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Research Original Article

Short-Term Forecasting of Electricity Consumption Using Fuzzy Logic

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Abstract

The high demand for electricity in the production process at PT Semen Padang requires a system that can cope with various kinds of disturbances. The problem is that the need for electrical loads is dynamic, especially in the short term, allowing fluctuations between electrical loads at uncertain times. A short-term electric energy consumption forecasting method is needed to determine load growth and distributed power supply. This research aims to use a fuzzy logic algorithm to perform short-term electrical energy consumption forecasting and compare the forecasting results with the actual load at PT Semen Padang. The results showed that short-term load forecasting for seven days using the fuzzy Mamdani method, namely Smallest of Maximum (SoM), obtained a percentage MAPE value of 8.15%. Meanwhile, the Weight of Average (WoA) Sugeno defuzzification method gets a portion of the MAPE value of 9.51%. The Sugeno method is more accurate than the Mamdani method in short-term electricity load forecasting for PPI Indarung V PT Semen Padang. If based on the time category, then forecasting the electricity load on holidays is better than predicting on weekdays. However, when viewed in terms of per day, in Wednesday has the smallest average MAPE value of 5.05%.

Keywords: Short-Term Forecasting; Fuzzy Logic; Mamdani; Sugeno; Electricity Consumption

Introduction

Utilization of electrical energy in the electricity system is distinguished according to the type of consumer demand for electrical loads. However, what happens in the field, electrical energy has a changing consumption pattern due to the influence of uncertainty factors (Tang et al., 2022). In addition, increasingly sophisticated technology in the modern era has led to a new way of life activity, namely dependence on electrical energy needs (Jamaaluddin et al., 2018). As a result, electrical energy has become a primary necessity to fulfill daily life activities. Not only in the household sector, but electrical energy is also a top priority in driving all aspects of productivity in the industrial sector, one of which is PT Semen Padang. In practice, electrical energy needs must be met sustainably without any minor or significant disturbances. However, the problem lies in the value of the electrical load requirement, which is random and dynamic, thus allowing fluctuations in the value of the electrical load at uncertain times.

The impact of fluctuations in the value of the electrical load triggers the occurrence of excess and shortage of electrical power supply to the electrical load (Hasibuan et al., 2022). Spare or lack of electrical power supply has in common, which results in losses from the company's business aspects. To deal with fluctuations in electricity consumption, a strategy for forecasting load growth and distributed power supply is needed at PT Semen Padang. With the load growth forecasting strategy, the magnitude of the electrical load value will be known, thus providing an overview of the dynamics of the electrical load value in the future. Besides, the electric load forecasting strategy also creates an optimally controlled electrical power distribution. The development of increasingly advanced intelligent systems also impacts the electric power system, which can present electrical load forecasting methods that can be combined with intelligent systems (Faysal et al., 2019).

Besides, research on electrical load forecasting has been carried out (Tang et al., 2022). The proposed model is to forecast the half-hour electrical load in the following week. Experimental results show that this is a practical approach that can significantly improve forecasting accuracy compared to benchmark models. The research of (Mado et al., 2022), proposed the Double Seasonal Autoregressive Integrated Moving Average (DSARIMA) method to predict or forecast the power demand model at PT. PLN Gresik Indonesia is based on three years of training and load testing data (daily data every half hour). Another study, (Tang et al., 2019) proposed a multi-layer bidirectional recurrent neural network model to predict short-term power loads and validated it on two data sets. Data from a power company in Chongqing, China, was used for this experiment by considering the difference in seasonal load and peak load per hour of different load data types.

Based on previous research, the author applies fuzzy logic in short-term electricity load forecasting at PT Semen Padang. In this study, in addition to forecasting the short-term electricity load at PT Semen Padang within the next seven days. This study also compares the results of electricity load forecasting with Mamdani fuzzy logic and Sugeno fuzzy logic against the actual load from the accuracy and error or Mean Absolute Percentage Error (MAPE).

Literature Review

Electricity Load Forecasting

The forecast method is a method used to measure or estimate future events (Mado et al., 2018). Estimates can be made in two forms: qualitative forecasts based on the opinions of those who make estimates and quantitative estimates using statistical methods. Forecasting is the process of estimating a future event considering data or variables of previous events (Emidiana, 2016). Concerning forecasting methods, there are the terms forecasting and prediction. Forecasting is the process of estimating or determining events that will occur in the future using qualitative and quantitative scientific methods. Meanwhile, projection, which is included in the forecasting method, is defined as estimating future events with subjective considerations from data on events that have occurred in the past.

The forecasting science applied to predict changes in the electricity load requested by consumers is called electricity load forecasting (Handayani et al., 2019). In addition to being needed by the electric power provider to improve operational and economic efficiency in the provision of electricity, electric load forecasting can also be applied to determine the characteristics of each type of electric load consumer. Load forecasting in electric power systems produces two results: forecasting of electric energy demand (Demand) and forecasting of electric power load (Load). The period load forecasting is divided into three periods, namely long anchor forecasting, medium-term forecasting, and short-term forecasting.

