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Performance Evaluation of Different Membership Function in Fuzzy Logic Based Short-Term Load Forecasting

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ABSTRACT

A mismatch between utility-scale electricity generation and demand often results in resources and energy wastage that needed to be minimized. Therefore, the utility company needs to be able to accurately forecast load demand as a guide for the planned generation. Short-term load forecast assists the utility company in projecting the future energy demand. The predicted load demand is used to plan ahead for the power to be generated, transmitted, and distributed and which is crucial to power system reliability and economics. Recently, various methods from statistical, artificial intelligence, and hybrid methods have been widely used for load forecasts with each having their merits and drawbacks. This paper investigates the application of the fuzzy logic technique for short-term load forecast of a day ahead load. The developed fuzzy logic model used time, temperature, and historical load data to forecast 24 hours load demand. The fuzzy models were based on both the trapezoidal and triangular membership function (MF) to investigate their accuracy and effectiveness for the load forecast. The obtained low Mean Absolute Percentage Error (MAPE), Mean Forecast Error (MFE), and Mean Absolute Deviation

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(MAD) values from the forecasted load results showed that both models are suitable for short-term load forecasting, however the trapezoidal MF showed better performance than the triangular MF.

Keywords: Artificial intelligence, fuzzy logic, load forecasting, mean absolute percentage error**,** MF, short-term

INTRODUCTION

The electrical load forecast involves the process of predicting future short, medium, and long term energy demand. This aids the optimal deployment of available resources to accurately generate power to match the load demand. In either a regulated or deregulated market, it is necessary for the supply authority to carry out load forecasting to balance the load demand with supply. The load forecasting is considered as an important aspect of electrical power systems operation as it allows the utility company to make proper planning for the power generation, transmission, and distribution of electrical energy. With accurate load forecasting, an operation such as unit commitment, economic dispatch, load balancing, power quality, and scheduled maintenance can be carried out effectively (Lei et al., 2019).

Load forecasting is broadly classified into three categories: the short-term load forecasting which forecasts from one hour to seven days, the medium-term load forecast starting from a week to several months, and long-term load forecasting starting from a year to several years. The short-term load forecasting is used by the supply authority for operational purposes such as unit commitment, economic dispatch, load flow, frequency control, security, and reliability of the system (Srivastava et al., 2016). The medium-term load forecasting predicts the load demand that provides information for system planning and operation while long term load forecasting is mainly used for power system planning (Ganguly et al., 2019; Peng et al., 2019).

This paper presents a short-term electrical load forecast using the fuzzy logic approach. Two fuzzy MF approaches were investigated: the trapezoidal MF and the triangular MF for their efficiency and accuracy in the short-term load forecast. The developed model performance was evaluated using typical load data and different error analysis techniques were adopted to ascertain the model degree of accuracy. The error analysis results showed that the fuzzy was suitable for short-term load forecast and the trapezoidal MF provided improved performance compared to the triangular MF.

RELATED WORK

There are three broad classification of approaches for carrying out electrical load forecasting in powers system planning and operational. The conventional approach is referred to as the classical statistical methods which include Autoregressive (AR), Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA), Seasonal Auto Regression Integrated Moving Average (SARIMA) and Multi-Linear Regression. The second approach involves the application of artificial intelligent techniques such as fuzzy logic, Artificial Neural Network (ANN), and Support Vector Machine (SVM) to predict future load demand. In recent times, there is an evolving approach termed hybrid methods which involves a combination of two of the aforementioned methods. This could be a combination of classical statistic method and artificial intelligent method or combination of two artificial intelligent methods.

Several methods have been investigated on short-term load forecasting including the conventional statistical methods such as autoregression moving average, multiple linear regression method, and single exponential smoothing (Dudek, 2016; Fan et al., 2016; Mi et al., 2018). Literatures have shown that classical statistical methods such as the AR and MA work seamlessly on non-seasonal load forecasts while the ARIMA and SARIMA accepts seasonality of the load pattern. The SARIMA requires deep knowledge of forecaster to determine the appropriate seasonal parameters (Chikobvu & Sigauke, 2012; Singhal et al., 2020).

In 2013, Ding et al. proposed a new method to implement short-term load forecasting in which statistical time series prediction methods of Autoregressive Integrated Moving Average Model with Exogenous Inputs (ARIMAX) and machine learning-based regression were used to forecast load demand. In the error result analysis, the ARIMAX method produce a more accurate forecast when compared with machine learning-based regression as it has the least MAPE in each of the ten selected smart meters (Ding et al., 2013). Razak et al. (2012) forecasted load by developing five different technique of SARIMA for different days of the week. The data from Peninsular Malaysia was used as the input to the developed techniques. The forecast produced high accuracy given MAPE that ranged between 1% to 3% for each of the model.

Also, in 2017, Bozkurt et al. compared the result of the ANN and SARIMA model for the electric power load of Turkish electricity market. The input to the model was the essential factors that affected the load forecasting such as the previous load data, electricity price, weather, and currency exchange rate. The ANN had a MAPE of 1.80% while SARIMA had MAPE of 2.60% (Bozkurt et al., 2017). In 2015, Cui and Peng proposed an improved ARIMAX by combining the series with regression analysis to forecast electric load for short-term period. The model filled the gaps of external effects on electric load and data from some selected city in China were used as the input. The improved ARIMAX model had least MAPE of 0.37% when compared with common time series methods like AR, MA and ARIMA (Cui & Peng, 2015). Generally, statistical methods are acceptable techniques for short-term load forecast even though the evolving artificial intelligent methods are seen performing better. Surveyed literature showed that ARIMA and SARIMA are among the best statistical approach for load forecast because they work efficiently with time series model and can consider the seasonality of load. The main challenge is that they involve complex computations that makes their implementation a bit difficult.

In recent time, artificial intelligent methods such as ANN, genetic algorithm, and fuzzy logic are being widely used and most recently the application of the hybrid system has been investigated (Jetcheva et al., 2014; Kumar et al., 2016; Siri, 2018; Yu & Xu, 2014). The ANN and fuzzy logic forecast methods are commonly used for load forecasting as they do not require rigorous mathematical modelling. Their implementation is much simplified and often results in high load forecasting accuracy. They often result in minimum error when forecast is compared with actual electrical load demand. Besides, these methods allow the forecaster to consider numerous exogenous factors such as temperature and humidity (Kuster et al., 2017). As reported in the literature, several researchers have investigated the performance of fuzzy logic on the electrical load forecasting efficiency and accuracy (Al-Kandari et al., 2004; Danladi et al., 2016; Faysal et al., 2019; Silva et al., 2017) and today fuzzy logic is widely used for load forecast.

