Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 7 Issue 3, March - 2020

Modelling And Forecasting Peak Load Demand In Uyo Metropolis Using Artificial Neural Network Technique

Clement Effiong[1]
Department of Electrical/Electronic and Computer Engineering, University of Uyo, AkwaIbom, Nigeria

Ozuomba Simeon[2]
Department of Electrical/Electronic and Computer Engineering University of Uyo Akwa Ibom State Nigeria
simeonoz@yahoo.com

Fina Otosi Faithpraise[3]
Department of Computer Engineering
University of Calabar Cross River State Nigeria

***Abstract*— In this paper artificial neural network (ANN) was used to model and forecast the peak load demand in Uyo metropolis using temperature, population and GDP as the explanatory variables. Particularly, sixteen (16) years (2000-2015) data on annual peak-load demand, population, GDP and temperature of Uyo were collected and then used in training and evaluating the ANN model. Furthermore, the ANN model was used to forecast the peak load demand in Uyo metropolis from 2016 to 2025. The results of the error analysis of the ANN model gave coefficient of determination value of 99.912 % squared error value of 1.102209 and mean squared error value of 0.068888. The forecast results also showed that the peak load demand will be 63.14MW in 2025, which is an increment of 23.80% when compared to the actual peak load in 2015. Essentially, in comparison to the power demand in 2015, additional 23.80% of electric power need to be produced in order to meet the peak load demand in Uyo metropolis in the year 2015.**

Keywords*— *Artificial Neural Network, Peak Load Demand, Forecast, Prediction Performance, ANN Validation, ANN Training

I. INTRODUCTION

Electric load forecasting is very important for electric energy generation planning, energy purchasing planning, contract evaluation, as well as, load switching and infrastructure development [1, 2, 3, 4, 5, 6, 7]. Particularly, electric peak-load forecasting is very important in effective and efficient planning since bogus future load estimation may lead to loss of revenue in overspending on the power infrastructure while underestimation of load may cause troubles and more outages in supplying the load and hence loss of revenue [8, 9, 10, 11, 12]. Therefore, method for accurate forecast of peak loads is needed. Such model should take into account the factors that affect the growth of the load over a number of years. Some of the factors for accurate modeling of peak load demand are: gross domestic product (GDP) , population (POP), GDP per capita (GDP/CAP) , power system losses (LOSS) , load factor (LF) , cost of one kilowatt-hour [11,12].

In general, load forecasting approaches are mostly categorized into conventional approaches and intelligent algorithm-based techniques. The conventional techniques are often statistical methods which use mathematical models that are developed based on the historic data to estimate the future values of a variable [13, 14, 15]. The ANN techniques are applicable in cases in which a full theoretical approach is not available [16, 17, 18, 19, 20, 21, 22]. ANN forecasting models compared to classical approaches, require less input data and computational time [23]. Moreover, unlike conventional computational approaches, adaptive learning approaches as used in ANN provide for the prediction of future peak load demand which make it more flexible in accommodating new data patterns and also unknown data patterns [24, 25]. Consequently, in this paper, artificial neural network (ANN) was used to model and forecast the peak load demand in Uyo metropolis using temperature, population and GDP as the explanatory variables. The choice of the explanatory variables is based on their relevance and availability for the cased study, which is Uyo metropolis.

II. METHODOLOGY

Relevant data for the ANN-based peak load modeling were collected and the data was used in training and evaluating the ANN model. Particularly, data on the population of Uyo was collected from the Ministry of Economic Development Uyo, Akwa Ibom State; the annual peak-load demand of Uyo was collected from the Transmission Company of Nigeria (TCN), Uyo and the temperature of Uyo was obtained from accweather [27]. After the ANN model was developed, the prediction performance was evaluation and then the ANN model was used to forecast the peak load demand in Uyo metropolis for fifteen years.

A. Development of the Artificial Neural Network Model

The generalized Delta rule (GDR) was used to train a three-layered perceptron-type ANN (Figure 1). An input pattern sent to the network is used to generate an output vector. For each input dataset and the ANN estimated output, there is a target (or actual output) which is then compared with the predicted output. The difference between the ANN-predicted output and the target output is used to adjust the weighting parameters (Wij) such that the difference between the predicted and the target output is minimized. Adjustments in the weighting parameters are also done at the hidden layer and the input layer.

