Short Term Load Forecasting of 132/33kv Kano Transmission Substation using Fuzzy Logic Model

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ABSTRACT
This paper provides a short term load forecasting methodology using fuzzy logic for accurately predicting the load requirement of a utility company located in the North-west region of Nigeria. Fuzzy logic approach is implemented on the daily average temperature data and historical load data of 132/33KV Kano Transmission Substation obtained from Power Holding Company of Nigeria (PHCN) for a period of one year for forecasting the load. The methodology employed uses fuzzy reasoning decision rules that capture the nonlinear relationships between inputs and outputs. Fuzzy rule base used for the forecast were prepared using mamdani implication. Simulink in MATLAB environment is used in this work. The results for the forecasted load are obtained from fuzzy logic model using triangular membership function. The forecast result deviation from the actual values is presented in the form of Mean Absolute Percentage Error (MAPE). From the analysis carried out, the simulated results of the developed model were found to be very close to the one obtained from the Power Utility with Mean Absolute Percentage Error (MAPE) value of 4.65% for Monday 3rd March 2014 and a MAPE value of 3.08% for Monday 9th March 2014 which is an indication that the results obtained using the fuzzy logic approach are accurate enough for electricity load forecast.

General Terms
Load Forecasting

Keywords
Short Term Load Forecast (STLF), Fuzzy Logic, Membership Function, Mean Absolute Percentage Error (MAPE), Fuzzy Inference System (FIS).

1. INTRODUCTION
Forecasting can be defined as the mechanism to use the historical data to determine the direction of future trends. In the field of power system, the electrical load forecasting is used to predict the future power demand of consumers. Future power demand is estimated on the basis of the historical load data. The forecast model processes the exogenous relation of the provided data and consequently anticipates the future load demand.

One of the main challenges of an electric utility company is to efficiently forecast load requirements at various times. One of the challenges behind this task is that power demand in a given place does vary with growth in population and economic activities [1]. Outcomes obtained from load forecasting progressions are used in different endeavors in power sector such as planning, system expansion, maintenance and operational schedule. For example, long-term load forecasting for at least a period of ten years ahead based on monthly and yearly values can be applied for resolution of some basic power sector challenges. Some of the problems can be expansion planning, inter-tie-tariff setting and long-term modeling of capital investment. Short-term load forecasting for few days to months ahead are considered necessary in unit commitment analysis, maintenance schedule and diagnosis of economic dispatch [2]. While medium-term and long-term load forecasts are mainly based on the prediction of the future economy status, growth rate of the population, the short-term load forecasting (STLF) is based largely on weather conditions [3].

In many organizations, planning and forecasting are seamlessly integrated together. Therefore, the forecasting function of a utility is normally assigned to the planning department. Nevertheless, the distinction between the two should not be lost. Planning provides the strategies, given certain forecasts, whereas forecasting estimates the results, given the plan. Planning relates to what the utility should do. Forecasting relates to what will happen if the utility tries to implement a given strategy in a possible environment.

Load forecasting methods can be divided into two main categories which are the statistical approach and Artificial Intelligent (AI) technique. Nowadays, several techniques for deriving load forecasting model have been proposed. Traditional load forecasting techniques includes regression technique, time series (univariate) approaches, expert system based methods, hybrid Kalman Filters and Box-Jenkins model (Hsu and Ho, 1992). Generally, these techniques are based on statistical methods and they are used to extrapolate the past load behavior while taking into account the effect of other influencing factors such as the weather and temperature. (Papalexopoulos *et al; 1992)* uses multivariate linear regression model with a transformation technique for STLF.

Various combinations of these techniques have also been studied and applied to STLF problems. Researchers have been seeking the most suitable variables for each particular problem and trying to generalize the conclusions to interpret the causality of the electric load consumption. Most of these efforts were embedded coherently into the development of the techniques. For instance, temperature and relative humidity were considered in (Ranaweera and Hubele, 1996) while the effect of humidity and wind speed were considered through a linear transformation of temperature in the improved version (Hippert and Pedreira 2004). In general, the electric load is mainly driven by nature and human activities. The effects of nature are normally reflected by weather variables, e.g., temperature, while the effects of human activities are normally reflected by the calendar variables, e.g., business hours.