Mean Absolute Percentages Error (MAPE)

Mean Absolute Percentages Error (MAPE) is one way of calculating the error value that can be calculated by finding the absolute error of each period, dividing by the observed value at the time under study, and averaging the total percentage (P. & Authsor, 2018). In simple terms, MAPE can also be a forecast's mean absolute percentage error. Therefore, to calculate the MAPE value, we can use Equation (1).

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{x_i - f_i}{x_i} \times 100\% \right|}{n} \tag{1}$$

Where n is the number of data, xi is the actual load and fi is the forecast load. The final stage is conducting a comparative analysis of the MAPE value from the Mamdani and Sugeno fuzzification models to see which fuzzification model is more effective in forecasting electrical loads. The interpretation of the MAPE value explanation is shown in Table 1.

Table 1. Interpretation of MAPE value

MAPE (%)	Interpretation
< 10	Highly accurate predictions
10 – 20	Good prediction
20 – 50	Viable predictions
> 50	Inaccurate predictions

Fuzzy Logic

Fuzzy is defined as fuzzy or vague, so fuzzy logic is logic that simultaneously has a value of vagueness or vagueness between true and false (Blancas & Noel, 2018). The amount of true and false values of a variable depends on its membership weight. The advantage of fuzzy logic over strict or classical logic is that it can define a value between 0 and 1. In rigorous logic, it only has two possible values 0 or 1. Fuzzy logic applications translate several numeric numbers into linguistic or language forms. However, fuzzy logic applications translate a numeric amount into linguistic or language form. For example, the value of the weight of an object is expressed as light, relatively light, heavy, and very heavy. There are some specially defined operations to combine and modify fuzzy sets. The membership value resulting from the process is often known as forex strength or $\propto$- predicate. Zadeh created three basic operators: the AND operator, the OR operator, and the NOT operator.

Membership Function

A membership function is a curve that shows the mapping of input data points into their membership values, often called membership degrees, with an interval of 0 to 1 (RULE, 2020). The membership function has several curves that are used to define a firm set into a fuzzy set, such as: linear representation, triangular curve representation, trapezoidal curve representation and curve function s

Linear Representation

In linear representation, the mapping of input to its membership degree is described as a straight line (Sadaei et al., 2019). There are two states of linear fuzzy sets: linear up and linear down. Linear up indicates an increase in domain value from the starting point to the endpoint of the linear line, while linear down is the opposite of linear up. This type of representation is shown in Fig. 1.

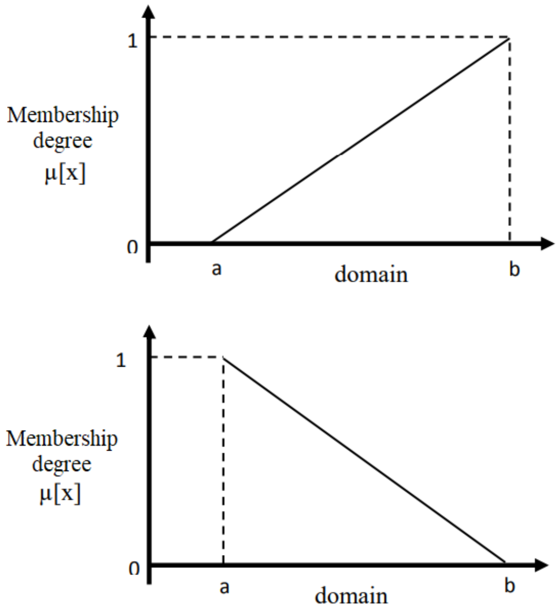

Figure 1. Representation of Ascending and Descending Linear Lines

To calculate the ascending linear membership function, can use Equation (2).

$$\mu[X] = \begin{cases} 0 & x \leq a \\ \dfrac{(x-a)}{(x-b)} & a \leq x \leq b \\ 1 & x \geq b \end{cases} \tag{2}$$

Meanwhile, to calculate the linear membership function down can use Equation (3).

$$\mu[X] = \begin{cases} 1 & x \leq a \\ \dfrac{(x-a)}{(x-b)} & a \leq x \leq b \\ 0 & x \geq b \end{cases} \tag{3}$$

Triangular Curve Representation

A triangular curve is a combination of an ascending linear line and a descending linear line (Kusuma et al., 2020). This type of representation can be shown as Fig. 2.