Rizwan et al. (2012) investigated daily hourly load demand using historical load data as input to the fuzzy logic model. This model did not consider exogenous factor such as temperature and error analysis have low MAPE value of 1.39% (Rizwan et al., 2012). In 2014, Gohil and Gupta presented short-term load forecasting using fuzzy logic with temperature, humidity, wind speed, and historical load data as inputs. The model was used to forecast hourly load of weekend and weekdays. The MAPE of the day's ranged from 10.55% to 11.74%. The high MAPE value was as a result of the inability of the model to accurately respond to daily abrupt load changes for a few hours of the days (Gohil & Gupta, 2014). Ganguly et al. (2017) presented two fuzzy logic models for short-term load forecast. The first model took day type and time as the input while the second model took day type, previous day load, and the peak forecasted load as its input. The models had MAPE of between 2.37 % to 2.53 % between the actual and forecasted load for three consecutive days.

It is worthy to note that the most available work on fuzzy logic load forecast focused on the application of specific MF which is an important phase in the fuzzy logic process. The MF defines how the input points are mapped to a fuzzy membership value ranging between 0 and 1. This stage does have a significant effect on the model performance as it plays a significant role in the decision making that directly influences the output. Among the common MF reported in the literature is the triangular and trapezoidal but researcher focuses more on one of these MFs for a specific application without necessarily investigate the performance of other available MFs. This paper tends to explore this hole by investigating the efficiency and performance accuracy of both triangular and trapezoidal MFs on a fuzzy model for short-term electrical load forecast.

In recent times, load forecast research is gearing towards the development of hybrid methods to take the advantages of some of the basic methods to bridge the gap of one approach with the others. The objective of hybrid methods is to take the merits of statistical and artificial intelligent methods to obtain an optimal load forecasting. With limited information, the hybrid method has the capacity to optimize the available information, integrate the individual model information, and make use of the merits of the multiple forecasting models to improve prediction accuracy. Although the techniques are usually complex to implement, they often give a more accurate result. Some of the investigated hybrid approach includes a combination of ANN and modified neural network with the fuzzy logic (Černe et al., 2018; Emarati et al, 2019; Sadaei et al., 2019; Wen et al., 2020). Electrical load forecasting from these approaches has contributed immensely to resources management and economics of power industries and indirectly on global warming mitigation.

METHODS

Fuzzy Logic Approach

Fuzzy logic is an approach of computation based on the degree of truth rather than the usual true or false. The fuzzy logic process comprised the inputs, the controller or fuzzy inference engine, the rules base, and the defuzzification stage as presented in Figure 1. The input stage is the point where the forecaster selects the number of inputs such as load data, time, or exogenous factors like the weather parameters for electrical load forecasting. At the input stage, the data is fuzzified where they are formulated to fuzzy sets without any crisp values or elements. The combination of the fuzzification output and the fuzzy rule base serves as input to the fuzzy inference engine or controller which is the heart of the system. The fuzzy controller processes the input data to produce an output. The controller implements the rules prepared by the electrical load forecaster based on the input data classification. The rule base is prepared by the forecaster for the fuzzy inference system and the accuracy of

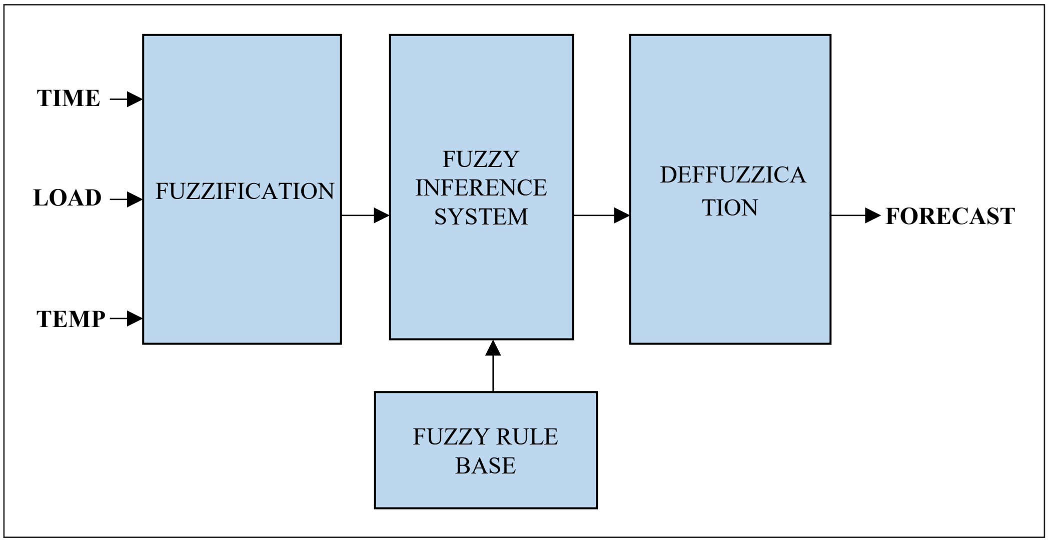


Figure 1. Fuzzy logic process

the system depends on these rules. The more the rules the better the accuracy of the system. In this application, the defuzzification block converts the processed fuzzy set into a crisp output that can be displayed on the graph as the forecasted load or load curve. The fuzzy short-term electrical load forecast uses the actual load, time, and temperature as input data to the fuzzy system. The block diagram in Figure 1 shows the basic fuzzy logic model for the load forecast starting with the fuzzification of input data to the fuzzy inference system with the rules and the defuzzification stage before the output display.

Fuzzification of Input Data

The historical load, time, and temperature are considered as the input, while the forecast load is considered as the output. The historical load data were first examined to study the parameter trends before the fuzzification of the input data. The maximum and minimum values of the parameters including the temperature and the load data were obtained and used for the fuzzification process. From the collected data, Table 1 shows the time fuzzy set, Table 2 presents the temperature fuzzy set, and Table 3 shows the fuzzy set for the load.

