

# Multifactorial Short-Term Load Forecasting for Enugu Load Center using Artificial Neural Network Concept.

Chika O. Ikaroha, M.Eng.<sup>1</sup> and Adegoke O. Melodi, Ph.D.<sup>2</sup>

Department of Electrical and Electronics Engineering, The Federal University of Technology,  
Akure, Nigeria.

E-mail: [favoredobinna@gmail.com](mailto:favoredobinna@gmail.com)<sup>1</sup>  
[aomelodi@futa.edu.ng](mailto:aomelodi@futa.edu.ng)<sup>2</sup>

## ABSTRACT

This paper presents a multifactorial short-term power load forecasting model for the Enugu Load Center using an Artificial Neural Network (ANN) concept. The aim is to improve forecasting accuracy by introducing more features such as temperature, per capita income, and load category to the model's feature set. Historical load data, temperature data, per capita income, and load category for the months of August 2012 – October 2012 were used in training the model. The previous day's data and previous week's data were used as inputs to the ANN model. The modeled ANN has a hidden layer with 50 neurons, and an output layer with a single neuron. The performance of the model was analyzed in terms of the mean squared error (MSE), which gave an average of 0.013 when the trained network was tested over one week's data. On average, this represents a high degree of accuracy in the load forecast.

(Keywords: short-term load forecasting, artificial neural network, back propagation algorithm, Enugu, Nigeria)

## INTRODUCTION

Forecasting is a phenomenon of knowing what may happen to a system in future time periods (Sarangi *et al.*, 2009). In electrical power systems, there is a great need for accurate forecasting of the load and energy requirements because electricity generation, transmission, as well as distribution are of a great financial liability to a nation. In a country like Nigeria, provision of electric power consumes a large part in the country's annual budget. Accurate load forecasts provide system dispatchers with timely information to plan and operate the system economically and reliably. It is also necessary

because availability of electricity is critical for industrial development, especially at this point in Nigeria's development.

The Nigerian power industry is presently undergoing structural and organizational changes. With the restructuring process taking place in the Power Holding Company of Nigeria (PHCN), the power industry is being positioned for better services to the Nigerian populace. This includes a plan to boost system generation capacity to meet prevailing and forecast demand.

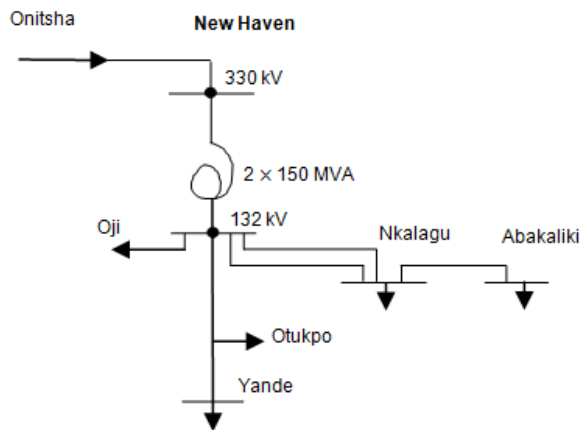
Load demand value has been identified to be a function of time. Apparent time depended factors of electricity demand include people's daily working time, leisure time and sleeping time. Load prediction periods may be one hour to one week for the short-term forecasts, more than a week to a year for the medium-term forecasts, and longer than a year for long-term forecasts (Feinberg *et al.*, 2010).

The short-term forecast is needed for control and scheduling of fuel prices, and also as inputs to load flow study or contingency analysis. The medium-term forecast is used for maintenance planning and scheduling of fuel supply, while the long forecast is used to determine the capacity of generation, transmission, or distribution system additions, and the type of facilities required in transmission expansion planning, annual hydro and thermal maintenance scheduling, etc. (Nweke, 2012; Buhari and Adamu, 2012).

The problem of load forecasting has been studied and the reported findings include the need to overcome the reliance on a functional form of a forecasting model. Artificial neural networks (ANNs) offer the potential of achieving that objective (Damborg *et al.*, 1990). Secondly, the operation of the power distribution system can

only translate to better and efficient services if, among other vital factors, there is a good and accurate system in place for forecasting the load that would be in demand by electricity customers (Adepoju *et al.*, 2007). Thirdly, the existing classical methods of load forecasting are heuristic in nature. However the learning property of ANN in solving nonlinear and complex problems makes it fit for its application to forecasting problems (Nweke, 2012). Current Nigerian systems operate without application of such modern techniques, and this condition results in difficult and uneconomical source-load management.

This study suggests application of model hourly load variations using artificial intelligence theory for Nigerian systems, especially the Enugu Center. Enugu is geographically located at latitude 6.5°, longitude 7.5°. Figure 1 shows the power transmission network for Enugu fed via Onitsha at 330kV. The voltage is stepped down to 132kV at the New Haven transmission station, which feeds other centers under the Enugu Load Center.



**Figure 1:** Enugu Power Transmission Network Diagram.

## ANN AND NEURON

In the current literature, the techniques of electric load forecasting are distinguished as such: Extrapolation Technique, End-Use Method, Scheer's Method, Stochastic Time Series, Iterative Reweighted Least-Squares Method, Adaptive Load Forecasting Method, Similar Day Approach, Exponential Smoothing Method, Multiple Regression, Knowledge-Based Expert

System, Fuzzy Logic Technique, Support Vector Machine, and Artificial Neural Networks (Alfares and Nazeeruddin, 2002; Vadhera 2004; Chakrabarti and Halder, 2008).

The uniqueness of the ANN method is that an ANN is an information processing system based on the operation of biological neural networks. In other words, it is an emulation of biological neural system (LANN.com, 2014). ANNs are among the newest signal processing technologies, appear to be the most popular approach to forecasting, and can be applied to incorporate certain area specific factors of power load, such as weather, economy, random disturbance, and time (Mishra, 2008; Sharma *et al.*, 2012). They have very wide applications because of their ability to learn.

