Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 10
October 2023

Examining the Fuzzy Inference on Mamdani Fuzzy Inference System and Takagi-Sugeno Fuzzy Model

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Abstract-
Fuzzy Inference Systems (FIS) have emerged as powerful tools for handling complex and uncertain systems in various domains. The two commonly used FIS models are the Mamdani Fuzzy Inference System (MFIS) and the Takagi-Sugeno Fuzzy Model (TSFM). This paper presents a comparative analysis of the fuzzy inference mechanisms employed in these two models. The Mamdani Fuzzy Inference System employs fuzzy rules to map input variables to output variables using linguistic variables and membership functions. It incorporates a fuzzy rule base, fuzzy logic operators, and defuzzification techniques to obtain crisp output values. The MFIS is particularly suitable for dealing with complex and nonlinear systems due to its ability to capture linguistic knowledge through rule-based modeling. On the other hand, the Takagi-Sugeno Fuzzy Model is a fuzzy rule-based model that approximates a system's behavior using a set of linear or nonlinear functions. Instead of employing linguistic variables, the TSFM uses input variables directly to formulate rule consequents. This model is known for its simplicity, interpretability, and computational efficiency. This paper investigates and compares the working principles, architecture, and key characteristics of the Mamdani Fuzzy Inference System and the Takagi-Sugeno Fuzzy Model. It discusses the rule inference process, membership functions, aggregation methods, and defuzzification techniques employed in each model. Additionally, it highlights the strengths and weaknesses of both models in terms of system modeling, interpretability, computational efficiency, and handling uncertainty.

1. Introduction

Fuzzy Inference Systems (FIS) have gained significant attention and have been widely applied in various fields due to their ability to handle complex and uncertain systems. Fuzzy logic provides a flexible framework for modeling and reasoning under uncertainty by incorporating linguistic variables, fuzzy rules, and membership functions. Two commonly used fuzzy inference models are the Mamdani Fuzzy Inference System (MFIS) and the Takagi-Sugeno Fuzzy Model (TSFM) [1].

The Mamdani Fuzzy Inference System, introduced by Mamdani in 1975, is one of the earliest and most widely known fuzzy inference models. The MFIS employs fuzzy rules to map input variables to output variables based on linguistic variables and membership functions. It consists of three main components: a fuzzy rule base, fuzzy logic operators, and a defuzzification method. The MFIS allows the representation and utilization of expert knowledge in the form of linguistic rules, making it suitable for systems that involve complex human reasoning. In contrast, the Takagi-Sugeno Fuzzy Model, proposed by Takagi and Sugeno in 1985, is a more generalized and efficient fuzzy inference model. The TSFM approximates the system behavior by using a set of linear or nonlinear functions. Unlike the MFIS, the TSFM does not use linguistic variables directly in the rule consequents. Instead, it employs input variables to formulate rule consequents as mathematical functions. The TSFM offers simplicity, computational efficiency, and interpretability, making it suitable for both modeling and control tasks [2].

The purpose of this paper is to analyze and compare the fuzzy inference mechanisms employed in the Mamdani Fuzzy Inference System and the Takagi-Sugeno Fuzzy Model. The analysis will encompass various aspects such as the rule inference process, membership functions, aggregation methods, and defuzzification techniques utilized in each model. By understanding the similarities and differences between these models, researchers and practitioners can make informed decisions

regarding the selection and application of fuzzy inference systems [3].
Moreover, this paper aims to provide insights into the strengths and weaknesses of the MFIS and the TSFM. It will explore the trade-offs between system modeling capabilities, interpretability, computational efficiency, and handling uncertainty for each model. Real-world applications where these models have been successfully employed will be discussed, shedding light on the domains in which the MFIS or the TSFM may be more appropriate.
This paper will present a comparative analysis of the fuzzy inference mechanisms employed in the Mamdani Fuzzy Inference System and the Takagi-Sugeno Fuzzy Model. The analysis will help researchers and practitioners gain a deeper understanding of these models, enabling them to make informed decisions when applying fuzzy inference systems in various applications.

