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Original Research Article

Short Term Electrical Energy Demand Forecasting using Artificial Neural Network Technique

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ABSTRACT

Under-estimation or over-estimation of electricity demand can affect the power infrastructures negatively, misleading the planners and wastes resources. Therefore, a precise and dependable model for forecasting electricity demand becomes highly imperative. This study developed an artificial neural network (ANN)-based short term load forecast model for projecting electrical energy demand. Hourly load data from 132/33 kV Ikeja West Transmission Station, Ayobo, Lagos State and temperature data from Nigeria Meteorological Agency, Oshodi, Lagos State, Nigeria were obtained for six months (April to September 2022). The back-propagation algorithm was used in training the ANN model. The three-layer network was trained using 80% of the load and temperature data while validation and testing of the model employed 10% each of the data. The model accuracy test was performed using five metrics which includes mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), chi square (χ2) and F- test. The results obtained revealed that the developed model performed excellently with minimal error of 2.54, 1.04, 3.11%, 1.55 and 1.26 for MSE, MAE, MAPE, χ2 and F-test respectively. Indication from the results shows that ANN model when properly trained with the appropriate data has the potential to effectively predict electrical energy demand on short term basis.

1. INTRODUCTION

Globally, one of the basic forms of energy that is greatly used by all in the running of day-to-day activities is electricity. Its importance cannot be over emphasized as it is available for diverse needs such as domestic and industrial purposes. Increase in electricity demand of a nation has been reported to have a corresponding rise in gross domestic product (GDP) of that nation with GDP as an indicator of the performance of the economy (Gordillo-Orquera *et al*., 2018; Aneeque *et al*., 2020; Matheri *et al*., 2021). Efficient management of the existing power system facilities and effectiveness of decisions regarding future power requirement are very germane in the planning supply of electricity (Comert and Yildiz, 2021). This will reduce unexpected cost which is a significant aspect of power system planning. Load demand of the customers must be known for adequate electricity to be supplied to match the demand. Development of an accurate planning model for adequate and regular supply of electricity remains a major challenging task (Oludare *et al*., 2018; IEA, 2019; Comert and Yildiz, 2021; Chien *et al*., 2022). An accurate energy forecast is a key component for power system planning, formulating strategies and recommending energy policies (IEA, 2020; Khwaja *et al*., 2020; Singhal *et al*., 2020).

Electrical energy forecasting is the projection of electrical load that will be needed by a particular geographical area considering past electrical load usage of the area (Singh and Dwivedi, 2018; Miguel *et al*., 2019). It is important to minimize error in load forecasting so as to prevent to under-estimation or over-estimation of load demand which can lead to wastage to energy resources or inadequacies. Some of the techniques available for forecasting electrical energy demand include regression analysis, time series, artificial intelligence methods such as fuzzy logic, artificial neural network (ANN) among others (Chheepa and Manglani, 2017; Kuster *et al*., 2017; Mahmoud *et al*., 2020). Each of these techniques has their uniqueness which adapt them suitably to the applications in which they are employed. Therefore, this study focuses on the application of ANN for short term load forecasting (STLF).

The process of predicting electrical load for one hour to one week is called Short term load forecasting. The STLF is a very important aspect of managing the operation of power infrastructure. The input data needed to analyse the flow and exigency of the power facility is obtained from the result of the STLF. The reduction in the risk associated in failure of substation and transmission equipment is achieved applying results from conducting STLF. The results obtained here allow for the planning of power generation. The STLF will reduce the tendency of loss in power supply and reduction in revenue. ANN has been reported to have the capability to accurately approximate any measurable function when properly trained and configured (Parth and Vaishali, 2017; Senthil, 2017; Oludare *et al*., 2018). It can resolve complicated correlation and at the same has vigour and ability to handle larger volume of datasets. It easy to use, quicker and effective depending on the amount of data in the input and output layers. Data that are lost and strident can be control even with enormous parameters though it converges slowly (Parth and Vaishali, 2017; Senthil, 2017; Oludare *et al*., 2018). Hence, in this study, ANN was employed for the projection of electrical energy demand on short-term basis.