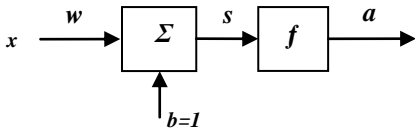
There are many types ANNs including multilayer perceptron network, self-organizing networks, etc. There may be one or more hidden layers in the network. In each hidden layer there are many processing elements called neurons. Inputs are multiplied by weights and are added to a threshold (bias) to form an inner product number called the net function. The net function NET is usually put through an activation function to produce the unit's final output.

Three basic components need to be considered when modeling an artificial neuron (AN) from the biological neuron, and they are *weights*, *linear combination*, and *activation function*. The synapse of the biological neuron is the one which interconnects the neural network and gives the strength of the connection. For an AN, the weight is a number, and represents the synapse. All inputs are summed altogether and modified by the weights; and this activity is referred as linear combination. Finally, an activation function controls the amplitude of the output. For example, an acceptable range of output is usually between 0 and 1, or it could be -1 and 1, depending on the function used (Anonymous, 2014). A model of an AN is as shown in Figure 2.

From this model the interval activity of the neuron is expressed mathematically as:

$$a = f(s) = f(wx + b) \quad (1)$$

where  $x$  is the input signal to the neuron,  $w$  is the weight assigned to the signal,  $b$  is external bias (usually 1),  $s$  is the net input argument,  $f$  is the activation function for the layer, and  $a$  is interval output of a neuron.



**Figure 2:** Graphical Model of an AN (MathWorks, 2009).

### **Operation of an ANN**

An ANN can function in either a training mode or a testing (forecasting) mode. The training mode employs any of the supervised learning, unsupervised learning, or reinforced learning processes. In a supervised learning process, input is presented to the neural network and a corresponding desired or target response is set at the output. An error is composed from the difference of the desired response and the real system output. The error information is fed back to the system which makes all adjustments to their parameters in a systematic fashion (commonly known as the learning rule). This process is repeated until the computed error is acceptable. The whole of this process is referred to as back propagation (BP) algorithm.

### **METHODOLOGY**

This study involves collecting model hourly-series data for the load center, applicable to load centers of the region when expressed in per unit terms, and modeling and training an artificial intelligence algorithm for hourly 24 hour-term load forecasting for the region and Nigerian systems in general.

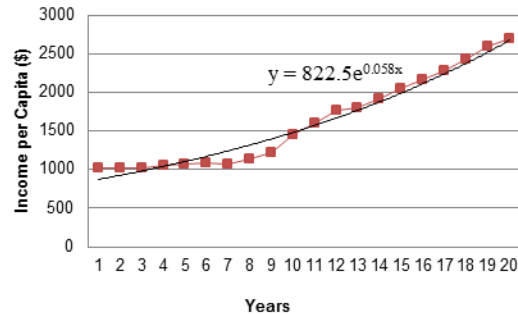
### **Research Data**

The data used for the research are historical load data, temperature data, per capita income data and, load category data. The load data used is the daily demand of electric power in Enugu Load Center, Nigeria, as contained in the Power Holding Company of Nigeria (PHCN), National Control Center, Osogbo daily hourly load reading sheet for the months of August, September, and October, 2012.

The temperature data used is daily maximum and minimum readings from the Nigerian Institute of

Meteorology (NIMET) Enugu, for the corresponding months of August, September and October, 2012.

Per capita income data also referred to as Gross Domestic Product (GDP) Per Capita is given on annual basis in dollars. Historical income per capita data as obtained from the International Monetary Fund (IMF, 2012) was used to carry out time series extrapolation using Excel software as shown in Figure 3.



**Figure 3:** Trend Curve of Income Per Capita from 1993 to 2012.

The trend equation was generated from the curve, and is given as:

$$y = 822.5e^{0.058x} \quad (2)$$

where  $x$  represents the time period in years.

In order to model approximate hourly income per capita in the data period, cumulative income per capita is assumed justifiably to increase from the beginning to the end of every year. This concept lead to the adoption of the forecast trend, adapted to hourly basis as follows:

$$x = 19 + T \quad (3)$$

where  $T$  is the fractional period of the 20<sup>th</sup> year, which represents the specific period of forecast.

$$T = \frac{N}{8784} \quad (4)$$

where  $N$  represents the specific hour of forecast, as a fraction of the total number of hours (i.e., 8784 hrs) of the year 2012 (i.e. 366 days).

Applying Equations 3 and 4 in Equation 2:

$$y = 822.5 e^{0.058(19 + \frac{N}{8784})} \quad (5)$$

Here the value of  $N$  ranges from 5113 to 7320 which represents number of hours from August to the end of October, 2012.

Equation 5 was implemented in MATLAB codes to generate the income per capita on hourly basis.

The category of load (load classes) was extracted from the PHCN energy billing schedule for Enugu load center. Assumptions were made hereby adopting the direct proportional relationship between energy and power as deduced from Equations 6 to 9.

$$\text{Energy, } E = IVt \quad (6)$$

$$\text{Power, } P = IV \quad (7)$$

Hence from Equations 6 and 7:

$$P = \frac{E}{t} = \left(\frac{1}{t}\right)E = kE \quad (8)$$

$$\text{Therefore, } P \propto E \quad (9)$$

where,  $I, V$  and  $T$  represent current, voltage and time, respectively.

The load categories were thus calculated in percentages of the total load. The hourly variations in power load for each category was adopted from typical load curves, and that was used to calculate the daily hourly load consumed by each of the four categories of load consumers. The categories were grouped into four namely, residential (average of 71.9% of the total load), commercial (average of 18.6% of the total load), industrial (average of 8% of the total load), and municipal load (average of 1.5% of the total load). In all, a total of 92 days (August, September, and October, 2012) data were utilized for the research.

