzy inference process or troubleshoot the performance of your FIS. To access this data, enable the corresponding parameters in the block, and connect signals to the corresponding output ports.

Block Parameter	Description	Output Port
Fuzzified Inputs	Fuzzified input values, obtained by evaluating the input membership functions of each rule at the current input values.	`fi`
Rule firing strengths	Rule firing strengths, obtained by evaluating the antecedent of each rule.	`rfs`
Rule outputs	Rule outputs, obtained by evaluating the consequent of each rule.	`ro`
Aggregated outputs	Aggregate output for each output variable, obtained by combining the corresponding outputs from all the rules.	`ao`

For more information, see Fuzzy Logic Controller.

Simulation Modes

The Fuzzy Logic Controller block has the following two simulation modes:

- `Interpreted execution` — Simulate fuzzy systems using precompiled MEX files. Using this option reduces the initial compilation time of the model.
- `Code generation` — Simulate fuzzy system without precompiled MEX files. Use this option when simulating fuzzy systems for code generation applications. Doing so simulates your system using the same code path used for generated code.

To select a simulation mode, set the **Simulate using** parameter of the block. By default, the block uses `Interpreted execution` mode for simulation.

Map Command-Line Functionality to Fuzzy Logic Controller Block

The parameters and ports of the Fuzzy Logic Controller block map to the input and output arguments of `evalfis` or the properties of `evalfisOptions`. The following table shows the block parameters and ports that map to `evalfis` arguments.

`evalfis` Argument	Description	Block Parameter or Port
`fis`	Fuzzy inference system	**FIS name**

`evalfis` Argument	Description	Block Parameter or Port
`input`, when a single row	Input variable values	`in`
`output`, when a single row	Output variable values	`out`
`fuzzifiedIn`	Fuzzified inputs	`fi`
`ruleOut`	Rule outputs	`ro`
`aggregateOut`	Aggregated outputs	`ao`
`ruleFiring`	Rule firing strengths	`rfs`

The following table shows the block parameters that map to `evalfisOptions` properties.

`evalfisOptions` Property	Description	Block Parameter or Port
`NumSamplePoints`	Number of points in output fuzzy sets	**Number of samples for output discretization**
`OutOfRangeInputValueMessage`	Diagnostic message behavior when an input is out of range	**Out of range input value**
`NoRuleFiredMessage`	Diagnostic message behavior when no rules fire	**No rule fired**
`EmptyOutputFuzzySetMessage`	Diagnostic message behavior when an output fuzzy set is empty	**Empty output fuzzy set**

The remaining parameters of the Fuzzy Logic Controller block do not map to arguments of `evalfis`. Also, unlike the Fuzzy Logic Controller, `evalfis` does not support fixed-point data for simulation or code generation.

See Also

Blocks
Fuzzy Logic Controller | Fuzzy Logic Controller with Ruleviewer

More About

- "Temperature Control in a Shower" on page 5-23

- “Water Level Control in a Tank” on page 5-15

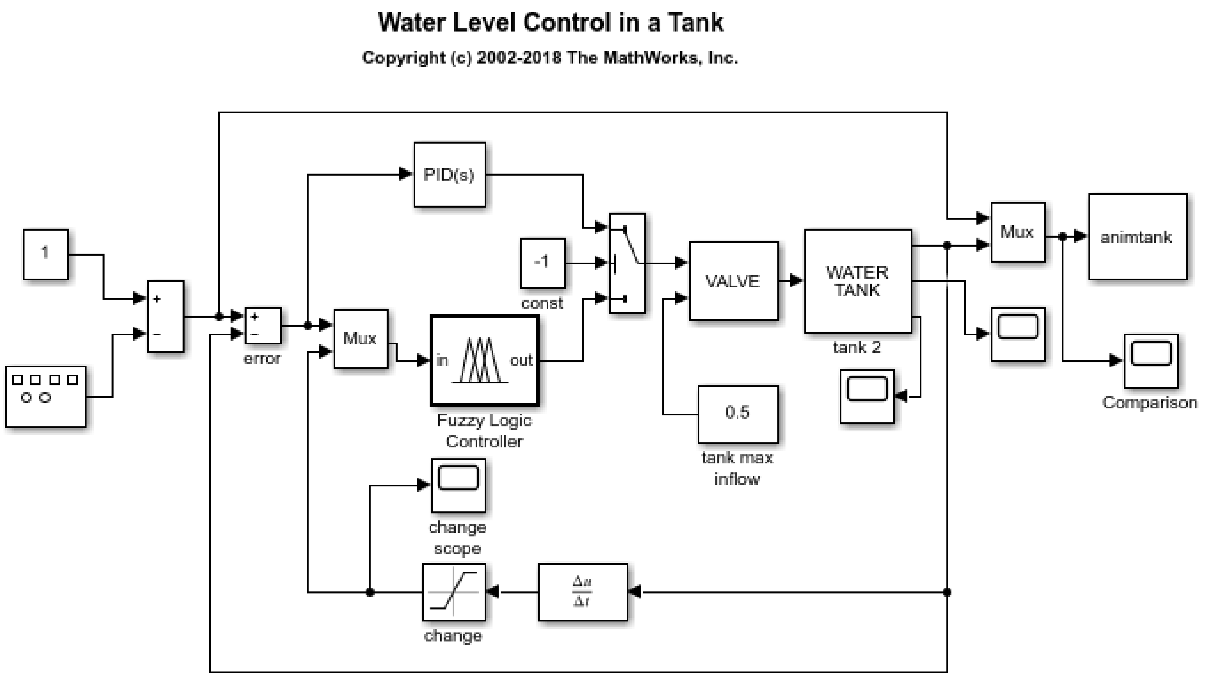
Water Level Control in a Tank

This model shows how to implement a fuzzy inference system (FIS) in a Simulink® model.

Simulink Model

This model controls the level of water in a tank using a fuzzy inference system implemented using a Fuzzy Logic Controller block. Open the `sltank` model.

```
open_system('sltank')
```



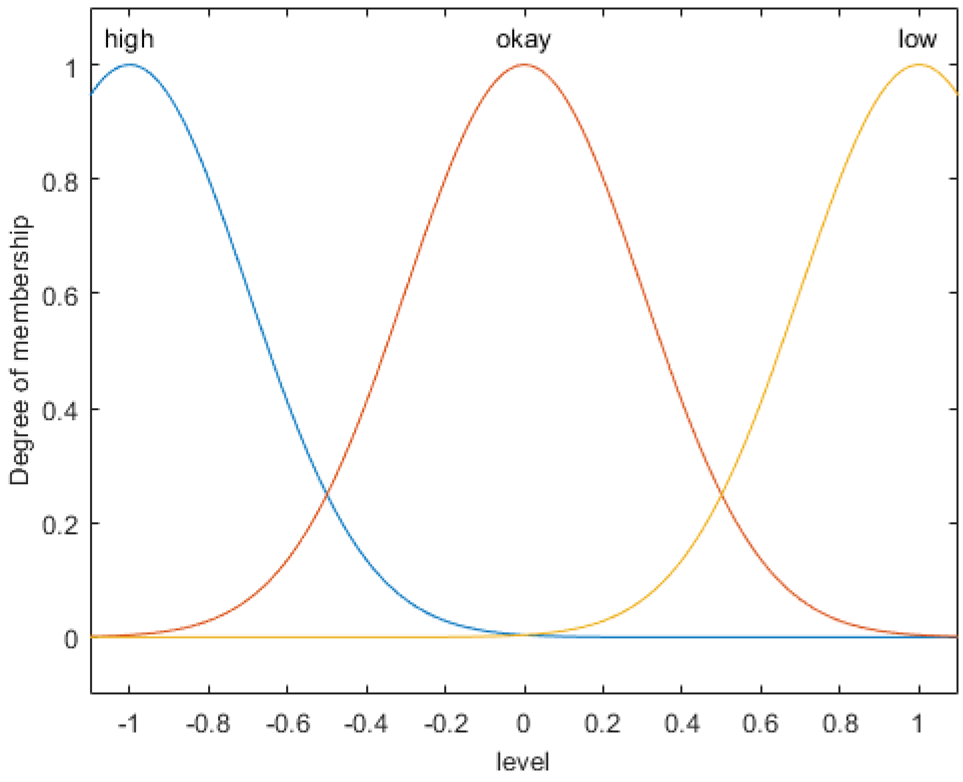
For this system, you control the water that flows into the tank using a valve. The outflow rate depends on the diameter of the output pipe, which is constant, and the pressure in the tank, which varies with water level. Therefore, the system has nonlinear characteristics.

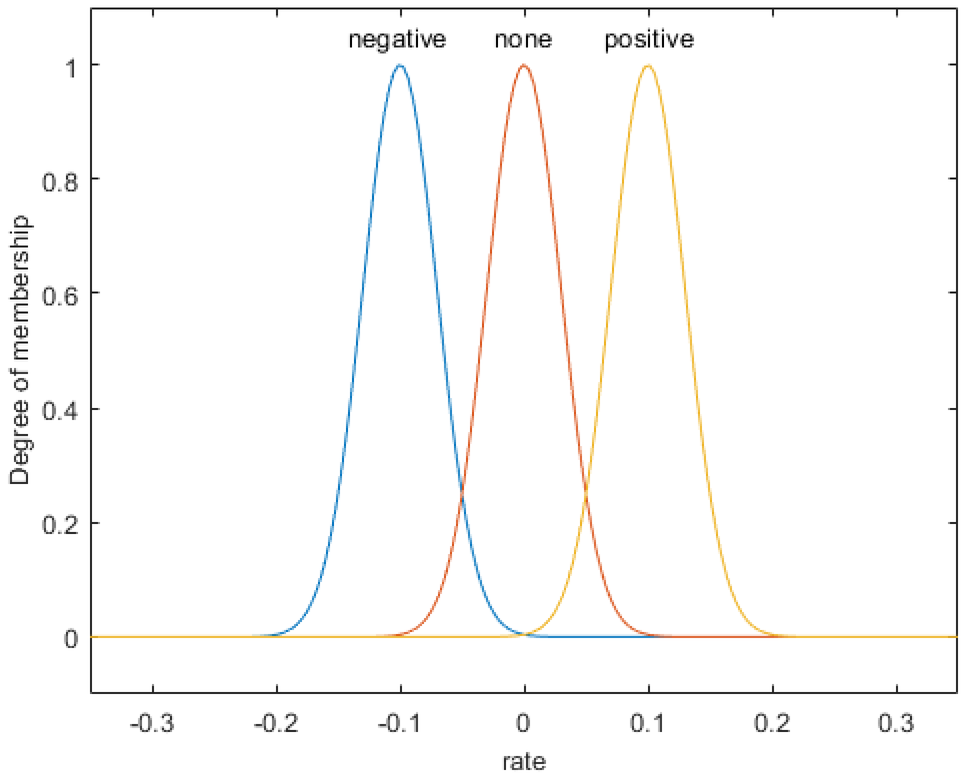
Fuzzy Inference System

The fuzzy system is defined in a FIS object, `tank`, in the MATLAB® workspace. For more information on how to specify a FIS in a Fuzzy Logic Controller block, see Fuzzy Logic Controller.

The two inputs to the fuzzy system are the water level error, `level`, and the rate of change of the water level, `rate`. Each input has three membership functions.

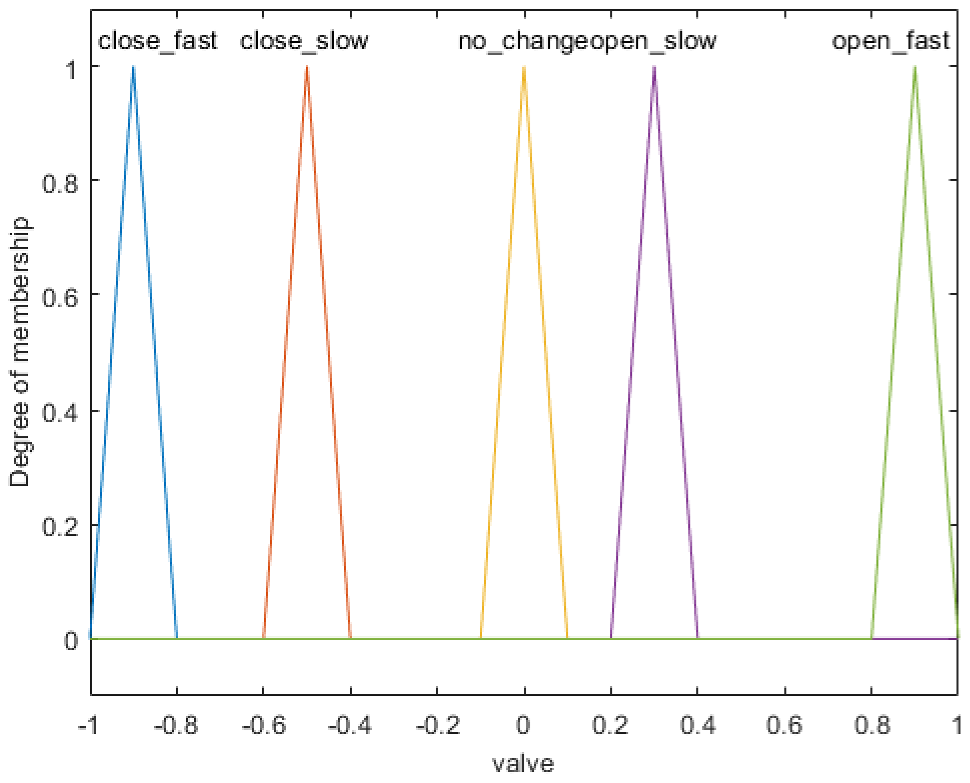
```
figure
plotmf(tank,'input',1)
figure
plotmf(tank,'input',2)
```





The output of the fuzzy system is the rate at which the control valve is opening or closing, `valve`, which has five membership functions.

```
plotmf(tank,'output',1)
```



Due to the diameter of the outflow pipe, the water tank in this system empties more slowly than it fills up. To compensate for this imbalance, the `close_slow` and `open_slow` valve membership functions are not symmetrical. A PID controller does not support such asymmetry.

The fuzzy system has five rules. The first three rules adjust the valve based on only the water level error.

- If the water level is okay, then do not adjust the valve.
- If the water level is low, then open the valve quickly.
- If the water level is high, then close the valve quickly.

The other two rules adjust the valve based on the rate of change of the water level when the water level is near the setpoint.

- If the water level is okay and increasing, then close the valve slowly.
- If the water level is okay and decreasing, then open the valve slowly.

```
tank.Rules
```

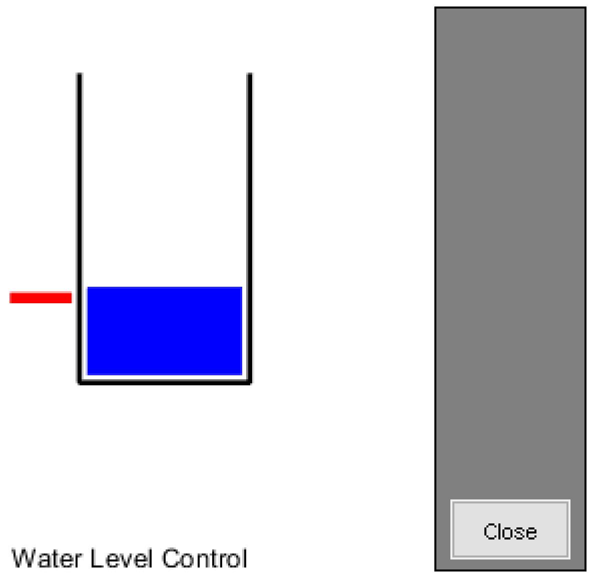
```
ans = 

  1x5 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                                Description
           ______________________________________________________

    1    "level==okay => valve=no_change (1)"
    2    "level==low => valve=open_fast (1)"
    3    "level==high => valve=close_fast (1)"
    4    "level==okay & rate==positive => valve=close_slow (1)"
    5    "level==okay & rate==negative => valve=open_slow (1)"
```

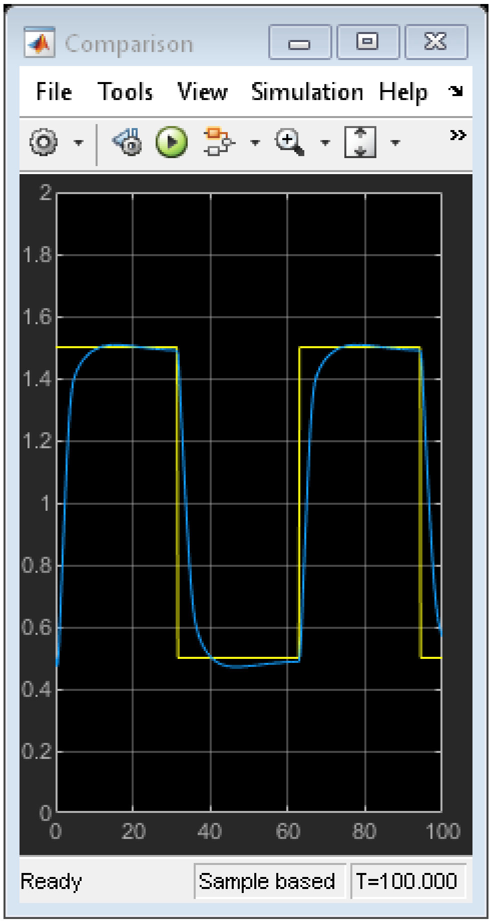
In this model, you can also control the water level using a PID controller. To switch to the PID controller, set the const block to a value greater than or equal to zero.

Simulation

The model simulates the controller with periodic changes in the setpoint of the water level. Run the simulation.

```
sim('sltank',100)
open_system('sltank/Comparison')
```


Close
Water Level Control



The water level tracks the setpoint well. You can adjust the performance of the controller by modifying the rules of the `tank` FIS. For example, if you remove the last two rules, which are analogous to a derivative control action, the controller performs poorly, with large oscillations in the water level.

See Also

Blocks
Fuzzy Logic Controller | Fuzzy Logic Controller with Ruleviewer

More About

- “Simulate Fuzzy Inference Systems in Simulink” on page 5-2
- “Temperature Control in a Shower” on page 5-23

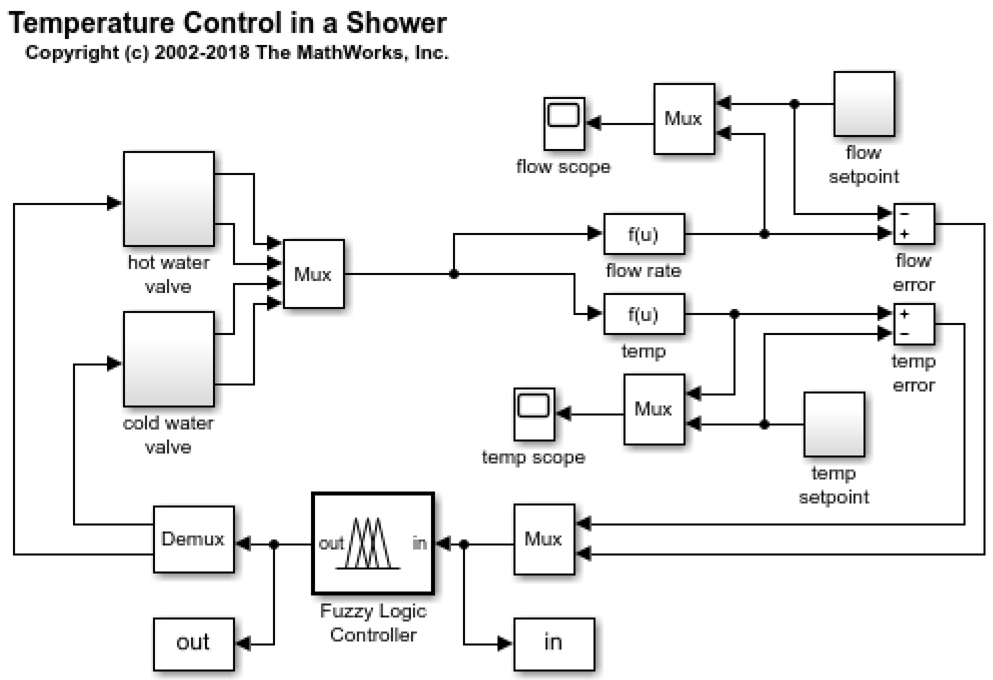
Temperature Control in a Shower

This model shows how to implement a fuzzy inference system (FIS) in a Simulink® model.

Simulink Model

The model controls the temperature of a shower using a fuzzy inference system implemented using a Fuzzy Logic Controller block. Open the `shower` model.

```
open_system('shower')
```



For this system, you control the flow rate and temperature of a shower by adjusting hot and cold water valves.

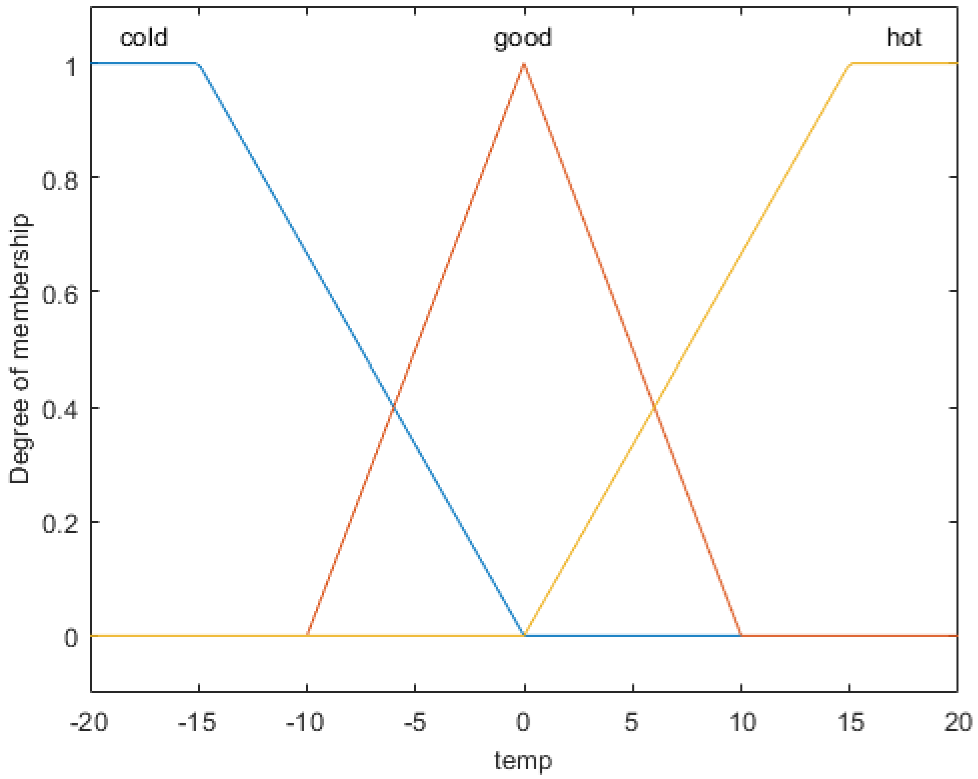
Since there are two inputs for the fuzzy system, the model concatenates the input signals using a Mux block. The output of the Mux block is connected to the input of the Fuzzy Logic Controller block. Similarly, the two output signals are obtained using a Demux block connected to the controller.

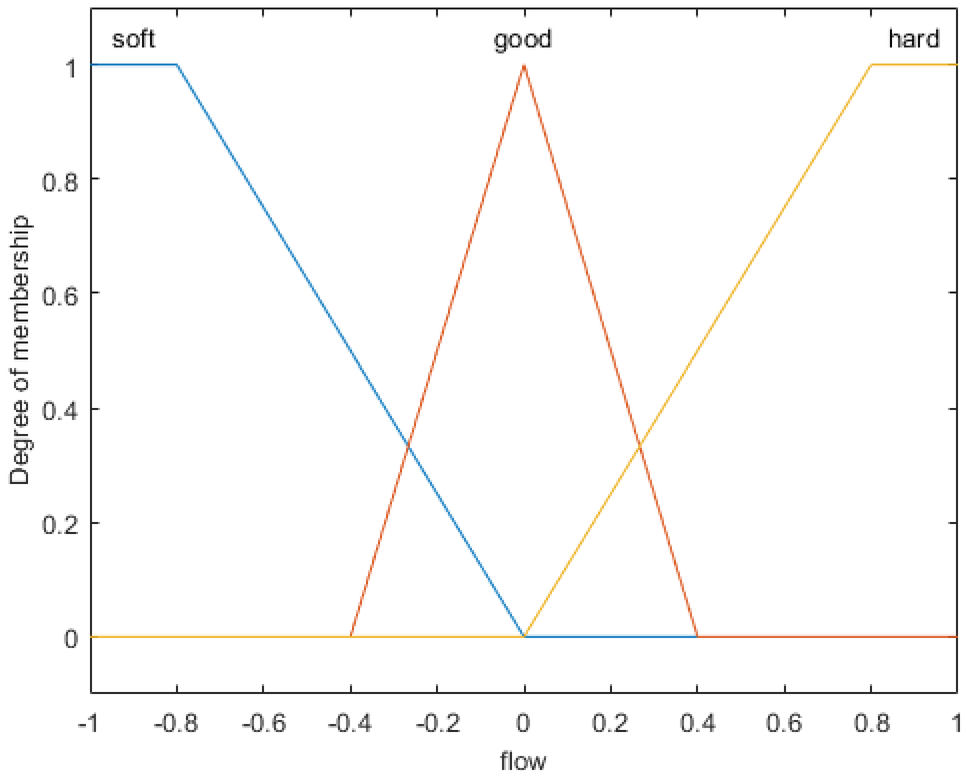
Fuzzy Inference System

The fuzzy system is defined in a FIS object, `fisMatrix`, in the MATLAB® workspace. For more information on how to specify a FIS in a Fuzzy Logic Controller block, see Fuzzy Logic Controller.

The two inputs to the fuzzy system are the temperature error, `temp`, and the flow rate error, `flow`. Each input has three membership functions.

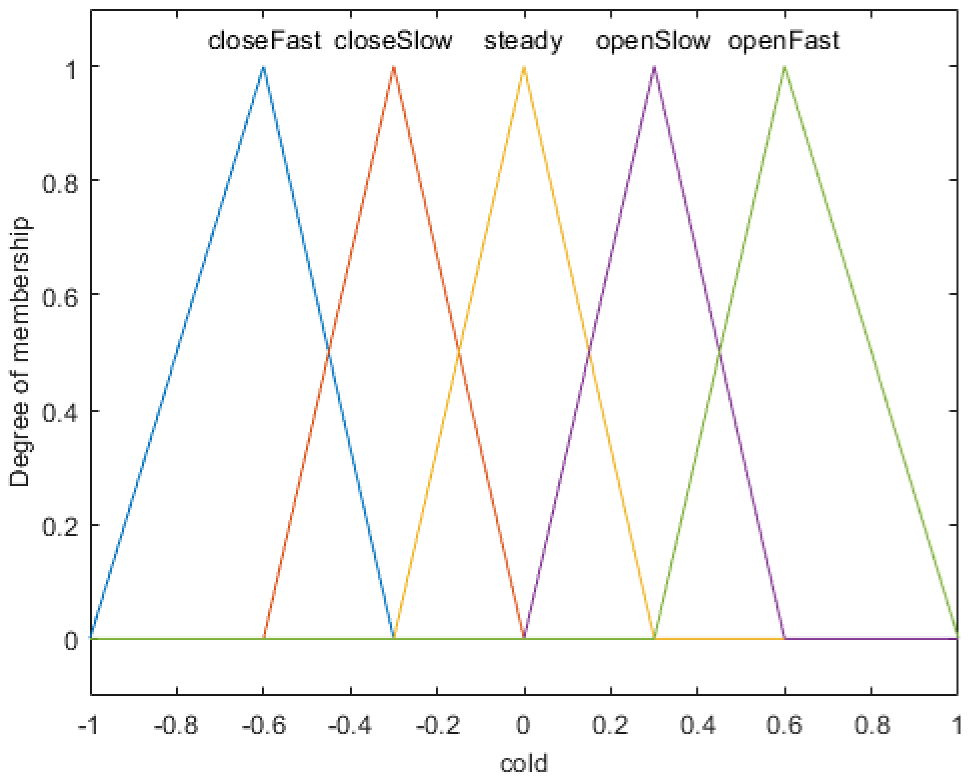
```
figure
plotmf(fisMatrix,'input',1)
figure
plotmf(fisMatrix,'input',2)
```

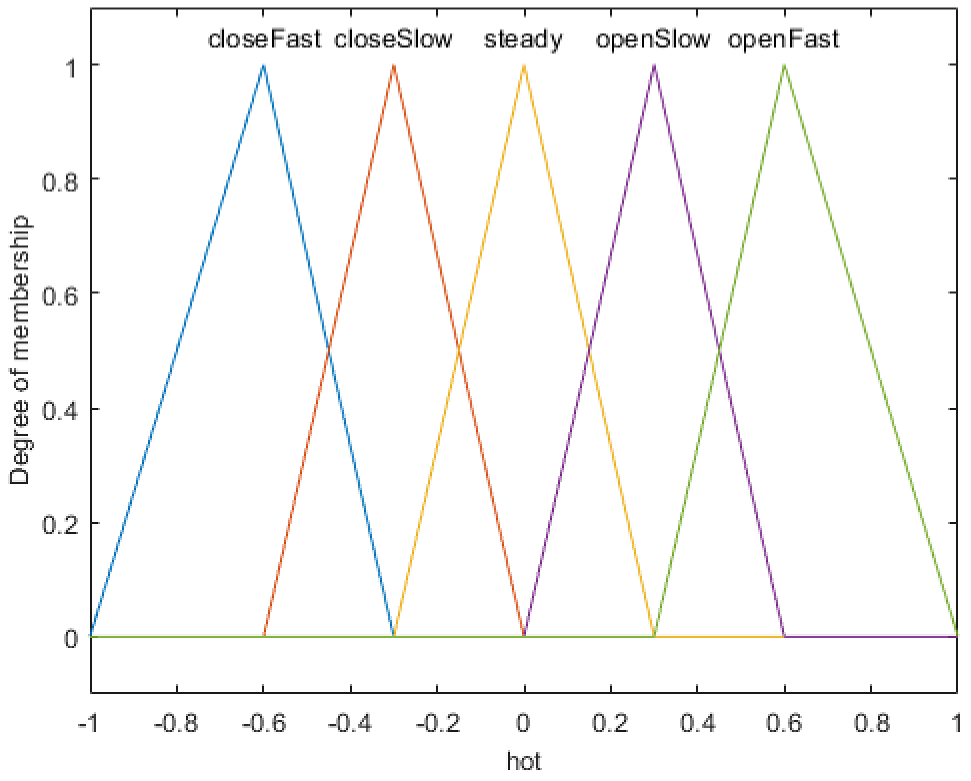




The two outputs of the fuzzy system are the rate at which the cold and hot water valves are opening or closing, `cold` and `hot` respectively. Each output has five membership functions.

```
figure
plotmf(fisMatrix,'output',1)
figure
plotmf(fisMatrix,'output',2)
```


closeFast
closeSlow
steady
openSlow
openFast
Degree of membership
0
0.2
0.4
0.6
0.8
1
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1
cold



The fuzzy system has nine rules for adjusting the hot and cold water valves based on the flow and temperature errors. The rules adjust the total flow rate based on the flow error, and adjust the relative hot and cold flow rates based on the temperature error.

```
fisMatrix.Rules
```

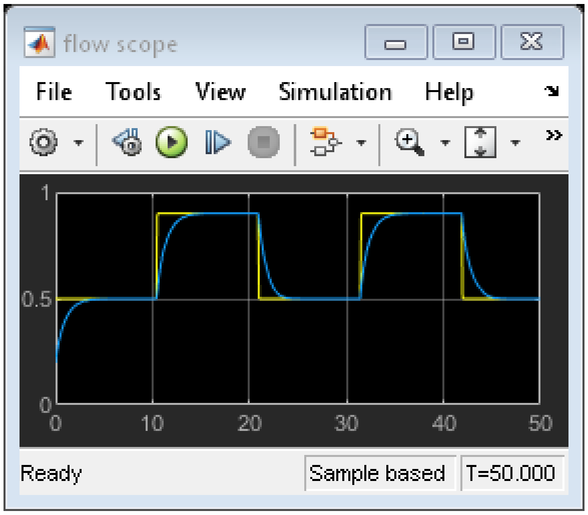
```
ans = 

  1x9 fisrule array with properties:

    Description
    Antecedent
    Consequent
```

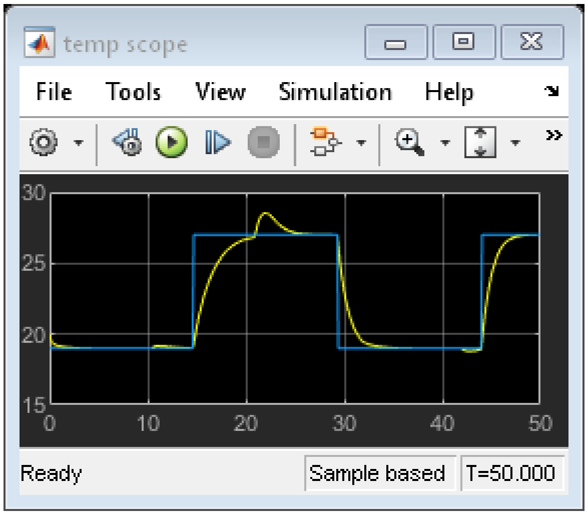
```
      Weight
      Connection

    Details:
                                   Description
         _______________________________________________________________

      1     "temp==cold & flow==soft => cold=openSlow, hot=openFast (1)"
      2     "temp==cold & flow==good => cold=closeSlow, hot=openSlow (1)"
      3     "temp==cold & flow==hard => cold=closeFast, hot=closeSlow (1)"
      4     "temp==good & flow==soft => cold=openSlow, hot=openSlow (1)"
      5     "temp==good & flow==good => cold=steady, hot=steady (1)"
      6     "temp==good & flow==hard => cold=closeSlow, hot=closeSlow (1)"
      7     "temp==hot & flow==soft => cold=openFast, hot=openSlow (1)"
      8     "temp==hot & flow==good => cold=openSlow, hot=closeSlow (1)"
      9     "temp==hot & flow==hard => cold=closeSlow, hot=closeFast (1)"
```

Simulation

The model simulates the controller with periodic changes in the setpoints of the water temperature and flow rate.

```
set_param('shower/flow scope','Open','on','Ymin','0','Ymax','1')
set_param('shower/temp scope','Open','on','Ymin','15','Ymax','30')
sim('shower',50)
```





The flow rate tracks the setpoint well. The temperature also tracks its setpoint, though there are temperature deviations when the controller adjusts to meet a new flow setpoint.

```
bdclose('shower') % Closing model also clears its workspace variables.
```

See Also

Blocks
Fuzzy Logic Controller

More About

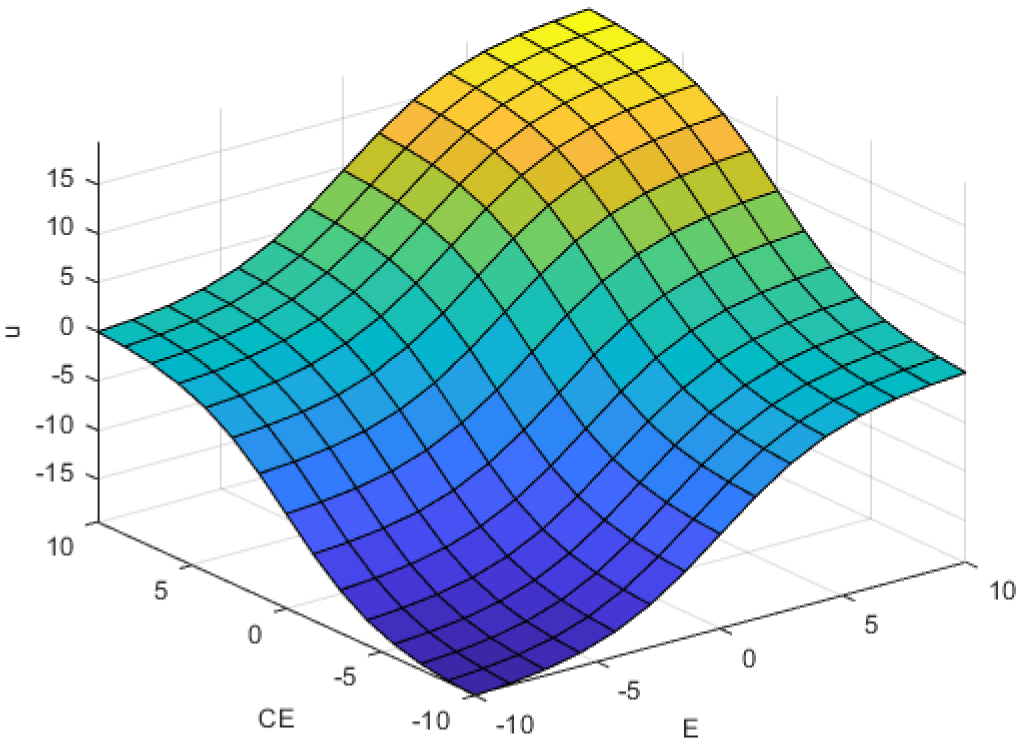
- “Simulate Fuzzy Inference Systems in Simulink” on page 5-2
- “Water Level Control in a Tank” on page 5-15

Implement Fuzzy PID Controller in Simulink Using Lookup Table

This example shows how to implement a fuzzy inference system for nonlinear PID control using a 2-D Lookup Table block.

Overview

A fuzzy inference system (FIS) maps given inputs to outputs using fuzzy logic. For example, a typical mapping of a two-input, one-output fuzzy controller can be depicted in a 3-D plot. The plot is often referred to as a *control* surface plot.



For control applications, typical FIS inputs are the error (`e(k)`) and change of error (`e(k)-e(k-1)`), `E` and `CE` respectively in the control surface plot. The FIS output is the control action inferred from the fuzzy rules, `u` in the surface plot. Fuzzy Logic Toolbox™ provides commands and apps for designing a FIS for a desired control surface. You can then simulate the designed FIS using the Fuzzy Logic Controller block in Simulink®.

You can often approximate nonlinear control surfaces using lookup tables to simplify the generated code and improve execution speed. For example, you can replace a Fuzzy Logic Controller block in Simulink with a set of Lookup Table blocks, one table for each output defined in the FIS. You can compute the data used in the lookup table using the `evalfis` command.

For this example, you design a nonlinear fuzzy PID controller for a plant in Simulink. The plant is a single-input, single-output system in discrete time. The design goal is to achieve good reference tracking performance.

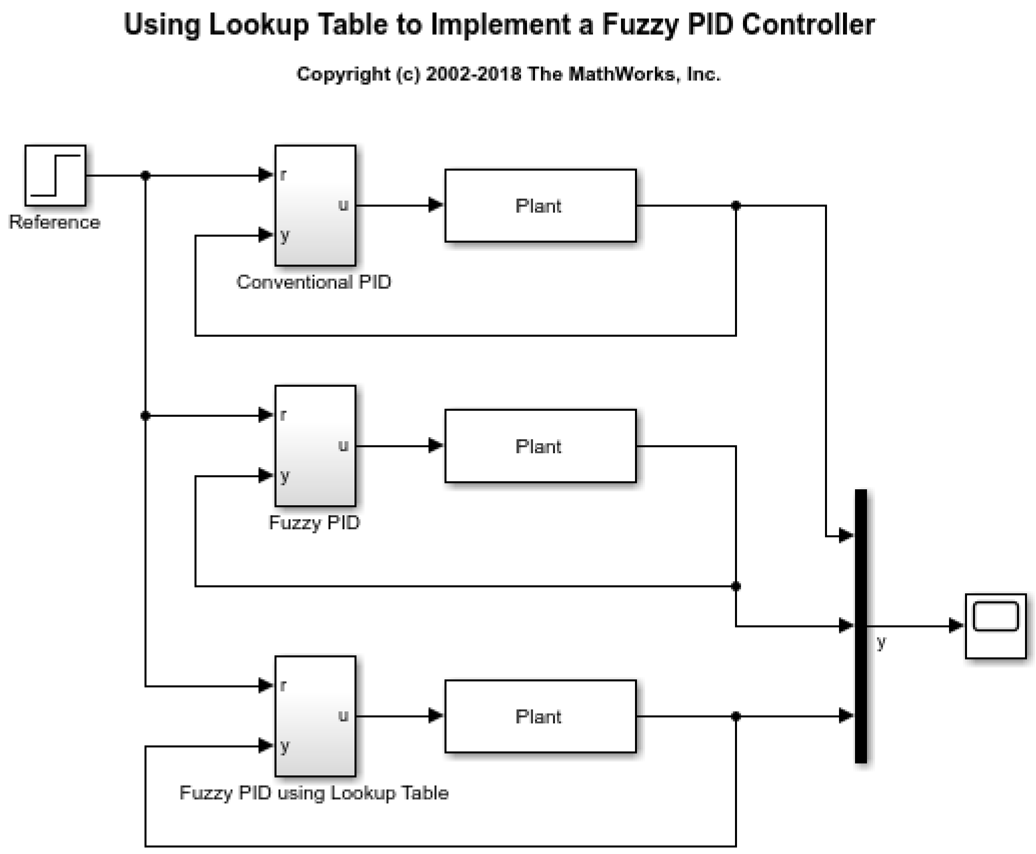
```
Ts = 0.1;
Plant = c2d(zpk([],[-1 -3 -5],1),Ts);
```

You also implement the fuzzy inference system using a 2-D lookup table that approximates the control surface and achieves the same control performance.

Fuzzy PID Controller Structure

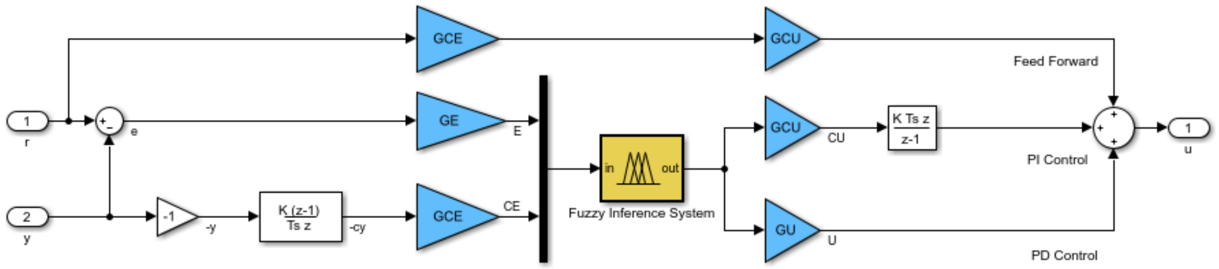
The fuzzy controller in this example is in the feedback loop and computes PID-like actions using fuzzy inference. Open the Simulink model.

```
open_system('sllookuptable')
```


Using Lookup Table to Implement a Fuzzy PID Controller
Copyright (c) 2002-2018 The MathWorks, Inc.
Reference
r
u
y
Conventional PID
Plant
Fuzzy PID
Fuzzy PID using Lookup Table
y

The fuzzy PID controller uses a parallel structure as shown in the Fuzzy PID subsystem. For more information, see [1]. The controller is a combination of fuzzy PI control and fuzzy PD control.

```
open_system('sllookuptable/Fuzzy PID')
```

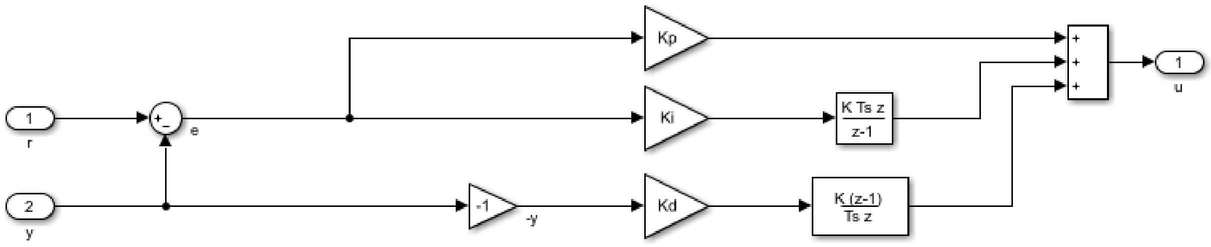


The fuzzy PID controller uses the change of the output `-(y(k)-y(k-1))`, instead of change of error `e(k)-e(k-1)`, as the second input signal to the FIS. Doing so prevents the step change in reference signal from directly triggering the derivative action. The two gain blocks, `GCE` and `GCU`, in the feed forward path from `r` to `u`, ensure that the error signal `e` is used in proportional action when the fuzzy PID controller is linear.

Design Conventional PID Controller

The conventional PID controller in this example is a discrete-time PID controller with Backward Euler numerical integration in both the integral and derivative actions. The controller gains are `Kp`, `Ki`, and `Kd`.

```
open_system('sllookuptable/Conventional PID')
```



Similar to the fuzzy PID controller, the input signal to the derivative action is `-y(k)`, instead of `e(k)`.

You can tune the PID controller gains manually or using tuning formulas. In this example, obtain the initial PID design using the `pidtune` command from Control System Toolbox™.

Define the PID structure, tune the controller, and extract the PID gains.

```
C0 = pid(1,1,1,'Ts',Ts,'IF','B','DF','B');
C = pidtune(Plant,C0)
[Kp,Ki,Kd] = piddata(C);
```

```
C =
 
             Ts*z               z-1
  Kp + Ki * ------  + Kd * ------
              z-1              Ts*z

  with Kp = 30.6, Ki = 25.2, Kd = 9.02, Ts = 0.1
 
Sample time: 0.1 seconds
Discrete-time PID controller in parallel form.
```

Design Equivalent Linear Fuzzy PID Controller

By configuring the FIS and selecting the four scaling factors, you can obtain a linear fuzzy PID controller that reproduces the control performance of the conventional PID controller.

First, configure the fuzzy inference system so that it produces a linear control surface from inputs `E` and `CE` to output `u`. The FIS settings are based on design choices described in [2]:

- Use a Sugeno style fuzzy inference system with default inference methods.
- Normalize the ranges of both inputs to [-10 10].
- Use triangular input membership functions that overlap their neighbor functions at a membership value of 0.5.
- Use an output range of [-20 20].
- Use constant output membership functions.

Construct the fuzzy inference system.

```
FIS = sugfis;
```

Define input variable `E`.

```
FIS = addInput(FIS,[-10 10],'Name','E');
FIS = addMF(FIS,'E','trimf',[-20 -10 0],'Name','Negative');
FIS = addMF(FIS,'E','trimf',[-10 0 10],'Name','Zero');
FIS = addMF(FIS,'E','trimf',[0 10 20],'Name','Positive');
```

Define input `CE`.

```
FIS = addInput(FIS,[-10 10],'Name','CE');
FIS = addMF(FIS,'CE','trimf',[-20 -10 0],'Name','Negative');
FIS = addMF(FIS,'CE','trimf',[-10 0 10],'Name','Zero');
FIS = addMF(FIS,'CE','trimf',[0 10 20],'Name','Positive');
```

Define output variable `u` with `constant` membership functions.

```
FIS = addOutput(FIS,[-20 20],'Name','u');
FIS = addMF(FIS,'u','constant',-20,'Name','LargeNegative');
FIS = addMF(FIS,'u','constant',-10,'Name','SmallNegative');
FIS = addMF(FIS,'u','constant',0,'Name','Zero');
FIS = addMF(FIS,'u','constant',10,'Name','SmallPositive');
FIS = addMF(FIS,'u','constant',20,'Name','LargePositive');
```

Define the following fuzzy rules:

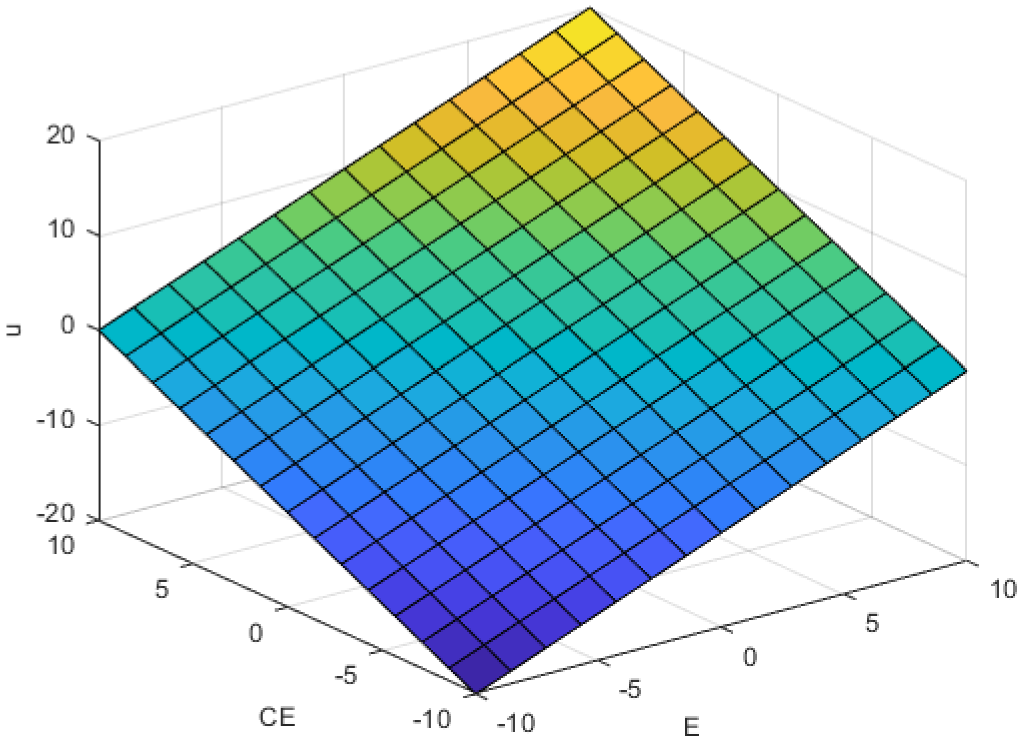
1. If `E` is negative and `CE` is negative, then `u` is `-20`.
2. If `E` is negative and `CE` is zero, then `u` is `-10`.
3. If `E` is negative and `CE` is positive then `u` is `0`.
4. If `E` is zero and `CE` is negative, then `u` is `-10`.
5. If `E` is zero and `CE` is zero, then `u` is `0`.
6. If `E` is zero and `CE` is positive, then `u` is `10`.
7. If `E` is positive and `CE` is negative, then `u` is `0`.
8. If `E` is positive and `CE` is zero, then `u` is `10`.
9. If `E` is positive and `CE` is positive, then `u` is `20`.

```
ruleList = [1 1 1 1 1;   % Rule 1
            1 2 2 1 1;   % Rule 2
            1 3 3 1 1;   % Rule 3
            2 1 2 1 1;   % Rule 4
            2 2 3 1 1;   % Rule 5
            2 3 4 1 1;   % Rule 6
            3 1 3 1 1;   % Rule 7
            3 2 4 1 1;   % Rule 8
            3 3 5 1 1];  % Rule 9
FIS = addRule(FIS,ruleList);
```

While you implement your FIS from the command line in this example, you can alternatively build your FIS using the **Fuzzy Logic Designer** app.

Plot the linear control surface.

```
gensurf(FIS)
```



Determine scaling factors GE, GCE, GCU, and GU from the Kp, Ki, and Kd gains of by the conventional PID controller. Comparing the expressions of the traditional PID and the linear fuzzy PID, the variables are related as follows:

- Kp = GCU * GCE + GU * GE
- Ki = GCU * GE

- Kd = GU * GCE

Assume that the maximum reference step is 1, and thus the maximum error e is 1. Since the input range of E is [-10 10], set GE to 10. You can then solve for GCE, GCU, and GU.

```
GE = 10;
GCE = GE*(Kp-sqrt(Kp^2-4*Ki*Kd))/2/Ki;
GCU = Ki/GE;
GU = Kd/GCE;
```

Implement Fuzzy Inference System Using 2-D Lookup Table

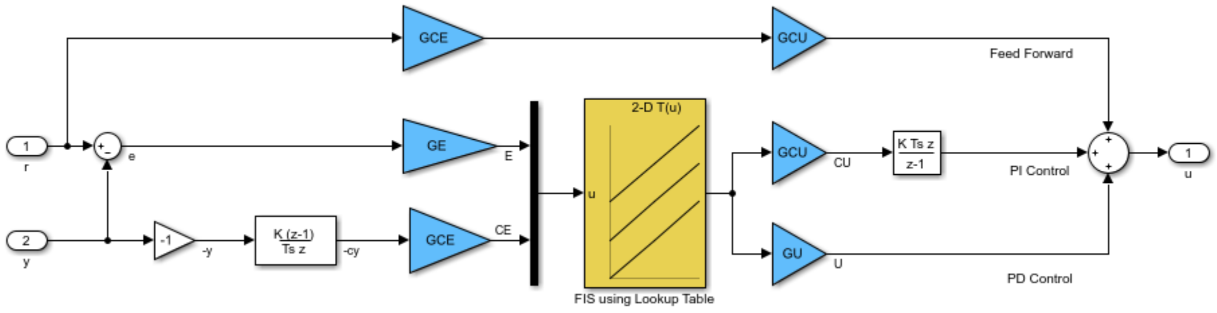
The fuzzy controller block has two inputs (E and CE) and one output (u). Therefore, you can replace the fuzzy system using a 2-D lookup table.

To generate a 2-D lookup table from your FIS, loop through the input universe, and compute the corresponding output values using evalfis. Since the control surface is linear, you can use a few sample points for each input variable.

```
Step = 10;
E = -10:Step:10;
CE = -10:Step:10;
N = length(E);
LookUpTableData = zeros(N);
for i=1:N
   for j=1:N
      % Compute output u for each combination of sample points.
      LookUpTableData(i,j) = evalfis(FIS,[E(i) CE(j)]);
   end
end
```

View the fuzzy PID controller using 2-D lookup table.

```
open_system('sllookuptable/Fuzzy PID using Lookup Table')
```



The only difference compared to the Fuzzy PID controller is that the Fuzzy Logic Controller block is replaced with a 2-D Lookup Table block.

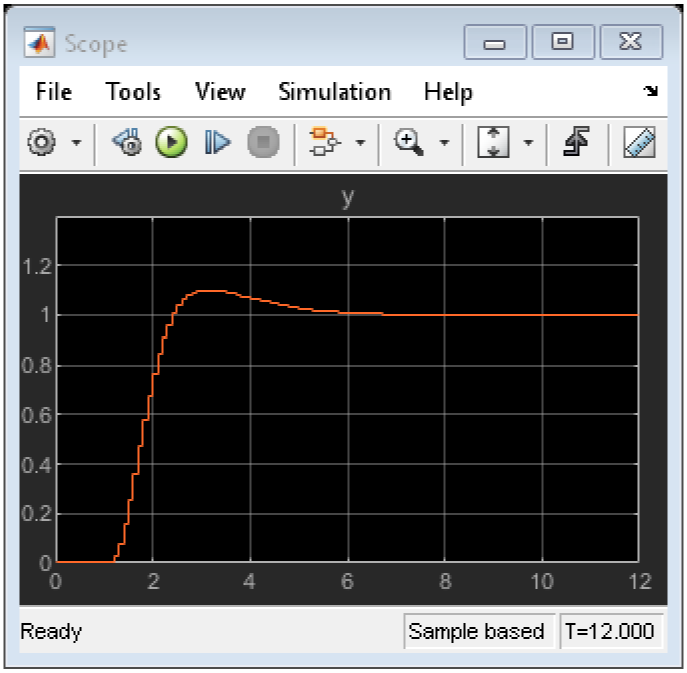
When the control surface is linear, a fuzzy PID controller using the 2-D lookup table produces the same result as one using the Fuzzy Logic Controller block.

Simulate Closed-Loop Response in Simulink

The Simulink model simulates three different controller subsystems, namely Conventional PID, Fuzzy PID, and Fuzzy PID using Lookup Table, to control the same plant.

Run the simulation. To compare the closed-loop responses to a step reference change, open the scope. As expected, all three controllers produce the same result.

```
sim('sllookuptable')
open_system('sllookuptable/Scope')
```



Design Fuzzy PID Controller with Nonlinear Control Surface

Once you have a linear fuzzy PID controller, you can obtain a nonlinear control surface by adjusting your FIS settings, such as its style, membership functions, and rule base.

For this example, design a steep control surface using a Sugeno-type FIS. Each input set has two terms (`Positive` and `Negative`), and the number of rules is reduced to four.

Construct the FIS.

```
FIS = sugfis;
```

Define input `E`.

```
FIS = addInput(FIS,[-10 10],'Name','E');
FIS = addMF(FIS,'E','gaussmf',[7 -10],'Name','Negative');
FIS = addMF(FIS,'E','gaussmf',[7 10],'Name','Positive');
```

Define input `CE`.

```
FIS = addInput(FIS,[-10 10],'Name','CE');
FIS = addMF(FIS,'CE','gaussmf',[7 -10],'Name','Negative');
FIS = addMF(FIS,'CE','gaussmf',[7 10],'Name','Positive');
```

Define output `u`.

```
FIS = addOutput(FIS,[-20 20],'Name','u');
FIS = addMF(FIS,'u','constant',-20,'Name','Min');
FIS = addMF(FIS,'u','constant',0,'Name','Zero');
FIS = addMF(FIS,'u','constant',20,'Name','Max');
```

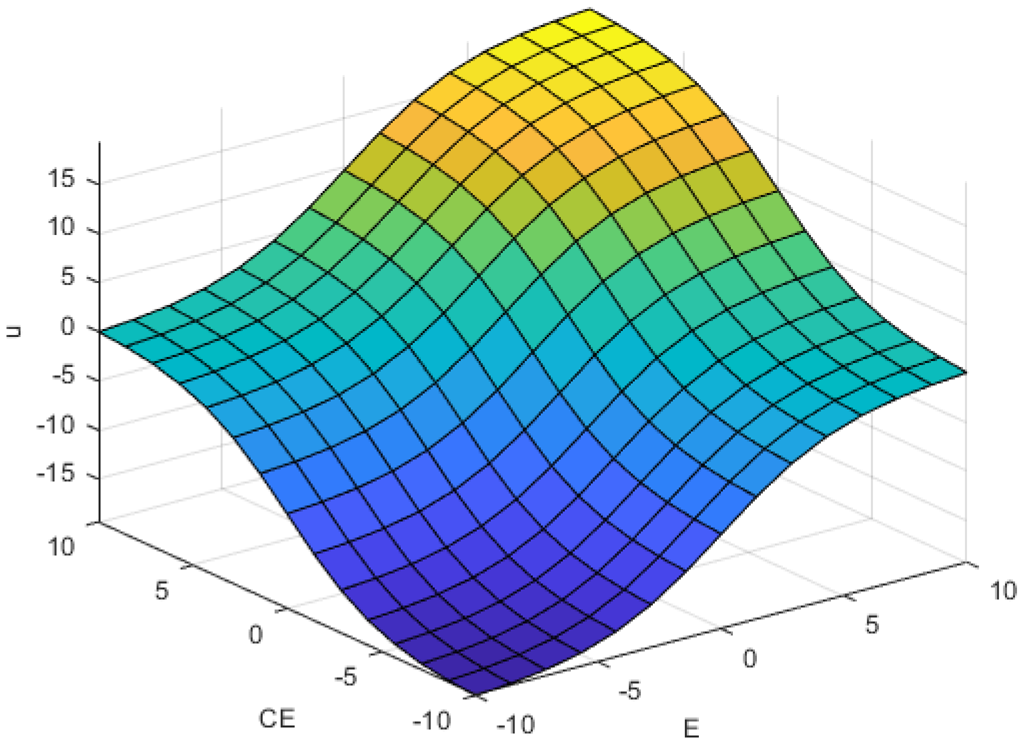
Define the following rules:

1. If `E` is negative and `CE` is negative, then `u` is `-20`.
2. If `E` is negative and `CE` is positive, then `u` is `0`.
3. If `E` is positive and `CE` is negative, then `u` is `0`.
4. If `E` is positive and `CE` is positive, then `u` is `20`.

```
ruleList = [1 1 1 1 1;...   % Rule 1
            1 2 2 1 1;...   % Rule 2
            2 1 2 1 1;...   % Rule 3
            2 2 3 1 1];     % Rule 4
FIS = addRule(FIS,ruleList);
```

View the 3-D nonlinear control surface. This surface has a higher gain near the center of the `E` and `CE` plane than the linear surface has, which helps reduce the error more quickly when the error is small. When the error is large, the controller becomes less aggressive to avoid possible saturation.

```
gensurf(FIS)
```



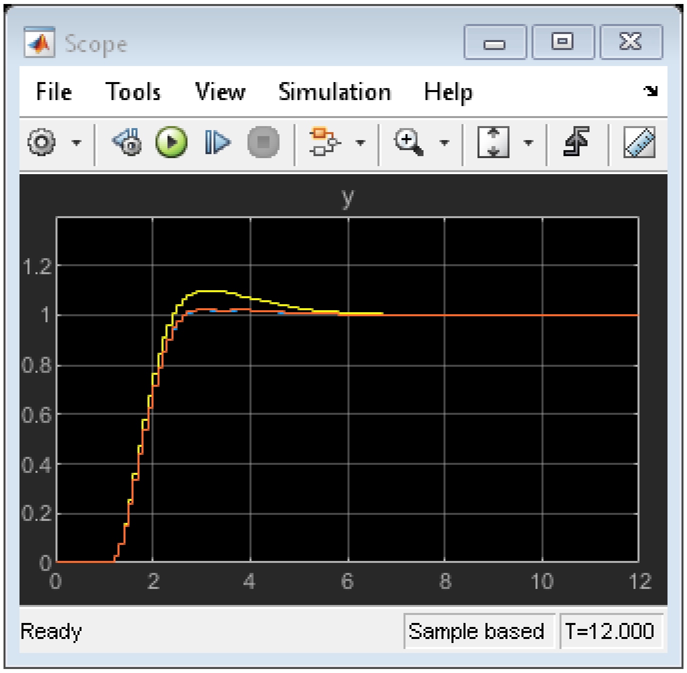
Before starting the simulation, update the lookup table with the new control surface data. Since the surface is nonlinear, to obtain a sufficient approximation, add more sample points.

```
Step = 1;
E = -10:Step:10;
CE = -10:Step:10;
N = length(E);
LookUpTableData = zeros(N);
for i=1:N
   for j=1:N
      % Compute output u for each combination of sample points.
      LookUpTableData(i,j) = evalfis(FIS,[E(i) CE(j)]);
```

```
    end
end
```

Run the simulation.

```
sim('sllookuptable')
```



Compared with the traditional linear PID controller (the response curve with large overshoot), the nonlinear fuzzy PID controller reduces the overshoot by 50%. The two response curves from the nonlinear fuzzy controllers almost overlap, which indicates that the 2-D lookup table approximates the fuzzy system well.

```
bdclose('sllookuptable') % Closing model also clears its workspace variables.
```

Conclusion

You can approximate a nonlinear fuzzy PID controller using a lookup table. By replacing a Fuzzy Logic Controller block with Lookup Table blocks in Simulink, you can deploy a fuzzy controller with simplified generated code and improved execution speed.

References

[1] Xu, J. X., Hang, C. C., Liu, C. "Parallel structure and tuning of a fuzzy PID controller." *Automatica*, Vol. 36, pp. 673-684. 2000.

[2] Jantzen, J. *Tuning of Fuzzy PID Controllers*, Technical Report, Dept. of Automation, Technical University of Denmark. 1999.

See Also

Blocks
2-D Lookup Table | Fuzzy Logic Controller

More About

- “Simulate Fuzzy Inference Systems in Simulink” on page 5-2

Deployment

Deploy Fuzzy Inference Systems

You can deploy a fuzzy inference system (FIS) by generating code in either Simulink or MATLAB. All fuzzy inference system options, including custom inference functions, support code generation.

Generate Code in Simulink

You can generate code for evaluating fuzzy inference systems in Simulink using the Fuzzy Logic Controller block. You can generate code for double-precision, single-precision, or fixed-point data using Simulink Coder™ or Simulink PLC Coder™.

For more information, see “Generate Code for Fuzzy System Using Simulink Coder” on page 6-4 and “Generate Structured Text for Fuzzy System Using Simulink PLC Coder” on page 6-9.

Generate Code in MATLAB

You can generate code for evaluating fuzzy inference systems in MATLAB. You can generate code for double-precision or single-precision data using MATLAB Coder.

Code generation in MATLAB does not support fuzzy inference system objects. Instead, convert your fuzzy system into a homogeneous structure using `getFISCodeGenerationData`, and pass the resulting structure to `evalfis`.

For more information, see “Generate Code for Fuzzy System Using MATLAB Coder” on page 6-12.

Note Code generation does not support the construction of fuzzy systems at the command line.

See Also

Functions
`evalfis` | `mamfis` | `sugfis`

Blocks
Fuzzy Logic Controller

More About

- “Build Fuzzy Systems at the Command Line” on page 2-38
- “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14

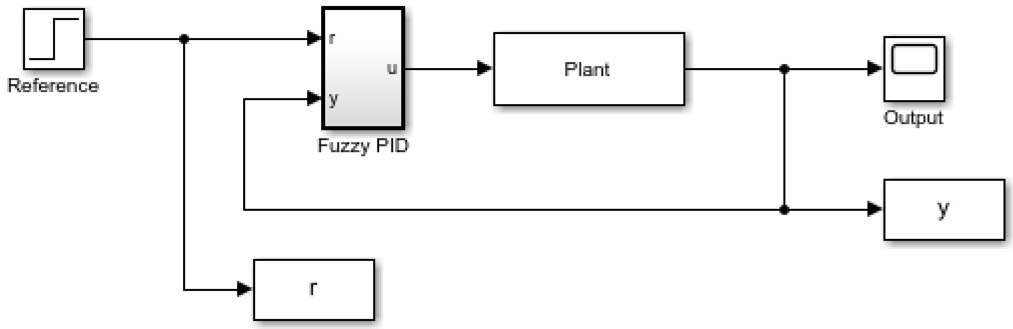
Generate Code for Fuzzy System Using Simulink Coder

You can generate code for a Fuzzy Logic Controller block using Simulink® Coder™. For more information on generating code, see "Generate Code Using Simulink® Coder™" (Simulink Coder).

