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Electricity Load Forecasting in Imo State Using Soft Computing Techniques

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Abstract— This paper presents electricity load forecast of Imo state Nigeria using fuzzy logic soft computing technique. Historical load data from Enugu Electricity Distribution Company (EEDC) Owerri, combined with hourly weather data from the online weather portal "www.wunderground.com/q/zmw:0000.3.WDNIM" were used for training and testing the fuzzy inference system (FIS). The inputs to the FIS are the hour-by-hour weather (temperature and humidity) for the forecast month (august 2015) and the mean of the previous similar day load (preload) data for August 2013 and August 2014 (2 months). The output is the forecasted load for the month of August 2015. The load data are influenced by variances in day types, namely the weekdays and weekends hence each of these day types has different load curve. Rules are developed for the FIS using the input data combined with the heuristic knowledge of the factors affecting the load (load driving parameters). Successful implementation and integration of the various stages of the testing, training and validation of the fuzzy logic system produced the complete, functional FIS model with a mean absolute percentage error (MAPE) of 0.8641%. The mean accuracy of the entire forecast result was 99.13%. The analysis shows satisfactory level of accuracy with regards to the FIS-based soft computing technique developed in forecasting future load demand of Imo state.

Index Terms— Fuzzy logic, Fuzzy inference system, Load forecasting, Short term load forecasting, Soft Computing

1 Introduction

Load forecasting refers to the prediction of load behavior for the future. It is one of the basic and perhaps the most important module of power system issues [1]. Power demands need to be estimated ahead of time for optimum generation and distribution scheduling. The importance of accurate load forecasts will increase in the future because of the dramatic changes occurring in the structure of the utility industry due to deregulation and competition [2]. Load forecasting techniques may be presented in three major groups which are the traditional forecasting technique, modified traditional forecasting technique and the soft computing technique [3]. In this paper, the soft computing technique using MATLAB fuzzy logic toolbox was adopted because it describes the system parameters in terms of a combination of numeric and linguistic (symbolic) variables which gives account of its ability to address and solve problems related to non-linearity, uncertainty and randomness of data. In fact the human mind is the role model of the soft computing technique [4]. The principal tools of soft computing are fuzzy logic, neural network, expert systems, evolutionary computation, probabilistic reasoning etc. It is mainly used as a forecasting technique where we have sufficient information about the load and the load driving parameters [4]. Depending on the period of forecast done (lead time); load forecasting can be classified into three different types [5].

- Short term load forecasting, which has a lead time of one week or less.
- Medium-term load forecasting, which has a lead time of one month to one year
- Long-term load forecasting, which has a lead time of more than one year.

In this paper, medium-term load forecasting is used to determine electricity load demand of Imo state for the month of August 2015. Medium and long-term load forecasts play important role in the management and planning of power system, while short-term load forecast is critical for a reliable and efficient power systems operation [6].

2 Load Driving Parameters

Load driving parameters are factors that affect the behavior of electrical load. They tend to determine the shape of the load curve. Typical examples of these factors include:

- Time factors such as; hours of the day (day or night), day of the week (weekday or weekend) and seasons.
- Weather conditions (temperature and humidity)
- Class of customers (residential, industrial, commercial)
- Special events (TV programmes, public holidays etc)
- Demographic factors (Population, Immigration etc)
- Economic indicators (Electricity price, per capital income, Gross National Products etc.)
- Trend in using new technologies

It is well understood that if the electricity price is predicted to be high, it results in reduced forecasted load. Obviously, it also depends on weather conditions; the class of customers, special events, demographic factors etc. As another example, special

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TV programmes have dominant effects on electricity usage of residential sector. On the other hand, if the economic indicators such as GNP and GDP show a promising future and new electricity based appliances or technologies is appearing in the market, the electricity consumption may increase nearly in all class of customer [1].

2.1 Fuzzy Logic Forecasting Tool

Fuzzy logic is a soft computing tool that deals with reasoning algorithms used to emulate human thinking and decision making in machine. It utilizes the fuzzy inference process which comprises of five parts [7]:

- Fuzzification of input and output variables
- Application of fuzzy operator (AND or OR) in the antecedent
- Implication from antecedent to consequent
- Aggregation of the consequent across the rule
- Defuzzification

This can further be divided into three distinct parts which are; fuzzification, rule base development and defuzzification as shown in figure 1.