2. LITERATURE REVIEW
Thousands of papers and reports were published in the load forecasting field in the past 50 years. Many researchers have been adopting or developing various techniques for STLF to tackle load forecasting problems. A lot of these techniques

can be roughly categorized into two groups: statistical approaches, such as Regression Analysis [4] and Time Series Analysis [5], and Artificial Intelligence (AI) based approaches, such as Artificial Neural Network (ANN) [6], Fuzzy Logic (FL) [7], and Support Vector Machine (SVM) [8]. Various combinations of these techniques have also been studied and applied to STLF problems. Researchers have been seeking the most suitable variables for each particular problem and trying to generalize the conclusions to interpret the causality of the electric load consumption. Most of these efforts were embedded coherently into the development of the techniques. For instance, temperature and relative humidity were considered in [9], while the effect of humidity and wind speed were considered through a linear transformation of temperature in the improved version [10]. In general, the electric load is mainly driven by nature and human activities. The effects of nature are normally reflected by weather factors. Weather factors include temperature, humidity, precipitation, wind speed, cloud cover, light intensity and so on. The change of the weather causes the change of consumers' comfort feeling and in turn the usage of some appliances such as water heater and air conditioners. Humidity is also an important factor, because it affects the human being's comfort feeling greatly. The effects of human activities are normally reflected by the calendar variables, e.g., business hours. Time factors influencing the load include time of the day, holidays, weekdays/weekends and season of the year. The combined effects of both elements exist as well but are nontrivial.

Although the majority of the literature in STLF is on the modeling process, there is some research concerning other aspects to improve the forecast. Weather forecast, as an input to the extrapolating process, is also very important to the accuracy of STLF. Consequently, another branch of research work is focusing on developing, improving or incorporating the weather forecast [11].

In the late 1980s and early 1990s, people were interested in building an expert system for STLF to incorporate the expert knowledge of the human operators [12]. Such a system was expected to provide robust and accurate forecast in a timely manner. Expert system based approach was investigated and advanced by Rahman et al, and applied to the STLF for the members of Old Dominion Electric Cooperative in Virginia [13]. Couple of years later, a fuzzy expert system developed by the same group was applied to the same utility [14]. The proposed fuzzy expert system can be updated hourly, and the uncertainties in weather variables and statistical models were modeled using fuzzy set theory. While the early expert systems required a lot of input from operators, researchers started to design automatic fuzzy inference systems [15, 16]. An investigation of fuzzy logic model for STLF was presented in [7], where the fuzzy rules were obtained from the historical data using a learning algorithm. The model was used to forecast daily peak load and daily energy. The inputs were "selected based on engineering judgments and statistical analysis". The inputs to the daily energy (or peak load) forecasts were the energy (or peak load) of the current day and the two composite temperature indices of the next day.

3. RESEARCH METHODOLOGY

3.1 Sources of Data Used

Raw historical data regarding the hourly load demand for 132/33kV Kumbotso substation in Kano state, Nigeria for a period of one year (1st January – 31st December 2013) was obtained from the daily log sheet of power Holding Company of Nigeria (PHCN) for the purpose of building/training the model used in this work. Another set of data for a week (3rd March – 9th March 2014) was also obtained from the same power station and used for testing the accuracy of the Short-term Load Forecast. The daily average temperature data for a period of one year (2013) was also extracted from the internet for Mallam Aminu Kano International Airport in Kano State at wunderground.com [17].

3.2 Developing of the Fuzzy System

The fuzzy based model was designed in the MATLAB® V7.7.0. (R2008b) environment. The fuzzy logic toolbox available in MATLAB was used to develop the fuzzy model. The following steps were employed in the development;

Step 1: The historical data are examined and the maximum and the minimum range of different parameters are obtained. These ranges are used in the process of the fuzzification of different parameters.

There are two input variables that were used to forecast electricity load which are:

(i) Time of the day
(ii) Temperature

The output variable is the forecasted load.

Step 2: Normalization of the input and output variables is done by analyzing the input and the output behavior. The input space is mapped to the membership value (0, 1)

Step 3: The shape of the fuzzy membership for each variable is selected and the membership function is varied when forecasting accuracy is not good enough. The shape of membership function selected is based on trial and error. The most suitable one was selected for this work. The triangular shaped mapping for the Fuzzy Inference System (FIS) is used in this study.