Over the last few years, series of studies had been conducted by power system engineers and researchers on forecasting future energy demand on short-term basis using ANN. Sylvia (2023) and Athanasios *et al*. (2021) employed an ANN for STLF using load data from a sample power network from Greece and Indonesia, respectively. Jiuyun *et al*. (2021) performed short-term load forecasting using an ANN approach with periodic and nonperiodic factors in Tai'an, Shandong province, China. Yuan-Yu *et al*. (2018) considered two-stage ANN model for STLF. The developed model was tested by considering a practical load data from Taiwan Power Company. Saurabh *et al*. (2017) applied an ANN for STLF. The neural network was trained for weekdays and weekends load. Analysing of the reviewed literature point to the fact that more extensive investigations are still greatly needed in the area of STLF using ANN. This is to ensure that potential of ANN to adequately, accurately and reliably predict electrical energy demand on short-term basis is critically assessed as inaccuracy of a forecasting model can further impact negatively on the electricity supply-demand gap which is already widened. Therefore, ANN model was applied in this study to forecast electrical energy demand on short-term basis considering load data from 132/33 kV Ikeja West Transmission Station, Ayobo, Lagos State, Nigeria.

M.A. Ita et al. / Nigerian Research Journal of Engineering and Environmental Sciences
8(2) 2023 pp. 499-509

2. MATERIALS AND METHODS

2.1. Artificial Neural Network

The flow chart in Figure 1 shows the steps needed to achieve an ANN model. The process starts by identifying the input and output parameters. This is followed by a suitable selection of the ANN architecture which was employed for the training of the network. The network is checked for errors and if the errors are minimal, validation and testing of the model are done. The model is subsequently accepted if the performance is satisfactory; otherwise, the training is repeated until acceptable results are obtained.

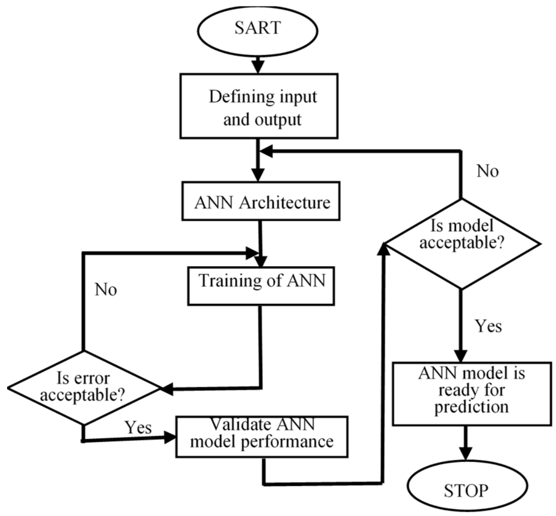

Figure 1: Flow chart of an ANN model

2.2. Network Architecture

The feed forward ANN with back propagation algorithm was the structure used for the hourly forecast of the load demand in this study. There are three layers in the architecture, namely input, hidden and output layers. The number of hidden layer is critical to the network as fewer hidden layers make the network less complicated and training time shorter. The number of neurons in the hidden layer was adjusted until the optimum training performance of ten neurons was obtained. The log sigmoid activation function was used in the hidden layer while pure linear activation function was used in the output layer. There are six neurons in the input layer and one neuron in the output layer. The arrangement of the three layered feed forward network employed for short-term load forecast is shown in Figure 2.

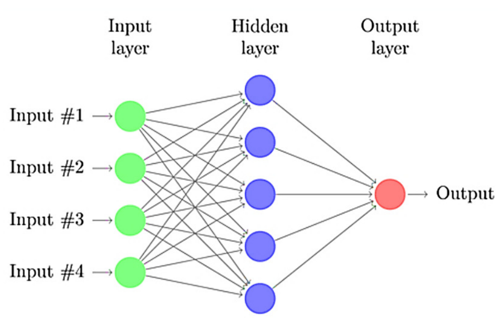

Figure 2: ANN three layers feed forward structure

2.3. ANN Training

The weights were varied to obtain the desired output. Afterwards, the forecasted output was compared with the target output using error correction learning. The error was minimised at each epoch of the training algorithm until a difference of zero was obtained. The process was repeated for all of the samples in the training data. The weights were multiplied by the input and the results acted upon by the activation function before it was presented as the predicted output. Lavenberg-Marquardt training algorithm was used for training the network with 80% of the input data, 10% for validation and 10% to predict the future load. The MATLAB R2018a software was used for modelling the ANN using six input and output data which include hours in a day, energy demand per hour, previous day same hourly energy demand, previous week maximum hourly energy demand, weekday (Sunday to Saturday), temperature in degree Celsius (℃) and target output.

