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The Use of Fuzzy Logic Model to Investigate the Effect of Weather Parameter Impact on Electrical Load Based on Short Term Forecasting: Further Study

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Authors' contributions

This work was carried out in collaboration between both authors. Author DA designed the study, developed from fuzzy logic control model, wrote the protocol and the first draft of the manuscript. Author GPV managed the literature searches. Both authors read and approved the final manuscript.

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ABSTRACT

Electrical load forecasting is very important for effective planning and management of power system. Accurate load forecasting helps the electrical power company to make some decisions on how to meet up with their consumers' demand. This paper presents a solution methodology using fuzzy logic approach for short term load forecasting (SLTF) for Adamawa State University. The proposed method used fuzzy reasoning decision rules that utilized the nonlinear relationship between inputs and output. The model developed was able to forecast the future load with mean absolute percentage error (MAPE) of 1.36% and forecasting without previous load at the input of the fuzzy logic model yields better prediction error. However, from the result obtained, it shows temperature has a significant impact on electrical load than the relative humidity. Also, electrical load shall increase by 1.84 kW on the 25th September, 2018 due to increase in temperature.

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Keywords: Load; forecasting; short-term; fuzzy logic; weather; electrical load and fuzzy rules.

1. INTRODUCTION

Accurate load forecasting can enhance reliable or uninterrupted power supply to the customers. Usually, power supply starts from generation to transmission and finally to distribution, where consumers directly benefit. But the transmission line is geographically exposed to many atmospheric conditions/factors such as temperature, relative humidity, wind speed, solar radiation and rainfall. These factors may affect electrical load. Therefore, it is necessary to take one or two of these factors into consideration when forecasting electrical load, this will help electrical utility companies with vital information on what to generate, transmit and distribute.

Nigerian government has spent a huge sum of money in the previous years to address the problems of power supply in the country. Up to date, practically, the capacity produced in Megawatts for consumption is far below nation's average, this is evident in the epileptic power supply that leads to persistent load shedding and power outages across the country. These short comings may be attributed to the lack of proper forecasting to authenticate future occurring problems, which is the focus of this work.

Load forecasting has played a vital role in improving power supply as reported by different authors across the globe [1–5]. Also, many works have been carried out to forecast an electrical load using fuzzy logic control (FLC) in terms of weather parameters. See for example, [6–10], developed models with mean percentage error of 11.74%, 12.4%, 6.19%, 5.57% and 6.81% respectively. Furthermore, [11] worked on long term load forecasting for Mubi town using fuzzy logic approach and obtained forecasting error of 6.9% [12] again utilized neuro – fuzzy to forecast an electrical load in terms of weather parameters and determined the MAPE as 1.22%. Other authors used different methods to forecast electrical. For example [13] used pattern similarity – based method for short-term load forecasting and obtained an error of 6.17% and [14] in separate developed fuzzy logic control model to forecast electrical load in terms of weather parameters, the authors applied temperature, relative humidity and previous day loads at the input of their model and obtained MAPE of 3.6%. However, all the researches mentioned, the authors did not consider the correlation between the electrical load and weather parameters of interest before developing their models because applying this can improve the performance of the models. Also, limited works are devoted to electrical load forecasting in Nigeria and this prompted for the emergence of work.

This work aims at developing a fuzzy logic model (FLCM) to forecast 25th September, 2018 electrical load with better forecasting error (performance) and following objectives shall be achieved: To test the correlation of the electrical load and the weather parameters (temperature and relative humidity), observe the effect of the weather parameter on the electrical load and finally, compare the prediction errors of the fuzzy logic model with and without previous loads at the input of the model. The remaining part of the work is organized in the following manner: methodology (classification of the inputs, outputs data, membership function assignment, the formation of fuzzy rules), results, discussion and conclusion.

2. MATERIAL, METHOD OF DATA COLLECTION AND PRESENTATION

2.1 Materials

There are several important factors that are used to forecast electrical load (EL), hourly and next day electrical load such as similar previous day load, weather parameters (temperature, wind speed, sunshine hours, rain fall and humidity). Among the parameters, this work shall take into consideration only weather parameter correlated with the electrical load. The following are the sets of data collected from Metrological Centre, Department of Geography and Maintenance Unit of Adamawa State University, Mubi and their average is depicted in Fig. 1.