Generate Code for Fuzzy Inference System

By default, the Fuzzy Logic Controller block uses double-precision data for simulation and code generation. The `fuzzyPID` model is configured to use double-precision data. For more information on configuring your fuzzy inference system for code generation, see Fuzzy Logic Controller.

```
mdl = 'fuzzyPID';
open_system(mdl)
```



It is good practice to validate the performance of the system in Simulink. Run the simulation. The model saves the output response, `u`, to the MATLAB® workspace.

```
sim(mdl)
```

To generate code for the model, use the `rtwbuild` function. For this example, suppress the Command Window output for the build process.

```
set_param(mdl,'RTWVerbose','off')
rtwbuild(mdl)
```

```
### Starting build procedure for model: fuzzyPID
### Successful completion of build procedure for model: fuzzyPID
```

By default, Simulink Coder generates C code for a generic real-time target. To select a different target file and language, in the Configuration Parameters dialog box, modify the **System target file** and **Language** parameters, respectively.

The generated code is stored in a new `fuzzyPID_grt_rtw` folder in your current working folder. The name of this folder depends on the selected target file.

On a Windows® system, by default, an executable file named `fuzzyPID.exe` is also added to the current working folder. To generate code without compilation, in the Configuration parameters dialog box, select the **Generate code only** parameter before generating code.

Run the executable.

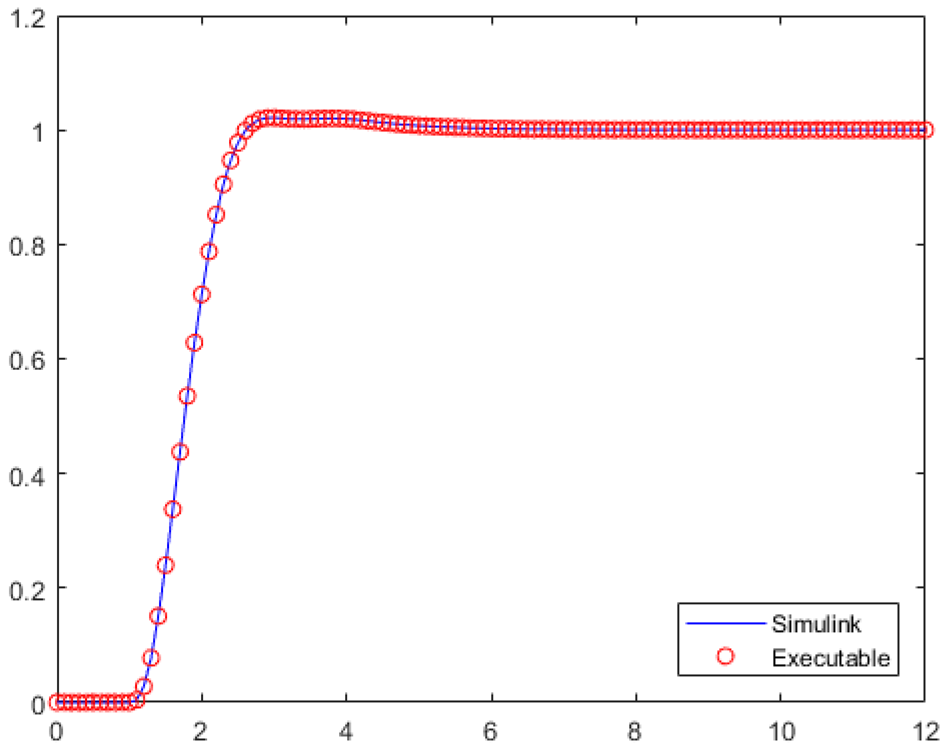
```
if ispc
    status = system(mdl);
else
    disp('The example only runs the executable on Windows system.');
end
```

```
** starting the model **
** created fuzzyPID.mat **
```

After the executable completes successfully (`status = 0`), the software creates a `fuzzyPID.mat` data file that contains the simulation results.

You can compare the output response from the generated code, `rtw_y`, with the output from the Simulink simulation, `y`, using the following code:

```
load fuzzyPID.mat
plot(tout,y,'b-',rt_tout,rt_y,'ro')
legend('Simulink','Executable','Location','Southeast')
```



The result from the generated code matches the Simulink simulation.

You can also generate code for just the controller subsystem in this model. To do so, specify the subsystem when calling the `rtwbuild` function.

```
rtwbuild([mdl '/Fuzzy PID'])
```

```
### Starting build procedure for model: Fuzzy0
### Successful completion of build procedure for model: Fuzzy0
```

You can deploy generated code according to your application needs. For example, you can configure the properties of executable files and create static or dynamic libraries. For more information, see “Build Process Workflow for Real-Time Systems” (Simulink Coder).

Generate Code for Other Data Types

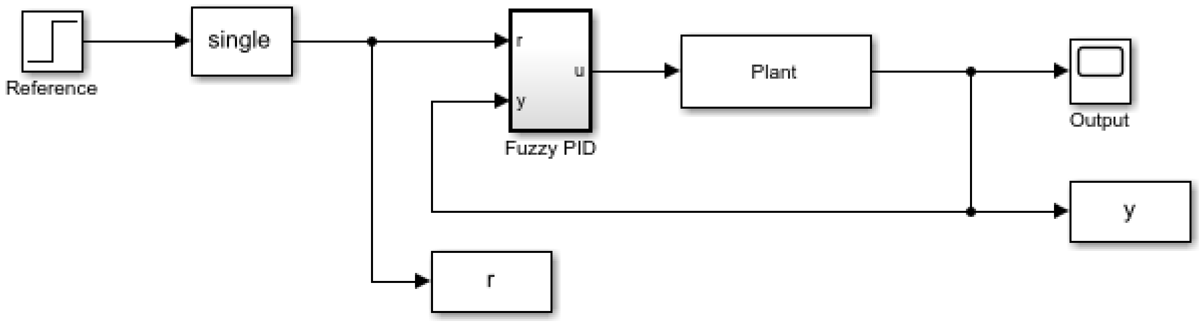
The Fuzzy Logic Controller block also supports single-precision and fixed-point data for simulation and code generation. In both cases, your resulting fuzzy system has decreased accuracy compared to an equivalent double-precision fuzzy system. Use:

- Single-precision data to reduce the memory footprint of your system.
- Fixed-point data if your target platform only supports fixed-point arithmetic.

To use one of these data types, set the **Data type** property of the block, and configure the other components in the model to use the same data type.

The `fuzzyPID_single` model is configured for single-precision data. Open the model.

```
mdl2 = 'fuzzyPID_single';
open_system(mdl2)
```



In this model, the **Data type** parameter of the Fuzzy Logic Controller block is set to `single`. The Fuzzy Logic Controller block automatically converts input signals to the specified data type. Also, the **Simulate using** parameter is set to `Code Generation`. The **Simulate using** option does not affect the code generation process. Instead, setting this option simulates your fuzzy system using the same code path used by generated code.

Generate code for this model.

```
set_param(mdl2,'RTWVerbose','off')
rtwbuild(mdl2)
```

```
### Starting build procedure for model: fuzzyPID_single
### Successful completion of build procedure for model: fuzzyPID_single
```

Setting the **Data type** parameter of a Fuzzy Logic Controller block ensures that all the inference steps use the specified data type. However, depending on the configuration of other blocks in the model, some of the generated code can still use double-precision data.

See Also

Fuzzy Logic Controller

More About

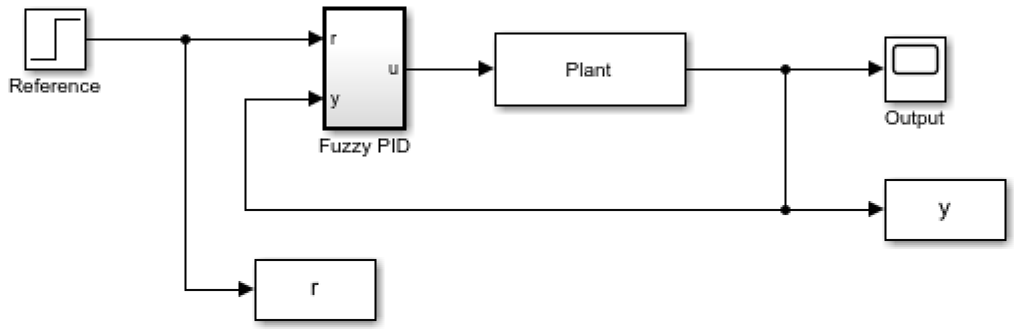
- “Deploy Fuzzy Inference Systems” on page 6-2
- “Generate Structured Text for Fuzzy System Using Simulink PLC Coder” on page 6-9
- “Generate Code for Fuzzy System Using MATLAB Coder” on page 6-12

Generate Structured Text for Fuzzy System Using Simulink PLC Coder

You can generate Structured Text for a Fuzzy Logic Controller block using Simulink® PLC Coder™. For more information on generating Structured Text, see “Code Generation” (Simulink PLC Coder).

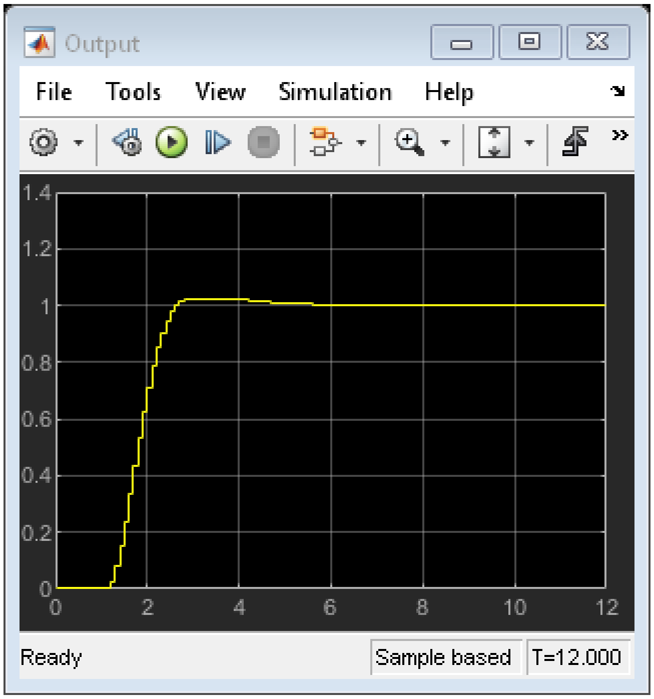
By default, the Fuzzy Logic Controller block uses double-precision data for simulation and code generation. The `fuzzyPID` model is configured to use double-precision data. You can also use either single-precision or fixed-point data. For more information on configuring your fuzzy inference system for code generation, see Fuzzy Logic Controller.

```
mdl = 'fuzzyPID';
open_system(mdl)
```



It is good practice to validate the performance of the system in Simulink before generating code. Run the simulation.

```
sim(mdl)
open_system([mdl '/Output'])
```



To generate Structured Text for the model, use the `plcgeneratecode` command. This command generates code for an *atomic subsystem* in a model. To generate code for the Fuzzy PID controller, configure the subsystem as an atomic subsystem by selecting the **Treat as atomic unit** parameter for the subsystem.

```
subsys = [mdl '/Fuzzy PID'];
set_param(subsys,'TreatAsAtomicUnit','on')
```

When generating code for just a Fuzzy Logic Controller block, place the block inside a subsystem, and set the **Treat as atomic unit** parameter of that subsystem.

Generate Structured Text for the Fuzzy PID subsystem.

```
plcgeneratecode(subsys);
```

```
PLC code generation successful for 'fuzzyPID/Fuzzy PID'.

Generated files:
<a href="matlab: edit('plcsrc\fuzzyPID.exp')">plcsrc\fuzzyPID.exp</a>
```

By default, the software saves the generated code in the following location:

```
plcsrc/fuzzy_PID.exp
```

See Also

Fuzzy Logic Controller

More About

- “Deploy Fuzzy Inference Systems” on page 6-2
- “Generate Code for Fuzzy System Using Simulink Coder” on page 6-4

Generate Code for Fuzzy System Using MATLAB Coder

You can generate code for evaluating a fuzzy inference system using MATLAB® Coder™. For more information on generating code, see “Code Generation” (MATLAB Coder).

To generate code for evaluating fuzzy systems, you must first create a fuzzy inference system (FIS). For more information, see “Build Fuzzy Systems at the Command Line” on page 2-38 and “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14.

Generating code using MATLAB Coder does not support `mamfis` or `sugfis` objects. To generate code for evaluating fuzzy systems, you must convert your fuzzy inference system objects into homogeneous structures using the `getFISCodeGenerationData` function.

Embed FIS Data in Generated Code

You can embed the data for your fuzzy inference system within the generated code. Use this option if you do not want to change the FIS data after compilation.

First, create a fuzzy system, or load a fuzzy system from a `.fis` file. For this example, load the fuzzy system from `tipper.fis`.

```
fisObject = readfis("tipper.fis");
```

To use this FIS for code generation, convert it to a homogeneous structure.

```
fis = getFISCodeGenerationData(fisObject);
```

Create a function for evaluating the fuzzy system `fis` for a given input vector `x`. Within this function, you can specify options for the `evalfis` function using `evalfisOptions`.

```
function y = evaluatefis1(fis,x)
    %#codegen
    opt = evalfisOptions('NumSamplePoints',51);
    y = evalfis(fis,x,opt);
end
```

Generate code for `evaluatefis1`, specifying that the `fis` input argument is constant. You can specify different targets for your build, such as a static library, an executable, or a MEX file. For this example, generate a MEX file.

```
codegen('evaluatefis1','-args',{coder.Constant(fis),[0 0]},'-config:mex')
```

To verify the execution of the MEX file:

1. Evaluate the MEX file for one or more input values. When you call the MEX file, specify the same FIS structure that you used at compile time.
2. Evaluate the original FIS for the same input values using `evalfis`. When evaluating using `evalfis`, use the same homogeneous FIS structure.
3. Compare the evaluation results.

```
mexOutput1 = evaluatefis1_mex(fis,[7 9])
```

```
mexOutput1 = 21.0327
```

```
opt = evalfisOptions('NumSamplePoints',51);
evalfisOutput = evalfis(fis,[7 9],opt)
```

```
evalfisOutput = 21.0327
```

The MEX file output matches the `evalfis` output.

Alternatively, you can embed the FIS data in the generated code by reading the FIS data from a file at code generation time. Specify a function for evaluating a fuzzy system for given input vector x. Within this function, read the FIS data from the file `tipper.fis`.

```
function y = evaluatefis2(x)
    %#codegen
    fis = getFISCodeGenerationData('tipper.fis');
    opt = evalfisOptions('NumSamplePoints',51);
    y = evalfis(fis,x,opt);
end
```

Generate code for `evaluatefis2`.

```
codegen('evaluatefis2','-args',{[0 0]},'-config:mex')
```

Verify the execution of the MEX file using the same input values for `x`. In this case, you do not have to specify the original FIS structure used at compile time.

```
mexOutput2 = evaluatefis2_mex([7 9])
```

```
mexOutput2 = 21.0327
```

```
evalfisOutput
```

```
evalfisOutput = 21.0327
```

Generate Code for Loading FIS Data at Run Time

You can generate code for evaluating a FIS that is read from a `.fis` file specified at run time. In this case, the FIS data is not embedded in the generated code. Specify a function for evaluating the fuzzy system defined in the specified file `fileName` for a given input vector `x`.

```
function y = evaluatefis3(fileName,x)
    %#codegen
    fis = getFISCodeGenerationData(fileName);
    opt = evalfisOptions('NumSamplePoints',51);
    y = evalfis(fis,x,opt);
end
```

Define input data types for this function.

```
fileName = coder.newtype('char',[1 Inf],[false true]);
x = coder.newtype('double',[1 Inf],[false true]);
```

Generate code for `evaluatefis3`.

```
codegen('evaluatefis3','-args',{fileName,x},'-config:mex')
```

Verify the execution of the MEX file using the same input values for `x`. In this case, you specify the name of the `.fis` file.

```
mexOutput3 = evaluatefis3_mex('tipper.fis',[7 9])
```

```
mexOutput3 = 21.0327
```

```
evalfisOutput
```

```
evalfisOutput = 21.0327
```

Each time you run `evaluatefis3`, it reloads the fuzzy system from the file. For computational efficiency, you can create a function that only loads the FIS when a new file name is specified.

```
function y = evaluatefis4(fileName,x)
    %#codegen
    %#internal

    persistent fisName fis
    if isempty(fisName)
        [fisName,fis] = loadFIS(fileName);
    elseif ~strcmp(fisName,fileName)
        [fisName,fis] = loadFIS(fileName);
    end

    opt = evalfisOptions('NumSamplePoints',51);
    y = evalfis(fis,x,opt);
end

function [fisName,fis] = loadFIS(fileName)
    fisName = fileName;
    fis = getFISCodeGenerationData(fisName);
end
```

Generate code `evaluatefis4`. The input data types for this function are the same as for `evaluatefis3`.

```
codegen('evaluatefis4','-args',{fileName,x},'-config:mex')
```

Verify the execution of the MEX file using the same input values file name.

```
mexOutput4 = evaluatefis4_mex('tipper.fis',[7 9])
```

```
mexOutput4 = 21.0327
```

```
evalfisOutput
```

```
evalfisOutput = 21.0327
```

Generate Code for Single-Precision Data

The preceding examples generated code for double-precision data. To generate code for single-precision data, specify the data type of the input values as `single`. For example, generate code for `evaluatefis2` using single-precision data.

```
codegen('evaluatefis2','-args',{single([0 0])},'-config:mex')
```

Verify the MEX file execution, passing in single-precision input values.

```
mexOutputSingle = evaluatefis2_mex(single([7 9]))
```

```
mexOutputSingle = single
    21.0327
```

```
evalfisOutput
```

```
evalfisOutput = 21.0327
```

See Also

`evalfis` | `getFISCodeGenerationData`

More About

- “Deploy Fuzzy Inference Systems” on page 6-2
- “Generate Code for Fuzzy System Using Simulink Coder” on page 6-4

Apps — Alphabetical List

Fuzzy Logic Designer

Design and test fuzzy inference systems

Description

The **Fuzzy Logic Designer** app lets you design and test fuzzy inference systems for modeling complex system behaviors.

Using this app, you can:

- Design Mamdani and Sugeno fuzzy inference systems.
- Add or remove input and output variables.
- Specify input and output membership functions.
- Define fuzzy if-then rules.
- Select fuzzy inference functions for:
  - And operations
  - Or operations
  - Implication
  - Aggregation
  - Defuzzification
- Adjust input values and view associated fuzzy inference diagrams.
- View output surface maps for fuzzy inference systems.
- Export fuzzy inference systems to the MATLAB workspace.

Open the Fuzzy Logic Designer App

- MATLAB Toolstrip: On the **Apps** tab, under **Control System Design and Analysis**, click the app icon.
- MATLAB command prompt: Enter `fuzzyLogicDesigner`.

Examples

- "Build Fuzzy Systems Using Fuzzy Logic Designer" on page 2-14

Programmatic Use

`fuzzyLogicDesigner` opens the **Fuzzy Logic Designer** app.

`fuzzyLogicDesigner(fis)` opens the app and loads the fuzzy inference system `fis`. `fis` can be any `mamfis` or `sugfis` object in the MATLAB workspace.

`fuzzyLogicDesigner(fileName)` opens the app and loads a fuzzy inference system from a file. `fileName` is the name of a `.fis` file on the MATLAB path.

To save a fuzzy inference system to a `.fis` file:

- In **Fuzzy Logic Designer**, select **File** > **Export** > **To File**.
- At the command line, use `writeFIS`.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

Apps
Neuro-Fuzzy Designer

Functions
`evalfis` | `mfedit` | `newfis` | `plotfis` | `ruleedit` | `ruleview` | `surfview`

Topics

“Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14
“What Is Fuzzy Logic?” on page 1-3
“Foundations of Fuzzy Logic” on page 1-10
“Fuzzy Inference Process” on page 1-28

Introduced in R2014b

Neuro-Fuzzy Designer

Design, train, and test Sugeno-type fuzzy inference systems

Description

The **Neuro-Fuzzy Designer** app lets you design, train, and test adaptive neuro-fuzzy inference systems (ANFIS) using input/output training data.

Using this app, you can:

- Tune membership function parameters of Sugeno-type fuzzy inference systems.
- Automatically generate an initial inference system structure based on your training data.
- Modify the inference system structure before tuning.
- Prevent overfitting to the training data using additional checking data.
- Test the generalization ability of your tuned system using testing data.
- Export your tuned fuzzy inference system to the MATLAB workspace.

You can use the **Neuro-Fuzzy Designer** to train a Sugeno-type fuzzy inference system that:

- Has a single output.
- Uses weighted average defuzzification.
- Has output membership functions all of the same type, for example `linear` or `constant`.
- Has complete rule coverage with no rule sharing; that is, the number of rules must match the number of output membership functions, and every rule must have a different consequent.
- Has unity weight for each rule.
- Does not use custom membership functions.

Open the Neuro-Fuzzy Designer App

- MATLAB Toolstrip: On the **Apps** tab, under **Control System Design and Analysis**, click the app icon.
- MATLAB command prompt: Enter `neuroFuzzyDesigner`.

Examples

- "Train Adaptive Neuro-Fuzzy Inference Systems" on page 3-97
- "Test Data Against Trained System" on page 3-102

Programmatic Use

`neuroFuzzyDesigner` opens the **Neuro-Fuzzy Designer** app.

`neuroFuzzyDesigner(fis)` opens the app and loads the fuzzy inference system `fis`. `fis` can be any valid `sugfis` object in the MATLAB workspace.

You can create an initial Sugeno-type fuzzy inference system from training data using the `genfis` command.

`neuroFuzzyDesigner(fileName)` opens the app and loads a fuzzy inference system. `fileName` is the name of a `.fis` file on the MATLAB path.

To save a fuzzy inference system to a `.fis` file:

- In the **Fuzzy Logic Designer**, select **File** > **Export** > **To File**
- At the command line, use `writeFIS`.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

Apps
Fuzzy Logic Designer

Functions
`anfis` | `genfis`

Topics
“Train Adaptive Neuro-Fuzzy Inference Systems” on page 3-97
“Test Data Against Trained System” on page 3-102
“Neuro-Adaptive Learning and ANFIS” on page 3-86
“Comparison of anfis and Neuro-Fuzzy Designer Functionality” on page 3-91

Introduced in R2014b

Functions — Alphabetical List

addInput

Add input variable to fuzzy inference system

Syntax

```
fisOut = addInput(fisIn)
fisOut = addInput(fisIn,range)
fisOut = addInput(___,Name,Value)
```

Description

`fisOut = addInput(fisIn)` adds a default input variable to `fisIn` and returns the resulting fuzzy system in `fisOut`. This input variable has a default name, default range, and no membership functions.

`fisOut = addInput(fisIn,range)` adds an input variable with the specified range.

`fisOut = addInput(___,Name,Value)`configures the input variable using one or more name-value pair arguments.

Examples

Add Input Variable to Fuzzy Inference System

Create a Sugeno fuzzy inference system.

```
fis = sugfis('Name','tipper');
```

Add an input variable with default specifications.

```
fis = addInput(fis);
```

You can configure the input variable properties using dot notation. For example, specify the name and range for the variable.

```
fis.Inputs(1).Name = "service";
fis.Inputs(1).Range = [0 10];
```

View the input variable.

```
fis.Inputs(1)
```

```
ans = 
  fisvar with properties:

                   Name: "service"
                  Range: [0 10]
    MembershipFunctions: [0x0 fismf]
```

You can also specify a variable name and range when you add it to the fuzzy system.

```
fis2 = sugfis('Name','tipper');
fis2 = addInput(fis2,[0 10],'Name',"service");
```

Add Input Variable with Membership Functions

Create a fuzzy inference system.

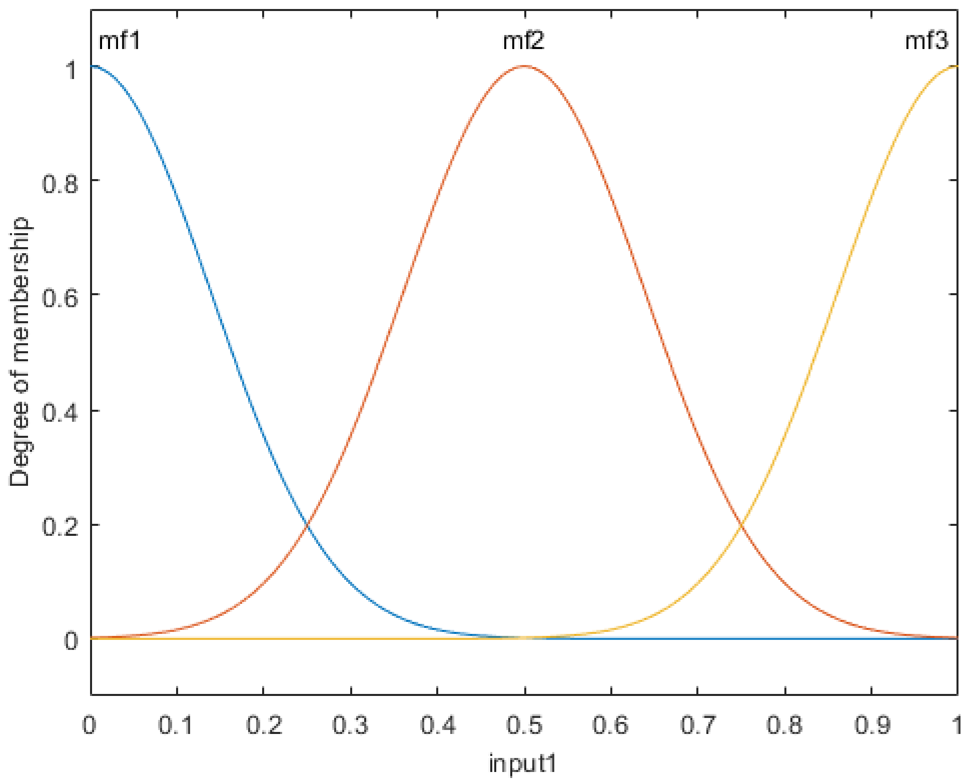
```
fis = mamfis('Name',"tipper");
```

Add an input variable with three Gaussian membership functions distributed over the input range.

```
fis = addInput(fis,'NumMFs',3,'MFType',"gaussmf");
```

View the membership functions.

```
plotmf(fis,'input',1)
```



Input Arguments

`fisIn` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

`range` — Variable range
`[0 1]` (default) | two-element vector

Variable range, specified as a two-element element vector where the first element is less than the second element. The first element specifies the lower bound of the range, and the second element specifies the upper bound of the range.

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'NumMFs',3` configures the variable to use three membership functions

Name — Variable name

string | character vector

Variable name, specified as the comma-separated pair consisting of `'Name'` and a string or character vector. The default variable name is `"input<uniqueIndex>"`, where `uniqueIndex` is automatically generated based on the current number of inputs in `fisIn`.

NumMFs — Number of membership functions

`0` (default) | nonnegative integer

Number of membership functions, specified as the comma-separated pair consisting of `'NumMFs'` and a nonnegative integer.

MFType — Membership function type

`"trimf"` (default) | `"gaussmf"`

Membership function type, specified as the comma-separated pair consisting of `'MFType'` and one of the following:

- `"trimf"` — Triangular membership functions
- `"gaussmf"` — Gaussian membership functions

The membership functions are uniformly distributed over the input variable range with approximately 80% overlap in the membership function supports.

Output Arguments

`fisOut` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, returned as a `mamfis` or `sugfis` object. `fisOut` contains the added input variable, with all other properties matching the properties of `fisIn`.

See Also

`addOutput` | `fisvar` | `mamfis` | `removeInput` | `sugfis`

Topics

"Build Fuzzy Systems at the Command Line" on page 2-38

Introduced in R2018b

addMF

Add membership function to fuzzy variable

Syntax

```
fisOut = addMF(fisIn,varName)
fisOut = addMF(fisIn,varName,type,parameters)
fisOut = addMF( ___ ,Name,Value)

varOut = addMF(varIn)
varOut = addMF(varIn,type,parameters)
varOut = addMF( ___ ,Name,Value)
```

Description

`fisOut = addMF(fisIn,varName)` adds a default membership function to the input or output variable `varName` in the fuzzy inference system `fisIn` and returns the resulting fuzzy system in `fisOut`.

`fisOut = addMF(fisIn,varName,type,parameters)` adds a membership function with the specified type and parameters.

`fisOut = addMF( ___ ,Name,Value)` configures the membership function using one or more name-value pair arguments.

`varOut = addMF(varIn)` adds a default membership function to fuzzy variable `varIn` and returns the resulting fuzzy variable in `varOut`.

`varOut = addMF(varIn,type,parameters)` adds a membership function with the specified type and parameters.

`varOut = addMF( ___ ,Name,Value)` specifies the name of the membership function using the `Name` name-value pair argument.

Examples

Add Membership Function to Fuzzy Inference System

Create a Mamdani fuzzy system, and add three input variables and one output variable. For this example, give the second input variable and the output variable the same name.

```
fis = mamfis;
fis = addInput(fis,[0 80],"Name","speed");
fis = addInput(fis,[0 100],"Name","throttle");
fis = addInput(fis,[0 10],"Name","distance");
fis = addOutput(fis,[0 100],"Name","throttle");
```

Add a membership function to the first input variable, specifying a trapezoidal membership function, and set the membership function parameters.

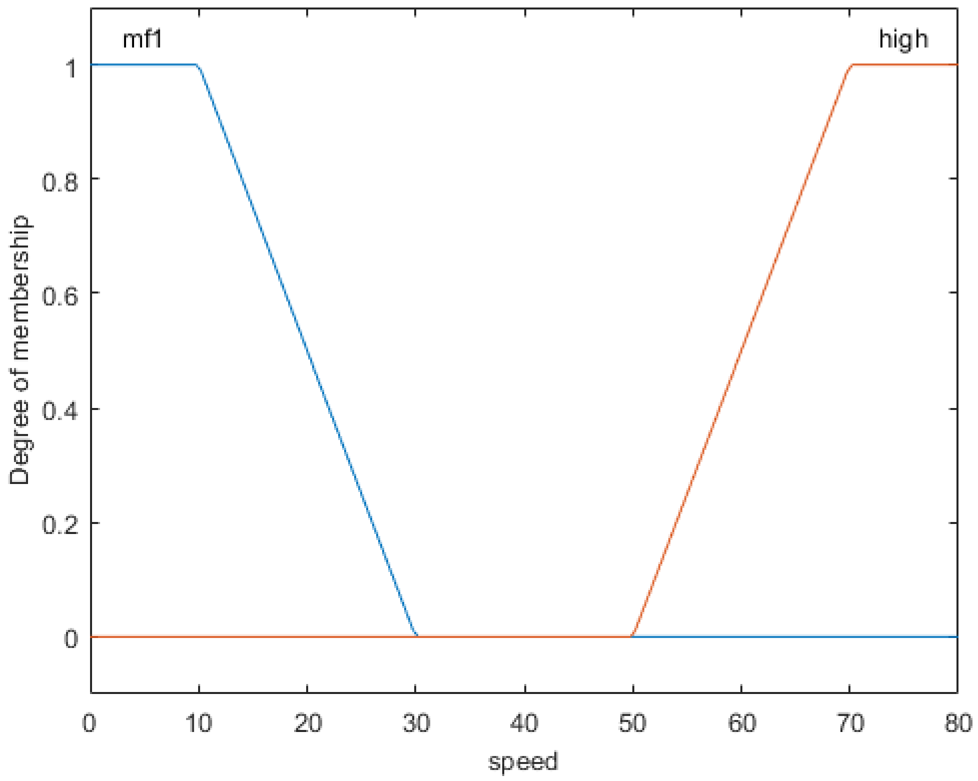
```
fis = addMF(fis,"speed","trapmf",[-5 0 10 30]);
```

You can also specify the name of your membership when you add it to a fuzzy system. Add a membership function called `"high"` to the first input variable.

```
fis = addMF(fis,"speed","trapmf",[50 70 80 85],'Name',"high");
```

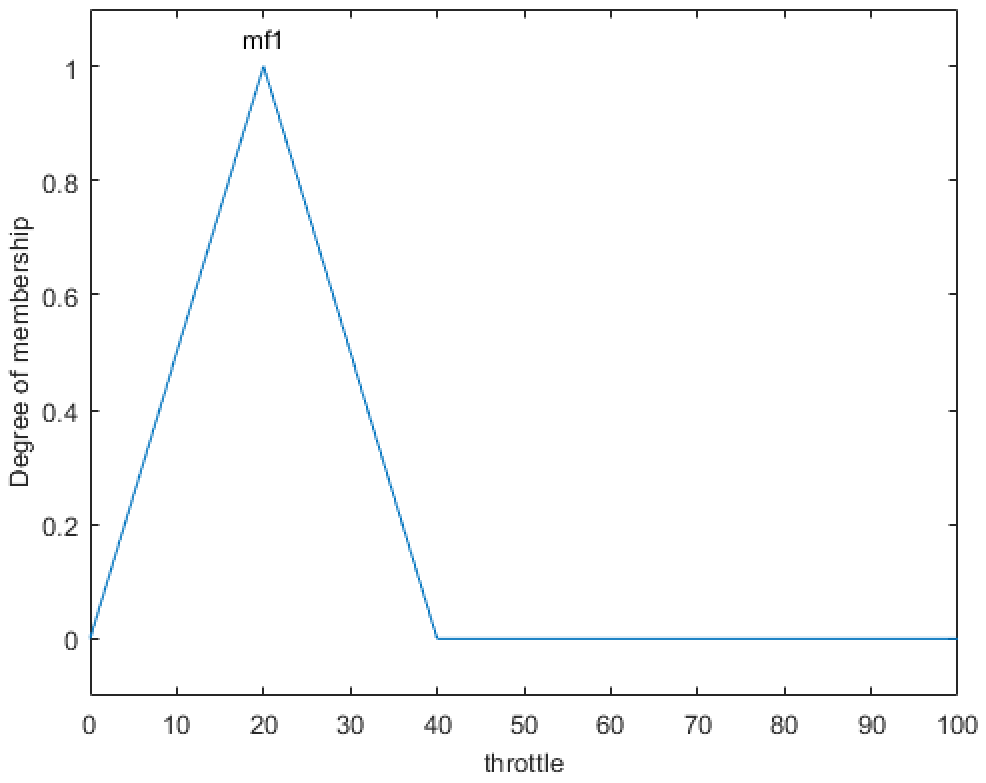
View the membership functions for the first input variable.

```
plotmf(fis,"input",1)
```



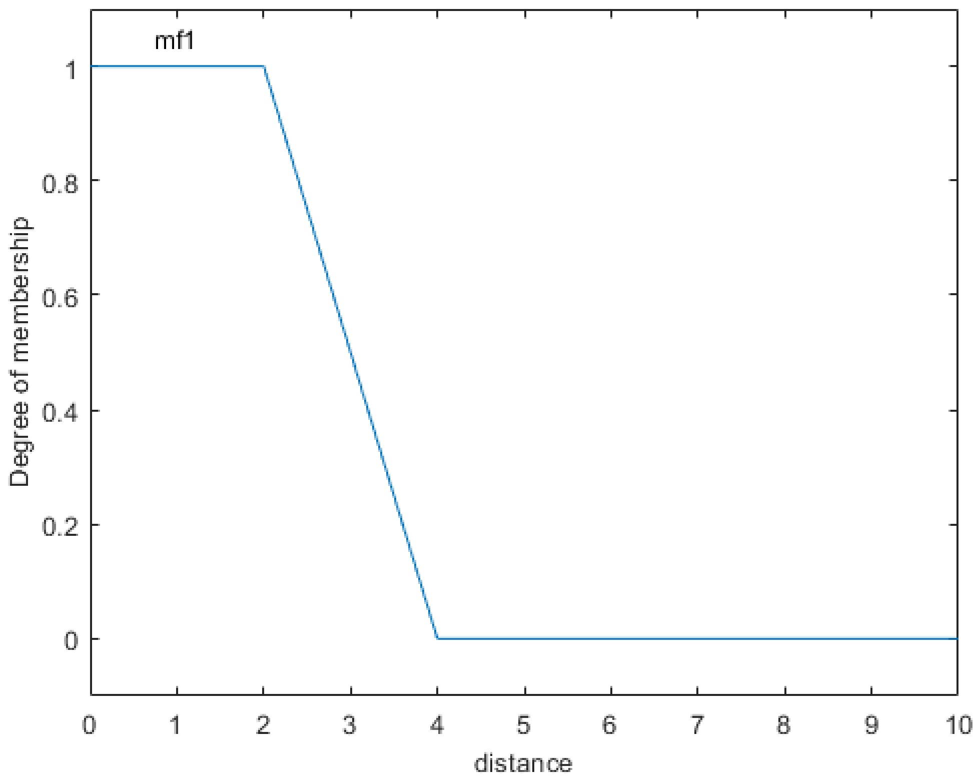
If your system has an input variable with the same name as an output variable, you must specify the variable type when adding a membership function. For example, add a membership function to the output variable.

```
fis = addMF(fis,"throttle","trimf",[0 20 40],'VariableType',"output");
plotmf(fis,"output",1)
```



Alternatively, you can add a default membership function to a fuzzy system and set its parameters using dot notation. For example, add and configure a membership function for the third input variable.

```
fis = addMF(fis,"distance");
fis.Inputs(3).MembershipFunctions(1).Type = "trapmf";
fis.Inputs(3).MembershipFunctions(1).Parameters = [-1 0 2 4];
plotmf(fis,"input",3)
```



Add Membership Function to Fuzzy Variable

Create a fuzzy variable with a specified range.

```
var = fisvar([0 1]);
```

Add a membership function to the variable, specifying a trapezoidal membership function, and set the membership function parameters.

```
var = addMF(var,"trapmf",[-0.5 0 0.2 0.4]);
```

You can also specify the name of your membership when you add it to a fuzzy variable. For example, add a membership function called `"large"`.

```
var = addMF(var,"trapmf",[0.6 0.8 1 1.5],'Name',"large");
```

View the membership functions.

```
var.MembershipFunctions

ans = 
  1x2 fismf array with properties:

    Name
    Type
    Parameters

  Details:
          Name        Type                 Parameters           
        _______    ________    ____________________________

    1    "mf1"      "trapmf"    -0.5      0      0.2      0.4
    2    "large"    "trapmf"     0.6    0.8        1      1.5
```

Alternatively, you can add a default membership function to a fuzzy variable and set its parameters using dot notation.

```
var = fisvar([0 1]);
var = addMF(var);
var.MembershipFunctions(1).Type = "trapmf";
var.MembershipFunctions(1).Parameters = [-0.5 0 0.2 0.4];
```

Input Arguments

`fisIn` — Fuzzy inference system

`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

`varName` — Variable name

string | character vector

Variable name, specified as a string or character vector. You can specify the name of either an input or output variable in your FIS. If your system has an input variable with the same name as an output variable, specify the type of the variable you want to add a membership function to using the `VariableType` name-value pair.

type — Membership function type
`"trimf"` (default) | string | character vector | function handle

Membership function type, specified as a string or character vector that contains the name of a function in the current working folder or on the MATLAB path. You can also specify a handle to such a function. When you specify `type`, you must also specify `parameters`.

This table describes the values that you can specify for `type`.

Membership Function Type	Description	For More Information
`"gbellmf"`	Generalized bell-shaped membership function	`gbellmf`
`"gaussmf"`	Gaussian membership function	`gaussmf`
`"gauss2mf"`	Gaussian combination membership function	`gauss2mf`
`"trimf"`	Triangular membership function	`trimf`
`"trapmf"`	Trapezoidal membership function	`trapmf`
`"sigmf"`	Sigmoidal membership function	`sigmf`
`"dsigmf"`	Difference between two sigmoidal membership functions	`dsigmf`
`"psigmf"`	Product of two sigmoidal membership functions	`psigmf`
`"zmf"`	Z-shaped membership function	`zmf`
`"pimf"`	Pi-shaped membership function	`pimf`
`"smf"`	S-shaped membership function	`smf`
`"constant"`	Constant membership function (not supported for output variables of Mamdani systems or for any input variables)	"What Is Sugeno-Type Fuzzy Inference?" on page 2-5

Membership Function Type	Description	For More Information
`"linear"`	Linear membership function (not supported for output variables of Mamdani systems or for any input variables)	
String or character vector	Name of a custom membership function in the current working folder or on the MATLAB path. Custom functions are not supported for output variables of Sugeno systems.	“Build Fuzzy Systems Using Custom Functions” on page 2-50
Function handle	Handle to a custom membership function in the current working folder or on the MATLAB path. Custom functions are not supported for output variables of Sugeno systems.	

`parameters` — Membership function parameters
`[0 0.5 1]` (default) | vector

Membership function parameters, specified as a vector. The length of the parameter vector depends on the membership function type. When you specify `parameters`, you must also specify `type`.

`varIn` — Fuzzy variable
`fisvar` object

Fuzzy variable, specified as a `fisvar` object.

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'Name',"large"` specifies the membership function name `"large"`

Name — Membership function name
string | character vector

Membership function name, specified as the comma-separated pair consisting of `'Name'` and a string or character vector. The default membership function name is `"mf<uniqueIndex>"`, where `uniqueIndex` is automatically generated based on the current number of membership functions in the associated variable.

`VariableType` — Variable type
`"input"` | `"output"`

Variable type, specified as the comma-separated pair `'VariableType'` and one of the following:

- `"input"` — Input variable
- `"output"` — Output variable

If your system has an input variable with the same name as an output variable, specify which variable to add the membership function to `VariableType`.

This name-value pair applies only when adding a membership function to a `mamfis` or `sugfis` object.

Output Arguments

`fisOut` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, returned as a `mamfis` or `sugfis` object. `fisOut` contains the added membership function, with all other properties matching the properties of `fisIn`.

`varOut` — Fuzzy variable
`fisvar` object

Fuzzy variable, returned as a `fisvar` object. `varOut` contains the added membership function, with all other properties matching the properties of `varIn`.

Compatibility Considerations

`addmf` is now `addMF` and its function syntax has changed

Behavior changed in R2018b

The name and behavior of the `addmf` function has changed. Now:

- `addmf` is `addMF`
- You specify the variable to which you want to add the membership function by name rather than by index.
- You specify the name of the membership function using a name-value pair argument.

These changes require updates to your code.

Update Code

The following table shows some typical usages of `addmf` for adding membership functions to fuzzy variables and how to update your code. In this table, `fis` is a fuzzy inference system with two inputs, `service` and `food`, and one output, `tip`.

If your code has this form:	Use this code instead:

`fis = addmf(fis'input',1,...`
`            'poor',...`
`            'gaussmf',[1.5 0])`
	`fis = addMF(fis,"service",...`
	`            "gaussmf",[1.5 0],`
	`            'Name',"poor")`

`fis = addmf(fis,'input',2,...`
`            'rancid',...`
`            'trapmf',[-2 0 1 3])`
	`fis = addMF(fis,"food",...`
	`            "trapmf",[-2 0 1 3],...`
	`            'Name',"rancid")`

`fis = addmf(fis,'output',1,...`
`            'cheap',...`
`            'trimf',[0 5 10])`
	`fis = addMF(fis,"tip",...`
	`            "trimf",[0 5 10],...`
	`            'Name',"cheap")`

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields.
- Objects store text data as strings rather than as character vectors.

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

`addInput` | `addOutput` | `addRule` | `fisvar` | `mamfis` | `removeMF` | `sugfis`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced in R2018b

addOutput

Add output variable to fuzzy inference system

Syntax

```
fisOut = addOutput(fisIn)
fisOut = addOutput(fisIn,range)
fisOut = addOutput(___,Name,Value)
```

Description

`fisOut = addOutput(fisIn)` adds a default output variable to `fisIn`, and returns the resulting fuzzy system in `fisOut`. This output variable has a default name, default range, and no membership functions.

`fisOut = addOutput(fisIn,range)` adds an output variable with the specified range.

`fisOut = addOutput(___,Name,Value)`configures the output variable using one or more name-value pair arguments.

Examples

Add Output Variable to Fuzzy Inference System

Create a Mamdani fuzzy inference system.

```
fis = mamfis('Name','tipper');
```

Add an output variable with default specifications.

```
fis = addOutput(fis);
```

You can configure the output variable properties using dot notation. For example, specify the name and range for the variable.

```
fis.Outputs(1).Name = "tip";
fis.Outputs(1).Range = [10 30];
```

View the output variable.

```
fis.Outputs(1)
```

```
ans = 
  fisvar with properties:

                   Name: "tip"
                  Range: [10 30]
    MembershipFunctions: [0x0 fismf]
```

You can also specify the variable name and range when you add it to the fuzzy system.

```
fis2 = mamfis('Name','tipper');
fis2 = addOutput(fis2,[10 30],'Name',"tip");
```

Add Output Variable with Membership Functions

Create a Sugeno fuzzy inference system.

```
fis = sugfis('Name',"tipper");
```

Add an output variable with three constant membership functions distributed over the output range.

```
fis = addOutput(fis,'NumMFs',3,'MFType',"constant");
```

View the membership functions.

```
fis.Outputs(1).MembershipFunctions
```

```
ans = 
  1x3 fismf array with properties:

    Name
    Type
    Parameters

  Details:
         Name        Type       Parameters
         _____    ___________    __________

    1    "mf1"    "constant"         0
    2    "mf2"    "constant"       0.5
    3    "mf3"    "constant"         1
```

Input Arguments

`fisIn` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

`range` — Variable range
`[0 1]` (default) | two-element vector

Variable range, specified as a two-element element vector where the first element is less than the second element. The first element specifies the lower bound of the range, and the second element specifies the upper bound of the range.

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'NumMFs',3` configures the variable to use three membership functions

`Name` — Variable name
string | character vector

Variable name, specified as the comma-separated pair consisting of `'Name'` and a string or character vector.

`NumMFs` — Number of membership functions
`0` (default) | nonnegative integer

Number of membership functions, specified as the comma-separated pair consisting of `'NumMFs'` and a nonnegative integer.

`MFType` — Membership function type
`"trimf"` (default) | `"gaussmf"`

Membership function type, specified as the comma-separated pair consisting of `'MFType'` and one of the following:

- `"trimf"` — Triangular membership functions for the outputs of Mamdani system
- `"gaussmf"` — Gaussian membership functions for the outputs of Mamdani systems
- `"constant"` — Constant membership functions for the outputs of Sugeno systems
- `"linear"` — Linear membership functions for the outputs of Sugeno systems. To add an output variable with linear membership functions, your FIS must have at least one input variable.

The membership functions are uniformly distributed over the variable range with approximately 80% overlap in the membership function supports.

Output Arguments

`fisOut` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, returned as a `mamfis` or `sugfis` object. `fisOut` contains the added output variable, with all other properties matching the properties of `fisIn`.

See Also

`addInput` | `fisvar` | `mamfis` | `removeOutput` | `sugfis`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced in R2018b

addRule

Add rule to fuzzy inference system

Syntax

```
fisOut = addRule(fisIn)
fisOut = addRule(fisIn,ruleDescription)
```

Description

`fisOut = addRule(fisIn)` adds a single fuzzy rule to fuzzy inference system `fisIn` with the default description `"input1==mf1 => output1=mf1"` and returns the resulting fuzzy system in `fisOut`.

`fisOut = addRule(fisIn,ruleDescription)` adds one or more fuzzy rules using the rule descriptions in `ruleDescription`.

Examples

Add Single Rule to Fuzzy Inference System

Load a fuzzy inference system (FIS), and clear the existing rules.

```
fis = readfis('tipper');
fis.Rules = [];
```

Add a rule to the FIS.

```
ruleTxt = 'If service is poor then tip is cheap';
fis2 = addRule(fis,ruleTxt);
```

`fis2` is equivalent to `fis`, except that the specified rule is added to the rule base.

```
fis2.Rules
```

```
ans = 
  fisrule with properties:

    Description: "service==poor => tip=cheap (1)"
     Antecedent: [1 0]
     Consequent: 1
         Weight: 1
     Connection: 1
```

Add Rules Using Symbolic Expressions

Load a fuzzy inference system (FIS), and clear the existing rules.

```
fis = readfis('tipper');
fis.Rules = [];
```

Specify the following rules using symbolic expressions:

- If `service` is `poor` or `food` is `rancid` then `tip` is `cheap`.
- If `service` is `excellent` and `food` is not `rancid` then `tip` is `generous`.

```
rule1 = "service==poor | food==rancid => tip=cheap";
rule2 = "service==excellent & food~=rancid => tip=generous";
rules = [rule1 rule2];
```

Add the rules to the FIS.

```
fis2 = addRule(fis,rules);
```

`fis2` is equivalent to `fis`, except that the specified rules are added to the rule base.

```
fis2.Rules
```

```
ans = 
  1x2 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection
  Details:
                             Description
           _______________________________________________________

    1    "service==poor | food==rancid => tip=cheap (1)"
    2    "service==excellent & food~=rancid => tip=generous (1)"
```

Add Rules Using Membership Function Indices

Load fuzzy inference system (FIS) and clear the existing rules.

```
fis = readfis('mam22.fis');
fis.Rules = [];
```

Specify the following rules using membership function indices:

- If `angle` is `small` and `velocity` is `big`, then `force` is `negBig` and `force2` is `posBig2`.
- If `angle` is not `small` and `velocity` is `small`, then `force` is `posSmall` and `force2` is `negSmall2`.

```
rule1 = [1 2 1 4 1 1];
rule2 = [-1 1 3 2 1 1];
rules = [rule1; rule2];
```

Add the rules to the FIS.

```
fis2 = addRule(fis,rules);
```

`fis2` is equivalent to `fis`, except that the specified rules are added to the rule base.

```
fis2.Rules
```

```
ans = 
  1x2 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
```

```
     Connection

   Details:
                                          Description
          ________________________________________________________________________

     1    "angle==small & velocity==big => force=negBig, force2=posBig2 (1)"
     2    "angle~=small & velocity==small => force=posSmall, force2=negSmall2 (1)"
```

Input Arguments

`fisIn` — Fuzzy inference system

`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

`ruleDescription` — Rule description

string | character vector | numeric row vector | string array | character array | numeric array

Rule description, specified using either a text or numeric rule definition

Text Rule Description

For a text rule description, specify `ruleDescription` as one of the following:

- String or character vector specifying a single rule

  ```
  rule = "If service is poor or food is rancid then tip is cheap";
  ```
- String array, where each element corresponds to a rule. For example:

  ```
  ruleList = ["If service is poor or food is rancid then tip is cheap";
              "If service is good then tip is average";
              "If service is excellent or food is delicious then tip is generous"];
  ```
- Character array where each row corresponds to a rule. For example:

  ```
  rule1 = 'If service is poor or food is rancid then tip is cheap';
  rule2 = 'If service is good then tip is average';
  rule3 = 'If service is excellent or food is delicious then tip is generous';
  ruleList = char(rule1,rule2,rule3);
  ```

For each rule, use one of the following rule text formats:

- Verbose — Linguistic expression in the following format, using the `IF` and `THEN` keywords:

  ```
  "IF <antecedent> THEN <consequent> (<weight>)"
  ```

  In `<antecedent>`, specify the membership function for each input variable using the `IS` or `IS NOT` keyword. Connect these conditions using the `AND` or `OR` keywords. If a rule does not use a given input variable, omit it from the antecedent.

  In `<consequent>`, specify the condition for each output variable using the `IS` or `IS NOT` keyword, and separate these conditions using commas. The `IS NOT` keyword is not supported for Sugeno outputs. If a rule does not use a given output variable, omit it from the consequent.

  Specify the weight using a positive numerical value.

  For example:

  ```
  "IF A IS a AND B IS NOT b THEN X IS x, Y IS NOT y (1)"
  ```

- Symbolic — Expression that uses the symbols in the following table instead of keywords. There is no symbol for the `IF` keyword.

Symbol	Keyword
==	`IS` (in rule antecedent)
~=	`IS NOT`
&	`AND`
|	`OR`
=>	`THEN`
=	`IS` (in rule consequent)

  For example, the following symbolic rule is equivalent to the previous verbose rule.

  ```
  "A==a & B~=b => X=x, Y~=y (1)"
  ```

Numeric Rule Description

For a numeric rule description, specify `ruleDescription` as one of the following:

- Row vector to specify a single fuzzy rule

- Array, where each row of `ruleValues` specifies one rule

For each row, the numeric rule description has $M+N+2$ columns, where M is the number of input variables and N is the number of output variables. Each column contains the following information:

- The first M columns specify input membership function indices and correspond to the `Antecedent` property of the rule. To indicate a `NOT` condition, specify a negative value. If a rule does not use a given input, set the corresponding index to `0`. For each rule, at least one input membership function index must be nonzero.
- The next N columns specify output membership function indices and correspond to the `Consequent` property of the rule. To indicate a `NOT` condition for Mamdani systems, specify a negative value. `NOT` conditions are not supported for Sugeno outputs. If a rule does not use a given output, set the corresponding index to `0`. For each rule, at least one output membership function index must be nonzero.
- Column $M+N+1$ specifies the rule weight and corresponds to the `Weight` property of the rule.
- The final column specifies the antecedent fuzzy operator and corresponds to the `Connection` property of the rule.

Output Arguments

`fisOut` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, returned as a `mamfis` or `sugfis` object. `fisOut` contains the added rules, with all other properties matching those of `fisIn`.

Compatibility Considerations

`addrule` is now `addRule`

Behavior changed in R2018b

`addrule` is now `addRule`. To update your code, change the function name from `addrule` to `addRule`. The syntaxes are equivalent.

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields.
- Objects store text data as strings rather than as character vectors.

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

`addInput` | `addMF` | `addOutput` | `mamfis` | `sugfis`

Topics

"Build Fuzzy Systems at the Command Line" on page 2-38

Introduced in R2018b

addvar

(To be removed) Add variable to fuzzy inference system

Note addvar will be removed in a future release. Use addInput or addOutput instead. For more information, see “Compatibility Considerations”.

Syntax

```
fis = addvar(fis,varType,varName,varBounds)
```

Description

addvar has four input arguments:

- fis — Fuzzy inference system in the MATLAB workspace, specified as a FIS structure.
- varType — Type of variable to add, specified as 'input' or 'output'.
- varName — Name of the variable to add, specified as a character vector or string.
- varBounds — Variable range, specified as a two-element vector, where the first element is the minimum value and the second element is the maximum value for the variable.

Indices are applied to variables in the order in which they are added. Therefore, the first input variable added to a system is always known as input variable number one for that system. Input and output variables are numbered independently.

Examples

Add Variable to Fuzzy Inference System

Create new FIS.

```
fis = newfis('tipper');
```

Add new input variable.

```
fis = addvar(fis,'input','service',[0 10]);
```

View new variable properties.

```
getfis(fis,'input',1)
```

```
ans = struct with fields:
      Name: 'service'
    NumMFs: 0
     range: [0 10]
```

Compatibility Considerations

addvar will be removed

Not recommended starting in R2018b

`addvar` will be removed in a future release. Use `addInput` or `addOutput` instead. There are differences between these functions that require updates to your code.

To add input or output variables to a fuzzy system, use `addInput` or `addOutput`, respectively.

Update Code

This table shows some typical usages of `addvar` and how to update your code to use `addInput` or `addOutput` instead.

If your code has this form:	Use this code instead:
`fis = addvar(fis,'input',... 'service',[0 10])`	`fis = addInput(fis,[0 10],... 'Name',"service")`
`fis = addvar(fis,'output',... 'tip',[0 30])`	`fis = addOutput(fis,[0 30],... 'Name',"tip")`

See Also

`addInput` | `addMF` | `addOutput` | `addRule` | `rmmf` | `rmvar`

Introduced before R2006a

anfis

Tune Sugeno-type fuzzy inference system using training data

Syntax

```
fis = anfis(trainingData)
fis = anfis(trainingData,options)

[fis,trainError] = anfis(___)
[fis,trainError,stepSize] = anfis(___)

[fis,trainError,stepSize,chkFIS,chkError] = anfis(trainingData,
options)
```

Description

`fis = anfis(trainingData)` generates a single-output Sugeno fuzzy inference system (FIS) and tunes the system parameters using the specified input/output training data. The FIS object is automatically generated using grid partitioning.

The training algorithm uses a combination of the least-squares and backpropagation gradient descent methods to model the training data set.

`fis = anfis(trainingData,options)` tunes an FIS using the specified training data and options. Using this syntax, you can specify:

- An initial FIS object to tune.
- Validation data for preventing overfitting to training data.
- Training algorithm options.
- Whether to display training progress information.

`[fis,trainError] = anfis(___)` returns the root mean square training error for each training epoch.

`[fis,trainError,stepSize] = anfis(___)` returns the training step size at each training epoch.

`[fis,trainError,stepSize,chkFIS,chkError] = anfis(trainingData, options)` returns the validation data error for each training epoch, `chkError`, and the tuned FIS object for which the validation error is minimum, `chkFIS`. To use this syntax, you must specify validation data using `options.ValidationData`.

Examples

Train Fuzzy Inference System Using ANFIS

Load training data. This data has a single input and a single output.

```
load fuzex1trnData.dat
```

Generate and train a fuzzy inference system. By default, the FIS structure is created using a grid partition of the input variable range with two membership functions.

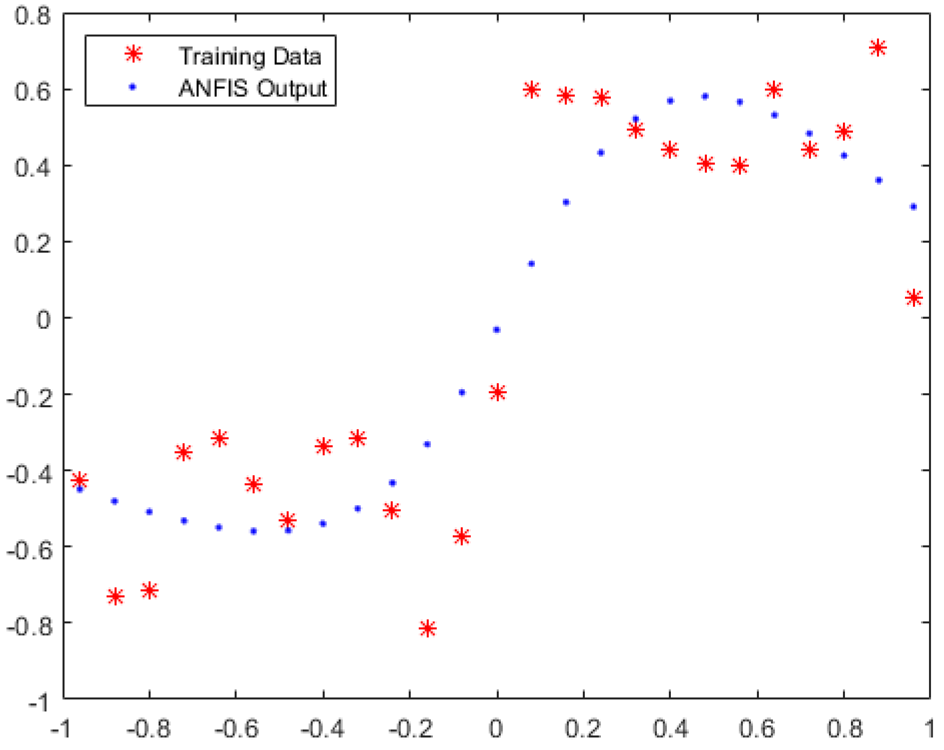
```
fis = anfis(fuzex1trnData);
```

```
ANFIS info:
    Number of nodes: 12
    Number of linear parameters: 4
    Number of nonlinear parameters: 6
    Total number of parameters: 10
    Number of training data pairs: 25
    Number of checking data pairs: 0
    Number of fuzzy rules: 2


Start training ANFIS ...

   1      0.229709
   2      0.22896
   3      0.228265
   4      0.227624
   5      0.227036
Step size increases to 0.011000 after epoch 5.
   6      0.2265
   7      0.225968
   8      0.225488
   9      0.225052
Step size increases to 0.012100 after epoch 9.
  10      0.22465
```

```
Designated epoch number reached --> ANFIS training completed at epoch 10.

Minimal training RMSE = 0.224650
```

Plot the ANFIS output and training data.

```
x = fuzex1trnData(:,1);
anfisOutput = evalfis(fis,x);
plot(x,fuzex1trnData(:,2),'*r',x,anfisOutput,'.b')
legend('Training Data','ANFIS Output','Location','NorthWest')
```



The ANFIS data does not match the training data well. To improve the match:

- Increase the number of membership functions in the FIS structure to 4. Doing so adds fuzzy rules and tunable parameters to the system.
- Increase the number of training epochs.

```
opt = anfisOptions('InitialFIS',4,'EpochNumber',40);
```

Suppress the error and step size Command Window display.

```
opt.DisplayErrorValues = 0;
opt.DisplayStepSize = 0;
```

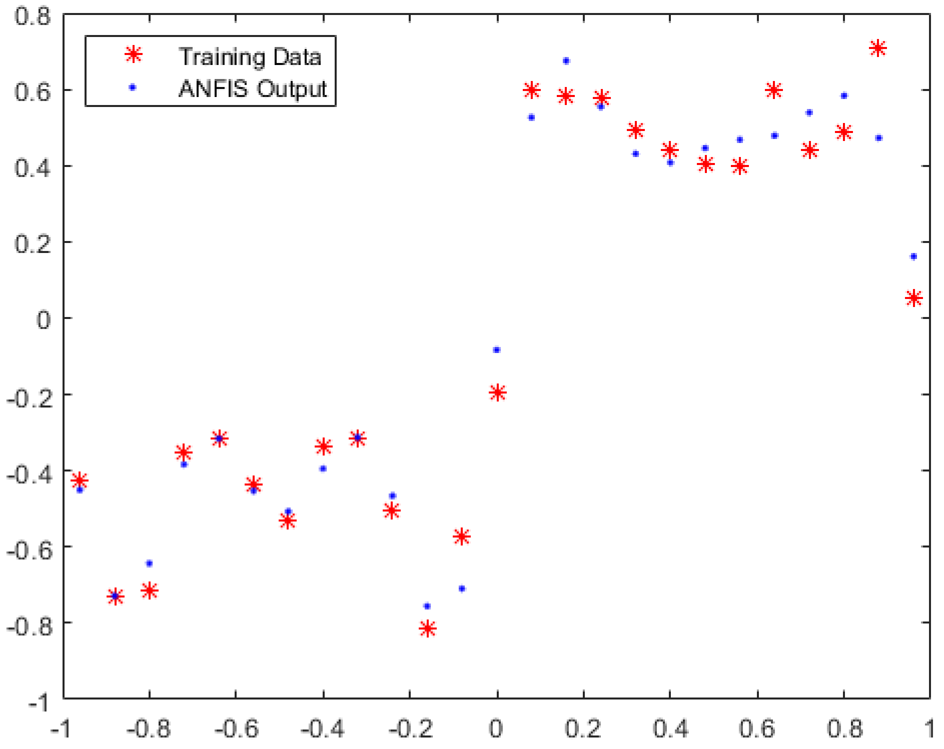
Train the FIS.

```
fis = anfis(fuzex1trnData,opt);
```

```
ANFIS info:
    Number of nodes: 20
    Number of linear parameters: 8
    Number of nonlinear parameters: 12
    Total number of parameters: 20
    Number of training data pairs: 25
    Number of checking data pairs: 0
    Number of fuzzy rules: 4

Minimal training RMSE = 0.083385
```

Plot the ANFIS output and training data.

```
figure
anfisOutput = evalfis(fis,x);
plot(x,fuzex1trnData(:,2),'*r',x,anfisOutput,'.b')
legend('Training Data','ANFIS Output','Location','NorthWest')
```



The match between the training data and ANFIS output has improved.

Create Initial FIS for ANFIS Training

Create single-input, single-output training data.

```
x = (0:0.1:10)';
y = sin(2*x)./exp(x/5);
```

Define an initial FIS structure with five Gaussian input membership functions.

```
genOpt = genfisOptions('GridPartition');
genOpt.NumMembershipFunctions = 5;
genOpt.InputMembershipFunctionType = 'gaussmf';
inFIS = genfis(x,y,genOpt);
```

Configure the ANFIS training options. Set the initial FIS, and suppress the training progress display.

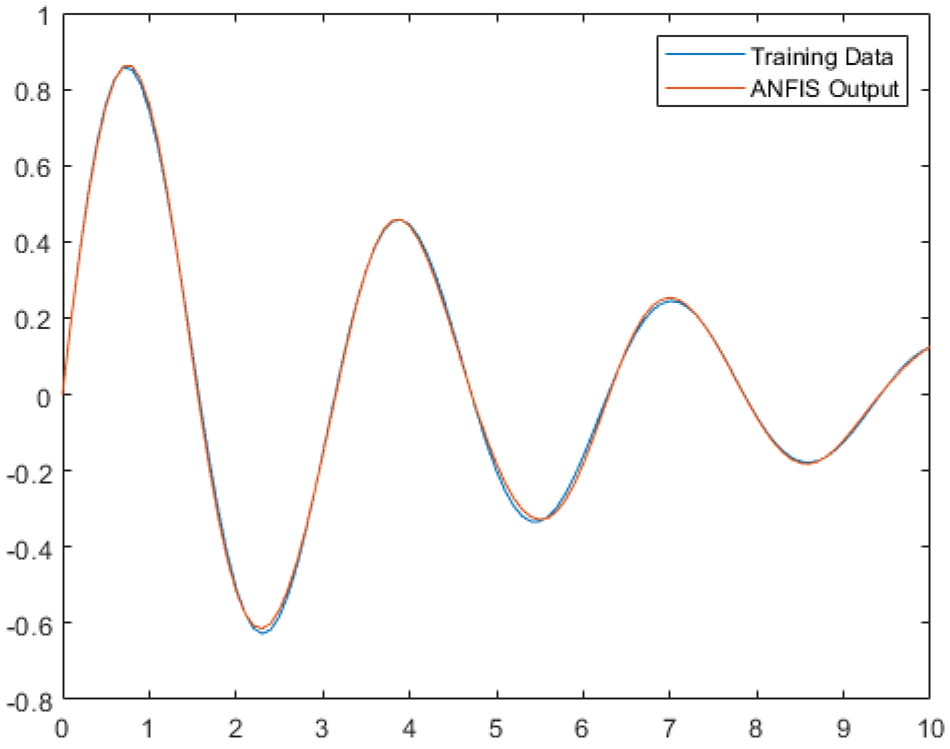
```
opt = anfisOptions('InitialFIS',inFIS);
opt.DisplayANFISInformation = 0;
opt.DisplayErrorValues = 0;
opt.DisplayStepSize = 0;
opt.DisplayFinalResults = 0;
```

Train the FIS using the specified options.

```
outFIS = anfis([x y],opt);
```

Compare the ANFIS output with the training data.

```
plot(x,y,x,evalfis(outFIS,x))
legend('Training Data','ANFIS Output')
```



Obtain ANFIS Training Error

Load training data. This data has a single input and a single output.

```
load fuzex2trnData.dat
```

Specify the training options.

```
opt = anfisOptions('InitialFIS',4,'EpochNumber',40);
opt.DisplayANFISInformation = 0;
opt.DisplayErrorValues = 0;
opt.DisplayStepSize = 0;
opt.DisplayFinalResults = 0;
```

Train the FIS, and return the training error.

```
[fis,trainError] = anfis(fuzex2trnData,opt);
```

`trainError` contains the root mean squared error for the training data at each training epoch. The training error for `fis` is the minimum value in `trainError`.

```
fisRMSE = min(trainError)
```

```
fisRMSE = 0.2572
```

Obtain ANFIS Step Size Profile

Create single-input, single-output training data.

```
x = (0:0.1:10)';
y = sin(2*x)./exp(x/5);
```

Configure the ANFIS training options. Set the initial FIS, and suppress the training progress display.

```
opt = anfisOptions('InitialFIS',4,'EpochNumber',60);
opt.DisplayANFISInformation = 0;
opt.DisplayErrorValues = 0;
opt.DisplayStepSize = 0;
opt.DisplayFinalResults = 0;
```

A larger step size increase rate can make the training converge faster. However, increasing the step size increase rate too much can lead to poor convergence. For this example, try doubling the step size increase rate.