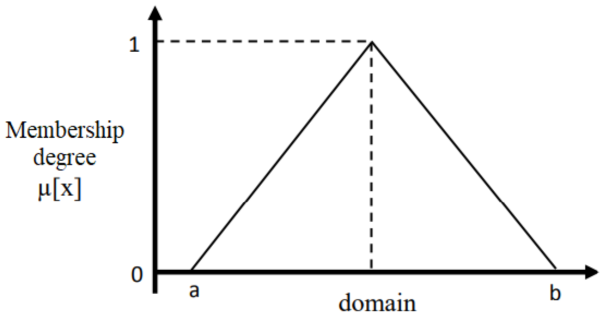

Figure 2. Triangular Curve Representation

To calculate the membership function of the triangular curve representation can use Equation (4).

$$\mu[X] = \begin{cases} 0 & x \leq a \\ \dfrac{(x-a)}{(x-b)} & a \leq x \leq b \\ \dfrac{(c-x)}{(c-b)} & b \leq x \leq c \\ 0 & c \geq x \end{cases} \tag{4}$$

Trapezoidal Curve Representation

The trapezoidal curve is also a combination of ascending and descending linear lines. The difference with the triangular curve is that some areas have a membership value of 1. The representation of this type of curve can be shown in Fig. 3.

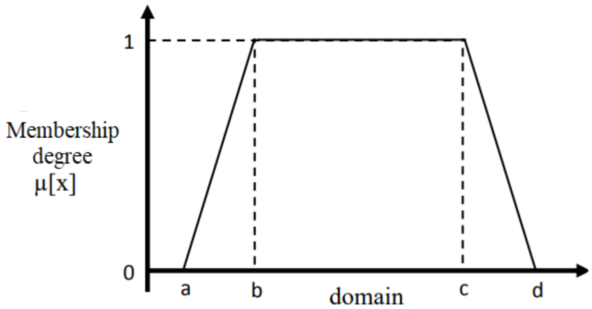

Figure 3. Trapezoidal curve representation

To calculate the membership function of the trapezoidal curve representation can use Equation 5.

$$\mu[X] = \begin{cases} 0 & x \le a \text{ or } x \le a \\ \dfrac{(x-a)}{(x-b)} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{(c-x)}{(c-b)} & x \ge d \end{cases} \tag{5}$$

S-Curve Function

The S or sigmoid curve is a curve that corresponds to a non-linear increase and decrease in the surface. Its membership function will rest on 50% of its membership value, often called the inflection point (Çevik & Çunka\cs, 2015). This type of curve can be shown in Fig. 4.

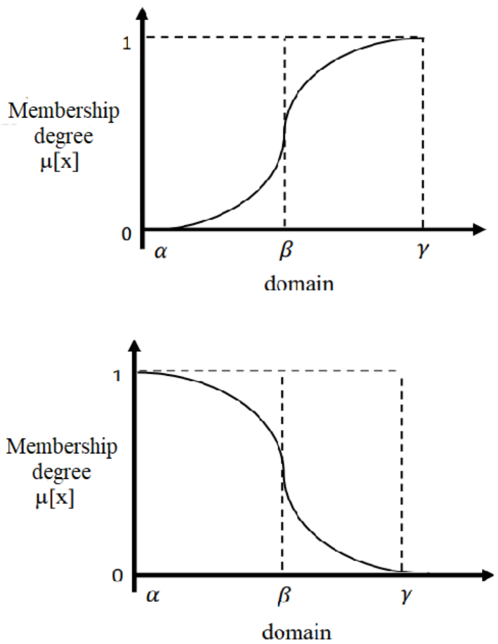

Figure 4. Growth and shrinkage S-curve function

To calculate the sigmoidal membership function, Equation (6) can be defined.

$$S(X;\alpha,\beta,\gamma) = \begin{cases} 0 & x \le \alpha \\ 2\left(\dfrac{(x-a)}{(x-b)}\right)^2 & \alpha \le x \le \beta \\ 1-2\left(\dfrac{(x-a)}{(x-b)}\right)^2 & \beta \le x \le \gamma \\ 1 & x \ge \gamma \end{cases} \tag{6}$$

Implication Function

An implication function is a logical structure that consists of several premises and one conclusion. The implication function helps us know the relationship between the premises and the conclusion. The general form of an implication function is: IF x is A, THEN y is B. The scalars or variables are expressed in x and y, while A and B are fuzzy sets. There are antecedent terms for propositions that follow IF and consequent terms for bids that follow THEN. In using the implication function, two methods can be used, namely (Viswavandya et al., 2020). First Min (minimum) the process that occurs from this function is cutting the output region of the fuzzy set, which has the smallest membership value. The application of the implication function is shown in Fig. 5. At the same time, the Dot (Product) function is used to adjust the scale or size of the fuzzy set output region. An example of using the Dot function is shown in Fig. 6.