Proposed Methodology
Research Background

Diabetes is universal concern. It is one of the diseases that is quickly increasing all over the world. Diabetes, also known as diabetes mellitus, is a biological process in which a person has increased blood glucose (blood sugar) either because insulin production is insufficient or because the body's cells do not respond appropriately in response to insulin that is produced. Diabetes is sometimes referred to as diabetes type 1 and diabetes type 2 .[9] An key point of contention is the need for early investigation of diabetes. In recent years, the number of diabetic patients has increased significantly, primarily as a result of an increase in population as well as western eating habits and a lack of physical activity. [10] There are primarily two different kinds of diabetes, which are differentiated by their names as diabetes type 1 and diabetes type 2. Diabetes type 1 is passed down through families' genetic histories.[11]

- Diabetes type 1, often known as insulin-dependent diabetes, occurs when the human body is unable to manufacture insulin.
- Type 2 diabetes, also known as adult-onset diabetes, is a non-insulin-dependent form of diabetes in which the human body cannot produce enough insulin to support normal bodily functions.

2. FUZZY LOGIC SOLUTION APPROACH

An approach to problem-solving known as fuzzy logic is one that can deal with ambiguity and imprecision in decision-making. It is predicated on the idea of fuzzy sets, which permit the representation and manipulation of information that is ambiguous or subjective. [3] The following procedures are included in the fuzzy logic approach to problem solving: Clearly identify the issue or choice that needs to be addressed. This step is essential in defining the problem. Find out the variables that are at play and the range of values they have. Define a linguistic variable by mapping the numerical variables at play in the situation to linguistic terms that stand in for qualitative explanations. [4] Typically, fuzzy sets are used to define linguistic concepts. These sets assign varying degrees of membership to each term dependent on the value that is inputted into the system. Design membership functions that specify the shape and range of each linguistic word. [5]

Method

Begin

Step1: Enter the crisp values for the cells A1, A2, A3, A4, A5, A6, and A7.
Step 2: Calculate the equation for the fuzzy number's triangle membership function, then set it.
Step 3: Constructed the fuzzy numbers for the input set using A1, A2, A3, A4, A5, A6, A7, and A8.
Step 3.1: Constructed the uncertain number for DM for the output set.
Step4: Mamdani's approach is used to perform fuzzy inference analysis.

- The Mamdani approach is well-known for its interpretability as well as its capacity to deal with complicated laws of language. It produces linguistic outputs that are simple enough for humans to comprehend and understand how to interpret. The process of defuzzification, on the other hand, may lead to a reduction in precision and may be computationally expensive for systems that have a high number of rules.
- When the link between the input variables and the output variables can be described using mathematical functions or

equations, the Sugeno technique is frequently chosen as the method of choice. In comparison to the Mamdani approach, it is capable of producing results that are both more accurate and less resource intensive to compute. However, due to the fact that it does not directly supply language outputs, the interpretability of the output may be diminished.

Both the Mamdani and the Sugeno approaches have advantages and disadvantages, and selecting one over the other is contingent on the nature of the issue at hand as well as the qualities that are sought for in a fuzzy inference system.

Step 4.1: Enter the rule in the format Rule 1,2,...k.

Step 4.2: Calculations are made to determine the matching degree of rule using OR fuzzy disjunction for the fuzzy input set (A11, A12, A13, A21, A22, A23, A31, A32, A33, A41, A42, A43, A51, A52, A53, A61, A62, A63, A71, A72, A73, A81, A82, A83, DM1, DM2, and DM3).

Step5: Using the centroid approach, defuzzify the data into its crisp values.

Step6: Organize the information so that it is presented in the language of human nature.

End.

