

Short Term Load Forecasting Using Artificial Neural Network Technique: Case Study of Choba Community in Rivers State, Nigeria

Engr. Esobinenwu Chizindu Stanley

Lecturer, Department of Electrical/Electronics Engineering, University of Port Harcourt, Nigeria

Abstract-- The importance of Load forecast towards the development of a nation cannot be overemphasized. It has become in recent years one of the major areas of research in electrical engineering. Most traditional forecasting models and artificial intelligence neural network techniques have been employed in this task. Artificial Neural Networks (ANN) have lately received much attention, and a reasonable number of researchers have reported success in experimenting this model with Multi-Layer Perception (MLP). This paper presents the development of an ANN-based short-term load forecasting model with improved accuracy for the Regional Power Control Centre of Choba Community which include the three campuses in University of Port-Harcourt, Choba, Rivers State of Nigeria. The proposed ANN is trained with special events indexes and historical electric load-related data using the data from the calendar years of February, 2016 for training. Different neural networks topologies have been trained and tested for achieve the optimal topology and ranking the input variables in terms of their importance. Based on the optimal neural network topology, the network has been trained with Back Propagation (BP) to predict ahead load at different time intervals.

Keywords-- Artificial Neural Networks (ANN), short-term load forecasting, Back Propagation (BP), Multi-Layer Perception (MLP).

I. BACKGROUND OF THE STUDY

The load growth of the geographical area served by a utility company is the most important factor influencing the expansion of the distribution system. Therefore forecasting of load increases and system reaction to these increases is essential to the planning process.

Electrical energy is a variable in which many factors affect its capacity. Load prediction is a complex procedure because of the nature of the influencing factors—weather factors, seasonal factors and social-economic factors. An electricity utility also can use forecasts in making important decisions related to purchasing and generating electric power, load switching and investing in infrastructure development. Also, energy suppliers, financial institutions and other “players” in the electric energy generation and distribution markets can benefit from reliable load forecasting.

Load forecasting has become in recent years one of the major areas of research in electrical engineering. Load forecasting is however a difficult task. First, because the load series is complex and exhibits several levels of seasonality. Second, the load at a given hour is dependent not only on the load at the previous day, but also on the load at the same hour on the previous day and previous week, and because there are many important exogenous variables that must be considered (Hippert et al 2001). Load forecasting plays an important role in power system planning and operation. Basic operating functions such as unit commitment, economic dispatch, fuel scheduling and

unit maintenance, can be performed efficiently with an accurate forecast (Alsayegh (2003), Senjyu (2002) and Baklrtzis (1996).

The need for accurate load forecasts will increase in the future because of the dramatic changes occurring in the structure of the utility industry due to deregulation and competition. This environment compels the utilities to operate at the highest possible efficiency, which, as indicated above, requires accurate load forecasts.

For decades the problem of improving the accuracy of load forecasts has been an important topic of research. Various types of load forecasting methodologies have their own advantages. Load forecasting can be performed using many techniques such as regression analysis, statistical methods, artificial neural networks, genetic algorithm, fuzzy logic etc.

II. LITERATURE REVIEW

Forecasting is a means of predicting what is going to happen in the future; next hour, day, month, year and decade, etc. Accurate forecasting requires high quality data, application of the appropriate forecasting technique and knowledgeable interpretation. The accuracy of such forecasts depends in large measure on the degree to which the past is a good guide to the future (Labruno and Taylor, 2001). In view of the on-going reform process, with associated unbundling of electricity supply services, tariff reforms and rising role of the private sector, a realistic assessment assumes greater importance. Utility companies must forecast demand for a long period (10-20 years). They also need to make plans to construct facilities and begin development well before the indices of forecast growth reverse or slow-down (Bansal and Pandey, 2005). The Electrical load forecast requires the determination of the future load requirement in a given power system.

Load forecast also play an important role in identifying the categories to be subsidized (Cancelo and Espasa, 1991). This involves the study of the past electrical power consumption in the power system as the basis to predict the future requirement. Such studies can be grouped into short term, medium term and long term depending on the number of years in the study. Short-term forecasts which are usually from one hour to one week and medium forecasts are usually from a week to year while long-term forecasts are longer than a year (Idoniboyeobu and Odubo, 2010). There are various methods of forecasting, the predictive and the explanatory, the predictive models attempt to determine what is going to happen in the future while explanatory models attempt to explain a situation based upon empirical evidence.

