# ARTIFICIAL NEURAL NETWORK ALGORITHM BASED SHORT-TERM LOAD FORECASTING FOR MEDIUM VOLTAGE NETWORKS

Lambe Mutalub Adesina[1], Busayo Hadir Adebiyi[2] and Olalekan Ogunbiyi[1]
[1]Department of Electrical and Computer Engineering, Kwara State University, Malete, Nigeria
[2]Department of Computer Engineering, Ahmadu Bello University, Zaria, Nigeria
E-Mail: lambe.adesina@kwasu.edu.ng

**ABSTRACT**

Electrical energy is generally known that it cannot be stored. Therefore, it is generated whenever there is need or demand for it. Thus, it is imperative for the power utility companies that the load on their systems should be estimated in advance while such estimation of load in advance is referred to as load forecasting. The forecasting could be Short term, Medium term and Long term depending on the certain parameters in consideration. Short term load forecasting method usually has period ranging from one hour to one week. It often assists in approximating load flow and to make decisions that can intercept overloading. Also, Short term forecasting provides obligatory information for the system management of daily operations and unit commitment. This paper presents an Artificial Neural Network-based model for Short-Term Electricity Load Forecasting. The performance of the model is evaluated by applying the hourly load data of a leading power utility company in Nigeria to predict the required load of the next day in advance. These hourly load data were obtained from two number 33KV feeders; namely the Government house and Sabo-Oke. Also, the data were normalized and then loaded into the model. The model was trained in MATLAB R2020a neural network Simulink environment. The simulation results show a good prediction accuracy for the two domains.

**Keywords:** load forecasting, artificial neural network, levenberg marquardt, mean square error, power system.

## 1. INTRODUCTION

Load forecasting is the process of determining the future trends of electrical power requirements by considering the historical power data [1]. In power system engineering, load forecasting being an important component plays a significant role in planning, coordination and operations of electrical functions. An accurate load forecasting helps the electricity distribution companies in making important decisions such as energy management, unit commitment and infrastructural development. On the other hand, improper forecasting will result into problems such as brownouts and blackouts which most times eventually leads to system collapsed [2].

According to the literatures, load forecasting can be divided in into three categories; short term, medium term and long term [3]-[5]. Our focus in this paper will be on short term load forecasting (STLF). The STLF denotes to the prediction of electrical loads for a period of hours, days, weeks or at times months. The weather condition and humidity are some of the factors that causes variations in load forecasting. The temperature, cloud cover and visibility are some of the weather variables that can affect the power consumptions. An average temperature for instance will determine the power consumption in a particular period of time [4]. Unlike the classical approach such as time series model, regression models, ANN is most suitable for short term load forecasting because it does not necessarily require any direct relationship between the electric load and its variables (such as weather conditions) [6]. In addition, ANN has the ability to learn complex and nonlinear relationship that exists between the patterns of the load.

In the last decade, Artificial Neural Network (ANN) have demonstrated an excellent result in STLF [5], [7]-[10]. In the work of (Gupta and Sarangi) [11], a forecasting model using GA-ANN algorithm was developed and it was found that the algorithm has good capability in function optimization and thus GA provide an efficient optimized neural network. (Buhari and Adamu) [12] Developed a back-propagation algorithm model using the Levenberg-Marquardt optimization technique for the Multilayer Feed Forward ANN. A good precision accuracy was achieved in forecast of future load demands in the power system distribution substation. In (Adepoju *et al*) [13], a multilayer perceptron networks with back propagation was adopted to distort the weight of the NN. Data were obtained from the then Power Holding Company of Nigeria (PHCN) was used to trained the neural network. In the work of (Ilic *et al*) [14] presented an SLTF based on ANN for a distribution management system (DMS). The model was tested on data obtained from Serbian electricity utility company. (Ding *et al*) [15] Proposed a machine learning model based on low voltage substation for distribution system. The results show that the neural network-based models outclass the time series model. In the work of (Kumar *et al*) [16], a comparative load fore casting was carried out using ANN and regression method. It was found that the ANN have a better performance than the regression approach. From the literature review, it is evident that Artificial Neural Network (ANN) has been used for Short Term Load Forecasting (SLTF). Several efforts have been made by researchers to address some of the problems associated with the distribution power systems using ANN. However, the use of this machine learning technique has not really been domesticated using data from any of the eleven (11) power Distribution Companies (DISCOs) in Nigeria to the best of our ability. Hence, this project proposes the use of load distribution obtained from Ibadan Electricity

 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences




Distribution Company (IBDEC), one of the leading DISCO Company.