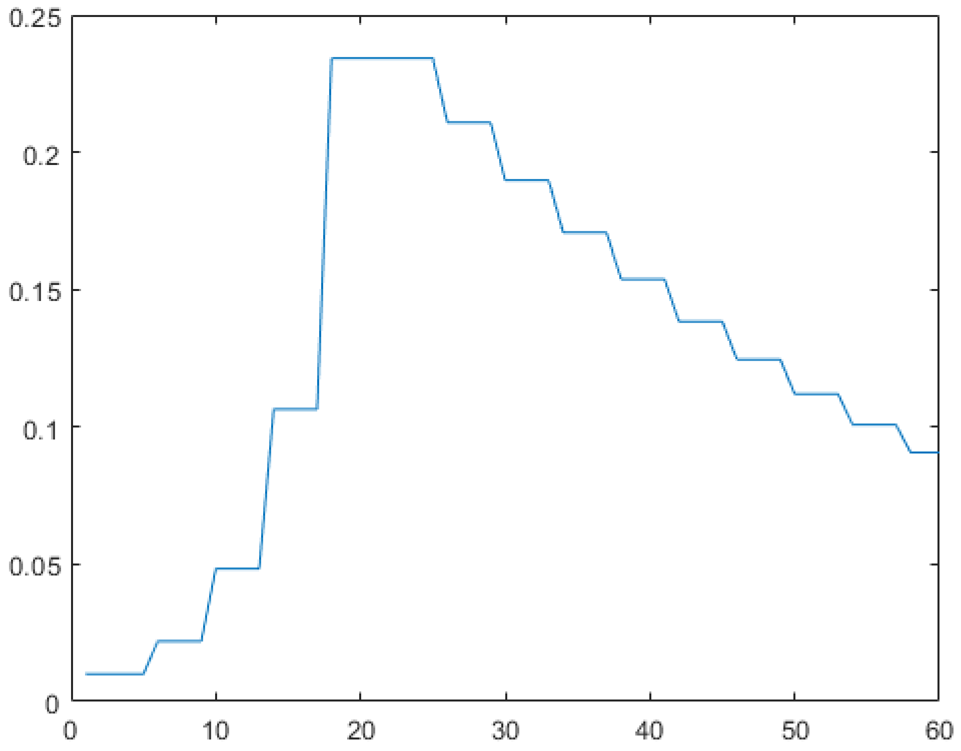
```
opt.StepSizeIncreaseRate = 2*opt.StepSizeIncreaseRate;
```

Train the FIS, and return the step size array.

```
[fis,~,stepSize] = anfis([x y],opt);
```

Plot the step size profile. An optimal step size profile should increase initially, reach a maximum, and then decrease for the rest of the training.

```
figure
plot(stepSize)
```



Validate ANFIS Training

Load training data.

```
load fuzex1trnData.dat
```

Load validation data.

```
load fuzex1chkData.dat
```

Specify the following training options:

- 4 input membership functions
- 30 training epochs
- Suppress training progress display

```
opt = anfisOptions('InitialFIS',4,'EpochNumber',30);
opt.DisplayANFISInformation = 0;
opt.DisplayErrorValues = 0;
opt.DisplayStepSize = 0;
opt.DisplayFinalResults = 0;
```

Add the validation data to the training options.

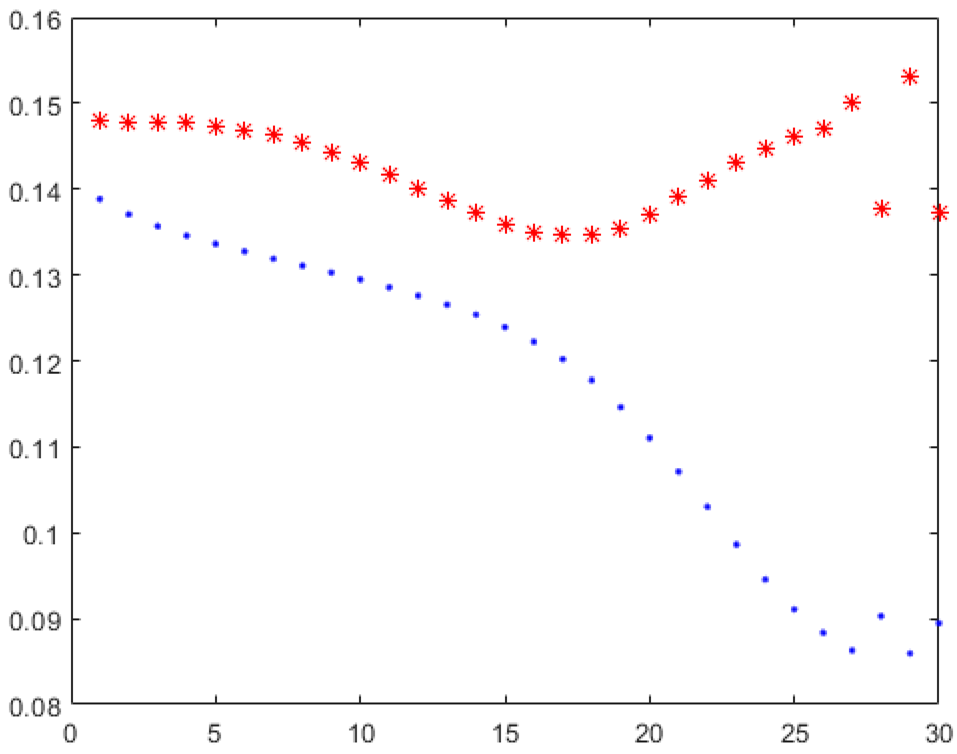
```
opt.ValidationData = fuzex1chkData;
```

Train the FIS, and return the validation results.

```
[fis,trainError,stepSize,chkFIS,chkError] = anfis(fuzex1trnData,opt);
```

The training error, `trainError`, and validation error, `chkError`, arrays each contain one error value per training epoch. Plot the training error and the validation error.

```
x = [1:30];
plot(x,trainError,'.b',x,chkError,'*r')
```



The minimum validation error occurs at epoch 17. The increase in validation error after this point indicates overfitting of the model parameters to the training data. Therefore, the tuned FIS at epoch 17, `chkFIS`, exhibits the best generalization performance.

Input Arguments

`trainingData` — Training data

array

Training data, specified as an array. For a fuzzy system with *N* inputs, specify `trainingData` as an array with *N*+1 columns. The first *N* columns contain input data, and the final column contains output data. Each row of `trainingData` contains one data point.

Generally, training data should fully represent the features of the data the FIS is intended to model.

`options` — Training options
`anfisOptions` option set

Training options, specified as an `anfisOptions` option set. Using `options`, you can specify:

- An initial FIS structure to tune, `options.InitialFIS`.
- Validation data for preventing overfitting to training data, `options.ValidationData`.
- Training algorithm options, such as the maximum number of training epochs, `options.EpochNumber`, or the training error goal, `options.ErrorGoal`.
- Whether to display training progress information, such as the training error values for each training epoch, `options.DisplayErrorValues`.

Output Arguments

`fis` — Trained fuzzy inference system
`mamfis` object | `sugfis` object

Trained fuzzy inference system with membership function parameters tuned using the training data, returned as a `mamfis` or `sugfis` object. This fuzzy system corresponds to the epoch for which the training error is smallest. If two epochs have the same minimum training error, the FIS from the earlier epoch is returned.

`trainError` — Root mean square training error
array

Root mean square training error for each training epoch, returned as an array. The minimum value in `trainError` is the training error for fuzzy system `fis`.

`stepSize` — Training step size
array

Training step size for each epoch, returned as an array. The `anfis` training algorithm tunes the FIS parameters using gradient descent optimization methods. The training step size is the magnitude of the gradient transitions in the parameter space.

Ideally, the step size increases at the start of training, reaches a maximum, and then decreases for the remainder of the training. To achieve this step size profile, adjust the initial step size (`options.InitialStepSize`), step size increase rate (`options.StepSizeIncreaseRate`), and step size decrease rate `options.StepSizeDecreaseRate`.

`chkFIS` — Tuned FIS for which the validation error is minimum
`mamfis` object | `sugfis` object

Tuned FIS for which the validation error is minimum, returned as a `mamfis` or `sugfis` object. If two epochs have the same minimum validation error, the FIS from the earlier epoch is returned.

`chkFIS` is returned only when you specify validation data using `options.ValidationData`.

`chkError` — Root mean square validation error
array

Root mean square training error, returned as an array with length equal to the number of training epochs. The minimum value in `chkError` is the training error for fuzzy system `chkFIS`.

`chkError` is returned only when you specify validation data using `options.ValidationData`.

Alternative Functionality

`tunefis` Function

Starting in R2019a, you can tune a fuzzy system using `tunefis`. This function provides several other options for tuning algorithms, specified by the `tunefisOptions` object.

To use ANFIS, specify the tuning algorithm as `"anfis"` in `tunefisOptions`. Then, use the options object as an input argument for `tunefis`. For example:

Create the initial fuzzy inference system, and define the tunable parameter settings.

```
x = (0:0.1:10)';
y = sin(2*x)./exp(x/5);
options = genfisOptions('GridPartition');
options.NumMembershipFunctions = 5;
fisin = genfis(x,y,options);
[in,out,rule] = getTunableSettings(fisin);
```

Tune the membership function parameters with `"anfis"`.

```
opt = tunefisOptions("Method","anfis");
fisout = tunefis(fisin,[in;out],x,y,opt);
```

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

References

[1] Jang, J.-S. R., "Fuzzy Modeling Using Generalized Neural Networks and Kalman Filter Algorithm," *Proc. of the Ninth National Conf. on Artificial Intelligence (AAAI-91)*. July 1991, pp. 762-767.

[2] Jang, J.-S. R., "ANFIS: Adaptive-Network-based Fuzzy Inference Systems," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 23, No. 3, May 1993, pp. 665-685.

See Also

Apps
Neuro-Fuzzy Designer

Functions
`anfisOptions` | `genfis` | `tunefis`

Topics
“Neuro-Adaptive Learning and ANFIS” on page 3-86
“Comparison of anfis and Neuro-Fuzzy Designer Functionality” on page 3-91
“Predict Chaotic Time-Series using ANFIS” on page 3-127
“Modeling Inverse Kinematics in a Robotic Arm” on page 3-137

Introduced before R2006a

anfisOptions

Option set for `anfis` command

Syntax

```
opt = anfisOptions
opt = anfisOptions(Name,Value)
```

Description

`opt = anfisOptions` creates a default option set for tuning a Sugeno fuzzy inference system using `anfis`. Use dot notation to modify this option set for your specific application. Any options that you do not modify retain their default values.

`opt = anfisOptions(Name,Value)` creates an option set with options specified by one or more `Name,Value` pair arguments.

Examples

Create Option Set for ANFIS Training

Create a default option set.

```
opt = anfisOptions;
```

Specify training options using dot notation. For example, specify the following options:

- Initial FIS with `4` membership functions for each input variable
- Maximum number of training epochs equal to `30`.

```
opt.InitialFIS = 4;
opt.EpochNumber = 30;
```

You can also specify options when creating the option set using one or more `Name,Value` pair arguments.

```
opt2 = anfisOptions('InitialFIS',4,'EpochNumber',30);
```

Input Arguments

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'EpochNumber',50` sets the maximum number of training epochs to `50`.

`InitialFIS` — Initial FIS structure

`2` (default) | positive integer greater than `1` | vector of positive integers | FIS structure

Initial FIS structure to tune, specified as the comma-separated pair consisting of `'InitialFIS'` and one of the following:

- Positive integer greater than `1` specifying the number of membership functions for all input variables. `anfis` generates an initial FIS structure with the specified number of membership functions using `genfis` with grid partitioning.
- Vector of positive integers with length equal to the number of input variables specifying the number of membership functions for each input variable. `anfis` generates an initial FIS structure with the specified numbers of membership functions using `genfis` with grid partitioning.
- FIS structure generated using `genfis` command with grid partitioning or subtractive clustering. The specified system must have the following properties:
  - Single output, obtained using weighted average defuzzification.
  - First or zeroth order Sugeno-type system; that is, all output membership functions must be the same type and be either `'linear'` or `'constant'`.
  - No rule sharing. Different rules cannot use the same output membership function; that is, the number of output membership functions must equal the number of rules.
  - Unity weight for each rule.

- No custom membership functions or defuzzification methods.

`EpochNumber` — Maximum number of training epochs
`10` (default) | positive integer

Maximum number of training epochs, specified as the comma-separated pair consisting of `'EpochNumber'` and a positive integer. The training process stops when it reaches the maximum number of training epochs.

`ErrorGoal` — Training error goal
`0` (default) | scalar

Training error goal, specified as the comma-separated pair consisting of `'ErrorGoal'` and a scalar. The training process stops when the training error is less than or equal to `ErrorGoal`.

`InitialStepSize` — Initial training step size
`0.01` (default) | positive scalar

Initial training step size, specified as the comma-separated pair consisting of `'InitialStepSize'` and a positive scalar.

The `anfis` training algorithm tunes the FIS parameters using gradient descent optimization methods. The training step size is the magnitude of each gradient transition in the parameter space. Typically, you can increase the rate of convergence of the training algorithm by increasing the step size. During optimization, `anfis` automatically updates the step size using `StepSizeIncreaseRate` and `StepSizeDecreaseRate`.

`StepSizeDecreaseRate` — Step size decrease rate
`0.9` (default) | positive scalar less than `1`

Step size decrease rate, specified as the comma-separated pair consisting of `'StepSizeDecreaseRate'` and a positive scalar less than `1`. If the training error undergoes two consecutive combinations of an increase followed by a decrease, then `anfis` scales the step size by the decrease rate.

`StepSizeIncreaseRate` — Step size increase rate
`1.1` (default) | scalar greater than `1`

Step size increase rate, specified as the comma-separated pair consisting of `'StepSizeIncreaseRate'` and a scalar greater than `1`. If the training error decreases for four consecutive epochs, then `anfis` scales the step size by the increase rate.

`DisplayANFISInformation` — Flag for showing ANFIS information

`1` (default) | `0`

Flag for showing ANFIS information at the start of the training process, specified as the comma-separated pair consisting of `'DisplayANFISInformation'` and one of the following:

- `1` — Display the following information about the ANFIS system and training data:
  - Number of nodes in the ANFIS system
  - Number of linear parameters to tune
  - Number of nonlinear parameters to tune
  - Total number of parameters to tune
  - Number of training data pairs
  - Number of checking data pairs
  - Number of fuzzy rules
- `0` — Do not display the information.

`DisplayErrorValues` — Flag for showing training error values

`1` (default) | `0`

Flag for showing training error values after each training epoch, specified as the comma-separated pair consisting of `'DisplayErrorValues'` and one of the following:

- `1` — Display the training error.
- `0` — Do not display the training error.

`DisplayStepSize` — Flag for showing step size

`1` (default) | `0`

Flag for showing step size whenever the step size changes, specified as the comma-separated pair consisting of `'DisplayStepSize'` and one of the following:

- `1` — Display the step size.
- `0` — Do not display the step size.

`DisplayFinalResults` — Flag for displaying final results

`1` (default) | `0`

Flag for displaying final results after training, specified as the comma-separated pair consisting of `'DisplayFinalResults'` and one of the following:

- `1` — Display the results.
- `0` — Do not display the results.

`ValidationData` — Validation data
`[]` (default) | array

Validation data for preventing overfitting to the training data, specified as the comma-separated pair consisting of `'ValidationData'` and an array. For a fuzzy system with *N* inputs, specify `ValidationData` as an array with *N*+1 columns. The first *N* columns contain input data and the final column contains output data. Each row of `ValidationData` contains one data point.

At each training epoch, the training algorithm validates the FIS using the validation data.

Generally, validation data should fully represent the features of the data the FIS is intended to model, while also being sufficiently different from the training data to test training generalization.

`OptimizationMethod` — Optimization method
`1` (default) | `0`

Optimization method used in membership function parameter training, specified as the comma-separated pair consisting of `'OptimizationMethod'` and one of the following:

- `1` — Use a hybrid method, which uses a combination of backpropagation to compute input membership function parameters, and least squares estimation to compute output membership function parameters.
- `0` — Use backpropagation gradient descent to compute all parameters.

Output Arguments

`opt` — Training options for `anfis` command
`anfisOptions` option set

Training options for `anfis` command, returned as an `anfisOptions` option set.

See Also

`anfis` | `genfis`

Introduced in R2017a

convertfis

Convert previous versions of fuzzy inference data in current format

In R2018b, the format of fuzzy inference systems changed from a structure format to an object format. To convert fuzzy systems in an old format to the new format, use `convertfis`.

Syntax

```
fisNew = convertfis(fisOld)
```

Description

`fisNew = convertfis(fisOld)` converts the old-format fuzzy inference system `fisOld` into the current object format.

Examples

Convert Old-Format Fuzzy Inference System

Load a fuzzy inference system created using an old format. For example, load a FIS structure from a MAT-file.

```
load fisStructure
```

View the fields of the structure.

```
fisStructure
```

```
fisStructure = struct with fields:
            name: 'tipper'
            type: 'mamdani'
       andMethod: 'min'
        orMethod: 'max'
    defuzzMethod: 'centroid'
```

```
        impMethod: 'min'
        aggMethod: 'max'
            input: [1x2 struct]
           output: [1x1 struct]
             rule: [1x3 struct]
```

Convert the structure to a `mamfis` object and view the object properties.

```
fisObject = convertfis(fisStructure)
```

```
fisObject = 
  mamfis with properties:

                      Name: "tipper"
                 AndMethod: "min"
                  OrMethod: "max"
         ImplicationMethod: "min"
         AggregationMethod: "max"
     DefuzzificationMethod: "centroid"
                    Inputs: [1x2 fisvar]
                   Outputs: [1x1 fisvar]
                     Rules: [1x3 fisrule]
    DisableStructuralChecks: 0

    See 'getTunableSettings' method for parameter optimization.
```

Input Arguments

`fisOld` — Old-format fuzzy inference system

structure | `matrix`

Old-format fuzzy inference system, specified as a structure or a matrix.

Output Arguments

`fisNew` — New-format fuzzy inference system

`mamfis` object | `sugfis` object

New-format fuzzy inference system, returned as a `mamfis` object or a `sugfis` object.

See Also

`mamfis` | `sugfis`

Introduced in R2018b

convertToStruct

Convert fuzzy inference system object into a structure

Syntax

```
fisStructure = convertToStruct(fisObject)
```

Description

`fisStructure = convertToStruct(fisObject)` converts a fuzzy inference system object into a structure.

Examples

Convert FIS Object into Structure

Load a fuzzy inference system.

```
fisObject = readfis('tipper')
```

```
fisObject = 
  mamfis with properties:

                       Name: "tipper"
                  AndMethod: "min"
                   OrMethod: "max"
          ImplicationMethod: "min"
          AggregationMethod: "max"
      DefuzzificationMethod: "centroid"
                     Inputs: [1x2 fisvar]
                    Outputs: [1x1 fisvar]
                      Rules: [1x3 fisrule]
    DisableStructuralChecks: 0
    See 'getTunableSettings' method for parameter optimization.
```

Convert the fuzzy inference system object into a structure.

```
fisStructure = convertToStruct(fisObject)
```

```
fisStructure = struct with fields:
            name: 'tipper'
            type: 'mamdani'
       andMethod: 'min'
        orMethod: 'max'
    defuzzMethod: 'centroid'
       impMethod: 'min'
       aggMethod: 'max'
           input: [1x2 struct]
          output: [1x1 struct]
            rule: [1x3 struct]
```

Input Arguments

`fisObject` — Fuzzy inference system object
`mamfis` object | `sugfis` object

Fuzzy inference system object, specified as a `mamfis` or `sugfis` object.

Output Arguments

`fisStructure` — Fuzzy inference system structure
structure

Fuzzy inference system structure, returned as a structure. The fields of the structure correspond to the properties of the FIS object. For object properties that are themselves objects, the corresponding structure field is a structure.

See Also

`mamfis` | `sugfis`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced in R2018b

convertToSugeno

Transform Mamdani fuzzy inference system into Sugeno fuzzy inference system

Syntax

```
sugenoFIS = convertToSugeno(mamdaniFIS)
```

Description

`sugenoFIS = convertToSugeno(mamdaniFIS)` transforms a Mamdani fuzzy inference system `mamdaniFIS` into a Sugeno fuzzy inference system `sugenoFIS`.

Examples

Transform Mamdani FIS into Sugeno FIS

Load a Mamdani fuzzy inference system.

```
mam_fismat = readfis('mam22.fis');
```

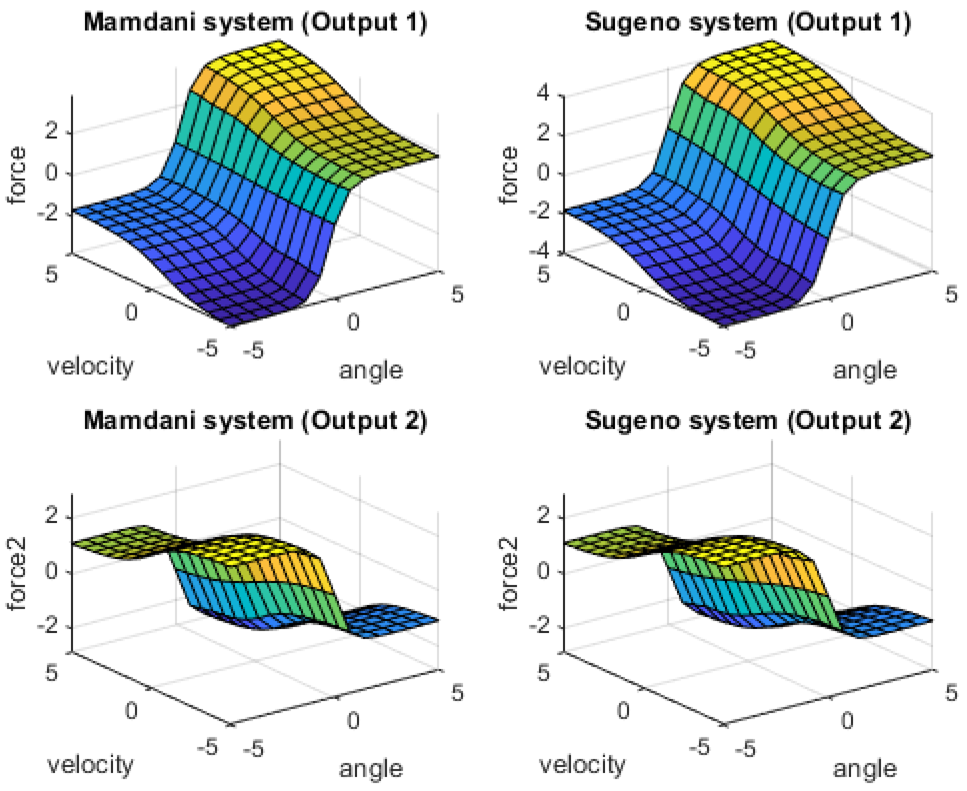
Convert this system to a Sugeno fuzzy inference system.

```
sug_fismat = convertToSugeno(mam_fismat);
```

Plot the output surfaces for both fuzzy systems.

```
subplot(2,2,1)
gensurf(mam_fismat)
title('Mamdani system (Output 1)')
subplot(2,2,2)
gensurf(sug_fismat)
title('Sugeno system (Output 1)')
subplot(2,2,3)
gensurf(mam_fismat,gensurfOptions('OutputIndex',2))
title('Mamdani system (Output 2)')
```

```
subplot(2,2,4)
gensurf(sug_fismat,gensurfOptions('OutputIndex',2))
title('Sugeno system (Output 2)')
```



The output surfaces for both systems are similar.

Input Arguments

`mamdaniFIS` — Mamdani fuzzy inference system
`mamfis` object

Mamdani fuzzy inference system, specified as a `mamfis` object. Construct `mamdaniFIS` at the command line or using **Fuzzy Logic Designer**. For more information, see “Build Fuzzy Systems at the Command Line” on page 2-38 and “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14.

Output Arguments

`sugenoFIS` — Sugeno fuzzy inference system
`sugfis` object

Sugeno fuzzy inference system, returned as a `sugfis` object. `sugenoFIS`:

- Has constant output membership functions, whose values correspond to the centroids of the output membership functions in `mamdaniFIS`
- Uses the weighted-average defuzzification method
- Uses the product implication method
- Uses the sum aggregation method

The remaining properties of `sugenoFIS`, including the input membership functions and rule definitions remain unchanged from `mamdaniFIS`.

Tips

- If you have a functioning Mamdani fuzzy inference system, consider using `convertToSugeno` to convert to a more computationally efficient Sugeno structure to improve performance.
- If `sugFIS` has a single output variable and you have appropriate measured input/output training data, you can tune the membership function parameters of `sugFIS` using `anfis`.

See Also

Functions
`mamfis` | `sugfis`

Apps
Fuzzy Logic Designer

Topics
"Build Fuzzy Systems at the Command Line" on page 2-38
"Comparison of Sugeno and Mamdani Systems" on page 2-12

Introduced in R2018b

defuzz

Defuzzify membership function

Syntax

```
out = defuzz(x,mf,type)
```

Description

`defuzz(x,mf,type)` returns a defuzzified value `out`, of a membership function `mf` positioned at associated variable value `x`, using one of several defuzzification strategies, according to the argument, `type`. The variable `type` can be one of the following:

- `'centroid'` — Centroid of the area under the output fuzzy set. This method is the default for Mamdani systems.
- `'bisector'` — Bisector of the area under the output fuzzy set
- `'mom'` — Mean of the values for which the output fuzzy set is maximum
- `'lom'` — Largest value for which the output fuzzy set is maximum
- `'som'` — Smallest value for which the output fuzzy set is maximum

You can also specify `type` using a character vector or string that contains the name of a custom function in the current working folder or on the MATLAB path. For more information on using custom functions, see "Build Fuzzy Systems Using Custom Functions" on page 2-50.

Examples

Obtain Defuzzified Value

```
x = -10:0.1:10;
mf = trapmf(x,[-10 -8 -4 7]);
out = defuzz(x,mf,'centroid')
out = -3.2857
```

See Also

Fuzzy Logic Designer

Topics

“Fuzzy Inference Process” on page 1-28

Introduced before R2006a

dsigmf

Difference between two sigmoidal membership functions

This function computes fuzzy membership values using the difference between two sigmoidal membership functions. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-67.

This membership function is related to the `sigmf` and `psigmf` membership functions.

Syntax

```
y = dsigmf(x,params)
```

Description

`y = dsigmf(x,params)` returns fuzzy membership values computed using the difference between two sigmoidal membership functions. Each sigmoidal function is given by:

$$f(x; a, c) = \frac{1}{1 + e^{-a(x - c)}}$$

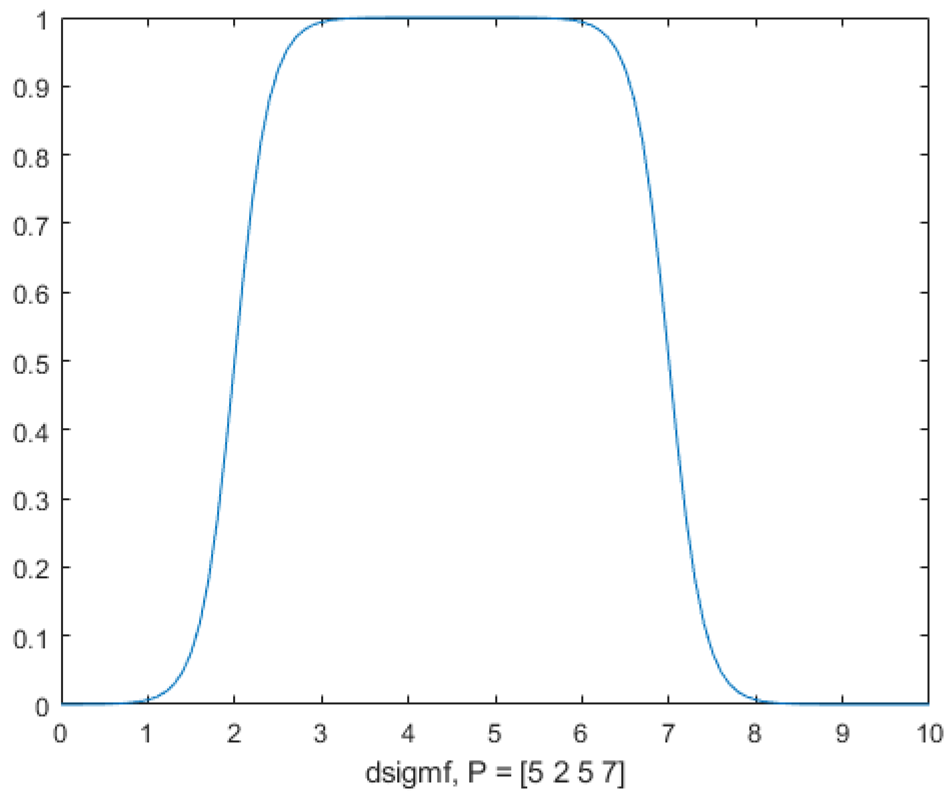
To specify the a and c parameters for each sigmoidal function, use `params`.

Membership values are computed for each input value in `x`.

Examples

Obtain Difference of Two Sigmoidal Functions

```
x = 0:0.1:10;
y = dsigmf(x,[5 2 5 7]);
plot(x,y)
xlabel('dsigmf, P = [5 2 5 7]')
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length four

Membership function parameters, specified as the vector [a_1 c_1 a_2 c_2]. Here, a_1 and c_1 are the parameters of the first sigmoidal function, and a_2 and c_2 are the parameters of the second sigmoidal function.

For each sigmoidal function, to open the function to the left or right, specify a negative or positive value for *a*, respectively. The magnitude of *a* defines the width of the transition area, and parameter *c* defines the center of the transition area.

To define a unimodal membership function with a maximum value of `1`, specify the same signs for a_1 and a_2, and select *c* values far enough apart to allow for both transition areas to reach `1`.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `dsigmf` membership function.

```
mf = fismf("dsigmf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `dsigmf`, respectively.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

See Also

`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

"Membership Functions" on page 1-14

Introduced before R2006a

evalfis

Evaluate fuzzy inference system

Syntax

```
output = evalfis(fis,input)
output = evalfis(fis,input,options)
[output,fuzzifiedIn,ruleOut,aggregatedOut,ruleFiring] = evalfis( ___ )
```

Description

`output = evalfis(fis,input)` evaluates the fuzzy inference system `fis` for the input values in `input` and returns the resulting output values in `output`.

`output = evalfis(fis,input,options)` evaluates the fuzzy inference system using specified evaluation options.

`[output,fuzzifiedIn,ruleOut,aggregatedOut,ruleFiring] = evalfis( ___ )` returns intermediate results from the fuzzy inference process. This syntax is not supported when `fis` is a `fistree` object.

Examples

Evaluate Fuzzy Inference System

Load FIS.

```
fis = readfis('tipper');
```

Evaluate the FIS when the first input is `2` and the second input is `1`.

```
output = evalfis(fis,[2 1])
```

```
output = 7.0169
```

Evaluate FIS for Multiple Input Combinations

Load FIS.

```
fis = readfis('tipper');
```

Specify the input combinations to evaluate using an array with one row per input combination.

```
input = [2 1;
         4 5;
         7 8];
```

Evaluate the FIS for the specified input combinations.

```
output = evalfis(fis,input)
```

```
output = 3×1

    7.0169
   14.4585
   20.3414
```

Each row of `output` is the defuzzified output value for the corresponding row of `input`.

Specify Number of Output Samples for FIS Evaluation

Load FIS.

```
fis = readfis('tipper');
```

Create an `evalfisOptions` option set, specifying the number of samples in the output fuzzy sets.

```
options = evalfisOptions('NumSamplePoints',50);
```

Evaluate the FIS using this option set.

```
output = evalfis(fis,[2 1],options);
```

Evaluate Tree of Fuzzy Inference Systems

Create a pair of Mamdani fuzzy inference systems.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = mamfis('Name','fis2','NumInputs',2,'NumOutputs',1);
```

Define the connection between the two.

```
con = ["fis1/output1" "fis2/input1"];
```

Create a tree of fuzzy inference systems.

```
tree = fistree([fis1 fis2],con);
```

Create an `evalfisOptions` option set, specifying the number of samples in the output fuzzy sets.

```
options = evalfisOptions('NumSamplePoints',50);
```

Evaluate the `fistree` object using a specified input combination and this option set.

```
y = evalfis(tree,[0.5 0.2 0.7],options)
```

```
y = 0.1553
```

Obtain Intermediate Fuzzy Inference Results

Load FIS.

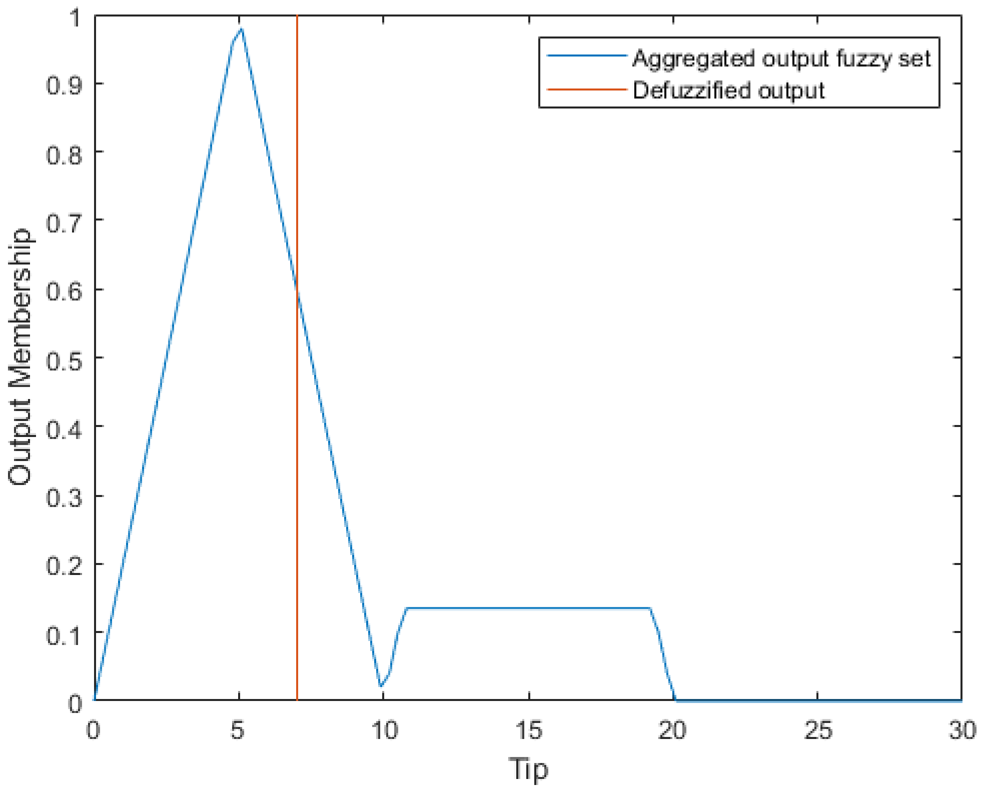
```
fis = readfis('tipper');
```

Evaluate the FIS, and return the intermediate inference results.

```
[output,fuzzifiedIn,ruleOut,aggregatedOut,ruleFiring] = evalfis(fis,[2 1]);
```

You can examine the intermediate results to understand or visualize the fuzzy inference process. For example, view the aggregated output fuzzy set, which is the fuzzy set that `evalfis` defuzzifies to find the output value. Also, plot the defuzzified output value.

```
outputRange = linspace(fis.output.range(1),fis.output.range(2),length(aggregatedOut))'
plot(outputRange,aggregatedOut,[output output],[0 1])
xlabel('Tip')
ylabel('Output Membership')
legend('Aggregated output fuzzy set','Defuzzified output')
```



The length of `aggregatedOutput` corresponds to the number of sample points used to discretize output fuzzy sets.

Input Arguments

fis — Fuzzy inference system

mamfis object | sugfis object | fistree object | homogeneous structure

Fuzzy inference system to be evaluated, specified as a mamfis object, sugfis object, or fistree object.

To create a fuzzy inference system, you can:

- Use the **Fuzzy Logic Designer** app. For an example, see “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14.
- Automatically generate the FIS object using the genfis command.
- Build the system at the command line. For an example, see “Build Fuzzy Systems at the Command Line” on page 2-38.

Use fistree to create a tree of interconnected fuzzy inference systems to evaluate. Multiple output arguments are not supported when using a fistree object.

For code generation applications, you can also specify fis as a homogeneous structure create using getFISCodeGenerationData. For an example, see “Generate Code for Fuzzy System Using MATLAB Coder” on page 6-12.

input — Input values

M-by-N_U array

Input values, specified as an M-by-N_U array, where N_U is the number of input variables in fis and M is the number of input combinations to evaluate.

evalfis supports double-precision or single-precision input values.

options — Evaluation options

evalfisOptions object

Evaluation options, specified as an evalfisOptions object.

Output Arguments

output — Output values

M-by-N_Y array

Output values, returned as an M-by-N_Y array, where N_Y is the number of output variables in `fis`. `evalfis` evaluates `fis` for each row of `input` and returns the resulting defuzzified outputs in the corresponding row of `output`.

`fuzzifiedIn` — Fuzzified input values

N_R-by-N_U array

Fuzzified input values, returned as an N_R-by-N_U array, where N_R is the number of rules in `fis`. Element (i,j) of `fuzzifiedIn` is the value of the input membership function for the jth input in the ith rule.

If `input` specifies multiple input combinations, then `fuzzifiedIn` corresponds to the combination in the last row of `input`.

For more information on fuzzifying input values, see “Fuzzify Inputs” on page 1-29.

`ruleOut` — Rule outputs

N_S-by-(N_RN_Y) array | N_R-by-N_Y array

Rule outputs, returned as an N_S-by-(N_RN_Y) array or an N_R-by-N_Y array, where N_S is the number of sample points used for evaluating output variable ranges. To obtain the output for each rule, `evalfis` applies the firing strength from the rule antecedent to the output membership function using the implication method specified in `fis`.

For a Mamdani system, each rule output is a fuzzy set. In this case, `ruleOut` is an N_S-by-(N_RN_Y) array. Each column of `ruleOut` contains the output fuzzy set for one rule. The first N_R columns contain the rule outputs for the first output variable, the next N_R columns correspond to the second output variable, and so on.

For a Sugeno system, each rule output is a scalar value. In this case, `ruleOut` is an N_R-by-N_Y array. Element (j,k) of `ruleOut` is the value of the kth output variable for the jth rule.

If `input` specifies multiple input combinations, then `ruleOut` corresponds to the combination in the last row of `input`.

For more information on fuzzy implication, see “Apply Implication Method” on page 1-31 and “What Is Sugeno-Type Fuzzy Inference?” on page 2-5

`aggregatedOut` — Aggregated output

N_S-by-N_Y array | row vector of length N_Y

Aggregated output for each output variable, returned as an N_S-by-N_Y array or a row vector of length N_Y. For each output variable, `evalfis` combines the corresponding outputs from all the rules using the aggregation method specified in `fis`.

For a Mamdani system, the aggregate result for each output variable is a fuzzy set. In this case, `aggregatedOut` is as an N_S-by-N_Y array. Each column of `aggregatedOut` contains the aggregate fuzzy set for one output variable.

For a Sugeno system, the aggregate result for each output variable is a scalar value. In this case, `aggregatedOut` is a row vector of length N_Y, where element k is the aggregate result for the kth output variable.

If `input` specifies multiple input combinations, then `aggregatedOut` corresponds to the combination in the last row of `input`.

For more information on fuzzy aggregation, see “Aggregate All Outputs” on page 1-31 and “What Is Sugeno-Type Fuzzy Inference?” on page 2-5

`ruleFiring` — Rule firing strengths
column vector of length N_R

Rule firing strength, returned as a column vector of length N_R. To obtain the firing strength for each rule, `evalfis` evaluates the rule antecedents; that is, it applies fuzzy operator to the values of the fuzzified inputs.

If `input` specifies multiple input combinations, then `ruleFiring` corresponds to the combination in the last row of `input`.

For more information on applying the fuzzy operator, see “Apply Fuzzy Operator” on page 1-30.

Alternative Functionality

App

You can evaluate fuzzy inference systems using the **Rule Viewer** in the **Fuzzy Logic Designer** app.

Simulink Block

You can evaluate fuzzy inference systems using the Fuzzy Logic Controller block. For more information on mapping the arguments of `evalfis` to the Fuzzy Logic Controller block, see “Simulate Fuzzy Inference Systems in Simulink” on page 5-2.

Compatibility Considerations

`evalfis` input argument order has changed

Behavior changed in R2018b

The order of input arguments for `evalfis` has changed, which requires updates to your code.

Update Code

Previously, to evaluate a fuzzy inference system, `fis`, you specified the input variable values, `input`, as the first input argument. For example:

```
output = evalfis(input,fis);
output = evalfis(input,fis,options);
```

Update your code to specify the fuzzy inference system as the first input argument. For example:

```
output = evalfis(fis,input);
output = evalfis(fis,input,options);
```

To specify the number of sample points for output fuzzy sets, you now us an `evalfisOptions` object

Behavior changed in R2018a

To specify the number of sample points for output fuzzy sets, you now us an `evalfisOptions` object, which requires updates to your code.

Update Code

Previously, to specify the number of sample points, `numPts`, to use when evaluating output fuzzy sets of fuzzy inference system `fis`, you used an input argument. For example:

```
output = evalfis(input,fis,numPts);
```

Update your code to specify the number of sample points using an `evalfisOptions` object. For example:

```
opt = evalfisOptions('NumSamplePoints',numPts);
output = evalfis(input,fis,opt);
```

`evalfis` diagnostic message behavior has changed

Behavior changed in R2018a

The diagnostic message behavior of the `evalfis` function has changed. Previously, the `evalfis` function had the following behaviors for diagnostic conditions.

Diagnostic Condition	Previous Behavior
Input values outside of their specified variable ranges	MATLAB warning
No rules fired for a given output at the current input values	MATLAB Command Window message
Empty output fuzzy sets	MATLAB Command Window message

Starting in R2018a, these diagnostic conditions are reported as MATLAB warnings by default. You can change this behavior by specifying the corresponding options in an `evalfisOptions` object.

Update Code

To disable the default warning messages, update your code to use an `evalfisOptions` object, and specify the diagnostic message options. For example, disable the empty output fuzzy set message.

```
opt = evalfisOptions('EmptyOutputFuzzySetMessage',"none");
output = evalfis(input,fis,opt);
```

Intermediate fuzzy inference outputs for Sugeno systems are now analogous to outputs for Mamdani systems

Behavior changed in R2018a

When evaluating a Sugeno system using the following syntax, the intermediate fuzzy inference results are now analogous to the intermediate results for Mamdani systems.

```
[output,fuzzifiedInputs,ruleOutputs,aggregatedOutput] = evalfis(input,fis);
```

For a Sugeno system:

- `ruleOutputs` now returns an array that contains the scalar output value for each rule; that is, the product of the rule firing strength and the rule output level.
- `aggregatedOutput` now returns the sum of all the rule output values for each output variable.

Previously, for a Sugeno fuzzy system:

- `ruleOutputs` returned an array that contained the output level for each rule.
- `aggregatedOutput` returned an array that contained the firing strength for each rule.

Starting in R2018a, if your code returns intermediate fuzzy inference results when evaluating a Sugeno system using `evalfis`, modify your code to use the new `ruleOutputs` and `aggregatedOutput` results.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- All `evalfis` syntaxes are supported for code generation. However, `mamfis`, `sugfis`, and `fistree` objects are not supported. To use `evalfis` for code generation, you must convert your FIS objects into homogenous structures using `getFISCodeGenerationData`.
- Unlike the Fuzzy Logic Controller, `evalfis` does not support fixed-point data for simulation or code generation.
- When evaluating a fuzzy inference system in Simulink, it is recommended to not use `evalfis` or `evalfisOptions` within a MATLAB Function block. Instead, evaluate your fuzzy inference system using the Fuzzy Logic Controller block.

See Also

Functions
`evalfisOptions` | `fistree` | `mamfis` | `sugfis`

Topics
“Fuzzy Inference Process” on page 1-28
“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced before R2006a

evalmf

Evaluate fuzzy membership function

Syntax

```
y = evalmf(mf,x)
```

Description

`y = evalmf(mf,x)` evaluates one or more membership functions in `mf` based on the input values in `x`.

Examples

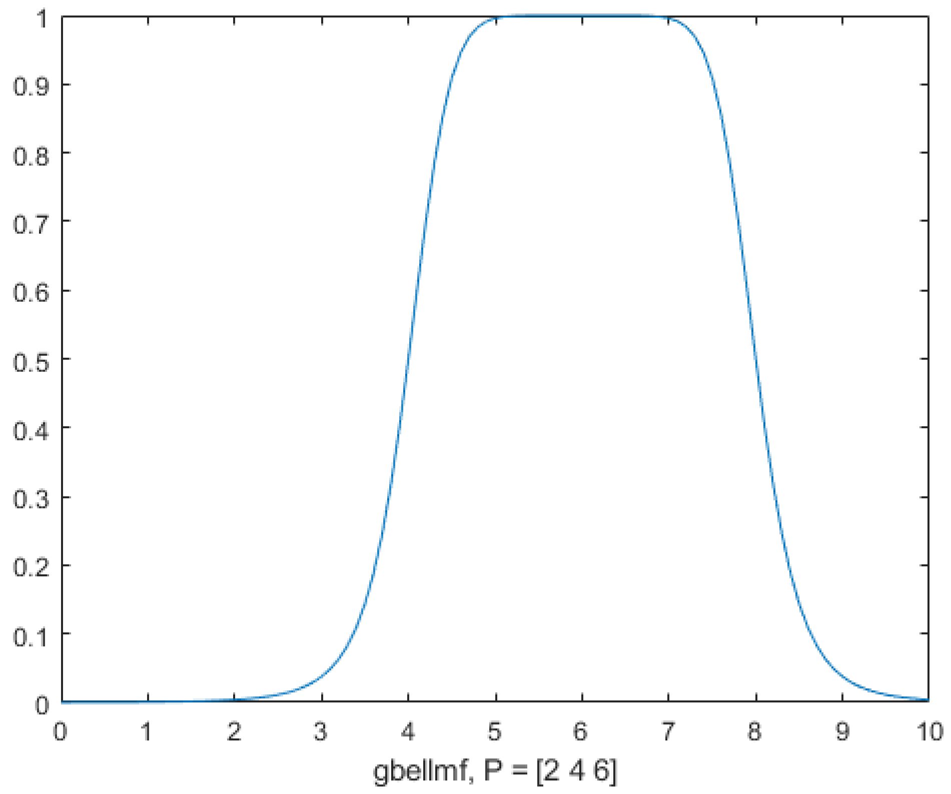
Evaluate Membership Function

Evaluate a generalized bell-shaped membership function across a range of input values from `0` through `10`.

```
x = 0:0.1:10;
mf = fismf("gbellmf",[2 4 6]);
y = evalmf(mf,x);
```

Plot the evaluation.

```
plot(x,y)
xlabel('gbellmf, P = [2 4 6]')
```



Evaluate Multiple Membership Functions

Create a vector of three Gaussian membership functions.

```
mf = [fismf("gaussmf",[0.9 2.5],'Name',"low");
      fismf("gaussmf",[0.9 5],'Name',"medium");
      fismf("gaussmf",[0.9 7.55],'Name',"high")];
```

Specify the input range over which to evaluate the membership functions.

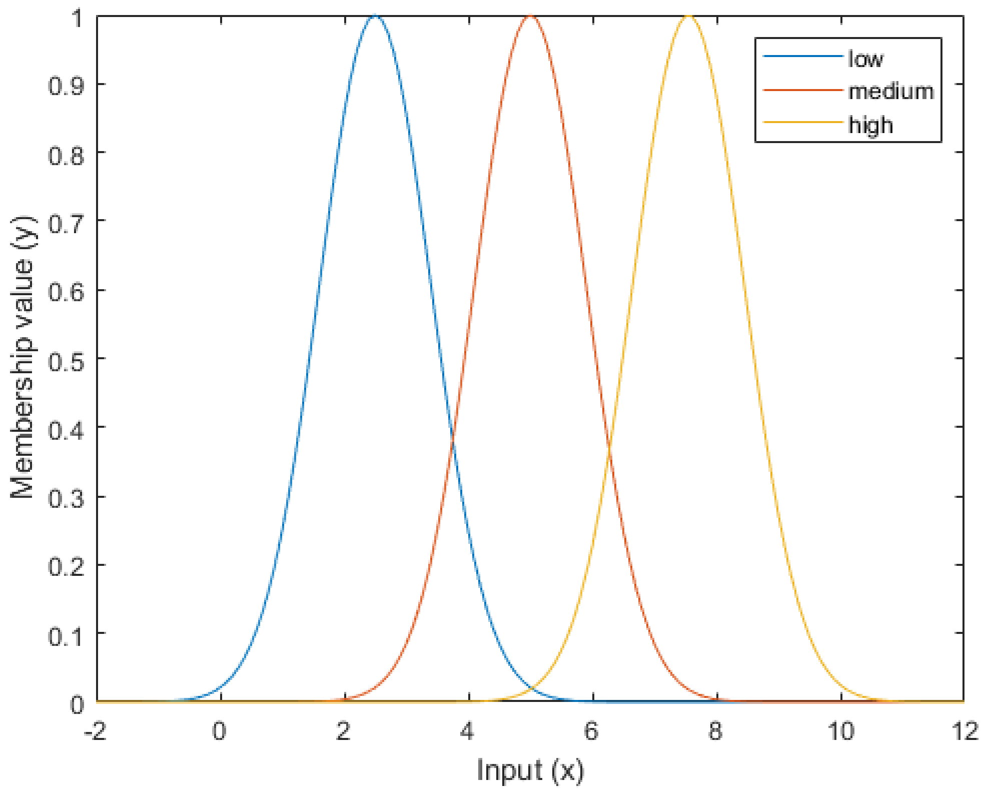
```
x = (-2:0.1:12)';
```

Evaluate the membership functions.

```
y = evalmf(mf,x);
```

Plot the evaluation results.

```
plot(x,y)
xlabel('Input (x)')
ylabel('Membership value (y)')
legend("low","medium","high")
```



Input Arguments

`mf` — Membership function
`fismf` object | vector of `fismf` objects

Membership function, specified as a `fismf` object or a vector of `fismf` objects.

`x` — Input value
scalar | vector | 2-D matrix

Input value, specified as a scalar, vector, or 2-D matrix. If `mf` is a:

- Single `fismf` object, then you can specify `x` as a scalar, vector, or matrix
- Vector of `fismf` objects, then you can specify `x` as a scalar or vector

Output Arguments

`y` — Output membership value
scalar | vector | 2-D matrix

Output membership value, returned as a scalar, vector, or 2-D matrix. If `mf` is a:

- Single `fismf` object, then `y` is a scalar, vector, or matrix with the same dimensions as `x`. Each element of `y` is the evaluated membership value for the corresponding element of `x`.
- Vector of `fismf` objects, then `y` is an *M*-by-*N* matrix, where *M* and *N* are the lengths of `mf` and `x`, respectively. `y`(*i*,*j*) is the evaluated value of membership function `mf`(*i*) for input value `x`(*j*).

Compatibility Considerations

`evalmf` now takes a `fismf` object as an input argument
Behavior changed in R2018b

`evalmf` now takes a `fismf` object as an input argument rather than the type and parameters of the membership function. Also, you can now evaluate multiple membership functions by passing an array of `fismf` objects to `evalmf`. There are differences between these approaches that require updates to your code.

Update Code

Previously, you evaluated a membership function for given input values, `x`, by specifying the type of membership function, `type`, and the membership functions parameters, `params`.

```
y = evalmf(x,params,type);
```

Update your code to first create a `fismf` object, `mf`. Then, pass this object to `evalmf`.

```
mf = fismf(type,params);
y = evalmf(mf,x);
```

Also, previously, to evaluate multiple membership functions you called `evalmf` once for each membership function.

```
y1 = evalmf(x,params1,type1);
y2 = evalmf(x,params2,type2);
y3 = evalmf(x,params3,type3);
```

Now, you can evaluate multiple membership functions by passing an array of `fismf` objects to `evalmf`.

```
mf1 = fismf(type1,params1);
mf2 = fismf(type2,params2);
mf2 = fismf(type3,params3);
y = evalmf([mf1 mf2 mf3],x);
```

Here, `y = [y1 y2 y3]';`

See Also
`fismf`

Topics
"Foundations of Fuzzy Logic" on page 1-10

Introduced before R2006a

fcm

Fuzzy c-means clustering

Syntax

```
[centers,U] = fcm(data,Nc)
[centers,U] = fcm(data,Nc,options)

[centers,U,objFunc] = fcm( ___ )
```

Description

`[centers,U] = fcm(data,Nc)` performs fuzzy c-means clustering on the given data and returns `Nc` cluster centers.

`[centers,U] = fcm(data,Nc,options)` specifies additional clustering options.

`[centers,U,objFunc] = fcm( ___ )` also returns the objective function values at each optimization iteration for all of the previous syntaxes.

Examples

Cluster Data Using Fuzzy C-Means Clustering

Load data.

```
load fcmdata.dat
```

Find 2 clusters using fuzzy c-means clustering.

```
[centers,U] = fcm(fcmdata,2);
```

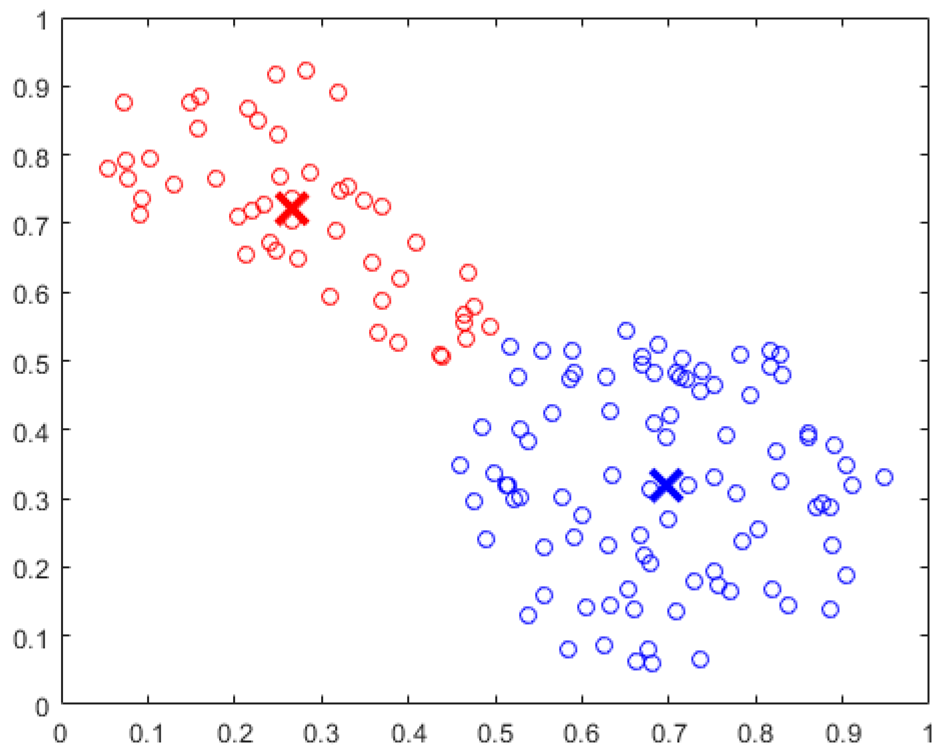
```
Iteration count = 1, obj. fcn = 8.970479
Iteration count = 2, obj. fcn = 7.197402
Iteration count = 3, obj. fcn = 6.325579
Iteration count = 4, obj. fcn = 4.586142
Iteration count = 5, obj. fcn = 3.893114
Iteration count = 6, obj. fcn = 3.810804
Iteration count = 7, obj. fcn = 3.799801
Iteration count = 8, obj. fcn = 3.797862
Iteration count = 9, obj. fcn = 3.797508
Iteration count = 10, obj. fcn = 3.797444
Iteration count = 11, obj. fcn = 3.797432
Iteration count = 12, obj. fcn = 3.797430
```

Classify each data point into the cluster with the largest membership value.

```
maxU = max(U);
index1 = find(U(1,:) == maxU);
index2 = find(U(2,:) == maxU);
```

Plot the clustered data and cluster centers.

```
plot(fcmdata(index1,1),fcmdata(index1,2),'ob')
hold on
plot(fcmdata(index2,1),fcmdata(index2,2),'or')
plot(centers(1,1),centers(1,2),'xb','MarkerSize',15,'LineWidth',3)
plot(centers(2,1),centers(2,2),'xr','MarkerSize',15,'LineWidth',3)
hold off
```



Specify Fuzzy Overlap Between Clusters

Create a random data set.

```
data = rand(100,2);
```

To increase the amount of fuzzy overlap between the clusters, specify a large fuzzy partition matrix exponent.

```
options = [3.0 NaN NaN 0];
```

Cluster the data.

```
[centers,U] = fcm(data,2,options);
```

Configure Clustering Termination Conditions

Load the clustering data.

```
load clusterdemo.dat
```

Set the clustering termination conditions such that the optimization stops when either of the following occurs:

- The number of iterations reaches a maximum of `25`.
- The objective function improves by less than `0.001` between two consecutive iterations.

```
options = [NaN 25 0.001 0];
```

The first option is `NaN`, which sets the fuzzy partition matrix exponent to its default value of `2`. Setting the fourth option to `0` suppresses the objective function display.

Cluster the data.

```
[centers,U,objFun] = fcm(clusterdemo,3,options);
```

To determine which termination condition stopped the clustering, view the objective function vector.

```
objFun
```

```
objFun = 13×1

   54.7257
   42.9867
   42.8554
   42.1857
   39.0857
   31.6814
   28.5736
   27.1806
   20.7359
   15.7147
```

⋮

The optimization stopped because the objective function improved by less than `0.001` between the final two iterations.

Input Arguments

`data` — Data set to be clustered
matrix

Data set to be clustered, specified as a matrix with N_d rows, where N_d is the number of data points. The number of columns in `data` is equal to the data dimensionality.

`Nc` — Number of clusters
integer greater than `1`

Number of clusters to create, specified as an integer greater than `1`.

`options` — Clustering options
vector

Clustering options, specified as a vector with the following elements:

Option	Description	Default
`options(1)`	Exponent for the fuzzy partition matrix, `U`, specified as a scalar greater than `1.0`. This option controls the amount of fuzzy overlap between clusters, with larger values indicating a greater degree of overlap. If your data set is wide with a lot of overlap between potential clusters, then the calculated cluster centers might be very close to each other. In this case, each data point has approximately the same degree of membership in all clusters. To improve your clustering results, decrease this value, which limits the amount of fuzzy overlap during clustering. For an example of fuzzy overlap adjustment, see “Adjust Fuzzy Overlap in Fuzzy C-Means Clustering” on page 4-8.	`2.0`

Option	Description	Default
`options(2)`	Maximum number of iterations, specified as a positive integer.	`100`
`options(3)`	Minimum improvement in objective function between two consecutive iterations, specified as a positive scalar.	`1e-5`
`options(4)`	Information display flag indicating whether to display the objective function value after each iteration, specified as one of the following: • `true` — Display objective function. • `false` — Do not display objective function.	`true`

If any element of `options` is `NaN`, the default value for that option is used.

The clustering process stops when the maximum number of iterations is reached or when the objective function improvement between two consecutive iterations is less than the specified minimum.

Output Arguments

`centers` — Cluster centers
matrix

Final cluster centers, returned as a matrix with `Nc` rows containing the coordinates of each cluster center. The number of columns in `centers` is equal to the dimensionality of the data being clustered.

`U` — Fuzzy partition matrix
matrix

Fuzzy partition matrix, returned as a matrix with `Nc` rows and N_d columns. Element `U(i,j)` indicates the degree of membership of the *j*th data point in the *i*th cluster. For a given data point, the sum of the membership values for all clusters is one.

`objFunc` — Objective function values
vector

Objective function values for each iteration, returned as a vector.

Tips

- To generate a fuzzy inference system using FCM clustering, use the `genfis` command. For example, suppose you cluster your data using the following syntax:

  ```
  [centers,U] = fcm(data,Nc,options);
  ```

  where the first `M` columns of `data` correspond to input variables, and the remaining columns correspond to output variables.

  You can generate a fuzzy system using the same training data and FCM clustering configuration. To do so:

  1. Configure clustering options.

     ```
     opt = genfisOptions('FCMClustering');
     opt.NumClusters = Nc;
     opt.Exponent = options(1);
     opt.MaxNumIteration = options(2);
     opt.MinImprovement = options(3);
     opt.Verbose = options(4);
     ```
  2. Extract the input and output variable data.

     ```
     inputData = data(:,1:M);
     outputData = data(:,M+1:end);
     ```
  3. Generate the FIS structure.

     ```
     fis = genfis(inputData,outputData,opt);
     ```

  The fuzzy system, `fis`, contains one fuzzy rule for each cluster, and each input and output variable has one membership function per cluster. For more information, see `genfis` and `genfisOptions`.

Algorithms

Fuzzy c-means (FCM) is a clustering method that allows each data point to belong to multiple clusters with varying degrees of membership.

FCM is based on the minimization of the following objective function

$$J_m = \sum_{i=1}^{D} \sum_{j=1}^{N} \mu_{ij}^{m} \|x_i - c_j\|^2,$$

where

- *D* is the number of data points.
- *N* is the number of clusters.
- *m* is fuzzy partition matrix exponent for controlling the degree of fuzzy overlap, with *m* > 1. Fuzzy overlap refers to how fuzzy the boundaries between clusters are, that is the number of data points that have significant membership in more than one cluster.
- x_i is the *i*th data point.
- c_j is the center of the *j*th cluster.
- μ_{ij} is the degree of membership of x_i in the *j*th cluster. For a given data point, x_i, the sum of the membership values for all clusters is one.

`fcm` performs the following steps during clustering:

1. Randomly initialize the cluster membership values, μ_{ij}.
2. Calculate the cluster centers:

$$c_j = \frac{\sum_{i=1}^{D} \mu_{ij}^m x_i}{\sum_{i=1}^{D} \mu_{ij}^m}.$$

3. Update μ_{ij} according to the following:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}.$$

4. Calculate the objective function, J_m.
5. Repeat steps 2–4 until J_m improves by less than a specified minimum threshold or until after a specified maximum number of iterations.

References

[1] Bezdec, J.C., *Pattern Recognition with Fuzzy Objective Function Algorithms*, Plenum Press, New York, 1981.

See Also

`findcluster` | `genfis`

Topics

“Fuzzy Clustering” on page 4-2
“Cluster Quasi-Random Data Using Fuzzy C-Means Clustering” on page 4-4
“Adjust Fuzzy Overlap in Fuzzy C-Means Clustering” on page 4-8

Introduced before R2006a

findcluster

Open Clustering tool

Syntax

`findcluster`

`findcluster(fileName)`

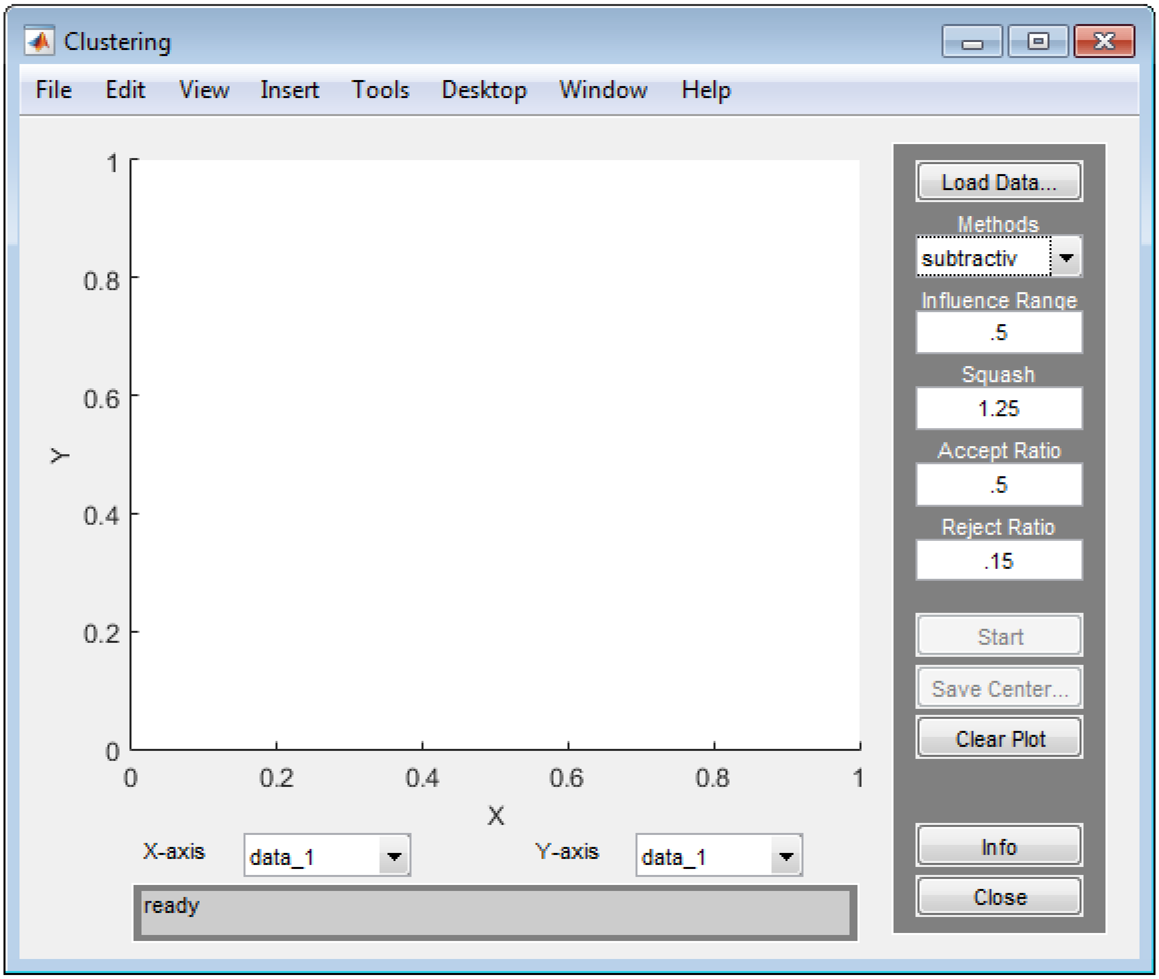
Description

`findcluster` opens a UI to implement either fuzzy c-means or fuzzy subtractive clustering. For more information on:

- Clustering methods, see "Fuzzy Clustering" on page 4-2.
- Using the Clustering tool, see "Data Clustering Using Clustering Tool" on page 4-48.

`findcluster(fileName)` opens the UI, loads the data set in the file `fileName`, specified as a character vector or string, and plots the first two dimensions of the data.

The data set file must have the extension `.dat`. Each line of the data set file contains one data point. For example, if you have 5-dimensional data with 100 data points,the file contains 100 lines, and each line contains five values.



Methods: subtractiv

Influence Range: .5

Squash: 1.25

Accept Ratio: .5

Reject Ratio: .15

X-axis data_1

Y-axis data_1

ready

Examples

Open Clustering Tool and Load Data Set

```
findcluster('clusterdemo.dat')
```

Tips

- Using the Clustering tool, you can obtain only the computed cluster centers. To obtain additional information for:

  - Fuzzy c-means clustering, such as the fuzzy partition matrix, cluster the data using `fcm`.
  - Subtractive clustering, such as the range of influence in each data dimension, cluster the data using `subclust`.
- To use the same clustering data with either `fcm` or `subclust`, first load the data file into the MATLABworkspace. For example, at the MATLAB command line, type:

  ```
  load clusterdemo.dat
  ```

See Also

`fcm` | `subclust`

Topics

"Data Clustering Using Clustering Tool" on page 4-48

Introduced before R2006a

fuzarith

Perform fuzzy arithmetic

Syntax

```
C = fuzarith(X,A,B,operator)
```

Description

Using interval arithmetic, `C = fuzarith(X,A,B,operator)` returns a fuzzy set `C` as the result of applying the function represented by the `operator`, which performs a binary operation on the sampled convex fuzzy sets `A` and `B`. The elements of `A` and `B` are derived from convex functions of the sampled universe, `X`:

- `A`, `B`, and `X` are vectors of the same dimension.
- `operator` is one of the following: `'sum'`, `'sub'`, `'prod'`, and `'div'`.
- The returned fuzzy set `C` is a column vector with the same length as `X`.

Note Fuzzy addition might generate the message `"divide by zero"` but this does not affect the accuracy of this function.

Examples

Perform Fuzzy Arithmetic

Specify Gaussian and Trapezoidal membership functions.