The network architecture used to carry out the training of the ANN in MATLAB is shown in Figure 1. According to the architecture in Figure 1, the ANN was structured in 3-10-1 form, which means that it has three layer network. The input layer is the first layer and it takes three inputs, the second layer is the hidden layer that has ten nodes or neurons connected to it and the third layer is the output layer that has just one node connected to it.

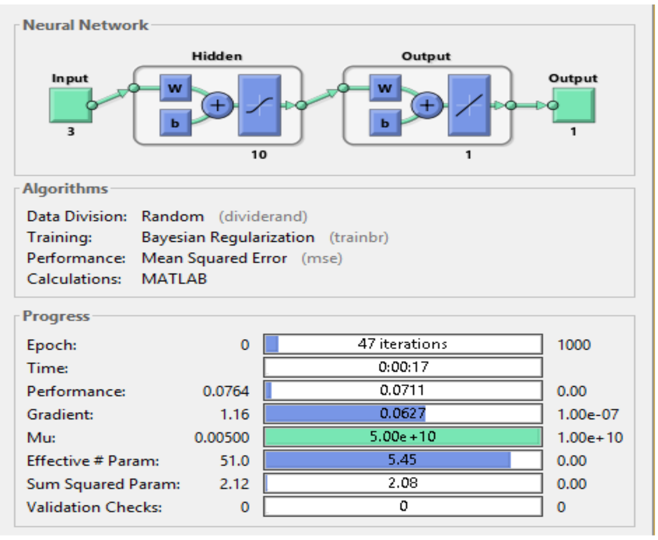


Figure 1: Neural Network Training Platform

B. The prediction performance for the ANN Model

The prediction performance of the models is evaluated using Root Mean Square Error, Mean Absolute Percentage Error, Mean Absolute Deviation (MAD) and coefficient of determination. The Mean Squared Error (MSE) is computed as:

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{1}^{\mathrm{n}}(\mathrm{Actual\ load} - \mathrm{Predicted\ Load})^2 \quad (1)$$

The Root Mean Squared Error (RMSE) is given as,

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \quad (2)$$

The Mean Absolute Percentage Error (MAPE) is given as,

$$\mathrm{MAPE}(\%) = \frac{1}{\mathrm{n}}\sum_{1}^{\mathrm{n}}\left|\frac{\mathrm{Actual\ load}-\mathrm{Predicted\ Load}}{\mathrm{Actual\ Load}}\right| \quad (3)$$

The Mean Absolute Deviation (MAD) is given as,

$$\mathrm{MAD}\ (\%) = \frac{1}{\mathrm{n}}\sum_{1}^{\mathrm{n}}|\mathrm{Actual\ load} - \mathrm{Predicted\ Load}| \quad (4)$$

Let $\bar{\boldsymbol{y}}$ be the mean of the observed data , then,

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \quad (5)$$

The variability of the data set can be measured using three sums of squares formulas. Let $\mathrm{SS_{tot}}$ be the total sum of squares where

$$SS_{tot} = \sum_i (Y_i - \bar{Y})^2 \quad (6)$$

Let $\mathrm{SS_{res}}$ be the sum of squares of residuals, also called the residual sum of squares where,

$$SS_{res} = \sum_i (Y_i - \hat{Y})^2 = e_i^2 \quad (7)$$

$$SS_{reg} = \sum_i \left(\hat{Y} - \bar{Y}\right)^2 \quad (8)$$

Then, the Coefficient of determination (denoted as R^2) is given as,

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (9)$$

$$SS_{tot} = SS_{res} + SS_{reg} \quad (10)$$

III. RESULTS AND DISCUSSIONS

The 16 years datasets used for the modeling is presented in Table 1. The ANN model predicted peak load and its error analysis are presented in Table 2 and Table 3 respectively.