## 2. THE MATERIAL AND METHOD

The ANN for forecasting been an iterative process begins by collection and preliminary processing of data to make the training well organized. In training the data, the data is divided into three (3) categories namely; training, validation and testing sets. A suitable architectural network for forecasting is then selected. Having done this, the next step is to select the training algorithm. In this work, the training algorithm employed is Levenberg Marquardt (LM) algorithm. Afterwards, we analyse the network in order to see if it has a satisfactory performance. Otherwise, we have to restart the process from beginning as shown in the Figure-1.

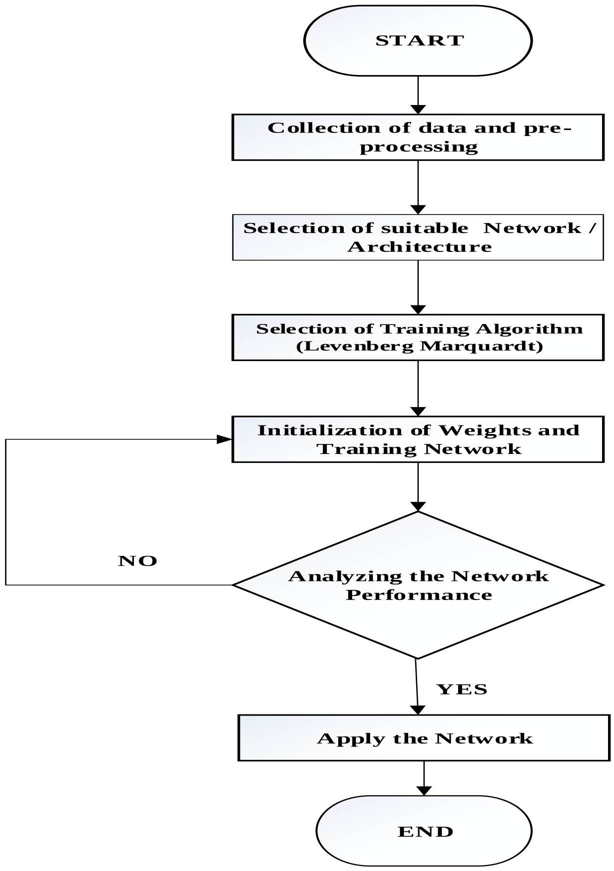


**Figure-1.** Flowchart of ANN load forecasting.

### 2.1 Data Input and ANN-Model

The model is trained on historical data obtained from Ibadan Electricity Distribution Company (IBDEC) of Nigeria, Ilorin (Challenge Business Hub). Data were obtained from December 2018 to December 2019 on hourly basis as shown in Figure-2. The collection of the data was done for two (2) different domains (feeders) namely Government house feeder (GHF) and Sabo-Oke (SOF) feeder all within Ilorin metropolis. The raw data collected is then scaled which necessary to minimize the unfairness is caused by the variation from the measuring unit of original input variables. This process is known as normalization [17]. The normalized data is then divided into training, validation and testing in 70, 30 and 30% respectively. Thereafter, the design of the network is carried out. This is done by selecting the network topology and determining the number of input nodes, output nodes, number of hidden nodes and number of hidden layers. The choice of network topology has to do with the nature of problem that needs to be solved [18]. In this paper, Multilayer feed forward is used. The number of hidden layers and the number of nodes in the hidden layer play a critical role in the design of ANN. This is because excessive hidden neuron lead to many trainable weights, which lead to ambiguity in neural network. On the other hand, few hidden layers restrict the learning characteristics of the neural network and consequently affects the performance [10, 12].