2.4. Collection of Data

The temperature data of Lagos State for six months (April to September 2022) were obtained from Nigerian Meteorological Agency (NiMet) at Oshodi, Lagos State, Nigeria while the load data were collected from 132/33 kV Ikeja West Transmission Station at Ayobo, Lagos State. Information collected from 3rd to 9th April 2022 were employed for the training of the model while data from 10th to 30th of April 2022 for testing the network.

2.5. Testing of Model Adequacy

The developed ANN model accuracy was tested on five metrics. These include the mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE), chi square (χ^2) test and F-test. MAE is the mean of the absolute values of each forecast errors at all point in the test set and the lower the MAE score the better the prediction. MAE is expressed mathematically by Equation (1):

$$MAE = \frac{\sum_{i=1}^{n} |Y_i - X_i|}{n} \tag{1}$$

Where Y_i is the forecast value, X_i is the actual value and n is the total number of variables.

MAPE evaluates in percentage the correctness of the forecast and the lower the value of MAPE the higher the accuracy of the prediction. MAPE is mathematically expressed by Equation (2):

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{actual\ (i) - forecast(i)}{actual(i)} \right| \tag{2}$$

MSE is the average of the square of variation between actual and forecast values. A lower value of MSE gives an indication of closeness between actual and forecast values. It is given mathematically by Equation (3):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (X_i - Y_i)^2 \tag{3}$$

χ^2 is a hypotheses test that is used to determine if there is a relationship between two definite variables and it is expressed by Equation (4):

$$\chi^2 = \sum \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}} \tag{4}$$

F-test is an index use to test the null hypothesis that the variation of two populations is equal. It is expressed by Equation (5):

$$\text{F} = \frac{\text{Larger estimate of variance}}{\text{Smaller estimate of variance}} \tag{5}$$

3. RESULTS AND DISCUSSION

3.1. Collected Data

Some samples of the data obtained for this study are presented in Tables 1 to 6. Tables 1 to 6 show information on hour of the day, hourly load, previous day same hourly load, previous week maximum load and temperature.

Table 1: The actual hourly energy demand and temperature data for Sunday 03/04/2022

Hour of the day	Hourly load (MW)	Previous day same hourly load (MW)	Previous week max load (MW)	Temperature (°C)
1.00	30.10	28.80	46.60	28.00
2.00	32.10	32.70	46.60	28.06
3.00	39.60	40.20	46.60	28.00
4.00	41.20	40.20	46.60	28.67
5.00	33.50	34.30	46.60	28.56
6.00	34.50	32.20	46.60	28.73
7.00	35.70	33.10	46.60	29.12
8.00	36.40	39.10	46.60	29.34
9.00	41.50	39.60	46.60	29.12
10.00	39.80	41.20	46.60	29.96
11.00	39.80	43.50	46.60	29.68
12.00	33.70	36.50	46.60	30.02
13.00	36.40	35.70	46.60	30.24
14.00	44.10	40.40	46.60	30.63
15.00	38.10	43.80	46.60	30.24
16.00	37.10	38.50	46.60	31.25
17.00	39.10	41.90	46.60	30.80
18.00	37.70	42.10	46.60	31.86
19.00	39.60	38.70	46.60	31.36
20.00	38.90	41.40	46.60	31.98
21.00	40.80	41.50	46.60	32.48
22.00	39.70	39.80	46.60	33.15
23.00	37.90	43.90	46.60	33.60
24.00	38.60	36.40	46.60	34.33

Table 2: The actual hourly energy demand and temperature data for Monday 04/04/2022