- Hourly electrical load for 23rd and 24th July, 2018
- Hourly temperature for 23rd and 24th July, 2018
- Hourly humidity for 23rd and 24th July, 2018

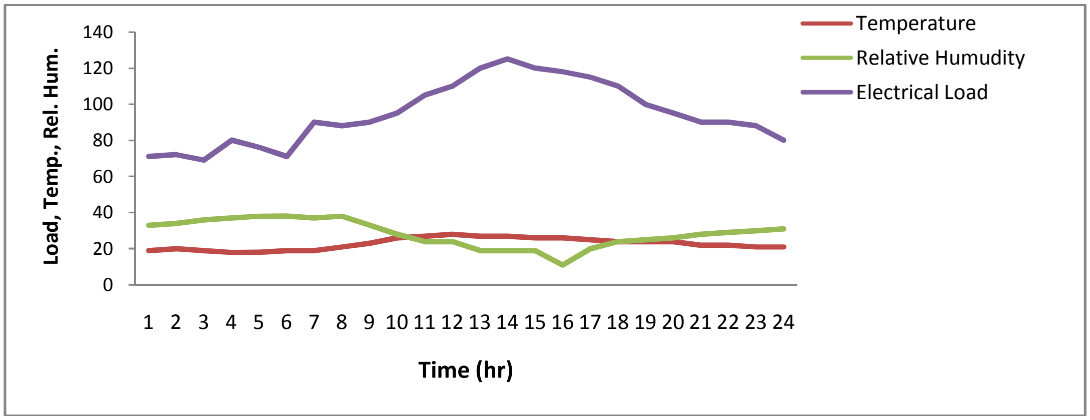

Fig. 1. Electrical load Vs temperature and humidity

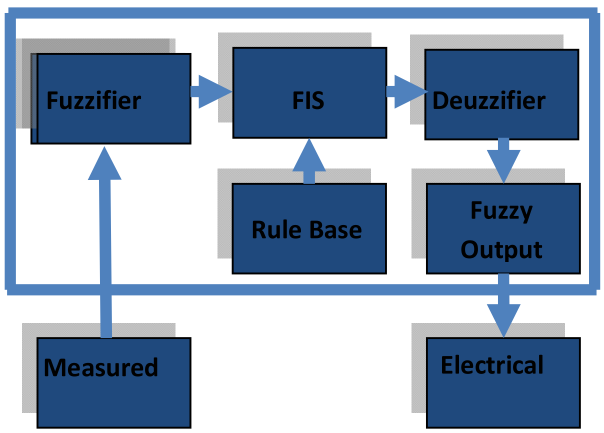

Fig. 2. Block diagram of fuzzy logic control model

2.2 Correlation Test

Relationships between the EL, temperature and relative humidity are tested using Eq. 1. Statistically, this coefficient evaluates how the variables affect each other. *r,* ranges as, $-1 \leq r \leq +1$ where negative *r,* indicates degree of negative correlation. Zero, means no relationship between the variables and positive *r,* shows degree of positive correlation.

$$r = \frac{n\sum TL - (T)\left(\sum L\right)}{\sqrt{\left[n\sum T^2 - \left(\sum T\right)^2\right]\left[n\sum L^2 - (L)^2\right]}} \tag{1}$$

where *n* represents the number of items, *y* represents electrical load and *T and H* represent temperature and relative humidity respectively.

2.3 Fuzzy Logic Control Simulation Model

The FLCM for the short term forecasting shall be developed based on the data in Fig. 1 and the procedures in the block diagram in Fig. 2 shall be followed to realize the FLM.

As shown in Fig. 2, Temperature *(T)* and Humidity *(H)* shall be served as the input parameters and the Load *(L)* as the output parameter of the FLCM. The input/output parameters are first fuzzified, and the output of fuzzier plus fuzzy rule base are fed into fuzzy inference system (FIS) where this information is processed, computed using *AND* operation and produced an output after defuzzification.

2.4 Classification of Input/Output Data

The input and output data are classified as shown in Table 1.