Table 1
Time fuzzy set

Time of the day	Notation	Time range
Midnight	MN	1-6
Morning	MG	4-10
For-Noon	FN	9-13
Afternoon	AN	12-17
Evening	EV	15-20
For-Night	FT	19-24

Table 2
Temperature fuzzy set

Temperature	Notation	Temperature range
Temperature very low	LT	20^oC-29^o C
Temperature low	HT	28^oC-36^oC
Temperature High	VT	35^o C - 42^oC

Table 3
Fuzzy set for the load

Load	Notation	Load range
Low load	LL	1MW-30MW
High load	HL	10MW-50MW
Very High load	VH	30MW -60MW

Fuzzy Logic MF

The MF is the curve that defines how each point in the input space is mapped to a membership value between 0 and 1. The common fuzzy logic MFs are the triangular, trapezoidal, and the Gaussian MF. In this study, the triangular and trapezoidal MFs were investigated to ascertain their computational efficiency and effectiveness in the electrical load forecast. The inputs to the fuzzy model for the load forecast are the time, load, and temperature which are fuzzified to data sets between 0 and 1 for the ranges specified in "Fuzzification of Input Data". The triangular MF allows the forecaster to fix the element of the time, load, and temperature into a fuzzy set with triangular shape as shown in Figures 2, 3, and 4, respectively. In this regard, the forecaster will be able to assign the elements of the fuzzy set between the boundary element and the middle element with the highest membership value. Also, for the trapezoidal MF, the boundary of the MF is selected and allowed to increase within the range of the elements with the highest membership value in the fuzzy set. The trapezoidal MF mapping for the three input: time, load, and temperature into membership value is presented in Figures 5, 6, and 7, respectively.