Hour of the day	Hourly load (MW)	Previous day same hourly load (MW)	Previous week max load (MW)	Temperature (°C)
1.00	33.70	30.10	46.60	28.00
2.00	37.30	32.10	46.60	28.00
3.00	40.60	39.60	46.60	28.00
4.00	39.00	41.20	46.60	28.56
5.00	36.20	33.50	46.60	28.56
6.00	31.80	34.50	46.60	28.56
7.00	38.00	35.70	46.60	29.12
8.00	38.70	36.40	46.60	29.12
9.00	41.20	41.50	46.60	29.12
10.00	39.60	39.80	46.60	29.68
11.00	41.30	39.80	46.60	29.68
12.00	38.80	33.70	46.60	29.68
13.00	39.40	36.40	46.60	30.24
14.00	38.00	44.10	46.60	30.24
15.00	41.00	38.10	46.60	30.24
16.00	35.90	37.10	46.60	30.80
17.00	41.30	39.10	46.60	30.80
18.00	36.50	37.70	46.60	31.36
19.00	37.00	39.60	46.60	31.36
20.00	40.00	38.90	46.60	31.92
21.00	37.90	40.80	46.60	32.48
22.00	40.70	39.70	46.60	33.04
23.00	35.20	37.90	46.60	33.60
24.00	40.10	38.60	46.60	34.16

Table 3: The actual hourly energy demand and temperature data for Tuesday 05/04/2022

Hour of the day	Hourly load (MW)	Previous day same hourly load (MW)	Previous week max load (MW)	Temperature (°C)
1.00	28.20	33.70	46.60	28.06
2.00	30.00	37.30	46.60	28.00
3.00	37.00	40.60	46.60	28.11
4.00	38.60	39.00	46.60	28.56
5.00	32.00	36.20	46.60	28.73
6.00	35.70	31.80	46.60	28.56
7.00	36.40	38.00	46.60	29.34
8.00	39.80	38.70	46.60	29.12
9.00	38.50	41.20	46.60	29.40
10.00	41.90	39.60	46.60	29.68
11.00	42.10	41.30	46.60	30.02
12.00	37.80	38.80	46.60	29.68
13.00	37.80	39.40	46.60	30.63
14.00	40.80	38.00	46.60	30.24
15.00	38.90	41.00	46.60	30.69
16.00	32.50	35.90	46.60	30.80
17.00	43.10	41.30	46.60	31.30
18.00	38.90	36.50	46.60	31.36
19.00	42.40	37.00	46.60	31.42
20.00	43.60	40.00	46.60	31.92
21.00	41.40	37.90	46.60	32.59
22.00	40.70	40.70	46.60	33.04
23.00	40.90	35.20	46.60	33.77
24.00	39.50	40.10	46.60	34.16

Table 4: The actual hourly energy demand and temperature data for Wednesday 06/04/2022

Hour of the day	Hourly load (MW)	Previous day same hourly load (MW)	Previous week max load (MW)	Temperature (°C)
1.00	30.00	28.20	46.60	28.01
2.00	33.00	30.00	46.60	28.56
3.00	35.10	37.00	46.60	29.13
4.00	43.00	38.60	46.60	29.68
5.00	37.90	32.00	46.60	30.26
6.00	30.60	35.70	46.60	30.80
7.00	37.60	36.40	46.60	31.38
8.00	38.10	39.80	46.60	31.92
9.00	38.40	38.50	46.60	32.51
10.00	39.70	41.90	46.60	33.04
11.00	39.00	42.10	46.60	33.63
12.00	32.30	37.80	46.60	34.16
13.00	32.10	37.80	46.60	34.76
14.00	39.80	40.80	46.60	35.28
15.00	43.10	38.90	46.60	35.88
16.00	38.50	32.50	46.60	36.40
17.00	39.80	43.10	46.60	37.01
18.00	40.50	38.90	46.60	37.52
19.00	42.20	42.40	46.60	38.09
20.00	41.70	43.60	46.60	38.65
21.00	41.80	41.40	46.60	39.20
22.00	45.50	40.70	46.60	39.78
23.00	40.40	40.90	46.60	40.32
24.00	39.90	39.50	46.60	40.90

M.A. Ita et al. / Nigerian Research Journal of Engineering and Environmental Sciences
8(2) 2023 pp. 499-509

Table 5: The actual hourly energy demand and temperature data for Thursday 07/04/2022