### **Data Pre-Processing**

For the load data and temperature data, missing values and outlying values were corrected. Missing load data could have arisen due to earth faults, line to line faults, opening of feeder for maintenance, or even system breakdown. For such cases, load information for the same hour, weekday, and week of the preceding month was used to refill the missing values. For outlying/outrageous values which could have

come due to wrong measurement, corrections were made by replacing them with average of both the preceding and succeeding values in the series. The working data were subjected to an initial statistical analysis to determine some significant trends that could support a need for the proposed hourly forecasting. For this, average hourly load statistics, and daily temperature statistics were determined.

The whole of the working data was divided into two parts (i.e., the training set and the test set). Both were subjected to digital processing known as data mapping. Data mapping reduces the redundancy of data, i.e., it removes the part of the data that does not contribute much to the variation in the values of the working data, and results in a standardized feature of which the mean is 0 and the standard deviation is 1. This action is achieved using MATLAB function "mapstd" (MathWorks, 2009).

### **Network Modeling**

Several neural network models are available in the MATLAB neural network toolbox. Examples of such are: Custom Neural Network, Cascade-Forward BP Network, Elman BP Network, Feed-Forward BP Network, Feed-Forward Input-Delay BP Network, Hopfield Neural Network, etc. However the choice of neural network model is problem-dependent. Some models may perform well in a particular application while others may not. One other notable network model is the Layered-Recurrent Network (LRN), which is a modified version of Elman's model (Quaiyum *et al.*, 2011).

The LRN is a partial feedback network model in which the feedback is implemented within same layer. That is to say, the output of the hidden layer neurons is fed back into the input of the same hidden layer neurons. LRN, as earlier defined, was adopted for this research because it has a good performance in terms of learning, speed and memory conservation. The LRN has two layers: the hidden layer and the output layer.

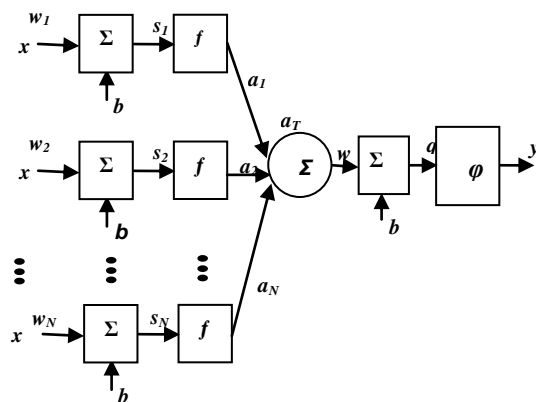
Networks with more than one hidden layer have been identified to be generally more complex and the network training more time-consuming. The number of neurons in the hidden layer must be carefully chosen; as too many neurons make the network overspecialized, leading to loss of generalizing capability. If there are not enough

hidden layer neurons, the network may find it difficult to learn the behavior of the series (Adepoju *et al.*, 2007).

However in this research, after experimenting with varying number of neurons ranging from 40 to 150, and fifty (50) neurons were finally utilized for the hidden layer. The output layer utilized only one neuron. The modeled network uses tan-sigmoid function and pure linear function respectively as the activation functions for the hidden layer and the output layer.

The input variables to the model were selected to be the previous day data and the previous week data. The rationale behind this was to capture the similar trend that usually accompanies the Nigerian power distribution system.

Figure 4 shows multiple neurons in parallel. The figure represents a two-layer neural network, in which the parallel neurons are the neurons in the first layer, while the last single series neuron is in the second layer.  $a_T$  would be the weighted sum of outputs of all the first layer neurons. The final output  $y$  which is from the second layer neuron would therefore be the outcome of some activation function  $\phi$  on the value of  $a_T$ .



**Figure 4:** Graphical Model of Artificial Parallel Neurons (Adopted from MathWorks, 2009).

The reading of the data into the applied ANN configuration in this study is as expressed in matrix algorithm:

Mathematically,

$$x_n = [p_{ij}, I_{ij}, T_{ij}, C_{ij}]; i = 1 \dots 78, j = 1 \dots 24 \quad (10)$$

where  $x_n$  is read input data for the  $n^{\text{th}}$  neuron,  $p_{ij}$  is active load (MW) for the  $i^{\text{th}}$  day and  $j^{\text{th}}$  hour,  $I_{ij}$  is the income per capita (\$) for the  $i^{\text{th}}$  day and  $j^{\text{th}}$  hour,  $T_{ij}$  is the temperature data ( $^{\circ}\text{C}$ ) for the  $i^{\text{th}}$  day and  $j^{\text{th}}$  hour,  $C_{ij}$  is the load category (% of the hourly peak load) for the corresponding periods,  $i$  is the number of days of the training data sets,  $j$  is number of hours of the day.  $x$  is read and the same at the input to each of the 50 neurons. The training input feature consists of a part known as the target set, which is used to teach the model how to respond to the input data during training.

The net input argument for the  $n^{\text{th}}$  neuron is:

$$s_n = w_n x_n + b \quad (11)$$

where  $w_n$  is the weight assigned to input data for  $n^{\text{th}}$  neuron,  $b$  is external bias (usually 1) used for triggering the activation function.

For the neuron, the tansig function will be:

$$a_n = f(s_n) = \tanh\left(\frac{s_n}{2}\right) = \frac{1 - e^{-(w_n x_n + b)}}{1 + e^{-(w_n x_n + b)}}; b = [1] \quad (12)$$

$$a_T = \sum_{n=1}^N a_n = \sum_{n=1}^N f(s_n) = \sum_{n=1}^N \frac{1 - e^{-(w_n x_n + b)}}{1 + e^{-(w_n x_n + b)}}; b = [1] \quad (13)$$

$$q = a_T w + b, b = [1] \quad (14)$$

$$y = \phi(q) = \phi(a_T w + b) \quad (15)$$

where  $a_n$  is the output of the  $n$ th neuron,  $b$  is external bias (usually 1),  $\Sigma$  is the summation function,  $s$  is the net input argument,  $f$  is a tan sigmoid activation function for the first layer  $a_T$  is the weighted sum of output of neurons in the first layer,  $w$  is the weight assigned to the signal in the output layer,  $q$  is the net input argument to the output layer,  $\phi$  is the linear activation function for the second layer; and  $y$  is the output of the second layer.