```
N = 101;
minx = -20;
maxx = 20;
x = linspace(minx,maxx,N);
```

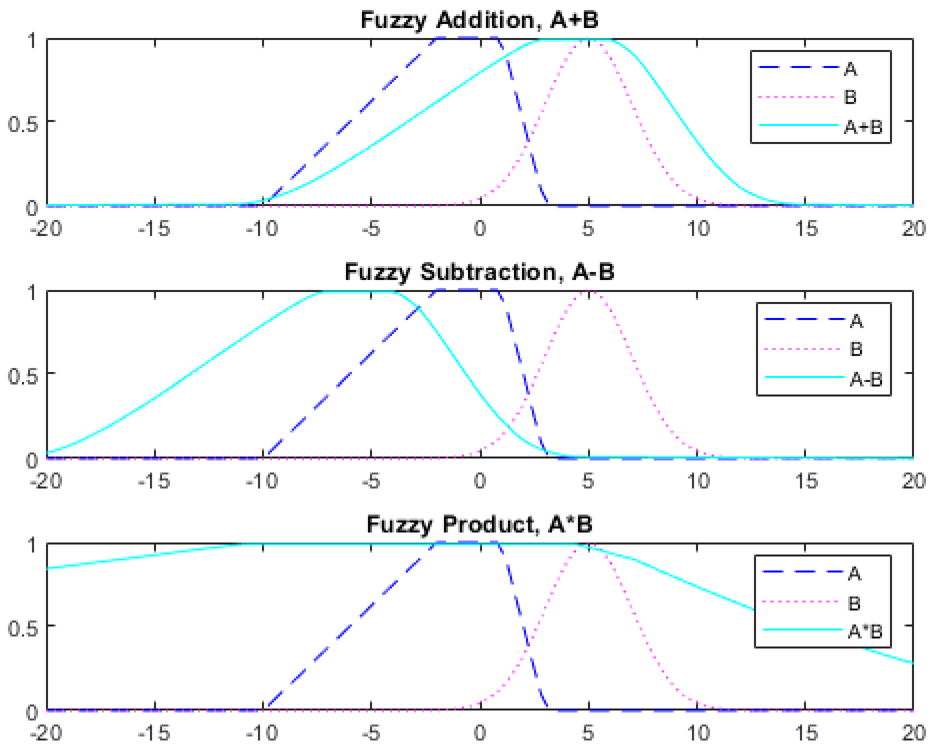
```
A = trapmf(x,[-10 -2 1 3]);
B = gaussmf(x,[2 5]);
```

Evaluate the sum, difference, and product of A and B.

```
Csum = fuzarith(x,A,B,'sum');
Csub = fuzarith(x,A,B,'sub');
Cprod = fuzarith(x,A,B,'prod');
```

Plot the results.

```
figure
subplot(3,1,1)
plot(x,A,'b--',x,B,'m:',x,Csum,'c')
title('Fuzzy Addition, A+B')
legend('A','B','A+B')
subplot(3,1,2)
plot(x,A,'b--',x,B,'m:',x,Csub,'c')
title('Fuzzy Subtraction, A-B')
legend('A','B','A-B')
subplot(3,1,3)
plot(x,A,'b--',x,B,'m:',x,Cprod,'c')
title('Fuzzy Product, A*B')
legend('A','B','A*B')
```



Introduced before R2006a

gauss2mf

Gaussian combination membership function

This function computes fuzzy membership values using a combination of two Gaussian membership functions. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-102.

Syntax

```
y = gauss2mf(x,params)
```

Description

`y = gauss2mf(x,params)` returns fuzzy membership values computed using a combination of two Gaussian membership functions computed. Each Gaussian function defines the shape of one side of the membership function and is given by:

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$$

To specify the standard deviation, σ, and mean, c, for each Gaussian function, use `params`.

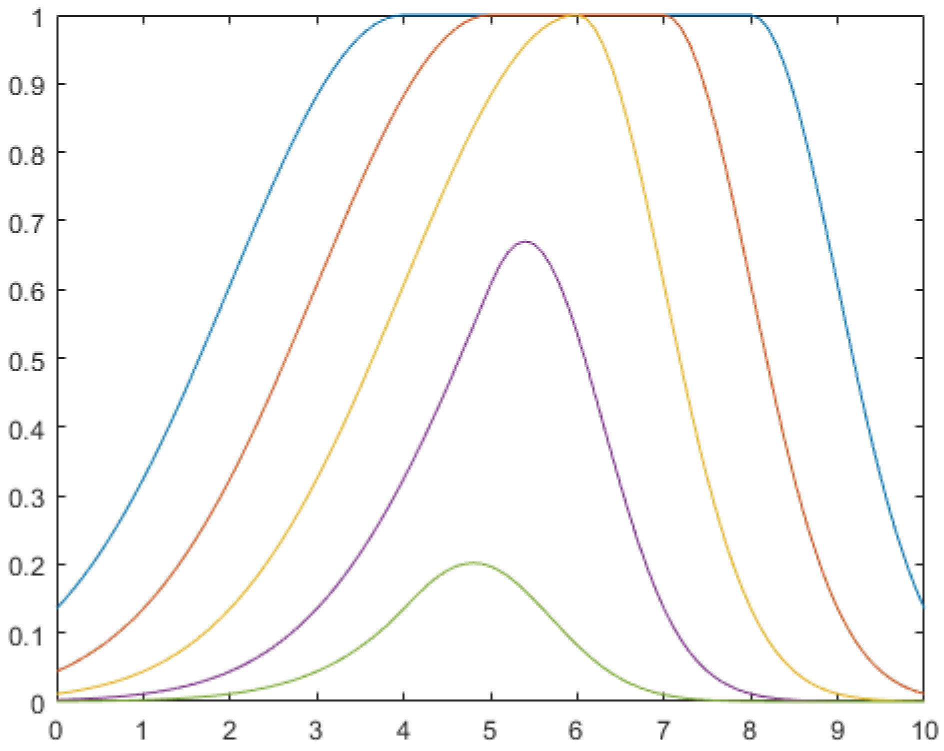
Membership values are computed for each input value in `x`.

Examples

Gaussian Combination Membership Functions

```
x = [0:0.1:10]';
y1 = gauss2mf(x,[2 4 1 8]);
y2 = gauss2mf(x,[2 5 1 7]);
y3 = gauss2mf(x,[2 6 1 6]);
y4 = gauss2mf(x,[2 7 1 5]);
```

```
y5 = gauss2mf(x,[2 8 1 4]);
plot(x,[y1 y2 y3 y4 y5])
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length four

Membership function parameters, specified as the vector [σ_1 c_1 σ_2 c_2]. Here:

- σ_1 and c_1 are the standard deviation and mean of the left Gaussian function, respectively.
- σ_2 and c_2 are the standard deviation and mean of the right Gaussian function, respectively.

When $c_1 \leq c_2$, the `gauss2mf` function reaches a maximum value of `1` over the range [c_1, c_2].

Otherwise, when $c_1 > c_2$, the maximum value is less than one.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `gauss2mf` membership function.

```
mf = fismf("gauss2mf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `gauss2mf`, respectively.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

See Also

`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

"Membership Functions" on page 1-14

Introduced before R2006a

gaussmf

Gaussian membership function

This function computes fuzzy membership values using a Gaussian membership function. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-106.

A Gaussian membership function is not the same as a Gaussian probability distribution. For example, a Gaussian membership function always has a maximum value of `1`. For more information on Gaussian probability distributions, see “Normal Distribution” (Statistics and Machine Learning Toolbox).

Syntax

```
y = gaussmf(x,params)
```

Description

`y = gaussmf(x,params)` returns fuzzy membership values computed using the following Gaussian membership function:

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$$

To specify the standard deviation, σ, and mean, c, for the Gaussian function, use `params`.

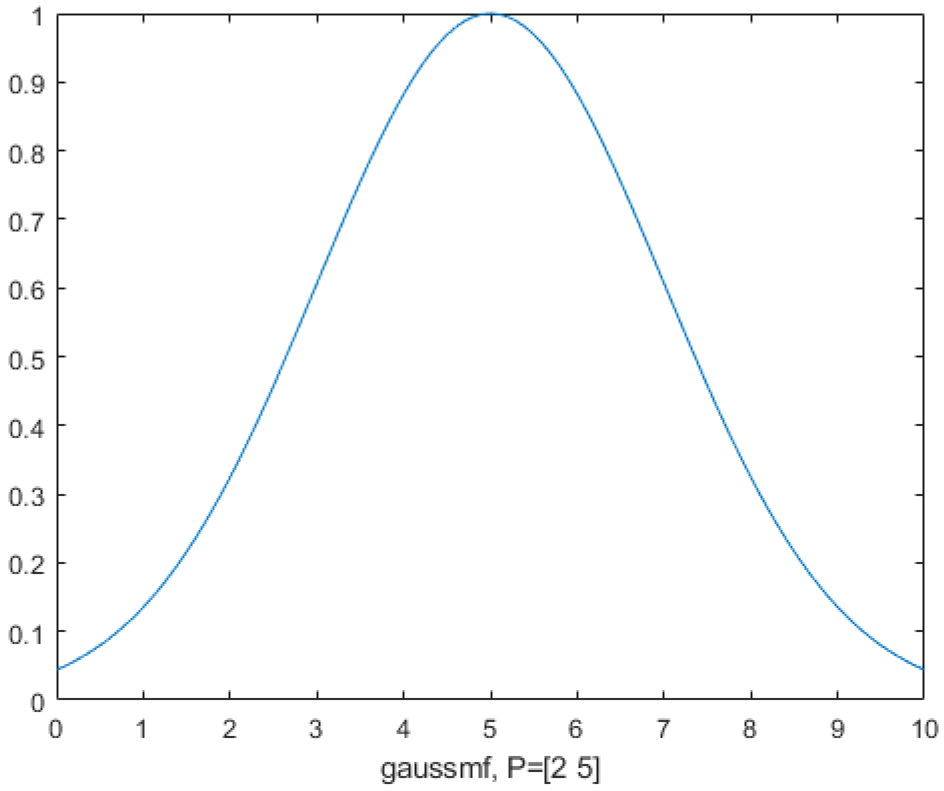
Membership values are computed for each input value in `x`.

Examples

Gaussian Membership Function

```
x = 0:0.1:10;
y = gaussmf(x,[2 5]);
```

```
plot(x,y)
xlabel('gaussmf, P=[2 5]')
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length two

Membership function parameters, specified as the vector [σ c], where σ is the standard deviation and c is the mean.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `gaussmf` membership function.

```
mf = fismf("gaussmf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `gaussmf`, respectively.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

See Also

`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

“Membership Functions” on page 1-14

Introduced before R2006a

gbellmf

Generalized bell-shaped membership function

This function computes fuzzy membership values using a generalized bell-shaped membership function. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-110.

Syntax

```
y = gbellmf(x,params)
```

Description

`y = gbellmf(x,params)` returns fuzzy membership values computed using the following generalized bell-shaped membership function:

$$f(x;a,b,c) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}}$$

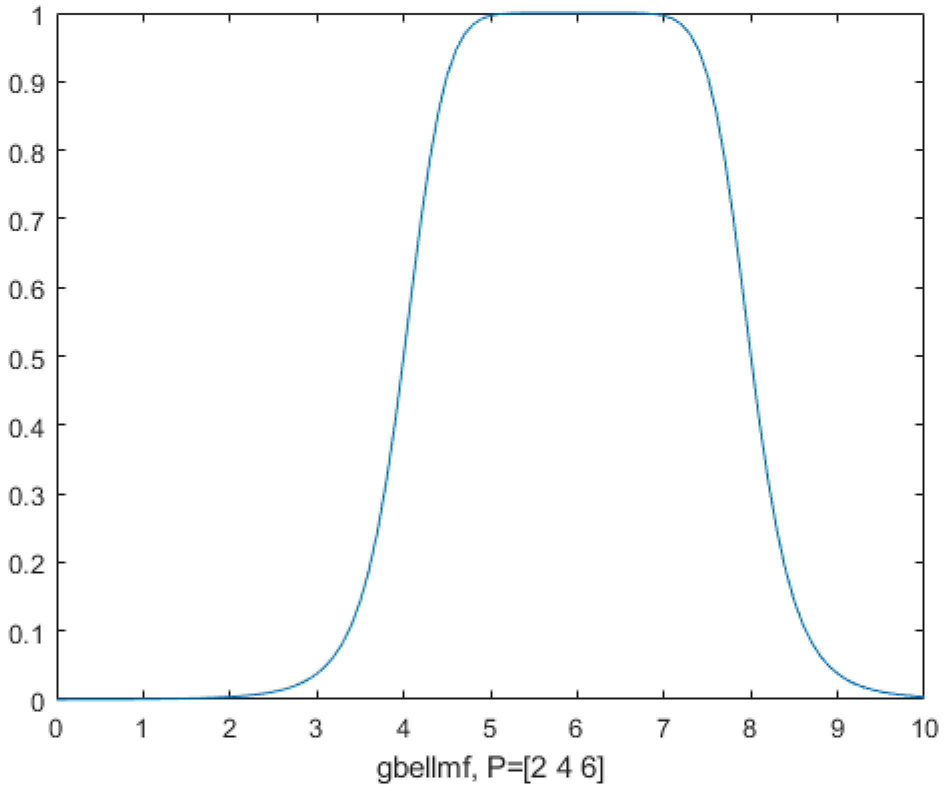
To configure the membership function, specify parameters, a, b, and c using `params`.

Membership values are computed for each input value in `x`.

Examples

Generalized Bell-Shaped Membership Function

```
x = 0:0.1:10;
y = gbellmf(x,[2 4 6]);
plot(x,y)
xlabel('gbellmf, P=[2 4 6]')
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length two

Membership function parameters, specified as the vector [*a* *b* *c*].

Here:

- *a* defines the width of the membership function, where a larger value creates a wider membership function.
- *b* defines the shape of the curve on either side of the central plateau, where a larger value creates a more steep transition.
- *c* defines the center of the membership function.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `gbellmf` membership function.

```
mf = fismf("gbellmf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `gbellmf`, respectively.

Extended Capabilities

C/C++ Code Generation
Generate C and C++ code using MATLAB® Coder™.

See Also

`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

"Membership Functions" on page 1-14

Introduced before R2006a

genfis

Generate fuzzy inference system object from data

Syntax

```
fis = genfis(inputData,outputData)
fis = genfis(inputData,outputData,options)
```

Description

`fis = genfis(inputData,outputData)` returns a single-output Sugeno fuzzy inference system (FIS) using a grid partition of the given input and output data.

`fis = genfis(inputData,outputData,options)` returns an FIS generated using the specified input/output data and `options`. You can generate fuzzy systems using grid partitioning, subtractive clustering, or fuzzy c-means (FCM) clustering.

Examples

Generate Fuzzy Inference System Using Default Options

Define training data.

```
inputData = [rand(10,1) 10*rand(10,1)-5];
outputData = rand(10,1);
```

Generate a fuzzy inference system.

```
fis = genfis(inputData,outputData);
```

The generated system, `fis`, is created using grid partitioning with default options.

Generate FIS Using Grid Partitioning

Define training data.

```
inputData = [rand(10,1) 10*rand(10,1)-5];
outputData = rand(10,1);
```

Create a default `genfisOptions` option set for grid partitioning.

```
opt = genfisOptions('GridPartition');
```

Specify the following input membership functions for the generated FIS:

- 3 Gaussian membership functions for the first input variable
- 5 triangular membership functions for the second input variable

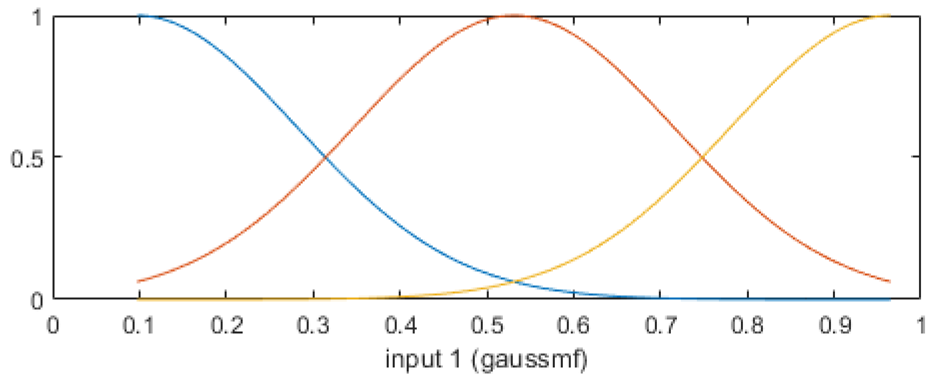
```
opt.NumMembershipFunctions = [3 5];
opt.InputMembershipFunctionType = ["gaussmf" "trimf"];
```

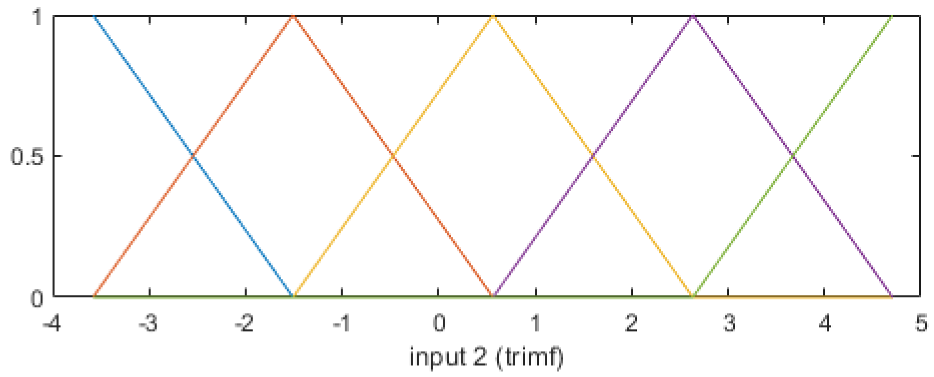
Generate the FIS.

```
fis = genfis(inputData,outputData,opt);
```

Plot the input membership functions. Each input variable has the specified number and type of input membership functions, evenly distributed over their input range.

```
[x,mf] = plotmf(fis,'input',1);
subplot(2,1,1)
plot(x,mf)
xlabel('input 1 (gaussmf)')
[x,mf] = plotmf(fis,'input',2);
subplot(2,1,2)
plot(x,mf)
xlabel('input 2 (trimf)')
```





Generate FIS Using Subtractive Clustering

Obtain input and output training data.

```
load clusterdemo.dat
inputData = clusterdemo(:,1:2);
outputData = clusterdemo(:,3);
```

Create a `genfisOptions` option set and specify the range of influence for each data dimension. Specify `0.5` and `0.25` as the range of influence for the first and second input variables. Specify `0.3` as the range of influence for the output data.

```
opt = genfisOptions('SubtractiveClustering',...
                    'ClusterInfluenceRange',[0.5 0.25 0.3]);
```

Generate the FIS.

```
fis = genfis(inputData,outputData,opt);
```

The generated FIS contains one rule for each cluster.

```
showrule(fis)
```

```
ans = 3x83 char array
    '1. If (in1 is in1cluster1) and (in2 is in2cluster1) then (out1 is out1cluster1) (
    '2. If (in1 is in1cluster2) and (in2 is in2cluster2) then (out1 is out1cluster2) (
    '3. If (in1 is in1cluster3) and (in2 is in2cluster3) then (out1 is out1cluster3) (
```

Generate FIS Using FCM Clustering

Obtain the input and output data.

```
load clusterdemo.dat
inputData = clusterdemo(:,1:2);
outputData = clusterdemo(:,3);
```

Create a `genfisOptions` option set for FCM Clustering, specifying a Mamdani FIS type.

```
opt = genfisOptions('FCMClustering','FISType','mamdani');
```

Specify the number of clusters.

```
opt.NumClusters = 3;
```

Suppress the display of iteration information to the Command Window.

```
opt.Verbose = 0;
```

Generate the FIS.

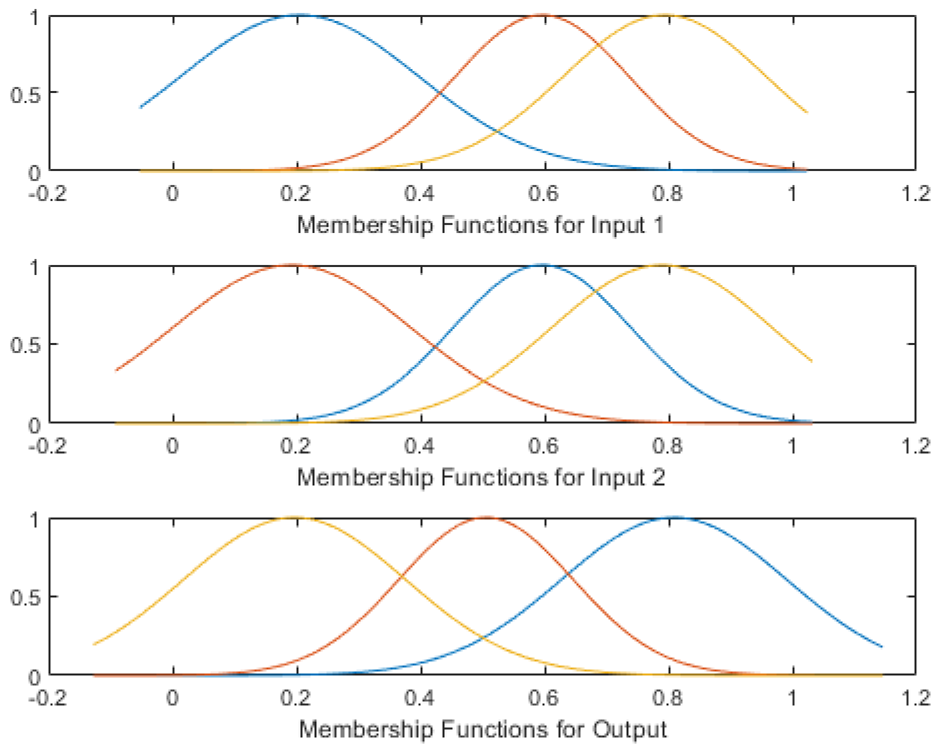
```
fis = genfis(inputData,outputData,opt);
```

The generated FIS contains one rule for each cluster.

```
showrule(fis)

ans = 3x83 char array
    '1. If (in1 is in1cluster1) and (in2 is in2cluster1) then (out1 is out1cluster1) (
    '2. If (in1 is in1cluster2) and (in2 is in2cluster2) then (out1 is out1cluster2) (
    '3. If (in1 is in1cluster3) and (in2 is in2cluster3) then (out1 is out1cluster3) (
```

Plot the input and output membership functions.

```
[x,mf] = plotmf(fis,'input',1);
subplot(3,1,1)
plot(x,mf)
xlabel('Membership Functions for Input 1')
[x,mf] = plotmf(fis,'input',2);
subplot(3,1,2)
plot(x,mf)
xlabel('Membership Functions for Input 2')
[x,mf] = plotmf(fis,'output',1);
subplot(3,1,3)
plot(x,mf)
xlabel('Membership Functions for Output')
```



Input Arguments

`inputData` — Input data
array

Input data, specified as an *N*-column array, where *N* is the number of FIS inputs.

`inputData` and `outputData` must have the same number of rows.

`outputData` — Output data
array

Output data, specified as an *M*-column array, where *M* is the number of FIS outputs.

When using grid partitioning, `outputData` must have one column. If you specify more than one column for grid partitioning, `genfis` uses the first column as the output data.

`inputData` and `outputData` must have the same number of rows.

`options` — FIS generation options

`genfisOptions` option set

FIS generation options, specified as a `genfisOptions` option set. If you do not specify `options`, `genfis` uses a default grid partitioning option set.

You can generate fuzzy systems using one of the following methods, which you specify when you create the option set:

- Grid partitioning — Generate input membership functions by uniformly partitioning the input variable ranges, and create a single-output Sugeno fuzzy system. The fuzzy rule base contains one rule for each input membership function combination.

  ```
  options = genfisOptions('GridPartition');
  ```
- Subtractive clustering — Generate a Sugeno fuzzy system using membership functions and rules derived from data clusters found using subtractive clustering of input and output data. For more information on subtractive clustering, see `subclust`.

  ```
  options = genfisOptions('SubtractiveClustering');
  ```
- FCM Clustering — Generate a fuzzy system using membership function and rules derived from data clusters found using FCM clustering of input and output data. For more information on FCM clustering, see `fcm`.

  ```
  options = genfisOptions('FCMClustering');
  ```

Output Arguments

`fis` — Fuzzy inference system

`mamfis` object | `sugfis` object

Fuzzy inference system, returned as a `mamfis` or `sugfis` object. The properties of `fis` depend on the type of clustering used and the corresponding `options`.

Clustering Type	Fuzzy System Type	Input Membership Functions	Fuzzy Rules	Output Membership Functions
Grid Partitioning	Sugeno	Each input variable has evenly distributed input membership function. Specify the number of membership functions using `options.NumMembershipFunctions`. Specify the membership function type using `options.InputMembershipFunctionType`.	One rule for each input membership function combination. The consequent of each rule corresponds to a different output membership function.	One output membership function for each fuzzy rule. Specify the membership function type using `options.OutputMembershipFunctionType`.
Subtractive Clustering	Sugeno	Each input variable has one `'gaussmf'` input membership function for each fuzzy cluster.	One rule for each fuzzy cluster	Each output variable has one `'linear'` output membership function for each fuzzy cluster.
FCM Clustering	Mamdani or Sugeno	Each input variable has one `'gaussmf'` input membership function for each fuzzy cluster.	One rule for each fuzzy cluster	Each output variable has one output membership function for each fuzzy cluster. The membership function type is `'gaussmf'` for Mamdani systems and `'linear'` for Sugeno systems.

If `fis` is a single-output Sugeno system, you can tune the membership function parameters using the `anfis` command.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

`anfis` | `fcm` | `genfisOptions` | `subclust`

Introduced in R2017a

genfis1

(To be removed) Generate Fuzzy Inference System structure from data using grid partition

---

Note `genfis1` will be removed in a future release. Use `genfis` instead. For more information, see “Compatibility Considerations”.

Syntax

```
fismat = genfis1(data)

fismat = genfis1(data,numMFs,inmftype,outmftype)
```

Description

`genfis1` generates a Sugeno-type FIS structure used as initial conditions (initialization of the membership function parameters) for `anfis` training.

`genfis1(data)` generates a single-output Sugeno-type fuzzy inference system using a grid partition on the data.

`genfis1(data,numMFs,inmftype,outmftype)` generates an FIS structure from a training data set, `data`, with the number and type of input membership functions and the type of output membership functions explicitly specified.

The arguments for `genfis1` are as follows:

- `data` is the training data matrix, which must be entered with all but the last columns representing input data, and the last column representing the single output.
- `numMFs` is a vector whose coordinates specify the number of membership functions associated with each input. If you want the same number of membership functions to be associated with each input, then specify `numMFs` as a single number.
- `inmftype` is a character array in which each row specifies the membership function type associated with each input. This can be a character vector if the type of membership functions associated with each input is the same.

- `outmftype` is a character vector that specifies the membership function type associated with the output. There can only be one output, because this is a Sugeno-type system. The output membership function type must be either `linear` or `constant`. The number of membership functions associated with the output is the same as the number of rules generated by `genfis1`.

The default number of membership functions, `numMFs`, is 2; the default input membership function type is `'gbellmf'`; and the default output membership function type is `'linear'`. These are used whenever `genfis1` is invoked without the last three arguments.

The following table summarizes the default inference methods.

Inference Method	**Default**
AND	`prod`
OR	`max`
Implication	`prod`
Aggregation	`max`
Defuzzification	`wtaver`

Examples

Generate FIS Using Grid Partitioning

Generate a FIS using grid partitioning.

```
data = [rand(10,1) 10*rand(10,1)-5 rand(10,1)];
numMFs = [3 7];
mfType = char('pimf','trimf');
fismat = genfis1(data,numMFs,mfType);
```

To see the contents of `fismat`, use `showfis(fismat)`.

Plot the FIS input membership functions.

```
[x,mf] = plotmf(fismat,'input',1);
subplot(2,1,1), plot(x,mf)
xlabel('input 1 (pimf)')
```

```
[x,mf] = plotmf(fismat,'input',2);
subplot(2,1,2), plot(x,mf)
xlabel('input 2 (trimf)')
```

Compatibility Considerations

genfis1 will be removed

Not recommended starting in R2017a

`genfis1` will be removed in a future release. Use `genfis` instead. There are differences between these functions that require updates to your code.

Update Code

To generate a fuzzy system using grid partitioning, first create a default `genfisOptions` set.

```
opt = genfisOptions('GridPartition');
```

You can modify the options using dot notation. Any options you do not modify remain at their default values.

Then, update your code to use `genfis`. For example, if your code has the following form:

```
fis = genfis1(data,numMFs,inmftype,outmftype);
```

Use the following code instead:

```
opt = genfisOptions('GridPartition');
opt.NumMembershipFunctions = numMFs;
opt.InputMembershipFunctionType = inmftype;
opt.OutputMembershipFunctionType = outmftype;
inputData = data(:,end-1);
outputData = data(:,end);
fis = genfis(inputData,outputData,opt);
```

See Also

`anfis` | `genfis` | `genfis2` | `genfis3`

Introduced before R2006a

genfis2

(To be removed) Generate Fuzzy Inference System structure from data using subtractive clustering

Note `genfis2` will be removed in a future release. Use `genfis` instead. For more information, see “Compatibility Considerations”.

Syntax

```
fismat = genfis2(Xin,Xout,radii)

fismat = genfis2(Xin,Xout,radii,xBounds)

fismat = genfis2(Xin,Xout,radii,xBounds,options)

fismat = genfis2(Xin,Xout,radii,xBounds,options,user_centers)
```

Description

`genfis2` generates a Sugeno-type FIS structure using subtractive clustering and requires separate sets of input and output data as input arguments. When there is only one output, `genfis2` may be used to generate an initial FIS for `anfis` training. `genfis2` accomplishes this by extracting a set of rules that models the data behavior.

The rule extraction method first uses the `subclust` function to determine the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule's consequent equations. This function returns an FIS structure that contains a set of fuzzy rules to cover the feature space.

The arguments for `genfis2` are as follows:

- `Xin` is a matrix in which each row contains the input values of a data point.
- `Xout` is a matrix in which each row contains the output values of a data point.
- `radii` is a vector that specifies a cluster center's range of influence in each of the data dimensions, assuming the data falls within a unit hyperbox.

For example, if the data dimension is 3 (e.g., `Xin` has two columns and `Xout` has one column), `radii` = [0.5 0.4 0.3] specifies that the ranges of influence in the first, second, and third data dimensions (i.e., the first column of `Xin`, the second column of `Xin`, and the column of `Xout`) are 0.5, 0.4, and 0.3 times the width of the data space, respectively. If `radii` is a scalar value, then this scalar value is applied to all data dimensions, i.e., each cluster center has a spherical neighborhood of influence with the given radius.

- `xBounds` is a 2-by-*N* optional matrix that specifies how to map the data in `Xin` and `Xout` into a unit hyperbox, where *N* is the data (row) dimension. The first row of `xBounds` contains the minimum axis range values and the second row contains the maximum axis range values for scaling the data in each dimension.

  For example, `xBounds` = [-10 0 -1; 10 50 1] specifies that data values in the first data dimension are to be scaled from the range [-10 +10] into values in the range [0 1]; data values in the second data dimension are to be scaled from the range [0 50]; and data values in the third data dimension are to be scaled from the range [-1 +1]. If `xBounds` is an empty matrix or not provided, then `xBounds` defaults to the minimum and maximum data values found in each data dimension.
- `options` is an optional vector for specifying algorithm parameters to override the default values. These parameters are explained in the help text for `subclust`. Default values are in place when this argument is not specified.
- `user_centers` is an optional matrix for specifying custom cluster centers. `user_centers` has a size of `J`-by-`N` where `J` is the number of clusters and `N` is the total number of inputs and outputs.

The input membership function type is `'gaussmf'`, and the output membership function type is `'linear'`.

The following table summarizes the default inference methods.

Inference Method	**Default**
AND	`prod`
OR	`probor`
Implication	`prod`
Aggregation	`max`
Defuzzification	`wtaver`

Examples

Specify One Cluster Center Range of Influence For All Data Dimensions

Generate an FIS using subtractive clustering, and specify the cluster center range of influence.

```
Xin = [7*rand(50,1) 20*rand(50,1)-10];
Xout = 5*rand(50,1);
fismat = genfis2(Xin,Xout,0.5);
```

`fismat` uses a range of influence of `0.5` for all data dimensions.

To see the contents of `fismat`, use `showfis(fismat)`.

Plot the input membership functions.

```
[x,mf] = plotmf(fismat,'input',1);
subplot(2,1,1)
plot(x,mf)
xlabel('Membership Functions for input 1')
[x,mf] = plotmf(fismat,'input',2);
subplot(2,1,2)
plot(x,mf)
xlabel('Membership Functions for input 2')
```

Specify Cluster Center Range of Influence For Each Data Dimension

Suppose the input data has two columns, and the output data has one column. Specify `0.5` and `0.25` as the range of influence for the first and second input data columns. Specify `0.3` as the range of influence for the output data.

```
Xin = [7*rand(50,1) 20*rand(50,1)-10];
Xout = 5*rand(50,1);
fismat = genfis2(Xin,Xout,[0.5 0.25 0.3]);
```

Specify Data Hyperbox Scaling Range

Suppose the input data has two columns, and the output data has one column. Specify the scaling range for the inputs and outputs to normalize the data into the [0 1] range. The ranges for the first and second input data columns and the output data are: [-10 +10], [-5 +5], and [0 20].

```
Xin = [7*rand(50,1) 20*rand(50,1)-10];
Xout = 5*rand(50,1);
fismat = genfis2(Xin,Xout,0.5,[-10 -5 0;10 5 20]);
```

Here, the third input argument, `0.5`, specifies the range of influence for all data dimensions. The fourth input argument specifies the scaling range for the input and output data.

Compatibility Considerations

genfis2 will be removed

Not recommended starting in R2017a

`genfis2` will be removed in a future release. Use `genfis` instead. There are differences between these functions that require updates to your code.

Update Code

To generate a fuzzy system using grid partitioning, first create a default `genfisOptions` set.

```
opt = genfisOptions('SubtractiveClustering');
```

You can modify the options using dot notation. Any options you do not modify remain at their default values.

Then, update your code to use `genfis`. For example, if your code has the following form:

```
fis = genfis2(inputData,outputData,radii,xBounds,options,userCenters);
```

Use the following code instead:

```
opt = genfisOptions('SubtractiveClustering');
opt.ClusterInfluenceRange = radii;
opt.DataScale = xBounds;
opt.SquashFactor = options(1);
opt.AcceptRatio = options(2);
opt.RejectRatio = options(3);
opt.Verbose = options(4);
opt.CustomClusterCenters = userCenters;
fis = genfis(inputData,outputData,opt);
```

See Also

`anfis` | `genfis` | `genfis1` | `genfis3` | `subclust`

Introduced before R2006a

genfis3

(To be removed) Generate Fuzzy Inference System structure from data using FCM clustering

Note genfis3 will be removed in a future release. Use genfis instead. For more information, see “Compatibility Considerations”.

Syntax

```
fismat = genfis3(Xin,Xout)

fismat = genfis3(Xin,Xout,type)

fismat = genfis3(Xin,Xout,type,cluster_n)

fismat = genfis3(Xin,Xout,type,cluster_n,fcmoptions)
```

Description

genfis3 generates an FIS using fuzzy c-means (FCM) clustering by extracting a set of rules that models the data behavior. The function requires separate sets of input and output data as input arguments. When there is only one output, you can use genfis3 to generate an initial FIS for anfis training. The rule extraction method first uses the fcm function to determine the number of rules and membership functions for the antecedents and consequents.

fismat = genfis3(Xin,Xout) generates a Sugeno-type FIS structure (fismat) given input data Xin and output data Xout. The matrices Xin and Xout have one column per FIS input and output, respectively.

fismat = genfis3(Xin,Xout,type) generates an FIS structure of the specified type, where type is either 'mamdani' or 'sugeno'.

fismat = genfis3(Xin,Xout,type,cluster_n) generates an FIS structure of the specified type and allows you to specify the number of clusters (cluster_n) to be generated by FCM.

The number of clusters determines the number of rules and membership functions in the generated FIS. `cluster_n` must be an integer or `'auto'`. When `cluster_n` is `'auto'`, the function uses the `subclust` algorithm with a `radii` of 0.5 and the minimum and maximum values of `Xin` and `Xout` as `xBounds` to find the number of clusters. See `subclust` for more information.

`fismat = genfis3(Xin,Xout,type,cluster_n,fcmoptions)` generates an FIS structure of the specified `type` and number of clusters and uses the specified `fcmoptions` for the FCM algorithm. If you omit `fcmoptions`, the function uses the default FCM values. See `fcm` for information about these parameters.

The input membership function type is `'gaussmf'`. By default, the output membership function type is `'linear'`. However, if you specify `type` as `'mamdani'`, then the output membership function type is `'gaussmf'`.

The following table summarizes the default inference methods.

Inference Method	**Default**
AND	`prod`
OR	`probor`
Implication	`prod`
Aggregation	`sum`
Defuzzification	`wtaver`

Examples

Generate Sugeno-Type FIS and Specify Number of Clusters

Obtain the input and output data.

```
Xin = [7*rand(50,1) 20*rand(50,1)-10];
Xout = 5*rand(50,1);
```

Generate a Sugeno-type FIS with 3 clusters.

```
opt = NaN(4,1);
opt(4) = 0;
fismat = genfis3(Xin,Xout,'sugeno',3,opt);
```

The fourth input argument specifies the number of clusters. The fifth input argument, `opt`, specifies the options for the FCM algorithm. The `NaN` entries of `opt` specify default option values. `opt(4)` turns off the display of iteration information at the command line.

To see the contents of `fismat`, use `showfis(fismat)`.

Plot the input membership functions.

```
[x,mf] = plotmf(fismat,'input',1);
subplot(2,1,1), plot(x,mf)
xlabel('Membership Functions for Input 1')
[x,mf] = plotmf(fismat,'input',2);
subplot(2,1,2), plot(x,mf)
xlabel('Membership Functions for Input 2')
```

Compatibility Considerations

genfis3 will be removed

Not recommended starting in R2017a

`genfis3` will be removed in a future release. Use `genfis` instead. There are differences between these functions that require updates to your code.

Update Code

To generate a fuzzy system using grid partitioning, first create a default `genfisOptions` set.

```
opt = genfisOptions('FCMClustering');
```

You can modify the options using dot notation. Any options you do not modify remain at their default values.

Then, update your code to use `genfis`. For example, if your code has the following form:

```
fis = genfis3(inputData,outputData,type,cluster_n,fcmoptions);
```

Use the following code instead:

```
opt = genfisOptions('FCMClustering');
opt.FISType = type;
opt.NumClusters = cluster_n;
opt.Exponent = fcmoptions(1);
opt.MaxNumIteration = fcmoptions(2);
opt.MinImprovement = fcmoptions(3);
opt.Verbose = fcmoptions(4);
fis = genfis(inputData,outputData,opt);
```

See Also

`anfis` | `fcm` | `genfis` | `genfis1` | `genfis2`

Introduced before R2006a

genfisOptions

Option set for `genfis` command

Syntax

```
opt = genfisOptions(clusteringType)
opt = genfisOptions(clusteringType,Name,Value)
```

Description

`opt = genfisOptions(clusteringType)` creates a default option set for generating a fuzzy inference system structure using `genfis`. The option set, `opt`, contains different options that depend on the specified clustering algorithm, `clusteringType`. Use dot notation to modify this option set for your specific application. Options that you do not modify retain their default values.

`opt = genfisOptions(clusteringType,Name,Value)` creates an option set with options specified by one or more `Name,Value` pair arguments.

Examples

Specify Options for FIS Generation

Create a default option set for the grid partitioning generation method.

```
opt = genfisOptions('GridPartition');
```

Modify the options using dot notation. For example, specify 3 membership functions for the first input and 4 membership functions for the second input.

```
opt.NumMembershipFunctions = [3 4];
```

You can also specify options when creating the option set. For example, create an option set for FCM clustering using 4 clusters.

```
opt2 = genfisOptions('FCMClustering','NumClusters',4);
```

Input Arguments

clusteringType — Clustering method
'GridPartition' | 'SubtractiveClustering' | 'FCMClustering'

Clustering method for defining membership functions and fuzzy rules, specified as one of the following:

- `'GridPartition'` — Generate input membership functions by uniformly partitioning the input variable ranges, and create a single-output Sugeno fuzzy system. The fuzzy rule base contains one rule for each input membership function combination.
- `'SubtractiveClustering'` — Generate a Sugeno fuzzy system using membership functions and rules derived from data clusters found using subtractive clustering of input and output data. For more information on subtractive clustering, see `subclust`.
- `'FCMClustering'` — Generate a fuzzy system using membership function and rules derived from data clusters found using FCM clustering of input and output data. For more information on FCM clustering, see `fcm`.

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'InputMembershipFunctionType','trimf'` sets triangular input membership functions for the grid partitioning algorithm.

Grid Partitioning Options

NumMembershipFunctions — Number of input membership functions
2 (default) | integer greater than 1 | vector of integers greater than 1

Number of input membership functions for each input variable, specified as the comma-separated pair consisting of `'NumMembershipFunctions'` and one of the following:

- Integer greater than 1 — Specify the same number of membership functions for all inputs.

- Vector of integer greater than 1 with length equal to the number of inputs — Specify a different number of membership functions for each input.

`InputMembershipFunctionType` — Input membership function type
`'gbellmf'` (default) | `'gaussmf'` | `'trimf'` | `'trapmf'` | character vector | string array | ...

Input membership function type, specified as the comma-separated pair consisting of `'InputMembershipFunctionType'` and one of the following:

- Character vector or string — Specify one of the following membership function types for all inputs.

Membership function type	Description	For more information
`'gbellmf'`	Generalized bell-shaped membership function	`gbellmf`
`'gaussmf'`	Gaussian membership function	`gaussmf`
`'gauss2mf'`	Gaussian combination membership function	`gauss2mf`
`'trimf'`	Triangular membership function	`trimf`
`'trapmf'`	Trapezoidal membership function	`trapmf`
`'sigmf'`	Sigmoidal membership function	`sigmf`
`'dsigmf'`	Difference between two sigmoidal membership functions	`dsigmf`
`'psigmf'`	Product of two sigmoidal membership functions	`psigmf`
`'zmf'`	Z-shaped membership function	`zmf`
`'pimf'`	Pi-shaped membership function	`pimf`
`'smf'`	S-shaped membership function	`smf`

Membership function type	**Description**	**For more information**
Character vector or string	Name of a custom membership function in the current working folder or on the MATLAB path	"Build Fuzzy Systems Using Custom Functions" on page 2-50

- Character array or string array — Specify a different membership function type for each input. For example, specify different membership functions for a three-input system:

  ```
  ["gbellmf","gaussmf","trimf"]
  ```

`OutputMembershipFunctionType` — Output membership function type

`'linear'` (default) | `'constant'`

Output membership function type for a single-output Sugeno system, specified as the comma-separated pair consisting of `'OutputMembershipFunctionType'` and one of the following:

- `'linear'` — The output of each rule is a linear function of the input variables, scaled by the antecedent result value.
- `'constant'` — The output of each rule is a constant, scaled by the antecedent result value.

Subtractive Clustering Options

`ClusterInfluenceRange` — Range of influence of the cluster center

`0.5` (default) | scalar value in the range [`0`, `1`] | vector

Range of influence of the cluster center for each input and output assuming the data falls within a unit hyperbox, specified as the comma-separated pair consisting of `'ClusterInfluenceRange'` one of the following:

- Scalar value in the range `[0 1]` — Use the same influence range for all inputs and outputs.
- Vector — Use different influence ranges for each input and output.

Specifying a smaller range of influence usually creates more and smaller data clusters, producing more fuzzy rules.

`DataScale` — Data scale factors

`'auto'` (default) | 2-by-*N* array

Data scale factors for normalizing input and output data into a unit hyperbox, specified as the comma-separated pair consisting of `'DataScale'` and a 2-by-*N* array, where *N* is the total number of inputs and outputs. Each column of `DataScale` specifies the minimum value in the first row and the maximum value in the second row for the corresponding input or output data set.

When `DataScale` is `'auto'`, the `genfis` command uses the actual minimum and maximum values in the data to be clustered.

`SquashFactor` — Squash factor
`1.25` (default) | positive scalar

Squash factor for scaling the range of influence of cluster centers, specified as the comma-separated pair consisting of `'SquashFactor'` and a positive scalar. A smaller squash factor reduces the potential for outlying points to be considered as part of a cluster, which usually creates more and smaller data clusters.

`AcceptRatio` — Acceptance ratio
`0.5` (default) | scalar value in the range [`0`, `1`]

Acceptance ratio, defined as a fraction of the potential of the first cluster center, above which another data point is accepted as a cluster center, specified as the comma-separated pair consisting of `'AcceptRatio'` and a scalar value in the range [`0`, `1`]. The acceptance ratio must be greater than the rejection ratio.

`RejectRatio` — Rejection ratio
`0.15` (default) | scalar value in the range [`0`, `1`]

Rejection ratio, defined as a fraction of the potential of the first cluster center, below which another data point is rejected as a cluster center, specified as the comma-separated pair consisting of `'RejectRatio'` and a scalar value in the range [`0`, `1`]. The rejection ratio must be less than acceptance ratio.

`Verbose` — Information display flag
`false` (default) | `true`

Information display flag indicating whether to display progress information during clustering, specified as the comma-separated pair consisting of `'Verbose'` and one of the following:

- `false` — Do not display progress information.

- `true` — Display progress information.

`CustomClusterCenters` — Custom cluster centers
`[]` (default) | *C*-by-*N* array

Custom cluster centers, specified the comma-separated pair consisting of `'CustomClusterCenters'` and as a *C*-by-*N* array, where *C* is the number of clusters and *N* is the total number of inputs and outputs.

FCM Clustering Options

`FISType` — Fuzzy inference system type
`'sugeno'` (default) | `'mamdani'`

Fuzzy inference system type, specified as the comma-separated pair consisting of `'FISType'` and one of the following:

- `'sugeno'` — Sugeno-type fuzzy system
- `'mamdani'` — Mamdani-type fuzzy system

For more information on the types of fuzzy inference systems, see “Types of Fuzzy Inference Systems” on page 2-2.

`NumClusters` — Number of clusters
`'auto'` | integer greater than `1`

Number of clusters to create, specified as the comma-separated pair consisting of `'NumClusters'` and `'auto'` or an integer greater than `1`. When `NumClusters` is `'auto'`, the `genfis` command estimates the number of clusters using subtractive clustering with a cluster influence range of `0.5`.

`NumClusters` determines the number of rules and membership functions in the generated FIS.

`Exponent` — Exponent for the fuzzy partition matrix
`2.0` (default) | scalar greater than `1.0`

Exponent for the fuzzy partition matrix, specified as the comma-separated pair consisting of `'Exponent'` and a scalar greater than `1.0`. This option controls the amount of fuzzy overlap between clusters, with larger values indicating a greater degree of overlap.

If your data set is wide with significant overlap between potential clusters, then the calculated cluster centers can be very close to each other. In this case, each data point has approximately the same degree of membership in all clusters. To improve your clustering results, decrease this value, which limits the amount of fuzzy overlap during clustering.

For an example of fuzzy overlap adjustment, see “Adjust Fuzzy Overlap in Fuzzy C-Means Clustering” on page 4-8.

`MaxNumIteration` — Maximum number of iterations
`100` (default) | positive integer

Maximum number of iterations, specified as the comma-separated pair consisting of `'MaxNumIteration'` and a positive integer.

`MinImprovement` — Minimum improvement in objective function
`1e-5` (default) | positive scalar

Minimum improvement in objective function between two consecutive iterations, specified as the comma-separated pair consisting of `'MinImprovement'` and a positive scalar.

`Verbose` — Information display flag
`true` (default) | `false`

Information display flag indicating whether to display the objective function value after each iteration, specified as the comma-separated pair consisting of `'Verbose'` and one of the following:

- `true` — Display objective function.
- `false` — Do not display objective function.

Output Arguments

`opt` — Option set for `genfis` command
`genfisOptions` option set

Option set for `genfis` command, returned as a `genfisOptions` option set. The options in the option set depend on the specified `clusteringType`.

See Also

`fcm` | `genfis` | `subclust`

Introduced in R2017a

gensurf

Generate fuzzy inference system output surface

Syntax

```
gensurf(fis)
gensurf(fis,options)
[X,Y,Z] = gensurf(___)
```

Description

`gensurf(fis)` generates the output surface for the fuzzy inference system, `fis`, plotting the first output variable against the first two input variables. For fuzzy systems with more than two inputs, the remaining input variables use the midpoints of their respective ranges as reference values.

`gensurf(fis,options)` generates the output surface using the specified `options`. To generate a surface using different inputs or outputs, or to specify nondefault plotting options, use this syntax.

`[X,Y,Z] = gensurf(___)` returns the variables that define the output surface for any of the previous syntaxes and suppresses the surface plot.

Examples

Generate FIS Output Surface

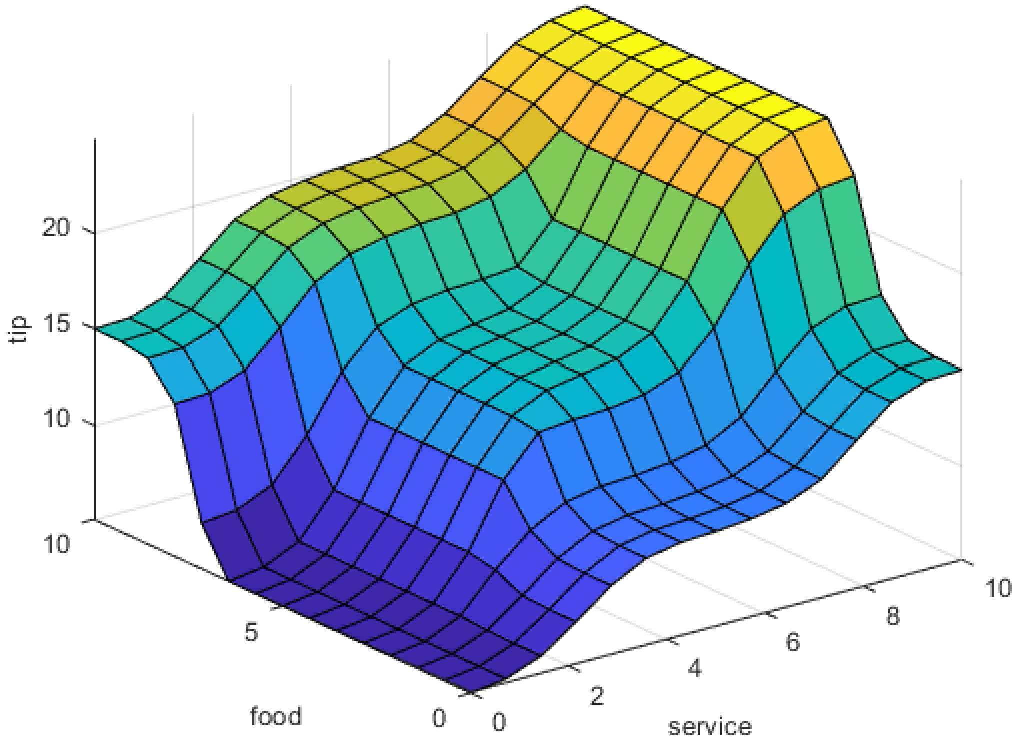
Load a fuzzy inference system.

```
fis = readfis('tipper');
```

This fuzzy system has two inputs and one output.

Generate the output surface for the system.

```
gensurf(fis)
```



Generate FIS Output Surface for Second Output

Load a fuzzy inference system with two inputs and two outputs.

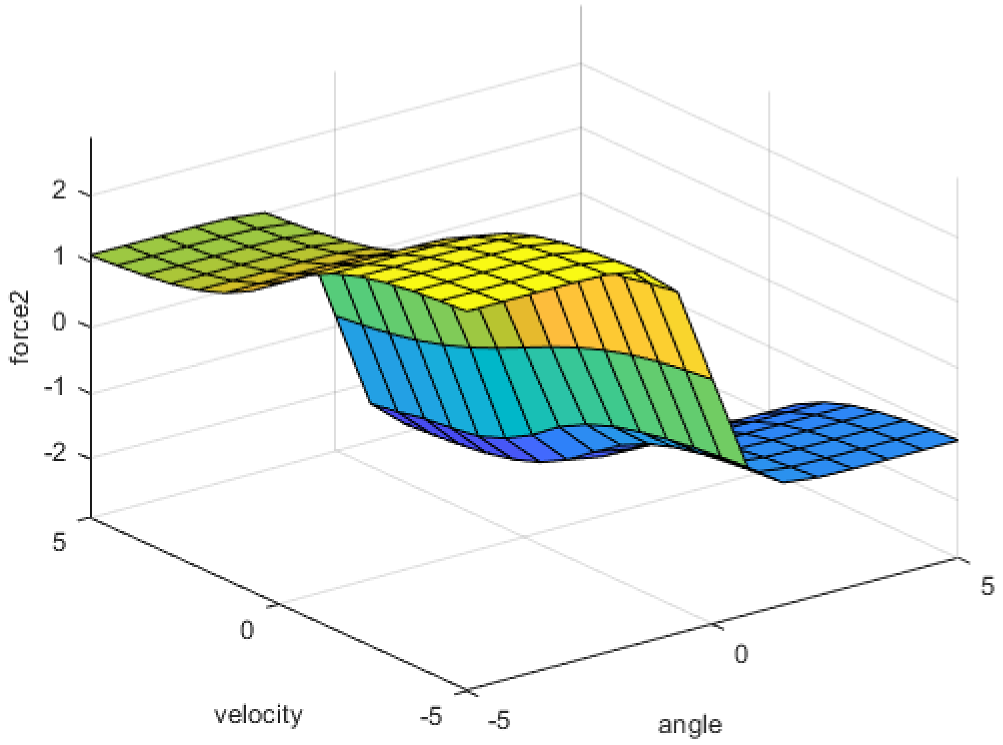
```
fis = readfis('mam22.fis');
```

Create a surface generation option set, specifying the second output as the output to plot. By default, this output is plotted against the first two input variables.

```
opt = gensurfOptions('OutputIndex',2);
```

Plot the surface, using the specified option set.

```
gensurf(fis,opt)
```



Specify Reference Inputs for Surface Plot

Load a fuzzy inference system with four inputs and one output.

```
fis = readfis('slbb.fis');
```

Create a default `gensurfOptions` option set.

```
opt = gensurfOptions;
```

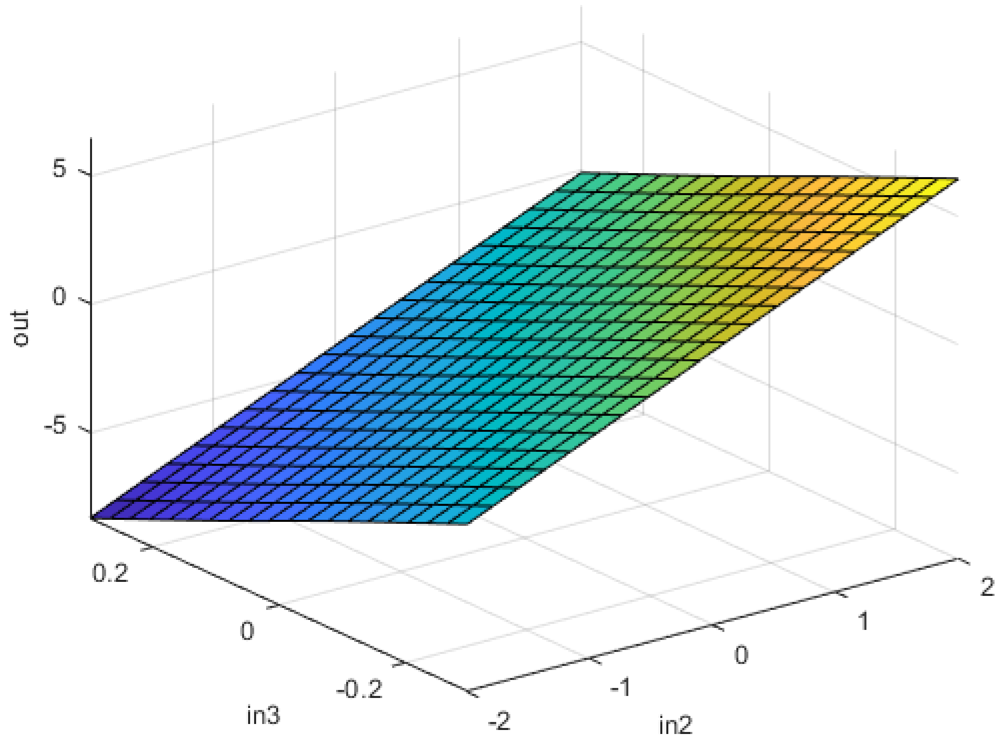
Specify plotting options to:

- Plot the output against the second and third input variable.
- Use 20 grid points for both inputs.
- Fix the first and fourth inputs at `-0.5` and `0.1` respectively. Set the reference values for the second and third inputs to `NaN`.

```
opt.InputIndex = [2 3];
opt.NumGridPoints = 20;
opt.ReferenceInputs = [-0.5 NaN NaN 0.1];
```

Plot the output surface.

```
gensurf(fis,opt)
```



Return Surface Values and Suppress Plot

Load a fuzzy inference system.

```
fis = readfis('tipper');
```

Generate the output surface, returning the surface data.

```
[X,Y,Z] = gensurf(fis);
```

The output values, Z, are the FIS output evaluated at the corresponding X and Y grid points.

Input Arguments

`fis` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

`options` — Surface generation options
`gensurfOptions` option set

Surface generation options, specified as a `gensurfOptions` option set.

Output Arguments

`X` — Grid values for first input variable
array | column vector

Grid values for first input variable, returned as one of the following:

- *M*-by-*N* array, where *N* and *M* are the number of grid points for the first and second inputs, respectively; that is `options.NumGridPoints = [N M]`. Each column of `X` contains one grid point value, repeated for every row.
- *P*-element column vector, where *P* is the number of grid points specified for a single input variable; that is `options.NumGridPoints = P`. Each element of contains one grid point value. This case applies when `fis` has only one input variable.

`Y` — Grid values for second input variable
array | `[]`

Grid values for second input variable, returned as one of the following:

- *M*-by-*N* array, where *N* and *M* are the number of grid points for the first and second inputs respectively; that is `options.NumGridPoints = [N M]`. Each row of `Y` contains one grid point value, repeated for every column.
- `[]` when you specify only one input variable; that is, if you specify `options.InputIndex` as an integer.

Z — Surface output values
array | vector

Surface output values for the output variable of `fis` specified by `options.OutputIndex`, returned as one of the following:

- *M*-by-*N* array, where *N* and *M* are the number of grid points for the first and second inputs respectively; that is `options.NumGridPoints = [N M]`. Each element of `Z` is the value of the FIS output, evaluated at the corresponding `X` and `Y` input values. For example, for a two-input system:

  ```
  Z(i,j) = evalfis([X(i,j) Y(i,j)],fis);
  ```
- *P*-element column vector, where *P* is the number of grid points specified for a single input variable; that is `options.NumGridPoints = P`. Each element of `Z` is the value of the FIS output evaluated at the corresponding `X` input value.

When computing the value of `Z`, `gensurf` sets the values of any inputs not specified by `options.InputIndex` to their corresponding reference values, as specified in `options.ReferenceInputs`.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

`evalfis` | `gensurfOptions` | `surfview`

Introduced before R2006a

gensurfOptions

Option set for `gensurf` command

Syntax

```
opt = gensurfOptions
opt = gensurfOptions(Name,Value)
```

Description

`opt = gensurfOptions` creates a default option set for generating a fuzzy inference system output surface using `gensurf`. Use dot notation to modify this option set for your specific application. Any options that you do not modify retain their default values.

`opt = gensurfOptions(Name,Value)` creates an option set with options specified by one or more `Name,Value` pair arguments.

Examples

Specify Options for Generating Output Surface

Create a default `gensurfOptions` option set.

```
opt = gensurfOptions;
```

Specify options using dot notation. For example, for a two-input, three-output fuzzy system, specify options to:

- Plot the surface for the second output against the values of the first and third inputs.
- Specify a reference value of `0.25` for the second input variable.

```
opt.OutputIndex = 2;
opt.InputIndex = [1 3];
opt.ReferenceInputs = [NaN 0.25 NaN];
```

Any values you do not specify remain at their default values.

You can also specify one or more options when creating the option set. For example, create an option set, specifying `25` grid points for both plotted input variables:

```
opt2 = gensurfOptions('NumGridPoints',25);
```

Input Arguments

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'InputIndex',[2 3]` plots the output against the second and third input variables using a 3-D surface plot.

`InputIndex` — Indices of input variables
`'auto'` (default) | positive integer less than or equal to the number of inputs | two-element vector of positive integers

Indices of input variables to plot the output against, specified as the comma-separated pair consisting of `'InputIndex'` and one of the following:

- Positive integer less than or equal to the number of inputs — Plot the output against a single input using a 2-D plot.
- Two-element vector of positive integers — Plot the output against two input variables using a 3-D surface plot.

When `InputIndex` is `'auto'`, `gensurf` uses the first two input variables by default.

`OutputIndex` — Index of output variable
`'auto'` (default) | positive integer less than or equal to the number of outputs

Index of output variable to plot, specified as the comma-separated pair consisting of `'OutputIndex'` and a positive integer less than or equal to the number of outputs.

When `OutputIndex` is `'auto'`, `gensurf` uses the first output variable by default.

NumGridPoints — Number of grid points to plot
15 (default) | integer greater than 1 | two-element vector of integers greater than 1

Number of grid points to plot, specified as the comma-separated pair consisting of 'NumGridPoints' and one of the following:

- Integer greater than 1 — Specify the number of grid points when using a single input variable, or the same number of grid points for both inputs when using two inputs variables.
- Two-element vector of integers greater than 1 — Specify a different number of grid points for each input variable.

If you specify InputIndex as an integer and NumGridPoints as a vector, then gensurf uses the first element of NumGridPoints as the number of grid points for the specified input variable.

To plot a smoother surface, increase the number of grid points.

ReferenceInputs — Reference values for input variables
'auto' (default) | vector

Reference values for input variables not shown in the surface plot, specified as the comma-separated pair consisting of 'ReferenceInputs' and a vector with length equal to the number of FIS inputs. Specify NaN for the inputs specified in InputIndex.

When ReferenceInputs is 'auto', gensurf uses the midpoint of the range of each unused variable as a reference value.

NumSamplePoints — Number of sample points
101 (default) | integer greater than 1

Number of sample points to use when evaluating membership functions over the output variable range, specified as the comma-separated pair consisting of 'NumSamplePoints' and an integer greater than 1. For more information on membership function evaluation, see evalfis.

Note NumSamplePoints is not used by Sugeno-type systems.

Output Arguments

`opt` — Option set for `gensurf` command
`gensurfOptions` option set

Option set for `gensurf` command, returned as a `gensurfOptions` option set.

See Also

`evalfis` | `gensurf`

Introduced in R2017a

getfis

(To be removed) Get fuzzy system properties

Note `getfis` will be removed in a future release. Access fuzzy inference system properties using dot notation instead. For more information, see “Compatibility Considerations”.

Syntax

```
getfis(sys)

fisInfo = getfis(sys)
fisInfo = getfis(sys,fisProperty)

varInfo = getfis(sys,varType,varIndex)
varInfo = getfis(sys,varType,varIndex,varProperty)

mfInfo = getfis(sys,varType,varIndex,'mf',mfIndex)
mfInfo = getfis(sys,varType,varIndex,'mf',mfIndex,mfProperty)
```

Description

`getfis(sys)` prints the properties of the specified fuzzy inference system, `sys`, to the Command Window.

`fisInfo = getfis(sys)` returns the properties of the specified fuzzy inference system.

`fisInfo = getfis(sys,fisProperty)` returns the value of the specified property of the fuzzy inference system.

`varInfo = getfis(sys,varType,varIndex)` returns the properties of the specified input or output variable of a fuzzy inference system.

`varInfo = getfis(sys,varType,varIndex,varProperty)` returns the value of the specified variable property.

`mfInfo = getfis(sys,varType,varIndex,'mf',mfIndex)` returns the properties of the specified membership function of an input or output variable.

`mfInfo = getfis(sys,varType,varIndex,'mf',mfIndex,mfProperty)` returns the value of the specified membership function property.

Examples

Display Properties of Fuzzy Inference System

Load a fuzzy inference system.