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

| | HOURLY LOAD FLOW | | | | | | | | | | | | | | | | | | | | | | | | LOAD UTILIZATION | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| INSTALLED CAPACITY PER FEEDER (MVA) | 0:00 | 1:00 | 2:00 | 3:00 | 4:00 | 5:00 | 6:00 | 7:00 | 8:00 | 9:00 | 10:00 | 11:00 | 12:00 | 13:00 | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 | DAILY MAX LOAD (MW) | AVERAGE LOAD | DAILY SUPPLY AVAI |
| | 3.6 | 3.2 | 3.2 | 3.2 | 3.2 | 3.6 | 4.4 | 5.3 | 4.8 | 4.3 | 3.1 | 3 | 2.8 | 3.1 | 3.1 | 2.8 | 3.2 | 3.3 | 3.5 | 3.9 | 4.3 | 5.1 | 4.7 | 3.7 | 5.3 | 3.7 | 24.0 |
| | 11.9 | 10.4 | 10.4 | 10.2 | 10 | 10.6 | 12.6 | 6.8 | 11.8 | 9.7 | 8.5 | 7.8 | 3.6 | 8.5 | 8 | 8.3 | 7.9 | 7.9 | 10.2 | 10.8 | 12.1 | 11.6 | 10.4 | 8.6 | 12.6 | 9.5 | 24.0 |
| MER VOLTAGE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | |
| | 132.0 | 124.0 | 116.0 | 112.0 | 112.0 | 112.0 | 124.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 183.0 | 182.0 | 180.0 | 187.0 | 190.0 | 150.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3.2 | 2.4 | 13.0 |
| ING VOLTAGE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | |
| | 132.0 | 124.0 | 116.0 | 112.0 | 112.0 | 112.0 | 124.0 | L/S | L/S | L/S | L/S | L/S | 143.0 | 140.0 | 141.0 | 147.0 | 148.0 | 150.0 | L/S | L/S | L/S | L/S | L/S | L/S | 2.5 | 2.2 | 13.0 |
| | L/S | L/S | L/S | L/S | L/S | L/S | L/S | L/S | L/S | L/S | L/S | L/S | 40.0 | 42.0 | 39.0 | 40.0 | 42.0 | L/S | L/S | L/S | L/S | L/S | L/S | L/S | 0.7 | 0.7 | 5.0 |
| | 336.0 | 290.0 | 276.0 | 272.0 | 75.0 | 80.0 | 90.0 | 108.0 | 423.0 | 313.0 | 299.0 | 267.0 | 40.0 | 52.0 | 45.0 | 51.0 | 65.0 | 47.0 | 320.0 | 367.0 | 377.0 | 364.0 | 324.0 | 302.0 | 7.1 | 3.6 | 24.0 |
| ING VOLTAGE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | | |
| | 244.0 | 212.0 | 200.0 | 197.0 | L/S | L/S | L/S | L/S | 312.0 | 280.0 | 255.0 | 234.0 | L/S | L/S | L/S | L/S | L/S | L/S | 276.0 | 327.0 | 334.0 | 321.0 | 290.0 | 272.0 | 5.6 | 4.5 | 14.0 |
| | 92.0 | 78.0 | 76.0 | 75.0 | 75.0 | 80.0 | 90.0 | 108.0 | 111.0 | 33.0 | 44.0 | 33.0 | 40.0 | 52.0 | 45.0 | 51.0 | 65.0 | 47.0 | 44.0 | 40.0 | 43.0 | 43.0 | 34.0 | 30.0 | 1.9 | 1.0 | 24.0 |
| 15MVA | 254.0 | 203.0 | 217.0 | 210.0 | 200.0 | 476.0 | 508.0 | 286.0 | 262.0 | 250.0 | 210.0 | 195.0 | 0.0 | 265.0 | 261.0 | 258.0 | 254.0 | 252.0 | 261.0 | 272.0 | 321.0 | 301.0 | 262.0 | 210.0 | | | |
| LTAGE | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | | | |
| | 254.0 | 203.0 | 217.0 | 210.0 | 200.0 | 239.0 | 254.0 | L/S | L/S | L/S | L/S | L/S | L/S | 265.0 | 261.0 | 258.0 | 254.0 | 252.0 | 261.0 | 272.0 | L/S | L/S | L/S | L/S | | | |
| | L/S | L/S | L/S | L/S | L/S | 237.0 | 254.0 | 286.0 | 262.0 | 250.0 | 210.0 | 195.0 | P/O | P/O | P/O | P/O | L/S | L/S | L/S | L/S | 321.0 | 301.0 | 262.0 | 210.0 | | | |
| | 13.1 | 10..5 | 10.5 | 10.2 | 9.2 | 9.3 | 9.8 | 10 | 15.6 | 10.2 | 15 | 15.2 | 14.8 | 13.8 | 13.5 | 13.4 | 14.2 | 14.6 | 14 | 15.8 | 9.7 | 10.8 | 13.9 | 13.4 | 15.8 | 12.6 | 23.0 |