### Model Training

The model was trained using conjugate gradient BP algorithm with Fletcher-Reeves Restart. Back-propagation algorithm is the basis for training supervised artificial neural networks (Yi, 2008). The algorithm consists of a forward and backward

passes. The data used as inputs (training set) are transmitted through the network, layer by layer, and up to the output layer where a set of outputs is obtained.

During this first forward pass, the weights of the network are set. The outputs obtained are compared with the desired output (target) values, and the difference is computed as error. This error is then propagated backwards moving from layer to layer in a direction opposite to the way activities propagate through the network. This is what gives BP its name. The calculated error being propagated backwards is then used to adjust the synaptic weights of the network in order to reduce the level of error in subsequent passes (Yi, *et al.*, 2008).

This process is called error back back-propagation training algorithm. This whole process is an iterative process, which continues until acceptable level of errors is obtained. Each time the network processes the whole set of data (both a forward and a backward pass) is called an **epoch**. The network is in this way trained and the error is reduced by every epoch until an acceptable level of error is gained.

The performance of the model was analyzed by investigating the error between the forecast values and the target values. This was achieved by using a generally accepted error assessment parameter known as the mean squared error (MSE), which is expressed mathematically as:

$$MSE = \frac{1}{N} \sum_{i=1}^N [P_F(i) - P_A(i)]^2 \quad (16)$$

where  $P_F(i)$ ,  $P_A(i)$ , and  $N$  denote forecasted load at  $i^{th}$  hour, actual load for the same hour  $i$ , and total number of hours, respectively.

Finally, keeping all other parameters constant, the model was also trained with load data alone and the performance was compared.

## RESULTS

The graphical results of the initial statistical analysis carried out on the working data of Enugu are shown in Figures 3, 5, 6, 7, and 8.

Figure 3 shows the income per capita trend curve from which the hourly income per capita was

forecasted. The trend equation depicts an exponential series.

Figure 5 shows the load curves of Enugu load center for the months of August, September and October respectively. The curves show variations of the hourly load values across the months, which support the need for 24-Hour load prediction for the studied system. Further, it is noted that each curve is characterized by double peak: first peak in the morning (between 7 A.M and 8 A.M), and the second peak in the night (between 8 P.M and 9 P.M). The evening peak is higher than the morning peak. The morning peak time can be attributed to the high demand of electric power as domestic, industrial and commercial activities commence, while the evening peak can also be attributed to domestic, industrial, and high evening social activities predominant in the region.

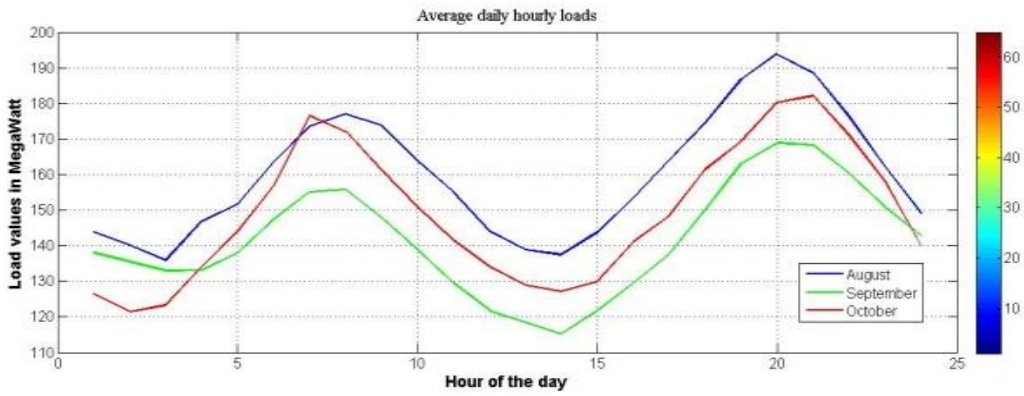
Figure 6 shows the average daily hourly load profiles for the prevalent categories of load consumers. This profile indicates a predominance of residential load for the whole period

Figure 7 shows the variability of the hourly load values. From the figure, the coefficient of variation lies between 0.12 (12%) to 0.21 (21%). This further establishes the significance of a 24-Hour forecast for power distribution operations and management for the studied system.

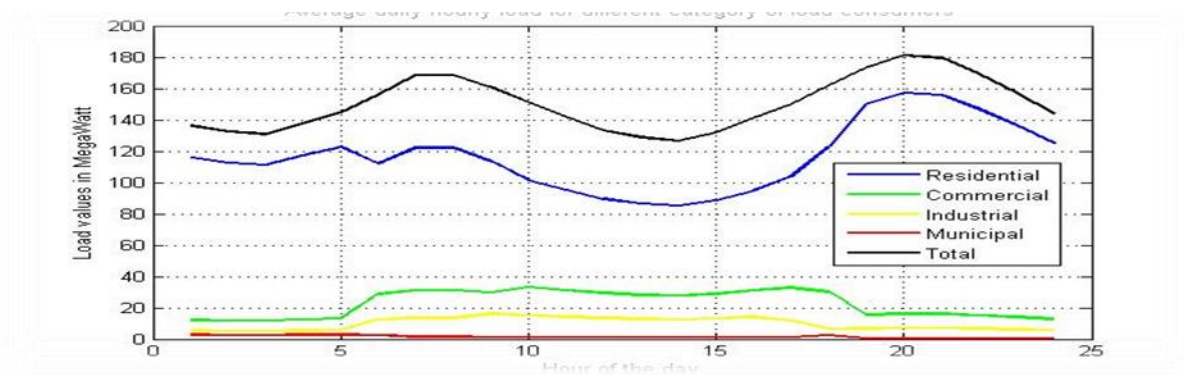
Figure 8 shows the daily maximum and minimum temperature values for the load region averaged over the duration of the working data sample. It shows significant variation in the maximum and the minimum values for each day.