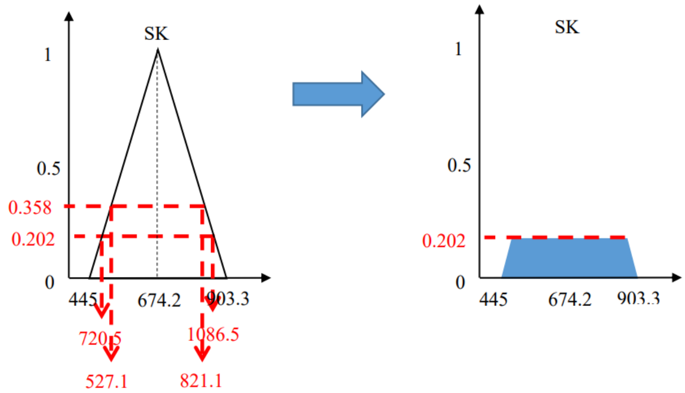

Figure 5. Implication function application min

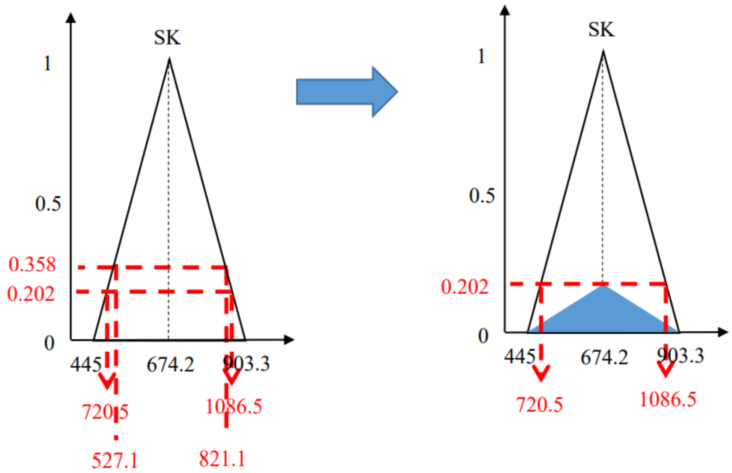

Figure 6. Applications of dot implication function

Fuzzy Inference System

A fuzzy inference system is a computational framework based on fuzzy set theory, fuzzy IF-THEN rules, and fuzzy reasoning. In general, a fuzzy inference system consists of four units, namely (Mart\'\inez et al., 2020): fuzzification unit, logic reasoning unit, knowledge base unit, and defuzzification unit. The defuzzification unit process to obtain a firm (crisp) output is carried out by the defuzzification method. This method translates the result set to the form of a firm (crisp) value. The fuzzy inference system process looks like in Fig. 7.

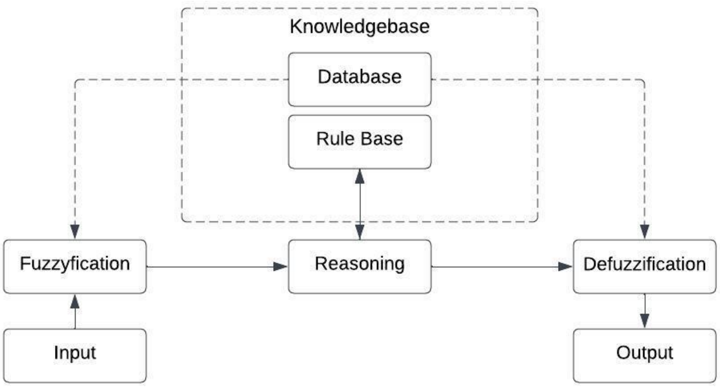

Figure 7. Fuzzy inference system process

In general, there are 3 models of fuzzy inference systems used in fuzzy logic, namely: tsukamoto model, mamdani fuzzy model, takagi sugeno kang fuzzy model.

a. Tsukamoto Model

In the Tsukamoto model, each consequent of an IF-THEN rule must be presented with a fuzzy set and a monotonous membership function. The result that will be obtained is the output of each direction which is given strictly (crisp) based on α-predicate. The final result is obtained using a weighted average. The inference stages of the Tsukamoto model are as follows (Tundo et al., 2020): fuzzy set formation, fuzzification, fuzzy knowledge base formation, implication with MIN function, and defuzzification. To calculate the defuzzification process, we can use the weighted average method with Equation (7).

$$Z = \frac{\sum(\alpha_i \times z_i)}{\sum \alpha_i} \qquad (7)$$

Where Z is the output variable, a_i is the α-predicate value, and z_i is the output variable value.

b. Fuzzy Mamdani Model

Every rule in the form of implication in the Mamdani model and antecedent in the form of conjunction (AND) has a minimum membership value (MIN). The Mamdani method is often known as the Max-Min Method. The Mamdani fuzzy model requires four stages to produce output, namely (Magzob et al., 2021): formation of fuzzy sets, use of implication functions, rule composition. The fuzzy set solution is obtained by taking the maximum value of the rule, then using it to modify the fuzzy region, and applying it to the output using the OR or Union operator (Nugraha, 2019). To calculate the general equation of the rule composition can use Equation (8).

$$\mu_{sf}[x_i] = max\left(\mu_{sf}[x_i], \mu_{kf}[x_i]\right) \qquad (8)$$

Defuzzification in the Mamdani method can be done with several defuzzification methods, including (Handayani et al., 2019): Centroid, this method is obtained by taking the center point of the fuzzy region, Bisector this method is obtained by taking a fuzzy domain that has a membership value of half of the total membership value in the fuzzy area, Mean of Maximum this method is obtained by taking the average value of the domain that has the maximum membership value, Largest of Maximum, this method is obtained by taking the most significant value of the field that has the maximum membership value, and the last is Smallest of Maximum this method is obtained by taking the smallest value of the domain that has the maximum membership value.