Membership Function

In fuzzy logic, the mapping of input or output values to fuzzy sets is accomplished with the use of membership functions. The level of honesty or membership that an element in a fuzzy set possesses is determined by a function known as a membership function. It does so by assigning a value in the range of 0 to 1 to each element, depending on its position within the set [6] [7] 8].

Membership functions can come in a wide variety of guises and configurations, depending on the kind of variable and the kind of problem that needs to be solved. The following are some examples of common types of membership functions:

1) Triangular:

This is one of the membership functions that is the easiest to understand and the one that is used the most frequently. It does so by forming a curve in the shape of a triangle, with left boundary, peak, and right boundary as its three parameters. When going from the left boundary to the peak of the membership function, the value of the function linearly grows, while when going from the peak to the right boundary, it linearly drops.

2) Trapezoidal:

The trapezoidal membership function, which is very similar to the triangle membership function, contains four parameters: the left shoulder, the left boundary, the right shoulder, and the right boundary. It curves in the shape of a trapezoid with a horizontal top between the left and right edges of the shape.

3) Gaussian:

The Gaussian membership function has a bell-shaped distribution and is characterized by two parameters: the mean and the standard deviation. It creates a curve that is symmetrical and has a peak at the mean value. According to a bell-shaped distribution, the degree of participation in the group drops as the input is moved further and further away from the mean value.

4) Sigmoidal:

The sigmoidal membership function depicts a gradual transition between two membership levels using a curve in the shape of a S. It is characterized by a set of parameters that determine the form and degree of incline of the curve.

Generalized bell the membership function of a generalized bell is a flexible curve that can be used to represent a broad variety of different forms. The form, the centre, and the width are the three factors that it has, and these are what determine the properties of the curve.

3. Results And Discussion

Surface Plot For Input Data With Mamdani Fuzzy Inference Output System

Visualizing how the output varies across different combinations of input variables makes it possible to generate a surface plot for input data with the output of a Mamdani fuzzy inference system. The following is an in-depth instruction that will walk you through the process of creating a surface plot:

1. Define the input variables and the ranges they fall within: Determine the input variables for your Mamdani fuzzy inference system and provide a range or value for each of those variables. For instance, if you have two input variables called "Temperature" and "Humidity," each of which has a range that falls between [0, 100] and [0, 1], you will need to determine which range of values you wish to view.

2. Produce the data for the inputs by generating a grid or a set of input values that encompass the possible values for each input variable. Create input values for both of the variables while making sure there is enough density to record the system's activity. You could, for instance, generate a grid with temperature values ranging from 0 to 100 with increments of 5, and humidity values ranging from 0 to 1 with increments of 0.1.
3. Fuzzify the input data by applying the membership functions of the input variables to the data before you use it to generate the fuzziness. Determine the level of membership that each linguistic term possesses depending on the values that are input. In this stage, a degree of membership is assigned to each linguistic word for each point in the input data set.
4. Carry out fuzzy inference by using the data that has been fuzzified to apply the fuzzy rules that your Mamdani fuzzy inference system has. Evaluate the level of activation for each rule based on the level of membership of the input data in the antecedent conditions. This should be done for each rule individually.
5. Aggregate the fuzzy outputs: Combine the outputs of the activated rules by using a rule aggregation mechanism such as maximum, minimum, or weighted average to the combined results. An aggregated fuzzy output is produced as a result of this step for each individual data point that was input.
6. Defuzzify the output by taking the aggregated fuzzy output and converting it into a crisp output value using a defuzzification procedure. For instance, if you want to locate the center of gravity of the aggregated fuzzy output, you may use the centroid approach.
7. Create the surface plot: Using a surface plot visualization tool, such as MATLAB's'surf' function, plot the input variables on the x and y axes, then plot the defuzzified output on the z-axis. This step is the seventh and last step in the process. Each point on the surface represents a different input combination, and the height of the surface indicates the value that is generated.