Table 1 and Figure 9 show the tested network architectures and their performances measured in terms of MSE. From the table, it can be seen that the model architecture that gave optimal performance in terms of forecast error is **50-1** architecture (i.e., a two layered ANN model with 50 neurons in the hidden layer/ input layer and a single neuron in the output layer).

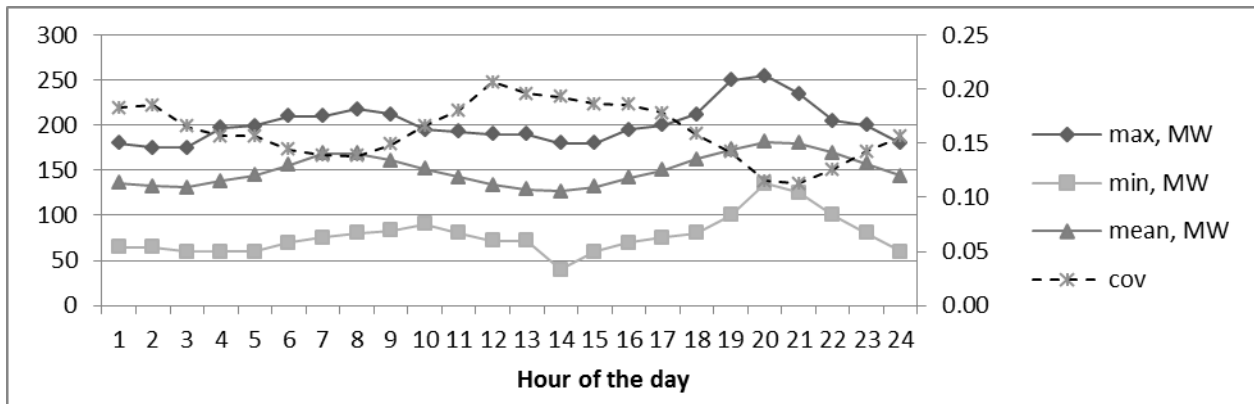
It can be observed from table that increasing or decreasing the number of neurons in the layer by few neurons about the optimal point, does not necessarily affect the model performance significantly when rounded to the nearest decimal point.



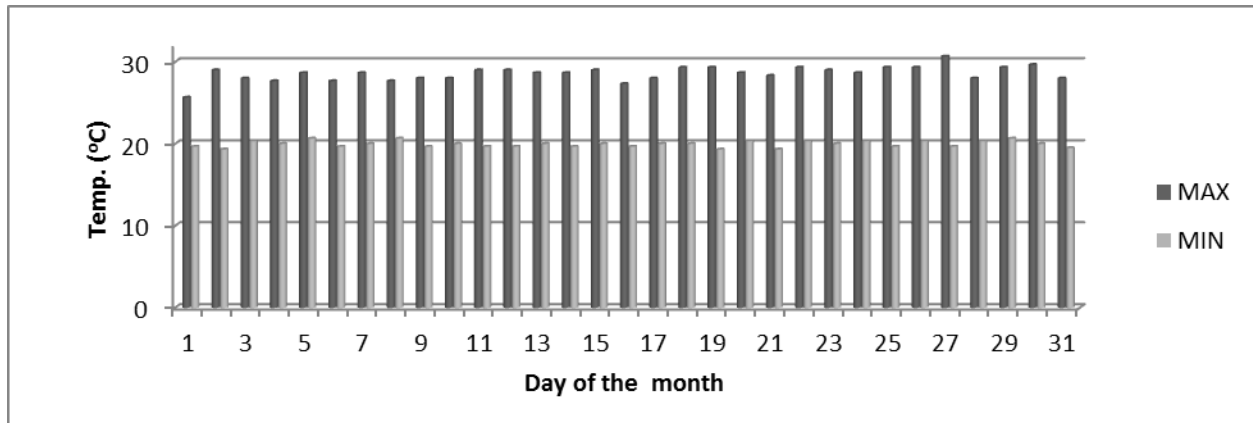
**Figure 5:** Average Hourly Load in a Day for August, September, and October Months.



**Figure 6:** Average Daily Hourly Loads for Different Categories of Load Consumers.



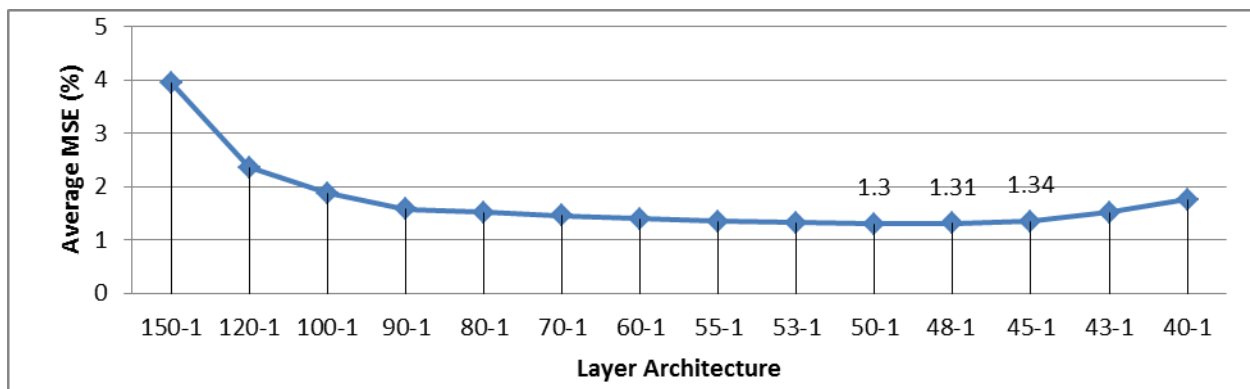
**Figure 7:** Hourly Statistics of Load Values for the System.