```
sys = readfis('tipper');
```

Display the system properties.

```
getfis(sys)
```

```
      Name      = tipper
      Type      = mamdani
      NumInputs = 2
      InLabels  =
            service
            food
      NumOutputs = 1
      OutLabels =
            tip
      NumRules = 3
      AndMethod = min
      OrMethod = max
      ImpMethod = min
      AggMethod = max
      DefuzzMethod = centroid
```

Obtain Fuzzy Inference System Properties

Load fuzzy system.

```
sys = readfis('tipper');
```

Obtain the system properties.

```
prop = getfis(sys);
```

To obtain the value of a given property, specify the property name. For example, obtain the type of the fuzzy system.

```
type = getfis(sys,'type');
```

Obtain Variable Properties

Load fuzzy system.

```
sys = readfis('tipper');
```

Obtain the properties of the first input variable.

```
prop = getfis(sys,'input',1);
```

To obtain the value of a given property, specify the property name. For example, obtain the range of the output variable.

```
range = getfis(sys,'output',1,'range');
```

Obtain Membership Function Properties

Load fuzzy system.

```
sys = readfis('tipper');
```

For the second input variable, obtain the properties of its first membership function.

```
prop = getfis(sys,'input',2,'mf',1);
```

To obtain the value of a given property, specify the property name. For example, obtain the parameters of the second membership function of the output variable.

```
params = getfis(sys,'output',1,'mf',2,'params');
```

Input Arguments

sys — Fuzzy inference system

FIS structure

Fuzzy inference system, specified as an FIS structure.

fisProperty — Fuzzy inference system property

'name' | 'type' | 'numInputs' | 'numOutputs' | ...

Fuzzy inference system property, specified as one of the following:

- 'name' — FIS name
- 'type' — FIS type
- 'numInputs' — Number of inputs
- 'numOutputs'— Number of outputs
- 'numRules' — Number of fuzzy rules.
- 'andMethod' — And method
- 'orMethod' — Or method
- 'defuzzMethod' — Defuzzification method
- 'impMethod' — Implication method
- 'aggMethod' — Aggregation method
- 'ruleList' — List of fuzzy rules

varType — Variable type

'input' | 'output'

Variable type, specified as either 'input' or 'output', for input and output variables, respectively.

varIndex — Variable index

positive integer

Variable index, specified as a positive integer.

`varProperty` — Variable property
`'name'` | `'range'` | `'nummfs'`

Variable property, specified as one of the following:

- `'name'` — Variable name
- `'range'` — Variable value range
- `'nummfs'` — Number of membership functions

`mfIndex` — Membership function index
positive integer

Membership function index, specified as a positive integer.

`mfProperty` — Membership function property
`'name'` | `'type'` | `'params'`

Membership function property, specified as one of the following:

- `'name'` — Membership function name
- `'type'` — Membership function type
- `'params'` — Membership function parameters

For more information on membership functions, see “Membership Functions” on page 1-14.

Output Arguments

`fisInfo` — Fuzzy inference system information
structure | character vector | nonnegative integer | array

Fuzzy inference system information, returned as a structure, character vector, nonnegative integer, or array, depending on the value of `fisProperty`.

If you do not specify `fisProperty`, then `fisInfo` is returned as a structure with the following fields.

Field	Description
`name`	FIS name, returned as a character vector.
`type`	FIS type, returned as a character vector.
`andMethod`	AND fuzzy operator method, returned as a character vector.
`orMethod`	OR fuzzy operator method, returned as a character vector.
`defuzzMethod`	Defuzzification method, returned as a character vector.
`impMethod`	Implication method, returned as a character vector.
`aggMethod`	Aggregation method, returned as a character vector.
`input`	Input variable information, returned as a structure or structure array. Each input variable structure contains the following fields: • `name` — Variable name • `range` — Variable range • `mf` — Membership function names
`output`	Output variable information, returned as a structure or structure array. Each output variable structure contains the following fields: • `name` — Variable name • `range` — Variable range • `mf` — Membership function names
`rule`	Fuzzy rule list, returned as a structure or structure array. Each rule structure contains the following fields: • `antecedent` — Input membership function indices • `consequent` — Output membership function indices • `weight` — Rule weight • `connection` — Fuzzy operator: `1` (AND), `2` (OR)

Otherwise, the value of `fisInfo` depends on the value of `fisProperty` according to the following table.

`fisProperty`	`fisInfo`
`'name'`	FIS name, returned as a character vector.

fisProperty	**fisInfo**
`'type'`	FIS type, returned as one of the following: • `'mamdani'` — Mamdani-type fuzzy system • `'sugeno'` — Sugeno-type fuzzy system
`'numinputs'`	Number of input variables, returned as a nonnegative integer.
`'numiutputs'`	Number of output variables, returned as a nonnegative integer.
`'numrules'`	Number of fuzzy rules, returned as a nonnegative integer.
`'andmethod'`	AND fuzzy operator method, returned as one of the following: • `'min'` — Minimum of fuzzified input values • `'prod'` — Product of fuzzified input values • Character vector — Name of a custom AND function in the current working folder or on the MATLAB path
`'ormethod'`	OR fuzzy operator method, returned as one of the following: • `'max'` — Maximum of fuzzified input values • `'probor'` — Probabilistic OR of fuzzified input values • Character vector — Name of a custom OR function in the current working folder or on the MATLAB path

fisProperty	fisInfo
'defuzzmethod'	Defuzzification method for computing crisp output values, returned as one of the following for Mamdani systems: • 'centroid' — Centroid of the area under the output fuzzy set • 'bisector' — Bisector of the area under the output fuzzy set • 'mom' — Mean of the values for which the output fuzzy set is maximum • 'lom' — Largest value for which the output fuzzy set is maximum • 'som' — Smallest value for which the output fuzzy set is maximum For Sugeno systems, specify the defuzzification method as one of the following: • 'wtaver' — Weighted average of all rule outputs • 'wtsum' — Weighted sum of all rule outputs The defuzzification method can also be returned as a character vector that contains the name of a custom defuzzification function in the current working folder or on the MATLAB path.
'impmethod'	Implication method for computing consequent fuzzy set, returned as one of the following: • 'min' — Truncate the consequent membership function at the antecedent result value. • 'prod' — Scale the consequent membership function by the antecedent result value. • Character vector — Name of a custom implication function in the current working folder or on the MATLAB path

fisProperty	**fisInfo**
`'aggmethod'`	Aggregation method for combining rule consequents, returned as one of the following: • `'max'` — Maximum of consequent fuzzy sets • `'sum'` — Sum of consequent fuzzy sets • `'probor'` — Probabilistic OR of consequent fuzzy sets • Character vector — Name of a custom aggregation function in the current working folder or on the MATLAB path.
`'rulelist'`	Fuzzy rule list, returned as an array. For each fuzzy rule, the rule list contains one row with the following columns: • N_u columns of input membership function indices, where N_u is the number of inputs. If a given variable is not included in a rule, the corresponding column entry is `0`. Negative values indicate a NOT operation. • N_y columns of output membership function indices, where N_y is the number of outputs. If a given variable is not included in a rule, the corresponding column entry is `0`. Negative values indicate a NOT operation. • Rule weight • Fuzzy operator: `1` (AND), `2` (OR)

`varInfo` — Variable information
structure | character vector | nonnegative integer | row vector of length 2

Variable information, returned as a structure, nonnegative integer, character vector, or row vector, depending on the value of `varProperty`.

If you do not specify `varProperty`, then `varInfo` is returned as a structure with the following fields.

Field	**Description**
`Name`	Variable name, returned as a character vector.
`NumMFs`	Number of membership functions, returned as a nonnegative integer.

Field	Description
mf1, mf2, ..., mfN	Membership function names, returned as character vectors. mfInfo contains one field for each membership function.
range	Variable range, returned as a row vector of length 2.

Otherwise, the value of varInfo depends on the value of varProperty according to the following table.

varProperty	varInfo
'name'	Variable name, returned as a character vector.
'nummfs'	Number of membership functions, returned as a nonnegative integer.
'range'	Variable range, returned as a row vector of length 2.

mfInfo — Membership function information
structure | character vector | row vector

Membership function information, returned as a structure, character vector, or row vector, depending on the value of mfProperty.

If you do not specify mfProperty, then mfInfo is returned as a structure with the following fields.

Field	Description
Name	Membership function name, returned as a character vector.
Type	Membership function type, returned as a character vector.
params	Membership function parameters, returned as a row vector.

Otherwise, the value of mfInfo depends on the value of mfProperty according to the following table.

mfProperty	mfInfo
'name'	Membership function name, returned as a character vector.
'type'	Membership function type, returned as a character vector.
'params'	Membership function parameters, returned as a row vector.

For more information on membership function, see “Membership Functions” on page 1-14.

Compatibility Considerations

`getfis` will be removed

Not recommended starting in R2018b

`getfis` will be removed in a future release. Access fuzzy inference system properties using dot notation instead. There are differences between these approaches that require updates to your code.

Update Code

This table shows some typical usages of `getfis` for accessing fuzzy inference system properties and how to update your code to use dot notation instead.

If your code has this form:	Use this code instead:
`get(fis,'andmethod')`	`fis.AndMethod`
`getfis(fis,'input',1)`	`fis.Inputs(1)`
`getfis(fis,'input',1,'name')`	`fis.Inputs(1).Name`
`getfis(fis,'input',2,'mf',1)`	`fis.Inputs(2).MembershipFunctions(1)`
`getfis(fis,'input',2,'mf',1,... params)`	`fis.Inputs(2).MembershipFunctions(1).Parameters`

Previously, fuzzy inference systems were represented as structures. Now, fuzzy inference systems are represented as objects. Fuzzy inference system object properties have different names than the corresponding structure fields. For more information on fuzzy inference system objects, see `mamfis` and `sugfis`.

See Also

`setfis` | `showfis`

Introduced before R2006a

getTunableValues

Obtain values of tunable parameters from fuzzy inference system

Syntax

```
paramvals = getTunableValues(fis,paramset)
```

Description

`paramvals = getTunableValues(fis,paramset)` returns tunable parameter values of the fuzzy system `fis` using `paramset`. The values are specified as a numeric row vector.

Examples

Obtain Values of Tunable Parameters from FIS

Create a fuzzy inference system, and define the tunable parameter settings of inputs, outputs, and rules.

```
fis = mamfis('NumInputs',2,'NumOutputs',1);
[in,out,rule] = getTunableSettings(fis);
```

Obtain tunable parameter values of the inputs, outputs, and rules of the fuzzy inference system.

```
paramVals = getTunableValues(fis,[in;out;rule]);
```

Input Arguments

`fis` — Fuzzy system

`mamfis` object | `sugfis` object | `fistree` object

Fuzzy system, specified as a `mamfis`, `sugfis`, or `fistree` object. The fuzzy system can be a fuzzy inference system or network of interconnected fuzzy inference systems. It is created using `mamfis`, `sugfis`, `genfis`, or `fistree`.

`paramset` — Tunable parameter settings
array

Tunable parameter settings, specified as an array of input, output, and rule parameter settings in the input FIS. To obtain these parameter settings, use `getTunableSettings` with the input FIS. `paramset` can be the input parameter, the output parameter, the rule parameter, or some combination of these parameters as an array. The contents of the array depend on which parameters you would like to obtain values for.

See Also

`getTunableSettings` | `mamfis` | `setTunableValues` | `sugfis` | `tunefis`

Introduced in R2019a

getFISCodeGenerationData

Create homogeneous fuzzy inference system structure

To generate code for evaluating a fuzzy inference system using MATLAB Coder, you must convert your fuzzy inference system object into a homogeneous structure using `getFISCodeGenerationData`.

Syntax

```
fisOut = getFISCodeGenerationData(fisIn)
```

Description

`fisOut = getFISCodeGenerationData(fisIn)` converts a fuzzy inference system `fisIn` into a homogeneous structure `fisOut`. `fisIn` can be a FIS object or the name of a `.fis` file.

Examples

Convert FIS Object into Homogeneous Structure

Create a fuzzy inference system. For this example, load a fuzzy system from a file.

```
fisObject = readfis('tipper');
```

Convert the resulting `mamfis` object into a homogeneous structure.

```
fisStructure = getFISCodeGenerationData(fisObject);
```

In this structure, if a field is a structure array, all the elements of that array are the same size. For example, consider the elements of input variable array `fisStructure.input`.

```
fisStructure.input(1)
```

```
ans = struct with fields:
              name: 'service'
```

```
    origNameLength: 7
             range: [0 10]
                mf: [1x3 struct]
         origNumMF: 3
```

```
fisStructure.input(2)
```

```
ans = struct with fields:
              name: 'food    '
    origNameLength: 4
             range: [0 10]
                mf: [1x3 struct]
         origNumMF: 2
```

The `name` fields are character vectors of the same length. Also, even though the second input variable has only two membership functions, the `mf` fields both contain three membership function structures. The original number of membership functions for a given input variable is stored in the `origNumMF` field.

Load Fuzzy Inference System from File into Homogenous Structure

Load the fuzzy inference system saved in the file `tipper.fis` into a homogeneous structure.

```
fis = getFISCodeGenerationData('tipper.fis');
```

Input Arguments

`fisIn` — Input fuzzy inference system

`mamfis` object | `sugfis` object | string | character vector

Input fuzzy inference system, specified as one of the following:

- `mamfis` or `sugfis` object. `getFISCodeGenerationData` supports fuzzy inference system objects for simulation only.

- String or character vector specifying a `.fis` file in the current working folder or on the MATLAB path. `getFISCodeGenerationData` supports fuzzy inference system file names for both simulation and code generation.

When `getFISCodeGenerationData` loads a fuzzy system that uses custom functions, it writes additional files to the current folder to support code generation for the custom functions.

Output Arguments

`fisOut` — Output fuzzy inference system
homogeneous structure

Output fuzzy inference system, returned as a homogeneous structure. In the homogeneous structure, if a field is a structure array, all the elements of that array are the same size. For example, in the input variable array `fisOut.input`:

- Names of all the variables are character vectors of the same length.
- Lengths of the membership function arrays for all variables are the same.

For any character vectors or structure arrays that are padded to increase their lengths, the original lengths of these elements are saved within the structure.

The `fisOut` structure is different than the structure created using `convertToStruct`.

Extended Capabilities

C/C++ Code Generation
Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- `getFISCodeGenerationData` supports fuzzy inference system objects for simulation only. To generate code for `getFISCodeGenerationData`, specify the input fuzzy inference system using a file name.

- It is good practice to not use `getFISCodeGenerationData` within a MATLAB Function block. This function is a utility function for generating code for evaluating a fuzzy inference system using MATLAB Coder.

See Also

`evalfis` | `evalfisOptions` | `mamfis` | `sugfis`

Introduced in R2018b

getTunableSettings

Obtain tunable settings from fuzzy inference system

Syntax

```
in = getTunableSettings(fis)
[~,out] = getTunableSettings(fis)
[~,~,rule] = getTunableSettings(fis)
[in,out,rule] = getTunableSettings(fis)
```

Description

`in = getTunableSettings(fis)` returns tunable settings of input variables of the fuzzy system `fis`.

`[~,out] = getTunableSettings(fis)` returns tunable settings of output variables of the fuzzy system `fis`.

`[~,~,rule] = getTunableSettings(fis)` returns tunable settings of rules of the fuzzy system `fis`.

`[in,out,rule] = getTunableSettings(fis)` returns tunable settings of inputs, outputs, and rules of the fuzzy system `fis`.

Examples

Obtain Tunable Settings from FIS

Create two fuzzy inference systems, and define the connection between the two.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = sugfis('Name','fis2','NumInputs',2,'NumOutputs',1);
con = ["fis1/output1" "fis2/input1"];
```

Create a tree of fuzzy inference systems.

```
tree = fistree([fis1 fis2],con);
```

Obtain the tunable settings of inputs, outputs, and rules of the fuzzy inference system.

```
[in,out,rule] = getTunableSettings(tree)

in = 
  4x1 VariableSettings array with properties:

    Type
    VariableName
    MembershipFunctions
    FISName


out = 
  2x1 VariableSettings array with properties:

    Type
    VariableName
    MembershipFunctions
    FISName


rule = 
  18x1 RuleSettings array with properties:

    Index
    Antecedent
    Consequent
    FISName
```

You can use dot notation to specify tunable settings.

For the first membership function of input 1:

- do not tune parameter 1,
- set the minimum ranges of the last two parameters to 0,
- and set the maximum ranges of the last two parameters to 1.

```
in(1).MembershipFunctions(1).Parameters.Free(1) = false;
in(1).MembershipFunctions(1).Parameters.Minimum(2:end) = 0;
in(1).MembershipFunctions(1).Parameters.Maximum(2:end) = 1;
```

For the first rule:

- set input 1 membership function index non-tunable,
- allow NOT logic for input 2 membership function index,
- and do not ignore output 1 membership function index.

```
rule(1).Antecedent.Free(1) = false;
rule(1).Antecedent.AllowNot(2) = true;
rule(1).Consequent.AllowEmpty(1) = false;
```

Input Arguments

`fis` — Fuzzy system
`mamfis` object | `sugfis` object | `fistree` object

Fuzzy system, specified as a `mamfis`, `sugfis`, or `fistree` object. The fuzzy system can be a fuzzy inference system or network of interconnected fuzzy inference systems. It is created using `mamfis`, `sugfis`, `genfis`, or `fistree`.

Output Arguments

`in` — Tunable settings of input variables
`VariableSettings` object

Tunable settings of input variables, specified as a `VariableSettings` object. Each membership function contains its own `VariableSettings` object, each of which consists of the properties `Type`, `VariableName`, `MembershipFunctions`, and `FISName`. `MembershipFunctions` are specified as `MembershipFunctionSettings` objects that contain further tunable settings for each membership function, as `NumericParameters` objects.

`out` — Tunable settings of output variables
`VariableSettings` object

Tunable settings of output variables, specified as a `VariableSettings` object. These settings are similar to those of the input variables.

`rule` — Tunable settings of rules
`RuleSettings` object

Tunable settings of rules, specified as a `RuleSettings` object. Each rule contains its own `RuleSettings` object, each of which consists of the properties `Index`, `Antecedent`, `Consequent`, and `FISName`. `Antecedent` and `Consequent` are specified as `ClauseParameters` objects.

See Also

`RuleSettings` | `VariableSettings` | `getTunableValues` | `mamfis` | `setTunableValues` | `sugfis` | `tunefis`

Introduced in R2019a

mam2sug

(To be removed) Transform Mamdani fuzzy inference system into Sugeno fuzzy inference system

---

Note `mam2sug` will be removed in a future release. Use `convertToSugeno` instead. For more information, see “Compatibility Considerations”.

Syntax

```
sugFIS = mam2sug(mamFIS)
```

Description

`sugFIS = mam2sug(mamFIS)` transforms a Mamdani fuzzy inference system into a Sugeno fuzzy inference system.

Examples

Transform Mamdani FIS into Sugeno FIS

Load a Mamdani fuzzy inference system.

```
mam_fismat = readfis('mam22.fis');
```

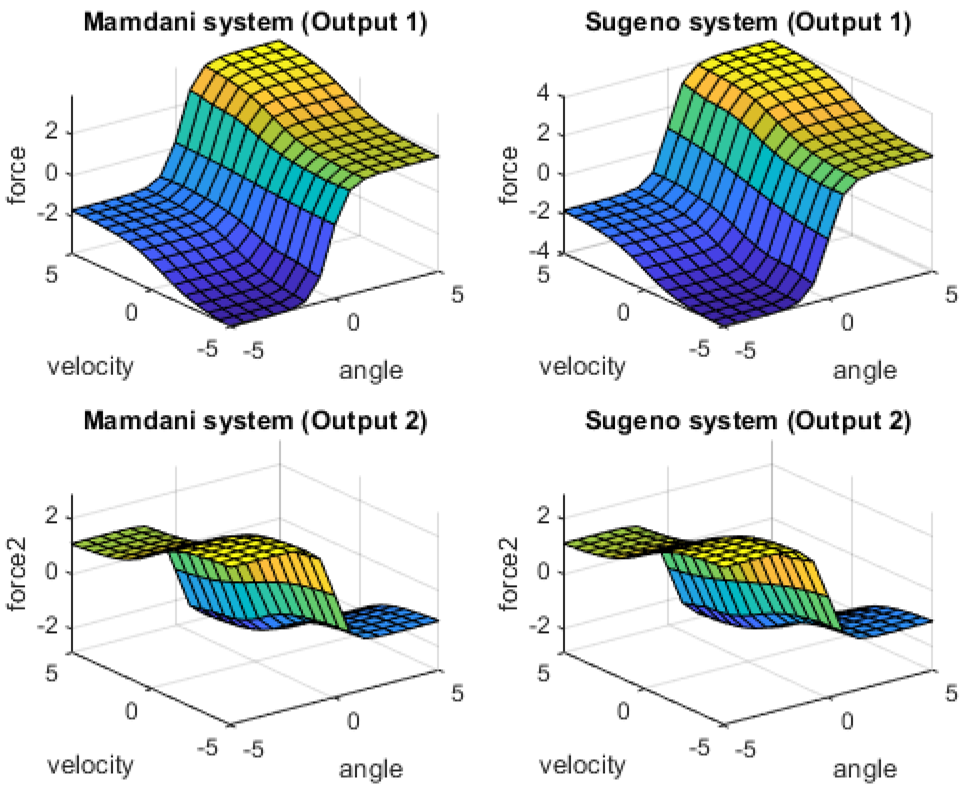
Convert this system to a Sugeno fuzzy inference system.

```
sug_fismat = mam2sug(mam_fismat);
```

Plot the output surfaces for both fuzzy systems.

```
subplot(2,2,1)
gensurf(mam_fismat)
title('Mamdani system (Output 1)')
subplot(2,2,2)
```

```
gensurf(sug_fismat)
title('Sugeno system (Output 1)')
subplot(2,2,3)
gensurf(mam_fismat,gensurfOptions('OutputIndex',2))
title('Mamdani system (Output 2)')
subplot(2,2,4)
gensurf(sug_fismat,gensurfOptions('OutputIndex',2))
title('Sugeno system (Output 2)')
```



The output surfaces for both systems are similar.

Input Arguments

`mamFIS` — Mamdani fuzzy inference system
structure

Mamdani fuzzy inference system, specified as a structure. Construct `mamFIS` at the command line or using the Fuzzy Logic Designer. For more information, see "Build Fuzzy Systems at the Command Line" on page 2-38 and "Build Fuzzy Systems Using Fuzzy Logic Designer" on page 2-14.

Output Arguments

`sugFIS` — Sugeno fuzzy inference system
structure

Sugeno fuzzy inference system, returned as a structure. `sugFIS`:

- Has constant output membership functions, whose values correspond to the centroids of the output membership functions in `mamFIS`
- Uses the weighted-average defuzzification method
- Uses the product implication method
- Uses the sum aggregation method

The remaining properties of `sugFIS`, including the input membership functions and rule definitions remain unchanged from `mamFIS`.

Tips

- If you have a functioning Mamdani fuzzy inference system, consider using `mam2sug` to convert to a more computationally efficient Sugeno structure to improve performance.
- If `sugFIS` has a single output variable and you have appropriate measured input/output training data, you can tune the membership function parameters of `sugFIS` using `anfis`.

Compatibility Considerations

`mam2sug` will be removed

Not recommended starting in R2018b

`mam2sug` will be removed in a future release. Use `convertToSugeno` instead. To update your code, change the function name from `mam2sug` to `convertToSugeno`. The syntaxes are equivalent.

See Also

Fuzzy Logic Designer | `convertToSugeno`

Topics

"What Is Mamdani-Type Fuzzy Inference?" on page 2-4
"What Is Sugeno-Type Fuzzy Inference?" on page 2-5
"Build Fuzzy Systems at the Command Line" on page 2-38
"Build Fuzzy Systems Using Fuzzy Logic Designer" on page 2-14

Introduced before R2006a

mf2mf

(To be removed) Translate parameters between membership functions

Note `mf2mf` will be removed in a future release. Convert membership functions using dot notation on `fismf` objects instead. For more information, see “Compatibility Considerations”.

Syntax

```
outParams = mf2mf(inParams,inType,outType)
```

Description

This function translates any built-in membership function type into another, in terms of its parameter set. In principle, `mf2mf` mimics the symmetry points for both the new and old membership functions.

Note Occasionally this translation results in lost information, so that if the output parameters are translated back into the original membership function type, the transformed membership function does not look the same as it did originally.

The input arguments for `mf2mf` are as follows:

- `inParams` — Parameters of the membership function you are transforming from, specified as a row vector.
- `inType` — Type of membership function you are transforming from.
- `outType` — Type of membership function you are transforming to.

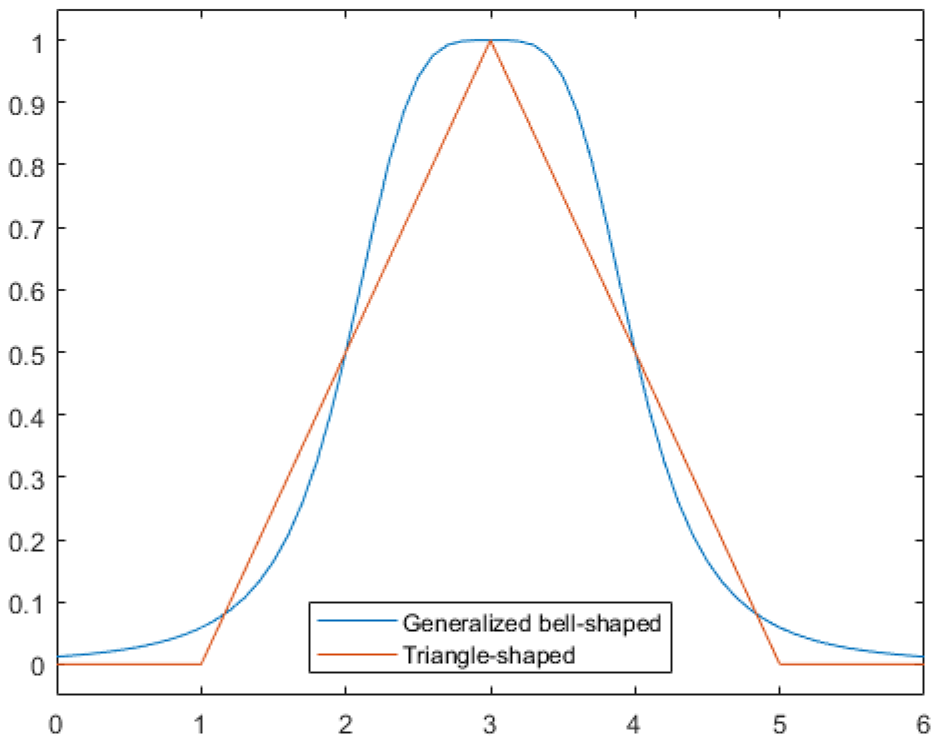
You can specify `inType` and `outType` as any of the following membership functions types:

Membership function type	Description	For more information
'gbellmf'	Generalized bell-shaped membership function	gbellmf
'gaussmf'	Gaussian membership function	gaussmf
'gauss2mf'	Gaussian combination membership function	gauss2mf
'trimf'	Triangular membership function	trimf
'trapmf'	Trapezoidal membership function	trapmf
'sigmf	Sigmoidal membership function	sigmf
'dsigmf	Difference between two sigmoidal membership functions	dsigmf
'psigmf	Product of two sigmoidal membership functions	psigmf
'zmf'	Z-shaped membership function	zmf
'pimf'	Pi-shaped membership function	pimf
'smf'	S-shaped membership function	smf

Examples

Translate Parameters Between Membership Functions

```
x = 0:0.1:5;
mf1 = [1 2 3];
mf2 = mf2mf(mf1,'gbellmf','trimf');
plot(x,gbellmf(x,mf1),x,trimf(x,mf2))
legend('Generalized bell-shaped','Triangle-shaped','Location','South')
ylim([-0.05 1.05])
```



Compatibility Considerations

`mf2mf` will be removed

Not recommended starting in R2018b

`mf2mf` will be removed in a future release. Convert membership functions using dot notation on `fismf` objects instead. There are differences between these approaches that require updates to your code.

Update Code

Previously, to change the type of a membership function in a fuzzy inference system, you converted the parameters using `mf2mf`.

```
fis = readfis('tipper');
oldType = fis.input(1).mf(1).type;
oldParams = fis.input(1).mf(1).params;
fis.input(1).mf(1).type = newType;
fis.input(1).mf(1).params = mf2mf(oldParams,oldType,newType);
```

Now, when you change the type of membership function, the parameters are converted automatically.

```
fis = readfis('tipper');
fis.Inputs(1).MembershipFunctions(1).Type = newType;
```

Previously, membership functions were represented as structures within a fuzzy inference system structure. Now, membership functions are represented as `fismf` objects within `mamfis` and `sugfis` objects. For more information on fuzzy inference system objects, see `mamfis` and `sugfis`.

See Also

`dsigmf` | `evalmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trapmf` | `trimf` | `trimf` | `zmf`

Topics

"Membership Functions" on page 1-14
"The Membership Function Editor" on page 2-22

Introduced before R2006a

mfedit

Open Membership Function Editor

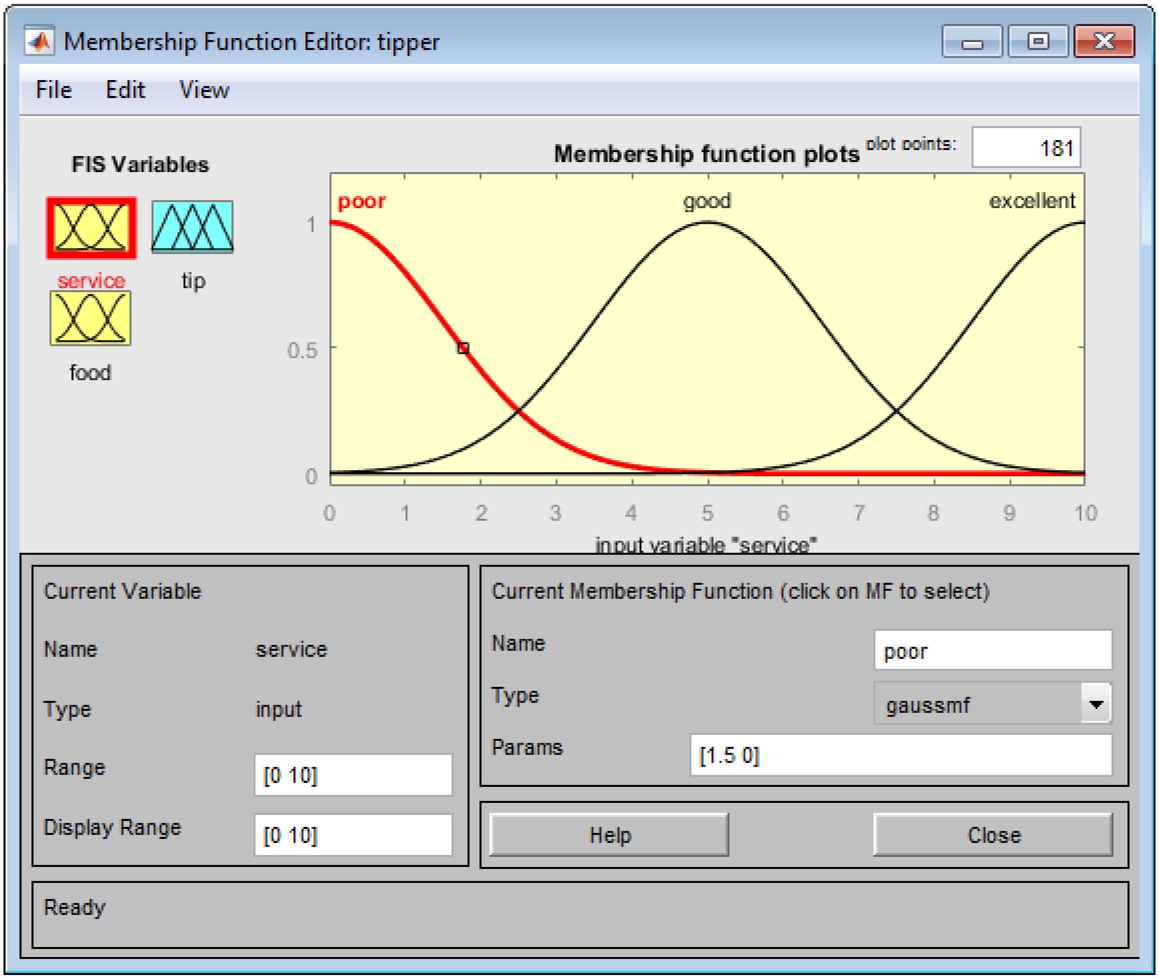
Syntax

```
mfedit(fileName)
```

```
mfedit(fis)
```

```
mfedit
```

Description



Current Variable

Name: service

Type: input

Range: [0 10]

Display Range: [0 10]

Current Membership Function (click on MF to select)

Name: poor

Type: gaussmf

Params: [1.5 0]

Ready

`mfedit(fileName)` generates a membership function editor that allows you to inspect and modify all the membership functions for the FIS stored in the file, `fileName`. Specify `fileName` as a character vector or string with or without the `.fis` extension.

`mfedit(fis)` operates on a `mamfis` or `sugfis` object, `fis`.

`mfedit` opens the membership function editor with no FIS loaded.

For each membership function you can change the name, the type, and the parameters. Eleven built-in membership functions are provided for you to choose from, although of course you can always create your own specialized versions. Refer to "The Membership Function Editor" on page 2-22 for more information about how to use `mfedit`.

Select the icon for the variable on the upper left side of the diagram (under **FIS Variables**) to display its associated membership functions in the plot region. Select membership functions by clicking once on them or their labels.

Menu Items

In the Membership Function Editor, there is a menu bar that allows you to open related UI tools, open and save systems, and so on. The **File** menu for the Membership Function Editor is the same as the one found in the **Fuzzy Logic Designer**.

- Under **Edit**, select:

  Undo to undo the most recent change.

  Add MFs to add membership functions to the current variable.

  Add Custom MF to add a customized membership function to the current variable.

  Remove Selected MF to delete the current membership function.

  Remove All MFs to delete all membership functions of the current variable.

  FIS properties to open the **Fuzzy Logic Designer**.

  Rules to invoke the Rule Editor.
- Under **View**, select:

  Rules to invoke the Rule Viewer.

  Surface to invoke the Surface Viewer.

Membership Function Pop-up Menu

There are 11 built-in membership functions to choose from, and you also have the option of installing a customized membership function.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

Apps
Fuzzy Logic Designer

Functions
`addMF` | `plotmf` | `ruleedit` | `ruleview` | `surfview`

Topics

"Membership Functions" on page 1-14
"The Membership Function Editor" on page 2-22

Introduced before R2006a

newfis

(To be removed) Create new fuzzy inference system

Note `newfis` will be removed in a future release. Use `mamfis` or `sugfis` instead. For more information, see “Compatibility Considerations”.

Syntax

```
fis = newfis(name)
fis = newfis(name,Name,Value)
```

Description

`fis = newfis(name)` returns a default Mamdani fuzzy inference system with the specified `name`.

`fis = newfis(name,Name,Value)` returns a fuzzy inference system with properties specified using one or more `Name,Value` pair arguments.

Examples

Create Fuzzy Inference System

Create a default Mamdani fuzzy inference system with the name, `'fis'`.

```
sys = newfis('fis')
```

```
sys = struct with fields:
            name: 'fis'
            type: 'mamdani'
       andMethod: 'min'
        orMethod: 'max'
    defuzzMethod: 'centroid'
       impMethod: 'min'
       aggMethod: 'max'
           input: []
          output: []
            rule: []
```

Create Sugeno Fuzzy Inference System

Create a default Sugeno fuzzy inference system with the name, `'fis'`.

```
sys = newfis('fis','FISType','sugeno')
```

```
sys = struct with fields:
            name: 'fis'
            type: 'sugeno'
       andMethod: 'prod'
        orMethod: 'probor'
    defuzzMethod: 'wtaver'
       impMethod: 'prod'
       aggMethod: 'sum'
           input: []
          output: []
            rule: []
```

Specify Implication Methods for New Fuzzy Inference System

Create a Mamdani fuzzy inference system that uses `'bisector'` defuzzification and `'prod'` implication.

```
sys = newfis('fis','DefuzzificationMethod','bisector',...
                   'ImplicationMethod','prod');
```

Input Arguments

name — Fuzzy inference system name
character vector | string

Fuzzy inference system name, specified as a character vector or string.

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'OrMethod','probor'` configures the fuzzy OR operator as a probabilistic OR function.

`FISType` — Fuzzy inference system type

`'mamdani'` (default) | `'sugeno'`

Fuzzy inference system type, specified as one of the following:

- `'mamdani'` — Mamdani-type fuzzy system
- `'sugeno'` — Sugeno-type fuzzy system

For more information on the types of fuzzy inference systems, see “Types of Fuzzy Inference Systems” on page 2-2.

`AndMethod` — AND fuzzy operator method

`'min'` | `'prod'` | character vector | string

AND fuzzy operator method, specified as one of the following:

- `'min'` — Minimum of fuzzified input values. This method is the default when `FISType` is `'mamdani'`.
- `'prod'` — Product of fuzzified input values. This method is the default when `FISType` is `'sugeno'`.
- Character vector or string — Name of a custom AND function in the current working folder or on the MATLAB path. For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on fuzzy operators and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`OrMethod` — OR fuzzy operator method

`'max'` | `'probor'` | character vector | string

OR fuzzy operator method, specified as one of the following:

- `'max'` — Maximum of fuzzified input values. This method is the default when `FISType` is `'mamdani'`.
- `'probor'` — Probabilistic OR of fuzzified input values. For more information, see `probor`. This method is the default when `FISType` is `'sugeno'`.
- Character vector or string — Name of a custom OR function in the current working folder or on the MATLAB path. For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on fuzzy operators and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`ImplicationMethod` — Implication method
`'min'` | `'prod'` | character vector | string

Implication method for computing consequent fuzzy set, specified as one of the following:

- `'min'` — Truncate the consequent membership function at the antecedent result value. This method is the default when `FISType` is `'mamdani'`.
- `'prod'` — Scale the consequent membership function by the antecedent result value. This method is the default when `FISType` is `'sugeno'`.
- Character vector or string — Name of a custom implication function in the current working folder or on the MATLAB path. For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

Note No matter what implication method you specify, Sugeno systems always use `'prod'` aggregation.

For more information on implication and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`AggregationMethod` — Aggregation method
`'max'` | `'sum'` | character vector | string

Aggregation method for combining rule consequents, specified as one of the following:

- `'max'` — Maximum of consequent fuzzy sets. This method is the default when `FISType` is `'mamdani'`.
- `'sum'` — Sum of consequent fuzzy sets. This method is the default when `FISType` is `'sugeno'`.

- `'probor'` — Probabilistic OR of consequent fuzzy sets. For more information, see `probor`.
- Character vector or string — Name of a custom aggregation function in the current working folder or on the MATLAB path. For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

Note No matter what aggregation method you specify, Sugeno systems always use `'sum'` aggregation.

For more information on aggregation and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

DefuzzificationMethod — Defuzzification method
`'centroid'` | `'bisector'` | `'mom'` | `'lom'` | `'som'` | `'wtaver'` | `'wtsum'` | character vector | string

Defuzzification method for computing crisp output values.

If `FISType` is `'mamdani'`, specify the defuzzification method as one of the following:

- `'centroid'` — Centroid of the area under the output fuzzy set. This method is the default for Mamdani systems.
- `'bisector'` — Bisector of the area under the output fuzzy set
- `'mom'` — Mean of the values for which the output fuzzy set is maximum
- `'lom'` — Largest value for which the output fuzzy set is maximum
- `'som'` — Smallest value for which the output fuzzy set is maximum

If `FISType` is `'sugeno'`, specify the defuzzification method as one of the following:

- `'wtaver'` — Weighted average of all rule outputs. This method is the default for Sugeno systems.
- `'wtsum'` — Weighted sum of all rule outputs

You can also specify the defuzzification method using a character vector or string that contains the name of a custom function in the current working folder or on the MATLAB path. For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on defuzzification and the fuzzy inference process, see "Fuzzy Inference Process" on page 1-28.

Output Arguments

`fis` — Fuzzy inference system
FIS structure

Fuzzy inference system with the specified `name`, returned as an FIS structure. The fuzzy system is configured using the specified `Name,Value` pair arguments.

`fis` has no input variables, output variables, or rules. To add variables or rules to `fis`, use `addvar` or `addRule`. You can also edit the fuzzy system using **Fuzzy Logic Designer**.

Compatibility Considerations

`newfis` will be removed

Not recommended starting in R2018b

`newfis` will be removed in a future release. Use `mamfis` or `sugfis` instead. There are differences between these functions that require updates to your code.

To create a Mamdani or Sugeno FIS, use `mamfis` or `sugfis`, respectively.

Update Code

This table shows some typical usages of `newfis` for creating fuzzy systems and how to update your code to use `mamfis` or `sugfis` instead.

If your code has this form:	Use this code instead:
`fis = newfis(name)`	`fis = mamfis('Name',name)`
`fis = newfis(name,'FISType','mamdani')`	`fis = mamfis('Name',name)`
`fis = newfis(name,'FISType','sugeno')`	`fis = sugfis('Name',name)`

If your code has this form:	Use this code instead:

`fis = newfis(name,...`
`             'FISType','mamdani',...`
`             'AndMethod','prod')`
	`fis = mamfis('Name',name,...`
	`             'AndMethod','prod')`

`fis = newfis(name,...`
`             'FISType','sugeno',...`
`             'OrMethod','probor')`
	`fis = sugfis('Name',name,...`
	`             'OrMethod','probor')`

See Also

`mamfis` | `readfis` | `sugfis` | `writeFIS`

Topics

“Foundations of Fuzzy Logic” on page 1-10
“Fuzzy Inference Process” on page 1-28

Introduced before R2006a

parsrule

(To be removed) Parse fuzzy rules

Note `parsrule` will be removed in a future release. Use `addRule` instead. For more information, see "Compatibility Considerations".

Syntax

```
outFIS = parsrule(inFIS,ruleList)
outFIS = parsrule(inFIS,ruleList,Name,Value)
```

Description

`outFIS = parsrule(inFIS,ruleList)` returns a fuzzy inference system, `outFIS`, that is equivalent to the input fuzzy system, `inFIS`. but with fuzzy rules replaced by the rules specified in `ruleList`.

`outFIS = parsrule(inFIS,ruleList,Name,Value)` parses the rules in `ruleList` using options specified by one or more `Name,Value` pair arguments.

Examples

Add Rules to Fuzzy Inference System

Load a fuzzy inference system (FIS).

```
fis = readfis('tipper');
```

Specify if-then rules using the default `'verbose'` format.

```
rule1 = "If service is poor or food is rancid then tip is cheap";
rule2 = "If service is excellent and food is not rancid then tip is generous";
rules = [rule1 rule2];
```

Add the rules to the FIS.

```
fis2 = parsrule(fis,rules);
```

`fis2` is equivalent to `fis`, except that the rule base is replaced with the specified rules.

Add Rules Using Symbolic Expressions

Load a fuzzy inference system (FIS).

```
fis = readfis('tipper');
```

Specify the following rules using symbols:

- If `service` is `poor` or `food` is `rancid` then `tip` is `cheap`.
- If `service` is `excellent` and `food` is not `rancid` then `tip` is `generous`.

```
rule1 = "service==poor | food==rancid => tip=cheap";
rule2 = "service==excellent & food~=rancid => tip=generous";
rules = [rule1 rule2];
```

Add the rules to the FIS using the `'symbolic'` format.

```
fis2 = parsrule(fis,rules,'Format','symbolic');
```

Add Rules Using Membership Function Indices

Load fuzzy inference system (FIS).

```
fis = readfis('mam22.fis');
```

Specify the following rules using membership function indices:

- If `angle` is `small` and `velocity` is `big`, then `force` is `negBig` and `force2` is `posBig2`.
- If `angle` is not `small` and `velocity` is `small`, then `force` is `posSmall` and `force2` is `negSmall2`.

```
rule1 = "1 2, 1 4 (1) : 1";
rule2 = "-1 1, 3 2 (1) : 1";
rules = [rule1 rule2];
```

Add rules to FIS using the `'indexed'` format.

```
fis2 = parsrule(fis,rules,'Format','indexed');
```

Add Rules Using French Language

Load a fuzzy inference system (FIS).

```
fis = readfis('tipper');
```

Specify if-then rules using French keywords.

```
rule1 = "Si service est poor ou food est rancid alors tip est cheap";
rule2 = "Si service est excellent et food n''est_pas rancid alors tip est generous";
rules = [rule1 rule2];
```

Add the rules to the FIS.

```
fis2 = parsrule(fis,rules,'Language','francais');
```

Add Single Rule to Fuzzy Inference System

Load a fuzzy inference system (FIS).

```
a = readfis('tipper');
```

Add a rule to the FIS.

```
ruleTxt = 'If service is poor then tip is cheap';
a2 = parsrule(a,ruleTxt,'verbose');
```

Input Arguments

`inFIS` — Fuzzy inference system
FIS structure

Input fuzzy inference system, specified as an FIS structure. `parsrule` does not modify `inFIS`.

`ruleList` — Fuzzy rules
character array | string array | character vector | string

Fuzzy rules, specified as one of the following:

- Character array where each row corresponds to a rule. For example:

  ```
  rule1 = 'If service is poor or food is rancid then tip is cheap';
  rule2 = 'If service is good then tip is average';
  rule3 = 'If service is excellent or food is delicious then tip is generous';
  ruleList = char(rule1,rule2,rule3);
  ```
- String array, where each element corresponds to a rule. For example:

  ```
  ruleList = ["If service is poor or food is rancid then tip is cheap";
              "If service is good then tip is average";
              "If service is excellent or food is delicious then tip is generous"];
  ```
- Character vector or string to specify a single rule.

You can change the rule format and language using the `Format` and `Language` options.

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'Format','symbolic'` sets the rule format to symbolic expressions.

`Format` — Rule format

`'verbose'` (default) | `'symbolic'` | `'indexed'`

Rule format, specified as the comma-separated pair consisting `'Format'` and one of the following:

- `'verbose'` — Use linguistic expressions.

  ```
  'If service is poor or food is rancid then tip is cheap 1'
  ```

  Specify the rule weight at the end of the rule text. If you omit the weight, a default value of `1` is used.

  You can specify the rule language using the `Language` option.
- `'symbolic'` — Use language-neutral symbolic expressions.

  ```
  'service==poor | food==rancid => tip=cheap 1'
  ```

  Specify symbolic expressions using the following symbols.

Rule Component	Symbol
AND	&
OR	|
IS (in antecedent)	==
IS (in consequent)	=
IS NOT	~=
Implication (then)	=>

Specify the rule weight at the end of the rule text. If you omit the weight, a default value of `1` is used.

- `'indexed'` — Use input and output membership function (MF) indices.

  Specify indexed rules in the following format:

  ```
  '<input MFs>, <output MFs>, (<weight>) : <logical operator - 1(AND), 2(OR)>'
  ```

  For example:

  ```
  '1 1, 1 (1) : 2'
  ```

  To indicate NOT operations for input and output membership functions, use negative indices. For example, to specify “not the second membership function,” use `-2`.

  To indicate a don’t care condition for an input or output membership function, use `0`.

Language — Rule language
`'english'` (default) | `'francais'` | `'deutsch'`

Rule language for `'verbose'` format, specified as one of the following:

- `'english'` — Specify rules in English.

  ```
  'If service is poor or food is rancid then tip is cheap'
  ```
- `'francais'` — Specify rules in French.

  ```
  'Si service est poor ou food est rancid alors tip est cheap'
  ```
- `'deutsch'` — Specify rules in German.

  ```
  'Wenn service ist poor oder food ist rancid dann tip ist cheap'
  ```

The software parses the rules in `ruleList` using the following keywords.

Rule Component	English	French	German
Start of antecedent	`if`	`si`	`wenn`
AND	`and`	`et`	`und`
OR	`or`	`ou`	`oder`
Start of consequent (implication)	`then`	`alors`	`dann`
IS	`is`	`est`	`ist`
IS NOT	`is not`	`n''est_pas`	`ist nicht`

Output Arguments

`outFIS` — Output fuzzy inference system
FIS structure

Fuzzy inference system, returned as an FIS structure. `outFIS` is the same as `inFIS`, except that the rule list contains only the rules specified in `ruleList`.

Compatibility Considerations

`parsrule` will be removed

Not recommended starting in R2018b

`parsrule` will be removed in a future release. Use `addRule` instead.

Update Code

If you previously added rules using linguistic or symbolic expressions with `parsrule`, you can specify rules using the same expressions with `addrule`. `addRule` automatically detects the format of the strings or character vectors in your rule list. Therefore, it is no longer necessary to specify the rule format. To add a rule list using `addRule`, use the following command:

```
fis = addRule(fis,rules);
```

Previously, you could add rules using indexed expressions with `parsrule`.

```
rule1 = "1 2, 1 4 (1) : 1";
rule2 = "-1 1, 3 2 (1) : 1";
rules = [rule1 rule2];
fis = parsrule(fis,rules,'Format','indexed');
```

Now, specify these rules using arrays of indices.

```
rule1 = [1 2 1 4 1 1];
rule2 = [-1 1 3 2 1 1];
rules = [rule1; rule2];
fis = addRule(fis,rules);
```

If you previously specified rules using the `'Lanuage'` name-value pair argument with `parsrule`, this functionality has been removed and there is no replacement. Specify your rules using `addRule` a different rule format.

Previously, `parsrule` replaced the entire rule list in your fuzzy system. `addRule` appends your specified rules to the rule list.

See Also

`addRule` | `ruleedit` | `showrule`

Introduced before R2006a

pimf

Pi-shaped membership function

This function computes fuzzy membership values using a spline-based pi-shaped membership function. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-203.

This membership function is related to the `smf` and `zmf` membership functions.

Syntax

`y = pimf(x,params)`

Description

`y = pimf(x,params)` returns fuzzy membership values computed using a spline-based pi-shaped membership function. This membership function is the product of an `smf` functions and a `zmf` function, and is given by:

$$f(x;a,b,c,d) = \begin{cases} 0, & x \le a \\ 2\left(\frac{x-a}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ 1-2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \le x \le b \\ 1, & b \le x \le c \\ 1-2\left(\frac{x-c}{d-c}\right)^2, & c \le x \le \frac{c+d}{2} \\ 2\left(\frac{x-d}{d-c}\right)^2, & \frac{c+d}{2} \le x \le d \\ 0, & x \ge d \end{cases}$$

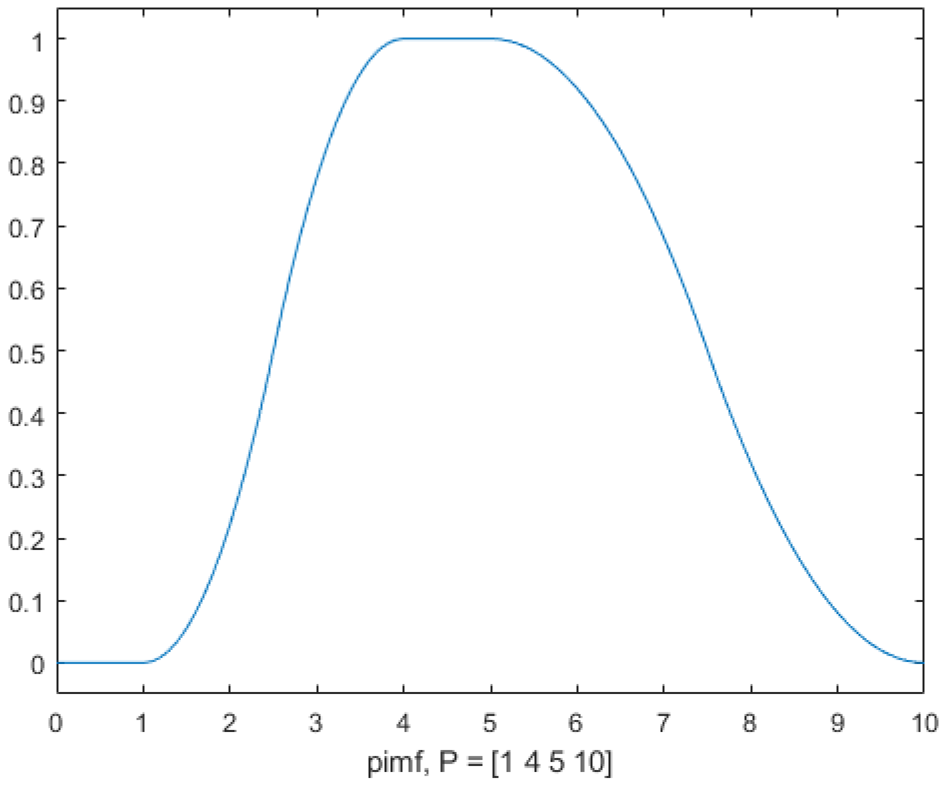
To specify the *a*, *b*, *c*, and *d* parameters, use `params`.

Membership values are computed for each input value in `x`.

Examples

Pi-Shaped Membership Function

```
x = 0:0.1:10;
y = pimf(x,[1 4 5 10]);
plot(x,y)
xlabel('pimf, P = [1 4 5 10]')
ylim([-0.05 1.05])
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length two

Membership function parameters, specified as the vector [*a b c d*]. Parameters *a* and *d* define the *feet* of the membership function, and *b* and *c* define its *shoulders*.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `pimf` membership function.

```
mf = fismf("pimf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `pimf`, respectively.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

See Also

`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

“Membership Functions” on page 1-14

Introduced before R2006a

plotfis

Display fuzzy inference system

Syntax

```
plotfis(fis)
```

Description

`plotfis(fis)` displays a high-level diagram of a fuzzy inference system (FIS). The center of the display shows the name, type, and rule count for the FIS. The input variables with associated membership functions are displayed to the right, and the outputs with their associated membership functions are displayed on the left.

Examples

Display Fuzzy Inference System

Create a fuzzy inference system (FIS). For this example, read the FIS from the `tipper.fis` file.

```
fis = readfis('tipper');
```

Display the fuzzy system.

```
plotfis(fis)
```

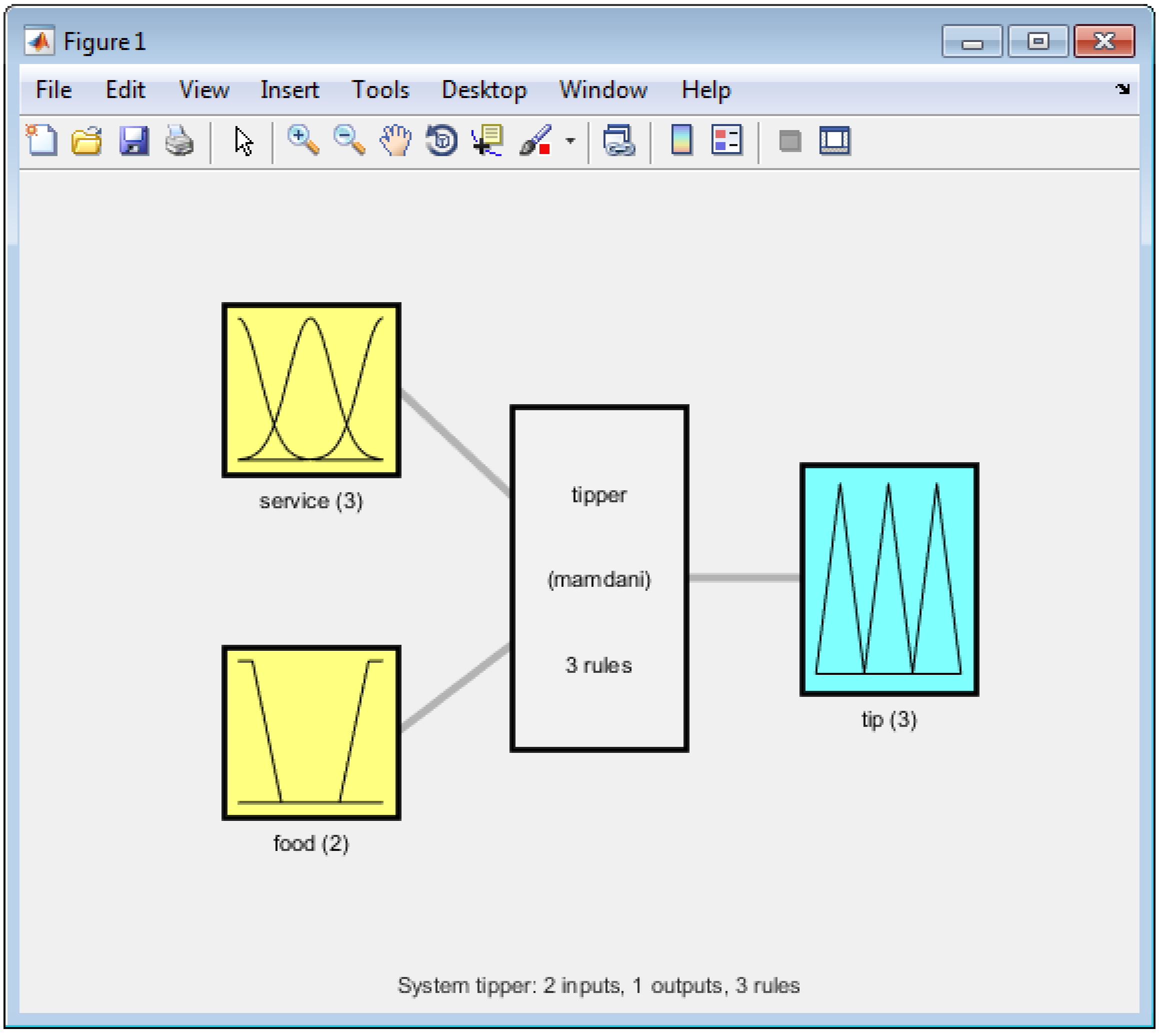


Figure 1
File Edit View Insert Tools Desktop Window Help
service (3)
food (2)
tipper
(mamdani)
3 rules
tip (3)
System tipper: 2 inputs, 1 outputs, 3 rules

Display Tree of Fuzzy Inference Systems

Create a `fistree` object from a pair of fuzzy inference systems.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = sugfis('Name','fis2','NumInputs',2,'NumOutputs',1);
con1 = ["fis1/output1" "fis2/input1"];
```

```
con2 = ["fis1/input1" "fis1/input2"];
tree = fistree([fis1 fis2],[con1; con2]);
```

Display the tree of fuzzy inference systems.

```
plotfis(tree)
```

```
FIS Names:
    fis1
    fis2

Connections:
    From            To
    ------------    -----------
    fis1/output1    fis2/input1
    fis1/input1     fis1/input2

Inputs:
    fis1/input1
    fis2/input2

Outputs:
    fis2/output1
```

For a `fistree` object, this function shows a description of the system in the Command Window instead of a figure.

Input Arguments

`fis` — Fuzzy inference system

`mamfis` object | `sugfis` object | `fistree` object

Fuzzy inference system, specified as one of the following:

- `mamfis` object — Mamdani fuzzy inference system
- `sugfis` object — Sugeno fuzzy inference system
- `fistree` object — tree of interconnected fuzzy inference systems

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

`evalmf` | `fistree` | `mamfis` | `plotmf` | `readfis` | `sugfis`

Topics

"Build Fuzzy Systems at the Command Line" on page 2-38

Introduced before R2006a

plotmf

Plot membership functions for input or output variable

Syntax

```
plotmf(fis,variableType,variableIndex)
plotmf(___,numPoints)

[xOut,yOut] = plotmf(___)
```

Description

`plotmf(fis,variableType,variableIndex)` plots the membership functions for an input or output variable in the fuzzy inference system `fis`.

`plotmf(___,numPoints)` specifies the number of data points to plot for each membership function.

`[xOut,yOut] = plotmf(___)` returns the x-axis and y-axis data for the membership functions without plotting them.

Examples

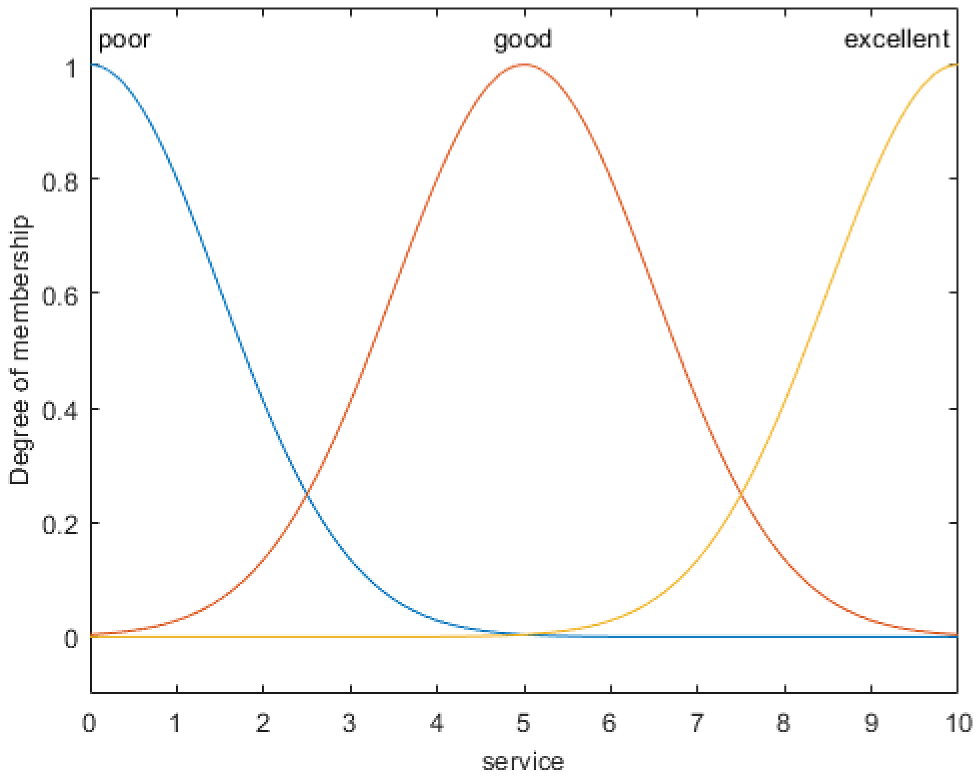
Plot Membership Functions for Input Variable

Create a fuzzy inference system.

```
fis = readfis('tipper');
```

Plot the membership functions for the first input variable.

```
plotmf(fis,'input',1)
```



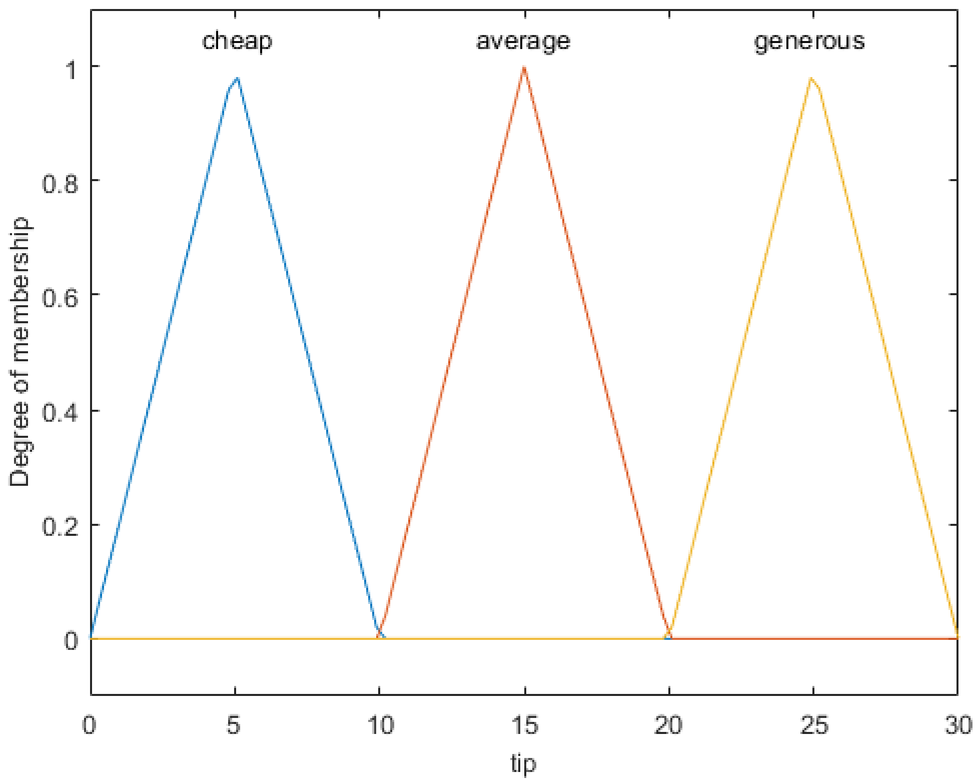
Specify Number of Points for Membership Function Plot

Create a fuzzy inference system.