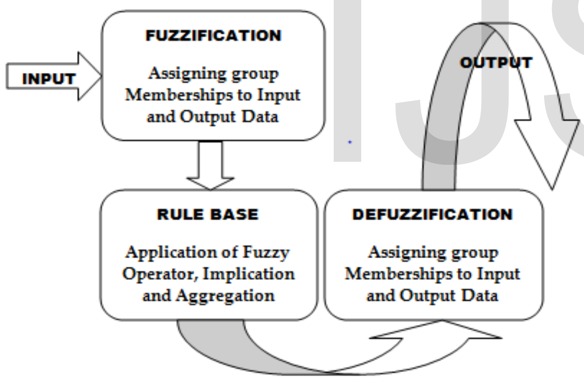

Fig. 1. Fuzzy Logic Forecasting model.

Fuzzification means assigning group memberships and membership values to input and output data. The second step is to use Zadeh's fuzzy logic set and fuzzy operators combined with the knowledge of the system to make a set of inferences and associations between and among members in various groups (Implication and Aggregation). The last step is to "defuzzify", which involves the conversion of the crisp output of the fuzzy inference block to the required output values [8].

3. MATERIALS AND METHODS

3.1 Description of Study Area

Imo state is located in South Eastern Nigeria at a latitude of 5.5215° N and longitude of 6.9209°E [9]. It has a total of six 33kV feeders feeding all the towns and villages in the state. The feeders are named below:

- Mbaise 33kV Feeder 1
- Owerri Airport 33kV Feeder 2
- Owerri Mains 33kV Feeder 3
- Oguta 33KV Feeder 4
- Orlu 33kV Feeder 5
- Okigwe 33kV Feeder 6

In this paper the combined total hourly load data of the six 33KV feeders serving Imo State are to be considered.

3.2 Collection of Data

The data on the six feeder lines feeding Imo state for August 2013 and August 2014 (2 months) were obtained from the daily load summary log sheets of Enugu Electricity Distribution Company (EEDC) Owerri. The hourly weather data (Temperature and humidity) of Imo State for the forecast month (August 2015) were collected from the online weather portal (www.wunderground.com /q/zmw:0000.3.WDNIM).

3.3 Assumptions

Several assumptions and constraints were necessary in order to implement the load forecasting algorithm. These are:

- One hour intervals were considered the shortest time scale for the forecast in order to calculate performance.
- The maximum period for load forecasting was limited to a full month to reduce the required amount of input data.
- Demographic factors, trend in new technologies and electricity price had minimal impact within the month long time scale and as such were neglected for the study.

These assumptions and constraints ensured the results obtained from the load forecasting algorithm would be accurate and valid, while remaining uncomplicated and prompt in operation.

3.3 Load Forecasting Procedure

In this paper, the fuzzy logic soft computing technique is applied to forecast the load of Imo State. It utilizes the fuzzy inference process to perform load forecast. The Mamdani-type inference is used for the inference process because it is intuitive, well suited to human input and has widespread acceptance. The four inputs taken for load forecasting are time, temperature, humidity and selected previous similar day loads. The input load data (preload) is obtained from the mean of the previous similar days' load data (mean of the load data for August 2013 and August 2014). Table 1 shows the input load data for forecasting the load demand of Monday August 24, 2015.

TABLE 1
INPUT DATA FOR MONDAY AUGUST 24, 2015

Time (Hr)	Temperature (° Celsius)	Humidity (%)	Preload (MW)
1	22.7	99	95.06
2	22.7	98	91.26
3	22	97	88.21
4	22.9	98	87.74
5	22.8	99	86.2
6	21.4	99	86.2
7	21.9	96	90.03
8	23.8	89	92.96
9	25.5	84	110.22
10	27.2	79	116.41
11	28.7	73	120.81
12	29.6	73	120.32
13	30.1	74	120.83
14	29.9	76	124.03
15	29.9	81	124.49
16	25.6	85	124.92
17	21.9	89	119.24
18	22.5	89	110.77
19	22.5	90	106.94
20	22.4	92	115.1
21	22.4	94	112.72
22	22	94	108.24
23	22.1	95	106.05
24	21.8	98	108.78

The input data are converted to degrees of memberships and membership values in a process called fuzzification. The triangular membership function is used for the four inputs as well as the output for simplicity. Time is divided into four triangular membership functions which are; dawn, morning, noon and night. Temperature is divided into four triangular membership functions which are as follow; very cool, cool, medium and hot. Humidity, previous similar load and the forecasted load are also divided into four membership functions which are as follows; very low, low, medium, and high. Fuzzification is performed in the MATLAB FIS Editor.