Table 1: Dataset used for ANN Model

S/N	YEAR	Population	GDP	Temperature (ºC)	Peak Load (MW)
1	2000	250347	8002	26.8	31
2	2001	258859	8274	28	32
3	2002	267660	8555	28	33
4	2003	276761	8846	27.7	34
5	2004	286171	9147	27.2	36
6	2005	295900	9458	26.3	37
7	2006	305961	9780	25.5	38
8	2007	316364	10112	25.6	39
9	2008	327120	10456	25.8	41
10	2009	338242	10811	26.3	42
11	2010	349742	11179	26.8	43
12	2011	361634	11559	26.6	45
13	2012	373929	11952	26.8	46
14	2013	386643	12358	28	48
15	2014	399789	12779	28	50
16	2015	413381	13213	27.7	51

According to the error analysis (Table 3), the coefficient of determination value of 0.99912 indicates that about 99.912 % of the peak load is explained by the selected explanatory variable. Also, with Sum of Squared Error (SSE) value of 1.102209 and Mean Squared Error (MSE) value of 0.068888 the prediction performance of the ANN model can be said to have predicted the peak load very accurately. The prediction performance of the ANN model is presented in Table 3 and Figure 2

Table 2: Actual Peak Load (MW) and the ANN model Predicted Peak Load (MW)

Year	Actual Peak Load (MW)	Predicted Peak Load (MW)
2000	31	31.15544
2001	32	32.01517
2002	33	33.12048
2003	34	34.32401
2004	36	35.60544
2005	37	36.89685
2006	38	38.02526
2007	39	39.25162
2008	41	40.55052
2009	42	41.998
2010	43	43.50257
2011	45	44.80235
2012	46	46.27119
2013	48	48.1684
2014	50	49.63934
2015	51	50.95117