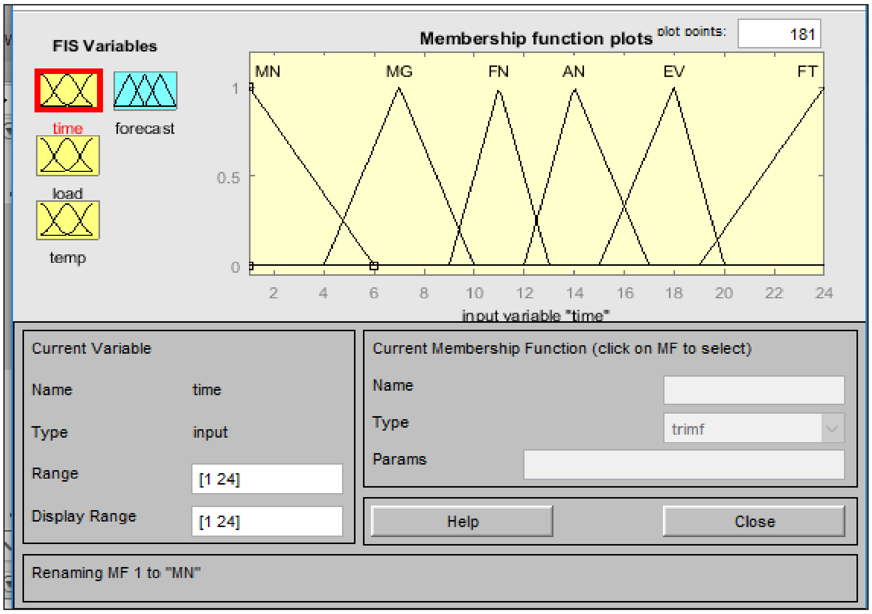


Figure 2. Fuzzy logic triangular MF of time input

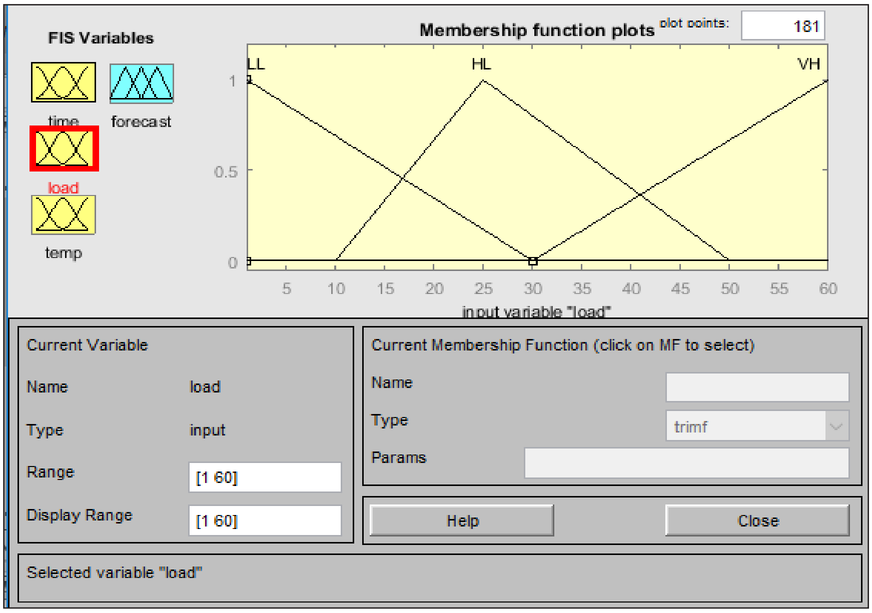


Figure 3. Fuzzy logic triangular MF of load input

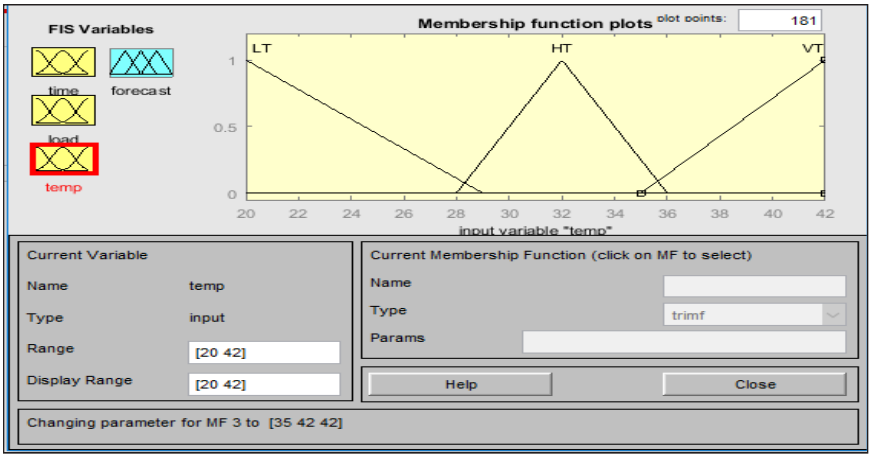


Figure 4. Fuzzy logic triangular MF of temperature input

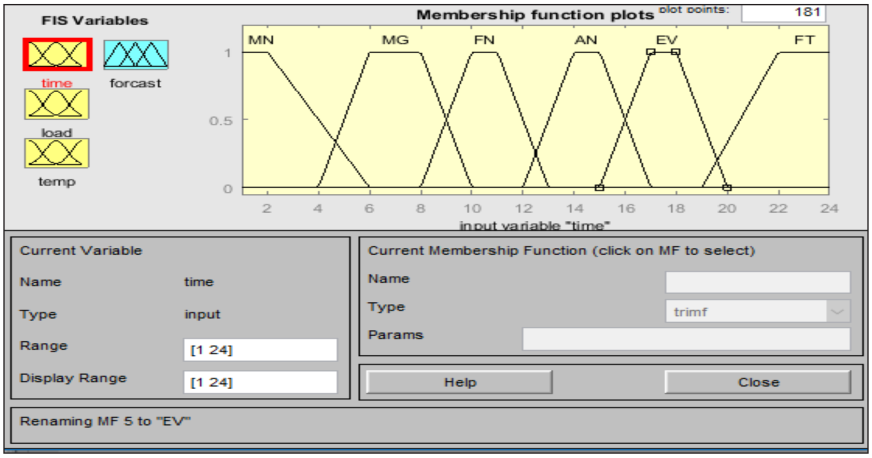


Figure 5. Fuzzy logic trapezoidal MF of time input

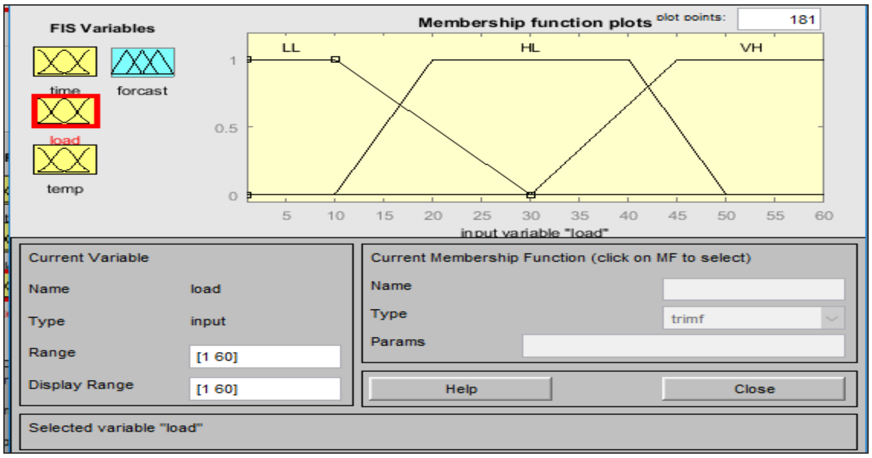


Figure 6. Fuzzy logic trapezoidal MF of load input

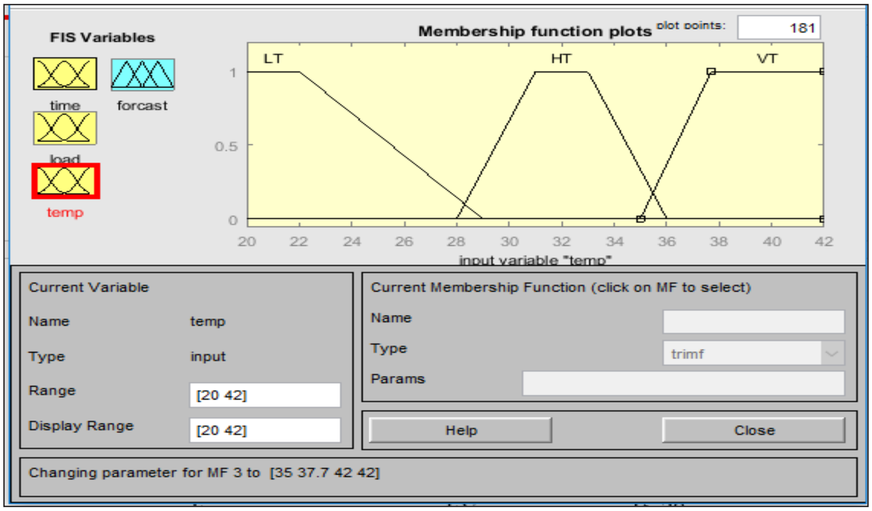


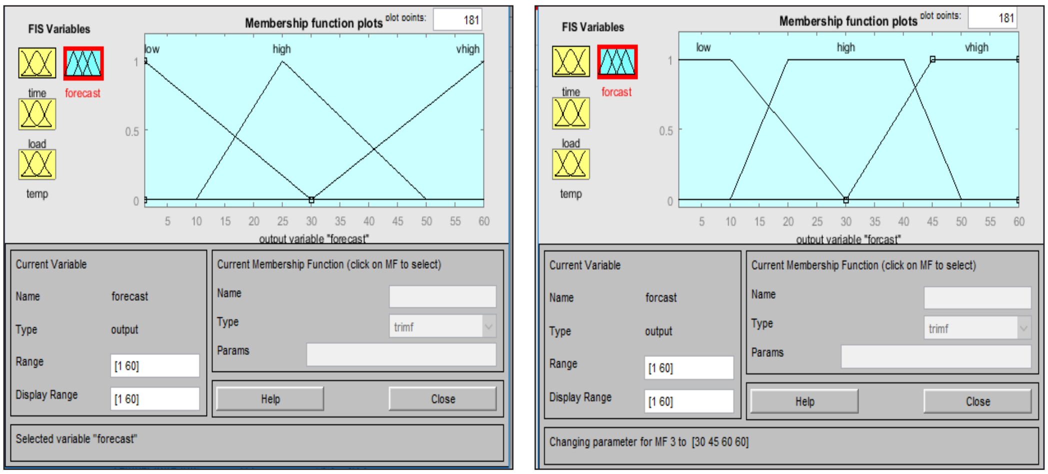
Figure 7. Fuzzy logic trapezoidal MF of temperature input

Fuzzy Rule Base

The fuzzy rule base is a crucial aspect of the fuzzy process because the fuzzy output largely depends on the set rules. In forecasting, the antecedents (input variables) are fed to the fuzzy controller and the rules are applied, then the controller acts on the antecedent and produces the consequences (output). Where there are multiple inputs as applicable in most cases and in this work, the fuzzy operators such as AND, OR and NOT, are used to combine the variable to form a fuzzy judgment. In this study, based on the fuzzy set for the input parameters of time, historic load data, and temperature of the day; sample of the formulated rules are as follows:

- *If* (time is MN) *and* (load is LL) *and* (temperature is LT) *then* (forecast is low)
- *If* (time is MN) *and* (load is HL) *and* (temperature is HT) *then* (forecast is high)
- *If* (time is AN) *and* (load is LL) *and* (temperature is LT) *then* (forecast is low)
- *If* (time is AN) *and* (load is HL) *and* (temperature is VT) *then* (forecast is high)
- *If* (time is FT) *and* (load is LL) *and* (temperature is LT) *then* (forecast is low)
- *If* (time is FT) *and* (load is VH) *and* (temperature is VT) *then* (forecast is very high)

Having three inputs of time, load and temperature that have been fuzzified into data sets as described in "Fuzzy Logic MF", the fuzzy inference engine or controller combine these inputs into fuzzy results or fuzzified output which is in turn defuzzified into single crisp output. As stated in the first sample formulated rules, when the time is morning with low load demand, and the temperature is low, the three input combination with *if-and-then* statement by the inference engine fuzzified the output to a shape with higher potential for predicting the forecast output load to be low. In the second statement, even though it is morning time, the load demand is high, and the temperature also high, thereby the fuzzy inference engine consequently fuzzified the membership output to have significant potential for high output load forecast. The fuzzified output MF for the sample rule statement for both the triangular and trapezoidal are presented in Figure 8 (a) and (b), respectively. This serves as the basis for the defuzzification stage to obtain a single crisp output load.



(a) (b)

Figure 8. Fuzzy logic (a) triangular MF load output (b) trapezoidal MF load output

Defuzzification

The final stage of the fuzzy process is the defuzzification that converts the fuzzy output to a quantifiable crisp value that can be displayed on the graph. There are different techniques for fuzzy defuzzification including the weighted average method, bisector method, mean of maximum methods, and center of area method (Sivanandam et al., 2007). The centroid of the area is the most commonly used method due to better outcomes, but its main disadvantage is computationally difficulty for complex MFs. In this work, the centroid method was chosen for the defuzzification stage and centroid position is calculated from the Equation 1:

$$W^* = \frac{\sum_{i=1}^{n} j_i A_i}{\sum_{i=1}^{n} A_i} \tag{1}$$

Where W^* is the centroid position, j_1 are the center of the area of the fuzzy set in consideration, while A_i is the area of the fuzzy set, and $i = 1, 2 \ldots n$

Fuzzy Logic Interface

The fuzzy logic programming interface is represented in Figure 9 shows the load forecast implementation environment. The time is one of the inputs where the time fuzzy set is classified, the load input is where the load is classified into three fuzzy sets and temperature is an input where the temperature is also classified into three sets. The Mamdani fuzzy typed was employed in the implementation forming the heart of the model where all the rules were actualized. The output of the process is the forecasted load.

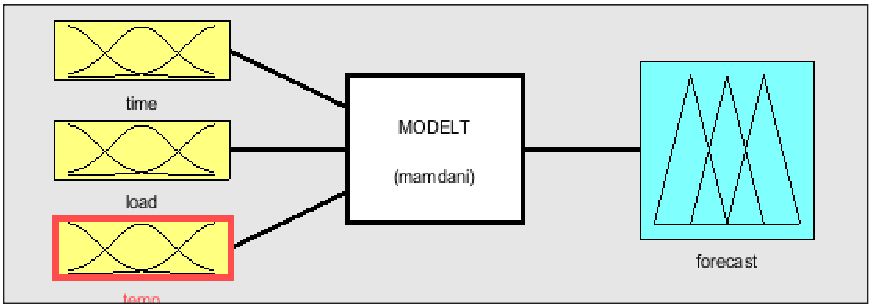


Figure 9. Fuzzy logic interface

Transmission Station Load Data

The electrical load data of the transmission station and the temperature data were collected for one month in March 2019 which served as input to the fuzzy logic controller for the electrical load forecast. The weather temperature was obtained from the world weather for the load center, while the historical load data were recorded at the transmission station on an hourly basis (WeatherOnline, 2019). The Ganmo Transmission Company of Nigeria (TCN) was used as case study and it operates on 330/132/33kV. It received High Voltage Alternating Current (HVAC) of 330kV from Jebba generating station and Oshogbo National Grid station. The Ganmo work center is an Area Control Centre (ACC) with a capacity of 240MW directly serving two sub-transmission stations under its command: Sawmill and Omu-Aran, both in kwara state Nigeria. The two sub-stations operate on 132/33kV from where 33kV is fed to the district's distribution companies and the eligible or special customers.

Presented in Figure 10 is a weekly load demand record between 1st to 7th March 2019 with 55MW maximum and 6MW minimum load demand. This hourly load data are the demands of customers from Sawmill substation comprising of commercial, industrial, and residential customers. As observed from load demand profile, there were quiet irregularity in the hourly load demand pattern as the huge difference between the same hour demand for different days does not represent true load demand. These were due to issues like low generation, non-picking of load by distribution companies and frequent fault on the transmission lines. To have adequate load data input to the fuzzy controller, averaged weekly hourly load data were computed for the one-month load data representing day 1 to day 4 load profile. Therefore, the average weekly hourly load data was then used as the input load of the station. Similarly, the hourly temperature daily data obtained from 1st to 7th March 2019 is presented in Figure 11.