Step 4: For each input and output variable (time of the day, daily average temperature and forecasted load), the number of fuzzy membership functions is tentatively defined.

The time of the day is divided into eight triangular membership functions which are as follows; Midnight (MNight), Dawn, Morning, Fore Noon (F. Noon), Afternoon (A. Noon), Evening, Dusk and Night. The daily average temperature is also fuzzified into five triangular membership function as follows; Very Cold (VCold), Cold, Normal, Hot and Very Hot (VHot).

The output which is the forecasted load is also fuzzified into five membership function as follows; Very Low (VLow), Low, Normal, High Very High (VHigh). Table 1 and 2 below shows the range of input and output data as used for the fuzzification process.

Step 5: The fuzzy rule from each pair of input-output data, also called training data is then constructed. For example: IF 'time of the day" is Morning and average temperature is Hot, THEN 'forecasted load' is HIGH.

Tuning the fuzzy inference system was done by changing the rule antecedents and conclusions, changing the centers of the inputs and/or output membership functions based on the error between the target output and the calculated value. No predetermined method was used for the tuning, but trial and error approach seeking to modify only the components pulling the output in the direction of the error.

These steps, supplemented by the resolution of conflicts and incorporation of expert opinion, constitute the construction of the fuzzy rule base. Fig. 1 below shows the fuzzy rule base;

Table 1: Input and output ranges of data set

VARIABLE TYPE	VARIABLE NAME	RANGE
Input Variable	Time of the day	0 to 24
	Temperature	10 to 38
Output variable	Forecasted Load	40 to 100

Table 2: Ranges of the input and output data as used for fuzzification.

Time (Hrs)	**Midnight**	**Dawn**	**Morning**	**F. Noon**	**A. Noon**	**Evening**	**Dusk**	**Night**
	[0 1 4]	[1 5 8]	[5 8 11]	[8 11 14]	[11 14 17]	[14 17 21]	[17 21 24]	[20 24 27]
Temp. (^oC)	**VCold**	**Cold**	**Normal**	**VHot**	**Hot**			
	[-5 10 20]	[12 20 26]	[20 26 32]	[32 38 42]	[26 32 38]			
Output (MW)	**VLow**	**Low**	**Normal**	**High**	**VHigh**	**EHigh**		
	[20 40 50]	[40 53 63]	[53 63 73]	[63 73 83]	[73 83 93]	[83 100 120]		