When you plot the surface, you may get a visual representation of how the output of the Mamdani fuzzy inference system varies in response to various permutations of the input variables. This aids in the understanding of the behavior and relationships inside the system, and it can yield insights that can be used for decision-making or the optimization of the system.[12]

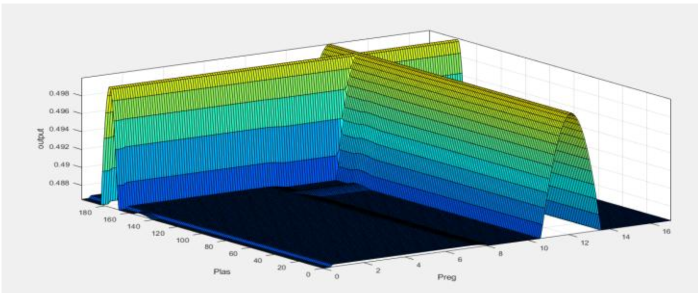

Figure 1 Surface plot of input variable Plas and Preg

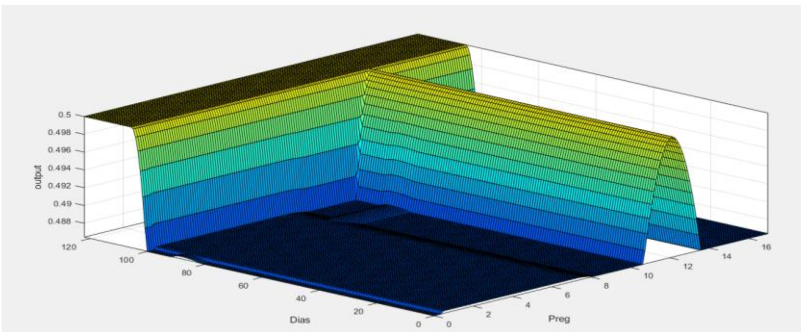

Figure 2 Surface plot of input variable Dlas and Preg

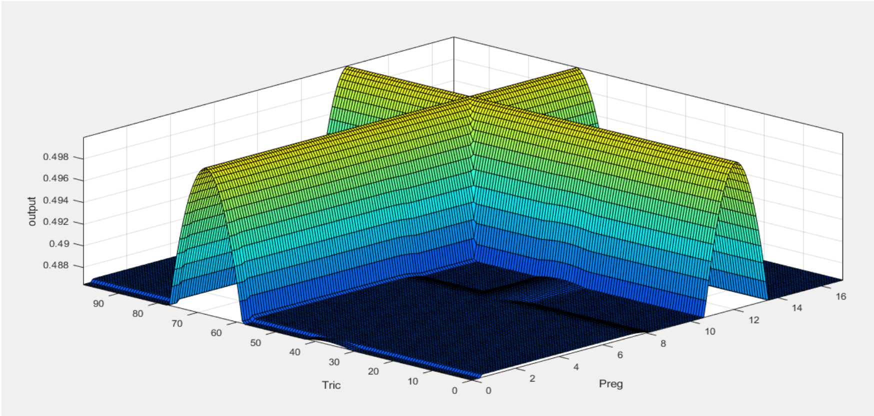

Figure 3 Surface plot of input variable Tric and Preg

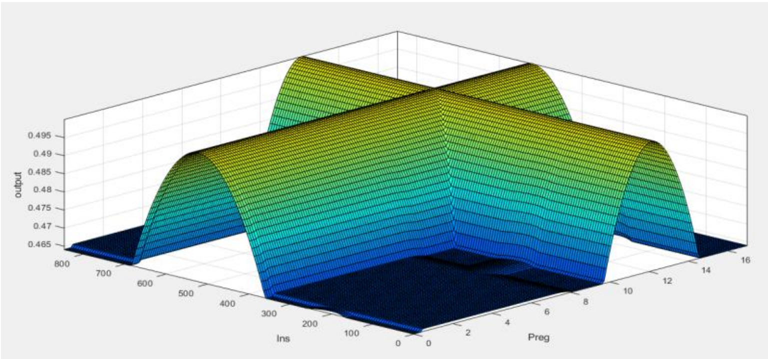

Figure 4 Surface plot of input variable Ins and Preg

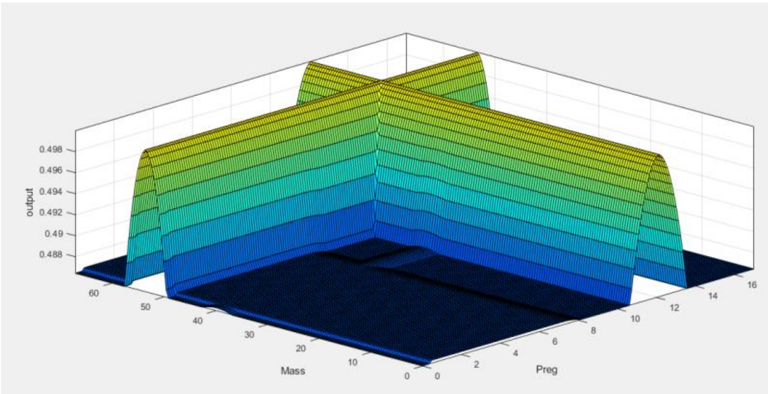

Figure 5 Surface plot of input variable Mass and Preg

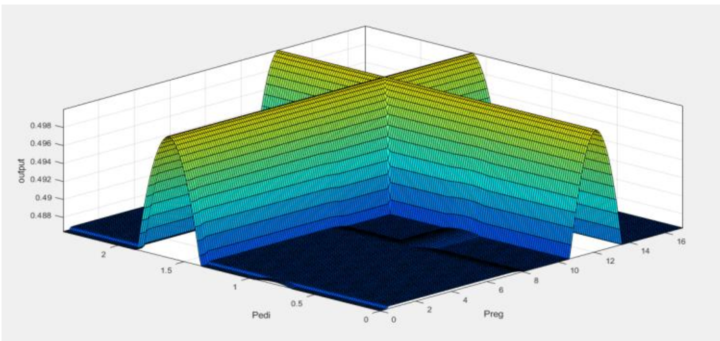

Figure 6 Surface plot of input variable Pedi and Preg

The surface plot of input variables with preg is depicted in figures 32 through 37. These figures include the plots for Plas and Preg, Dlas and Preg, Tric and Preg, Ins and Preg, Mass and Preg, and Pedi and Preg.

4. SUGENO RULES

A rule-based framework known as Sugeno rules is commonly used in the field of fuzzy logic. Professors Takagi and Sugeno, both of whom are recognised by their namesake designations, first conceived of them in the early 1980s. Sugeno rules are often employed in fuzzy inference systems to model complex interactions between the input and output variables.[12]

A Sugeno rule-based system's rules are composed of a number of conditional assertions, and the statements are frequently arranged in a "IF-THEN" pattern. Unlike Mamdani-type fuzzy systems, which employ fuzzy sets and language variables for the antecedents and consequents of the rules, sugeno rules use crisp (non-fuzzy) input variables and linear functions for the rule consequences.[13]

The following format is used for every rule in a Sugeno system:

IF (condition) THEN (consequence)

The expression's conditional part specifies the conditions that must be satisfied based on the input variables, and its consequent part specifies the output that must satisfy the condition. A Sugeno rule's output is frequently a linear function of the variables used as input. This outcome can be expressed as a constant value, a linear combination of the input variables, or a weighted average of the input variables. Take the simple Sugeno rule-based system for controlling the speed at which a fan turns in response to variations in temperature and relative humidity as an example. This is an example rule:

The first guideline states that the fan speed should be 80 when the temperature is high and the humidity is low.

The temperature must be very high and the humidity must be very low in order for this rule's conditional component to be satisfied. The fan speed is given a fixed constant value of 80 in the consequence component.