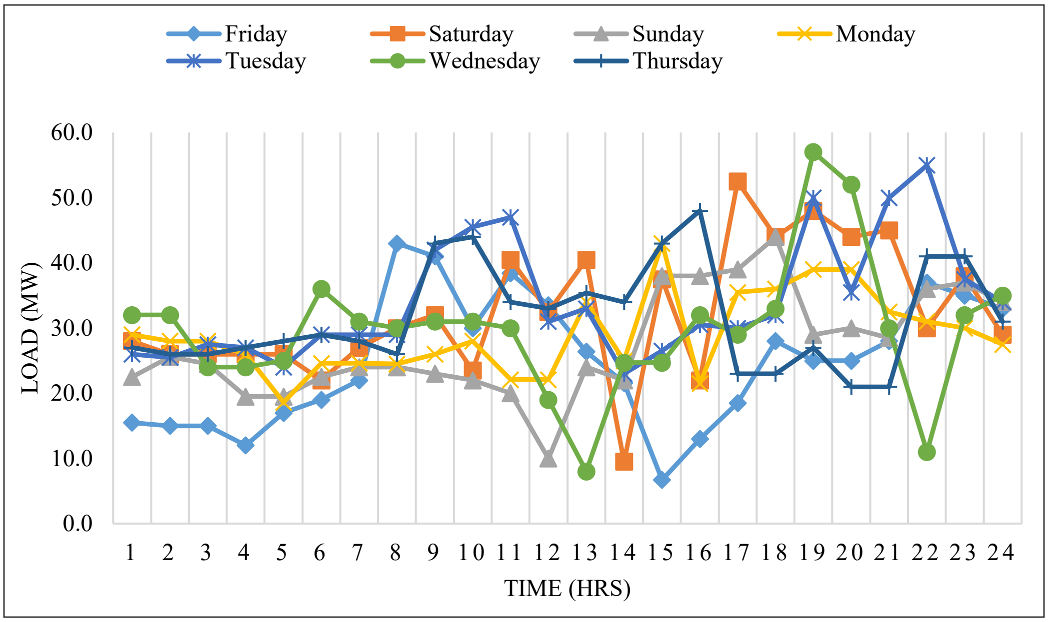


Figure 10. Typical one week daily demand profile

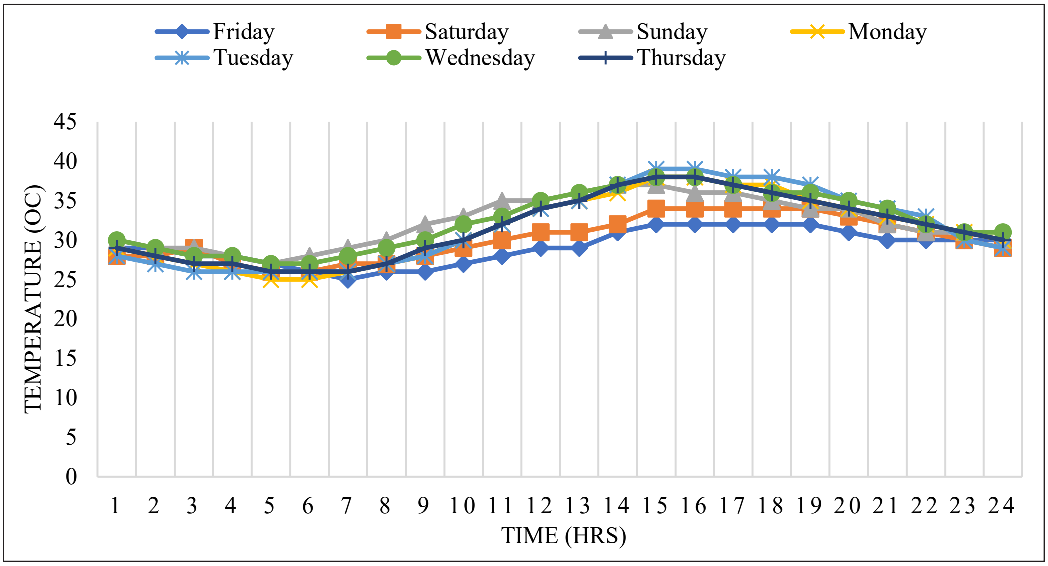


Figure 11. Typical one week daily temperature

Model Error Analysis

Forecast model validation is an important task when forecasting or predicting the future behavior of a system. Comparing the forecasted values with the actual discloses information on the efficiency and accuracy of a forecast model. The testing or validation process involves evaluating the deviation error between the forecasted and the actual data. The statistical approach such as absolute percentage error (APE), MAPE, MFE, and MAD are the most popular method for testing model performance. The aforementioned statistical error analysis methods were used in this study to compute the percentage deviation between the forecasted electrical load and the actual load. The error analysis further shows the effectiveness of the two investigated MFs; triangular and trapezoidal. The APE and MAPE are computed using Equation 2 and 3, respectively. Also, the MFE and MAD were computed using the Equation 4 and 5, respectively.

$$\text{APE }(\%) = \left| \frac{actual(i) - forecast(i)}{actual(i)} \right| \times 100 \tag{2}$$

$$\text{MAPE }(\%) = \frac{1}{\text{n}} \sum_{i=1}^{n} \left| \frac{actual(i) - forecast(i)}{actual(i)} \right| \times 100 \tag{3}$$

$$\text{MFE }(\%) = \frac{1}{n} \sum_{i=1}^{n} \left(actual(i) - forecast(i) \right) \times 100 \tag{4}$$

$$\text{MAD }(\%) = \frac{1}{n} \sum_{i=1}^{n} \left| actual(i) - forecast(i) \right| \times 100 \tag{5}$$

RESULTS AND DISCUSSION

The fuzzy logic-based electrical load forecast for a transmission substation considering the time of the day, historic load profile, and temperature as input data has been implemented in the MATLAB Simulink environment. The fuzzy logic load forecast model was used to predict the next day load demand and compared with the actual load to ascertain the model performance. Two fuzzy MFs: triangular and trapezoidal were investigated and the percentage error difference between the actual load and forecasted load showed the effectiveness of the forecast model for a day ahead load demand.

Presented in Table 4 is the results of the Day 1 load forecast for 24 hours ahead period with the computed APE and MAPE between the forecast and actual load for both the triangular and trapezoidal MF. It was observed that the APE between the actual and forecasted load for the triangular MF varied between 1.55 % minimum to a maximum of 17.35 %. The trapezoidal MF was between 0 % minimum to a maximum of 14.48 %. The trapezoidal MF produced improved load forecast with less deviation as this was obvious at 14:00 hours where the forecasted load of 30MW was exact of the 30MW actual load for the day. The MAPE obtained for the triangular membership was 8.93% while that of the trapezoidal membership was 6.34% for the 24 hours.