**Figure-2.** Sample of Hourly data from IBDEC, Challenge Businnes Office.

## 2.2 Simulation Process

Two Microsoft excel spreadsheets were prepared. The two spreadsheets comprised of hourly load demand sample collected from Challenge Business office of IBDEC, Ilorin, Kwara State, Nigeria. The first spreadsheet contains data taken from the GHF while the second spreadsheet contains data from SOF. The data obtained were trained using MATLAB R2020a NN simulation tool box. The model accuracy is based on the Mean Square Error (MSE) as the performance index. The MSE is defined by this mathematical expression:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}\right) \quad (1)$$

where,

n = the number of data points

$Y_i$ = the value returned by the model and

$\hat{Y}_i$ = the actual value for the data point $i$ .

The ANN adopted in the forecasting as illustrated in Figures 3 and 4, has two input layers, a hidden layer and output layer.

The simulation illustrations are shown in Figures 3 and 4 while the plots generated are discussed section III.

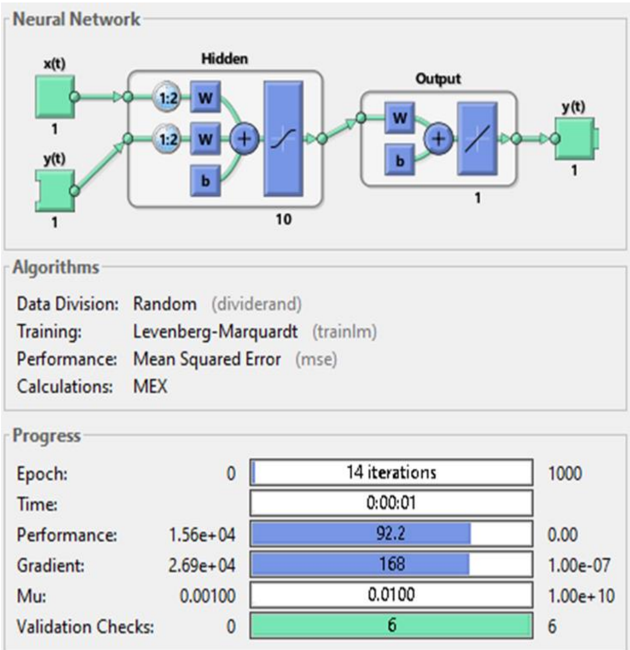


**Figure-3.** ANN Model of GHF using Lavenberg Marquardt Algorithm.

VOL. 16, NO. 15, AUGUST 2021 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