**Figure 8:** Daily Values of Temperature Data for the Region.

**Table 1:** Tested Network Architecture and their Performances in terms of MSE.

Layer architecture	MSE (%) on Test Sets							Average MSE
	1	2	3	4	5	6	7	
150-1	4.12	3.43	4.11	4.02	4.00	3.95	3.99	3.95
120-1	2.79	1.97	2.70	2.48	2.33	2.10	2.12	2.36
100-1	2.30	1.69	2.42	1.03	2.01	1.83	1.87	1.88
90-1	2.04	1.30	2.06	0.77	1.80	1.52	1.58	1.58
80-1	1.91	1.26	1.98	0.73	1.74	1.47	1.55	1.52
70-1	1.84	1.13	1.95	0.69	1.67	1.43	1.50	1.45
60-1	1.73	1.01	1.92	0.66	1.60	1.40	1.46	1.39
55-1	1.66	0.95	1.86	0.64	1.54	1.32	1.42	1.34
53-1	1.64	0.93	1.83	0.62	1.53	1.29	1.40	1.32
50-1	1.66	0.90	1.82	0.59	1.53	1.25	1.38	1.30
48-1	1.67	0.90	1.83	0.59	1.54	1.26	1.38	1.31
45-1	1.69	0.94	1.85	0.62	1.57	1.28	1.40	1.34
43-1	1.80	1.03	1.91	0.88	1.80	1.51	1.72	1.52
40-1	2.10	1.33	2.06	1.11	2.02	1.83	1.90	1.76



**Figure 9:** Performance of Various Tested Architectures in Terms of the MSE (%).



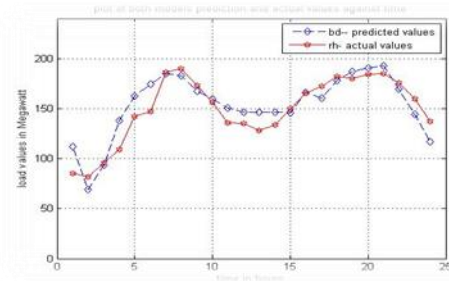
It was also observed that some of the non-optimal layer architectures could give the same values of forecasting errors with respect to each other. This can be seen in the case of 80-1 and 43-1 architectures which gave the same forecasting error of 1.52% for this model. This occurrence is of course of little relevance in this study since only the optimal architecture is applied. Figure 9 shows that average MSE curve has its lowest value (i.e. 1.30%) at 50-1 architecture, thus establishing this particular architecture as optimal.

Figures 10a to 16b show the obtained actual and forecasts of daily load variation from the trained ANN model using a new set of data of historical load together with temperature, income per capita, and load category that never participated in the training process as input. The test was done on the new set of data over one week period. The MSE (%) values between the 'forecast' and the 'target' load values are indicated in the captions of the figures and also summarized in Table 2.

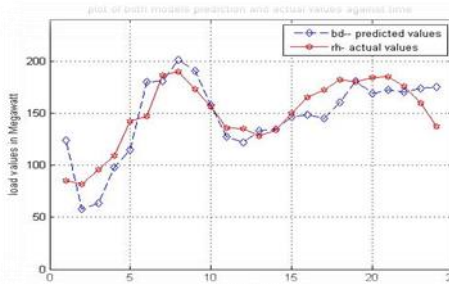
Table 2 shows that the proposed ANN model displayed higher forecasting error in the days when people have specific start-up activities such as Mondays and Thursdays, and variant activities such as Saturdays. The above translate to greater deviation about the minimum demand point.

In general, the error values in the forecast translate to an average error of **1.30%** for the network model trained with historical load data together with other variables (weather, econometric, and load category), and **2.66%** for the model trained with historical load data alone. From results of the model trained with multiple variables, an improvement of **1.36%** in the forecasted results was obtained. This stands for a high degree of forecasting accuracy for this model considering the simplicity of the network architecture, and the complex nature of the input variables.

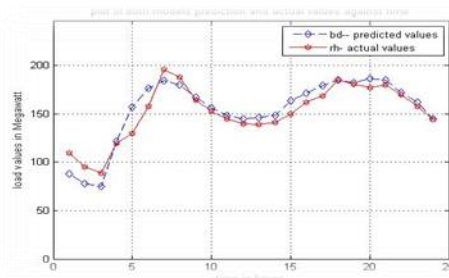
It might be important to note that forecasting errors reported for various ANN load forecasting models in some literatures are in the wide range of 12.8% - 1.18%. With an accuracy of 1.30% and 2.66% respectively, the model presented in this research is reliable, more so when the environments and applied study objects in some other studies reported in literature are different and single factor based.



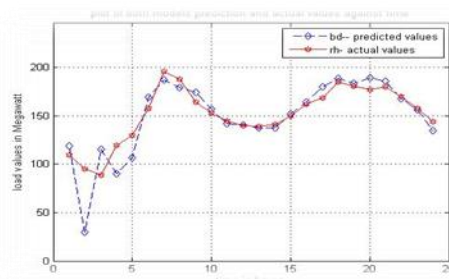
**Figure 10a:** Test Result for Thursday, 25<sup>th</sup> October, 2012 (with factors; MSE = 1.66%).



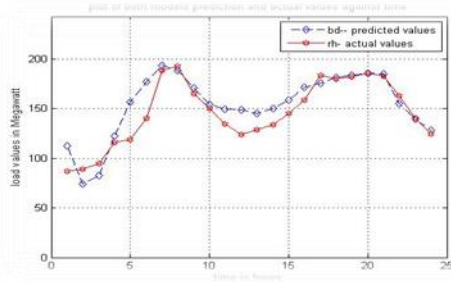
**Figure 10b:** Test Result for Thursday, 25<sup>th</sup> October, 2012 (without factors; and MSE = 2.85%).