Hour of the day	Hourly load (MW)	Previous day same hourly load (MW)	Previous week max load (MW)	Temperature (°C)
1.00	30.90	30.00	46.60	28.00
2.00	33.50	33.00	46.60	28.06
3.00	35.20	35.10	46.60	28.00
4.00	42.90	43.00	46.60	28.62
5.00	36.80	37.90	46.60	28.56
6.00	32.10	30.60	46.60	28.63
7.00	35.20	37.60	46.60	29.12
8.00	39.80	38.10	46.60	29.19
9.00	39.40	38.40	46.60	29.12
10.00	38.90	39.70	46.60	29.76
11.00	40.20	39.00	46.60	29.68
12.00	33.20	32.30	46.60	29.76
13.00	34.40	32.10	46.60	30.24
14.00	39.20	39.80	46.60	30.33
15.00	42.60	43.10	46.60	30.24
16.00	38.70	38.50	46.60	30.90
17.00	38.50	39.80	46.60	30.80
18.00	43.90	40.50	46.60	30.90
19.00	41.40	42.20	46.60	31.36
20.00	40.20	41.70	46.60	31.47
21.00	41.20	41.80	46.60	31.92
22.00	45.80	45.50	46.60	32.03
23.00	40.40	40.40	46.60	32.48
24.00	40.60	39.90	46.60	33.21

Table 6: The actual hourly energy demand and temperature data for Friday 08/04/2022

Hour of the day	Hourly load (MW)	Previous day same hourly load (MW)	Previous week max load (MW)	Temperature (°C)
1.00	30.80	30.90	46.60	28.00
2.00	34.60	33.50	46.60	28.06
3.00	34.30	35.20	46.60	28.06
4.00	42.50	42.90	46.60	28.63
5.00	36.80	36.80	46.60	28.63
6.00	33.60	32.10	46.60	28.64
7.00	34.10	35.20	46.60	29.20
8.00	41.30	39.80	46.60	29.21
9.00	40.40	39.40	46.60	29.22
10.00	39.10	38.90	46.60	29.78
11.00	39.80	40.20	46.60	29.79
12.00	33.10	33.20	46.60	29.79
13.00	34.70	34.40	46.60	30.36
14.00	39.20	39.20	46.60	30.36
15.00	42.50	42.60	46.60	30.37
16.00	38.70	38.70	46.60	30.93
17.00	38.90	38.50	46.60	30.94
18.00	43.00	43.90	46.60	31.51
19.00	41.20	41.40	46.60	31.51
20.00	41.60	40.20	46.60	32.08
21.00	42.60	41.20	46.60	32.08
22.00	44.90	45.80	46.60	32.65
23.00	40.50	40.40	46.60	32.65
24.00	41.90	40.60	46.60	33.22

3.2. The Developed ANN Model

The developed graphical user interfaces (GUIs) for the ANN model are presented in Figures 3 to 6. The GUI for validation and testing is presented in Figure 3 where the percentage of data used for training, testing and validation of the ANN model was indicated. Figures 4 and 5 respectively present training and trained GUIs. Figure 6 is the GUI for the regression plot. The regression (R) values 0.999999 from the training, 0.999999 from the validation and 0.999999 from the testing revealed that the output is closely related to the targeted prediction.