The MFE measures the average deviation of the forecast from actual loads while MAD measures the average absolute deviation of the forecast from the actual value. The model accuracy depends on the closeness of the MFE and MAD to zero, where the closer to zero the more accurate the model. As presented in Table 4, the error analysis shows that the

Table 4
Time, temperature, actual and forecast load for Day 1

Actual load (MW)	Time (hour)	Tempera-ture (^{o}C)	Forecast Triangular MF (MW)	FE	APE (%)	Forecast Trapezoidal MF (MW)	FE	APE (%)
25.7	1	28	25.3	0.4	1.55642	27.1	-1.4	5.447471
25.4	2	28	24.9	0.5	1.968504	26.4	-1	3.937008
24.4	3	28	23.6	0.8	3.278689	25	-0.6	2.459016
23.1	4	28	22.9	0.2	0.865801	24.1	-1	4.329004
22.6	5	27	23.3	-0.7	3.097345	24.1	-1.5	6.637168
26	6	27	23.8	2.2	8.461538	24.6	1.4	5.384615
26.5	7	28	25.8	0.7	2.641509	27.8	-1.3	4.90566
29.5	8	29	25.8	3.7	12.54237	28.1	1.4	4.745763
34	9	30	28.1	5.9	17.35294	30.3	3.7	10.88235
32	10	32	26.5	5.5	17.1875	29.1	2.9	9.0625
33.1	11	34	27.9	5.2	15.70997	30.3	2.8	8.459215
25.9	12	36	26.4	-0.5	1.930502	28.8	-2.9	11.19691
29	13	38	30	-1	3.448276	33.2	-4.2	14.48276
30	14	39	27.4	2.6	8.666667	30	0	0
31.3	15	41	26.5	4.8	15.33546	29.1	2.2	7.028754
29.3	16	40	27.6	1.7	5.802048	30	-0.7	2.389078
32.5	17	39	27.5	5	15.38462	30	2.5	7.692308
30	18	39	24.1	5.9	19.66667	26.3	3.7	12.33333
28	19	38	24.3	3.7	13.21429	25.2	2.8	10
29	20	37	24.1	4.9	16.89655	26	3	10.34483
29	21	36	25.9	3.1	10.68966	28.4	0.6	2.068966
28	22	32	25.4	2.6	9.285714	27.9	0.1	0.357143
27	23	30	26.3	0.7	2.592593	28.8	-1.8	6.666667
28	24	29	26.1	1.9	6.785714	28.4	-0.4	1.428571
				2.49167 (MFE)	**8.93172 (MAPE)**		**0.42917 (MFE)**	**6.34330 (MAPE)**

MFE for trapezoidal MF is 0.4292 which is closer to zero compared to that of the triangular MF with a value of 2.4917. Similarly, the MAD computation from the absolute values of the FE for trapezoidal MF gives a lower error value compared to the Triangular MF. This indicates that the trapezoidal MF load forecast was much closer to actual load demand and produced better performance on short-term load forecasting than the triangular MF.

The Day 2 load forecast is presented in Table 5. It was observed that the load forecast with the trapezoidal MF showed greater linearity with the actual load as compared to the triangular MF. This was further established by the computed MAPE where trapezoidal MF was 6.24% compared to that of a triangular MF of 11.70%. Consistent high daily load demand was observed between the hours of 13:00 hours to 16:00 hours which was due to

Table 5
Time, temperature, actual and forecast load for Day 2

Actual load (MW)	Time (hour)	Tempera-ture (^oC)	Forecast Triangular MF (MW)	FE	APE (%)	Forecast Trapezoidal MF (MW)	FE	APE (%)
31.9	1	29	26.8	5.1	15.9875	29.3	2.6	8.1505
32.5	2	28	26.7	5.8	17.8462	29	3.5	10.7692
34.1	3	28	26.2	7.9	23.1672	28.4	5.7	16.7155
28.8	4	27	25.2	3.6	12.5	27.1	1.7	5.90278
31.1	5	27	24.5	6.6	21.2219	26.7	4.4	14.1479
30.7	6	27	27.1	3.6	11.7264	29.4	1.3	4.23453
30	7	28	28.4	1.6	5.33333	29.7	0.3	1
30	8	28	30.8	-0.8	2.66667	31	-1	3.33333
35.5	9	29	30.8	4.7	13.2394	34.7	0.8	2.25352
34.7	10	31	31.3	3.4	9.7985	32	2.7	7.7810
30.7	11	33	25.5	5.2	16.9381	33.3	-2.6	8.46906
36.1	12	34	28.4	7.7	21.3296	29.2	6.9	19.1136
31.7	13	36	28.5	3.2	10.0946	30.5	1.2	3.78549
34.2	14	37	29.2	5	14.6199	31.7	2.5	7.30994
32.4	15	39	28.3	4.1	12.6543	31.7	0.7	2.16049
34.2	16	39	31.2	3	8.7719	31.1	3.1	9.06433
31.5	17	38	31.1	0.4	1.26984	32.3	-0.8	2.53968
31.2	18	38	28.7	2.5	8.01282	31	0.2	0.64103
32.5	19	36	27.9	4.6	14.1539	30	2.5	7.69231
29	20	35	28.5	0.5	1.72414	31.2	-2.2	7.58621
30.8	21	34	28.5	2.3	7.46753	30.7	0.1	0.32466
30.8	22	32	27.8	3	9.74026	30	0.8	2.59740
30.3	23	31	27.3	3	9.9010	30	0.3	0.99001
31	24	31	27.7	3.3	10.6452	30	1	3.22581
				3.72080 (MFE)	**11.70041 (MAPE)**		**1.48750 (MFE)**	**6.24118 (MAPE)**

an increase in temperature and more energy was required for temperature control through the use of air-conditioning systems. Considering the lower APE and MAPE errors between the forecasted and real load obtained for both trapezoidal and triangular MF implies that the Fuzzy model performed moderately for a day ahead load forecast.

The error analysis results for Day 2 presented in Table 5 also show that the MFE of triangular MFE was 3.7208 which much greater than zero when compared to that MFE of Trapezoidal MF 1.4875. Likewise, the computed MAD for the triangular MF load forecast had a large value of 3.7875 when compared to that of trapezoidal MF with 2.0375 value.