With the worldwide deregulation of the power industry, load forecasting is becoming even more important, not only for system operators, but also for market operators, transmission owners, and any other market participants, so that adequate energy transactions can be scheduled, and appropriate operational plans and bidding strategies can be established.

Thus, load forecasting has also become an important component of energy brokerage systems Slutsker. et al (1998)

A. Brief Outlook Of Electricity Generation In Nigeria And Planned Scenarios

The first electricity generation in Nigeria happened during the pre-colonial era in the then Lagos colony. Low capacity generating sets were used to supply electric power to the premises of the then colonial masters. Later, Electricity Corporation of Nigeria (ECN) was established through an act of parliament in 1951. Subsequently, intention to exploit hydropower potential of the country brought about the establishment of Niger Dams Authority (NDA). In 1972, NDA and ECN were amalgamated to form the National Electric power Authority (NEPA). Electric power sector reform of 2005 brought a change of name to the utility company, Power Holding Company of Nigeria (PHCN). The sole objective being that the government intends to revamp the already dying sector for improved efficiency, then privatization of the sector was

then considered a viable way-out in the reform agenda. This goal is to be realized through the participation of independent power producers (IPPs). Through this IPPs projects more plan of actions towards increasing electricity generation in the country is expected to be sustained. For example, Agip has planned a 450MW power plant capacity in Kwale in the Niger delta region. On the same track under the IPPs are 276MW by Siemens, 700MW Afam power plant, ABBs plant (450MW), Sapele plant (451MW) and Chinas EXIM Bank Su Zhong and Sino Hydro planning for the development of Mambilla (3,900MW) and Zungeru (950MW). Currently, Chevron is entrusting fund for the development of 780MW, Egbema (338MW), Omoku (230MW) and Caliber (561MW). Many other planned and ongoing means of expanding power supply in the country are still being discussed for sustainability. Today, more IPPs are being granted license for generating power in the country. With all these accomplishments, there is likelihood that future energy demand in the country could be met

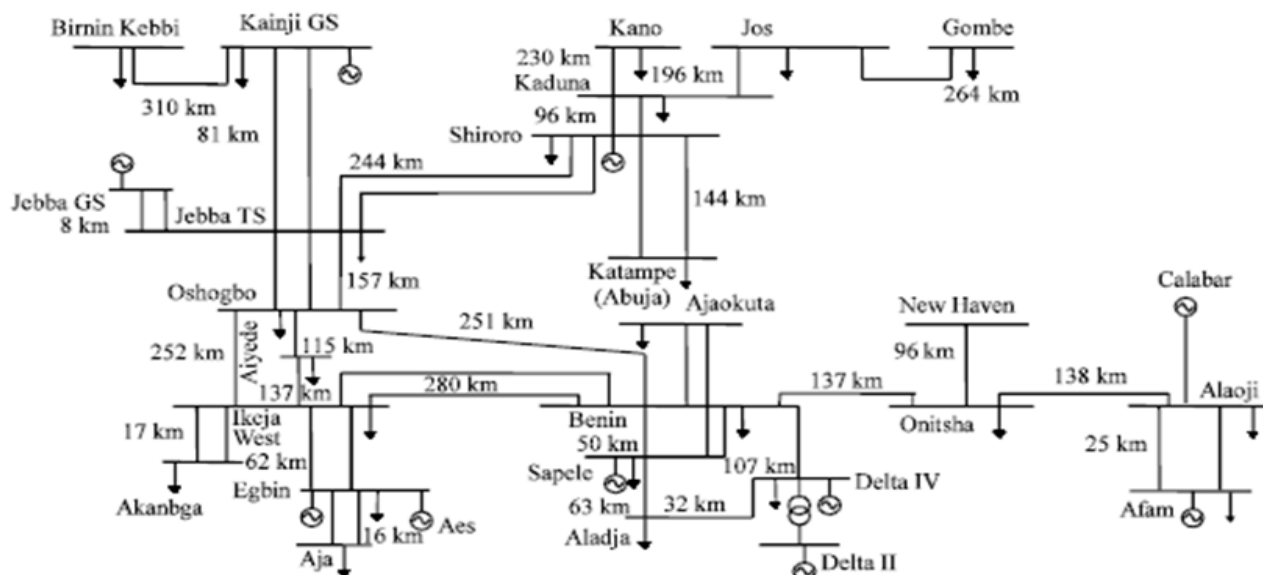


Figure 1: One-line diagram of Nigerian 330KV grid (Emmanuel, et al 2016)