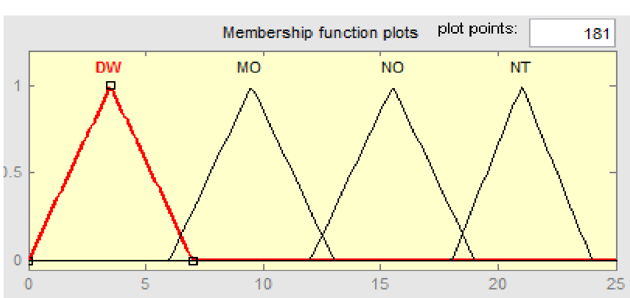

Fig. 2. Triangular Membership Function for Time

3.4 Fuzzy Rule Development

The rule base is the heart of the fuzzy system. The accuracy of the forecast is determined by the knowledge level of expertise performing the fuzzy rule. The heuristic knowledge of the forecasted load is stored in terms of "IF-THEN" rules. It sends information to the fuzzy inference system (FIS), which evaluates the inputs to get the ouput as forecasted load. This operation is performed in MATLAB fuzzy rule editor. Table 2 shows the fuzzy rule combination used for the FIS.

TABLE 2
RULE COMBINATIONS FOR THE FIS-BASED MODEL

S/N	Time	Temp.	Humidity	Preload	Forecasted Load
1	Dawn	Cool	High	Low	Low
2	Night	Cool	High	V. Low	Low
3	Dawn	V. cool	High	V. Low	V. low
4	Dawn	Cool	High	V. Low	V. low
5	Dawn	V. cool	High	Low	V. low
6	Night	Medium	High	Low	Low
7	Night	Cool	High	Low	Low
8	Morning	Medium	Medium	Medium	Medium
9	Noon	High	Low	High	High
10	Noon	High	Low	Medium	High
11	Noon	Medium	Low	High	High
12	Morning	High	Medium	Medium	Medium
13	Morning	V. cool	High	Medium	Medium
14	Morning	V. cool	High	Medium	Medium
15	Morning	Medium	Medium	Medium	Low
16	Noon	Medium	Low	High	High
17	Night	Medium	High	Low	Low
18	Noon	Not cool	Low	High	High
19	Noon	Medium	High	Not High	Low
20	Night	Cool	Medium	Low	Medium

There is no limit to the number of rules formed. However the more the number of rules, the more robust the FIS Model. Typical rule combinations for the medium term load forecasting are shown below:

- If Time is DAWN and Temperature is COOL or Humidity is High and Preload Low, then Forecasted load is LOW.
- If Time is NOON or Temp is HIGH and Humidity is LOW and Preload is HIGH, then Forecasted Load is HIGH.

After the firing strength has been assigned to each rule, the consequent is reshaped according to the firing strength. This is referred to as implication from antecedent to consequent. The fuzzy sets representing the output of each rule are then combined in a process called aggregation. Figure 3 shows the process of Implication and aggregation of the fuzzy rule.

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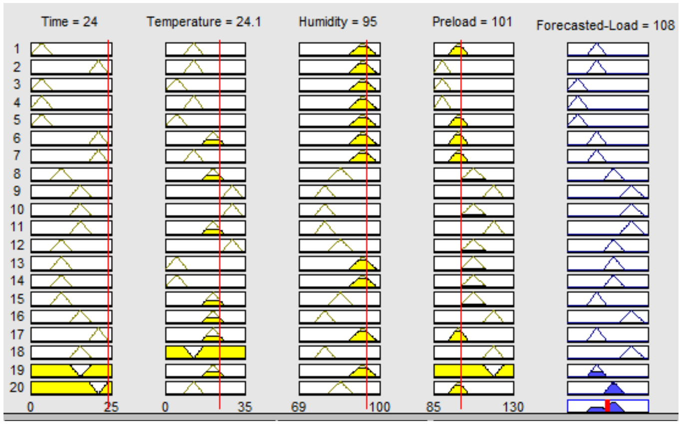

Fig. 3. Rule Viewer of the Fuzzy Inference System

3.5 Defuzzification

The results generated by the fuzzy inference system are fuzzy sets with no distinct boundaries; hence it is necessary to convert the fuzzy quantities into crisp output for further processing. This can be achieved by the process of defuzzification. The centroid method, max-membership principle and the centre of largest area are some examples of defuzzification methods. For the purpose of this work the centroid defuzzification method is used as it is simpler and gives more accurate output. Figure 4 shows the typical FIS Surface Viewer for centroid defuzzification. The forecast results can also be obtained directly from the MATLAB command window by using the following command line.