```
fis = readfis('tipper');
```

Plot the membership functions for the first output variable using `101` data points for each membership function.

```
plotmf(fis,'output',1,101)
```



Obtain Membership Function Plot Data

Create a fuzzy inference system.

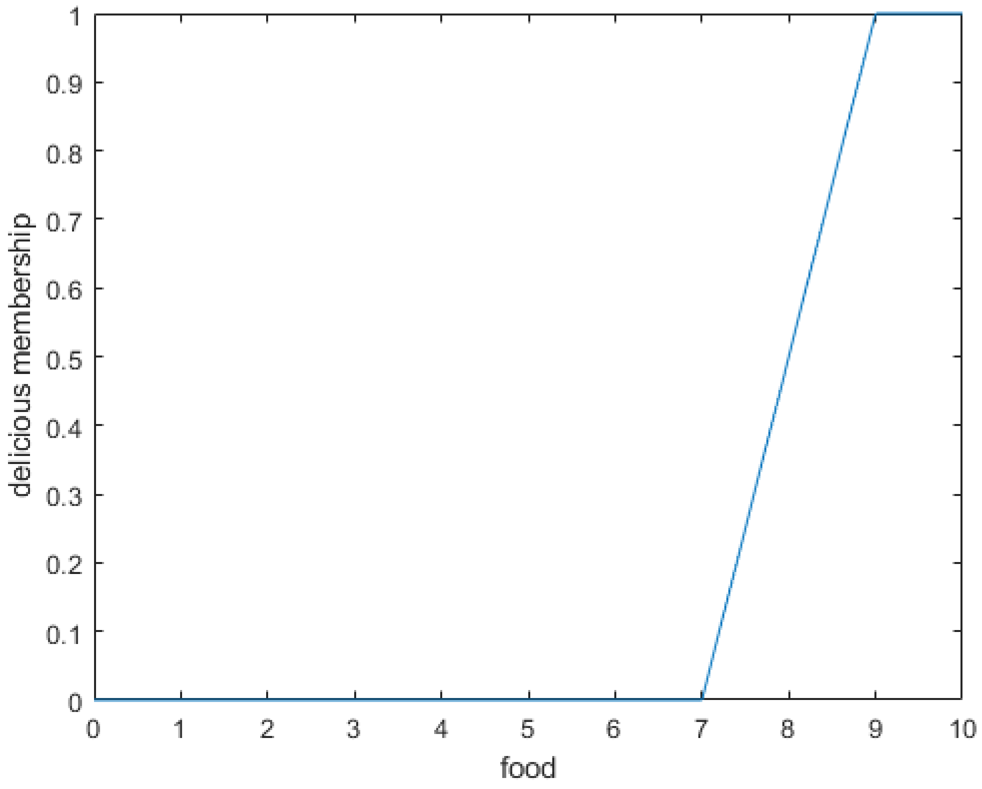
```
fis = readfis('tipper');
```

Obtain the x-axis and y-axis data for the membership functions of the second input variable.

```
[xOut,yOut] = plotmf(fis,'input',2);
```

You can then, for example, plot a single membership function using this data.

```
plot(xOut(:,2),yOut(:,2))
xlabel('food')
ylabel('delicious membership')
```



Input Arguments

`fis` — Fuzzy inference system

`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object. Construct `fis` at the command line or using the **Fuzzy Logic Designer**. For more information, see “Build

Fuzzy Systems at the Command Line” on page 2-38 and “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14.

`plotmf` does not support plotting output membership functions of Sugeno systems.

`variableType` — Variable type
`'input'` | `'output'`

Variable type, specified as one of the following:

- `'input'` — Input variable
- `'output'` — Output variable

`variableIndex` — Variable index
positive integer

Variable index, specified as a positive integer. If `variableType` is:

- `'input'`, then `variableIndex` must be less than or equal to the number of input variables in `fis`
- `'output'`, then `variableIndex` must be less than or equal to the number of output variables in `fis`

`numPoints` — Number of data points to plot
`181` (default) | positive integer

Number of data points to plot, specified as a positive integer.

Output Arguments

`xOut` — Plot x-axis data
array

Plot x-axis data, returned as a `numPoints`-by-N_{MF} array, where N_{MF} is the number of membership functions for the variable specified by `variableType` and `variableIndex`.

`yOut` — Plot y-axis data
array

Plot y-axis data, returned as a `numPoints`-by-N_{MF} array, where N_{MF} is the number of membership functions for the variable specified by `variableType` and `variableIndex`.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

Functions
`evalmf` | `plotfis`

Introduced before R2006a

probor

Probabilistic OR

Syntax

```
y = probor(x)
```

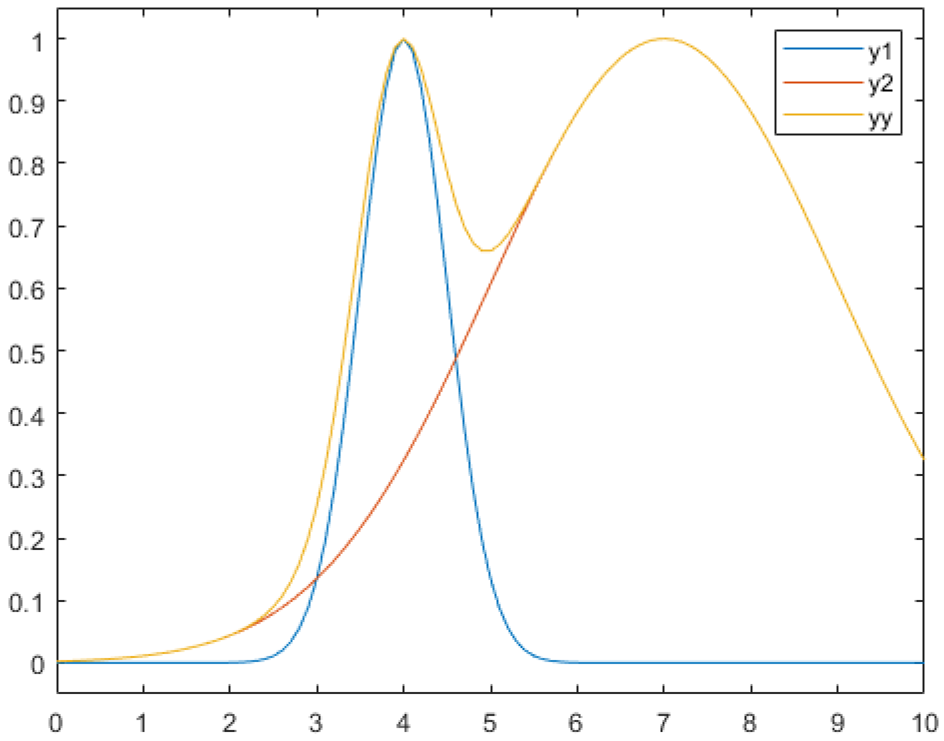
Description

`y = probor(x)` returns the probabilistic OR (also known as the *algebraic sum*) of the columns of `x`. if x has two rows such that `x = [a; b]`, then `y = a + b - ab`. If x has only one row, then `y = x`.

Examples

Probabilistic OR

```
x = 0:0.1:10;
y1 = gaussmf(x,[0.5 4]);
y2 = gaussmf(x,[2 7]);
yy = probor([y1;y2]);
plot(x,[y1;y2;yy])
legend('y1','y2','yy')
ylim([-0.05 1.05])
```



See Also

Introduced before R2006a

psigmf

Product of two sigmoidal membership functions

This function computes fuzzy membership values using the product of two sigmoidal membership functions. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-219.

This membership function is related to the `sigmf` and `dsigmf` membership functions.

Syntax

```
y = psigmf(x,params)
```

Description

`y = psigmf(x,params)` returns fuzzy membership values computed using the product of two sigmoidal membership functions. Each sigmoidal function is given by:

$$f(x;a,c) = \frac{1}{1 + e^{-a(x - c)}}$$

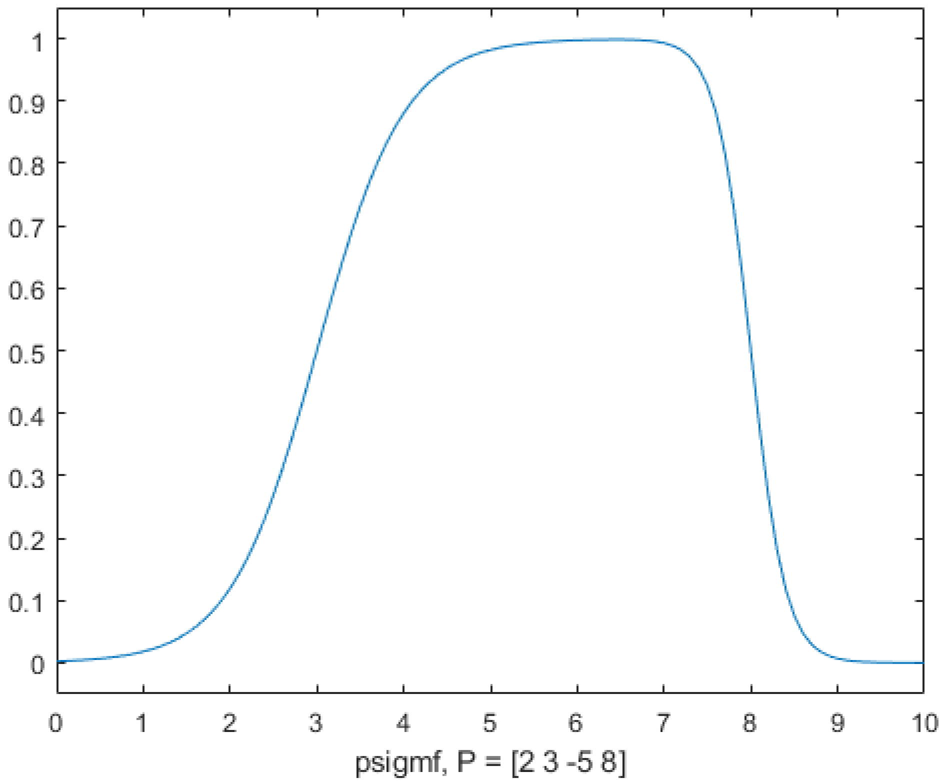
To specify the a and c parameters for each sigmoidal function, use `params`.

Membership values are computed for each input value in `x`.

Examples

Product of Two Sigmoidal Membership Functions

```
x = 0:0.1:10;
y = psigmf(x,[2 3 -5 8]);
plot(x,y)
xlabel('psigmf, P = [2 3 -5 8]')
ylim([-0.05 1.05])
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length four

Membership function parameters, specified as the vector [a_1 c_1 a_2 c_2]. Here, a_1 and c_1 are the parameters of the first sigmoidal function, and a_2 and c_2 are the parameters of the second sigmoidal function.

For each sigmoidal function, to open the function to the left or right, specify a negative or positive value for a, respectively. The magnitude of a defines the width of the transition area, and parameter c defines the center of the transition area.

To define a unimodal membership function with a maximum value of `1`, specify opposite signs for a_1 and a_2, and select c values far enough apart to allow for both transition areas to reach `1`.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `psigmf` membership function.

```
mf = fismf("psigmf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `psigmf`, respectively.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

See Also

`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

"Membership Functions" on page 1-14

Introduced before R2006a

readfis

Load fuzzy inference system from file

You can load a fuzzy inference system (FIS) from a `.fis` file using the `readfis` function. To save a FIS to a file, use the `writeFIS` function.

Note Do not manually edit the contents of a `.fis` file. Doing so can produce unexpected results when loading the file using `readfis`.

Syntax

```
fis = readfis(fileName)
fis = readfis
```

Description

`fis = readfis(fileName)` reads a FIS from the file specified by `fileName`.

`fis = readfis` opens a dialog box for selecting and opening loading a `.fis` file.

Examples

Load Fuzzy Inference System from File

Load the fuzzy system stored in the file `tipper.fis`.

```
fis = readfis('tipper')
```

```
fis = 
  mamfis with properties:

                       Name: "tipper"
                  AndMethod: "min"
                   OrMethod: "max"
```

```
         ImplicationMethod: "min"
         AggregationMethod: "max"
     DefuzzificationMethod: "centroid"
                    Inputs: [1x2 fisvar]
                   Outputs: [1x1 fisvar]
                     Rules: [1x3 fisrule]
   DisableStructuralChecks: 0

   See 'getTunableSettings' method for parameter optimization.
```

Input Arguments

`fileName` — File name
string | character vector

File name specified as a string or character vector with or without the `.fis` extension. This file must be in the current working directory or on the MATLAB path.

Output Arguments

`fis` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, returned as one of the following:

- `mamfis` object — Mamdani fuzzy inference system
- `sugfis` object — Sugeno fuzzy inference system

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed
Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

`writeFIS`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced before R2006a

removeInput

Remove input variable from fuzzy inference system

Syntax

```
fisOut = removeInput(fisIn,inputName)
```

Description

`fisOut = removeInput(fisIn,inputName)` removes the input variable with the name `inputName` from fuzzy inference system `fisIn` and returns the resulting fuzzy system in `fisOut`.

Examples

Remove Input Variable from Fuzzy Inference System

Load fuzzy system.

```
fis = readfis("tipper");
```

View the input variables of `fis`.

```
fis.Inputs
```

```
ans = 
  1x2 fisvar array with properties:

    Name
    Range
    MembershipFunctions

  Details:
             Name         Range      MembershipFunctions
           _________     _______     ___________________
    1    "service"    0    10         [1x3 fismf]
    2    "food"       0    10         [1x2 fismf]
```

View the rules of `fis`.

```
fis.Rules
```

```
ans = 
  1x3 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                                Description                    
         __________________________________________________________

    1    "service==poor | food==rancid => tip=cheap (1)"           
    2    "service==good => tip=average (1)"                        
    3    "service==excellent | food==delicious => tip=generous (1)"
```

Remove the `service` input variable.

```
fis = removeInput(fis,"service");
```

View the updated input variables.

```
fis.Inputs
```

```
ans = 
  fisvar with properties:

                   Name: "food"
                  Range: [0 10]
    MembershipFunctions: [1x2 fismf]
```

View the updated rules.

```
fis.Rules
```

```
ans = 
  1x2 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                       Description
         _____________________________________

    1    "food==rancid => tip=cheap (1)"
    2    "food==delicious => tip=generous (1)"
```

`service` has been removed from the variables and rules of `fis`.

Input Arguments

`fisIn` — Fuzzy inference system

`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

`inputName` — Input variable name

string | character vector

Input variable name, specified as a string or character vector.

Output Arguments

`fisOut` — Fuzzy inference system

`mamfis` object | `sugfis` object

Fuzzy inference system, returned as a `mamfis` or `sugfis` object. `fisOut` has the same properties as `fisIn` except:

- The input variable with the specified name is removed.
- The specified input variable is removed from any fuzzy rules. If a rule has only the specified input variable in its antecedent, then the entire rule is removed. If a rule has more than one input variable in its antecedent, then the specified input variable is removed from the antecedent.

See Also

`addInput` | `fisvar` | `mamfis` | `sugfis`

Topics

"Build Fuzzy Systems at the Command Line" on page 2-38

Introduced in R2018b

removeMF

Remove membership function from fuzzy variable

Syntax

```
fisOut = removeMF(fisIn,varName,mfName)
fisOut = removeMF(fisIn,varName,mfName,'VariableType',varType)

varOut = removeMF(varIn,varName,mfName)
```

Description

`fisOut = removeMF(fisIn,varName,mfName)` removes the membership function `mfName` from the input or output variable `varName` in the fuzzy inference system `fisIn` and returns the resulting fuzzy system in `fisOut`. To use this syntax, `varName` must be a unique variable name within `fisIn`.

`fisOut = removeMF(fisIn,varName,mfName,'VariableType',varType)` removes the membership function from either an input or output variable as specified by `varType`. Use this syntax when your FIS has an input variable with the same name as an output variable.

`varOut = removeMF(varIn,varName,mfName)` removes the membership function `mfName` from the fuzzy variable `varIn` and returns the resulting fuzzy variable in `varOut`.

Examples

Remove Membership Function from Fuzzy Inference System

Create a Mamdani fuzzy inference system with two inputs and one output. By default, when you specify the number of inputs and outputs, `mamfis` adds three membership functions to each variable.

```
fis = mamfis('NumInputs',3,'NumOutputs',1)
```

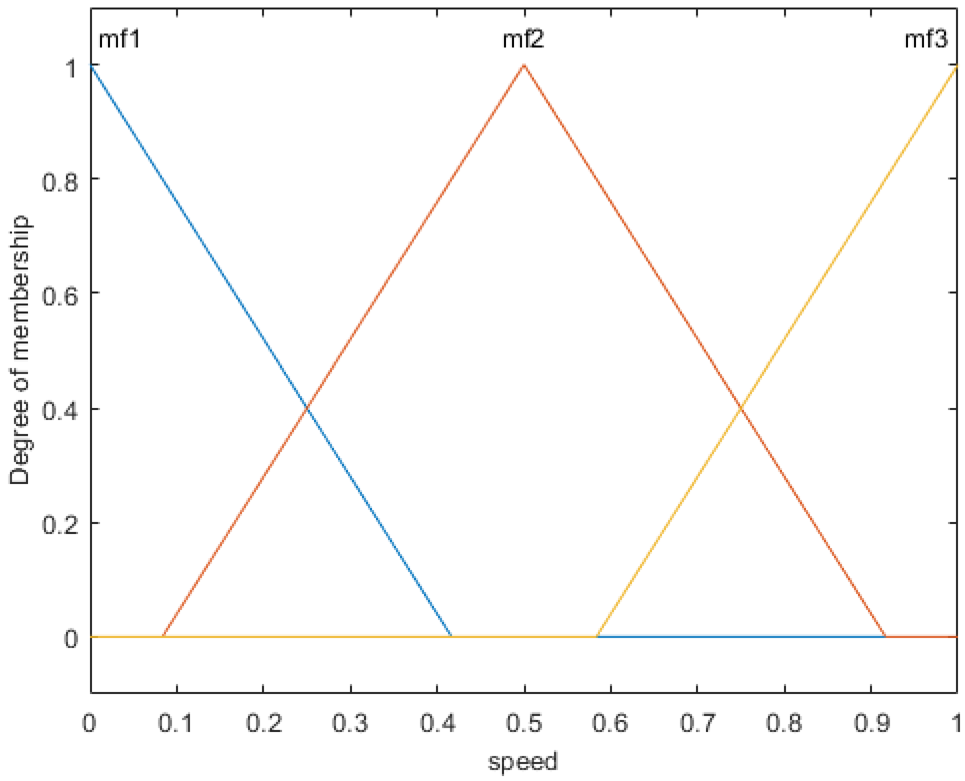
```
fis = 
  mamfis with properties:

                      Name: "fis"
                 AndMethod: "min"
                  OrMethod: "max"
         ImplicationMethod: "min"
         AggregationMethod: "max"
     DefuzzificationMethod: "centroid"
                    Inputs: [1x3 fisvar]
                   Outputs: [1x1 fisvar]
                     Rules: [1x27 fisrule]
    DisableStructuralChecks: 0

    See 'getTunableSettings' method for parameter optimization.
```

Name the variables. For this example, give the second input variable and the output variable the same name.

```
fis.Inputs(1).Name = "speed";
fis.Inputs(2).Name = "throttle";
fis.Inputs(3).Name = "distance";
fis.Outputs(1).Name = "throttle";
```

View the membership functions for the first input variable.

```
plotmf(fis,"input",1)
```

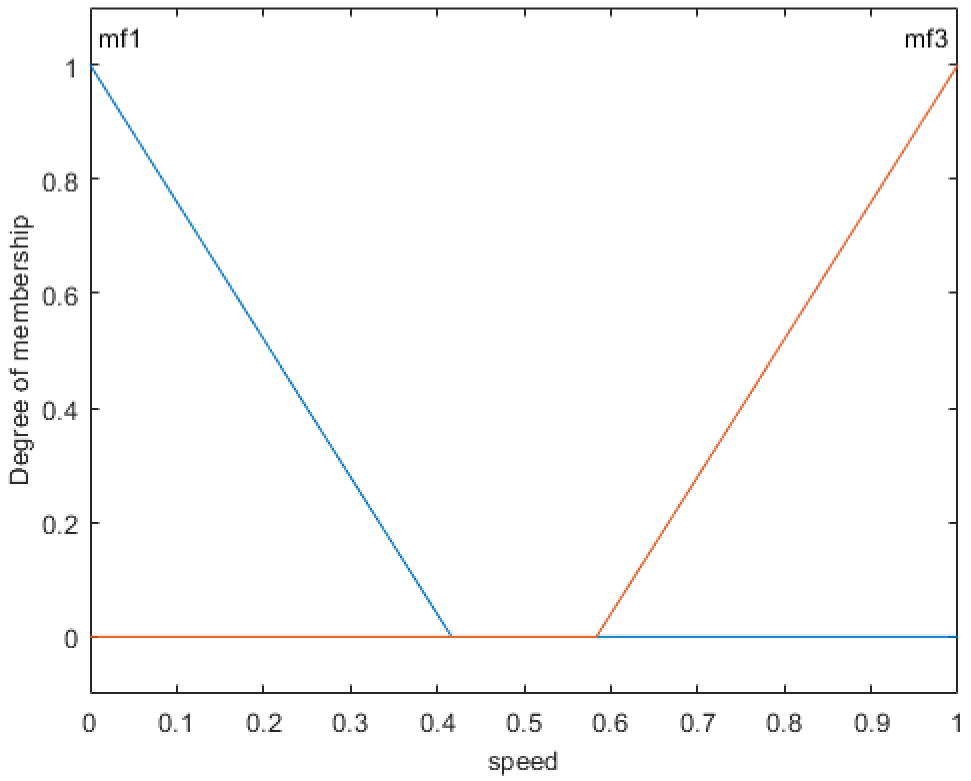


Remove the second membership function, `mf2`, from the first input variable.

```
fis = removeMF(fis,"speed","mf2");
```

View the membership functions again. The specified membership function has been removed.

```
plotmf(fis,"input",1)
```

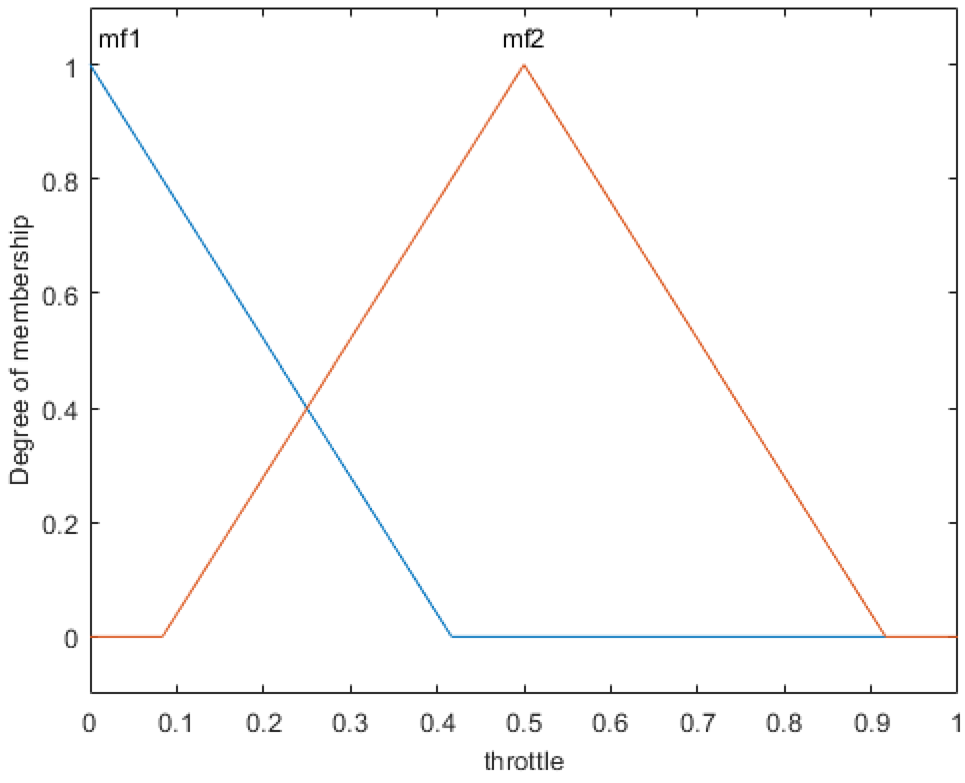


If your system has an input variable with the same name as an output variable, you must specify the variable type when removing a membership function. For example, remove the `mf3` membership function from the output variable.

```
fis = removeMF(fis,"throttle","mf3",'VariableType',"output");
```

View the membership functions of the output variable.

```
plotmf(fis,"output",1)
```



Remove Membership Function from Fuzzy Variable

Create a fuzzy variable with a specified range and add three membership functions

```
var = fisvar([0 10]);
var = addMF(var,"trimf",[0 2.5 5],"Name","small");
var = addMF(var,"trimf",[2.5 5 7.5],"Name","medium");
var = addMF(var,"trimf",[5 7.5 10],"Name","large");
```

View the membership functions.

```
var.MembershipFunctions
```

```
ans = 
  1x3 fismf array with properties:

    Name
    Type
    Parameters

  Details:
           Name        Type          Parameters    
         ________    _______    __________________

    1    "small"     "trimf"      0    2.5       5
    2    "medium"    "trimf"    2.5      5     7.5
    3    "large"     "trimf"      5    7.5      10
```

Remove the `medium` membership function from the variable.

```
var = removeMF(var,"medium");
```

Verify that the membership was removed.

```
var.MembershipFunctions
```

```
ans = 
  1x2 fismf array with properties:

    Name
    Type
    Parameters

  Details:
          Name        Type         Parameters   
         _______    _______    ________________

    1    "small"    "trimf"    0    2.5       5
    2    "large"    "trimf"    5    7.5      10
```

Input Arguments

`fisIn` — Input fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

`varName` — Variable name
string | character vector

Variable name, specified as a string or character vector. You can specify the name of either an input or output variable in your FIS.

`mfName` — Membership function name
string | character vector

Membership function name, specified as a string or character vector.

`varType` — Variable type
string | character vector

Variable type, specified as one of the following:

- `"input"` — Input variable
- `"output"` — Output variable

If your system has an input variable with the same name as an output variable, specify which variable to remove the membership function from using `varType`.

`varIn` — Fuzzy variable
`fisvar` object

Fuzzy variable, specified as a `fisvar` object.

Output Arguments

`fisOut` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, returned as a `mamfis` or `sugfis` object. `fisOut` has the same properties as `fisIn` except:

- The membership function with the specified name is removed from the specified variable.
- The specified membership function is removed from any fuzzy rules. If a rule has only the specified membership function in its antecedent, then the entire rule is removed. If

a rule has more than one membership function in its antecedent, then the specified membership function is removed from the antecedent.

`varOut` — Fuzzy variable
`fisvar` object

Fuzzy variable, returned as a `fisvar` object. `varOut` has the same properties as `varIn` except the membership function with the specified name is removed.

See Also
`addMF` | `fisvar` | `mamfis` | `sugfis`

Topics
"Build Fuzzy Systems at the Command Line" on page 2-38

Introduced in R2018b

removeOutput

Remove output variable from fuzzy inference system

Syntax

```
fisOut = removeOutput(fisIn,outputName)
```

Description

`fisOut = removeOutput(fisIn,outputName)` removes the output variable with the name `outputName` from fuzzy inference system `fisIn` and returns the resulting fuzzy system in `fisOut`.

Examples

Remove Output Variable from Fuzzy Inference System

Load fuzzy system.

```
fis = readfis("mam22");
```

View the output variables of `fis`.

```
fis.Outputs
```

```
ans = 
  1x2 fisvar array with properties:

    Name
    Range
    MembershipFunctions

  Details:
             Name        Range       MembershipFunctions
           ________    ________    ___________________
    1    "force"     -5     5         [1x4 fismf]
    2    "force2"    -5     5         [1x4 fismf]
```

View the rules of `fis`.

```
fis.Rules
```

```
ans = 
  1x4 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                                     Description                               
         ______________________________________________________________________

    1    "angle==small & velocity==small => force=negBig, force2=posBig2 (1)"    
    2    "angle==small & velocity==big => force=negSmall, force2=posSmall2 (1)"
    3    "angle==big & velocity==small => force=posSmall, force2=negSmall2 (1)"
    4    "angle==big & velocity==big => force=posBig, force2=negBig2 (1)"      
```

Remove the `forceBig` output variable.

```
fis = removeOutput(fis,"force2");
```

View the updated output variables.

```
fis.Outputs
```

```
ans = 
  fisvar with properties:

                   Name: "force"
                  Range: [-5 5]
    MembershipFunctions: [1x4 fismf]
```

View the updated rules.

```
fis.Rules

ans = 
  1x4 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                           Description                  
         ____________________________________________________

    1    "angle==small & velocity==small => force=negBig (1)"
    2    "angle==small & velocity==big => force=negSmall (1)"
    3    "angle==big & velocity==small => force=posSmall (1)"
    4    "angle==big & velocity==big => force=posBig (1)"
```

`force2` has been removed from the variables and rules of `fis`.

Input Arguments

`fisIn` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

`outputName` — Output variable name
string | character vector

Output variable name, specified as a string or character vector.

Output Arguments

`fisOut` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, returned as a `mamfis` or `sugfis` object. `fisOut` has the same properties as `fisIn` except:

- The input variable with the specified name is removed.
- The specified input variable is removed from any fuzzy rules. If a rule has only the specified input variable in its antecedent, then the entire rule is removed. If a rule has more than one input variable in its antecedent, then the specified input variable is removed from the antecedent.

See Also
`addOutput` | `fisvar` | `mamfis` | `sugfis`

Topics
"Build Fuzzy Systems at the Command Line" on page 2-38

Introduced in R2018b

rmmf

(To be removed) Remove membership function from fuzzy inference system

Note `rmmf` will be removed in a future release. Use `removeMF` instead. For more information, see “Compatibility Considerations”.

Syntax

```
fis = rmmf(fis,varType,varIndex,'mf',mfIndex)
```

Description

`fis = rmmf(fis,varType,varIndex,'mf',mfIndex)` removes the membership function, `mfIndex`, of variable type `varType`, of index `varIndex`, from the fuzzy inference system associated with the workspace FIS structure, `fis`:

- Specify `varType` as either `'input'` or `'output'`.
- `varIndex` is an integer for the index of the variable. This index represents the order in which the variables are listed.
- `mfIndex` is an integer for the index of the membership function. This index represents the order in which the membership functions are listed.

Examples

Remove Membership Function From Variable

Create fuzzy inference system.

```
fis = newfis('mysys');
```

Add an input variable with a single membership function to the system.

```
fis = addvar(fis,'input','temperature',[0 100]);
fis = addmf(fis,'input',1,'cold','trimf',[0 30 60]);
```

View the variable properties.

```
getfis(fis,'input',1)
```

```
ans = struct with fields:
      Name: 'temperature'
    NumMFs: 1
       mf1: 'cold'
     range: [0 100]
```

Remove the membership function. To do so, remove membership function `1` from input `1`.

```
fis = rmmf(fis,'input',1,'mf',1);
```

View the variable properties.

```
getfis(fis,'input',1)
```

```
ans = struct with fields:
      Name: 'temperature'
    NumMFs: 0
     range: [0 100]
```

The variable now has no membership function.

Compatibility Considerations

`rmmf` will be removed

Not recommended starting in R2018b

`rmmf` will be removed in a future release. Use `removeMF` instead. There are differences between these functions that require updates to your code.

Update Code

The following table shows some typical usages of `rmmf` and how to update your code to use `removeMF` instead. Previously, you specified the index of the variable from which you wanted to remove the membership function and the index of the membership function that you wanted to remove. Now, to remove a membership function, specify the variable name and the membership function name.

If your code has this form:	Use this code instead:
`fis = rmmf(fis,'input',1,'mf',1)`	`fis = removeMF(fis,"service","poor")`
`fis = rmmf(fis,'output',1,'mf',1)`	`fis = removeMF(fis,"tip","cheap")`

See Also

`addMF` | `addRule` | `addvar` | `plotmf` | `removeMF` | `rmvar`

Topics

"Membership Functions" on page 1-14
"The Membership Function Editor" on page 2-22

Introduced before R2006a

rmvar

(To be removed) Remove variables from fuzzy inference system

Note `rmvar` will be removed in a future release. Use `removeInput` or `removeOutput` instead. For more information, see "Compatibility Considerations".

Syntax

```
fis = rmvar(fis,varType,varIndex)
[fis,errorStr] = rmvar(fis,varType,varIndex)
```

Description

`fis = rmvar(fis,varType,varIndex)` removes the variable `varType`, of index `varIndex`, from the fuzzy inference system associated with the workspace FIS structure, `fis`:

- Specify`varType` as either `'input'` or `'output'`.
- `varIndex` is an integer for the index of the variable. This index represents the order in which the variables are listed.

`[fis,errorStr] = rmvar(fis,varType,varIndex)` returns any error messages to the character vector, `errorStr`.

This command automatically alters the rule list to keep its size consistent with the current number of variables. You must delete from the FIS any rule that contains a variable you want to remove, before removing it. You cannot remove a fuzzy variable currently in use in the rule list.

Examples

Remove Membership Function From Variable

Create fuzzy inference system.

```
fis = newfis('mysys');
```

Add an input variable with a single membership function to the system.

```
fis = addvar(fis,'input','temperature',[0 100]);
fis = addmf(fis,'input',1,'cold','trimf',[0 30 60]);
```

View the variable properties.

```
getfis(fis,'input',1)
```

```
ans = struct with fields:
      Name: 'temperature'
    NumMFs: 1
       mf1: 'cold'
     range: [0 100]
```

Remove the membership function. To do so, remove membership function `1` from input `1`.

```
fis = rmmf(fis,'input',1,'mf',1);
```

View the variable properties.

```
getfis(fis,'input',1)
```

```
ans = struct with fields:
      Name: 'temperature'
    NumMFs: 0
     range: [0 100]
```

The variable now has no membership function.

Compatibility Considerations

`rmvar` will be removed

Not recommended starting in R2018b

`rmvar` will be removed in a future release. Use `removeInput` or `removeOutput` instead. There are differences between these functions that require updates to your code.

To remove input or output variables from a fuzzy system, use `removeInput` or `removeOutput`, respectively.

Update Code

This table shows some typical usages of `rmvar` and how to update your code to use `removeInput` or `removeOutput` instead. Previously, you specified the index of the variable that you wanted to remove. Now, to remove a variable, specify the variable name.

If your code has this form:	Use this code instead:
`fis = rmvar(fis,'input',1)`	`fis = removeInput(fis,"service")`
`fis = rmvar(fis,'output',1)`	`fis = removeOutput(fis,"tip")`

Previously, you had to delete any rules from your fuzzy system that contained the variable you wanted to remove. `removeInput` and `removeOutput` automatically remove these variables from the rule set of your fuzzy system.

See Also

`addMF` | `addRule` | `addvar` | `removeInput` | `removeOutput` | `rmmf`

Introduced before R2006a

ruleedit

Open Rule Editor

Syntax

`ruleedit(fileName)`

`ruleedit(fis)`

Description

`ruleedit(fileName)` opens the Rule Editor for the FIS stored in the file, `fileName`. Specify `fileName` as a character vector or string with or without the `.fis` extension. You can use the Rule Editor to view or modify the rules of an FIS.

To use this editor to create rules, you must first define all of the input and output variables you want to use with the FIS Editor. You can create the rules using the drop-down and check box choices for input and output variables, connections, and weights. Refer to "The Rule Editor" on page 2-30 for more information about how to use `ruleedit`.

`ruleedit(fis)` operates on a `mamfis` or `sugfis` object, `fis`.

Menu Items

In the Rule Editor, there is a menu bar that allows you to open related UI tools, open and save systems, and so on. The **File** menu for the Rule Editor is the same as the one found **Fuzzy Logic Designer**:

- Use the following **Edit** menu item:

  Undo to undo the most recent change.

  FIS properties to open the **Fuzzy Logic Designer**.

  Membership functions to invoke the Membership Function Editor.

- Use the following **View** menu items:

  Rules to invoke the Rule Viewer.

  Surface to invoke the Surface Viewer.
- Use the **Options** menu items:

  Language to select the language: **English**, **Deutsch**, and **Francais**

  Format to select the format:

  Verbose uses the words "if," "then," "AND," "OR," and so on to create actual sentences.

  Symbolic substitutes some symbols for the words used in the verbose mode. For example, *“*if *A* AND *B* then *C*" becomes "*A* & *B* => *C*."

  Indexed mirrors how the rule is stored in the FIS object.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

Apps
Fuzzy Logic Designer

Functions
`addRule` | `mfedit` | `ruleview` | `showrule` | `surfview`

Topics

"The Rule Editor" on page 2-30

Introduced before R2006a

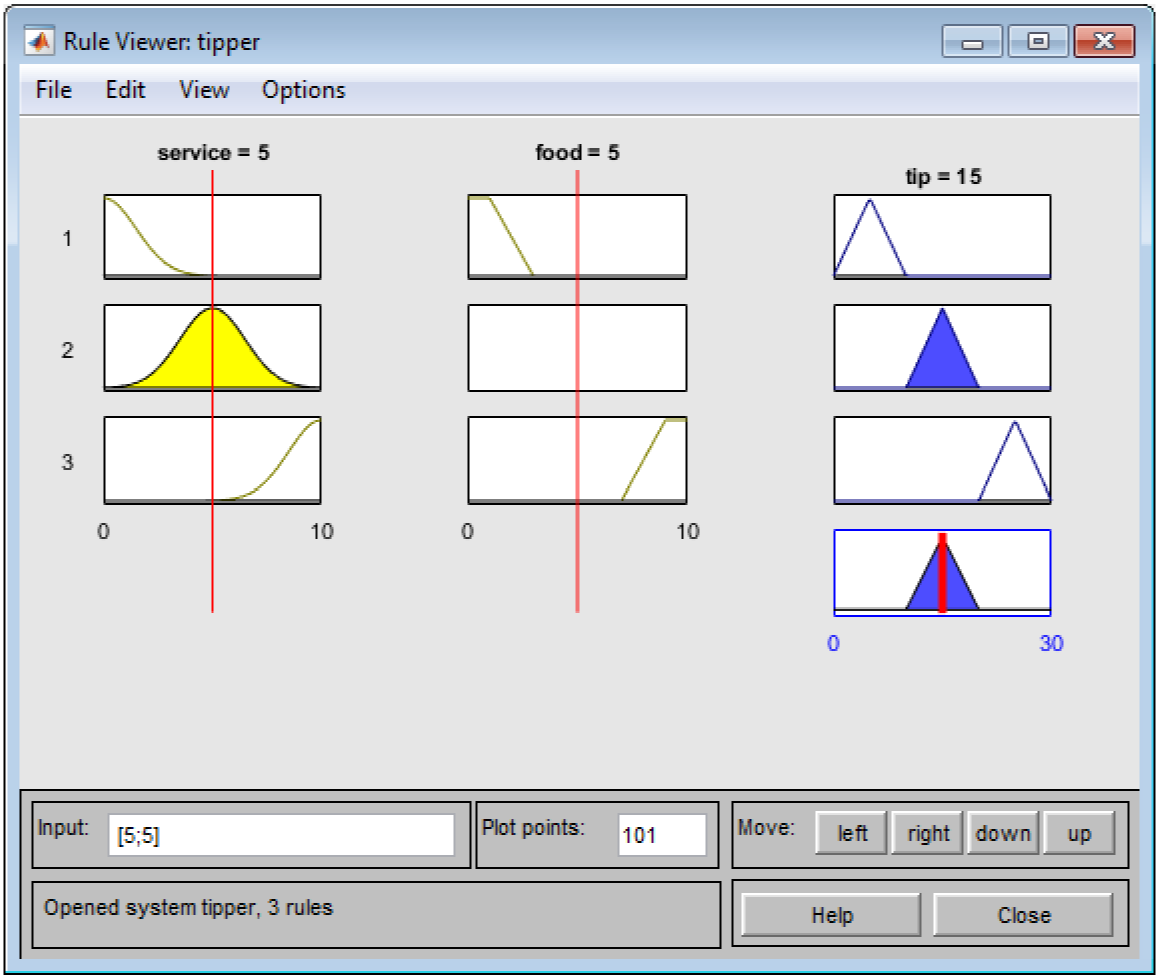
ruleview

Open Rule Viewer

Syntax

```
ruleview(fis)
ruleview(fileName)
```

Description



Opened system tipper, 3 rules

`ruleview(fis)` opens the Rule Viewer for the fuzzy inference system, `fis`. Specify `fis` as a `mamfis` or `sugfis` object. The Rule Viewer is used to view the entire implication process from beginning to end. You can move around the line indices that correspond to the inputs and then watch the system readjust and compute the new output. Refer to “The Rule Viewer” on page 2-33 for more information about how to use `ruleview`.

`ruleview(fileName)` depicts the fuzzy inference diagram for the fuzzy inference system stored in file `fileName`. Specify `fileName` as a character vector or string with or without the `.fis` extension.

Menu Items

In the Rule Viewer, there is a menu bar that allows you to open related UI tools, open and save systems, and so on. The **File** menu for the Rule Viewer is the same as the one found in the **Fuzzy Logic Designer**.

- Use the **Edit** menu items:

  Undo to undo the most recent action

  FIS properties to open the **Fuzzy Logic Designer**

  Membership functions to invoke the Membership Function Editor

  Rules to invoke the Rule Editor
- Use the **View** menu item:

  Surface to invoke the Surface Viewer
- Use the **Options** menu item:

  Format to set the format in which the rule appears: **Verbose, Symbolic,** or **Indexed**.

If you click on the rule numbers on the left side of the fuzzy inference diagram, the rule associated with that number appears in the status bar at the bottom of the Rule Viewer.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

Apps
Fuzzy Logic Designer

Functions
`addRule` | `mfedit` | `ruleedit` | `showrule` | `surfview`

Topics
“The Rule Viewer” on page 2-33

Introduced before R2006a

setfis

(To be removed) Set fuzzy system properties

Note `setfis` will be removed in a future release. Set fuzzy inference system properties using dot notation instead. For more information, see "Compatibility Considerations".

Syntax

```
fis = setfis(fis,fisPropName,fisPropVal)
```

```
fis = setfis(fis,varType,varIndex,varPropName,varPropVal)
```

```
fis = setfis(fis,varType,varIndex,'mf',mfIndex,mfPropName,mfPropVal)
```

Description

The command `setfis` can be called with three, five, or seven input arguments, depending on whether you want to set a property of the entire FIS structure, for a particular variable belonging to that FIS structure, or for a particular membership function belonging to one of those variables. The arguments are:

- `fis` — FIS structure in the MATLAB workspace.
- `varType` — Variable type, specified as either `'input'` or `'output'`.
- `varIndex` — Variable index, specified as a positive integer.
- `mfIndex` — Membership function index, specified as a positive integer.
- `fisPropName` — FIS property you want to set, specified as one of the following:
  - `'name'`
  - `'type'`
  - `'andmethod'`
  - `'ormethod'`
  - `'impmethod'`

  - `'aggmethod'`
  - `'defuzzmethod'`
- `fisPropVal` — New value of the FIS property you want to set, specified as a character vector or string.
- `varPropName` — Variable property you want to set, specified as either `'name'` or `'range'`.
- `varPropVal` — New value of the variable property you want to set, specified as a character vector or string (for `'name'`), or a two-element row vector (for `'range'`).
- `mfPropName` — Membership function property you want to set, specified as either `'name'`, `'type'`, or `'params'`.
- `mfPropVal` — New value of the membership function property you want to set, specified as a character vector or string (for `'name'` or `'type'`), or a numerical row vector (for `'params'`).

Examples

Set Fuzzy Inference System Properties

Load a fuzzy inference system.

```
fis = readfis('tipper');
```

Set the defuzzification method to the bisector method.

```
fis = setfis(fis,'defuzzmethod','bisector');
```

View the defuzzification method of the updated FIS.

```
getfis(fis,'defuzzmethod')
```

```
ans =
'bisector'
```

Set Variable Properties in FIS

Load fuzzy inference system.

```
fis = readfis('tipper');
```

Set the name of the first input variable to `'help'`.

```
fis = setfis(fis,'input',1,'name','help');
```

View the name of the variable in the updated system.

```
getfis(fis,'input',1,'name')
```

```
ans =
'help'
```

Set Membership Function Properties in FIS

Load a fuzzy inference system.

```
fis = readfis('tipper');
```

Change the type of the second membership function of the first input variable to a triangular membership function.

```
fis = setfis(fis,'input',1,'mf',2,'type','trimf');
```

When changing the type of a membership function, you must also set the parameters accordingly. To convert the original Gaussian membership function parameters to triangular membership function parameters, use the `mf2mf` command.

```
gaussParams = getfis(fis,'input',1,'mf',2,'params');
triParams = mf2mf(gaussParams,'gaussmf','trimf');
```

Set the membership function parameters to the converted values.

```
fis = setfis(fis,'input',1,'mf',2,'params',triParams);
```

View the updated membership function properties.

```
getfis(fis,'input',1,'mf',2)
```

```
ans = struct with fields:
      Name: 'good'
      Type: 'trimf'
```

```
    params: [1.4680 5 8.5320]
```

Compatibility Considerations

`setfis` will be removed

Not recommended starting in R2018b

`setfis` will be removed in a future release. Set fuzzy inference system properties using dot notation instead. There are differences between these approaches that require updates to your code.

Update Code

This table shows some typical usages of `setfis` for setting fuzzy inference system properties and how to update your code to use dot notation instead.

If your code has this form:	Use this code instead:
`fis = setfis(fis,'andmethod','prod')`	`fis.AndMethod = 'prod'`
`fis = setfis(fis,'input',1,... 'name','service')`	`fis.Inputs(1).Name = "service"`
`fis = setfis(fis,'input',2,... 'mf',1,... params,[5 10 15])`	`fis.Inputs(2).MembershipFunctions(1).Parameters [5 10 15]`

Previously, fuzzy inference systems were represented as structures. Now, fuzzy inference systems are represented as objects. Fuzzy inference system object properties have different names than the corresponding structure fields. For more information on fuzzy inference system objects, see `mamfis` and `sugfis`.

See Also

`getfis`

Introduced before R2006a

setTunable

Set specified parameter settings as tunable or nontunable

Syntax

```
paramset = setTunable(paramset,boolflag)
```

Description

`paramset = setTunable(paramset,boolflag)` sets `paramset` as tunable or nontunable using `boolflag`.

Examples

Specify Tunability of a Parameter Setting

Create a fuzzy inference system, and define the tunable parameter settings of inputs, outputs, and rules.

```
fis = mamfis("NumInputs",2,"NumOutputs",2);
[in,out,rule] = getTunableSettings(fis);
```

Specify a parameter setting, and set its tunability.

Set the first input of the FIS as nontunable.

```
in(1) = setTunable(in(1),false);
```

You can set individual membership functions as nontunable. For example, set the first membership function of output 1 as nontunable.

```
out(1).MembershipFunctions(1) = setTunable(out(1).MembershipFunctions(1),false);
```

You can also specify multiple parameter settings. Set the first two rules as nontunable.

```
rule(1:2) = setTunable(rule(1:2),false);
```

Input Arguments

`paramset` — Tunable parameter settings
array

Tunable parameter settings, specified as an array of input, output, and rule parameter settings of a fuzzy system. To obtain these parameter settings, use `getTunableSettings` with the input FIS. `paramset` can be the input parameter, the output parameter, the rule parameter, or some combination of these parameters as an array. The contents of the array depend on which parameters you would like to set.

`boolflag` — Fuzzy system tunability
`true` or `1` | `false` or `0`

Fuzzy system tunability, specified as a numeric or logical `1` (`true`) or `0` (`false`). If `true`, `paramset` can be used for tuning parameters of a fuzzy system.

See Also

`getTunableSettings` | `mamfis` | `sugfis` | `tunefis`

Introduced in R2019a

setTunableValues

Specify tunable parameter values of a fuzzy inference system

Syntax

```
fis = setTunableValues(fis,paramset,paramvals)
fis = setTunableValues( ___ ,'IgnoreInvalidParameters',ignoreInvalid)
```

Description

`fis = setTunableValues(fis,paramset,paramvals)` sets the tunable parameter values of `fis` to the new values in `paramvals` using `paramset`.

`fis = setTunableValues( ___ ,'IgnoreInvalidParameters',ignoreInvalid)` sets a flag for ignoring invalid parameters values.

Examples

Specify Tunable Parameter Values of a FIS

Create a fuzzy inference system and define the tunable parameter settings of inputs, outputs, and rules.

```
fis = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
[in,out,rule] = getTunableSettings(fis);
```

Obtain tunable parameter values of the inputs, outputs, and rules of the fuzzy inference system.

```
paramVals = getTunableValues(fis,[in;out;rule]);
```

Redefine some of the values and update the tunable parameter values of the FIS.

```
paramVals(1:3) = [0 0 1];
fis = setTunableValues(fis,[in;out;rule],paramVals);
```

Input Arguments

`fis` — Fuzzy system
`mamfis` object | `sugfis` object | `fistree` object

Fuzzy system, specified as a `mamfis`, `sugfis`, or `fistree` object. The fuzzy system can be a fuzzy inference system or network of interconnected fuzzy inference systems. It is created using `mamfis`, `sugfis`, `genfis`, or `fistree`.

`paramset` — Tunable parameter settings
array

Tunable parameter settings, specified as an array of input, output, and rule parameter settings in the input FIS. To obtain these parameter settings, use `getTunableSettings` with the input FIS. `paramset` can be the input parameter, the output parameter, the rule parameter, or some combination of these parameters as an array. The contents of the array depend on which parameters you would like to set.

`paramvals` — Tunable parameter values
array

Tunable parameter values, specified as a numeric array. These are the updated tunable parameter values of `fis`. Use `getTunableValues` to obtain the full array of tunable parameter values. Then, specify the values in the array that you would like to change.

`ignoreInvalid` — Flag to ignore invalid parameters
array

Flag to ignore invalid parameters, specified as either `true` or `false`. If `true`, invalid `paramvals` are replaced with the existing parameter values of a fuzzy system.

See Also

`getTunableSettings` | `getTunableValues` | `mamfis` | `sugfis` | `tunefis`

Introduced in R2019a

showfis

(To be removed) Display annotated Fuzzy Inference System

Note `showfis` will be removed in a future release. View the properties of your FIS directly instead. For more information, see “Compatibility Considerations”.

Syntax

```
showfis(fismat)
```

Description

`showfis(fismat)` prints a version of the MATLAB workspace variable FIS, `fismat`, allowing you to see the significance and contents of each field of the structure.

Examples

```
a = readfis('tipper');
showfis(a)
```

Returns:

```
1.  Name             tipper
2.  Type             mamdani
3.  Inputs/Outputs   [2 1]
4.  NumInputMFs      [3 2]
5.  NumOutputMFs     3
6.  NumRules         3
7.  AndMethod        min
8.  OrMethod         max
9.  ImpMethod        min
10. AggMethod        max
11. DefuzzMethod     centroid
12. InLabels         service
13.                  food
```

```
14. OutLabels        tip
15. InRange          [0 10]
16.                  [0 10]
17. OutRange         [0 30]
18. InMFLabels       poor
19.                  good
20.                  excellent
21.                  rancid
22.                  delicious
23. OutMFLabels      cheap
24.                  average
25.                  generous
26. InMFTypes        gaussmf
27.                  gaussmf
28.                  gaussmf
29.                  trapmf
30.                  trapmf
31. OutMFTypes       trimf
32.                  trimf
33.                  trimf
34. InMFParams       [1.5 0 0 0]
35.                  [1.5 5 0 0]
36.                  [1.5 10 0 0]
37.                  [0 0 1 3]
38.                  [7 9 10 10]
39. OutMFParams      [0 5 10 0]
40.                  [10 15 20 0]
41.                  [20 25 30 0]
42. Rule Antecedent  [1 1]
43.                  [2 0]
44.                  [3 2]
42. Rule Consequent  1
43.                  2
44.                  3
42. Rule Weight      1
43.                  1
44.                  1
42. Rule Connection  2
43.                  1
44.                  2
```

Compatibility Considerations

`showfis` will be removed

Not recommended starting in R2018b

`showfis` will be removed in a future release. View the properties of your FIS directly instead.

Previously, you could view the properties of your fuzzy system, `myFIS`, using the `showfis` function.

```
showfis(myFIS)
```

Now, you can view the properties directly instead.

```
myFIS
```

To view additional FIS properties, use dot notation. For example, view information about the membership functions of the first input variable.

```
myFIS.Inputs(1).MembershipFunctions
```

For more information on fuzzy inference systems and their properties, see `mamfis` and `sugfis`.

See Also

`getfis`

Introduced before R2006a

showrule

Display fuzzy inference system rules

Syntax

```
showrule(fis)
showrule(fis,Name,Value)
```

Description

`showrule(fis)` displays the rules in the fuzzy inference system, `fis`.

`showrule(fis,Name,Value)` displays rules using options specified by one or more `Name,Value` pair arguments.

Examples

Display All Rules for a Fuzzy Inference System

Load fuzzy inference system.

```
fis = readfis('tipper');
```

Display rules using linguistic expressions.

```
showrule(fis)
```

```
ans = 3x78 char array
    '1. If (service is poor) or (food is rancid) then (tip is cheap) (1)           '
    '2. If (service is good) then (tip is average) (1)                             '
    '3. If (service is excellent) or (food is delicious) then (tip is generous) (1)'
```

Display rules using symbolic expressions.

```
showrule(fis,'Format','symbolic')
```

```
ans = 3x65 char array
    '1. (service==poor) | (food==rancid) => (tip=cheap) (1)           '
    '2. (service==good) => (tip=average) (1)                          '
    '3. (service==excellent) | (food==delicious) => (tip=generous) (1)'
```

Display rules using membership function indices.

```
showrule(fis,'Format','indexed')
```

```
ans = 3x15 char array
    '1 1, 1 (1) : 2 '
    '2 0, 2 (1) : 1 '
    '3 2, 3 (1) : 2 '
```

Select Fuzzy Rules to Display

Load fuzzy inference system.

```
fis = readfis('tipper');
```

Display the first and third rules.

```
showrule(fis,'RuleIndex',[1 3])
```

```
ans = 2x78 char array
    '1. If (service is poor) or (food is rancid) then (tip is cheap) (1)           '
    '3. If (service is excellent) or (food is delicious) then (tip is generous) (1)'
```

Display Fuzzy Rules in German Language

Load fuzzy inference system.

```
fis = readfis('tipper');
```

Display the rules in German using the `'deutsch'` language.

```
showrule(fis,'Language','deutsch')

ans = 3x85 char array
    '1. Wenn (service ist poor) oder (food ist rancid) dann (tip ist cheap) (1)
    '2. Wenn (service ist good) dann (tip ist average) (1)
    '3. Wenn (service ist excellent) oder (food ist delicious) dann (tip ist generous)
```

Input Arguments

fis — Fuzzy inference system
mamfis object | sugfis object

Fuzzy inference system, specified as a mamfis or sugfis object.

Name-Value Pair Arguments

Specify optional comma-separated pairs of Name,Value arguments. Name is the argument name and Value is the corresponding value. Name must appear inside quotes. You can specify several name and value pair arguments in any order as Name1,Value1,...,NameN,ValueN.

Example: 'Format','symbolic' sets the rule display format to use language-neutral symbolic expressions.

RuleIndex — Rules to display
positive integer | vector of positive integers

Rules to display, specified as the comma-separated pair consisting of 'RuleIndex' and one of the following:

- Positive integer — Index of a single rule to display
- Vector of positive integers — Indices of multiple rules to display

The default vector includes the indices for all the rules in fis.

Format — Rule format
'verbose' (default) | 'symbolic' | 'indexed'

Rule format, specified as the comma-separated pair consisting of `'Format'` and one of the following:

- `'verbose'` — Use linguistic expressions.

  ```
  'If (service is poor) or (food is rancid) then (tip is cheap) (1)'
  ```

  The rule weight is displayed in parentheses at the end of the rule.

  You can specify the rule language using the `Language` option.
- `'symbolic'` — Use language-neutral symbolic expressions.

  ```
  '(service==poor) | (food==rancid) => (tip=cheap) (1)'
  ```

  The symbolic rules use the following symbols.

Rule Component	Symbol
AND	&
OR	|
IS (in antecedent)	==
IS (in consequent)	=
IS NOT	~=
Implication (then)	=>

  The rule weight is displayed in parentheses at the end of the rule.
- `'indexed'` — Use input and output membership function (MF) indices and integer representation of fuzzy operators.

  The indexed rules display in the following format:

  ```
  '<input MFs>, <output MFs>, (<weight>) : <logical operator - 1 (AND), 2 (OR)>'
  ```

  For example:

  ```
  '1 1, 1 (1) : 2'
  ```

  To indicate NOT operations for input and output membership functions, the software uses negative indices. For example, to indicate “not the second membership function,” the software uses `-2`.

To indicate a don't care condition for an input or output membership function, the software uses `0`.

Language — Rule language
`'english'` (default) | `'francais'` | `'deutsch'`

Rule language for `'verbose'` format, specified as the comma-separated pair consisting of `'Language'` and one of the following:

- `'english'` — Display rules in English.

  ```
  'If (service is poor) or (food is rancid) then (tip is cheap) (1)'
  ```
- `'francais'` — Display rules in French.

  ```
  'Si (service est poor) ou (food est rancid) alors (tip est cheap) (1)'
  ```
- `'deutsch'` — Display rules in German.

  ```
  'Wenn (service ist poor) oder (food ist rancid) dann (tip ist cheap) (1)'
  ```

The software displays the FIS rules using the following keywords.

Rule Component	English	French	German
Start of antecedent	`if`	`si`	`wenn`
AND	`and`	`et`	`und`
OR	`or`	`ou`	`oder`
Start of consequent (implication)	`then`	`alors`	`dann`
IS	`is`	`est`	`ist`
IS NOT	`is not`	`n''est_pas`	`ist nicht`

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed
Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

`addRule` | `ruleedit`

Introduced before R2006a

sigmf

Sigmoidal membership function

This function computes fuzzy membership values using the difference between two sigmoidal membership functions. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-272.

This membership function is related to the `dsigmf` and `psigmf` membership functions.

Syntax

```
y = dsigmf(x,params)
```

Description

`y = dsigmf(x,params)` returns fuzzy membership values computed using the sigmoidal membership function given by:

$$f(x;a,c) = \frac{1}{1 + e^{-a(x-c)}}$$

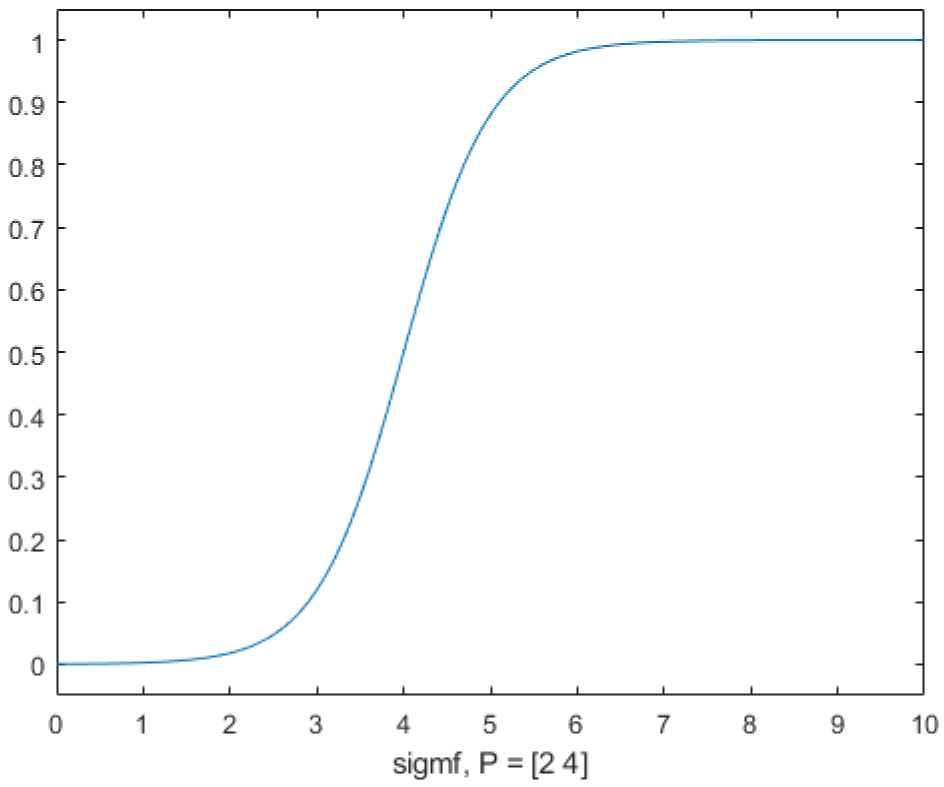
To specify the a and c parameters, use `params`.

Membership values are computed for each input value in `x`.

Examples

Sigmoidal Membership Function

```
x = 0:0.1:10;
y = sigmf(x,[2 4]);
plot(x,y)
xlabel('sigmf, P = [2 4]')
ylim([-0.05 1.05])
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length four

Membership function parameters, specified as the vector [*a* *c*]. To open the membership function to the left or right, specify a negative or positive value for *a*, respectively. The magnitude of *a* defines the width of the transition area, and *c* defines the center of the transition area.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `sigmf` membership function.

```
mf = fismf("igmf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `sigmf`, respectively.

Extended Capabilities

C/C++ Code Generation
Generate C and C++ code using MATLAB® Coder™.

See Also
`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

"Membership Functions" on page 1-14

Introduced before R2006a

smf

S-shaped membership function

This function computes fuzzy membership values using a spline-based S-shaped membership function. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-276.

This membership function is related to the `zmf` and `pimf` membership functions.

Syntax

```
y = smf(x,params)
```

Description

`y = smf(x,params)` returns fuzzy membership values computed using the spline-based S-shaped membership function given by:

$$f(x;a,b) = \begin{cases} 0, & x \le a \\ 2\left(\frac{x-a}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ 1-2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \le x \le b \\ 1, & x \ge b \end{cases}$$

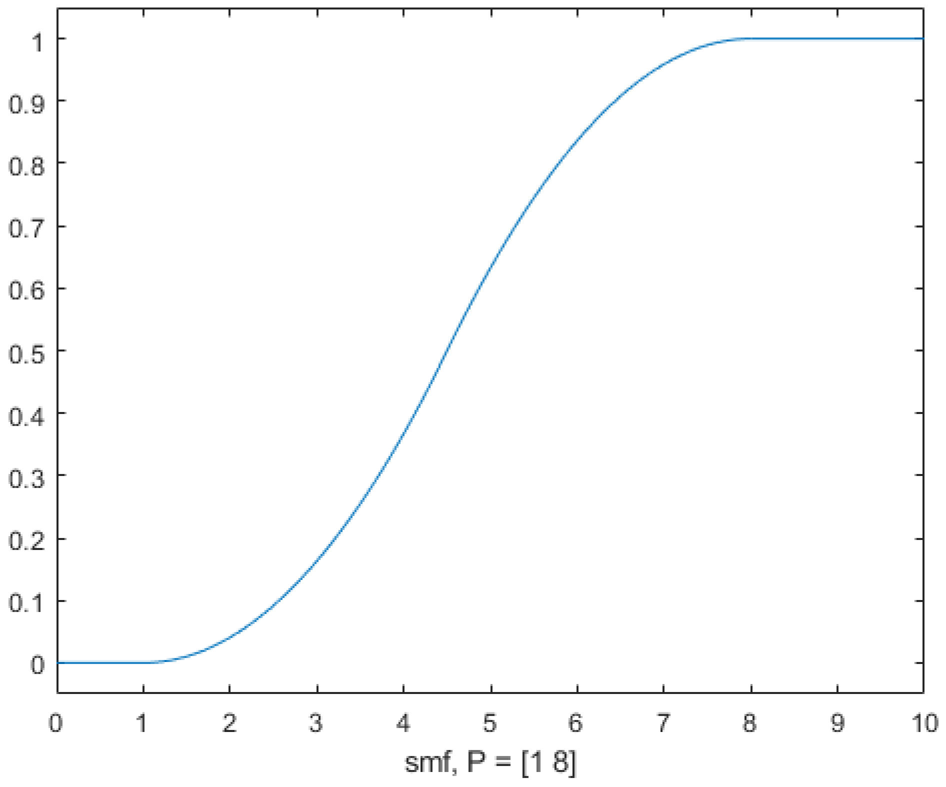
To specify the *a* and *b* parameters, use `params`.

Membership values are computed for each input value in `x`.

Examples

S-Shaped Membership Function

```
x = 0:0.1:10;
y = smf(x,[1 8]);
plot(x,y)
xlabel('smf, P = [1 8]')
ylim([-0.05 1.05])
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

params — Membership function parameters
vector of length two

Membership function parameters, specified as the vector [*a* *b*]. Parameter *a* defines the *foot* of the membership function, and *b* defines its *shoulder*.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `smf` membership function.

```
mf = fismf("smf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `smf`, respectively.

Extended Capabilities

C/C++ Code Generation
Generate C and C++ code using MATLAB® Coder™.

See Also

`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

"Membership Functions" on page 1-14

Introduced before R2006a

subclust

Find cluster centers using subtractive clustering

Syntax

```
centers = subclust(data,clusterInfluenceRange)
centers = subclust(data,clusterInfluenceRange,Name,Value)
[centers,sigma] = subclust( ___ )
```

Description

`centers = subclust(data,clusterInfluenceRange)` clusters input data using subtractive clustering with the specified cluster influence range, and returns the computed cluster centers. The subtractive clustering algorithm on page 8-283 estimates the number of clusters in the input data.

`centers = subclust(data,clusterInfluenceRange,Name,Value)` clusters data using algorithm options specified by one or more `Name,Value` pair arguments.

`[centers,sigma] = subclust( ___ )` returns the sigma values specifying the range of influence of a cluster center in each of the data dimensions.

Examples

Find Cluster Centers Using Subtractive Clustering

Load data set.

```
load clusterdemo.dat
```

Find cluster centers using the same range of influence for all dimensions.

```
C = subclust(clusterdemo,0.6);
```

Each row of `C` contains one cluster center.