Table 6
Time, temperature, actual and forecast load for Day 3

Actual load (MW)	Time (hour)	Tem-per-ature (°C)	Forecast Triangular MF (MW)	FE	APE (%)	Forecast Trapezoidal MF (MW)	FE	APE (%)
31	1	29	27.4	3.6	12	30	1	3.225806
32	2	28	26.5	5.5	17.57188	28.7	3.3	10.3125
33	3	28	25.8	7.2	25.62278	27.8	5.2	15.75758
25.8	4	27	24.7	1.1	3.914591	26.5	-0.7	2.713178
30	5	27	26.8	3.2	9.69697	29.5	0.5	1.666667
31.3	6	27	26.5	4.8	14.95327	28.6	2.7	8.626198
28.1	7	28	26.6	1.5	5.050505	29	-0.9	3.202847
28.1	8	28	26.7	1.4	3.966006	29.1	-1	3.558719
33	9	29	28.6	4.4	13.7931	29.5	3.5	10.60606
32.1	10	30	28.4	3.7	10.27778	30.6	1.5	4.672897
29.7	11	32	28.1	1.6	4.705882	30.4	-0.7	2.356902
35.3	12	35	30.2	5.1	15.45455	32.5	2.8	7.932011
31.9	13	36	30.6	1.3	4.193548	33.4	-1.5	4.702194
36	14	37	30.8	5.2	16.25	32.6	3.4	9.444444
34	15	38	29.8	4.2	13.54839	34.7	-0.7	2.058824
33	16	38	33.1	-0.1	0.344828	36.4	-3.4	10.30303
31	17	37	28.1	2.9	9.666667	30.2	0.8	2.580645
32	18	37	30.4	1.6	5.16129	32.2	-0.2	0.625
31	19	35	30.2	0.8	2.666667	32.5	-1.5	4.83871
29	20	34	27.4	1.6	5.333333	30	-1	3.448276
30	21	33	27.7	2.3	7.666667	30	0	0
31	22	32	29	2	6.451613	31.3	-0.3	0.967742
30	23	31	28.7	1.3	4.333333	31.3	-1.3	4.333333
30	24	30	28.9	1.1	3.666667	31.4	-1.4	4.666667
				2.80417 (MFE)	**9.01210 (MAPE)**		**0.42083 (MFE)**	**5.10834 (MAPE)**

The results from the error analysis on the prediction accuracy of the two investigated triangular and trapezoidal fuzzy MF showed that the triangular MF had better performance.

To further evaluate the performance of the fuzzy load forecast model, a third-day load forecast was performed using the Day 2 actual load, and the results are presented in Table 6. The trapezoidal MF MAPE is 5.11% and triangular MF has a 9.01% error between the predicted and the actual load consumption for the day. Observing the error trend between the actual and forecasted load from Day 1 to Day 3, it can be inferred that the trapezoidal MF performed better than the triangular MF for the fuzzy input mapping. In Table 6, the MFE of triangular MF is 2.8041 while that of trapezoidal MF is 0.4208. This clearly shows that the trapezoidal MF model load forecast prediction is much more accurate compared to the triangular MF. Also, MAD values follows the same pattern where the trapezoidal MF model having 2.8125 and lower than the triangular 1.6375.

The summary of the MAPE, MFE, and MAD error variations between the triangular MF and trapezoidal MF is presented in Figure 12. The error analysis for both MFs is moderate with that of trapezoidal MF producing the lowest error between the actual and forecasted load as compared with that of triangular MF. It is appropriate to note that forecasting errors reported for various short-term load forecasting models in the literature range from 1% to 20%. Having the MAPE, MFE, and MAD values lower than 12% confirm the suitability of the developed fuzzy logic model for short-term load forecasting. With a high degree of closeness between the forecasted and actual load means that utility companies can rely on such outcomes in planning and operating their power generating plants to meet the load demand.

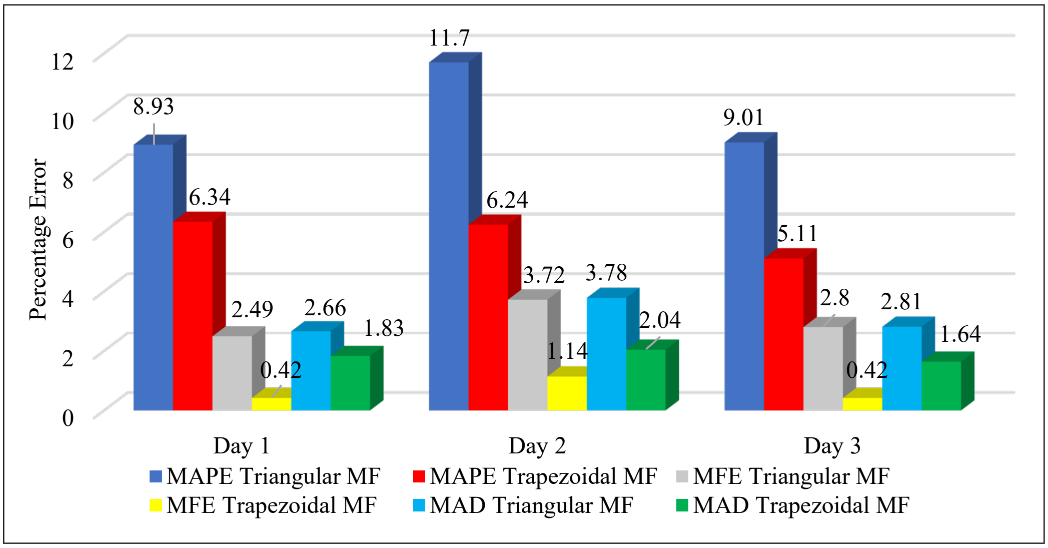


Figure 12. MAPE, MFE and MAD for the Fuzzy logic load forecast model

CONCLUSION

Electrical load forecast models play vital role in the planning and operation of electric power system and consequently lead to improved network reliability. In this work, a fuzzy logic forecast model was developed for short-term load forecast of a day ahead and two MFs; triangular and trapezoidal MFs were investigated. The error analysis between the actual and forecasted load shows that the fuzzy logic is suitable for short-term load forecast of power transmission stations. The fuzzy logic load forecast model performed efficiently with triangular MF having MAPE of 8.93%, 11.7% and 9.01% and trapezoidal 6.34%, 6.24% and 5.11% for the three days tested. The MAPE error for both MF is considerably low, and less than 20% benchmark been reported in the literature. The results show the effect of input data MF mapping on the efficiency and accuracy of the fuzzy logic process as the two investigated functions produce various degree of prediction accuracy between the actual and forecasted load. It was observed from the error analysis results that the trapezoidal MF produced better performance with improved accuracy of load forecast than the triangular MF. To this end, other MFs such as Gaussian, piece-wise, and quadratic polynomial MFs can also be investigated. Aside the MFs, effect of other parts of the fuzzy logic process should be further investigated on short-term load forecast such as rules for the hierarchical fuzzy system. The results in this study have shown that transmission stations can rely on the use of fuzzy model for accurate load forecast.

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