Analysing all of the rules and integrating their consequences in accordance with particular aggregation techniques, like weighted average, produces the output of a Sugeno system. The end outcome is produced by this procedure. At the conclusion of the defuzzification process, a clear value is often supplied.

In circumstances where the relationship between the input and output variables can be accurately described by linear functions, Sugeno rules are very useful. They produce a model that is clear and easy to understand, making it straightforward for domain experts to understand and modify the model.

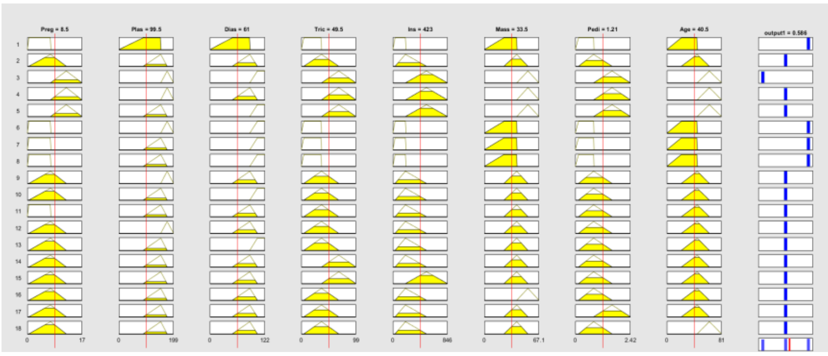

Figure 7 Sugeno Rules

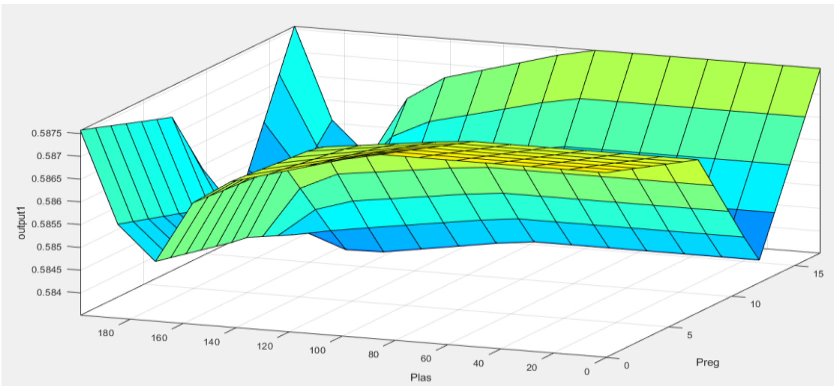

Figure 8 Surface plot of input variable Plas and Preg of sugeno

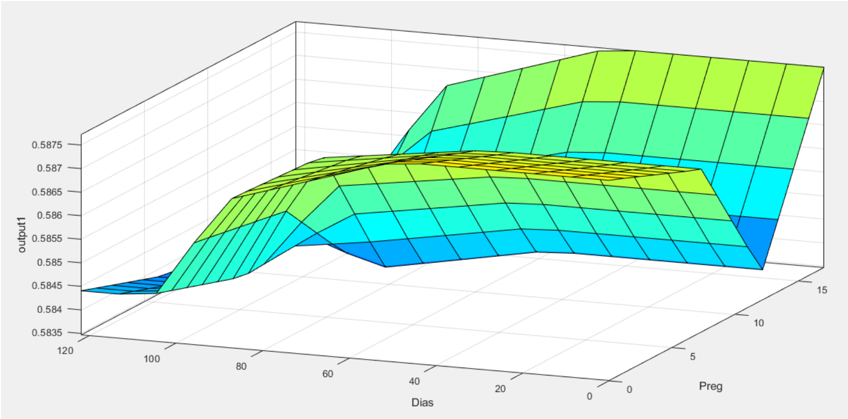

Figure 9 Surface plot of input variable Dlas and Preg of sugeno

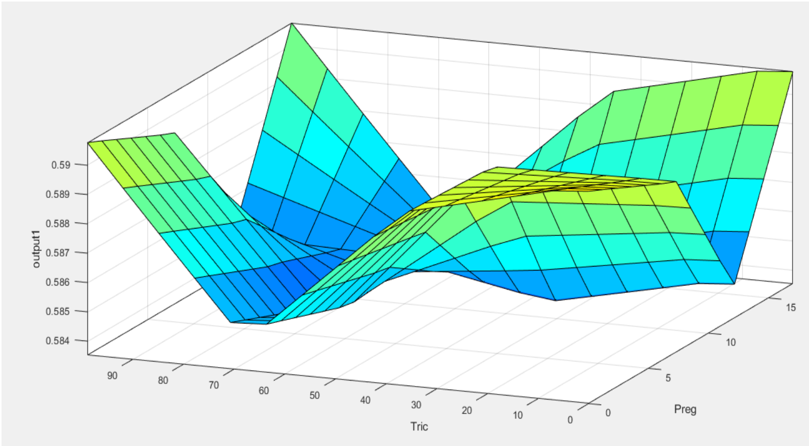

Figure 10 Surface plot of input variable Tric and Preg

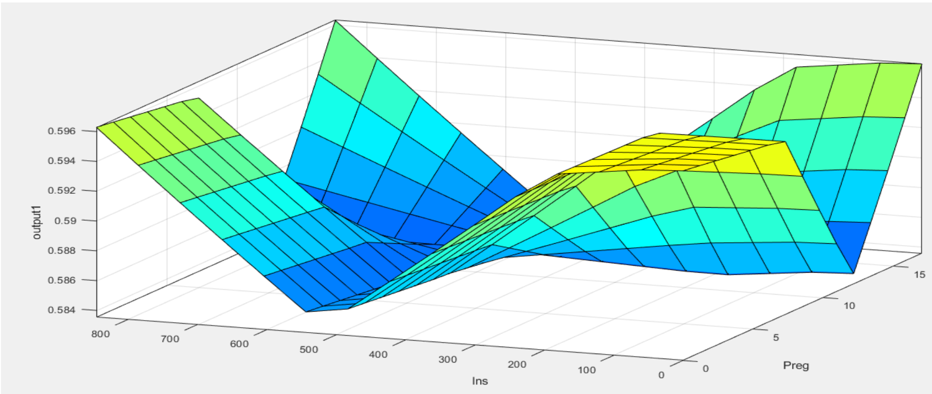

Figure 42 Surface plot of input variable Ins and Preg of sugeno

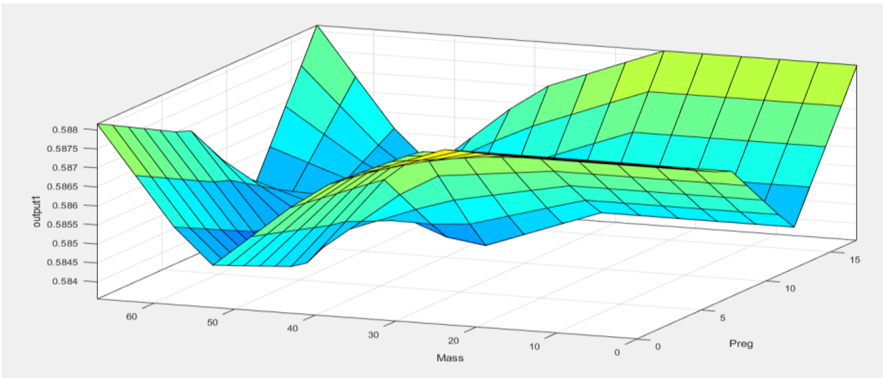

Figure 11 Surface plot of input variable Mass and Preg of Sugeno