B. Method Of Forecasting

There are basically three methods of load forecast which include:

a. Short-Term Load Forecasting (STLF)

This is basically aimed at predicting system load with a leading time of one hour to seven days, which is necessary for adequate scheduling and operation of power systems. STLF traditionally has been an essential component of Energy Management Systems (EMS) as it provides the input data for load flow and contingency analysis. Chen (1996) and Papalexopoulos (1994).

Various forecasting techniques have been applied to STLF to improve accuracy and efficiency. In general, STLF techniques can be classified as either traditional or modern.

1. Traditional Statistical Load Forecasting Techniques

These techniques which comprises regression, time series, pattern recognition, Kalman filters, etc., have been used in practice for a long time, showing the forecasting accuracy that is system dependent. These traditional methods can be combined using weighted multi-model forecasting techniques, showing adequate results in practical systems. However, these methods cannot properly represent the complex nonlinear relationships that exist between the load and a series of factors

that influence it, which are typically dependent on system changes (e.g., season or time of day).

2. Modern Load Forecasting Techniques

These methods includes expert systems, Artificial Neural Networks (ANN) (Dash et al 1997 and Vermaak et al 1998), fuzzy logic, wavelets, have been developed recently, showing encouraging results. Among them, ANN methods are particularly attractive, as they have the ability to handle the nonlinear relationships between load and the factors affecting it directly from historical data and without having to select a given model. Different types of ANNs have been applied to STLF; for example, multilayer feed-forward with one hidden layer (Lu et al 1993), recurrent, and functional links (Vermaak et al 1998). In this paper, the more common multi-layer feed-forward ANN is used for STLF

b. Long-Term Load Forecast

For period covering seven years and above. This is used in the planning of investment in generating capacity and the development of fuel supplies. The importance of accurate forecasts in planning is that it ensures the availability of supply of electricity, as well as providing the means of avoiding over and under-utilization of generating capacity and making the

best possible use of capacity. Errors in forecasting can lead to bad planning which can be costly (A.O Ibe, 2002).

Also according to (Ibe A.O), forecasting future demand is not an isolated activity. It has to reflect the role of electric energy in the society. Government policy is also a very important factor. Unfortunately precise forecasting is impossible. And to tie the future plans too rigidly to a single projection or forecast, no matter how sophisticated, is to risk making costly mistakes. When all these factors are taken into future account one will realize that the emphasis of planning should shift from making an accurate forecast to constructing a system that can adapt readily to change.

C. Neural Network

The Neural Network was designed and introduced by two scientists namely Pitts W and McCulloch E.S, in the year 1943. The Neural Network was also designed alongside its mathematical model, which is known as MP model. The construction model of the network, alongside the neuron's formalization mechanics and the method of constructing the network. They also confirmed that a neuron can activate the function logically, thus the research of the new Neural Network time can be started. The discovery of Neural Network can be dissected into three steps. The first step is derived from the MP method designed in the year 1960. Thus, this first stage has an aim of conforming the learning algorithm and then the production of the Neural Network. In the course of designing, people experienced much difficulties that emanated from overlapping limit of electronic circuit which causes the Neural Network to ascend into a low ebb duration starting from 1980s. This makes Neural Network theory to be in a good period. Neural Network does have so many network methods that are marginal, active, and cross subject. In health, control, electricity demand forecasting, the application of Neural Network has been highly adopted.

According to the authors Thangaraj C and Kannan S, they stated that in from the year 1990, forecasting of electric energy has been utilised through the concept of Neural Network. Thus, Neural Network are not linear but they have the ability to tackle unlinear curves or fitting although the outputs sometimes linear and sometimes not linear. The inputs used in Neural Network may sometimes become the output of other network models. The Network elements set in a smaller number of interconnected stages of elements that exist either from the input and the output (Cho M.Y).