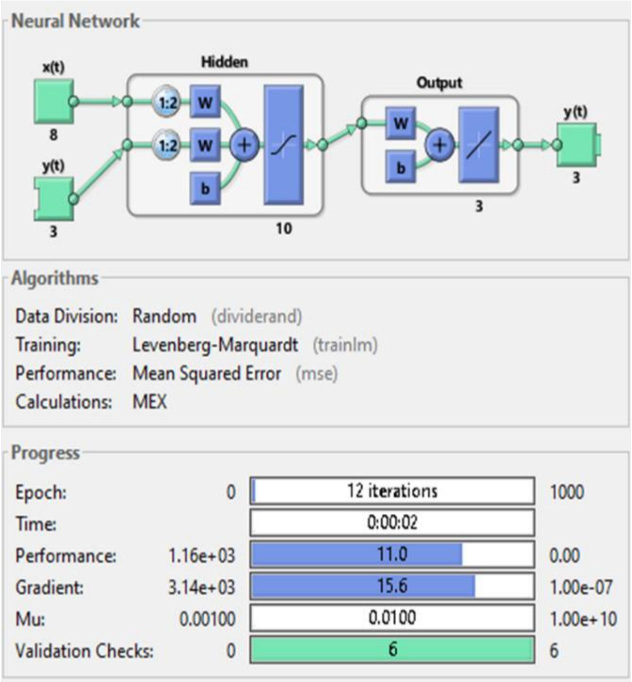


**Figure-4.** ANN Model of SOF using Lavenberg Marquardt Algorithm.

## 3. RESULTS AND DISCUSSIONS

It is quite interesting to note that some plots were generated from the simulations carried out in these research. The performance plots are shown in Figures 4 and 5 which represents the performance of the network during the three target time steps i.e training, validation and testing. This performance was satisfied at 14 epochs (i.e number of iterations) and 12 epochs for GHF and SOF feeders respectively. The mean square error (MSE) shown in Figures 4 and 5 are on the declining side throughout the learning process. Furthermore, the regression plot shows the correlation between the output and the target. If the value of regression (R) is equal to 1, then a perfect correlation between the output and the target exists. Thus, for the regression plot shown in Figure 4; R = 0.96570 for training, R = 0.97544 for validation, R = 0.97832 for testing and while the overall regression $R_1$ = 0.96904. But, for the regression plot shown in Figure-5; R = 0.99465 for training, R = 0.99186 for validation, R = 0.99296 for testing and the overall regression $R_2$ = 0.99394. This analysis implies that the output and the target values have a perfect connection which further shows that the network has made an acceptable prediction in the study.