c. Model Fuzzy Takagi Sugeno-Kang

The Takagi Sugeno-Kang (TSK) fuzzy inference system is similar to the Mamdani model. The difference lies in the system output, not in the form of a fuzzy set but in a constant or linear equation. The defuzzification process of the Takagi Sugeno Kang (TSK) model can be done using the Weight of Average method. This method is often used in fuzzy applications because it is one of the more efficient computational methods. The weakness of this method is that it is limited to symmetrical output membership functions. The Weight of the Average process is formed by weighting each membership function in the output at its maximum membership value.

Materials & Methods

The flowchart of the short-term electricity load forecasting (Suyono et al., 2020) process using MATLAB Graphical User Interface (GUI) in this research can be seen in Fig. 8.

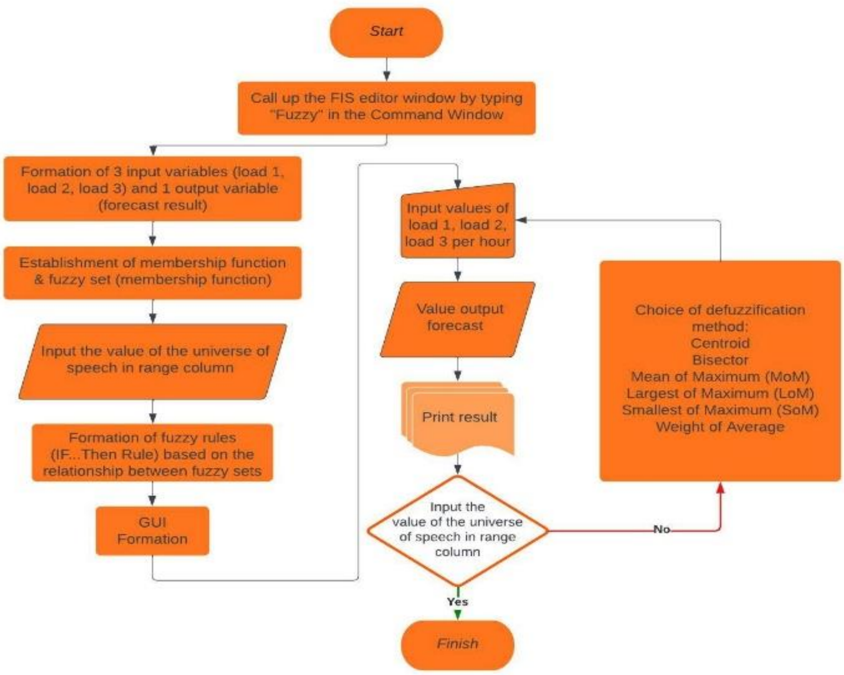

Figure 8. Flowchart of short-term electricity load forecasting

Data Description Analysis

This section discusses the data that will be used in forecasting short-term electrical loads at PT Semen Padang. The stages of work are carried out systematically to obtain the relationship between electricity load data and time, namely working days (Monday - Friday) and holidays (Saturday - Sunday). The next stage is to collect electricity load data at Substation 1 of Indarung VI Plant PT Semen Padang. The data will be channeled to Packing Plant Indarung V (PPI) or Transformer 6 Feeder F27 PPI, as shown in the single-line diagram of PPI Indarung V PT Semen Padang in Fig. 9. The research variable data is in the form of electrical load (MW) in July 2021 (July 1 - 21, 2021) to forecast the electrical load for the next seven days (July 22 - 28, 2021). While the data for the comparison variable is time, divided into working days (Monday – Friday) and holidays (Saturday – Sunday). The load-sharing data is divided into three, namely load 1, load 2, and load 3, as shown in Table 2.

Table 2. Data Sharing for July

Days	Load 1	Load 2	Load 3	Load Forecast
Thursday	01 July	08 July	15 July	22 July
Friday	02 July	09 July	16 July	23 July
Saturday	03 July	10 July	17 July	24 July
Sunday	04 July	11 July	18 July	25 July
Monday	05 July	12 July	19 July	26 July
Tuesday	06 July	13 July	20 July	27 July
Wednesday	07 July	14 July	21 July	28 July