In applying a neural network to electric load forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bidirectional or unidirectional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally. Back propagation thus is mainly the best recognized Neural Network method for the prediction of electric energy. Supervised learning is been adopted by the Back propagation and also it makes use of functions that are recognized continuously. The inputs can be found by joining historical data that were matched to the input by the actual weight which were calculated under supervised learning to the outputs when the system was under training. If the Neural Network has no supervised learning system, the Artificial Neural Network does not in any way need to apply preoperational training.

a. Properties of Neural Network

The back propagation algorithm is the most commonly used ANN learning technique. It is appropriate for problems with the following characteristics (Mitchell, 1997):

1. Instances are represented by many value pairs. The target function to be learned is defined over instances that can be described by a vector of predefined features, such as the pixel values. These input attributes may be highly correlated or independent of one another. Input values can be any real values.
2. The target function output may be discrete-valued, real-valued, or a vector of several real- or discrete-valued attributes.
3. The training examples may contain errors. ANN learning methods are quite robust to noise in the training data.
4. Long training times are acceptable. Network training algorithms typically require longer training times than, say, decision tree learning algorithms. Training times can range from a few seconds to many hours, depending on factors such as the number of weights in the network, the number of training examples considered, and the settings of various learning algorithm parameters.
5. Fast evaluation of the learning target function may be required. Although ANN learning times are relatively long, evaluating the learning network, in order to apply it to a subsequent instance, is typically very fast.
6. The ability of humans to understand the learning target function is not important. The weights learned by neural networks are often difficult for humans to interpret. Learned neural networks are less easily communicated to humans than learned rules.

D. Some Related Works On Load Forecast

Orie et al presented a Short-term load forecast using Artificial Neural Network (ANN) method and applied it to Secretariat's 33KV feeder in Port Harcourt Metropolis electric power system. This predicts future load one hour in advance for 24 hours using past load readings data over the years, obtained from Port Harcourt Electricity Distribution Company (PHEDC) zonal office for the month of March and June 2015. The main stages include pre-processing of past data sets, network training and forecasting. The proposed Artificial neural network is composed of 3 layers: an input, a hidden, and an output layer consisting of six (6) and one (1) neuron in the input and output layers respectively, while that of the hidden layer vary for the different performance of the network, Levenberg- Marquardt (TRAINLM) training algorithm was used for the training process and a Mean squared error and Root mean squared error of 0.39% and 0.63% respectively were obtained when the trained neural network was tested on a week's data

George et al proposed a new hybrid model, a combination of the manifold learning Principal Components (PC) technique and the traditional multiple regression (PC-regression), for short and medium-term forecasting of daily, aggregated, day-ahead, electricity system-wide load in the Greek Electricity Market for the period 2004–2014. PC-regression is shown to effectively capture the intraday, intraweek and annual patterns of load. they compare their model with a number of classical statistical approaches (Holt-Winters exponential smoothing of its generalizations Error-Trend-Seasonal, ETS models, the Seasonal Autoregressive Moving Average with exogenous variables, Seasonal Autoregressive Integrated Moving Average with exogenous (SARIMAX) model as well as with the more sophisticated artificial intelligence models, Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Using

a number of criteria for measuring the quality of the generated in-and out-of-sample forecasts

Bakirtzis et al. developed an ANN based model for the Energy Control Center of the Greek Public Power Corporation. In the development they used a fully connected three-layer feed forward ANN and back propagation algorithm was used for training. Input variables include historical hourly load data, temperature, and the day of the week. The model can forecast load profiles from one to seven days.

Papalexopoulos et al. developed and implemented a multilayered feed forward ANN for system load forecasting. In the model three types of variables were used as inputs to the neural network: season related inputs, weather related inputs, and historical loads.

Khotanzad et al. described a load forecasting system known as ANNSTLF. ANNSTLF is based on multiple ANN strategies that capture various trends in the data. In the development they used a multilayer perceptron trained with the error back propagation algorithm. An improvement of the above system was described in (Papalexopoulos et al). In the new generation, ANNSTLF includes two ANN forecasters, one predicts the base load and the other forecasts the change in load. The final forecast is computed by an adaptive combination of these forecasts. The effects of humidity and wind speed are considered through a linear transformation of temperature. As reported, ANNSTLF was being used by 35 utilities across the USA and Canada.

Chen et al. developed a three layer fully connected feed forward neural network and the back propagation algorithm was used as the training method. Their ANN though considers the electricity price as one of the main characteristics of the system load. Many published studies use artificial neural networks in conjunction with other forecasting techniques such as with regression trees (Douglas J. Leoth).