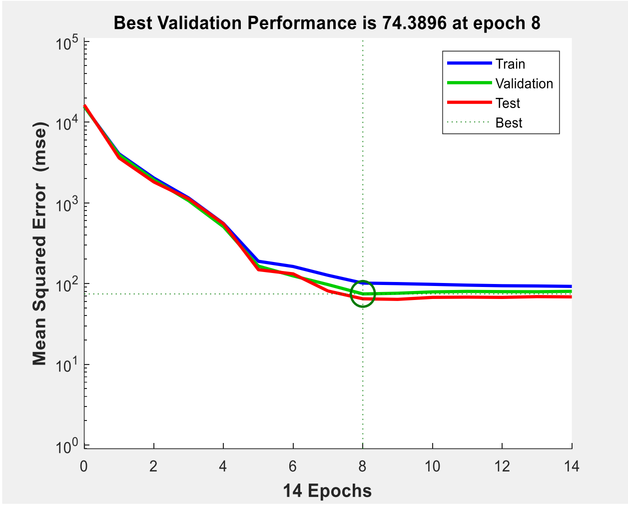


**Figure-5.** Performance plot of GHF .

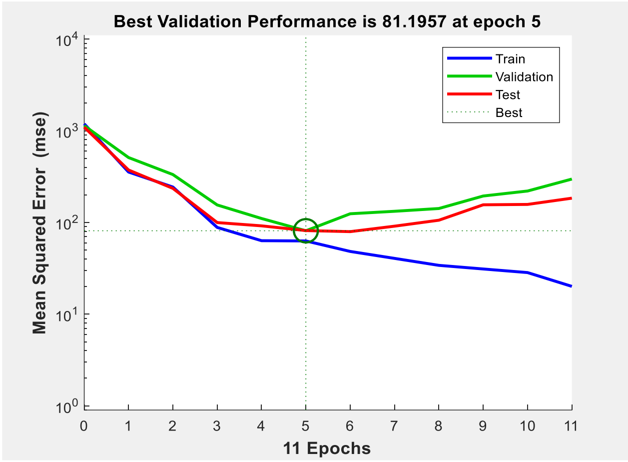


**Figure-6.** Performance plot of SOF.

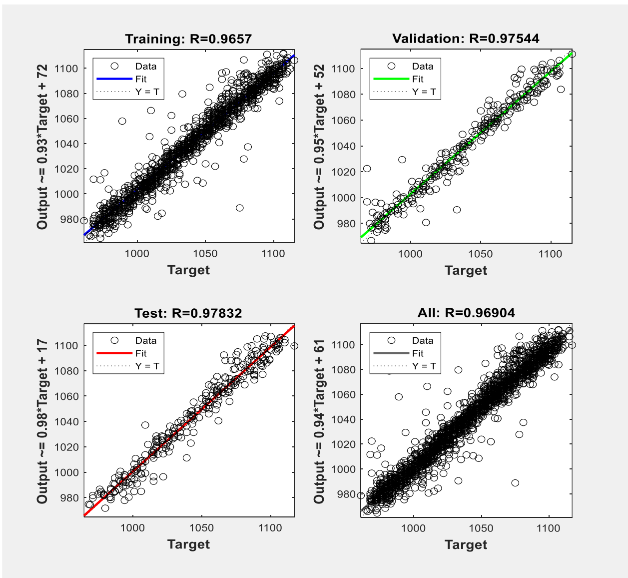


**Figure-7.** Regression plot of GHF.

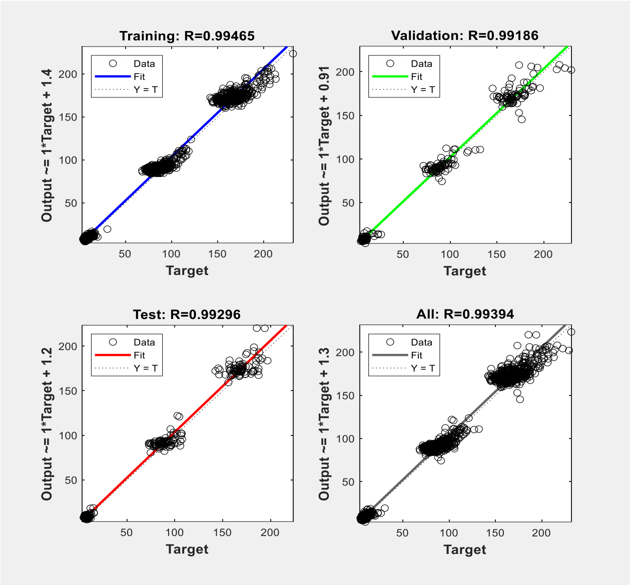


**Figure-8.** Regression plot of SOF.

## 4. CONCLUSIONS

This paper has presented the short-term load forecasting of Feeders under Ibadan Electricity Distribution Company (IBDEC), Nigeria. Levenberg Marquardt back propagation algorithm was employed in MATLAB R2020a neural network tool box so as to obtain an accurate, reliable and efficient load forecast. The collection of the data was done for two (2) different domains (feeders) namely Government House Feeder (GHF) and Sabo-Oke feeder (SOF), all within Ilorin metropolis, Kwara State, Nigeria. At the end of the training, validation and testing of the data, the performance goal was met at 14 and 12 epochs for the GHF and SOF respectively. The regression plots in Fig. 7 and 8 confirms that the target and output values are very close. This closeness is an indication that the network considered has predicted the output in a satisfactory manner.

## ACKNOWLEDGEMENT

The authors appreciate Ilorin Challenge Office of Ibadan Electricity Distribution Company (IBDEC), Nigeria, for making the appropriate data required for this research work available.

## REFERENCES

[1] Dwijayanti D. and Hanga M. 2014. Short Term Load Forecasting using a Neural Network Based Time Series Approach. 1st International Conference on Artificial Intelegence, Modelling and Simulation. IEEE Xplore. Dec 2013, Malaysia. DOI: 10.1109/AIMS.2013.11. Available at: https://ieeexplore.ieee.org/abstract/document/6959888/.

[2] Gao X., Li X., Zhao B., Ji W., Jing X. and He Y. 2019. Short-term electricity load forecasting model based on EMD-GRU with feature selection. Energies. 12(6): 1140. DOI: 10.3390/en12061140.