2.5 Membership Function Assignment

Membership function (MF) is a graph that relates how input and output are mapped between 0 and

1. It is usually denoted by a symbol (μ). MF can be classified into various types this includes triangular, gbell, trapezoidal, Gaussian, piecewise generic singleton and singleton. In this work, triangular shall be adopted. This MF is chosen because of its flexibility on all kinds of data. It consists of a vector say *L*, considered in this work as load and three parameters namely *a, b, c,* where *a* and *c* locate the lower limits, *b* locates the upper limit of the triangular MF and *f* is function of the variables (*L, a, b, c*) given by;

$$(L:a,b,c)=\begin{bmatrix} 0 & L\le a \\ \frac{L-a}{b-a} & a\le L\le b \\ \frac{c-L}{c-b} & b\le L\le c \\ 0 & c\le L \end{bmatrix} \tag{2}$$

Table 1. Classification of the input and output data

Classification	Low	Medium	High
L(kW)	60 - 95	90 -115	110 -125
T(°C)	20 - 24	23 - 27	26 -30
H(%)	18 - 24	23 -30	28 -39

Table 2. Linguistic terms and interval

Linguistic terms	Intervals		
	a	b	c
LT	18	23	29
MT	21	17	35
HT	24	30	29

LT = low temperature, MT = medium temperature and HT = high temperature

The formula (2) shall be used to form the MF of the *T, H* and *L.* The MFs depicted in Figs. 3 - 5 are formed based on the data in Table 1, using the coordinate positions *a, b, c*. Detail values of the parameters *a, b* and *c* are given in Tables 2–4 and the corresponding MF are depicted in Figs. 3–5 respectively.

Table 3. Linguistic terms and interval

Linguistic terms	Intervals		
	a	b	c
LH	20	23	26
MH	22	25	27
HH	24	27	30

LH =low humidity, MH = medium humidity and HH = high humidity

Table 4. Linguistic terms and interval

Linguistic terms	Intervals		
	a	b	c
LLT	69	90	110
ML	75	105	115
HL	95	115	125

LL = low load, ML = medium load and HL = high load

Let $\mu_T(L)$ and $\mu_H(L)$ present the degree of membership of the MF $\mu_T(.)$ and $\mu_H(.)$ of the input sets *T* and *H*, where $L \in X$, then the Mamdani's logic operator can be written as;

$$\phi[\mu_T(L),\mu_H(L)] = \min[\mu_T(L),\mu_H(L)] \\ = \mu_T(L)\wedge\mu_H(L) \tag{3}$$

If $\mu_L(L)$ denotes the degree of membership of the MF $\mu_T(.)$ of the fuzzy output set *L*, also, $L \in X$, then the expression of the MF of the *L* can be expressed as;