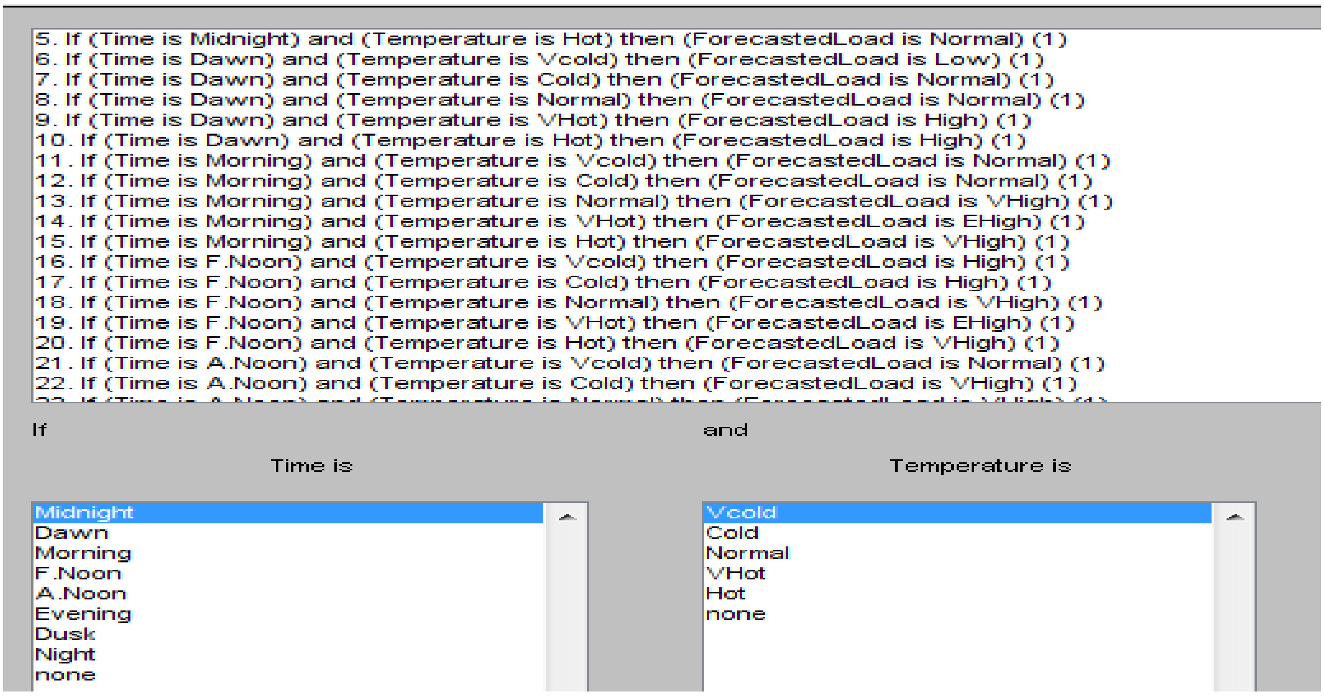

Fig 1: Fuzzy Rule Base

After the rule base has been designed, the procedure prescribed in the next stage is used to generate the point forecast for a given set of input value. Fig. 2 shows the rule viewer of the membership function rule base.