[3] Jiang L. and Hu G. 2018. A Review on Short-Term Electricity Price Forecasting Techniques for Energy Markets. 15th International Conference on Control, Automation, Robotics and Vision (ICARCV), 937-944, DOI: 10.1109/ICARCV.2018.8581312.

[4] Sahay K. B., Sahu S. and Singh P. 2016. Short-term load forecasting of Toronto Canada by using different ANN algorithms. IEEE 6th International Conference on Power Systems (ICPS), DOI: 10.1109/ICPES.2016.7584044.

[5] Singh A. and Sahay K. B. 2018. Short-Term Demand Forecasting by Using ANN Algorithms. In: 6th International Electrical Engineering Congress. iEECON2018, Krabi, Thailand.

[6] Moturi C. A. and Kioko F. K. 2013. Use of Artificial Neural Networks for Short-Term Electricity Load Forecasting of Kenya National Grid Power System. International Journal of Computer Application. 63(2): 25-30. DOI: 10.5120/10439-5123.

[7] Bento P. M. R., Pombo J., Mariano S. and Calado M. D. R. 2018. Short-Term Load Forecasting using optimized LSTM Networks via Improved Bat Algorithm. International Conference on Intelligent Systems (IS). 351-357. DOI: 10.1109/IS.2018.8710498

[8] Sharma P. and Saxena A. 2017. Critical investigations on performance of ANN and wavelet fault classifiers. Cogent Engineering 4: 1286730. DOI: 10.1109/icit.2000.854220.

[9] Dodamani S. N., Shetty V. J. and Magadum R. B. 2015. Short term load forecast based on time series analysis: A case study. Proceedings of IEEE International Conference on Technological Advancements in Power and Energy (TAP Energy). 299-303. DOI: 10.1109/TAPENERGY.2015.7229635.

[10] Marma H. U. M., Iqbal M. T. and Seary C. T. 2020. Short-term Power Load Forecast of an Electrically Heated House in St. John’s, Newfoundland, Canada. European Journal of Electrical Engineering and Computer Science. 4(3): 1-8. DOI: 10.24018/ejece.2020.4.3.210.

[11] Gupta A. and Sarangi P. K. 2012. Electrical load forecasting using genetic algorithm based back-propagation method. Researchgate.net. 7(8): 1-13.

[12] Buhari M. and Adamu S. S. 2012. Short-term load forecasting using artificial neural network. In: Proceedings of the International MultiConference of Engineers and Computer Scientists (IMECS), Vol. 1, Hong. Kong.

[13] Adepoju G. A., Ogunjuyigbe S. O. A. and Alawode K. O. 2007. Application of Neural network to Load Forecasting in Nigerian Electrical Power System. The Pacific Journal of Science and Technology. 8(1): 68-72.

[14] Ilić S., Selakov A., Vukmirović S., Erdeljan A. and Kulić F. 2013. Short-term load forecasting in large scale electrical utility using artificial neural network. J. Sci. Ind. Res., India. 72(12): 739-745.

[15] Ding N., Benoit C., Foggia G., Besanger Y. and Wurtz F. 2016. Neural network-based model design for short-term load forecast in distribution systems. IEEE Trans. on Power System. 31(1): 72-81. DOI: 10.1109/TPWRS.2015.2390132.

[16] Kumar S., Mishra S. and Gupta S. 2016. Short term load forecasting using ANN and multiple linear regression. Confetrence Proceedings of 2nd International Conference on Computational Intelligence and Communication Technology (CICT). 184-186, DOI: 10.1109/CICT.2016.44.

[17] Olagoke M. D., Ayeni A. A. and Hambali A. M. 2016. Short Term Electric Load Forecasting using Neural Network and Genetic Algorithm. International Journal of Applied Information Systems. 10(4): 22-28, DOI: 10.5120/ijais2016451490.

[18] Zhao H., Ren Z. and Huang W. 1997. Short term load forecasting method based on PAR model. Zhongguo Dianji Gongcheng Xuebao/Proceedings Chinese Society of Electrical Engineering. 17(5): 348-351.