- Calling the FIS Editor with the name 'LOAD FORECAST' using the command fisedit ('LOAD FORECAST')
- Read the model using the command line
  B = readfis ('model name')
- Evaluate the output using the command linebb = evalfis (['time, temp., humidity, preload'])

From the command line above, the forecasted load output will be obtained for the month of august 2015 using the input data for August 2013 and August 2014.

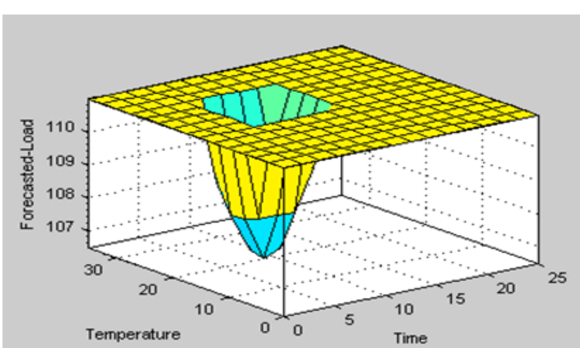

Fig. 4. FIS surface viewer showing the relationship between the input data.

3.6 Simulation work.

MATLAB R2009b is used for the simulation purpose. The input data as well as actual load are loaded to the fuzzy logic controller. Figure 5 shows the simulation of fuzzy logic methodology for medium term load forecasting.

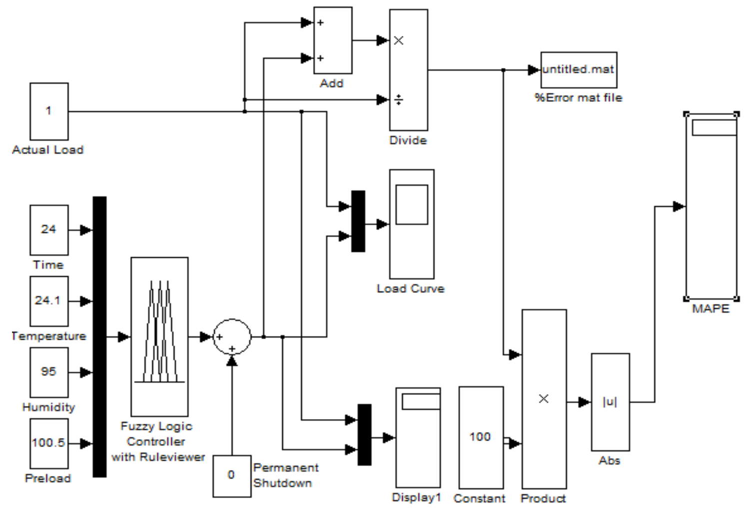

Fig. 5. Fuzzy Logic simulation of Short term load forecasting

Based on the rules prepared, the fuzzy logic controller gives forecasted output corresponding to the input data. Then the permanent shut down block is added. If a substation is in operation for previous similar day and there is a permanent shutdown for the forecasted day, then the megawatts supplied by the substation need to be subtracted from the forecasted load and vice versa. Thus, final forecast of the day is obtained. Also, the error is calculated along with the forecasted load.

4. RESULTS AND DISCUSSION

4.1 Load forecasting result

The performance of the fuzzy-based forecaster is tested by loading the hourly temperature, humidity, time and previous similar day load data to the generated FIS controller. This is done using the entire weather data for the forecast month and the mean of the previous similar load data for August 2013 and August 2014. The method has being simulated using the fuzzy logic toolbox in MATLAB. Forecast results are obtained for the month of August 2015 with a mean accuracy of 99.13%.
Table 3 and table 4 shows the forecast result for a typical weekday (August 24, 2015) and a typical weekend (August 30, 2015) respectively.

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4.2 Error analysis

The deviation of the forecast result from the actual values is represented in the form of Mean Absolute Percentage error (MAPE).

$$MAPE = 1/N \sum_{J=1}^{N} \left(\left| \frac{P_u^j - P_v^j}{Actual} \right| * 100 \right)$$

Where P_u^j and P_v^j stands for actual load and forecast load values respectively.

j stands for the jth time of the day.