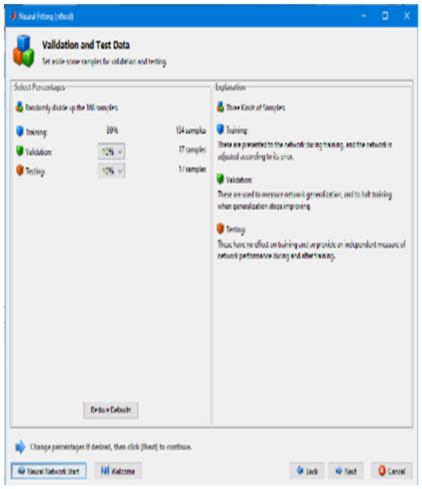

Figure 3: GUI for validation and testing

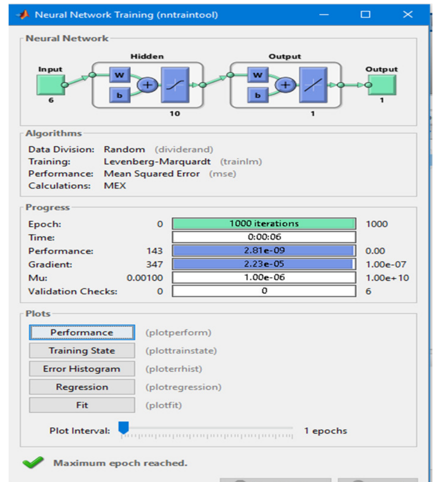

Figure 4: GUI for ANN training

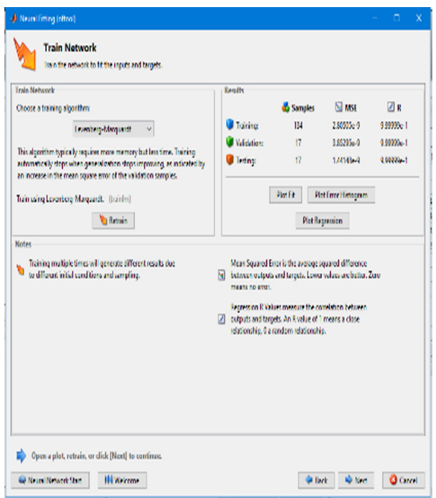

Figure 5: GUI for the trained network

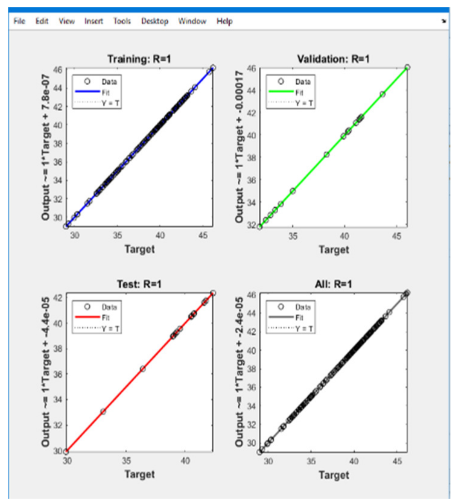

Figure 6: Graphical user interface for regression plot

3.3. Results of Load Demand Forecasting from the Developed ANN Model

The results of comparison of the obtained load demand from the ANN model developed considering new data for 24 hours for different days in the month of April with the actual load demand are presented in Figures 7 to 12. Figures 7 to 12 revealed that load demand increase is dependent on the time of the day where consumption of energy tends to rise. Those times where consumption activities tend to increase include 4 – 5 am, 9 am – 12 noon, 2 – 3 pm and 7 – 10 pm. The results obtained showed that the hourly predicted load profiles from the developed ANN model are in close relationship with the actual load demand and the two plots almost overlap for most times of the day. The validation of the performance of the developed model showed average computed MSE of 2.54, MAE of 1.04, MAPE of 3.11%, $\chi 2$ of 1.55 and F-test of 1.26. The ANN model used for projection is better for short term electrical energy demand with a high degree of accuracy.