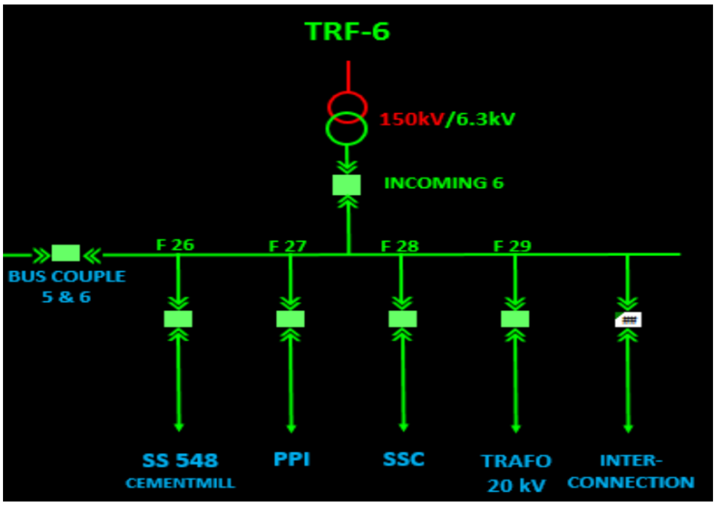

Figure 9. Single-line diagram of PPI Indarung V PT Semen Padang

Proposed Fuzzy Logic Model

In this section, we will discuss the implementation of fuzzy logic in processing electrical load data from PPI V PT Semen Padang using the MATLAB GUI. This stage begins with the formation of fuzzy sets and membership functions. The membership function that will be used is the triangular function. The fuzzy set for the input and output electrical load variables consists of seven: minimum, very small, small, medium, large, large, and maximum. The value of the universe of talk is obtained from a set of electric load values on the same day. The domain value is obtained after inputting the conversation universe value into the FIS editor in the Range column. Then the reasoning process setting (Interference Machine) is set by setting the Min implication function and the Max rule composition function (Aggregation). The implication and aggregation function settings can be seen in Fig. 10.

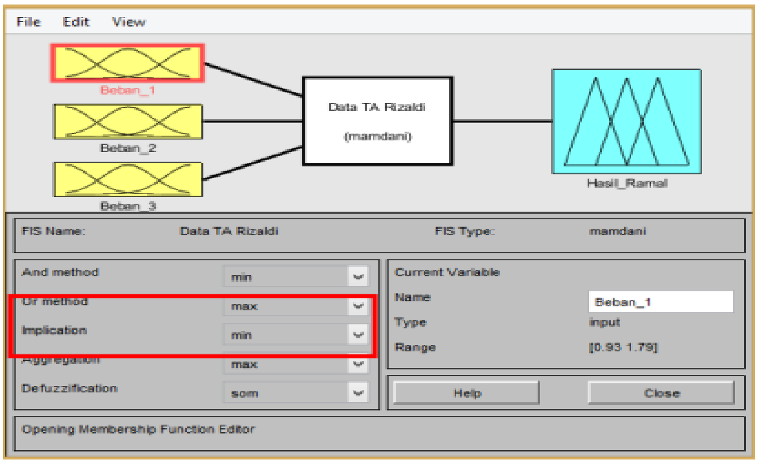

Figure 10. FIS Editor Window Implication and Aggregation Function Settings

The following process is the formation of fuzzy basic rules. The basic fuzzy rules are based on associating fuzzy sets of three load variables. The number of fuzzy rules that can be arranged is 343, as shown in Fig. 11.

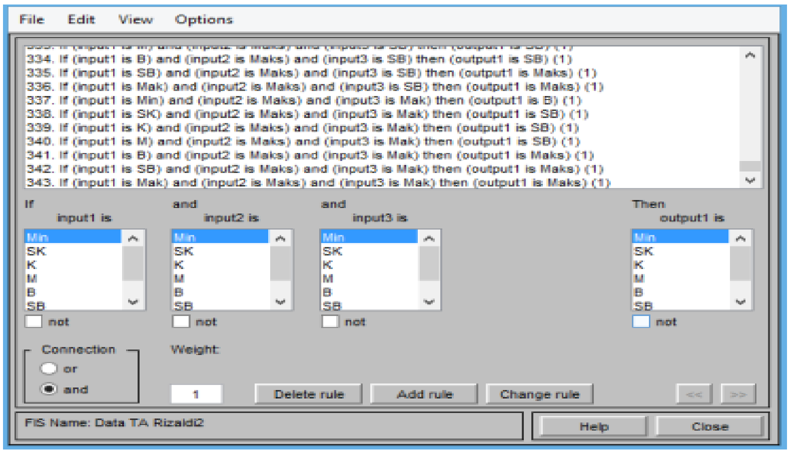

Figure 11. Added Fuzzy Ground Rules

The following process is defuzzification. This process will use five Mamdani defuzzification methods, such as the centroid, bisector method, the Mean of Maximum (MoM) method, the Largest of Maximum (LoM) method, and the Smallest of Maximum (SoM) method. Meanwhile, Sugeno's defuzzification uses one way as Weight of Average. The last stage is after assembling a fuzzy inference system framework with the formation of a MATLAB GUI to forecast the value of the electrical load. The interface of the MATLAB GUI consists of input boxes, outputs, and forecast methods, as shown in Fig. 12.