N is the number of hours of the day i.e. N=1, 2…24.

Using the concept above, the MAPE value of 1.518% and 0.6862% were obtained for a typical Monday (weekday) and Saturday (weekend) of August 2015. The MAPE value of 0.8641% was obtained for the overall test data. The results obtained from testing the trained fuzzy logic system on the input data for 24 hours of Monday August 24, 2015 and Sunday August 30, 2015 are presented in Tables 3 and 4 respectively.

TABLE 3
RESULTS AND ERROR ANALYSIS FOR MONDAY AUGUST 24, 2015

Time (Hr)	Temp (° C)	Humidity (%)	Preload (MW)	Forecast load(MW)	Actual load (MW)	Error (MAPE)
1	22.7	99	95.06	110.99	109	1.832
2	22.7	98	91.26	108.78	105	3.602
3	22	97	88.21	107.58	108	0.3855
4	22.9	98	87.74	108.78	110	1.107
5	22.8	99	86.2	110.99	109	1.832
6	21.4	99	86.2	110.99	108	2.775
7	21.9	96	90.03	106.92	109	1.911
8	23.8	89	92.96	108.78	110	1.107
9	25.5	84	110.22	109.61	111	3.873
10	27.2	79	116.41	110.99	110	0.9062
11	28.7	73	120.81	110.99	108	2.775
12	29.6	73	120.32	110.99	109	1.832
13	30.1	74	120.83	110.99	112	0.8956
14	29.9	76	124.03	113.58	111	2.322
15	29.9	81	124.49	112.56	114	1.262
16	21.9	85	124.92	110.99	110	0.906
17	25.6	89	119.24	110.38	109	1.267
18	21.9	89	110.77	108.78	108	0.7239
19	22.5	90	106.94	107.11	107	0.111
20	22.4	92	115.1	104.93	105	0.0591
21	22.4	94	112.72	101.49	99	2.523
22	22	94	108.24	104.73	105	0.2434
23	22.1	95	104.52	106.05	104	1.977
24	21.8	98	98.13	108.78	109	0.2002

Figure 6 and Figure 7 below shows the actual load versus forecasted load curve of Monday August 24, 2015 and Saturday August 29, 2015 respectively. From the analysis of the results From Figure 6 and figure 7 it is observed that the variation of the actual load from the forecasted load is quite minimal. This shows that the FIS-based model has high forecasting accuracy when trained and tested with sufficient load data.