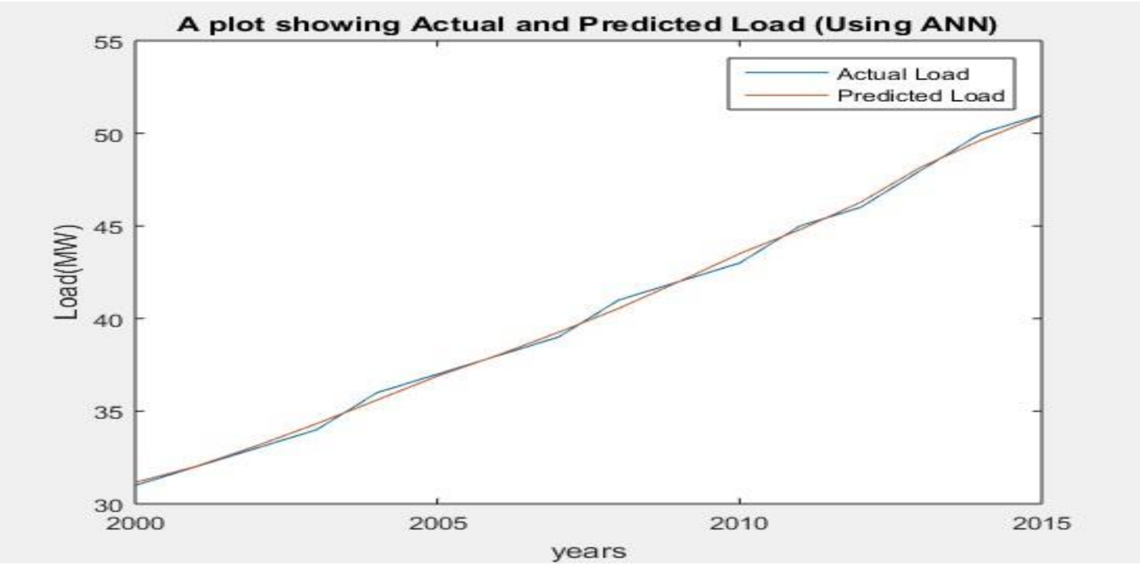


Figure 2: Actual and predicted peak load demand for the year 2000 to 2015

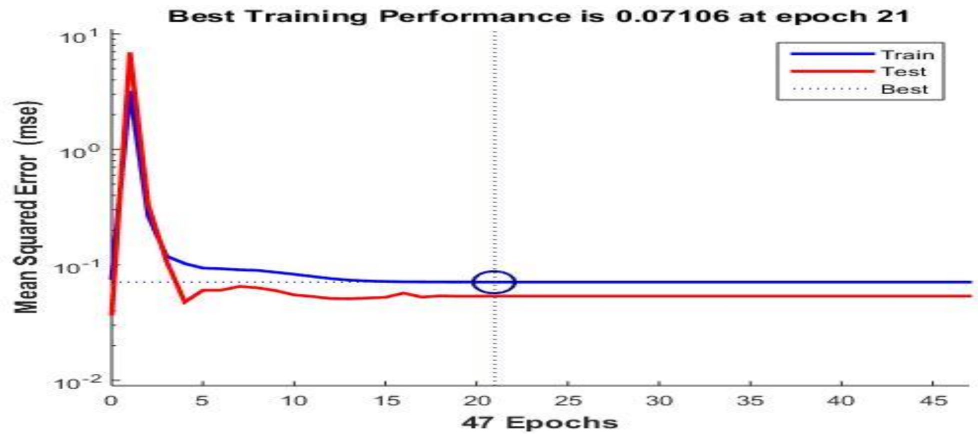
Table 3: Model prediction performance measures

Prediction Performance Measure Description	Prediction Performance Measure Value
Mean Absolute Percentage Error (MAPE)	0.005262
Mean Absolute Error (MAE)	0.211905
Sum of Squared Error (SSE)	1.102209
Mean Squared Error (MSE)	0.068888
Coefficient of Determination (R^2)	0.99912

The trained neural network MSE is compared with that of the testing samples. This gives a sense of how well the network will do when applied to other datasets other than the one used for training the ANN model. From the MSE versus epoch plot (Figure 3) it can be seen that the MSE decreases for all the datasets of the model and attained its best value at epoch 21 of the iterative evaluation. This value is

0.07106 at where the circle is shown in the plot (Figure 3).

Regression plot (Figure 4) was also used to assess the performance of the ANN in fitting the data.



.

Figure 3: MSE performance curve for the ANN Model

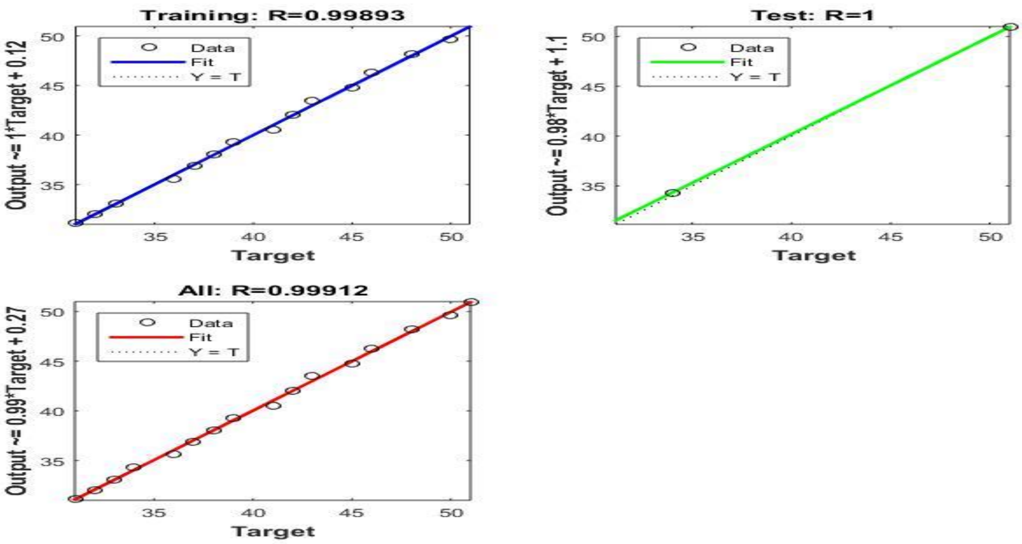


Figure 4 : Regression Performance Plots For The ANN Model

The ANN model is used to forecast the peak load demand in Uyo metropolis for the next 10 years as shown in Table 4 and Figure 5. According to Figure 5, the forecasted peak load demand will be 63.14MW in 2025, which is an increase of 23.80% in comparison to the peak load in 2015. Consequently, when compared with the power demand in 2015, about 23.80% extra electric power need to be generated for Uyo Metropolis in the next ten (10) years.