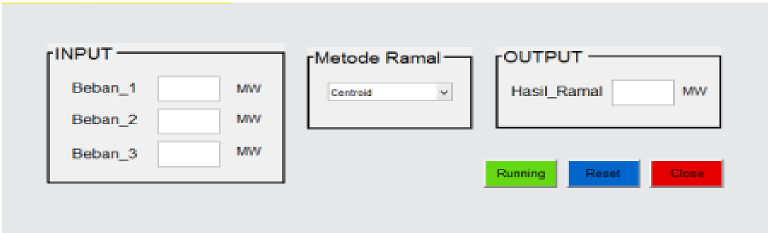

Figure 12. Electrical Load Forecasting Display in MATLAB GUI

After obtaining the predicted value of the electrical load from each defuzzification method, the deal Mean Absolute Percentage Error (MAPE) is calculated. In simple terms, MAPE can be said to be the mean absolute percentage error of a forecast.

Results and Discussion

Implementing fuzzy logic in short-term electricity load forecasting at PT Semen Padang is analyzed based on 2-time categories. The time variable is also used as a comparison variable consisting of working days (Monday-Friday) and holidays (Saturday-Sunday). Then the level of load forecasting accuracy using six types of defuzzification methods, holidays get an excellent forecasting ability category with an average value of 6.82%. At the same time, the average value of load forecasting on weekdays is 11.00%. The smaller the MAPE value indicates a better forecasting ability. Conversely, the greater the MAPE value, the worse the forecasting ability.

Based on the forecasting category per day, electricity load forecasting on Wednesday obtained the smallest average MAPE value of 5.05% compared to other days. This indicates that on Wednesday, the historical electrical load characteristics of PPI Indarung V on 7, 14, and 21 July 2021 were the same as the actual load characteristics on 28 July 2021. In other words, the historical load forecasting data on Wednesday has a fluctuation value that is not too large. Thus, the value of the load forecast results is close to the actual load value, by the theory of load forecasting, which refers to past statistics and is based on analysis of past load characteristics. The results of obtaining the average value of MAPE from short-term electricity load forecasting of PPI Indarung V PT Semen Padang, based on time as a comparison variable, are shown in Table 3.

Table 3. MAPE Value of Comparison Variable

Variable comparator	Days	Value MAPE (%)	Category capabilities forecasting	Value variable comparator
	Monday	15,68	Good	
	Tuesday	6,96	Very good	
Working day	Wednesday	5,05	Very good	11,00
	Thursday	15,33	Good	
	Friday	11,96	Good	
Day off	Saturday	6,45	Very good	6,82
	Sunday	7,18	Very good	

Load Forecasting Using Fuzzy Mamdani Method

After implementing Mamdani fuzzy logic on electricity load data at PPI Indarung V PT Semen Padang, the MAPE value of the load forecasting results using five Mamdani defuzzification methods is obtained, as shown in Table 4.

Table 4. Nilai Rata-rata MAPE Metode Mamdani

Days	Centeroid (%)	Bisector (%)	MoM (%)	LoM (%)	SoM (%)
Monday	15.51	15.73	16.27	20.12	12.47
Tuesday	6.53	6.59	7.02	9.95	5.18
Wednesday	5.06	4.67	4.30	4.27	6.05
Thursday	14.75	14.89	15.65	19.27	12.37
Friday	11.40	11.52	12.10	15.20	9.49
Saturday	5.65	5.94	6.73	9.04	5.10
Sunday	6.84	6.92	7.30	8.93	6.37
Average	**9.39**	**9.47**	**9.91**	**12.40**	**8.15**

The result of the smallest average MAPE value of the five Mamdani defuzzification methods used for short-term electricity load forecasting is the Smallest of the Maximum (SoM) method at 8.15%. At the same time, the most significant average MAPE value uses the Large of Maximum (LoM) method of 12.40%. The Smallest of Maximum (SoM) method takes crisp solutions from the smallest domain value with full membership, making it better than other methods. So that the Smallest of Maximum (SoM) method is considered to have better accuracy and performance of the forecasting model. The performance graph of the MAPE value of the Mamdani defuzzification method for seven days can be seen in Fig. 13.