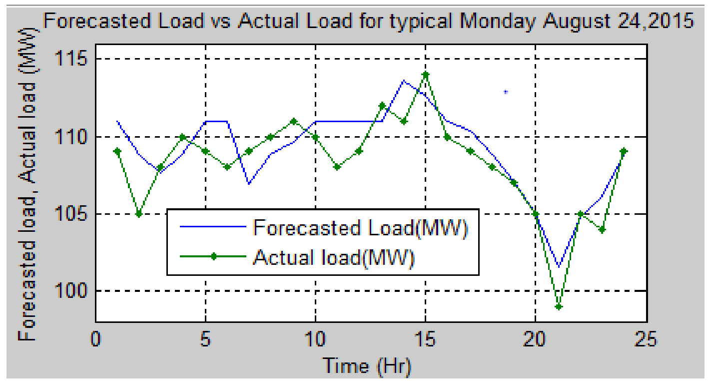

Fig. 6. Plot of actual vs. forecasted load with time for Monday August 24, 2015

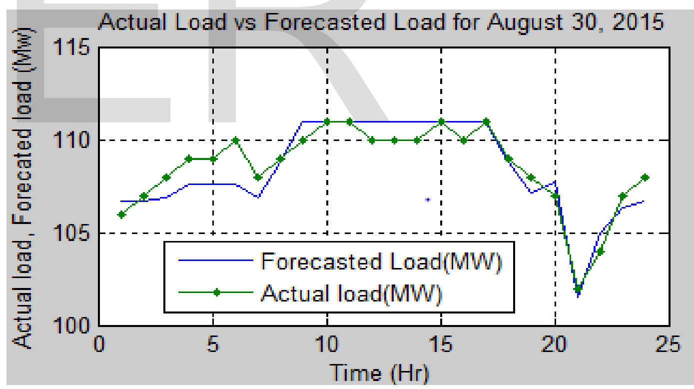

Fig.. 7. Plot of Actual vs. Forecasted Load with time for Sunday August 30, 2015

TABLE 4
RESULTS AND ERROR ANALYSIS FOR SUNDAY AUGUST 30, 2015

Time (Hr)	Temp (C)	Humidity (%)	Preload (MW)	Forecast load(MW)	Actual load (MW)	Error (MAPE)
1	22.7	95	99.06	106.7	106	0.6216
2	22.7	95	95.26	106.7	107	0.3188
3	23	96	92.21	106.9	108	1.003
4	22.9	97	91.74	107.6	109	1.299
5	22.8	97	90.2	107.6	109	1.299
6	22.4	97	90.2	107.6	110	2.197
7	22.9	96	94.03	106.9	108	1.003
8	24.8	89	96.96	108.8	109	0.2003
9	26.5	81	114.22	111	110	0.9062
10	28.2	76	120.41	111	111	0.0028
11	29.7	73	124.81	111	109	1.832
12	30.6	70	124.32	111	110	0.9062
13	31.1	70	124.83	114.7	111	0.9062
14	30.9	72	128.03	116	111	0.9062
15	30.9	77	128.49	114.4	111	0.0028
16	26.6	82	128.92	111	111	0.0028
17	22.9	87	123.24	110.7	111	0.0028
18	23.5	89	114.77	109.9	109	0.2002
19	23.3	90	110.94	107.9	108	0.816
20	23.4	92	119.9	106.5	107	0.6406
21	233	94	116.72	101.5	102	0.4966
22	23	94	112.24	105.8	104	0.9962
23	23.1	95	108.52	107.9	107	0.6163
24	22.8	95	112.13	107.5	108	0.2841

4.3 Discussion of result

Imo state is a popular hub for business and other economic activities which constitute the major load driving parameter. Figure 6 and figure 7 shows that Imo state electricity load tend to higher on weekdays (Mondays to Fridays) reaching its peak on Saturday (weekend). This is due to high commercial activities in the state during the weekdays. However Sundays experience the least load consumption due to low commercial activities. It is further observed that the load tend to be high from 5am to 8am and drops around 9am before rising from 12pm to its peak value around 3pm. It tends to drop from 4pm to 5pm and rises again from 6pm to around 10pm and drops gradually till 4am. Figure 8 below is a plot of forecasted load, humidity and temperature against time. It shows that when the temperature or humidity is extreme, either on the high side or on the low side, the load would be high. Similarly the load tends to be high when previous similar days' load is high and vice versa. This is because at such extreme weather conditions, the level of discomfort among residential electricity consumers increases thus they tend to use more heavy voltage consuming home appliances such as air-conditioner, water heater etc.

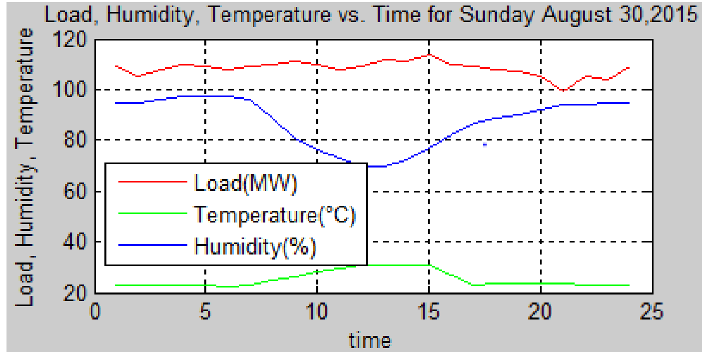

Fig. 8: Plot of forecasted load, temperature, humidity and Time for Sunday, August 30, 2015.

5. CONCLUSION

In this paper, electricity load forecasting using Fuzzy Logic soft computing technique was presented. The effect of humidity, temperature and selected similar day load were taken into consideration to perform load forecast. To verify the forecasting ability of the proposed methodology, forecast was done for the month of August 2015 using data set of 2 months (August 2013 and August 2014). The results obtained from the simulation show that the proposed forecasting methodology gives a highly accurate forecast with an error margin of 1.518% (MAPE) and will be appropriate for forecasting Imo state electrical load demand for future planning, development and management. In addition, the fuzzy approach does not only give better forecasting performance but it uses IF-THEN statement which is a simple procedure to handle electricity forecast. As with any new approach for forecasting load demand, there are some areas for possible future improvement. The use of more load driving parameters such as electricity price, trend in new technology and demographic factors as input to the FIS model will further improve the accuracy of forecast.

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