$$\mu_L(L) = \phi[\mu_T(L),\mu_H(L)].\mu_L(.) \tag{4}$$

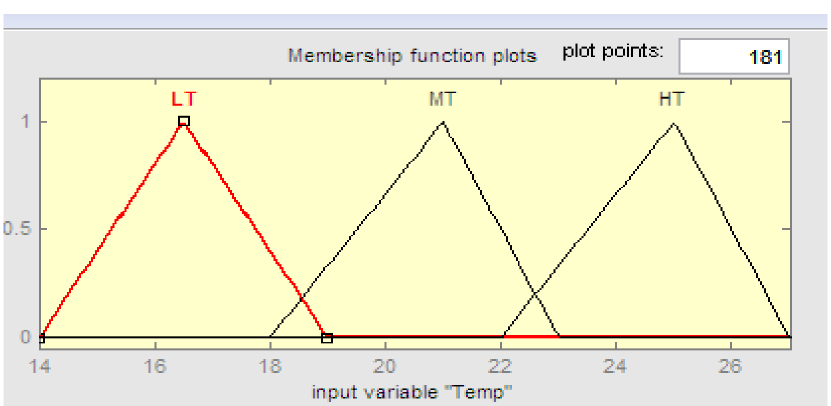

Fig. 3. Membership function of temperature

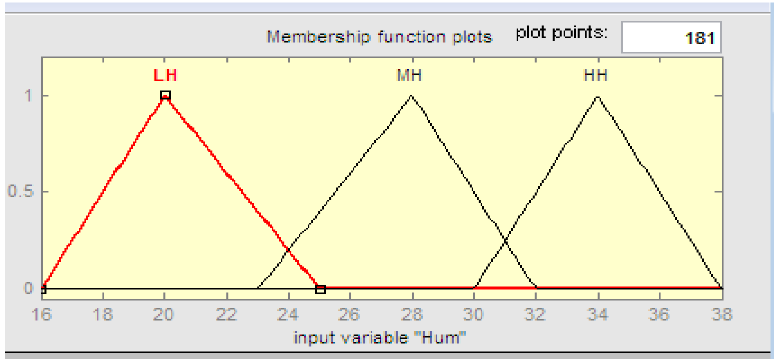

Fig. 4. MF of H

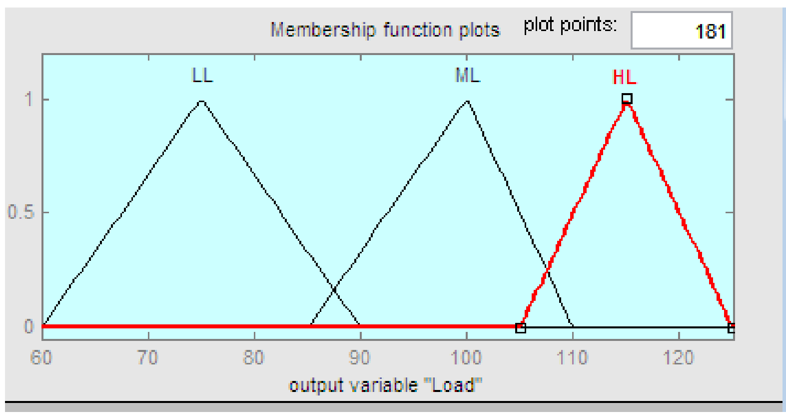

Fig. 5. MF of L

F. Fuzzification of input/output

2.6 Formation of Fuzzy Rule Base

This area is the heart of the fuzzy system. This is where the fuzzy rules are formulated based on how the input/output relates with each other. Care needs to be taken when developing these rules because; all the knowledge of the forecasting is stored in the fuzzy inference system (FIS) in terms of "*IF-THEN*" statement. These statements of the rules help the forecaster to obtain the best output. The following are the set of fuzzy rules formulated based on the information given in Table 4.

if T is LT and H is ML then L is LL
if T is MT and H is MH then L is ML
if T is HT and H is MH then L is HL
if T is HT and H is LH then L is HL
if T is LT and H is HH then L is LL
if T is MT and H is HH then L is MT

2.7 Defuzzification

In defuzzification the centroid with a discrete universe of discourse may be obtained as;

$$L_{out} = \frac{\sum_{i=1}^{n} L_i \mu_{out}(L_i)}{\sum_{i=1}^{n} \mu_{out}(L_i)} \tag{5}$$

where L_{out} is the crisp output value, L_i is the crisp variable, $\mu_{out}(L_i)$ is the degree of membership of the output fuzzy values and i is the number of the discrete output refers to as the element of the universe of discourse. Haven satisfied all conditions in Fig. 2, a sample of the data collected is simulated as follows;

2.8 Simulation Model

Fig. 6 depicts the simulation model developed in the SIMULINK MATLAB environment, which is a translation of Fig. 2.