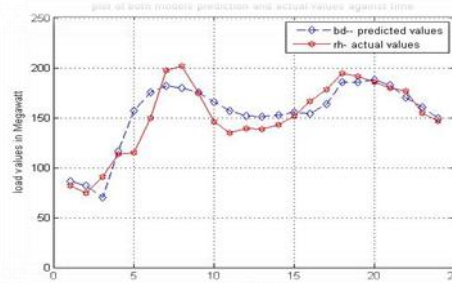
**Figure 11a:** Test Result for Friday, 26<sup>th</sup> October, 2012 (with factors; and MSE = 0.90%).



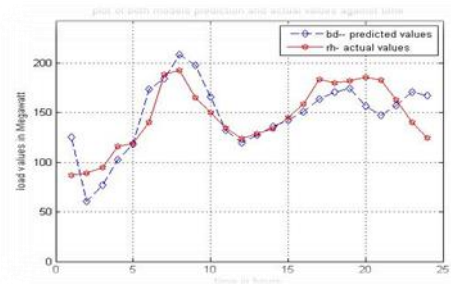
**Figure 11b:** Test Result for Friday, 26<sup>th</sup> October, 2012 (without factors; and MSE = 2.29%).



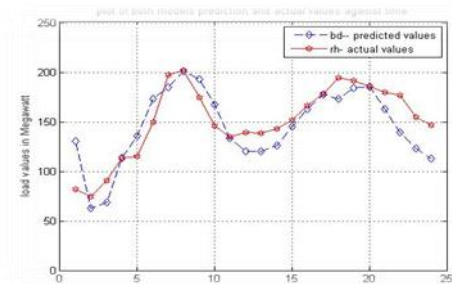
**Figure 12a:** Test Result for Saturday, 27<sup>th</sup> October, 2012 (with factors; and MSE = 1.82%).



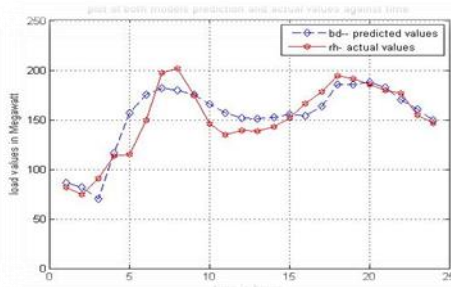
**Figure 14a:** Test Result for Monday, 29<sup>th</sup> October, 2012 (with factors; and MSE = 1.53%).



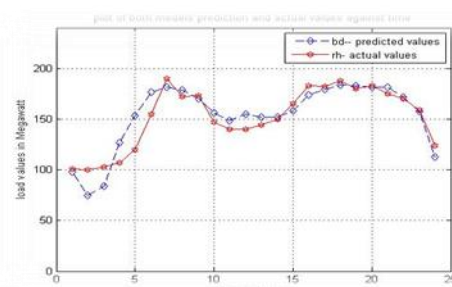
**Figure 12b:** Test Result for Saturday, 27<sup>th</sup> October, 2012 (without factors; and MSE = 2.95%).



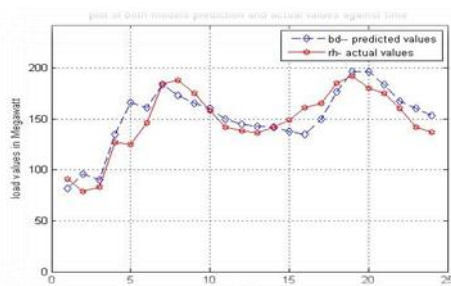
**Figure 14b:** Test Result for Monday, 29<sup>th</sup> October, 2012 (without factors; and MSE = 3.11%).



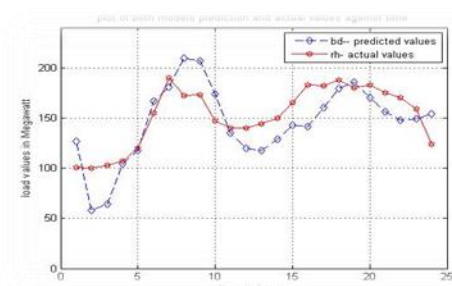
**Figure 13a:** Test Result for Sunday, 28<sup>th</sup> October, 2012 (with factors; and MSE = 0.59%).



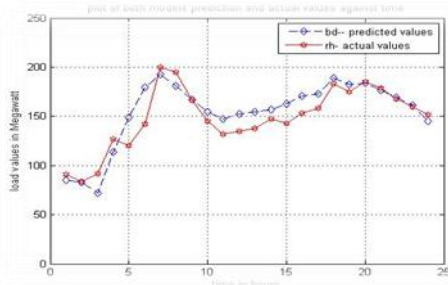
**Figure 15a:** Test Result for Tuesday, 30<sup>th</sup> October, 2012 (with factors; and MSE = 1.25%).



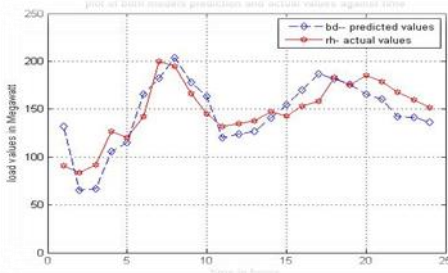
**Figure 13b:** Test Result for Sunday, 28<sup>th</sup> October, 2012 (without factors; and MSE = 1.89%).



**Figure 15b:** Test Result for Tuesday, 30<sup>th</sup> October, 2012 (without factors; and MSE = 3.22%).



**Figure 16a:** Test Result for Wednesday, 31<sup>th</sup> October, 2012 (with factors; and MSE = 1.38%).



**Figure 16b:** Test Result for Wednesday, 31<sup>th</sup> October, 2012 (without factors; and MSE = 2.32%).

**Table 2:** MSE Measure of Forecast.

Test day	MSE(%) on Load data	
	with factors	without factors
Thursday, 25 <sup>th</sup> October	1.66	2.85
Friday, 26 <sup>th</sup> October	0.90	2.29
Saturday, 27 <sup>th</sup> October	1.82	2.95
Sunday, 28 <sup>th</sup> October	0.59	1.89
Monday, 29 <sup>th</sup> October	1.53	3.11
Tuesday, 30 <sup>th</sup> October	1.25	3.22
Wednesday, 31 <sup>st</sup> October	1.38	2.32
Average	1.30	2.66

## CONCLUSION

This study has been able to establish the possibility of applying artificial intelligence network or ANN to provide hourly power load for a 24-Hour forecast period for Enugu Load Center and for other load centers in the region. The level of forecast accuracy, measured in MSE term, gives insignificant error values in the range 0.59% - 1.82% for the forecast trials.