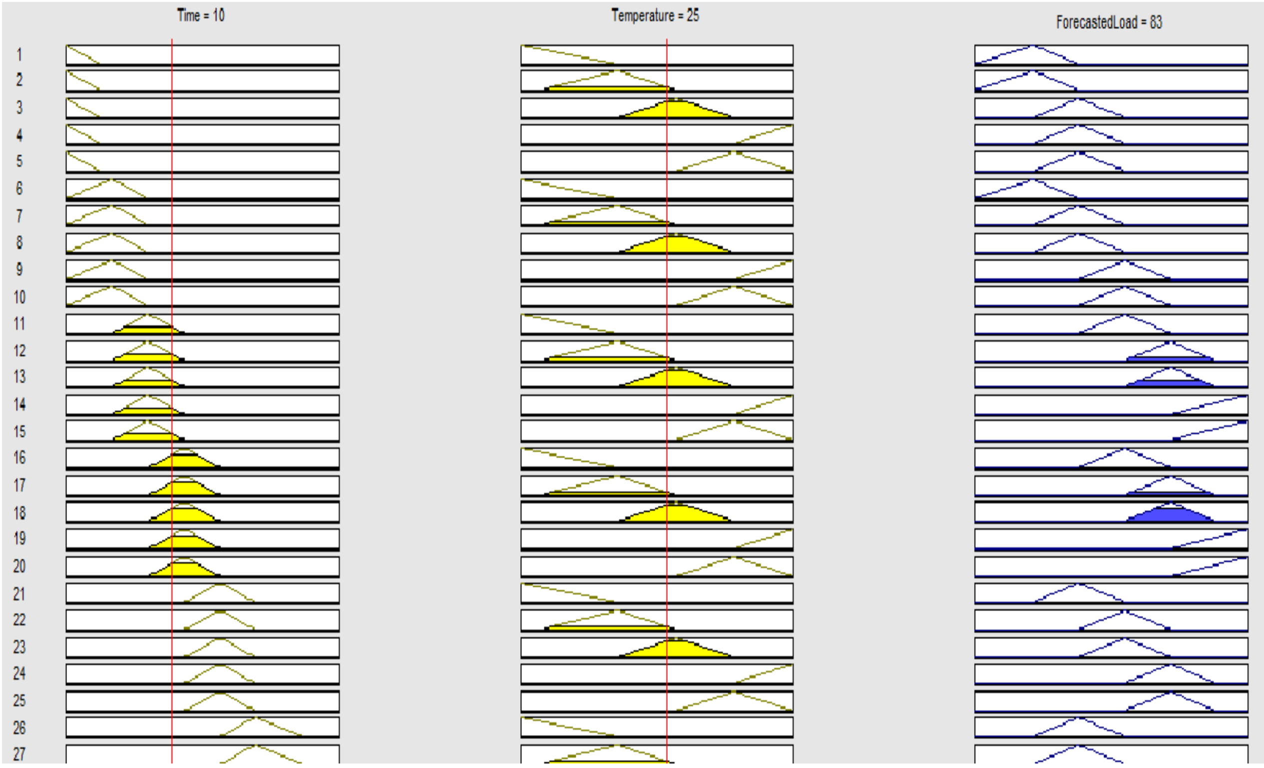

Fig 2: Fuzzy Rule Viewer

3.3 Compute the Point Forecast Value

After forming the rule base, it is then to use for forecasting with the inputs. Mamdani and Sugeno Fuzzy Inference System (FIS) can be used. The most fundamental difference between Mamdani type FIS and Sugeno type FIS is the way the crisp output is generated from the fuzzy inputs. Mamdani FIS allows us to describe the expertise in more intuitive, more human-like manner. For these reasons, the Mamdani FIS was employed in this work.

A method called defuzzification is performed to determine the point estimate of the forecast from the fuzzy forecasts. The centroid of area method is the most prevalent and physically appealing of all the defuzzication methods (Sugeno, 1985; Lee, 1990). It is often called center of area or center of gravity. Hence, the centroid of area is used as the method of defuzzication here.

3.4 Testing the Performance of the Rule Base

After creating the fuzzy rule base and the centroid method of defuzzification selected, the forecast accuracy is tested using a separate set of historical data set (test set) from that used to create the rule base. If the result obtained is unsatisfactory, the shape of the fuzzy membership functions and/or the number of fuzzy membership functions can be changed and a new fuzzy rule base is obtained. The iterative process of creating the rule base, selecting a defuzzification algorithm, and testing the system performance is repeated several times with a different number of fuzzy membership functions and/or different shapes of fuzzy memberships till the result obtained is satisfactory enough. The fuzzy rule base that will provide the least error measure for the test set is selected and used for real time forecasting.

The forecast result deviation from the actual values is represented in the form of Mean Absolute Percentage Error (MAPE) and it is defined as:

$$\frac{1}{N}\sum_{i=1}^{N}\frac{|P_A^i - P_F^i|}{P_A^i}\ x\ 100 \qquad (1)$$

Where P_A, P_F are the actual and forecast values of the loads respectively. N is the number of the hours of the day i.e. N = 1,2,….24,

3. RESULTS AND DISCUSSIONS

The forecast results are presented in terms of the Average Percentage Error (APE) and the Mean Absolute Percentage Error (MAPE).

The load curve is plotted which is the comparison between the actual load and the fuzzy forecasted load. Table 3 and 4 shows the comparison between the Actual Load Absolute Percentage Error (APE) and Mean Absolute Percentage Error (MAPE) for 3rd March 2014 and 9th March 2014 respectively. Fig. 3 and Fig. 4 show the load curve plots for 3rd March 2014 and 9th March 2014 respectively. The need for these tables and figures were necessary in order to check the accuracy of the model. From the tables and curve it is observed that fuzzy forecasted load curve is very close to the actual load.

Table 3: Hourly Load Forecast for Monday 3rd March 2014

		Temperature at 31^{0}C		
TIME (Hrs)	ACTUAL (MW)	FORECASTED (MW)	APE (%)	MAPE (%)
1:00	61	63.0	3.278689	0.136612
2:00	63	66.0	4.761905	0.198413
3:00	64	68.9	7.65625	0.31901
4:00	65	70.9	9.076923	0.378205
5:00	65	70.9	9.076923	0.378205
6:00	73	77.9	6.712329	0.27968
7:00	80	82.3	2.875	0.119792
8:00	86	91.8	6.744186	0.281008
9:00	88	91.3	3.75	0.15625
10:00	87	91.3	4.942529	0.205939
11:00	87	91.8	5.517241	0.229885
12:00	91	96.9	6.483516	0.270147
13:00	81	84.1	3.82716	0.159465
14:00	83	80.9	2.53012	0.105422
15:00	82	80.8	1.463415	0.060976
16:00	81	80.8	0.246914	0.010288
17:00	82	83.0	1.219512	0.050813
18:00	80	80.1	0.125	0.005208
19:00	84	78.0	7.142857	0.297619
20:00	81	75.0	7.407407	0.308642
21:00	73	70.2	3.835616	0.159817
22:00	72	68.5	4.861111	0.202546
23:00	66	66.5	0.757576	0.031566
24:00	62	66.5	7.258065	0.302419
			MAPE VALUE = 4.65%	