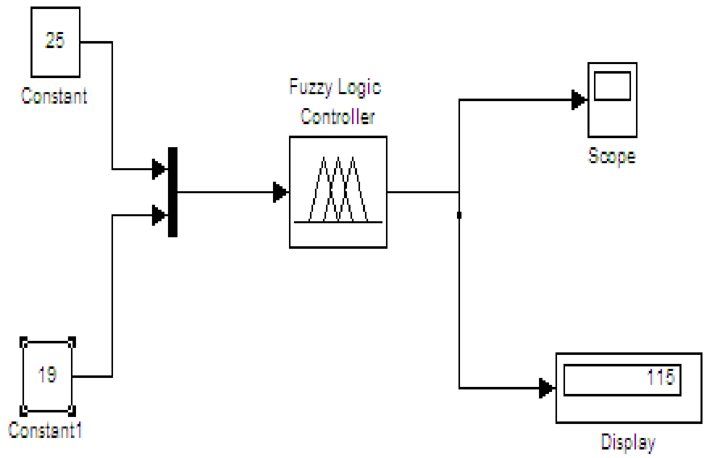

Fig. 6. Fuzzy logic simulation model

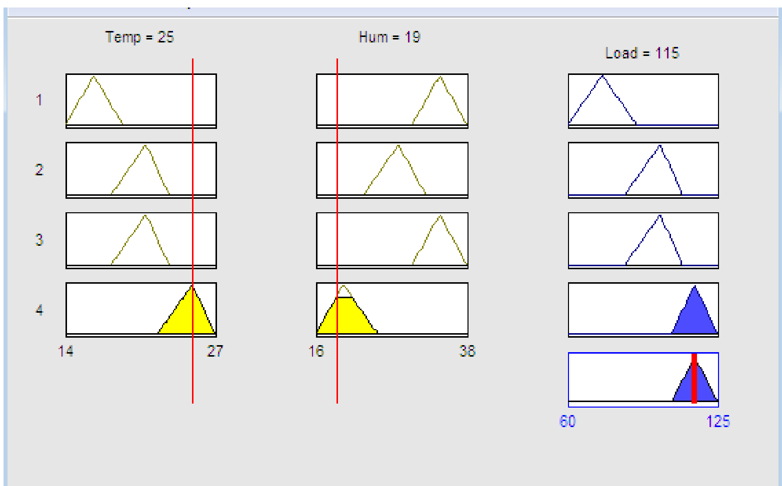

Fig. 7. Rule viewer

2.9 Error Analysis

The Mean average percentage error (M) of the data is computed using Eq. (6);

$$M = \frac{1}{n_1}\left(\sum_{i=2}^{n}\frac{Actual\ Load - Forecasted\ Load}{Actual\ Load}\right)\times 100\% \qquad (6)$$

Where n_1 represents the number of hours a day

3. RESULTS AND DISCUSSION

Eq. 1 was used to confirm the correlation between the EL and the weather parameters. The test shows that EL is correlated with temperature and relative humidity by 0.712 and 0.038 coefficients respectively. Both parameters are positively correlated. However, temperature is highly correlated with the EL than the relative humidity.

Fig. 1 represents the average values of electrical load, temperature and relative humidity collected for two days (23rd and 24th July, 2018). It can be seen that EL increased as temperature increased, while relative humidity does not show notable effect on the EL.

Figs. 3–5, depict the MF of the FLCM inputs (temperature and relative humidity) and output (electrical load) which are presented in the sets of triangles overlapping one another at the base. The triangular information is first fuzzified using Eq. 2 as given in Tables 2 - 4, fuzzy rules were formulated in the expert domain, and these rules acted on the fuzzified inputs/output using firing strength in the FIS as indicated in Eqs. 3 – 4 and the defuzzified output are computed using Eq. 5, given as the forecasted load in Table 5. Furthermore, the model MAPE was computed as 1.36% using Eq. 6.

Fig. 6, shows the FLCM. As it can be seen, a pairs of sample data, such as temperature (25°C) and humidity (19%) are selected at random and simulated which produced an output of 115kW as the load forecasted for 25th September, 2018 at 15:00 pm. While, the other values of forecasted load and their corresponding hours are summarized in Table 5 and these loads can also be obtained from the rule viewer in Fig. 7. On the rule viewer, is the temperature, relative humidity as the input and EL as the output of the FLCM, it indicates the value of the electrical load when the temperature and the relative humidity are selected at arbitrary and matched together as also summarized in Table 5.

Fig. 8 compares the measured and forecasted load. Forecasted load at an interval of one hour from 0.00 am – 23.00 pm. The forecasted load becomes higher than the measured load by 3.33 kW, 6.13 kW, 6.13 kW, 0.54 kW, 2.70 kW, 8.67 kW, 0.20 kW, 1.74 kW, 0.87 kW, 6.70 kW, 10,20 kW, 8.80 kW accept at 4.00 am, 9.00 am where forecasted remains unchanged and at 12.00 pm – 19.00 pm the measured load is higher than the forecasted by 2.00 kW.7.00 kW, 5.00 kW, 1.00 kW, 7.0 kW, 4.00 kW, 11.50 kW and 10.00kW, 7.00 kW due to variation in temperature respectively.