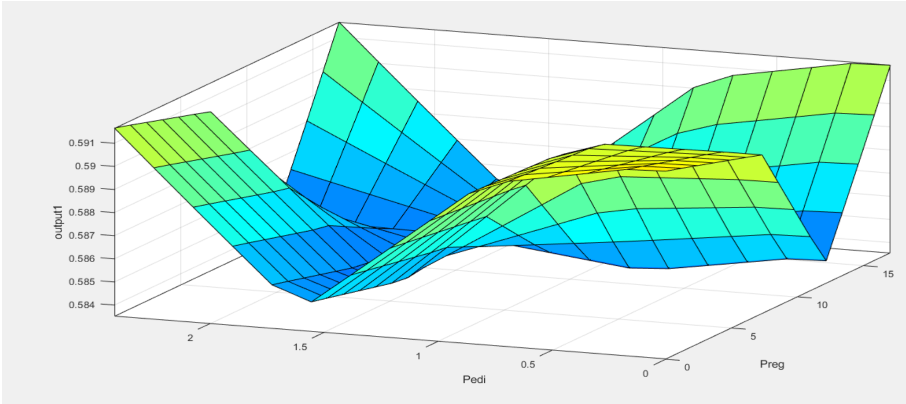

Figure 12 Surface plot of input variable Pedi and Preg of Sugeno

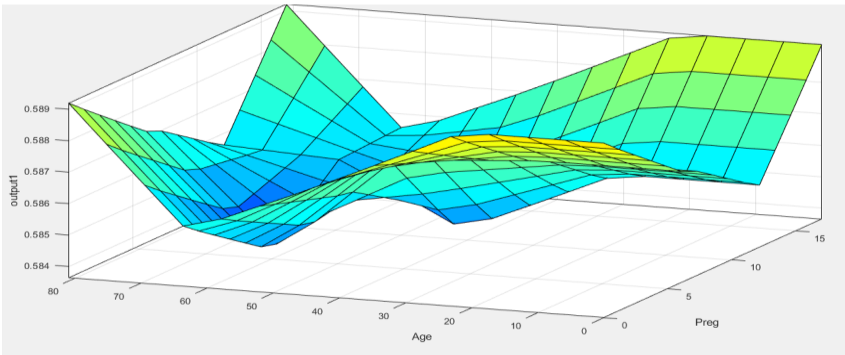

Figure 13 Surface plot of input variable Age and Preg of Sugeno

5. Conclusion

In this paper, we conducted a comparative analysis of the fuzzy inference mechanisms employed in the Mamdani Fuzzy Inference System (MFIS) and the Takagi-Sugeno Fuzzy Model (TSFM). [14] We examined various aspects of these models, including the rule inference process, membership functions, aggregation methods, and defuzzification techniques. The Mamdani Fuzzy Inference System (MFIS) is known for its ability to capture linguistic knowledge through fuzzy rules and membership functions. [15] It allows for the representation of expert knowledge and is suitable for systems that involve complex human reasoning. The MFIS provides interpretable results but can be computationally demanding, especially for large rule bases. It is widely used in various domains, including control systems, decision support systems, and pattern recognition. On the other hand, the Takagi-Sugeno Fuzzy Model (TSFM) offers simplicity, computational efficiency, and interpretability. The TSFM approximates system behavior using a set of linear or nonlinear functions. It directly uses input variables to formulate rule consequents, eliminating the need for linguistic variables. The TSFM is particularly suitable for modeling and control tasks where efficiency is crucial. However, it may lack the linguistic interpretability provided by the MFIS. The choice between the MFIS and the TSFM depends on the specific requirements of the application. If interpretability and linguistic representation of knowledge are essential, the MFIS is a suitable choice. On the other hand, if computational efficiency and simplicity are prioritized, the TSFM may be more appropriate. Both the MFIS and the TSFM have been successfully applied in various real-world applications. The MFIS has been utilized in fields such as decision support systems, traffic control, and medical diagnosis, where interpretability and human-like reasoning are crucial. The TSFM has found applications in areas such as system modeling, pattern recognition, and control systems, where computational efficiency and simplicity are valued.

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