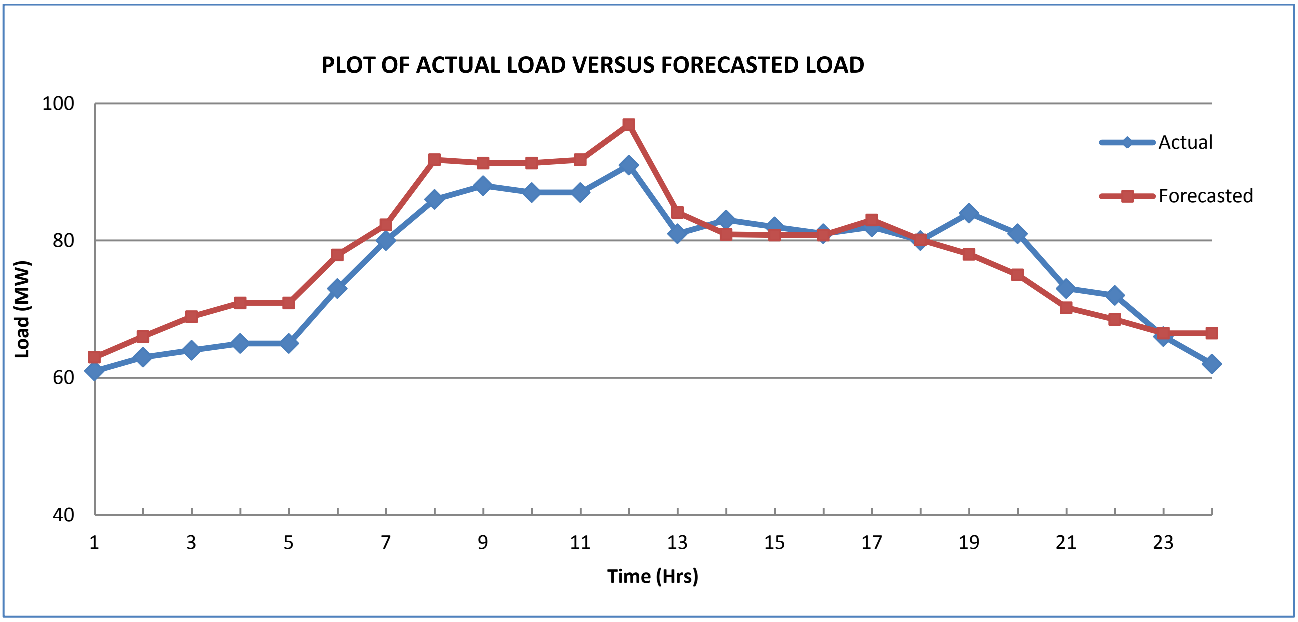

Fig-3: Comparison between Actual Load and Forecasted Load for 3rd March, 2014.

Table 4: Hourly Load Forecast for Monday 9th March 2014

TIME (Hrs)	ACTUAL (MW)	Temperature at 24^0C FORECAST (MW)	APE (%)	MAPE (%)
1:00	59	58.3	1.186441	0.049435
2:00	60	58.3	2.833333	0.118056
3:00	61	57.8	5.245902	0.218579
4:00	63	63.0	0	0
5:00	63	63.0	0	0
6:00	68	70.7	3.970588	0.165441
7:00	79	75.3	4.683544	0.195148
8:00	78	83.0	6.410256	0.267094
9:00	80	83.0	3.75	0.15625
10:00	80	83.0	3.75	0.15625
11:00	83	83.0	0	0
12:00	79	79.4	0.506329	0.021097
13:00	76	76.6	0.789474	0.032895
14:00	77	73.0	5.194805	0.21645
15:00	74	73.0	1.351351	0.056306
16:00	74	75.1	1.486486	0.061937
17:00	76	75.3	0.921053	0.038377
18:00	72	75.2	4.444444	0.185185
19:00	71	74.1	4.366197	0.181925
20:00	71	73.0	2.816901	0.117371
21:00	69	70.0	1.449275	0.060386
22:00	66	69.4	5.151515	0.214646
23:00	66	69.4	5.151515	0.214646
24:00	64	69.4	8.4375	0.351563
				MAPE VALUE: 3.08%