```
C
```

```
C = 3×3

    0.5779    0.2355    0.5133
    0.7797    0.8191    0.1801
    0.1959    0.6228    0.8363
```

Specify Bounds for Subtractive Clustering

Load data set.

```
load clusterdemo.dat
```

Define minimum and maximum normalization bounds for each data dimension. Use the same bounds for each dimension.

```
dataScale = [-0.2 -0.2 -0.2;
              1.2  1.2  1.2];
```

Find cluster centers.

```
C = subclust(clusterdemo,0.5,'DataScale',dataScale);
```

Specify Options for Subtractive Clustering

Load data set.

```
load clusterdemo.dat
```

Specify the following clustering options:

- Squash factor of `2.0` - Only find clusters that are far from each other.
- Accept ratio `0.8` - Only accept data points with a strong potential for being cluster centers.
- Reject ratio of `0.7` - Reject data points if they do not have a strong potential for being cluster centers.

- Verbosity flag of `0` - Do not print progress information to the command window.

```
options = [2.0 0.8 0.7 0];
```

Find cluster centers, using a different range of influence for each dimension and the specified options.

```
C = subclust(clusterdemo,[0.5 0.25 0.3],'Options',options);
```

Obtain Cluster Influence Range for Each Data Dimension

Load data set.

```
load clusterdemo.dat
```

Cluster data, returning cluster sigma values, `S`.

```
[C,S] = subclust(clusterdemo,0.5);
```

Cluster sigma values indicate the range of influence of the computed cluster centers in each data dimension.

Input Arguments

data — Data set to be clustered
M-by-*N* array

Data to be clustered, specified as an *M*-by-*N* array, where *M* is the number of data points and *N* is the number of data dimensions.

`clusterInfluenceRange` — Range of influence of the cluster center
scalar value in the range [`0`, `1`] | vector

Range of influence of the cluster center for each input and output assuming the data falls within a unit hyperbox, specified as the comma-separated pair consisting of `'ClusterInfluenceRange'` one of the following:

- Scalar value in the range `[0 1]` — Use the same influence range for all inputs and outputs.

- Vector — Use different influence ranges for each input and output.

Specifying a smaller range of influence usually creates more and smaller data clusters, producing more fuzzy rules.

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'DataScale','auto'`sets the normalizing factors for the input and output signals using the minimum and maximum values in the data set to be clustered.

`DataScale` — Data scale factors

`'auto'` (default) | 2-by-*N* array

Data scale factors for normalizing input and output data into a unit hyperbox, specified as the comma-separated pair consisting of `'DataScale'` and a 2-by-*N* array, where *N* is the total number of inputs and outputs. Each column of `DataScale` specifies the minimum value in the first row and the maximum value in the second row for the corresponding input or output data set.

When `DataScale` is `'auto'`, the `genfis` command uses the actual minimum and maximum values in the data to be clustered.

`Options` — Clustering options

vector

Clustering options, specified as the comma-separated pair consisting of `'Options'` and a vector with the following elements:

`Options(1)` — Squash factor

`1.25` (default) | positive scalar

Squash factor for scaling the range of influence of cluster centers, specified as a positive scalar. A smaller squash factor reduces the potential for outlying points to be considered as part of a cluster, which usually creates more and smaller data clusters.

`Options(2)` — Acceptance ratio

`0.5` (default) | scalar value in the range [`0`, `1`]

Acceptance ratio, defined as a fraction of the potential of the first cluster center, above which another data point is accepted as a cluster center, specified as a scalar value in the range [`0`, `1`]. The acceptance ratio must be greater than the rejection ratio.

`Options(3)` — Rejection ratio
`0.15` (default) | scalar value in the range [`0`, `1`]

Rejection ratio, defined as a fraction of the potential of the first cluster center, below which another data point is rejected as a cluster center, specified as a scalar value in the range [`0`, `1`]. The rejection ratio must be less than acceptance ratio.

`Options(4)` — Information display flag
`false` (default) | `true`

Information display flag indicating whether to display progress information during clustering, specified as one of the following:

- `false` — Do not display progress information.
- `true` — Display progress information.

Output Arguments

`centers` — Cluster centers
J-by-*N* array

Cluster centers, returned as a *J*-by-*N* array, where *J* is the number of clusters and *N* is the number of data dimensions.

`sigma` — Range of influence of cluster centers
N-element row vector

Range of influence of cluster centers for each data dimension, returned as an *N*-element row vector. All cluster centers have the same set of `sigma` values.

Tips

- To generate a fuzzy inference system using subtractive clustering, use the `genfis` command. For example, suppose you cluster your data using the following syntax:

  ```
  C = subclust(data,clusterInfluenceRange,'DataScale',dataScale,'Options',options);
  ```

where the first `M` columns of `data` correspond to input variables, and the remaining columns correspond to output variables.

You can generate a fuzzy system using the same training data and subtractive clustering configuration. To do so:

1. Configure clustering options.

   ```
   opt = genfisOptions('SubtractiveClustering');
   opt.ClusterInfluenceRange = clusterInfluenceRange;
   opt.DataScale = dataScale;
   opt.SquashFactor = options(1);
   opt.AcceptRatio = options(2);
   opt.RejectRatio = options(3);
   opt.Verbose = options(4);
   ```
2. Extract input and output variable data.

   ```
   inputData = data(:,1:M);
   outputData = data(:,M+1:end);
   ```
3. Generate FIS structure.

   ```
   fis = genfis(inputData,outputData,opt);
   ```

The fuzzy system, `fis`, contains one fuzzy rule for each cluster, and each input and output variable has one membership function per cluster. You can generate only Sugeno fuzzy systems using subtractive clustering. For more information, see `genfis` and `genfisOptions`.

Algorithms

Subtractive clustering assumes that each data point is a potential cluster center. The algorithm does the following:

1. Calculate the likelihood that each data point would define a cluster center, based on the density of surrounding data points.
2. Choose the data point with the highest potential to be the first cluster center.
3. Remove all data points near the first cluster center. The vicinity is determined using `clusterInfluenceRange`.
4. Choose the remaining point with the highest potential as the next cluster center.

5 Repeat steps 3 and 4 until all the data is within the influence range of a cluster center.

The subtractive clustering method is an extension of the mountain clustering method proposed in [2].

References

[1] Chiu, S., "Fuzzy Model Identification Based on Cluster Estimation," *Journal of Intelligent & Fuzzy Systems*, Vol. 2, No. 3, Sept. 1994.

[2] Yager, R. and D. Filev, "Generation of Fuzzy Rules by Mountain Clustering," *Journal of Intelligent & Fuzzy Systems*, Vol. 2, No. 3, pp. 209-219, 1994.

See Also

`genfis`

Topics

“Fuzzy Clustering” on page 4-2
“Model Suburban Commuting Using Subtractive Clustering” on page 4-22

Introduced before R2006a

surfview

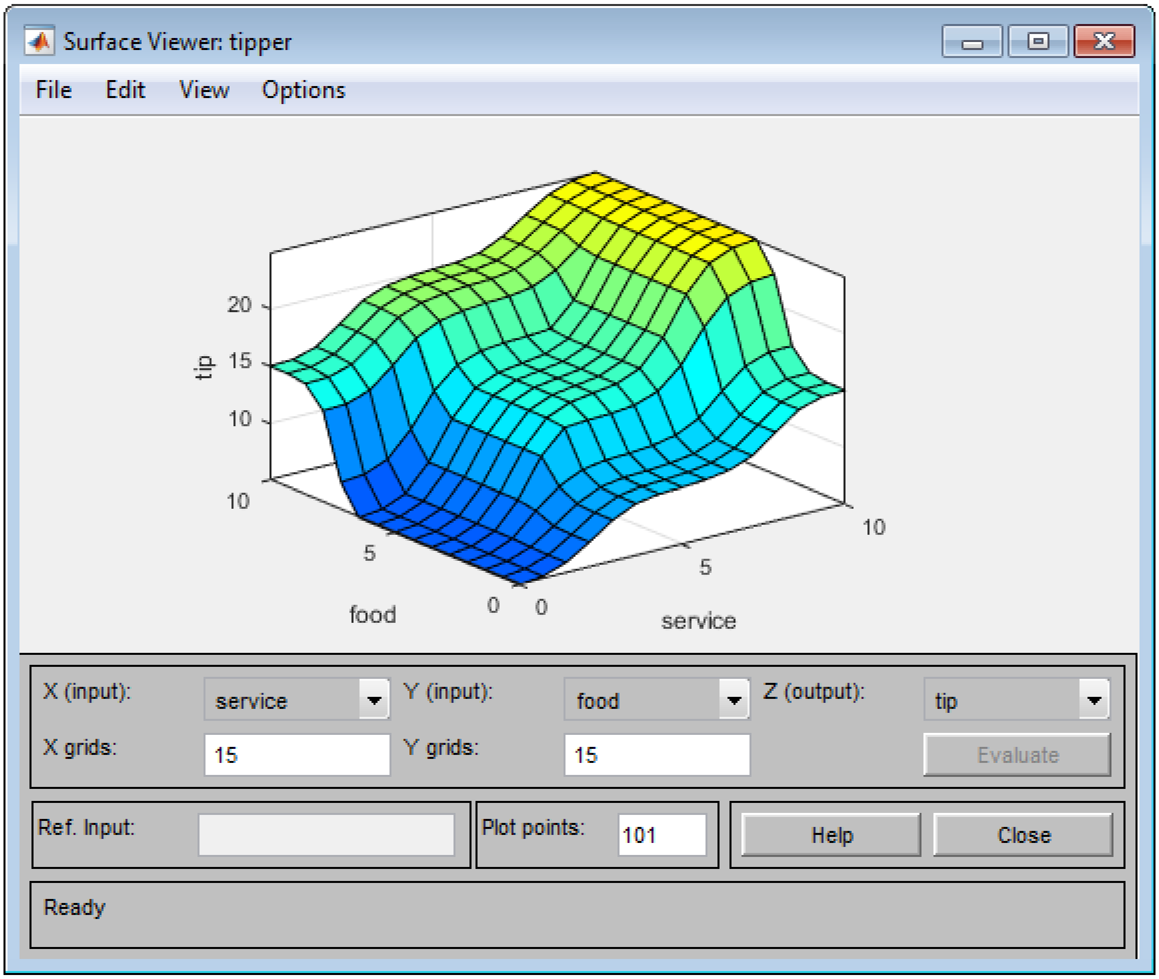
Open Surface Viewer

Syntax

```
surfview(fis)
```

```
surfview(fileName)
```

Description



The Surface Viewer is a graphical interface that lets you examine the output surface of an FIS for any one or two inputs. You can examine an FIS that is:

- Stored in a file using `surfview(fileName)`, where `fileName` is a character vector or string with or without the `.fis` extension.

- In the MATLAB workspace using `surfview(fis)`, where `fis` is a `mamfis` or `sugfis` object.

Because it does not alter the fuzzy system or its associated FIS object in any way, Surface Viewer is a read-only editor. Using the drop-down menus, you select the two input variables you want assigned to the two input axes (X and Y), as well the output variable you want assigned to the output (or Z) axis.

By default, the surface plot updates automatically when you change the input or output variable selections or the number of grid points. To disable automatic plot updates, in the **Options** menu, clear the **Always evaluate** option. When this option is disabled, to update the plot, click **Evaluate**.

If you want to create a smoother plot, use the **Plot points** field to specify the number of points on which the membership functions are evaluated in the input or output range. This field defaults to the minimum number of plot plots, `101`. If you specify fewer plot points, the field value automatically resets to `101`. When you specify the number of plot points, the surface plot automatically updates.

By clicking on the plot axes and dragging the mouse, you can manipulate the surface so that you can view it from different angles.

If there are more than two inputs to your system, you must supply the constant values associated with any unspecified inputs in the reference input section.

Refer to “The Surface Viewer” on page 2-35 for more information about how to use `surfview`.

Menu Items

In the Surface Viewer, there is a menu bar that allows you to open related UI tools, open and save systems, and so on. The Surface Viewer uses the same **File** menu as the one on the **Fuzzy Logic Designer**:

- Use the **Edit** menu items:

  Undo to undo the most recent action

  FIS properties to open the **Fuzzy Logic Designer**

  Membership functions to invoke the Membership Function Editor

Rules... to invoke the Rule Editor

- Use the **View** menu item:

  Rules to invoke the Rule Viewer
- Use the **Options** menu items:

  Plot to choose among eight different kinds of plot styles.

  Color Map to choose among several different color schemes.

  Always evaluate to automatically evaluate and plot a new surface every time you make a change that affects the plot, such as changing the number of grid points. This option is selected by default. To clear this option, select it once more.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

Apps
Fuzzy Logic Designer

Functions
`gensurf` | `mfedit` | `ruleedit` | `ruleview`

Topics
"The Surface Viewer" on page 2-35

Introduced before R2006a

trapmf

Trapezoidal membership function

This function computes fuzzy membership values using a trapezoidal membership function. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-292.

This membership function is related to the `trimf` membership function.

Syntax

```
y = trapmf(x,params)
```

Description

`y = trapmf(x,params)` returns fuzzy membership values computed using the following trapezoidal membership function:

$$f(x;a,b,c,d) = \left\{ \begin{array}{cc} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{array} \right\}$$

or, more compactly:

$$f(x;a,b,c,d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), o\right)$$

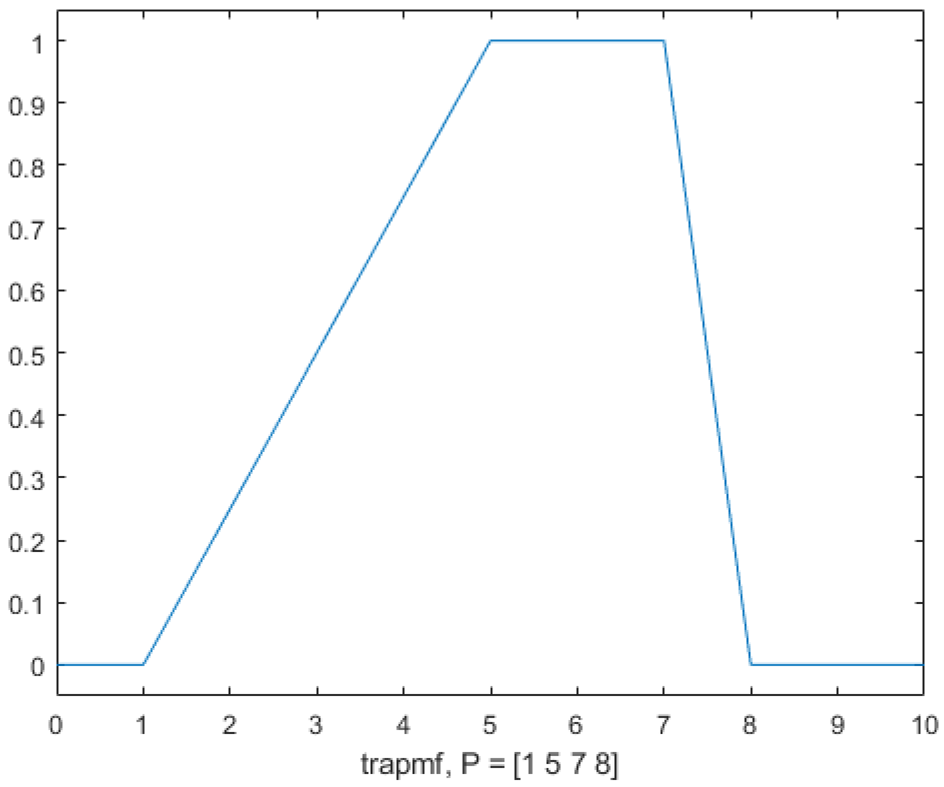
To specify the parameters, *a*, *b*, *c*, and *d*, use `params`.

Membership values are computed for each input value in `x`.

Examples

Trapezoid-Shaped Membership Function

```
x = 0:0.1:10;
y = trapmf(x,[1 5 7 8]);
plot(x,y)
xlabel('trapmf, P = [1 5 7 8]')
ylim([-0.05 1.05])
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

params — Membership function parameters
vector of length two

Membership function parameters, specified as the vector [*a b c d*]. Parameters *b* and *c* define the *shoulders* of the membership function, and *a* and *d* define its *feet*.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of y match the dimensions of x. Each element of y is the membership value computed for the corresponding element of x.

Alternative Functionality

fismf Object

You can create and evaluate a fismf object that implements the trapmf membership function.

```
mf = fismf("trapmf",P);
Y = evalmf(mf,X);
```

Here, X, P, and Y correspond to the x, params, and y arguments of trapmf, respectively.

Extended Capabilities

C/C++ Code Generation
Generate C and C++ code using MATLAB® Coder™.

See Also
`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics
"Membership Functions" on page 1-14

Introduced before R2006a

trimf

Triangular membership function

This function computes fuzzy membership values using a triangular membership function. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-296.

This membership function is related to the `trapmf` membership function.

Syntax

```
y = trimf(x,params)
```

Description

`y = trimf(x,params)` returns fuzzy membership values computed using the following triangular membership function:

$$f(x;a,b,c) = \left\{\begin{matrix} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{matrix}\right\}$$

or, more compactly:

$$f(x;a,b,c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), o\right)$$

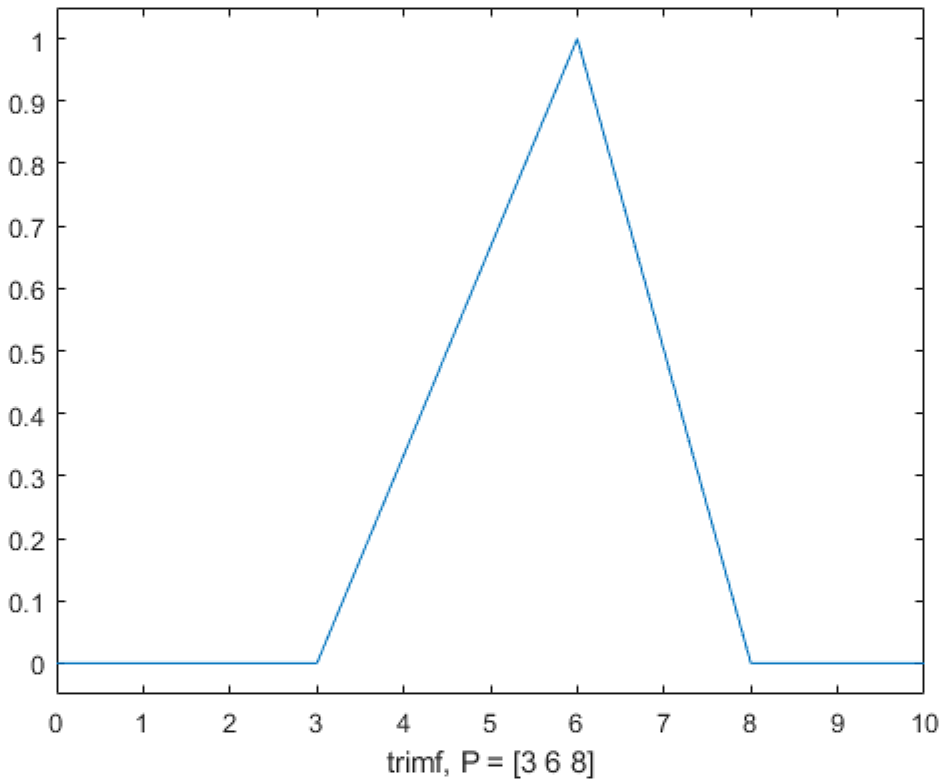
To specify the parameters, *a*, *b*, and *c*, use `params`.

Membership values are computed for each input value in `x`.

Examples

Triangle-Shaped Membership Function

```
x = 0:0.1:10;
y = trimf(x,[3 6 8]);
plot(x,y)
xlabel('trimf, P = [3 6 8]')
ylim([-0.05 1.05])
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length three

Membership function parameters, specified as the vector [*a* *b* *c*]. Parameters *a* and *c* define the *feet* of the membership function, and *b* defines its *peak*.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `trimf` membership function.

```
mf = fismf("trimf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `trimf`, respectively.

Extended Capabilities

C/C++ Code Generation
Generate C and C++ code using MATLAB® Coder™.

See Also
`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `zmf`

Topics
“Membership Functions” on page 1-14

Introduced before R2006a

tunefis

Tune fuzzy inference system or tree of fuzzy inference systems

Syntax

```
fisout = tunefis(fisin,paramset,in,out)
fisout = tunefis(fisin,paramset,in,out,options)
fisout = tunefis(fisin,paramset,custcostfcn,options)
[fisout,optoutputs] = tunefis( ___ )
```

Description

`fisout = tunefis(fisin,paramset,in,out)` tunes the fuzzy system `fisin` using parameters identified by `paramset` and the training data specified by `in` and `out`.

`fisout = tunefis(fisin,paramset,in,out,options)` tunes the fuzzy system with additional options from the object `options` created using `tunefisOptions`.

`fisout = tunefis(fisin,paramset,custcostfcn,options)` tunes the fuzzy system using `custcostfcn`, a function handle to a custom cost function.

`[fisout,optoutputs] = tunefis( ___ )` tunes the fuzzy system and returns an additional output `optoutputs` with information about tuning algorithm.

Examples

Tune a Fuzzy Inference System

Create the initial fuzzy inference system using `genfis`.

```
x = (0:0.1:10)';
y = sin(2*x)./exp(x/5);
options = genfisOptions('GridPartition');
```

```
options.NumMembershipFunctions = 5;
fisin = genfis(x,y,options);
```

Obtain the tunable settings of inputs, outputs, and rules of the fuzzy inference system.

```
[in,out,rule] = getTunableSettings(fisin);
```

Tune the membership function parameters with `"anfis"`.

```
fisout = tunefis(fisin,[in;out],x,y,tunefisOptions("Method","anfis"));
```

```
ANFIS info:
    Number of nodes: 24
    Number of linear parameters: 10
    Number of nonlinear parameters: 15
    Total number of parameters: 25
    Number of training data pairs: 101
    Number of checking data pairs: 0
    Number of fuzzy rules: 5


Start training ANFIS ...

   1      0.0694086
   2      0.0680259
   3      0.066663
   4      0.0653198
   5      0.0639961
Step size increases to 0.011000 after epoch 5.
   6      0.0626917
   7      0.0612787
   8      0.0598881
   9      0.0585193
Step size increases to 0.012100 after epoch 9.
  10      0.0571712

Designated epoch number reached --> ANFIS training completed at epoch 10.

Minimal training RMSE = 0.057171
```

Tune Specific Parameter Setting of Fuzzy Inference System

Create the initial fuzzy inference system using `genfis`.

```
x = (0:0.1:10)';
y = sin(2*x)./exp(x/5);
options = genfisOptions('GridPartition');
options.NumMembershipFunctions = 5;
fisin = genfis(x,y,options);
```

Obtain the tunable settings of inputs, outputs, and rules of the fuzzy inference system.

```
[in,out,rule] = getTunableSettings(fisin);
```

Tune the rule parameter only. In this example, the pattern search method is used.

```
fisout = tunefis(fisin,rule,x,y,tunefisOptions("Method","patternsearch"));
```

```
Iter     Func-count       f(x)      MeshSize     Method
    0           1      0.346649             1      
    1          19      0.346649           0.5     Refine Mesh
    2          37      0.346649          0.25     Refine Mesh
    3          55      0.346649         0.125     Refine Mesh
    4          73      0.346649        0.0625     Refine Mesh
    5          91      0.346649       0.03125     Refine Mesh
    6         109      0.346649       0.01563     Refine Mesh
    7         127      0.346649      0.007813     Refine Mesh
    8         145      0.346649      0.003906     Refine Mesh
    9         163      0.346649      0.001953     Refine Mesh
   10         181      0.346649     0.0009766     Refine Mesh
   11         199      0.346649     0.0004883     Refine Mesh
   12         217      0.346649     0.0002441     Refine Mesh
   13         235      0.346649     0.0001221     Refine Mesh
   14         253      0.346649     6.104e-05     Refine Mesh
   15         271      0.346649     3.052e-05     Refine Mesh
   16         289      0.346649     1.526e-05     Refine Mesh
   17         307      0.346649     7.629e-06     Refine Mesh
   18         325      0.346649     3.815e-06     Refine Mesh
   19         343      0.346649     1.907e-06     Refine Mesh
   20         361      0.346649     9.537e-07     Refine Mesh
Optimization terminated: mesh size less than options.MeshTolerance.
```

Tune a Fuzzy Inference System with Custom Parameter Settings

Create the initial fuzzy inference system using `genfis`.

```
x = (0:0.1:10)';
y = sin(2*x)./exp(x/5);
options = genfisOptions('GridPartition');
options.NumMembershipFunctions = 5;
fisin = genfis(x,y,options);
```

Obtain the tunable settings of inputs, outputs, and rules of the fuzzy inference system.

```
[in,out,rule] = getTunableSettings(fisin);
```

You can tune with custom parameter settings using `setTunable` or dot notation.

Do not tune input 1.

```
in(1) = setTunable(in(1),false);
```

For output 1:

- do not tune membership functions 1 and 2,
- do not tune membership function 3,
- set the minimum parameter range of membership function 4 to -2,
- and set the maximum parameter range of membership function 5 to 2.

```
out(1).MembershipFunctions(1:2) = setTunable(out(1).MembershipFunctions(1:2),false);
out(1).MembershipFunctions(3).Parameters.Free = false;
out(1).MembershipFunctions(4).Parameters.Minimum = -2;
out(1).MembershipFunctions(5).Parameters.Maximum = 2;
```

For the rule settings,

- do not tune rules 1 and 2,
- set the antecedent of rule 3 to non-tunable,
- allow NOT logic in the antecedent of rule 4,
- and do not ignore any outputs in rule 3.

```
rule(1:2) = setTunable(rule(1:2),false);
rule(3).Antecedent.Free = false;
rule(4).Antecedent.AllowNot = true;
rule(3).Consequent.AllowEmpty = false;
```

Set the maximum number of iterations to 20 and tune the fuzzy inference system.

```
opt = tunefisOptions("Method","particleswarm");
opt.MethodOptions.MaxIterations = 20;
fisout = tunefis(fisin,[in;out;rule],x,y,opt);
```

```
                                 Best            Mean     Stall
Iteration     f-count            f(x)            f(x)    Iterations
    0             90           0.3265           1.857        0
    1            180           0.3265           4.172        0
    2            270           0.3265           3.065        1
    3            360           0.3265           3.839        2
    4            450           0.3265           3.386        3
    5            540           0.3265           3.249        4
    6            630           0.3265           3.311        5
    7            720           0.3265           2.901        6
    8            810           0.3265           2.868        7
    9            900           0.3181            2.71        0
   10            990           0.3181           2.068        1
   11           1080           0.3181           2.692        2
   12           1170           0.3165           2.146        0
   13           1260           0.3165           1.869        1
   14           1350           0.3165           2.364        2
   15           1440           0.3165            2.07        0
   16           1530           0.3164           1.678        0
   17           1620           0.2978           1.592        0
   18           1710           0.2977           1.847        0
   19           1800           0.2954           1.666        0
   20           1890           0.2947           1.608        0
Optimization ended: number of iterations exceeded OPTIONS.MaxIterations.
```

Input Arguments

`fisin` — Fuzzy system

`mamfis` object | `sugfis` object | `fistree` object

Fuzzy system, specified as a `mamfis`, `sugfis`, or `fistree` object. The fuzzy system can be a fuzzy inference system or network of interconnected fuzzy inference systems. It is created using `mamfis`, `sugfis`, `genfis`, or `fistree`.

`paramset` — Tunable parameter settings

array

Tunable parameter settings, specified as an array of input, output, and rule parameter settings of the input fuzzy system `fisin`. To obtain these parameter settings, use `getTunableSettings` with the input fuzzy system `fisin`. `paramset` can be the input parameter, the output parameter, the rule parameter, or some combination of these parameters as an array. The contents of the array depend on which parameters you would like to tune.

`in` — Input training data
matrix

Input training data, specified as an m-by-n matrix, where m is the total number of input datasets and n is the number of inputs. The number of input and output datasets must be the same.

`out` — Output training data
matrix

Output training data, specified as an m-by-n matrix, where m is the total number of output datasets and n is the number of outputs. The number of input and output datasets must be the same.

`options` — FIS tuning options
`tunefisOptions` option set

FIS tuning options, specified as a `tunefisOptions` object. You can specify the tuning algorithm method and other options for the tuning process.

`custcostfcn` — custom cost functions
function handle

Custom cost function, specified as a function handle. The custom cost function evaluates `fisout` to calculate its cost with respect to an evaluation criterion, such as input/output data. `custcostfcn` must accept at least one input argument for `fisout` and returns a cost value. You can provide an anonymous function handle to attach additional data for cost calculation, as described in this example:

```
function fitness = custcost(cost,trainingData)
  ...
end
custcostfcn = @(fis)custcost(fis,trainingData);
```

Output Arguments

`fisout` — Fuzzy system
`mamfis` object | `sugfis` object | `fistree` object

Fuzzy system, specified as a `mamfis`, `sugfis`, or `fistree` object. The fuzzy system can be a fuzzy inference system or network of interconnected fuzzy inference systems. It is created using `mamfis`, `sugfis`, `genfis`, or `fistree`. `fisout` is the tuned FIS.

`optoutputs` — Tuning algorithm summary
structure

Tuning algorithm summary, specified as a structure containing the following fields:

- `tuningOutputs`
- `errorMessage`

`tuningOutputs` is a structure with information about the tuning algorithm method specified by `tunefisOptions` in the `options` input argument. The specific outputs differ for each tuning algorithm. See the specific tuning method for details about its outputs:

- `'ga'` — genetic algorithm
- `'particleswarm'` — particle swarm
- `'patternsearch'` — pattern search
- `'simulannealbnd'` — simulated annealing algorithm
- `'anfis'` — adaptive neuro-fuzzy

`errorMessage` is the message generated when updating `fisin` with new parameter values.

See Also

`fistree` | `getTunableSettings` | `mamfis` | `sugfis` | `tunefisOptions`

Introduced in R2019a

update

Update fuzzy rule using fuzzy inference system

Syntax

```
ruleOut = update(ruleIn,fis)
```

Description

`ruleOut = update(ruleIn,fis)` updates the fuzzy rule `ruleIn` using the information in fuzzy inference system `fis` and returns the resulting fuzzy rule in `ruleOut`.

Examples

Create Fuzzy Rule Using Text Description

Create a fuzzy rule using a verbose text description.

```
rule = fisrule("if service is poor and food is delicious then tip is average (1)");
```

Alternatively, you can specify the same rule using a symbolic text description.

```
rule = fisrule("service==poor & food==delicious => tip=average")
```

```
rule = 
  fisrule with properties:

    Description: "service==poor & food==delicious => tip=average (1)"
     Antecedent: []
     Consequent: []
         Weight: 1
     Connection: 1
```

Before using `rule` with a fuzzy system, update the rule `Antecedent` and `Consequent` properties using the `update` function.

```
fis = readfis("tipper");
rule = update(rule,fis)
```

```
rule = 
  fisrule with properties:

    Description: "service==poor & food==delicious => tip=average (1)"
     Antecedent: [1 2]
     Consequent: 2
         Weight: 1
     Connection: 1
```

Create Fuzzy Rule Using Numeric Description

Create a fuzzy rule using a numeric description. Specify that the rule has two input variables.

```
rule = fisrule([1 2 2 0.5 1],2)
```

```
rule = 
  fisrule with properties:

    Description: "input1==mf1 & input2==mf2 => output1=mf2 (0.5)"
     Antecedent: [1 2]
     Consequent: 2
         Weight: 0.5000
     Connection: 1
```

Before using `rule` with a fuzzy system, update the rule `Description` property using the `update` function.

```
fis = readfis("tipper");
rule = update(rule,fis)
```

```
rule = 
  fisrule with properties:

    Description: "service==poor & food==delicious => tip=average (0.5)"
     Antecedent: [1 2]
     Consequent: 2
```

```
          Weight: 0.5000
      Connection: 1
```

Input Arguments

`ruleIn` — Fuzzy rule
`fisrule` object | array of `fisrule` objects

Fuzzy rule, specified as a `fisrule` object or an array of `fisrule` objects. If `ruleIn` was created using a:

- Text description, its `Antecedent` and `Consequent` properties are updated using the input and output membership function indices in `fis` that correspond to the membership function names in the `Description` property of `ruleIn`
- Numeric description, its `Description` property is updated using the input and output membership function names in `fis` that correspond to the membership function indices in the `Antecedent` and `Consequent` properties of `ruleIn`

If you specify `ruleIn` as an array of `fisrule` objects, then all of the rules are updated accordingly.

`fis` — Fuzzy inference system
`mamfis` object | `sugfis` object

Fuzzy inference system, specified as a `mamfis` or `sugfis` object.

Output Arguments

`ruleOut` — Fuzzy rule
`fisrule` object | array of `fisrule` objects

Fuzzy rule, returned as a `fisrule` object or an array of `fisrule` objects.

See Also

`fisrule` | `mamfis` | `sugfis`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced in R2018b

writeFIS

Save fuzzy inference system to file

You can save a fuzzy inference system (FIS) in a `.fis` file using the `writeFIS` function. To load the saved file, use the `readfis` function.

Note Do not manually edit the contents of a `.fis` file. Doing so can produce unexpected results when loading the file using `readfis`.

Syntax

```
writeFIS(fis,fileName)
```

```
writeFIS(fis)
writeFIS(fis,fileName,"dialog")
```

Description

`writeFIS(fis,fileName)` saves the fuzzy inference system `fis` to the current working folder using file name `fileName`.

`writeFIS(fis)` opens a dialog box for saving a FIS. In this dialog box, specify the name and location of the `.fis` file.

`writeFIS(fis,fileName,"dialog")` opens a dialog box for saving a FIS, setting the name of the file in the dialog box to `fileName`. In the dialog box, specify the location for the file.

Examples

Save Fuzzy Inference System to File

Create a fuzzy inference system, and add an input variable with membership functions.

```
fis = mamfis('Name','tipper');
fis = addInput(fis,[0 10],'Name','service');
fis = addMF(fis,'service','gaussmf',[1.5 0],'Name','poor');
fis = addMF(fis,'service','gaussmf',[1.5 5],'Name','good');
fis = addMF(fis,'service','gaussmf',[1.5 10],'Name','excellent');
```

Save the fuzzy system in the current working folder in the file `myFile.fis`.

```
writeFIS(fis,'myFile');
```

Input Arguments

`fis` — Fuzzy inference system

`mamfis` object | `sugfis` object

Fuzzy inference system, specified as one of the following:

- `mamfis` object — Mamdani fuzzy inference system
- `sugfis` object — Sugeno fuzzy inference system

`fileName` — File name

string | character vector

File name specified as a string or character vector. If you do not specify the `.fis` extension in the file name, `writeFIS` adds the extension.

Compatibility Considerations

`writefis` is now `writeFIS`

Behavior changed in R2018b

`writefis` is now `writeFIS`. To update your code, change the function name from `writefis` to `writeFIS`. The syntaxes are equivalent.

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields.
- Objects store text data as strings rather than as character vectors.

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

See Also

`readfis`

Topics

"Build Fuzzy Systems at the Command Line" on page 2-38

Introduced in R2018b

zmf

Z-shaped membership function

This function computes fuzzy membership values using a spline-based Z-shaped membership function. You can also compute this membership function using a `fismf` object. For more information, see “fismf Object” on page 8-314.

This membership function is related to the `smf` and `pimf` membership functions.

Syntax

```
y = zmf(x,params)
```

Description

`y = zmf(x,params)` returns fuzzy membership values computed using the spline-based Z-shaped membership function given by:

$$f(x;a,b) = \begin{cases} 1, & x \le a \\ 1 - 2\left(\frac{x-a}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ 2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \le x \le b \\ 0, & x \ge b \end{cases}$$

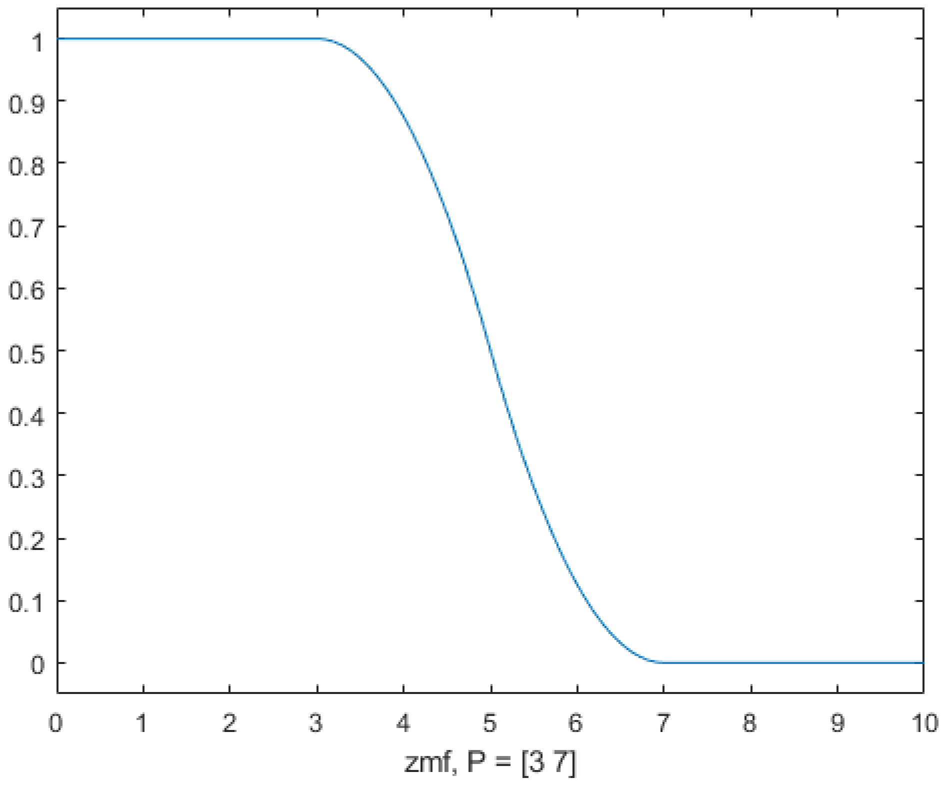
To specify the *a* and *b* parameters, use `params`.

Membership values are computed for each input value in `x`.

Examples

Z-Shaped Membership Function

```
x = 0:0.1:10;
y = zmf(x,[3 7]);
plot(x,y)
xlabel('zmf, P = [3 7]')
ylim([-0.05 1.05])
```



Input Arguments

x — Input values
scalar | vector

Input values for which to compute membership values, specified as a scalar or vector.

`params` — Membership function parameters
vector of length two

Membership function parameters, specified as the vector [*a* *b*]. Parameter *a* defines the *shoulder* of the membership function, and *b* defines its *foot*.

Output Arguments

y — Membership value
scalar | vector

Membership value returned as a scalar or a vector. The dimensions of `y` match the dimensions of `x`. Each element of `y` is the membership value computed for the corresponding element of `x`.

Alternative Functionality

`fismf` Object

You can create and evaluate a `fismf` object that implements the `zmf` membership function.

```
mf = fismf("zmf",P);
Y = evalmf(mf,X);
```

Here, `X`, `P`, and `Y` correspond to the `x`, `params`, and `y` arguments of `zmf`, respectively.

Extended Capabilities

C/C++ Code Generation
Generate C and C++ code using MATLAB® Coder™.

See Also

`dsigmf` | `gauss2mf` | `gaussmf` | `gbellmf` | `pimf` | `psigmf` | `sigmf` | `smf` | `trapmf` | `trimf` | `zmf`

Topics

“Membership Functions” on page 1-14

Introduced before R2006a

Objects — Alphabetical List

ClauseParameters

Parameter settings for rule clauses

Description

A `ClauseParameters` object is created using the `getTunableSettings` function with a `mamfis`, `sugfis`, or `fistree` object. When the third output is specified, `getTunableSettings` returns clause parameter settings within the rule parameter settings.

Creation

Create a `ClauseParameters` object using `getTunableSettings` with three outputs. The `Antecedent` and `Consequent` properties of the third output are specified as `ClauseParameters` objects.

Properties

`Free` — Clause parameter values available for tuning
`true` or `1` | `false` or `0`

Clause parameter values available for tuning, specified as a numeric or logical `1` (`true`) or `0` (`false`).

`AllowNot` — Whether to allow NOT logic in rule clauses
`true` or `1` | `false` or `0`

Whether to allow NOT logic in rule clauses, specified as a numeric or logical `1` (`true`) or `0` (`false`).

`AllowEmpty` — Whether to allow ignoring inputs and outputs in rule clauses
`true` or `1` | `false` or `0`

Whether to allow ignoring inputs and outputs in rule clauses, specified as a numeric or logical `1` (`true`) or `0` (`false`).

Examples

Obtain Tunable Settings of Rules from FIS

Create two fuzzy inference systems, and define the connection between the two.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = sugfis('Name','fis2','NumInputs',2,'NumOutputs',1);
con = ["fis1/output1" "fis2/input1"];
```

Create a tree of fuzzy inference systems.

```
tree = fistree([fis1 fis2],con);
```

Obtain the tunable settings of rules of the fuzzy inference system.

```
[~,~,rule] = getTunableSettings(tree)
```

```
rule = 
  18x1 RuleSettings array with properties:

    Index
    Antecedent
    Consequent
    FISName
```

You can use dot notation to specify the tunable settings of rules.

For the first rule, do not tune input 1 membership function index and do not ignore output 1 membership function index.

```
rule(1).Antecedent.Free(1) = false;
rule(1).Consequent.AllowEmpty(1) = false;
```

For the second rule, allow NOT logic for input 2 membership function index.

```
rule(2).Antecedent.AllowNot(2) = true;
```

See Also

RuleSettings | VariableSettings | getTunableSettings

Introduced in R2019a

evalfisOptions

Option set for `evalfis` function

Description

Use an `evalfisOptions` object to specify options for the `evalfis` function.

Creation

Syntax

```
opt = evalfisOptions
opt = evalfisOptions(Name,Value)
```

Description

`opt = evalfisOptions` creates an option set for the `evalfis` function with default options. To modify the properties of this option set, use dot notation.

`opt = evalfisOptions(Name,Value)` sets properties using name-value pairs. For example, `evalfisOptions('NumSamplePoints',51)` creates an option set and sets the number of output fuzzy set samples to `51`. You can specify multiple name-value pairs. Enclose each property name in single quotes.

Properties

`NumSamplePoints` — Number of sample points in output fuzzy sets
101 (default) | integer greater than `1`

Number of sample points in output fuzzy sets, specified as an integer greater than `1`.

To reduce memory usage while evaluating a Mamdani FIS, specify fewer samples. Doing so sacrifices the accuracy of the defuzzified output value.

Reducing the number of samples can make the output area for defuzzification zero. In this case, the defuzzified output value is the midpoint of the output variable range.

Note `evalfis` ignores this property when evaluating a Sugeno FIS.

`OutOfRangeInputValueMessage` — Diagnostic message behavior when an input is out of range

`"warning"` (default) | `"error"` | `"none"`

Diagnostic message behavior when an input is out of range, specified as one of the following:

- `"warning"` — Report the diagnostic message as a warning.
- `"error"` — Report the diagnostic message as an error.
- `"none"` — Do not report the diagnostic message.

When an input value is out of range, corresponding rules in the fuzzy system can have unexpected firing strengths.

`NoRuleFiredMessage` — Diagnostic message behavior when no rules fire

`"warning"` (default) | `"error"` | `"none"`

Diagnostic message behavior when no rules fire, specified as one of the following:

- `"warning"` — Report the diagnostic message as a warning.
- `"error"` — Report the diagnostic message as an error.
- `"none"` — Do not report the diagnostic message.

When `NoRuleFiredMessage` is `"warning"` or `"none"` and no rules fire for a given output, the defuzzified output value is set to its mean range value.

`EmptyOutputFuzzySetMessage` — Diagnostic message behavior when an output fuzzy set is empty

`"warning"` (default) | `"error"` | `"none"`

Diagnostic message behavior when an output fuzzy set is empty, specified as one of the following:

- `"warning"` — Report the diagnostic message as a warning.

- `"error"` — Report the diagnostic message as an error.
- `"none"` — Do not report the diagnostic message.

When `EmptyOutputFuzzySetMessage` is `"warning"` or `"none"` and an output fuzzy set is empty, the defuzzified value for the corresponding output is set to its mean range value.

This diagnostic message applies only to Mamdani systems.

Object Functions

evalfis	Evaluate fuzzy inference system

Examples

Create Option Set for Evaluating FIS

Create option set object, specifying the number of sample points for output fuzzy sets.

```
options = evalfisOptions('NumSamplePoints',51)
```

```
options = 
  EvalFISOptions with properties:

                NumSamplePoints: 51
    OutOfRangeInputValueMessage: "warning"
             NoRuleFiredMessage: "warning"
     EmptyOutputFuzzySetMessage: "warning"
```

Alternatively, create a default option set, and configure properties using dot notation.

```
options = evalfisOptions;
options.NumSamplePoints = 51;
```

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using MATLAB® Coder™.

Usage notes and limitations:

- When used for code generation, an `evalfisOptions` object stores its `OutOfRangeInputValueMessage`, `NoRuleFiredMessage`, and `EmptyOutputFuzzySetMessage` properties as character vectors rather than strings.
- When evaluating a fuzzy inference system in Simulink, it is recommended to not use `evalfis` or `evalfisOptions` within a MATLAB Function. Instead, evaluate your fuzzy inference system using the Fuzzy Logic Controller block.

See Also

Functions
`evalfis`

Introduced in R2018a

fismf

Fuzzy membership function

Description

Use `fismf` objects to represent fuzzy membership functions. For each input and output variable in a fuzzy inference system (FIS), one or more membership functions define the possible linguistic sets for that variable. For more information on membership functions, see “Foundations of Fuzzy Logic” on page 1-10.

Creation

Syntax

```
mf = fismf
mf = fismf(type,parameters)
mf = fismf('Name',name)
mf = fismf(type,parameters,'Name',name)
```

Description

`mf = fismf` creates a fuzzy membership function (MF) with default type, parameters, and name. To change the membership function properties, use dot notation.

`mf = fismf(type,parameters)` sets the `Type` and `Parameters` properties.

`mf = fismf('Name',name)` sets the `Name` property.

`mf = fismf(type,parameters,'Name',name)` sets the `Type`, `Parameters`, and `Name` properties.

Properties

Name — Membership function name
`"mf"` (default) | string | character vector

Membership function name, specified as a string or character vector.

Type — Membership function type
`"trimf"` (default) | string | character vector | function handle

Membership function type, specified as a string or character vector that contains the name of a function in the current working folder or on the MATLAB path. You can also specify a handle to such a function. When you specify `Type`, you must also specify `Parameters`.

This table describes the values that you can specify for `Type`.

Membership Function Type	Description	For More Information
`"gbellmf"`	Generalized bell-shaped membership function	`gbellmf`
`"gaussmf"`	Gaussian membership function	`gaussmf`
`"gauss2mf"`	Gaussian combination membership function	`gauss2mf`
`"trimf"`	Triangular membership function	`trimf`
`"trapmf"`	Trapezoidal membership function	`trapmf`
`"sigmf"`	Sigmoidal membership function	`sigmf`
`"dsigmf"`	Difference between two sigmoidal membership functions	`dsigmf`
`"psigmf"`	Product of two sigmoidal membership functions	`psigmf`
`"zmf"`	Z-shaped membership function	`zmf`
`"pimf"`	Pi-shaped membership function	`pimf`
`"smf"`	S-shaped membership function	`smf`

Membership Function Type	Description	For More Information
`"constant"`	Constant membership function for Sugeno output membership functions	“What Is Sugeno-Type Fuzzy Inference?” on page 2-5
`"linear"`	Linear membership function for Sugeno output membership functions	
String or character vector	Name of a custom membership function in the current working folder or on the MATLAB path. Custom output membership functions are not supported for Sugeno systems.	“Build Fuzzy Systems Using Custom Functions” on page 2-50
Function handle	Handle to a custom membership function in the current working folder or on the MATLAB path. Custom output membership functions are not supported for Sugeno systems.	

Note When you change `Type` using dot notation, the values in `Parameters` are automatically converted for the new membership function type.

`Parameters` — Membership function parameters

`[0 0.5 1]` (default) | vector

Membership function parameters, specified as a vector. The length of the parameter vector depends on the membership function type. When you specify `Parameters`, you must also specify `Type`.

Object Functions

evalmf	Evaluate fuzzy membership function

Examples

Create Membership Function

Create fuzzy membership function with default settings.

```
mf = fismf;
```

To modify the membership function settings, use dot notation. For example, specify a Gaussian membership function with a standard deviation of `2` and a mean of `10`.

```
mf.Type = "gaussmf";
mf.Parameters = [2 10];
```

Create Membership Function with Specified Parameters

Create a trapezoidal membership function with specified parameters.

```
mf = fismf("trapmf",[10 15 20 25]);
```

Create Membership Function with Specified Name

Create a membership function with the name `"large"`.

```
mf = fismf("Name","large");
```

See Also

`fisrule` | `fisvar` | `mamfis` | `sugfis`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced in R2018b

fisrule

Fuzzy rule

Description

Use `fisrule` objects to represent fuzzy if-then rules that relate input membership function conditions to corresponding output membership functions. The *if* portion of a fuzzy rule is the *antecedent*, which specifies the membership function for each input variable. The *then* portion of a fuzzy rule is the *consequent*, which specifies the membership function for each output variable. For more information on membership functions and fuzzy rules, see "Foundations of Fuzzy Logic" on page 1-10.

Creation

To create fuzzy rule objects, use the `fisrule` function. Using this function, you can create a single fuzzy rule or a vector of multiple fuzzy rules.

Syntax

```
rule = fisrule
rule = fisrule(ruleText)
rule = fisrule(ruleValues,numInputs)
```

Description

`rule = fisrule` creates a single fuzzy rule with the default description `"input1==mf1 => output1=mf1"`.

`rule = fisrule(ruleText)` creates one or more fuzzy rules using the text descriptions in `ruleText`.

`rule = fisrule(ruleValues,numInputs)` creates one or more fuzzy rules using the numeric rule values in `ruleValues`. Specify the number of rule input variables using `numInputs`.

Input Arguments

`ruleText` — Text rule description

string | character vector | string array | character array

Text rule description, specified as one of the following:

- String or character vector specifying a single rule

  ```
  rule = "If service is poor or food is rancid then tip is cheap";
  ```
- String array, where each element corresponds to a rule. For example:

  ```
  ruleList = ["If service is poor or food is rancid then tip is cheap";
              "If service is good then tip is average";
              "If service is excellent or food is delicious then tip is generous"];
  ```
- Character array where each row corresponds to a rule. For example:

  ```
  rule1 = 'If service is poor or food is rancid then tip is cheap';
  rule2 = 'If service is good then tip is average';
  rule3 = 'If service is excellent or food is delicious then tip is generous';
  ruleList = char(rule1,rule2,rule3);
  ```

For each rule, use one of the following rule text formats:

- Verbose — Linguistic expression in the following format, using the `IF` and `THEN` keywords:

  ```
  "IF <antecedent> THEN <consequent> (<weight>)"
  ```

  In `<antecedent>`, specify the membership function for each input variable using the `IS` or `IS NOT` keyword. Connect these conditions using the `AND` or `OR` keywords. If a rule does not use a given input variable, omit it from the antecedent.

  In `<consequent>`, specify the condition for each output variable using the `IS` or `IS NOT` keyword, and separate these conditions using commas. The `IS NOT` keyword is not supported for Sugeno outputs. If a rule does not use a given output variable, omit it from the consequent.

  Specify the weight using a positive numerical value.

  For example:

  ```
  "IF A IS a AND B IS NOT b THEN X IS x, Y IS NOT y (1)"
  ```
- Symbolic — Expression that uses the symbols in the following table instead of keywords. There is no symbol for the `IF` keyword.

Symbol	Keyword
`==`	`IS` (in rule antecedent)
`~=`	`IS NOT`
`&`	`AND`
`|`	`OR`
`=>`	`THEN`
`=`	`IS` (in rule consequent)

For example, the following symbolic rule is equivalent to the previous verbose rule.

```
"A==a & B~=b => X=x, Y~=y (1)"
```

When you specify a rule using a text description, `fisrule` sets the `Description`, `Weight`, and `Connection` properties of the rule based on the description.

`ruleValues` — Numeric rule description
row vector | numeric array

Numeric rule description, specified as one of the following:

- Row vector to specify a single fuzzy rule
- Array, where each row of `ruleValues` specifies one rule

For each row, the numeric rule description has M+N+2 columns, where M is the number of input variables and N is the number of output variables. Each column contains the following information:

- The first M columns specify input membership function indices and correspond to the `Antecedent` property of the rule. To indicate a `NOT` condition, specify a negative value. If a rule does not use a given input, set the corresponding index to `0`. For each rule, at least one input membership function index must be nonzero.
- The next N columns specify output membership function indices and correspond to the `Consequent` property of the rule. To indicate a `NOT` condition for Mamdani systems, specify a negative value. `NOT` conditions are not supported for Sugeno outputs. If a rule does not use a given output, set the corresponding index to `0`. For each rule, at least one output membership function index must be nonzero.
- Column M+N+1 specifies the rule weight and corresponds to the `Weight` property of the rule.

- The final column specifies the antecedent fuzzy operator and corresponds to the `Connection` property of the rule.

When you specify a rule using `ruleVlaues`, `fisrule` sets the `Description` property using default variable and membership function names.

`numInputs` — Number of input variables
positive integer

Number of input variables for the rule, specified as a positive integer. If you specify the rule description using `ruleValues`, you must also specify the number of input variables. `fisrule` parses the rule antecedent values into the membership function indices for the input and output variables using `numInputs`.

Properties

`Description` — Text rule description
string | character vector

Text rule description, specified as a string or character vector. The rule description is stored as a symbolic expression no matter how you specify the rule. For example, if you specify the following verbose rule using `ruleText`:

```
"IF A IS a AND B IS NOT b THEN X IS x, Y IS NOT y (1)"
```

The stored rule is:

```
"A==a & B~=b => X=x, Y~=y (1)"
```

For more information on the verbose and symbolic rule formats, see the `ruleText` input argument.

When you specify a rule using `ruleVlaues`, `fisrule` sets the `Description` property using default variable and membership function names. Before using the rule in a fuzzy system, you must update the description to use the variable and membership function names from that fuzzy system using the `update` function.

`Antecedent` — Rule antecedent
numeric vector

Rule antecedent, specified as a numeric vector of length *M*, where *M* is the number of input variables. Each element of `Antecedent` contains one of the following values:

- Positive integer — The index of an input membership function, which represents an `IS` condition
- Negative integer — The negative of an input membership function, which represents an `IS NOT` condition
- `0` — A *don't care* condition, which means that the rule does not use the corresponding input variable

This value is set when you create a fuzzy rule using `ruleValues`. If you create a fuzzy rule using `ruleText`, before using the rule in a fuzzy system, you must populate the `Antecedent` property using the `update` function.

If you update the indices in the rule antecedent using dot notation, the `Description` property is not updated to reflect the changes. To update the rule description, use the `update` function.

`Consequent` — Rule consequent
numeric vector

Rule consequent, specified as a numeric vector of length *N*, where *N* is the number of output variables. Each element of `Consequent` contains one of the following values:

- Positive integer — The index of an output membership function, which represents an `IS` condition
- Negative integer — The negative of an output membership function, which represents an `IS NOT` condition
- `0` — A *don't care* condition, which means that the rule does not use the corresponding output variable

This value is set when you create a fuzzy rule using `ruleValues`. If you create a fuzzy rule using `ruleText`, before using the rule in a fuzzy system, you must populate the `Consequent` property using the `update` function.

If you update the indices in the rule consequent using dot notation, the `Description` property is not updated to reflect the changes. To update the rule description, use the `update` function.

`Weight` — Rule weight
`1` (default) | positive numeric scalar

Rule weight, specified as a positive numeric scalar in the range [`0 1`].

If you update the rule weight using dot notation, the weight value in the `Description` property text is also updated.

`Connection` — Rule antecedent connection
1 | 2

Rule antecedent connection, specified as one of the following:

- `1` — Evaluate rule antecedents using the AND operator.
- `2` — Evaluate rule antecedents using the OR operator.

If you update the rule connection using dot notation, the antecedent operators in the `Description` property text are also updated.

Object Functions

update	Update fuzzy rule using fuzzy inference system

Examples

Create Fuzzy Rule

Create a default fuzzy rule.

```
rule = fisrule
```

```
rule = 
  fisrule with properties:

    Description: "input1==mf1 => output1=mf1 (1)"
     Antecedent: 1
     Consequent: 1
         Weight: 1
     Connection: 1
```

To modify the rule properties, use dot notation. For example, specify a rule weight of `0.5`.

```
rule.Weight = 0.5;
```

Create Fuzzy Rule Using Text Description

Create a fuzzy rule using a verbose text description.

```
rule = fisrule("if service is poor and food is delicious then tip is average (1)");
```

Alternatively, you can specify the same rule using a symbolic text description.

```
rule = fisrule("service==poor & food==delicious => tip=average")
```

```
rule = 
  fisrule with properties:

    Description: "service==poor & food==delicious => tip=average (1)"
     Antecedent: []
     Consequent: []
         Weight: 1
     Connection: 1
```

Before using `rule` with a fuzzy system, update the rule `Antecedent` and `Consequent` properties using the `update` function.

```
fis = readfis("tipper");
rule = update(rule,fis)
```

```
rule = 
  fisrule with properties:

    Description: "service==poor & food==delicious => tip=average (1)"
     Antecedent: [1 2]
     Consequent: 2
         Weight: 1
     Connection: 1
```

Create Fuzzy Rule Using Numeric Description

Create a fuzzy rule using a numeric description. Specify that the rule has two input variables.

```
rule = fisrule([1 2 2 0.5 1],2)
```

```
rule = 
  fisrule with properties:

    Description: "input1==mf1 & input2==mf2 => output1=mf2 (0.5)"
     Antecedent: [1 2]
     Consequent: 2
         Weight: 0.5000
     Connection: 1
```

Before using `rule` with a fuzzy system, update the rule `Description` property using the `update` function.

```
fis = readfis("tipper");
rule = update(rule,fis)
```

```
rule = 
  fisrule with properties:

    Description: "service==poor & food==delicious => tip=average (0.5)"
     Antecedent: [1 2]
     Consequent: 2
         Weight: 0.5000
     Connection: 1
```

Create Multiple Fuzzy Rules

Create a string array of text rule descriptions.

```
rules1 = ["if service is poor or food is rancid then tip is cheap (0.5)"...
          "if service is excellent and food is not rancid then tip is generous (0.75)"
```

Create an array of fuzzy rules using these descriptions.

```
fuzzyRules1 = fisrule(rules1)
```

```
fuzzyRules1 = 
  1x2 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                              Description
         ___________________________________________________________

    1    "service==poor | food==rancid => tip=cheap (0.5)"
    2    "service==excellent & food~=rancid => tip=generous (0.75)"
```

Alternatively, you can specify multiple rules using an array of numeric rule descriptions.

```
rules2 = [1 1 1 0.5 2;
          2 -1 3 0.75 1];
fuzzyRules2 = fisrule(rules2,2)
```

```
fuzzyRules2 = 
  1x2 fisrule array with properties:

    Description
    Antecedent
    Consequent
    Weight
    Connection

  Details:
                          Description
         __________________________________________________

    1    "input1==mf1 | input2==mf1 => output1=mf1 (0.5)"
    2    "input1==mf2 & input2~=mf1 => output1=mf3 (0.75)"
```

See Also

`fismf` | `fisvar` | `mamfis` | `sugfis`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced in R2018b

fistree

Network of connected fuzzy inference systems

Description

Use a `fistree` object to represent a tree of interconnected fuzzy inference systems.

Creation

Syntax

```
fisTree = fistree(fis,connections)
fisTree = fistree( ___ ,'DisableStructuralChecks',disableChecks)
```

Description

`fisTree = fistree(fis,connections)` creates a network of interconnected `mamfis` and `sugfis` objects using the specified `connections` between them.

`fisTree = fistree( ___ ,'DisableStructuralChecks',disableChecks)` sets the `DisableStructuralChecks` property of the `fistree` object.

Input Arguments

`fis` — Fuzzy inference systems
array

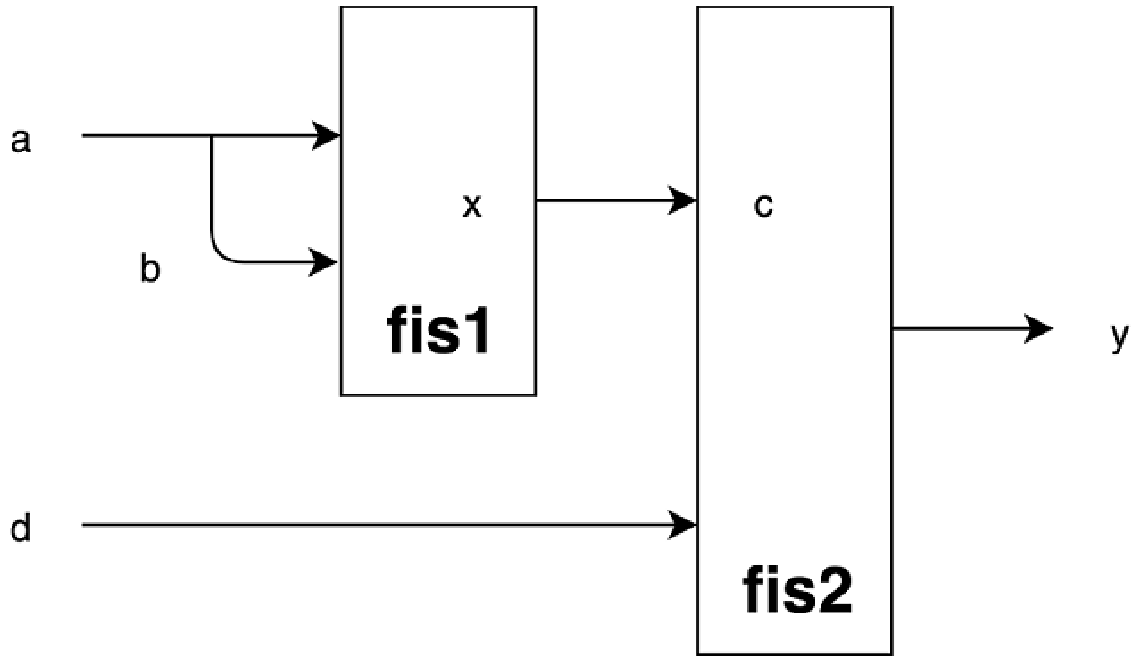
Fuzzy inference systems, specified as an array of `mamfis` and `sugfis` objects. Each fuzzy inference system in the `fis` array must have at least one input and output for `fistree` construction. To evaluate a `fistree`, each fuzzy inference system must have at least one rule.

`connections` — Connections between two fuzzy inference systems
string array

Connections between two fuzzy inference systems, specified as a two-dimensional string array. Each row represents a connection between two FIS objects. Connections are specified as follows:

1. Output-to-input connections, `["fromFISName/fromFISOutputName" "toFISName/toFISInputName"]`. In this case, output of `"fromFISName"` is used as the input of `"toFISName"`. `"fromFISName"` and `"toFISName"` must be different.
2. Input-to-input connections, `["fromFISName/fromFISInputName" "toFISName/toFISInputName"]`. In this case, inputs of `"fromFISName"` and `"toFISName"` use the same input values for evaluation. `"fromFISName"` and `"toFISName"` can be same or different.

The following diagram describes different connection types.



Connection `["fis1/x" "fis2/c"]` is specified between output "x" of "fis1" and input "c" of "fis2". Connection `["fis1/a" "fis1/b"]` is specified between inputs "a" and "b" of "fis1". In this diagram, the `fistree` inputs are "fis1/a" and "fis2/d" and the output is "fis2/y".

Connections must satisfy the following conditions:

1. A `fistree` object must have at least one FIS input without any incoming connection and one FIS output without any outgoing connection.
2. A FIS input cannot have more than one incoming connection.
3. A FIS output can have more than one outgoing connection.
4. An input and output of the same FIS cannot be connected. In other words, you cannot create loops between connected FIS objects.
5. Symmetric connections cannot be specified between two inputs, `["fis1/a" "fis1/b";"fis1/b" "fis1/a"]` is not allowed. Either `["fis1/a" "fis1/b"]` or `["fis1/b" "fis1/a"]` can be specified.
6. Self-input loops are not allowed, `["fis1/a" "fis1/a"]` cannot be specified.

Properties

`FIS` — Fuzzy inference systems
array

This property is read-only.

Fuzzy inference systems, specified as an array of `mamfis` and `sugfis` objects. Each fuzzy inference system in the `fis` array must have at least one input and output for `fistree` construction. To evaluate a `fistree`, each fuzzy inference system must have at least one rule.

`Connections` — Connections between two fuzzy inference systems
string array

Connections between two fuzzy inference systems, specified as a two-dimensional string array. Each row represents a connection between two FIS objects. Connections are specified as follows:

1. Output-to-input connections, `["fromFISName/fromFISOutputName" "toFISName/toFISInputName"]`. In this case, output of `"fromFISName"` is used as the input of `"toFISName"`. `"fromFISName"` and `"toFISName"` must be different.
2. Input-to-input connections, `["fromFISName/fromFISInputName" "toFISName/toFISInputName"]`. In this case, inputs of `"fromFISName"` and `"toFISName"` use the same input values for evaluation. `"fromFISName"` and `"toFISName"` can be same or different.

`Inputs` — Inputs to the FIS tree
string array

Inputs to the FIS tree, specified as an array of strings. `Inputs` are automatically determined using the specified connections of the `fistree` object. FIS inputs with no incoming connections are included in `Inputs`. Update this property by updating the connections of the `fistree` object.

`Outputs` — Outputs of the FIS tree
string

Outputs of the FIS tree, specified as a string. `Outputs` are automatically determined using the specified connections of the `fistree` object. FIS outputs without any outgoing connections are included in `Outputs`. You can update this property after initial construction of the `fistree` object. Existing outputs can be removed or new outputs can be added. `Outputs` cannot be empty.

`DisableStructuralChecks` — Flag for disabling structural checks
false (default) | true

Flag for disabling structural checks, inputs, and outputs, specified as either `false` or `true`. Set `DisableStructuralChecks` to `true` to disable automatic updates of connections, inputs, and outputs when a FIS is updated after construction of a `fistree` object. Disabling structural checks can produce an unexpected failure in the `evalfis` function.

Object Functions

evalfis	Evaluate fuzzy inference system
getTunableSettings	Obtain tunable settings from fuzzy inference system
getTunableValues	Obtain values of tunable parameters from fuzzy inference system
setTunableValues	Specify tunable parameter values of a fuzzy inference system

Examples

Create a Tree of Connected Fuzzy Inference Systems

Create a Mamdani fuzzy inference system and a Sugeno fuzzy inference system.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = sugfis('Name','fis2','NumInputs',2,'NumOutputs',1);
```

Define the desired connections between the two fuzzy inference systems.

```
con1 = ["fis1/output1" "fis2/input1"];
con2 = ["fis1/input1" "fis1/input2"];
```

Create a tree of fuzzy inference systems.

```
tree = fistree([fis1 fis2],[con1; con2])
```

```
tree = 
  fistree with properties:

                        FIS: [1x2 FuzzyInferenceSystem]
                Connections: [2x2 string]
                     Inputs: [2x1 string]
                    Outputs: "fis2/output1"
    DisableStructuralChecks: 0

    See 'getTunableSettings' method for parameter optimization.
```

Update Fuzzy Inference Systems in a FIS Tree

Create a FIS tree.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = mamfis('Name','fis2','NumInputs',2,'NumOutputs',1);

fisT = fistree([fis1 fis2],[]);
```

Display the FIS tree configuration.