Table 4 : Peak load forecast from 2016 to 2020 using ANN Model

Year	Population	GDP	Temperature.(℃)	Forecast Load (MW)
2016	427436	13662	27.2	52.06
2017	441969	14127	26.3	52.78
2018	456996	14607	25.5	53.44
2019	472534	15104	25.6	54.83
2020	488600	15617	25.8	56.29
2021	505213	16148	26.3	57.96
2022	522390	16697	26.8	59.55
2023	540151	17265	26.6	60.57
2024	558516	17852	26.8	61.83
2025	506577	18459	27.2	63.14

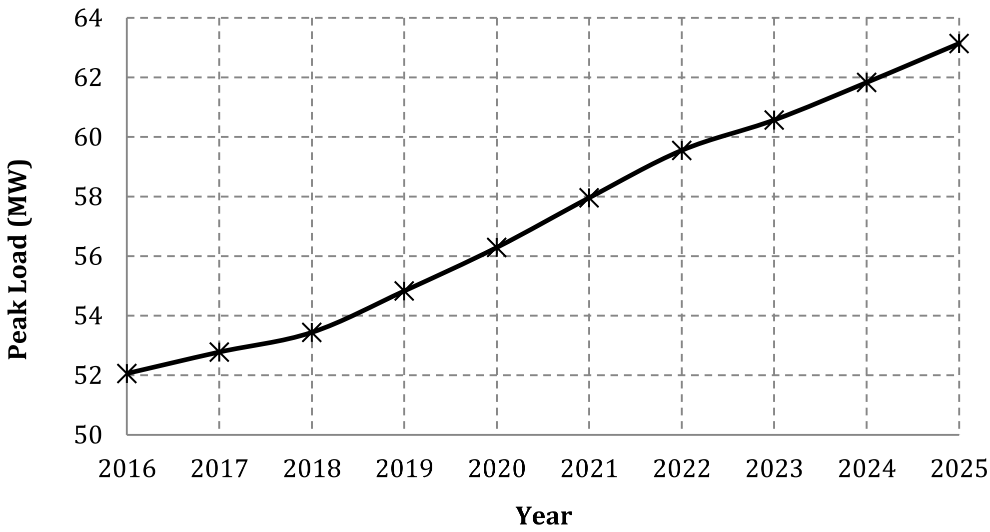


Figure 5: Peak load forecast for year 2016 to 2025

IV. CONCLUSION

Artificial Neural Network (ANN)–based modeling and forecasting of the peak load demand in Uyo metropolis is presented. Temperature, population and GDP are used as the explanatory variables. Sixteen (16) years (2000-2015) data on annual peak-load demand, population, GDP and temperature of Uyo are used in training and evaluating the ANN model. The prediction performances were evaluated and then the ANN model was used to forecast the peak load demand in Uyo metropolis from 2016 to 2025. The ANN model gave very high prediction performance when assessed in terms of coefficient of determination, squared error and mean squared error values. The forecast results also showed that when compared with the power demand in 2015, about 23.80% extra electric power need to be generated for Uyo Metropolis in the next ten (10) years.