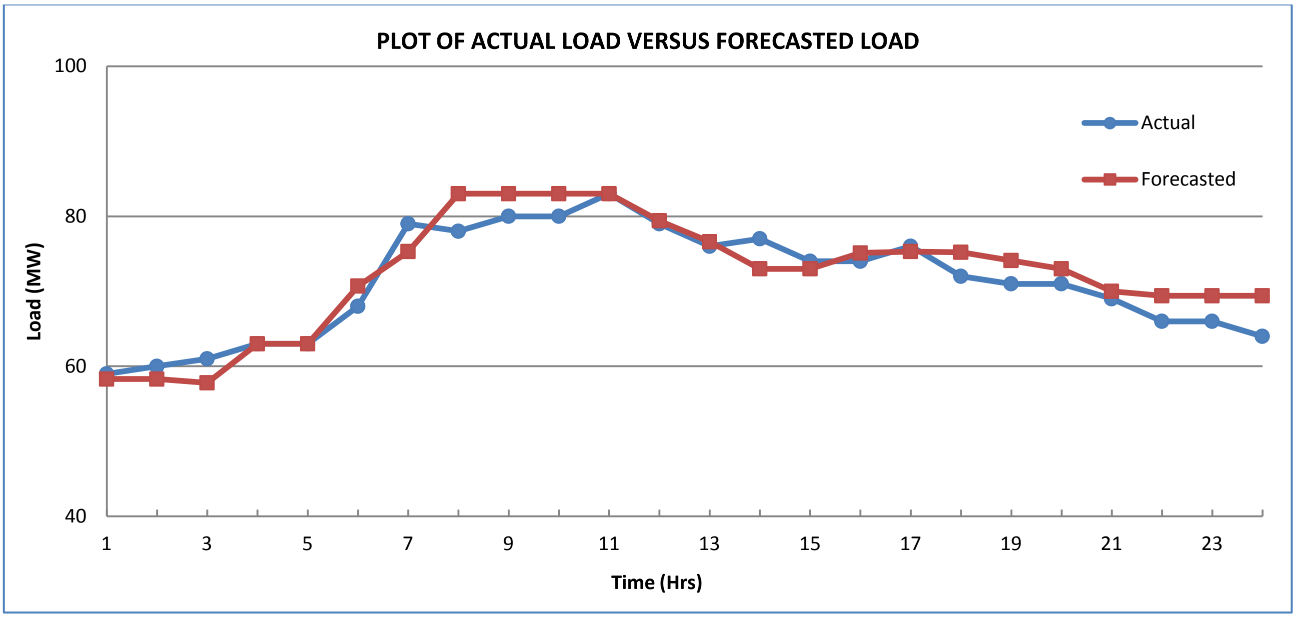

Fig-4: Comparison between Actual and Forecasted Load for 9th March, 2014

4. CONCLUSION

The Nigerian power sector has been confronted with problems like proper lack of planning, delay in maintenance of power facilities, poor technical knowledge of maintenance crew, obsolete equipment, insufficient energy supply mix and inadequate funding mechanism. The performance of the sector has been unimpressive over the years. This work seeks to resolve the issue of proper planning by proposing a method for forecasting the load demand of electricity consumers for a short period of time. In this work, fuzzy logic methodology for short term load forecasting is presented. It is concluded that using time of the day and daily average temperature as

the inputs and by formulating rule base of fuzzy logic using available data, load forecasting is done with MAPE value of 4.65% for Monday 3rd March 2014 and a MAPE value of 3.08% for Monday 9th March 2014. It is also concluded that fuzzy logic approach is very easy for the forecaster to understand as it works on simple “IF-THEN” statements. It also helps electric utility companies in making unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance for the Power Utility Company.
The training and testing of the model were conducted offline, and the hourly load data used was collected from one grid. The model needs to be tested on data set from other grids, so that the accuracy of the model can be verified for other load patterns.