Fig. 9, Shows that, load increases, with increase in temperature as also reported by Manoj and Ashish [5], [15]–19] and humidity does not show notable impact on the loads. Therefore, it can be said that load is a function of temperature as reported by Song et al. [20], Jagbir and Yadwinder [21].

The prediction error of FLCM without the previous load obtained in this work is lower than what is obtained by [5] by 4.81. In a nutshell, prediction without previous load gives better result. In addition, the performance of the model developed is compared with the other works as given in Table 6.

The information in Table 6 clearly indicates that the model 1, has better performance than the models 2 – 5 by 10.36%, 4.38%, 5.44% and 4.31% respectively.

Table 5. Average Hourly load forecasted day for 23rd and 24th September, 2018

Time (Hrs)	Temperature (°C)	Relative Humidity (%)	Forecasted Load (kW)
0.00 am	19.00	33.00	69.25
1:00 am	20.00	34.00	70.50
2:00 am	19.00	35.88	60.50
3:00 am	18.00	37.00	82.25
4:00 am	18.00	37.75	77.75
5:00 am	19.00	37.75	84.00
6:00 am	19.00	36.50	84.75
7:00 am	20.50	38.25	84.75
8:00 am	23.00	33.25	95.00
9:00 am	26.00	38.25	95.00
10:00 am	27.00	24.00	112.50
11:00 am	27.00	24.50	116.00
12:00 pm	27.00	19.00	121.00
13:00 pm	27.00	18.75	124.50
14:00 pm	26.40	11.25	119.00
15:00 pm	25.40	19.00	115.00
16:00 pm	24.50	19.75	112.50
17:00 pm	24.00	23.50	105.00
18:00 pm	24.00	24.50	95.50
19:00 pm	23.50	26.00	94.00
20:00 pm	22.00	27.75	90.00
21:00 pm	22.00	29.25	89.00
22:00 pm	21.00	30.00	89.00
23:00 pm	20.50	30.50	85.00

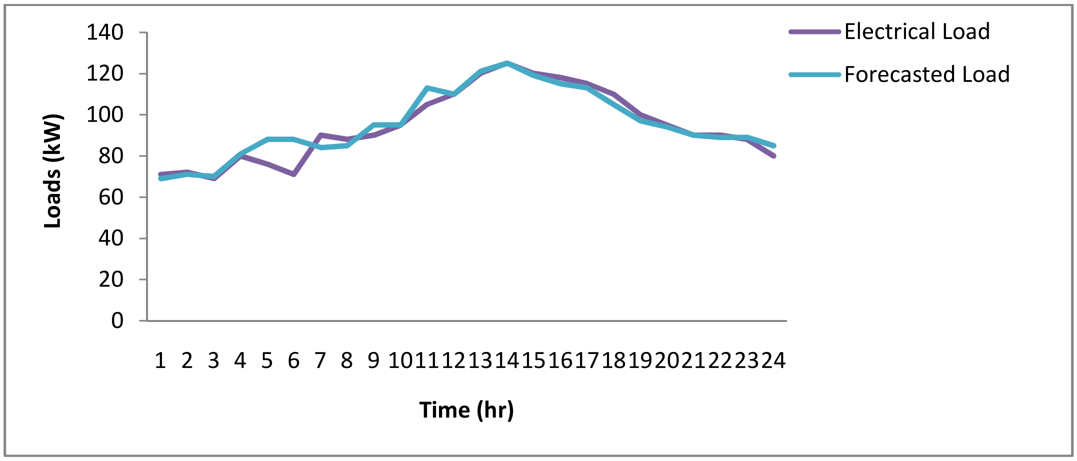

Fig. 8. Comparison between average measured and forecasted loads

Fig. 10 compares the average measured load (ML) and the next day load (NDL) for 25th September 2017. It is observed that from 12.00 pm – 4.00 pm the measured and the forecasted loads for 25th September, 2018 differ by 0.5 kW, 2.0 kW, 3.0 kW, 0.5 kW, 1.0 kW and 2.0 kW due change in temperature respectively.