REFERENCES

1. Bhardwaj, A., &Manglani, T. (2017). Gravitational Search Algorithm for Bidding Strategy in Uniform Price Spot Market. *dimension*, *6*(2), 1.
2. Alkhathami, M. (2015). Introduction to electric load forecasting methods. *Journal of Advanced Electrical and Computer Engineering*, *2*(1), 1-12.
3. Samuel, I. A., Chihurumanya, F. N., Adewale, A. A., &Awelewa, A. A. (2014). Medium-term load forecasting of covenant university using the regression analysis methods. *Journal of Energy Technologies and Policy*, *4*(4).
4. Janjua, J. I., & Khan, Z. A. (2013). Real-time, Efficient E-Infrastructure Development Framework for Corporate Energy Sector. *International Journal of Future Computer and Communication*, *2*(6), 642.
5. Armel, K. C., Gupta, A., Shrimali, G., & Albert, A. (2013). Is disaggregation the holy grail of energy efficiency? The case of electricity. *Energy Policy*, *52*, 213-234.
6. Islam, B. U. (2011). Comparison of conventional and modern load forecasting techniques based on artificial intelligence and expert systems. *IJCSI International Journal of Computer Science Issues*, *8*(3), 504-513.
7. Feinberg, E. A., & Genethliou, D. (2005). Load forecasting. *Applied mathematics for restructured electric power systems*, 269-285.
8. Khan, A. R., Mahmood, A., Safdar, A., Khan, Z. A., & Khan, N. A. (2016). Load forecasting, dynamic pricing and DSM in smart grid: A review. *Renewable and Sustainable Energy Reviews*, *54*, 1311-1322.

9. Oğurlu, H., &Çetinkaya, N. (2016). Electrical Load Forecasting between 2015 and 2035 for Turkey using Mathematical Modelling and Dynamic Programming. *IJSTE-International Journal of Science Technology & Engineering*, *2*(08).
10. Sanstad, A. H., McMenamin, S., Sukenik, A., Barbose, G. L., & Goldman, C. A. (2014). Modeling an aggressive energy-efficiency scenario in long-range load forecasting for electric power transmission planning. *Applied Energy*, *128*, 265-276.
11. Soliman, S. A. H., & Al-Kandari, A. M. (2010). *Electrical load forecasting: modeling and model construction*. Elsevier.
12. Soliman, S. A., Alammari, R. A., El-Hawary, M. E., &Temraz, H. K. (2004). Long-term electric peak load forecasting for power system planning: A comparative study.
13. Amjady N., (2001) "Short-Term Hourly Load Forecasting Using Time Series Modeling with Peak Load Estimation Capability", IEEE Transactions on Power Systems, Vol. 16, No. 3, pp. 498-505, August 2001.
14. Al-Hamadi, H. M., &Soliman, S. A. (2005). Long-term/mid-term electric load forecasting based on short-term correlation and annual growth. *Electric power systems research*, *74*(3), 353-361.
15. Kandil, M. S., El-Debeiky, S. M., &Hasanien, N. E. (2001). Overview and comparison of long-term forecasting techniques for a fast developing utility: part I. *Electric Power Systems Research*, *58*(1), 11-17.
16. Scott, J. (2017). *Social network analysis*. Sage.
17. Herdt, V. (2016). Introduction. In *Complete Symbolic Simulation of SystemC Models* (pp. 1-6). Springer Fachmedien Wiesbaden.
18. Gentles, S. J., Charles, C., Ploeg, J., &McKibbon, K. A. (2015). Sampling in qualitative research: Insights from an overview of the methods literature. *The Qualitative Report*, *20*(11), 1772.
19. Barnett-Page, E., & Thomas, J. (2009). Methods for the synthesis of qualitative research: a critical review. *BMC medical research methodology*, *9*(1), 59.
20. Krizek, K., Forysth, A., &Slotterback, C. S. (2009). Is there a role for evidence-based practice in urban planning and policy?.*Planning Theory & Practice*, *10*(4), 459-478.
21. Iacono, J., Brown, A., &Holtham, C. (2009). Research Methods--a Case Example of Participant Observation. *Electronic Journal of Business Research Methods*, *7*(1).
22. Sales, A., Smith, J., Curran, G., &Kochevar, L. (2006). Models, strategies, and tools. *Journal of General Internal Medicine*, *21*(S2).
23. Grant, J., Eltoukhy, M., &Asfour, S. (2014). Short-term electrical peak demand forecasting in a large government building using artificial neural networks. *Energies*, *7*(4), 1935-1953.
24. Cai, M.; Yin, Y.; Xie, M. (2009) Prediction of hourly air pollutant concentrations near urban arterials using artificial neural network approach. Transp. Res. Part D Transp. Environ. 2009, 14, 32–41
25. Accuweather. (2013). Weather Forecast. Available at http://www.accweather.com/en/ng/uyo/251973/weather-forecast/251973). Accessed: 2016.12.10.