The results were obtained from simulations and experimentations. No mathematical justifications could be provided for the same. Further studies on this work can incorporate additional fuzzy inputs such as humidity, season of the year and other parameters like wind speed, sky cover and rainfall etc. into the model so as to obtain a more representative forecast of future load.

6. REFERENCES

[1] Hippert, H. S. and Pedreira C. E., (2004) "Estimating temperature profiles for short-term load forecasting: neural networks compared to linear models," *IEE Proceedings - Generation, Transmission and Distribution*, vol. 151, pp. 543-547.

[2] M. A. Abu-El-Magd and N. K. Sinha, (1982) "Short-Term Load Demand Modeling and Forecasting: A Review," *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 12, pp. 370-382.

[3] Moghram, I. and Rahman, S., (1989) "Analysis and evaluation of five short-term load forecasting techniques," *IEEE Transactions on Power Systems*, vol. 4, pp. 1484-1491.

[4] D. Papalexopoulos and T. C. Hesterberg, (1990) "A regression-based approach to short-term system load forecasting," *IEEE Transactions on Power Systems*, Vol. 5, pp. 1535-1547.

[5] M. T. Hagan and S. M. Behr, (1987) "The Time Series Approach to Short Term Load Forecasting," *IEEE Transactions on Power Systems*, Vol. 2, pp. 785-791.

[6] H. S. Hippert, C. E. Pedreira, and R. C. Souza, (2001) "Neural networks for short-term load forecasting: a review and evaluation," *IEEE Transactions on Power Systems*, Vol. 16, pp. 44-55.

[7] D. K. Ranaweera, N. F. Hubele, and G. G. Karady, (1996) "Fuzzy logic for short term load forecasting," *International Journal of Electrical Power & Energy Systems*, Vol. 18, pp. 215 222.

[8] B.-J. Chen, M.-W. Chang, and C.-J. Lin, (2004) "Load forecasting using support vector Machines: a study on EUNITE competition 2001," *IEEE Transactions on Power Systems*, Vol. 19, pp. 1821-1830.

[9] A. Khotanzad, R. Afkhami-Rohani, L. Tsun-Liang, A. Abaye, M. Davis, and D. J. Maratukulam, "ANNSTLF-a neural-network-based electric load.

[10] A. Khotanzad, Z. Enwang, and H. Elragal, (2002) "A neuro-fuzzy approach to short-term load forecasting in a price-sensitive environment," *IEEE Transactions on Power Systems*, Vol. 17, pp. 1273-1282.

[11] H. S. Hippert and C. E. Pedreira, (2004) "Estimating temperature profiles for short-term load forecasting: neural networks compared to linear models," *IEE Proceedings - Generation, Transmission and Distribution*, Vol. 151, pp. 543-547.

[12] K.-L. Ho, Y.-Y. Hsu, C.-F. Chen, T.-E. Lee, C.-C. Liang, T.-S. Lai, and K.-K. Chen, (1990) "Short term load forecasting of Taiwan power system using a knowledge-based expert system," *IEEE Transactions on Power Systems*, Vol. 5, pp. 1214-1221.

[13] S. Rahman and R. Bhatnagar, (1988) "An expert system based algorithm for short term load forecast," *IEEE Transactions on Power Systems*, Vol. 3, pp. 392-399.

[14] Y. Y. Hsu and K. L. Ho, (1992) "Fuzzy expert systems: an application to short-term load forecasting," *IEE Proceedings - Generation, Transmission and Distribution*, Vol. 139, pp. 471-477.

[15] H. Mori and H. Kobayashi, (1996) "Optimal fuzzy inference for short-term load forecasting," *IEEE Transactions on Power Systems*, Vol. 11, pp. 390-396.

[16] H. C. Wu and C. Lu, (1999) "Automatic fuzzy model identification for short-term load forecast," *IEE Proceedings - Generation, Transmission and Distribution*, Vol. 146, pp. 477-482.

[17] Weather History for DNKN - September, 2017 http://www.wunderground.com/history/airport/DNKN/