The results obtained in this study shows that incorporating weather information, econometric and costumer class information into the load

forecasting model can help to capture a better representative forecast. Also from the results of this research, it can be seen that artificial neural networks can be applied in short-term electric power load forecasting in the Nigerian power system, with high degree of efficiency.

## RECOMMENDATION

The ANN structure, configured and implemented in this study can and should be applied for daily load scheduling or planning for optimal application of resources in Nigerian systems, which are currently in dire need of providing standard reliability value of service. Further, the load curve models obtained from training the ANN model, using only historical hourly load series, are useful for optimal load management in the Enugu load center. Although the model proposed in the this study utilized available three months data for both its training and testing, it is suggested that future ANN training can incorporate a much larger dataset in order to improve the forecast output. Electric utility companies should adopt the use of ANN based short-term load forecasting models as one of the robust methods for daily load prediction.

Even though this research incorporates weather information, customer class, and econometric factors into the model in order to obtain a better representative forecast; it is recommended that further research should be carried out to determine the individual contribution of the above mentioned factors to the model forecasting accuracy. Also, it is suggested that only seasonal data should be used in training the ANN model in order to reduce error due to seasonal variations in weather.

## REFERENCES

1. Adepoju, G.A., S.O.A. Ogunjuyigbe, and K.O. Alawode. 2007. "Application of Neural Network to Load Forecasting in Nigerian Electric Power System". *The Pacific Journal of Science and Technology*, 8(1):68-72.
2. Alfares, H.K. and M. Nazeeruddin. 2002. "Electric Load Forecasting: Literature Survey and Classification of Methods". *International Journal of System Science*, 33(1):23-34.
3. LearnArtificialNeuralNetworks.com. (LANN.com) 2014. "Introduction to Neural Networks".

[www.learnartificialneuralnetworks.com/introduction-to-neural-networks.html](http://www.learnartificialneuralnetworks.com/introduction-to-neural-networks.html) (site accessed on February 3, 2014).

4. Buhari, M. and S.S. Adamu. 2012. "Short-Term Load Forecasting Using Artificial Neural Network". *Proceedings of the International Multi-conference of Engineers and Scientists*.1:1-6.
5. Chakrabarti, A. and S. Halder. 2008. *Power System Analysis, Operation and Control*. 2nd Edition. PHI Learning Private Ltd.: New Delhi, India.
6. Damborg, M.J., M.A. El-Sharkawi, M.E. Aggoune, and R.J. Marks. 1990. "Potential of Artificial Neural Network to Power Systems Operation". *Proceedings of the IEEE International Symposium on Circuits and Systems*. New Orleans, LA. 2933-2937.
7. Feinberg, E.A., J.T. Hajagos, and D. Genethliou. 2003. "Statistical Load Modelling". *Proceedings of the 7th IASTED International Conference on Power and Energy Systems*. Palm Springs, CA. 88-99.
8. Hsu, C.C. and C.Y. Chen. 2003. "Regional Load Forecasting in Taiwan". *Applications of Artificial Neural Networks. Energy Conversion and Management*. 44:1941-1949.
9. International Monetary Fund. 2013. "Nigeria Gross Domestic Product Based on Purchasing-Power-Parity (PPP) Per Capita". *Publication on World Economic Outlook*. [http://www.indexmundi.com/nigeria/gdp\\_per\\_capita\\_\(ppp\).html](http://www.indexmundi.com/nigeria/gdp_per_capita_(ppp).html)
10. Mishra, S. 2008. "Short Term Load Forecasting using Computational Intelligence Methods". Masters Thesis. Department of Electronics and Communication Engineering, National Institute of Technology: Rourkela, India. 89 pp.
11. Nweke, E.F. 2012. "Electric Power Forecasting in the Nigerian Power System Using Artificial Neural Network (ANN) Technique". M.Eng. Thesis Report (unpublished), Department of Electrical Engineering, University of Nigeria. 80 pp.
12. Quaiyum, S., Y.I. Khan, S. Rahman, and P. Barman. 2011. "Artificial Neural Network Based Short-Term Load Forecasting of Power System". *International Journal of Computer Applications*. 30(4):0975-8887.
13. Sarangi, P.K., N. Singh, R.K. Chanhana, and R. Singh. 2009. "Short-Term Load Forecasting Using ANN: A Comparison with Genetic Algorithm Implementation". *Asian Research Publishing Network (ARP) Journal of Engineering and Applied Sciences*. 4 (9).
14. Sharma, L., M. Chakrawarti, A. Dutta, and N. Adhikari. 2012. "Neural Network Based Approach

for Short-Term Load Forecasting". *International Journal of Science, Environment and Technology*. 1(5):416 – 424.

15. MathWorks, Inc., 2009. "Neural Network Toolbox". <http://www.mathworks.com>
16. Vadhera, S.S. 2004. *Power System Analysis and Stability*. Khana Publishers: Naisarak, Delhi, India.
17. Yi, M.M., K.S. Linn, and M. Kyaw. 2008. "Implementation of Neural Network Based Electricity Load Forecasting". *World Academy of Science, Engineering and Technology*. 42.

## SUGGESTED CITATION

Ikaraocha, C.O. and A.O. Melodi. 2014. "Multifactorial Short-Term Load forecasting for Enugu Load center using Artificial Neural Network Concept". *Pacific Journal of Science and Technology*. 16(1):38-49.