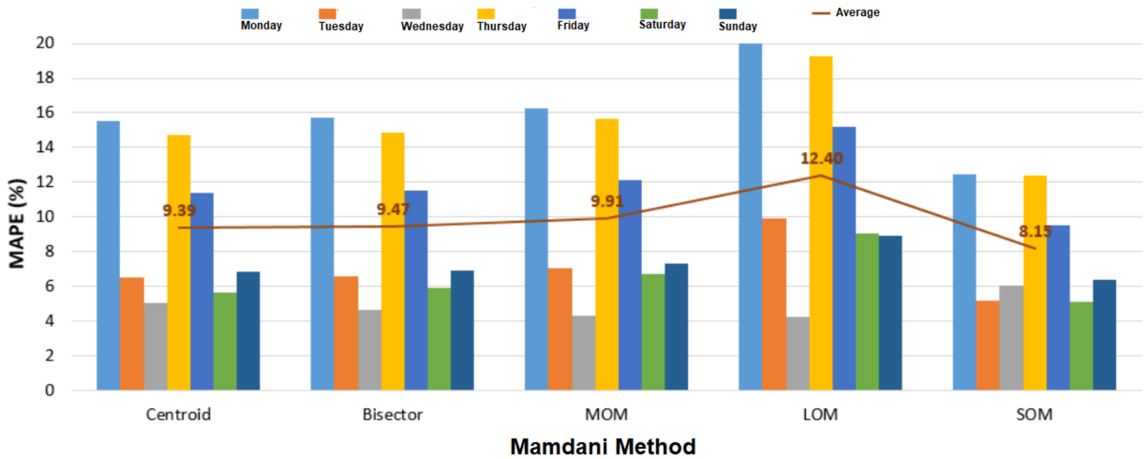

Figure 13. Performance Graph of MAPE Value of Mamdani Method

Load Forecasting Using Fuzzy Sugeno Method

In the next experiment, short-term electricity load forecasting at PPI Indarung V PT Semen Padang uses Sugeno fuzzy logic. Where the results of the MAPE value of load forecasting using the Sugeno defuzzification method are shown in Table 5.

Table 5. Average of the MAPE value using the Sugeno

Days	Weight of Average (%)
Monday	13.97
Tuesday	6.49
Wednesday	5.95
Thursday	15.03
Friday	12.07
Saturday	6.28
Sunday	6.75
Average	**9.51**

The average MAPE value using the Sugeno defuzzification method for short-term electricity load forecasting is 9.51%. This method's average MAPE value is excellent (< 10%). The technique of weighting the average value of the output variable with the characteristics of historical load data and actual data in the Sugeno method makes the results of the MAPE value of this method excellent. Compared to the five Mamdani methods, the Sugeno defuzzification method is one of the load forecasting methods calculated to forecast the value of electricity load. The performance graph of the MAPE value of the Sugeno defuzzification method can be seen in Fig. 14.

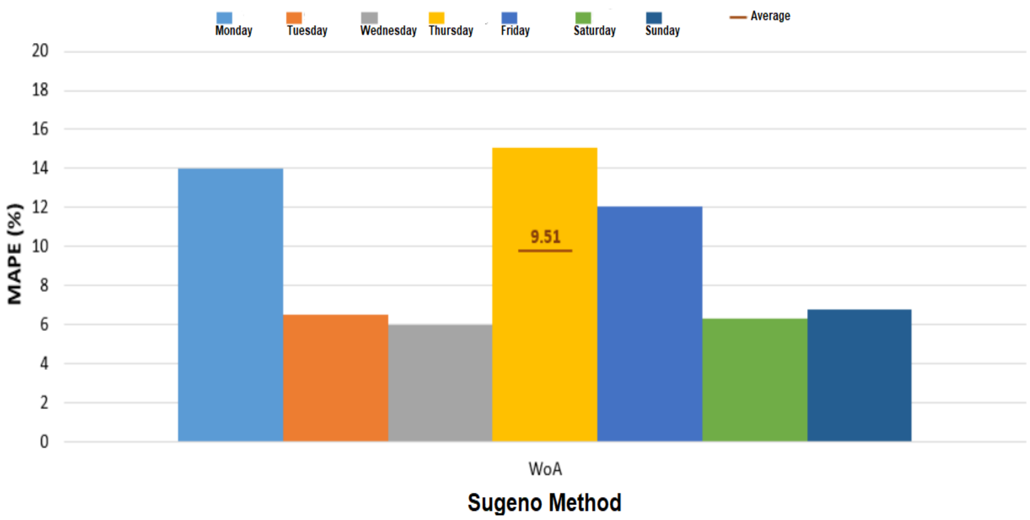

Figure 14. Performance Graph of MAPE Value of Sugeno Method

Based on the results of experiments on forecasting electricity load per day for one week using fuzzy logic, it is obtained that the results of short-term electricity load forecasting for PPI Indarung V PT Semen Padang using the Sugeno method have an average MAPE value of 9.51%. Meanwhile, short-term electricity load forecasting results using the Mamdani defuzzification method have an average MAPE value of 9.86%. The results of this study reinforce the assumption that electricity load forecasting using the Sugeno method is more accurate than the Mamdani method in previous studies.

Conclusions

The results showed that short-term load forecasting for seven days using the fuzzy Mamdani method, namely Smallest of Maximum (SoM), obtained a percentage MAPE value of 8.15%. Meanwhile, the Weight of Average (WoA) Sugeno defuzzification method gets a portion of the MAPE value of 9.51%. According to the short-term electricity load forecasting test results at PPI V PT Semen Padang, the Sugeno method is more accurate than the Mamdani method in forecasting electricity load for seven days. Based on the electricity load forecasting category per day, in Wednesday tends to have historical data and actual data on electricity loads that are more stable than on other days. Then short-term electricity load forecasting at PPI V PT Semen Padang on holidays (Saturday-Sunday) obtained better forecasting results than on working days (Monday-Friday).

Acknowledgments

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