```
plotfis(fisT)
```

```
FIS Names:
    fis1
    fis2

Connections:
    []
```

```
Inputs:
    fis1/input1
    fis1/input2
    fis2/input1
    fis2/input2

Outputs:
    fis1/output1
    fis2/output1
```

Add FIS

Add `fis3` to `fisT`.

```
fis3 = mamfis('Name','fis3','NumInputs',2,'NumOutputs',1);
fisT.FIS(end+1) = fis3;
```

Add connections between `fis1`, `fis2`, and `fis3`.

```
fisT.Connections = ["fis1/output1" "fis3/input1";"fis2/output1" "fis3/input2"];
```

Display the updated FIS tree configuration.

```
plotfis(fisT)
```

```
FIS Names:
    fis1
    fis2
    fis3

Connections:
    From            To
    ------------    -----------
    fis1/output1    fis3/input1
    fis2/output1    fis3/input2

Inputs:
    fis1/input1
    fis1/input2
    fis2/input1
    fis2/input2

Outputs:
    fis3/output1
```

Remove FIS

Remove `fis1` from `fisT`.

```
fisT.FIS(1) = [];
```

Display the updated FIS tree configuration.

```
plotfis(fisT)
```

```
FIS Names:
    fis2
    fis3

Connections:
    From            To
    ------------    -----------
    fis2/output1    fis3/input2

Inputs:
    fis2/input1
    fis2/input2
    fis3/input1

Outputs:
    fis3/output1
```

Use Same Value for Multiple Inputs of a FIS Tree

Create `fis1`, `fis2`, and `fis3`, each with two inputs and one input.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = mamfis('Name','fis2','NumInputs',2,'NumOutputs',1);
fis3 = mamfis('Name','fis3','NumInputs',2,'NumOutputs',1);
```

Create a connection between output 1 of `fis1` and input 1 of `fis3`.

```
con1 = ["fis1/output1" "fis3/input1"];
```

Create a connection between output 1 of `fis2` and input 2 of `fis3`.

```
con2 = ["fis2/output1" "fis3/input2"];
```

Create a connection between input 2 of `fis1` and input 1 of `fis2`.

```
con3 = ["fis1/input2" "fis2/input1"];
```

Create the FIS tree.

```
fuzzTree = fistree([fis1 fis2 fis3],[con1;con2;con3]);
```

Display the inputs of the FIS tree.

```
fuzzTree.Inputs
```

```
ans = 3x1 string array
    "fis1/input1"
    "fis1/input2"
    "fis2/input2"
```

Evaluate the fuzzy tree. Specify values for input 1 of `fis1`, input 2 of `fis1`, and input 2 of `fis2`. The value for input 2 of `fis1` is also sent to input 1 of `fis2`.

```
output = evalfis(fuzzTree,[0.8 0.25 0.7]);
```

Update FIS Tree Outputs

This example shows how to add or remove FIS tree outputs.

Add Outputs

Create `fis1`, `fis2`, and `fis3`, each with two inputs and one input.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = mamfis('Name','fis2','NumInputs',2,'NumOutputs',1);
fis3 = mamfis('Name','fis3','NumInputs',2,'NumOutputs',1);
```

Create a connection between output 1 of `fis1` and input 1 of `fis3`.

```
con1 = ["fis1/output1" "fis3/input1"];
```

Create a connection between output 1 of `fis2` and input 2 of `fis3`.

```
con2 = ["fis2/output1" "fis3/input2"];
```

Create the FIS tree.

```
fuzzTree = fistree([fis1 fis2 fis3],[con1;con2]);
```

Display outputs of the FIS tree. By default, the only open FIS output (from `fis3`) is an output of the FIS tree.

```
fuzzTree.Outputs
```

```
ans = 
"fis3/output1"
```

Add the output of `fis2` outputs to the tree output list.

```
fuzzTree.Outputs(end+1) = "fis2/output1";
```

Display the updated output list of the FIS tree.

```
fuzzTree.Outputs
```

```
ans = 2x1 string array
    "fis3/output1"
    "fis2/output1"
```

Evaluate the FIS tree. The result contains the outputs from `fis3` and `fis2`.

```
evalfis(fuzzTree,[0.5 0.2 0.8 0.45])
```

```
ans = 1×2

    0.1507    0.1579
```

Remove Outputs

Remove the first output from the list.

```
fuzzTree.Outputs(1) = [];
```

Display the updated output list of the FIS tree.

```
fuzzTree.Outputs
```

```
ans = 
"fis2/output1"
```

Evaluate the FIS tree again. The result now contains the output of only `fis2`.

```
evalfis(fuzzTree,[0.5 0.2 0.8 0.45])
```

```
ans = 0.1579
```

Create Incremental FIS Tree

This example shows construction of an incremental FIS tree. For more information on the types of fuzzy tree structures, see “Fuzzy Trees” on page 2-65.

Create fuzzy systems `fis1`, `fis2`, and `fis3`, each with two inputs and one input.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis1.Inputs(1).Name = "color";
fis1.Inputs(2).Name = "doors";
fis2 = mamfis('Name','fis2','NumInputs',2,'NumOutputs',1);
fis2.Inputs(2).Name = "power";
fis3 = mamfis('Name','fis3','NumInputs',2,'NumOutputs',1);
fis3.Inputs(2).Name = "autopilot";
fis3.Outputs(1).Name = "predition";
```

Create a connection between output 1 of `fis1` and input 1 of `fis2`.

```
con1 = ["fis1/output1" "fis2/input1"];
```

Create a connection between output 1 of `fis2` and input 1 of `fis3`.

```
con2 = ["fis2/output1" "fis3/input1"];
```

Create the FIS tree.

```
incTree = fistree([fis1 fis2 fis3],[con1;con2]);
```

Display the inputs of the FIS tree.

```
incTree.Inputs
```

```
ans = 4x1 string array
    "fis1/color"
    "fis1/doors"
    "fis2/power"
    "fis3/autopilot"
```

Display outputs of the FIS tree.

```
incTree.Outputs

ans = 
"fis3/predition"
```

Create Cascaded FIS Tree

This example shows construction of a cascaded FIS tree. For more information on the types of fuzzy tree structures, see “Fuzzy Trees” on page 2-65.

Create fuzzy systems `fis1`, `fis2`, `fis3`, and `fis4`, each with two inputs and one input.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis1.Inputs(1).Name = "dist_obs";
fis1.Inputs(2).Name = "angle_obs";
fis2 = mamfis('Name','fis2','NumInputs',2,'NumOutputs',1);
fis2.Inputs(1).Name = "dist_tar";
fis2.Inputs(2).Name = "angle_tar";
fis3 = mamfis('Name','fis3','NumInputs',2,'NumOutputs',1);
fis4 = mamfis('Name','fis4','NumInputs',2,'NumOutputs',1);
fis4.Inputs(2).Name = "preheading_robot";
fis4.Outputs(1).Name = "heading_robot";
```

Create a connection between output 1 of `fis1` and input 1 of `fis3`.

```
con1 = ["fis1/output1" "fis3/input1"];
```

Create a connection between output 1 of `fis2` and input 2 of `fis3`.

```
con2 = ["fis2/output1" "fis3/input2"];
```

Create a connection between output 1 of `fis3` and input 1 of `fis4`.

```
con3 = ["fis3/output1" "fis4/input1"];
```

Create the FIS tree.

```
casTree = fistree([fis1 fis2 fis3 fis4],[con1;con2;con3]);
```

Display the inputs of the FIS tree.

```
casTree.Inputs
```

```
ans = 5x1 string array
    "fis1/dist_obs"
    "fis1/angle_obs"
    "fis2/dist_tar"
    "fis2/angle_tar"
    "fis4/preheading_robot"
```

Display the outputs of the FIS tree.

```
casTree.Outputs
```

```
ans = 
"fis4/heading_robot"
```

Create Aggregated FIS Tree

This example shows construction of an aggregated FIS tree. For more information on the types of fuzzy tree structures, see “Fuzzy Trees” on page 2-65.

Create fuzzy systems `fis1`, `fis2`, and `fis3`, each with two inputs and one input.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis1.Inputs(1).Name = "dist_obs";
fis1.Inputs(2).Name = "angle_obs";
fis2 = mamfis('Name','fis2','NumInputs',2,'NumOutputs',1);
fis2.Inputs(1).Name = "dist_tar";
fis2.Inputs(2).Name = "angle_tar";
fis3 = mamfis('Name','fis3','NumInputs',2,'NumOutputs',1);
fis3.Outputs(1).Name = "heading_robot";
```

Create a connection between output 1 of `fis1` and input 1 of `fis3`.

```
con1 = ["fis1/output1" "fis3/input1"];
```

Create a connection between output 1 of `fis2` and input 2 of `fis3`.

```
con2 = ["fis2/output1" "fis3/input2"];
```

Create the FIS tree.

```
aggTree = fistree([fis1 fis2 fis3],[con1;con2]);
```

Display the inputs of the FIS tree.

```
aggTree.Inputs
```

```
ans = 4x1 string array
    "fis1/dist_obs"
    "fis1/angle_obs"
    "fis2/dist_tar"
    "fis2/angle_tar"
```

Display the outputs of the FIS tree.

```
aggTree.Outputs
```

```
ans = 
"fis3/heading_robot"
```

Create and Evaluate Parallel FIS Tree

This example shows construction of a parallel FIS tree. For more information on the types of fuzzy tree structures, see “Fuzzy Trees” on page 2-65.

Create fuzzy systems `fis1`, `fis2`, and `fis3`, each with two inputs and one input.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = mamfis('Name','fis2','NumInputs',2,'NumOutputs',1);
```

Create the FIS tree such that all of the FIS ibjects are in parallel; that is, there are no interconnections and all the FIS outputs are FIS tree outputs.

```
parTree = fistree([fis1 fis2],[]);
```

Display the inputs of the FIS tree.

```
parTree.Inputs
```

```
ans = 4x1 string array
    "fis1/input1"
    "fis1/input2"
    "fis2/input1"
    "fis2/input2"
```

Display the outputs of the FIS tree.

```
parTree.Outputs
```

```
ans = 2x1 string array
    "fis1/output1"
    "fis2/output1"
```

Evaluate the FIS tree.

```
output = evalfis(parTree,[0.1 0.3 0.8 0.4]);
```

Generate the final output by summing the FIS tree outputs.

```
finalOutput = sum(output);
```

See Also
`evalfisOptions` | `mamfis` | `sugfis` | `tunefis`

Topics
"Fuzzy Trees" on page 2-65

Introduced in R2019a

fisvar

Fuzzy variable

Description

Use `fisvar` objects to represent the input and output variables in a fuzzy inference system (FIS). For more information on creating fuzzy inference systems, see `mamfis` and `sugfis`.

Creation

Syntax

```
var = fisvar
var = fisvar(range)
var = fisvar('Name',name)
var = fisvar(range,'Name',name)
```

Description

`var = fisvar` creates a fuzzy variable with a default name, default range, and no membership functions. To change the variable properties, use dot notation.

`var = fisvar(range)` sets the `Range` property.

`var = fisvar('Name',name)` sets the `Name` property.

`var = fisvar(range,'Name',name)` sets both the `Range` and `Name` properties.

Properties

Name — Variable name
`"var"` (default) | string | character vector

Variable name, specified as a string or character vector.

Range — Variable range
`[0 1]` (default) | two-element vector

Variable range, specified as a two-element element vector where the first element is less than the second element. The first element specifies the lower bound of the range, and the second element specifies the upper bound of the range.

`MembershipFunctions` — Membership functions
`[]` (default) | vector of `fismf` objects

Membership functions, specified as a vector of `fismf` objects. To add membership functions to a fuzzy variable:

- Use the `addMF` function.
- Create a vector of `fismf` objects, and assign it to `MembershipFunctions`.

You can modify the properties of the membership functions using dot notation.

Object Functions

addMF	Add membership function to fuzzy variable
removeMF	Remove membership function from fuzzy variable

Examples

Create Fuzzy Variable

Create a fuzzy variable with default properties.

```
var = fisvar;
```

To modify the properties of a `fisvar` object, use dot notation. For example, specify the range of the fuzzy variable to be from `-5` to `5`.

```
var.Range = [-5 5];
```

Create Fuzzy Variable with Specified Range

Create a fuzzy variable with an input range from `-10` to `10`.

```
var = fisvar([-10 10]);
```

Create Fuzzy Variable with Specified Name

Create a fuzzy variable with the name `"speed"`.

```
var = fisvar("Name","speed");
```

See Also

`fismf` | `fisrule` | `mamfis` | `sugfis`

Topics

"Build Fuzzy Systems at the Command Line" on page 2-38

Introduced in R2018b

mamfis

Mamdani fuzzy inference system

Description

Use a `mamfis` object to represent a Mamdani fuzzy inference system (FIS). For more information on Mamdani systems, see “What Is Mamdani-Type Fuzzy Inference?” on page 2-4

As an alternative to Mamdani systems, you can create a Sugeno FIS using a `sugfis` object. For a comparison of Mamdani and Sugeno systems, see “Comparison of Sugeno and Mamdani Systems” on page 2-12.

Creation

To create a Mamdani FIS object, use one of the following methods:

- The `mamfis` function.
- If you have input and output training data (`inputData` and `outputData`, respectively), you can use the `genfis` function with the FCM clustering method.

  ```
  opt = genfisOptions('FCMClustering','FISType','mamdani');
  fis = genfis(inputData,outputData,opt);
  ```
- If you have a `.fis` file for a Mamdani system, you can use the `readfis` function.

Syntax

```
fis = mamfis
fis = mamfis(Name,Value)
```

Description

`fis = mamfis` creates a Mamdani FIS with default property values. To modify the properties of the fuzzy system, use dot notation.

`fis = mamfis(Name,Value)` specifies FIS configuration information or sets object properties using name-value pair arguments. You can specify multiple name-value pairs. Enclose names in quotes.

Input Arguments

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'NumInputs',2` configures the fuzzy system to have two input variables

`NumInputs` — Number of FIS inputs
`0` (default) | nonnegative integer

Number of FIS inputs, specified as the comma-separated pair consisting of `'NumInputs'` and a nonnegative integer.

`NumInputMFs` — Number of membership functions for each FIS input
`3` (default) | positive integer

Number of membership functions for each FIS input, specified as the comma-separated pair consisting of `'NumInputMFs'` and a positive integer.

`NumOutputs` — Number of FIS outputs
`0` (default) | nonnegative integer

Number of FIS outputs, specified as the comma-separated pair consisting of `'NumOutputs'` and a nonnegative integer.

`NumOutputMFs` — Number of membership functions for each FIS output
`3` (default) | positive integer

Number of membership functions for each FIS output, specified as the comma-separated pair consisting of `'NumOutputMFs'` and a positive integer.

`MFType` — Membership function type
`"trimf"` (default) | `"gaussmf"`

Membership function type for both input and output variables, specified as the comma-separated pair consisting of `"MFType"` and either `"trimf"` (triangular MF) or `"gaussmf"` (Gaussian MF). For each input and output variable, the membership functions are uniformly distributed over the variable range with approximately 80% overlap in the MF supports.

`AddRules` — Flag for automatically adding rules
`"allcombinations"` (default) | `"none"`

Flag for automatically adding rules, specified as the comma-separated pair consisting of `"AddRules"` and one of the following:

- `"allcombinations"` — If both `NumInputs` and `NumOutputs` are greater than zero, create rules with antecedents that contain all input membership function combinations. Each rule consequent contains all the output variables and uses the first membership function of each output.
- `"none"` — Create a FIS without any rules.

Properties

`Name` — FIS name
`"fis"` (default) | string | character vector

FIS name, specified as a string or character vector.

`AndMethod` — AND operator method
`"min"` (default) | `"prod"` | string | character vector | function handle

AND operator method for combining fuzzified input values in a fuzzy rule antecedent, specified as one of the following:

- `"min"` — Minimum of fuzzified input values
- `"prod"` — Product of fuzzified input values
- String or character vector — Name of a custom AND function in the current working folder or on the MATLAB path
- Function handle — Custom AND function in the current working folder or on the MATLAB path

For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on fuzzy operators and the fuzzy inference process, see "Fuzzy Inference Process" on page 1-28.

`OrMethod` — OR operator method
`"max"` (default) | `"probor"` | string | character vector | function handle

OR operator method for combining fuzzified input values in a fuzzy rule antecedent, specified as one of the following:

- `"max"` — Maximum of fuzzified input values.
- `"probor"` — Probabilistic OR of fuzzified input values. For more information, see `probor`.
- String or character vector — Name of a custom OR function in the current working folder or on the MATLAB path.
- Function handle — Custom OR function in the current working folder or on the MATLAB path.

For more information on using custom functions, see "Build Fuzzy Systems Using Custom Functions" on page 2-50.

For more information on fuzzy operators and the fuzzy inference process, see "Fuzzy Inference Process" on page 1-28.

`ImplicationMethod` — Implication method
`"min"` (default) | `"prod"` | string | character vector | function handle

Implication method for computing the consequent fuzzy set, specified as one of the following:

- `"min"` — Truncate the consequent membership function at the antecedent result value.
- `"prod"` — Scale the consequent membership function by the antecedent result value.
- String or character vector — Name of a custom implication function in the current working folder or on the MATLAB path.
- Function handle — Custom implication function in the current working folder or on the MATLAB path.

For more information on using custom functions, see "Build Fuzzy Systems Using Custom Functions" on page 2-50.

For more information on implication and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`AggregationMethod` — Aggregation method
`"max"` (default) | `"sum"` | `"probor"` | string | character vector | function handle

Aggregation method for combining rule consequents, specified as one of the following:

- `"max"` — Maximum of consequent fuzzy sets
- `"sum"` — Sum of consequent fuzzy sets
- `"probor"` — Probabilistic OR of consequent fuzzy sets. For more information, see `probor`.
- String or character vector — Name of a custom aggregation function in the current working folder or on the MATLAB path
- Function handle — Custom aggregation function in the current working folder or on the MATLAB path

For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on aggregation and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`DefuzzificationMethod` — Defuzzification method
`"centroid"` (default) | `"bisector"` | `"mom"` | `"lom"` | `"som"` | string | character vector | function handle

Defuzzification method for computing crisp output values from the aggregated output fuzzy set, specified as one of the following:

- `"centroid"` — Centroid of the area under the output fuzzy set
- `"bisector"` — Bisector of the area under the output fuzzy set
- `"mom"` — Mean of the values for which the output fuzzy set is maximum
- `"lom"` — Largest value for which the output fuzzy set is maximum
- `"som"` — Smallest value for which the output fuzzy set is maximum
- String or character vector — Name of a custom defuzzification function in the current working folder or on the MATLAB path
- Function handle — Custom defuzzification function in the current working folder or on the MATLAB path

For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on defuzzification and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`Inputs` — FIS input variables
vector of `fisvar` objects

FIS input variables, specified as a vector of `fisvar` objects. To add and remove input variables, use `addInput` and `removeInput`, respectively.

You can also create a vector of `fisvar` objects and assign it to `Inputs` using dot notation.

You can add membership functions to input variables using the `addMF` function.

`Outputs` — FIS output variables
vector of `fisvar` objects

FIS output variables, specified as a vector of `fisvar` objects. To add and remove output variables, use `addOutput` and `removeOutput`, respectively.

You can also create a vector of `fisvar` objects and assign it to `Outputs` using dot notation.

You can add membership functions to output variables using the `addMF` function.

`Rules` — FIS rules
vector of `fisrule` objects

FIS input variables, specified as a vector of `fisrule` objects. To add fuzzy rules, use the `addRule` function.

You can also create a vector of `fisrule` objects and assign it to `Rules` using dot notation.

To remove a rule, set the corresponding rule vector element to `[]`. For example, to remove the tenth rule from the rule list, type:

```
fis.Rules(10) = [];
```

`DisableStructuralChecks` — Flag for disabling consistency checks
`false` (default) | `true`

Flag for disabling consistency checks when property values change, specified as a logical value.

By default, when you change the value of a property of a `mamfis` object, the software verifies whether the new property value is consistent with the other object properties. These checks can affect performance, particularly when creating and updating fuzzy systems within loops.

To disable these checks, which results in faster FIS construction, set `DisableSturcturalChecks` to `true`.

Note Disabling structural checks can result in an invalid `mamfis` object.

To reenable the consistency checks, first verify that the changes you made to the FIS are consistent and produce a valid `mamfis` object. Then, set `DisableSturcturalChecks` to `false`. If the `mamfis` object is invalid, reenabling the consistency checks generates an error.

Object Functions

addInput	Add input variable to fuzzy inference system
removeInput	Remove input variable from fuzzy inference system
addOutput	Add output variable to fuzzy inference system
removeOutput	Remove output variable from fuzzy inference system
addRule	Add rule to fuzzy inference system
addMF	Add membership function to fuzzy variable
removeMF	Remove membership function from fuzzy variable
evalfis	Evaluate fuzzy inference system
writeFIS	Save fuzzy inference system to file

Examples

Create Mamdani Fuzzy Inference System

Create a Mamdani fuzzy inference system with default property values.

```
fis = mamfis;
```

Modify the system properties using dot notation. For example, configure `fis` to use centroid defuzzification.

```
fis.DefuzzificationMethod = "centroid";
```

Alternatively, you can specify one of more FIS properties when you create a fuzzy system. For example, create a Mamdani fuzzy system with specified AND and OR methods.

```
fis = mamfis("AndMethod","prod","OrMethod","probor");
```

Specify Number of Inputs and Outputs for Mamdani System

Create a Mamdani fuzzy inference system with three inputs and one output.

```
fis = mamfis("NumInputs",3,"NumOutputs",1);
```

Alternative Functionality

App

You can interactively create a Mamdani FIS using the **Fuzzy Logic Designer** app. You can then export the system to the MATLAB workspace.

See Also

`fismf` | `fisrule` | `fisvar` | `sugfis`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced in R2018b

MembershipFunctionSettings

Tunable parameter settings of fuzzy membership functions

Description

A `MembershipFunctionSettings` object is created using the `getTunableSettings` function with a `mamfis`, `sugfis`, or `fistree` object. When the first output is specified, `getTunableSettings` returns tunable parameter settings of input membership functions within the input variable parameter settings. When the second output is specified, `getTunableSettings` returns tunable parameter settings of output membership functions within the output variable parameter settings. Specify the settings of the `Parameters` property.

Creation

Create a `MembershipFunctionSettings` object using `getTunableSettings` with one or two outputs. The `MembershipFunctions` property of the first or second output is specified as a `MembershipFunctionSettings` object.

Properties

`Parameters` — Membership function parameter settings
`NumericParameters` object

Membership function parameter settings, specified as a `NumericParameters` object. The membership function parameter settings consist of the properties `Minimum`, `Maximum`, and `Free`.

Object Functions

setTunable	Set specified parameter settings as tunable or nontunable

Examples

Obtain Tunable Settings of Input and Output Variables from FIS

Create two fuzzy inference systems, and define the connection between the two.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = sugfis('Name','fis2','NumInputs',2,'NumOutputs',1);
con = ["fis1/output1" "fis2/input1"];
```

Create a tree of fuzzy inference systems.

```
tree = fistree([fis1 fis2],con);
```

Obtain the tunable settings of input and output variables of the fuzzy inference system.

```
[in,out] = getTunableSettings(tree)
```

```
in = 
  4x1 VariableSettings array with properties:

    Type
    VariableName
    MembershipFunctions
    FISName


out = 
  2x1 VariableSettings array with properties:

    Type
    VariableName
    MembershipFunctions
    FISName
```

You can use dot notation to specify the tunable settings of input and output variables.

For the first membership function of input 1, set the first and third parameters to tunable.

```
in(1).MembershipFunctions(1).Parameters.Free = [1 0 1];
```

For the first membership function of input 2, set the minimum parameter range to 0.

```
in(2).MembershipFunctions(1).Parameters.Minimum = 0;
```

For the first membership function of output 2, set the maximum parameter range to 1.

```
out(2).MembershipFunctions(1).Parameters.Maximum = 1;
```

See Also

`NumericParameters` | `VariableSettings` | `getTunableSettings`

Introduced in R2019a

NumericParameters

Tunable numeric parameter settings of membership functions

Description

A `NumericParameters` object is created using the `getTunableSettings` function with a `mamfis`, `sugfis`, or `fistree` object. When the first output is specified, `getTunableSettings` returns numeric parameter settings of input membership functions within the input variable parameter settings. When the second output is specified, `getTunableSettings` returns numeric parameter settings of output membership functions within the output variable parameter settings.

Creation

Create a `NumericParameters` object using `getTunableSettings` with one or two outputs. The `Parameters` property of the `MembershipFunctions` property of the first or second output is specified as a `NumericParameters` object.

Properties

Free — Parameter values available for tuning
`true` or `1` | `false` or `0`

Parameter values available for tuning, specified as an array of numeric or logical `1` (`true`) or `0` (`false`).

`Minimum` — Minimum range of parameter values
double

Minimum range of parameter values, specified as an array of integers.

`Maximum` — Maximum range of parameter values
double

Maximum range of parameter values, specified as an array of integers.

Examples

Obtain Tunable Settings of Input and Output Variables from FIS

Create two fuzzy inference systems, and define the connection between the two.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = sugfis('Name','fis2','NumInputs',2,'NumOutputs',1);
con = ["fis1/output1" "fis2/input1"];
```

Create a tree of fuzzy inference systems.

```
tree = fistree([fis1 fis2],con);
```

Obtain the tunable settings of input and output variables of the fuzzy inference system.

```
[in,out] = getTunableSettings(tree)
```

```
in = 
  4x1 VariableSettings array with properties:

    Type
    VariableName
    MembershipFunctions
    FISName


out = 
  2x1 VariableSettings array with properties:

    Type
    VariableName
    MembershipFunctions
    FISName
```

You can use dot notation to specify the tunable settings of input and output variables.

For the first membership function of input 1, set the first and third parameters to tunable.

```
in(1).MembershipFunctions(1).Parameters.Free = [1 0 1];
```

For the first membership function of input 2, set the minimum parameter range to 0.

```
in(2).MembershipFunctions(1).Parameters.Minimum = 0;
```

For the first membership function of output 2, set the maximum parameter range to 1.

```
out(2).MembershipFunctions(1).Parameters.Maximum = 1;
```

See Also

`MembershipFunctionSettings` | `VariableSettings` | `getTunableSettings`

Introduced in R2019a

RuleSettings

Tunable parameter settings of fuzzy rules

Description

A `RuleSettings` object is created using the `getTunableSettings` function with a `mamfis`, `sugfis`, or `fistree` object. When the third output is specified, `getTunableSettings` returns tunable parameter settings of fuzzy rules. Specify the settings of the `Antecedent` and `Consequent` properties.

Creation

Create a `RuleSettings` object using `getTunableSettings` with three outputs.

Properties

`FISName` — Name of fuzzy inference system
string

This property is read-only.

Name of fuzzy inference system, specified as a string.

`Index` — Index of rule in fuzzy inference system
double

This property is read-only.

Index of rule in fuzzy inference system, specified as an integer.

`Antecedent` — Antecedent parameter settings of rule
`ClauseParameters` object

Antecedent parameter settings of rule, specified as a `ClauseParameters` object. Each antecedent parameter consists of the properties `AllowNot`, `AllowEmpty`, and `Free`. You can specify these properties.

Consequent — Consequent parameter settings of rule
`ClauseParameters` object

Consequent parameter settings of rule, specified as a `ClauseParameters` object. Each consequent parameter consists of the properties `AllowNot`, `AllowEmpty`, and `Free`. You can specify these properties.

Object Functions

setTunable	Set specified parameter settings as tunable or nontunable

Examples

Obtain Tunable Settings of Rules from FIS

Create two fuzzy inference systems, and define the connection between the two.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = sugfis('Name','fis2','NumInputs',2,'NumOutputs',1);
con = ["fis1/output1" "fis2/input1"];
```

Create a tree of fuzzy inference systems.

```
tree = fistree([fis1 fis2],con);
```

Obtain the tunable settings of rules of the fuzzy inference system.

```
[~,~,rule] = getTunableSettings(tree)
```

```
rule = 
  18x1 RuleSettings array with properties:

    Index
    Antecedent
    Consequent
    FISName
```

You can use dot notation to specify the tunable settings of rules.

For the first rule, do not tune input 1 membership function index and do not ignore output 1 membership function index.

```
rule(1).Antecedent.Free(1) = false;
rule(1).Consequent.AllowEmpty(1) = false;
```

For the second rule, allow NOT logic for input 2 membership function index.

```
rule(2).Antecedent.AllowNot(2) = true;
```

See Also

`ClauseParameters` | `VariableSettings` | `getTunableSettings`

Introduced in R2019a

sugfis

Sugeno fuzzy inference system

Description

Use a `sugfis` object to represent a Sugeno fuzzy inference system (FIS). For more information on Sugeno systems, see “What Is Sugeno-Type Fuzzy Inference?” on page 2-5

As an alternative to Sugeno systems, you can create a Mamdani FIS using a `mamfis` object. For a comparison of Sugeno and Mamdani systems, see “Comparison of Sugeno and Mamdani Systems” on page 2-12.

Creation

To create a Sugeno FIS object, use one of the following methods:

- The `sugfis` function.
- If you have input/output data, you can use the `genfis` function.
- If you have a `.fis` file for a Sugeno system, you can use the `readfis` function.
- Convert an existing Mamdani FIS to a Sugeno FIS using `convertToSugeno`.

Syntax

```
fis = sugfis
fis = sugfis(Name,Value)
```

Description

`fis = sugfis` creates a Sugeno FIS with default property values. To modify the properties of the fuzzy system, use dot notation.

`fis = sugfis(Name,Value)` specifies FIS configuration information or sets object properties using name-value pair arguments. You can specify multiple name-value pairs. Enclose names in quotes.

Input Arguments

Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name,Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'NumInputs',2` configures the fuzzy system to have two input variables

`NumInputs` — Number of FIS inputs
`0` (default) | nonnegative integer

Number of FIS inputs, specified as the comma-separated pair consisting of `'NumInputs'` and a nonnegative integer.

`NumInputMFs` — Number of membership functions for each FIS input
`3` (default) | positive integer

Number of membership functions for each FIS input, specified as the comma-separated pair consisting of `'NumInputMFs'` and a positive integer.

`NumOutputs` — Number of FIS outputs
`0` (default) | nonnegative integer

Number of FIS outputs, specified as the comma-separated pair consisting of `'NumOutputs'` and a nonnegative integer.

`NumOutputMFs` — Number of membership functions for each FIS output
`3` (default) | positive integer

Number of membership functions for each FIS output, specified as the comma-separated pair consisting of `'NumOutputMFs'` and a positive integer.

`MFType` — Membership function type
`"trimf"` (default) | `"gaussmf"`

Membership function type for input variables, specified as the comma-separated pair consisting of `'MFType'` and either `"trimf"` (triangular MF) or `"gaussmf"` (Gaussian MF). For each input variable, the membership functions are uniformly distributed over the variable range with approximately 80% overlap in the MF supports.

Output membership functions are set to `"constant"` and uniformly distributed over the output variable ranges.

`AddRules` — Flag for automatically adding rules
`"allcombinations"` (default) | `"none"`

Flag for automatically adding rules, specified as the comma-separated pair consisting of `"AddRules"` and one of the following:

- `"allcombinations"` — If both `NumInputs` and `NumOutputs` are greater than zero, create rules with antecedents that contain all input membership function combinations. Each rule consequent contains all the output variables and uses the first membership function of each output.
- `"none"` — Create a FIS without any rules.

Properties

`Name` — FIS name
`"fis"` (default) | string | character vector

FIS name, specified as a string or character vector.

`AndMethod` — AND operator method
`"prod"` (default) | `"min"` | string | character vector | function handle

AND operator method for combining fuzzified input values in a fuzzy rule antecedent, specified as one of the following:

- `"prod"` — Product of fuzzified input values
- `"min"` — Minimum of fuzzified input values
- String or character vector — Name of a custom AND function in the current working folder or on the MATLAB path
- Function handle — Custom AND function in the current working folder or on the MATLAB path

For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on fuzzy operators and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`OrMethod` — OR operator method

`"probor"` (default) | `"max"` | string | character vector | function handle

OR operator method for combining fuzzified input values in a fuzzy rule antecedent, specified as one of the following:

- `"probor"` — Probabilistic OR of fuzzified input values. For more information, see `probor`.
- `"max"` — Maximum of fuzzified input values.
- String or character vector — Name of a custom OR function in the current working folder or on the MATLAB path.
- Function handle — Custom OR function in the current working folder or on the MATLAB path.

For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on fuzzy operators and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`ImplicationMethod` — Implication method

`"prod"` (default)

Implication method for computing consequent fuzzy set, specified as `"prod"`. Sugeno systems always use the `"prod"` implication method, which scales the consequent membership function by the antecedent result value.

For more information on implication and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`AggregationMethod` — Aggregation method

`"sum"` (default)

Aggregation method for combining rule consequents, specified as `"sum"`. Sugeno systems always use the `"sum"` aggregation method, which is the sum of the consequent fuzzy sets.

For more information on aggregation and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`DefuzzificationMethod` — Defuzzification method

`"wtaver"` (default) | `"wtsum"`

Defuzzification method for computing crisp output values from the aggregated output fuzzy set, specified as one of the following:

- `"wtaver"` — Weighted average of all rule outputs
- `"wtsum"` — Weighted sum of all rule outputs

For more information on using custom functions, see “Build Fuzzy Systems Using Custom Functions” on page 2-50.

For more information on defuzzification and the fuzzy inference process, see “Fuzzy Inference Process” on page 1-28.

`Inputs` — FIS input variables

vector of `fisvar` objects

FIS input variables, specified as a vector of `fisvar` objects. To add and remove input variables, use `addInput` and `removeInput`, respectively. You can modify the properties of the input variables using dot notation.

You can also create a vector of `fisvar` objects and assign it to `Inputs` using dot notation.

You can add membership functions to input variables using the `addMF` function.

`Outputs` — FIS output variables

vector of `fisvar` objects

FIS output variables, specified as a vector of `fisvar` objects. To add and remove output variables, use `addOutput` and `removeOutput`, respectively.

You can also create a vector of `fisvar` objects and assign it to `Outputs` using dot notation.

You can add membership functions to output variables using the `addMF` function.

`Rules` — FIS rules

vector of `fisrule` objects

FIS input variables, specified as a vector of `fisrule` objects. To add fuzzy rules, use the `addRule` function.

You can also create a vector of `fisrule` objects and assign it to `Rules` using dot notation.

To remove a rule, set the corresponding rule vector element to `[]`. For example, to remove the tenth rule from the rule list, type:

```
fis.Rules(10) = [];
```

`DisableStructuralChecks` — Flag for disabling consistency checks
`false` (default) | `true`

Flag for disabling consistency checks when property values change, specified as a logical value.

By default, when you change the value of a property of a `sugfis` object, the software verifies whether the new property value is consistent with the other object properties. These checks can affect performance, particularly when creating and updating fuzzy systems within loops.

To disable these checks, which results in faster FIS construction, set `DisableSturcturalChecks` to `true`.

Note Disabling structural checks can result in an invalid `sugfis` object.

To reenable the consistency checks, first verify that the changes you made to the FIS are consistent and produce a valid `sugfis` object. Then, set `DisableSturcturalChecks` to `false`. If the `sugfis` object is invalid, reenabling the consistency checks generates an error.

Object Functions

addInput	Add input variable to fuzzy inference system
removeInput	Remove input variable from fuzzy inference system
addOutput	Add output variable to fuzzy inference system
removeOutput	Remove output variable from fuzzy inference system
addRule	Add rule to fuzzy inference system

addMF	Add membership function to fuzzy variable
removeMF	Remove membership function from fuzzy variable
evalfis	Evaluate fuzzy inference system
writeFIS	Save fuzzy inference system to file

Examples

Create Sugeno Fuzzy Inference System

Create a Sugeno fuzzy inference system with default property values.

```
fis = sugfis;
```

Modify the system properties using dot notation. For example, configure `fis` to use weighted-sum defuzzification.

```
fis.DefuzzificationMethod = "wtsum";
```

Alternatively, you can specify one of more FIS properties when you create a fuzzy system. For example, create a Sugeno fuzzy system with specified AND and OR methods.

```
fis = sugfis("AndMethod","min","OrMethod","max");
```

Specify Number of Inputs and Outputs for Sugeno System

Create a Sugeno fuzzy inference system with three inputs and one output.

```
fis = sugfis("NumInputs",3,"NumOutputs",1);
```

Alternative Functionality

App

You can interactively create a Sugeno FIS using the **Fuzzy Logic Designer** or **Neuro-Fuzzy Designer** apps. You can then export the system to the MATLAB workspace.

See Also

`fismf` | `fisrule` | `fisvar` | `mamfis`

Topics

“Build Fuzzy Systems at the Command Line” on page 2-38

Introduced in R2018b

tunefisOptions

Option set for `tunefis` function

Description

Use a `tunefisOptions` object to specify options for tuning fuzzy systems. Specify options such as the optimization method, optimization type, and distance metric for cost measurement. Then, use this object as an input for the `tunefis` command.

Creation

Syntax

```
opt = tunefisOptions
opt = tunefisOptions(Name,Value)
```

Description

`opt = tunefisOptions` creates a default option set for tuning a fuzzy system using `tunefis`. Use dot notation to modify the properties of this option set for your specific application.

`opt = tunefisOptions(Name,Value)` creates an option set with the specified “Properties” on page 9-66 using name-value pair arguments. You can specify multiple name-value pairs.

Properties

`Method` — Tuning algorithm
`'ga'` (default) | `'particleswarm'` | `'patternsearch'` | `'simulannealbnd'` | `'anfis'`

Tuning algorithm, specified as one of the following:

- `'ga'` — genetic algorithm
- `'particleswarm'` — particle swarm
- `'patternsearch'` — pattern search
- `'simulannealbnd'` — simulated annealing algorithm
- `'anfis'` — adaptive neuro-fuzzy

These tuning algorithms use solvers from the “Global Optimization Toolbox”, except for `'anfis'`. The `'MethodOptions'` property differs for each algorithm, and corresponds to the options input argument for the respective solver. If you specify `'MethodOptions'` without specifying algorithm name, then `'Method'` is determined based on `'MethodOptions'`.

`MethodOptions` — Tuning algorithm options
options created using `optimoptions`

Tuning algorithm options, specified as an option object for the specified tuning algorithm `Method`. This property differs for each algorithm and is created using `optimoptions`. If `MethodOptions` is not specified, it is created according to `Method`. Use dot notation to modify options in `MethodOptions`.

`OptimizationType` — Type of optimization
`'tuning'` (default) | `'learning'`

Type of optimization, specified as one of the following:

- `'tuning'`
- `'learning'`

When `tuning` is selected, the existing input, output, and rule parameters are optimized without learning new rules. When `learning` is selected, new rules are added based on `NumMaxRules`. The `anfis` algorithm supports only tuning.

`NumMaxRules` — Maximum number of rules in FIS
inf (default) | integer

Maximum number of rules in FIS after optimization, specified as an integer. The number of rules in a FIS (after optimization) may be less than `'NumMaxRules'` since duplicate rules with same antecedent values are removed from the rule base. Default value is `inf`, which indicates existing rules are used when `'OptimizationType'` is `'tuning'` and maximum number of possible rules are used when `'OptimizationType'` is 'learning'. For a fistree object, 'NumMaxRules' indicates that the number of rules in each FIS of a fistree is less than or equal to the specified value. anfis does not support rule parameter optimization.

IgnoreInvalidParameters — Invalid parameter use
true (default) | false

Invalid parameter use, specified as either true or false. If true, the tunefis function ignores invalid parameter values generated in the tuning process. Default value is true. anfis ignores this parameter value.

DistanceMetric — Type of distance metric
'rmse' (default) | 'norm1 | 'norm2'

Type of distance metric used for cost measurement of the optimized parameter values with respect to the training data, specified as 'rmse', 'norm1', or 'norm2'. anfis supports only 'rmse'.

UseParallel — Parallel computation
false (default) | true

Parallel computation, specified as either true or false. If true, tunefis function uses parallel computation in the optimization process. anfis does not support parallel optimization.

Examples

Specify Options for FIS Tuning

Create a default option set using the particle swarm tuning algorithm.

```
opt = tunefisOptions("Method","particleswarm")
```

```
opt = 
  tunefisOptions with properties:

                 Method: "particleswarm"
          MethodOptions: [1x1 optim.options.Particleswarm]
       OptimizationType: "tuning"
            NumMaxRules: Inf
```

```
    IgnoreInvalidParameters: 1
             DistanceMetric: "rmse"
                UseParallel: 0
```

You can modify the options using dot notation. For example, set the maximum number of iterations to 20.

```
opt.MethodOptions.MaxIterations = 20;
```

You can also specify other options when creating the option set. In this example, set the `OptimizationType` to `"learning"` to learn new rules.

```
opt2 = tunefisOptions("Method","particleswarm","OptimizationType","learning")
```

```
opt2 = 
  tunefisOptions with properties:

                     Method: "particleswarm"
              MethodOptions: [1x1 optim.options.Particleswarm]
           OptimizationType: "learning"
                NumMaxRules: Inf
    IgnoreInvalidParameters: 1
             DistanceMetric: "rmse"
                UseParallel: 0
```

See Also

`fistree` | `getTunableSettings` | `mamfis` | `sugfis` | `tunefis`

Introduced in R2019a

VariableSettings

Tunable parameter settings of fuzzy variables

Description

A `VariableSettings` object is created using the `getTunableSettings` function with a `mamfis`, `sugfis`, or `fistree` object. When the first output is specified, `getTunableSettings` returns tunable parameter settings of input variables. When the second output is specified, `getTunableSettings` returns tunable parameter settings of output variables. Specify the settings of the `MembershipFunctions` property.

Creation

Create a `VariableSettings` object using `getTunableSettings` with one or two outputs.

Properties

`FISName` — Name of fuzzy inference system
string

This property is read-only.

Name of fuzzy inference system, specified as a string.

Type — Type of variable
`"input"` | `"output"`

This property is read-only.

Type of variable, specified as either `"input"` or `"output"`.

`VariableName` — Name of variable
string

This property is read-only.

Name of variable, specified as a string.

MembershipFunctions — Membership function settings
MembershipFunctionSettings object

Membership function settings, specified as a `MembershipFunctionSettings` objects. Each membership function consists of the property `Parameters`, which is specified as a `NumericParameters` object. You can specify this property.

Object Functions

setTunable	Set specified parameter settings as tunable or nontunable

Examples

Obtain Tunable Settings of Input and Output Variables from FIS

Create two fuzzy inference systems, and define the connection between the two.

```
fis1 = mamfis('Name','fis1','NumInputs',2,'NumOutputs',1);
fis2 = sugfis('Name','fis2','NumInputs',2,'NumOutputs',1);
con = ["fis1/output1" "fis2/input1"];
```

Create a tree of fuzzy inference systems.

```
tree = fistree([fis1 fis2],con);
```

Obtain the tunable settings of input and output variables of the fuzzy inference system.

```
[in,out] = getTunableSettings(tree)
```

```
in = 
  4x1 VariableSettings array with properties:

    Type
    VariableName
    MembershipFunctions
    FISName
```

```
out = 
  2x1 VariableSettings array with properties:

    Type
    VariableName
    MembershipFunctions
    FISName
```

You can use dot notation to specify the tunable settings of input and output variables.

For the first membership function of input 1, set the first and third parameters to tunable.

```
in(1).MembershipFunctions(1).Parameters.Free = [1 0 1];
```

For the first membership function of input 2, set the minimum parameter range to 0.

```
in(2).MembershipFunctions(1).Parameters.Minimum = 0;
```

For the first membership function of output 2, set the maximum parameter range to 1.

```
out(2).MembershipFunctions(1).Parameters.Maximum = 1;
```

See Also

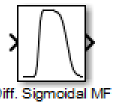
`MembershipFunctionSettings` | `RuleSettings` | `getTunableSettings`

Introduced in R2019a

Blocks — Alphabetical List

Diff. Sigmoidal MF

Difference of two sigmoids membership function in Simulink software



Description

The Diff. Sigmoidal MF block implements a membership function in Simulink based on the difference between two sigmoids. The two sigmoid curves are given by

$$f_k(x) = \frac{1}{1 + \exp(-a_k(x - c_k))}$$

where k=1,2. The parameters $a_1$and a_2 control the slopes of the left and right curves. The parameters c_1 and c_2 control the points of inflection for the left and right curves. The parameters a_1 and a_2 should be positive.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

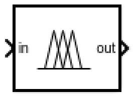
See Also

`dsigmf`

Introduced before R2006a

Fuzzy Logic Controller

Evaluate fuzzy inference system
Library: Fuzzy Logic Toolbox



Description

The Fuzzy Logic Controller block implements a fuzzy inference system (FIS) in Simulink. You specify the FIS to evaluate using the **FIS name** parameter.

For more information on fuzzy inference, see "Fuzzy Inference Process" on page 1-28.

To display the fuzzy inference process in the Rule Viewer during simulation, use the Fuzzy Logic Controller with Ruleviewer block.

Ports

Input

in — Input signal
scalar | vector

For a single-input fuzzy inference system, the input is a scalar signal. For a multi-input fuzzy system, combine the inputs into a vector signal using blocks such as:

- Mux
- Vector Concatenate
- Bus Creator

Output

`out` — Defuzzified output signal
scalar | vector

For a single-output fuzzy inference system, the output is a scalar signal. For a multi-output fuzzy system, the output is a vector signal. To split system outputs into scalar signals, use the Demux block.

`fi` — Fuzzified input values
matrix

Fuzzified input values, obtained by evaluating the input membership functions of each rule at the current input values.

`fi` is an N_R-by-N_U matrix signal, where N_R is the number of FIS rules and N_U is the number of FIS inputs. Element (i,j) of `fi` is the value of the input membership function for the *j*th input in the *i*th rule.

For more information on fuzzifying input values, see “Fuzzify Inputs” on page 1-29.

Dependencies

To enable this port, select the **Fuzzified inputs (fi)** parameter.

`rfs` — Rule firing strengths
column vector

Rule firing strengths, obtained by evaluating the antecedent of each rule; that is, applying the fuzzy operator to the values of the fuzzified inputs.

`rfs` is a column vector signal of length N_R, where element *i* is the firing strength of the *i*th rule.

For more information on applying fuzzy operators, see “Apply Fuzzy Operator” on page 1-30.

Dependencies

To enable this port, select the **Rule firing strengths (rfs)** parameter.

`ro` — Rule outputs
matrix

Rule outputs, obtained by applying the rule firing strengths to the output membership functions using the implication method specified in the FIS.

For a Mamdani system, each rule output is a fuzzy set. In this case, `ro` is an N_S-by-($N_R N_Y$) matrix signal. Here N_S is the number of sample points used for evaluating output variable ranges, and N_Y is the number of output variables. Each column of `ro` contains the output fuzzy set for one rule. The first N_R columns contain the rule outputs for the first output variable, the next N_R columns correspond to the second output variable, and so on.

For a Sugeno system, each rule output is a scalar value. In this case, `ro` is an N_R-by-N_Y matrix signal. Element (j,k) of `ro` is the value of the kth output variable for the jth rule.

For more information on fuzzy implication, see “Apply Implication Method” on page 1-31 and “What Is Sugeno-Type Fuzzy Inference?” on page 2-5

Dependencies

- To enable this port, select the **Rule outputs (ro)** parameter.
- To specify N_S, use the **Number of samples for output discretization** parameter.

ao — Aggregated output

matrix | row vector

Aggregate output for each output variable, obtained by combining the corresponding outputs from all the rules using the aggregation method specified in the FIS.

For a Mamdani system, the aggregate result for each output variable is a fuzzy set. In this case, `ao` is as an N_S-by-N_Y matrix signal. Each column of `ao` contains the aggregate fuzzy set for one output variable.

For a Sugeno system, the aggregate result for each output variable is a scalar value. In this case, `ao` is a row vector signal of length N_Y, where element k is the aggregate result for the kth output variable.

For more information on fuzzy aggregation, see “Aggregate All Outputs” on page 1-31 and “What Is Sugeno-Type Fuzzy Inference?” on page 2-5

Dependencies

- To enable this port, select the **Aggregated outputs (ao)** parameter.
- To specify N_S, use the **Number of samples for output discretization** parameter.

Parameters

General

`FIS name` — Fuzzy inference system

`mamfis`object | `sugfis`object | file name

Fuzzy inference system to evaluate, specified as one of the following:

- `mamfis` or `sugfis` object — Specify the name of a FIS object in the MATLAB workspace.

  To create a fuzzy inference system, you can:

  - Use the **Fuzzy Logic Designer** app. For an example, see "Build Fuzzy Systems Using Fuzzy Logic Designer" on page 2-14.
  - Automatically generate the FIS object using the `genfis` command.
  - Build the system at the command line. For an example, see "Build Fuzzy Systems at the Command Line" on page 2-38.
- File name — Specify the name of a `.fis` file in the current working folder or on the MATLAB path. Including the file extension in the file name is optional.

  To save a fuzzy inference system to a `.fis` file:

  - In **Fuzzy Logic Designer** or **Neuro-Fuzzy Designer**, select **File > Export > To File**.
  - At the command line, use `writeFIS`.

`Number of samples for output discretization` — Number of points in output fuzzy sets

101 (default) | integer greater than `1`

Number of samples for discretizing the range of output variables, specified as an integer greater than `1`. This value corresponds to the number of points in the output fuzzy set for each rule.

To reduce memory usage while evaluating a Mamdani FIS, specify a lower number of samples. Doing so sacrifices the accuracy of the defuzzified output value. Specifying a low number of samples can make the output area for defuzzification zero. In this case, the defuzzified output value is the midpoint of the output variable range.

Note The block ignores this parameter when evaluating a Sugeno FIS.

`Data type` — Signal data type
`double` (default) | `single` | `fixed-point` | `expression`

Signal data type, specified as one of the following:

- `double` — Double-precision signals
- `single` — Single-precision signals
- `fixdt(1,16,0)` — Fixed-point signals with binary point scaling
- `fixdt(1,16,2^0,0)` — Fixed-point signals with slope and bias scaling
- Expression — Expression that evaluates to one of these data types

For fixed-point data types, you can configure the signedness, word length, and scaling parameters using the **Data Type Assistant**. For more information, see “Specifying a Fixed-Point Data Type” (Simulink).

`Fuzzified inputs (fi)` — Enable `fi` output port
`off` (default) | `on`

Enable output port for accessing intermediate fuzzified input data.

`Rule firing strengths (rfs)` — Enable `rfs` output port
`off` (default) | `on`

Enable output port for accessing intermediate rule firing strength data.

`Rule outputs (ro)` — Enable `ro` output port
`off` (default) | `on`

Enable output port for accessing intermediate rule output data.

`Aggregated outputs (ao)` — Enable `ao` output port
`off` (default) | `on`

Enable output port for accessing intermediate aggregate output data.

`Simulate using` — Simulation mode
`Interpreted execution` (default) | `Code generation`

Simulation mode, specified as one of the following:

- `Interpreted execution` — Simulate fuzzy systems using precompiled MEX files for `single` and `double` data types. Using this option reduces the initial compilation time of the model.
- `Code generation` — Simulate fuzzy system without precompiled MEX files. Use this option when simulating fuzzy systems for code generation applications.

For fixed-point data types, the Fuzzy Logic Controller block always simulates using `Code generation` mode.

Diagnostics

`Out of range input value` — Diagnostic message behavior when an input is out of range

`warning` (default) | `error` | `none`

Diagnostic message behavior when an input is out of range, specified as one of the following:

- `warning` — Report the diagnostic message as a warning.
- `error` — Report the diagnostic message as an error.
- `none` — Do not report the diagnostic message.

When an input value is out of range, corresponding rules in the fuzzy system can have unexpected firing strengths.

Dependencies

- Diagnostic messages are provided only when the **Simulate using** parameter is `Interpreted execution`.

`No rule fired` — Diagnostic message behavior when no rules fire

`warning` (default) | `error` | `none`

Diagnostic message behavior when no rules fire for a given output variable, specified as one of the following:

- `warning` — Report the diagnostic message as a warning.
- `error` — Report the diagnostic message as an error.
- `none` — Do not report the diagnostic message.

When **No rule fired** is `warning` or `none` and no rules fire for a given output, the defuzzified output value is set to its mean range value.

Dependencies

- Diagnostic messages are provided only when the **Simulate using** parameter is `Interpreted execution`.

`Empty output fuzzy set` — Diagnostic message behavior when an output fuzzy set is empty

`warning` (default) | `error` | `none`

Diagnostic message behavior when an output fuzzy set is empty, specified as one of the following:

- `warning` — Report the diagnostic message as a warning.
- `error` — Report the diagnostic message as an error.
- `none` — Do not report the diagnostic message.

When **Empty output fuzzy set** is `warning` or `none` and an output fuzzy set is empty, the defuzzified value for the corresponding output is set to its mean range value.

Dependencies

- This diagnostic message applies to Mamdani systems only.
- Diagnostic messages are provided only when the **Simulate using** parameter is `Interpreted execution`.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields

- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

Extended Capabilities

C/C++ Code Generation
Generate C and C++ code using Simulink® Coder™.

PLC Code Generation
Generate Structured Text code using Simulink® PLC Coder™.

Fixed-Point Conversion
Convert floating-point algorithms to fixed point using Fixed-Point Designer™.

See Also

Blocks
Fuzzy Logic Controller with Ruleviewer

Apps
Fuzzy Logic Designer | Neuro-Fuzzy Designer

Functions
`evalfis` | `genfis` | `mamfis` | `readfis` | `sugfis` | `writeFIS`

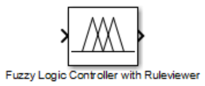
Topics
"Fuzzy Inference Process" on page 1-28

"Simulate Fuzzy Inference Systems in Simulink" on page 5-2

Introduced before R2006a

Fuzzy Logic Controller with Ruleviewer

Evaluate fuzzy inference system and view rules
Library: Fuzzy Logic Toolbox



Description

The Fuzzy Logic Controller with Ruleviewer block implements a fuzzy inference system (FIS) in Simulink and displays the fuzzy inference process in the Rule Viewer during the simulation. You specify the FIS to evaluate using the **FIS matrix** parameter. To change the time between Rule Viewer updates, specify the **Refresh rate** in seconds.

For more information on fuzzy inference, see "Fuzzy Inference Process" on page 1-28.

The Fuzzy Logic Controller with Ruleviewer block does not support all the features supported by the Fuzzy Logic Controller block. The Fuzzy Logic Controller with Ruleviewer block:

- Only supports double-precision data.
- Uses `101` points for discretizing output variable ranges.
- Only supports `Interpreted execution` simulation mode.
- Does not have additional output ports for accessing intermediate fuzzy inference results.

Ports

Input

`Port_1(In1)` — Input signal
scalar | vector

For a single-input fuzzy inference system, the input is a scalar. For a multi-input fuzzy system, combine the inputs into a vector signal using blocks such as:

- Mux
- Vector Concatenate
- Bus Creator

Output

`Port_1(Out1)` — Defuzzified output signal
scalar | vector

For a single-output fuzzy inference system, the output is a scalar. For a multi-output fuzzy system, the output is a vector. To split system outputs into scalar signals, use the Demux block.

Parameters

`FIS matrix` — Fuzzy inference system
`mamfis`object | `sugfis`object

Fuzzy inference system to evaluate, specified as a `mamfis` or `sugfis` object. Specify the name of a FIS object in the MATLAB workspace.

To create a fuzzy inference system, you can:

- Use the **Fuzzy Logic Designer** app. For an example, see “Build Fuzzy Systems Using Fuzzy Logic Designer” on page 2-14.
- Automatically generate the FIS object using the `genfis` command.
- Build the system at the command line. For an example, see “Build Fuzzy Systems at the Command Line” on page 2-38.

`Refresh rate` — Time between rule viewer updates
scalar

Time between rule viewer updates in seconds, specified as a scalar. During simulation, the Rule Viewer display updates at the specified rate to show the inference process for the latest input signal values.

Compatibility Considerations

Support for representing fuzzy inference systems as structures will be removed

Not recommended starting in R2018b

Support for representing fuzzy inference systems as structures will be removed in a future release. Use `mamfis` and `sugfis` objects instead. There are differences between these representations that require updates to your code. These differences include:

- Object property names that differ from the corresponding structure fields
- Objects that store text data as strings rather than as character vectors

Also, all Fuzzy Logic Toolbox functions that accepted or returned fuzzy inference systems as structures now accept and return either `mamfis` or `sugfis` objects.

To convert existing fuzzy inference system structures to objects, use the `convertfis` function.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

Usage notes and limitations:

- Generating code using the Fuzzy Logic Controller with Ruleviewer block produces the same code as using the Fuzzy Logic Controller block. However, the Fuzzy Logic Controller with Ruleviewer block does not support:
  - Generating code for single-point or fixed-point data.
  - Changing the number of samples for discretizing the output variable range.

See Also

Blocks
Fuzzy Logic Controller

Apps
Fuzzy Logic Designer | Neuro-Fuzzy Designer

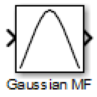
Functions
`evalfis` | `mamfis` | `readfis` | `sugfis`

Topics
"Fuzzy Inference Process" on page 1-28
"Simulate Fuzzy Inference Systems in Simulink" on page 5-2

Introduced before R2006a

Gaussian MF

Gaussian membership function in Simulink software



Description

The Gaussian MF block implements a membership function in Simulink based on a symmetric Gaussian. The Gaussian curve is given by:

$$f(x) = \exp\left(\frac{-0.5(x-c)^2}{\sigma^2}\right)$$

where c is the mean and σ is the standard deviation.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

See Also

`gaussmf`

Introduced before R2006a

Gaussian2 MF

Combination of two Gaussian membership functions in Simulink software

Description

The Gaussian2 MF block implements a membership function based on a combination of two Gaussian functions. The two Gaussian functions are given by:

$$f_k(x) = \exp\left(\frac{-0.5(x - c_k)^2}{\sigma_k{}^2}\right)$$

where k=1,2. The parameters c_1 and σ_1 are the mean and standard deviation defining the left-most curve. The parameters c_2 and σ_2 are the mean and standard deviation defining the right-most curve.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

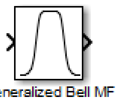
See Also

`gauss2mf`

Introduced before R2006a

Generalized Bell MF

Generalized bell membership function in Simulink software



Description

The Generalized Bell MF block implements a membership function in Simulink based on a generalized bell-shaped curve. The generalized bell-shaped curve is given by

$$f(x) = \frac{1}{1 + \left|\frac{x - c}{a}\right|^{2b}}$$

where the parameters *a* and *b* vary the width of the curve and the parameter *c* locates the center of the curve. The parameter *b* should be positive.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

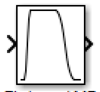
See Also

`gbellmf`

Introduced before R2006a

Pi-shaped MF

Pi-shaped membership function in Simulink software



Description

The Pi-shaped MF block implements a membership function in Simulink based on a spline-based curve, so named because of its Π shape. The parameters *a* and *d* locate the left and right base points or "feet" of the curve. The parameters *b* and *c* set the left and right top point or "shoulders" of the curve.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

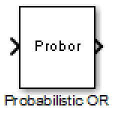
See Also

`pimf`

Introduced before R2006a

Probabilistic OR

Probabilistic OR function in Simulink software



Description

The Probabilistic OR block outputs the probabilistic OR value for the vector signal input, based on

$$y = 1 - \mathrm{prod}(1 - x)$$

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

See Also

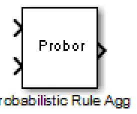
Blocks
Probabilistic Rule Agg

Functions
`probor`

Introduced before R2006a

Probabilistic Rule Agg

Probabilistic OR function, rule aggregation method



Description

The Probabilistic Rule Agg block outputs the element-wise(.*) probabilistic OR value of the two inputs based on

$$y = 1 - \mathrm{prod}(1 - [a; b])$$

The two inputs, *a* and *b*, are row vectors.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

See Also

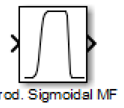
Blocks
Probabilistic OR

Functions
`probor`

Introduced before R2006a

Prod. Sigmoidal MF

Product of two sigmoid membership functions in Simulink software



Description

The Prod. Sigmoidal MF block implements a membership function based on the product of two sigmoidal curves. The two sigmoidal curves are given by

$$f_k(x) = \frac{1}{1 + \exp(-a_k(x - c_k))}$$

where k=1,2 The parameters a_1 and a_2 control the slopes of the left and right curves. The parameters c_1 and c_2 control the points of inflection for the left and right curves. Parameters a_1 and a_2 should be positive and negative respectively.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

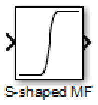
See Also

`psigmf`

Introduced before R2006a

S-shaped MF

S-shaped membership function in Simulink software



Description

The S-shaped MF block implements an S-shaped membership function in Simulink. Going from left to right the function increases from 0 to 1. The parameters a and b locate the left and right extremes of the sloped portion of the curve.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

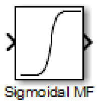
See Also

`smf`

Introduced before R2006a

Sigmoidal MF

Sigmoidal membership function in Simulink software



Description

The Sigmoidal MF block implements a sigmoidal membership function given by

$$f(x) = \frac{1}{1 + \exp(-a(x - c))}$$

When the sign of *a* is positive the curve increases from left to right. Conversely, when the sign of *a* is negative the curve decreases from left to right. The parameter *c* sets the point of inflection of the curve.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

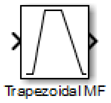
See Also

`sigmf`

Introduced before R2006a

Trapezoidal MF

Trapezoidal membership function in Simulink software



Description

The Trapezoidal MF block implements a trapezoidal-shaped membership function. The parameters a and d set the left and right "feet," or base points, of the trapezoid. The parameters b and c set the "shoulders," or top of the trapezoid.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

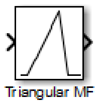
See Also

`trapmf`

Introduced before R2006a

Triangular MF

Triangular membership function in Simulink software



Description

The Triangular MF block implements a triangular-shaped membership function. The parameters a and c set the left and right “feet,” or base points, of the triangle. The parameter b sets the location of the triangle peak.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

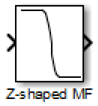
See Also

`trimf`

Introduced before R2006a

Z-shaped MF

Z-shaped membership function in Simulink software



Description

The Z-shaped MF block implements a Z-shaped membership function. Going from left to right the function decreases from 1 to 0. The parameters a and b locate the left and right extremes of the sloped portion of the curve.

Extended Capabilities

C/C++ Code Generation

Generate C and C++ code using Simulink® Coder™.

See Also

`zmf`

Introduced before R2006a

11

Appendices

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See Also

More About

- “What Is Fuzzy Logic?” on page 1-3
- “Foundations of Fuzzy Logic” on page 1-10
- “Fuzzy Inference Process” on page 1-28

Glossary

A

Adaptive neuro-fuzzy inference system (ANFIS)

Technique for automatically tuning Sugeno-type inference systems based on training data.

Aggregation

Combination of the consequents of each rule in a Mamdani fuzzy inference system in preparation for defuzzification.

Antecedent

Initial (or "if") part of a fuzzy rule.

C

Consequent

Final (or "then") part of a fuzzy rule.

D

Defuzzification

Process of transforming a fuzzy output of a fuzzy inference system into a crisp output.

Degree of fulfillment

See **firing strength**

Degree of membership

Output of a membership function, this value is always limited to between 0 and 1. Also known as a membership value or membership grade.

F

Firing strength

Degree to which the antecedent part of a fuzzy rule is satisfied. The firing strength may be the result of an AND or an OR operation, and it shapes the output function for the rule. Also known as *degree of fulfillment*.

Fuzzification

Process of generating membership values for a fuzzy variable using membership functions.

Fuzzy c-means clustering

Data clustering technique wherein each data point belongs to a cluster to a degree specified by a membership grade.

Fuzzy inference system (FIS)

Overall name for a system that uses fuzzy reasoning to map an input space to an output space.

Fuzzy operators

AND, OR, and NOT operators. These are also known as *logical connectives*.

Fuzzy set

Set that can contain elements with only a partial degree of membership.

Fuzzy singleton

Fuzzy set with a membership function that is unity at a one particular point and zero everywhere else.

I

Implication

Process of shaping the fuzzy set in the consequent based on the results of the antecedent in a Mamdani-type FIS.

M

Mamdani-type inference

A type of fuzzy inference in which the fuzzy sets from the consequent of each rule are combined through the aggregation operator and the resulting fuzzy set is defuzzified to yield the output of the system.

Membership function (MF)

Function that specifies the degree to which a given input belongs to a set or is related to a concept.

S

Singleton output function

Output function that is given by a spike at a single number rather than a continuous curve. In the Fuzzy Logic Toolbox software, it is only supported as part of a zero-order Sugeno model.

Subtractive clustering

Technique for automatically generating fuzzy inference systems by detecting clusters in input-output training data.

Sugeno-type inference

Type of fuzzy inference in which the consequent of each rule is a linear combination of the inputs. The output is a weighted linear combination of the consequents.

T

T-conorm

Two-input function that describes a superset of fuzzy union (OR) operators, including maximum, algebraic sum, and any of several parameterized T-conorms. Also known as *S-norm*.

T-norm

Two-input function that describes a superset of fuzzy intersection (AND) operators, including minimum, algebraic product, and any of several parameterized T-norms.

See Also

More About

- “What Is Fuzzy Logic?” on page 1-3
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