Table 6. Comparison of FLCM

Models	Performance (%)
Danladi A. & Vasira G. P.	98.64
Priti G. & Monika G.	88.26
Danladi A. et al	93.81
Swaroop R. et al	93.20
Hasan H. C. & Mehnet C.	94.43

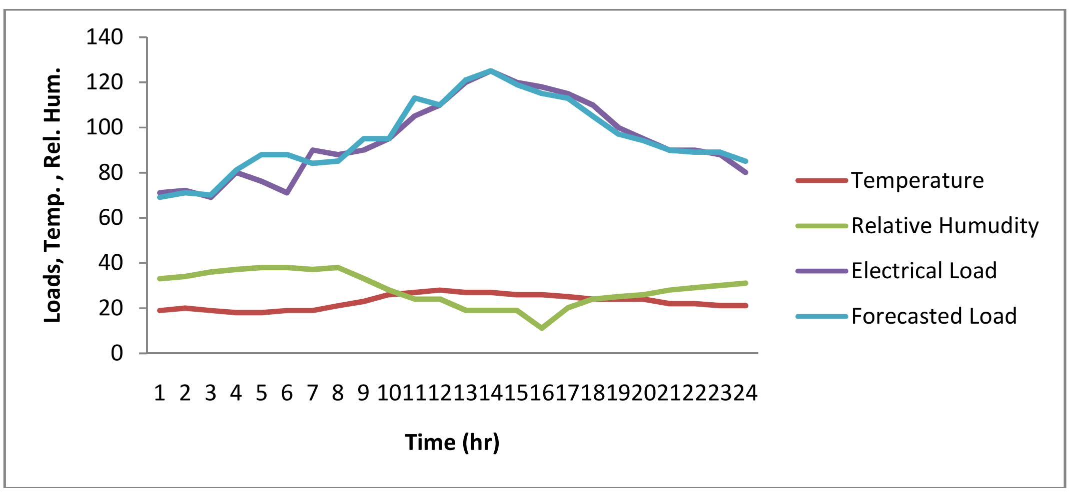

Fig. 9. Forecasted, measured loads and weather parameters

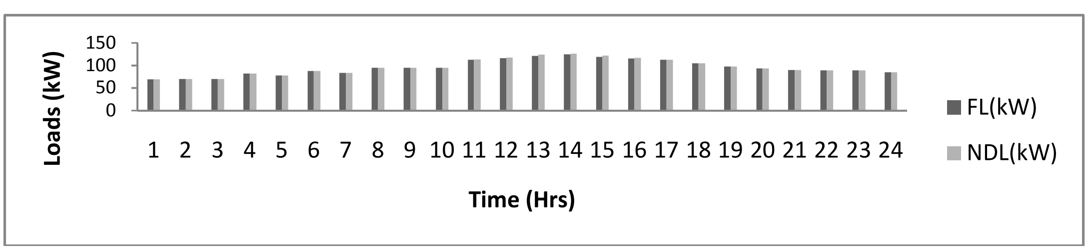

Fig. 10. Comparison between average forecasted and measured loads for 4th January, 2016

4. CONCLUSION

In this work, a fuzzy methodology for short term load forecasting is discussed. Short term load forecasting gives an idea to the power companies on what to generate, transmit and distribute. Fuzzy logic model is developed to forecast short term electrical load for Adamawa State University, Mubi. Correlation test was carried out between the electrical load and weather parameters (temperature and relative humidity) and it is found electrical load correlates with temperature and humidity by 0.712 and 0.038 respectively the result of the research revealed that temperature has impact on the electrical load more than the relative humidity. The forecasting is achieved with an efficiency margin of 98.64%, it is observed that forecasting without previous load at the input of fuzzy logic control model gives better prediction result, and recommended that, three scenarios such as when the University is on session, break and weekends should be considered and neuro-fuzzy model should be used to reduce the forecasting error obtained in this work.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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