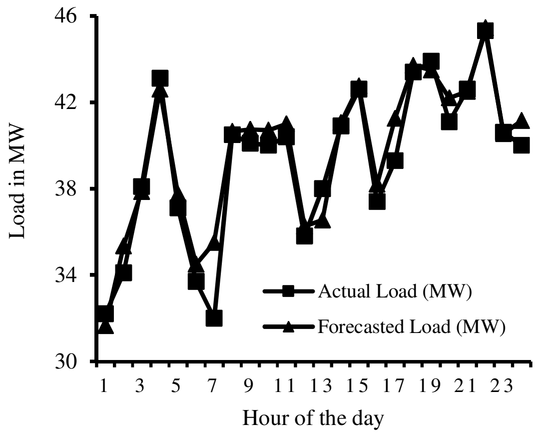

Figure 7: ANN actual and forecasted hourly load for Sunday 10/04/2022

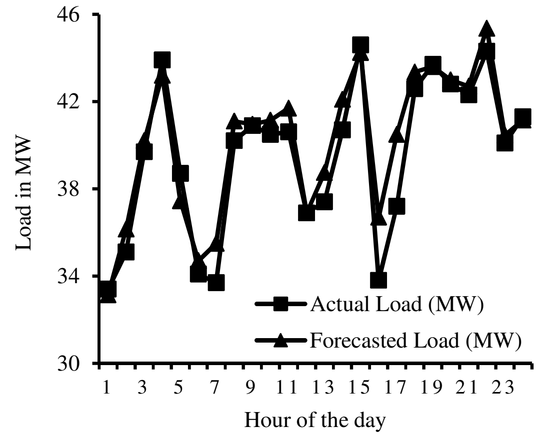

Figure 8: ANN actual and forecasted hourly load for Monday 11/04/2022

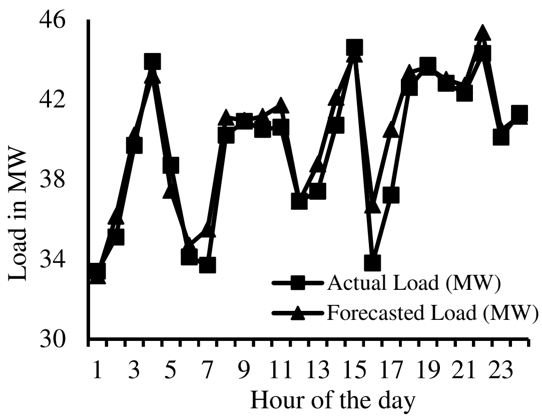

Figure 9: ANN actual and forecasted hourly load for Tuesday 12/04/2022

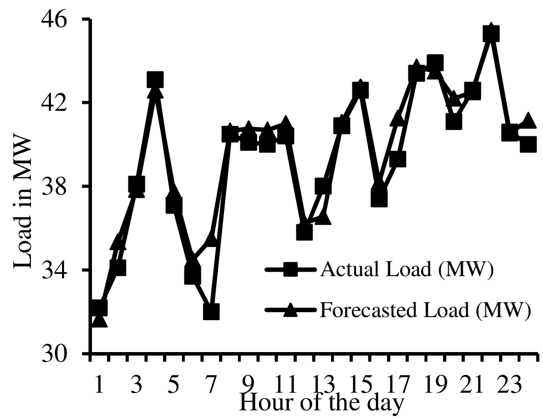

Figure 10: ANN actual and forecasted hourly load for Wednesday 13/04/2022

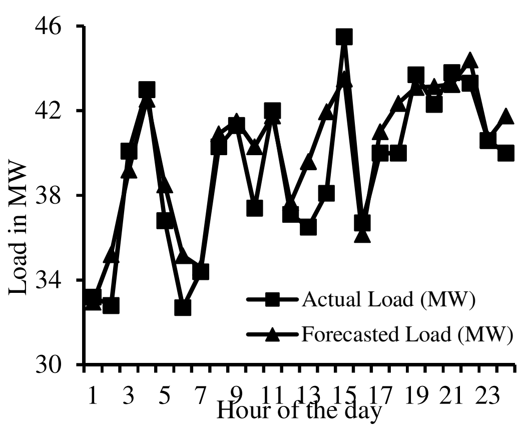

Figure 11: ANN actual and forecasted hourly load for Thursday 14/04/2022

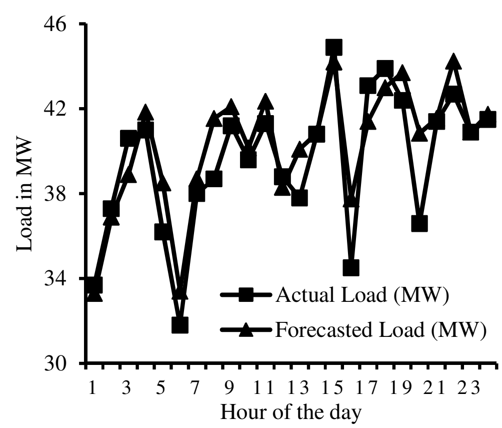

Figure 12: ANN actual and forecasted hourly load for Friday 15/04/2022

4. CONCLUSION

Electrical energy predictions are useful and important tools for formulating energy policies for power utility operators. Accurate load demand forecasts help in making right supply of electricity. This study employed the use of ANN for short-term electrical energy forecast considering load data from 132/33 kV Ikeja West Transmission Station in Lagos State, Nigeria as a case study. The results obtained established that ANN model when appropriately trained using the right technique and data can serve a useful tool in projecting electrical energy demand on short-term.

5. ACKNOWLEDGMENT

The authors wish to acknowledge the assistance and contributions of the 132/33 kV Ikeja West transmission station Ayobo, Lagos state and Nigeria meteorological agency (NiMet), Oshodi, Lagos State, Nigeria toward the success of this work.

6. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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