Mohammed and Bodger, (2006) in their work, they used their country New Zealand and predicted the energy consumption demand and thus compared the efficiency of the three methods which were put in place to achieve or determine the accurate model for their energy consumption. The three methods or techniques adopted in this work involves the Linear Regression Method, the Systemised Logistic Method and finally the System Arima Method. Mohammed and Bodger, when using the Systemised Logistic method, they didn't involve or entertain many variables that are entertained which were required for the improvement of the forecasting factors which will predict or forecast the energy consumption. For Logistic model

$$F = fx + \exp(Co + C1t)$$

where; fx means that the function value is thus saturated, F in the equation means data consumed per annum, t means the time set, where as C1 and Co are the system constants. Mohammed and Bodger explained in their work that the method may lead to low values of consumption. Later they also commended the System Arima method.

Arima method is another system recognised method and the French man Jenkins introduced it in the year 1970. This system was recognised in many areas of time series load prediction. The method has a disadvantage which was that it has to be used only for short term energy prediction. The equation is shown below;

$$Kt = x + O1e^{-T-1} + O2e^{-T} + \dots + Ohe^{-T-q} + e^{-T}$$

The method was later abandoned because it wouldn't give correct and complete load prediction.

Martin Heidl and John V. Ringwood (2004), shows that when demographic and economic factors are taken into account that using Linear Regression should be adopted since the model should be employed or used for both long term and short term forecasting of electric current. There are many examples that are used in the method and they include price of electricity, Gross Domestic Product (GDP), population etc. Generally, the method has the form;

$$Y = a + C1X1 + C2X2 + C3X3 + \dots + CnXn + d$$

Whereas Y can be the energy consumption (KWh), X1 is the Gross Domestic Product (millions), X2 is the energy price (cents/kWh), X3 is the population, d means the error (disturbance term).

III. METHODOLOGY

A. Introduction

This chapter presents the procedure involved in a Short-term load forecast using Artificial Neural Network (ANN) method and applied it to the 33KV feeder supplying Choba, in Port-Harcourt Metropolis electric power system. This predicts future load of one hour in advance for 24 hours using past load readings data over the years, obtained from Port Harcourt Electricity Distribution Company (PHEDC) for the month of February, 2016.

B. Analysis of the Proposed System

Success in designing a neural network depends on a clear understanding of the problem. Our problem is to predict the daily (24 hours) electric load demand, so that the planning and distribution of load may be more successful. Technical historical data or actual power been delivered to the area in focus generally. The system requirement includes the system input variables which comprises the input variables. The algorithm of the proposed system integrates the neural network system and load prediction problem with the objective to find optimal solution to the problem. The proposed neural network model is analysed by Jamal et al. (2008) as follows:

a. Forward Propagation

Forward propagation is a supervised learning rule that explains the movement of information in a neural network starting from the input through to its output. The feed forward algorithm is used to calculate the optimal weights of the load prediction. The mathematical models for the feed forward algorithm are as follows:

$$Input_j = x_j = \sum y_i w_{ij} \dots \dots \dots 3.1$$

y_i is the generated output and w_{ij} represents weights

$$f(x) = \frac{1}{1 + e^{-x_j}} \dots \dots \dots 3.2$$

$f(x)$ is a sigmoid that is used as the activation function

$$Error = T_k - O_k \dots \dots \dots 3.3$$

T_k is the observed (True) output while O_k is the calculated (actual) output.

C. STLF Modeling and Procedure

ANN-based methods are a good choice to study the STLF problem, as these techniques are characterized by not requiring

explicit models to represent the complex relationship between the load and the factors that determine it.

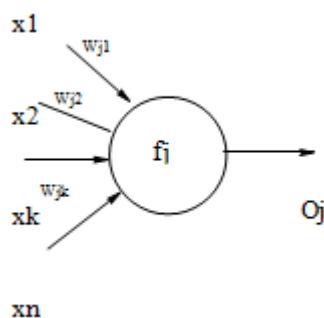


Figure 2: Mathematical model of an ANN neuron.

a. Modeling

1. Neuron model

ANNs are made up of a number of simple and highly interconnected Processing Elements (PE), called neurons, as depicted in Fig. 1. Lau (1992). Its mathematical model is expressed as

$$O_j = f_j \sum_k (w_{jk} x_k) \quad (3.1)$$

Where:

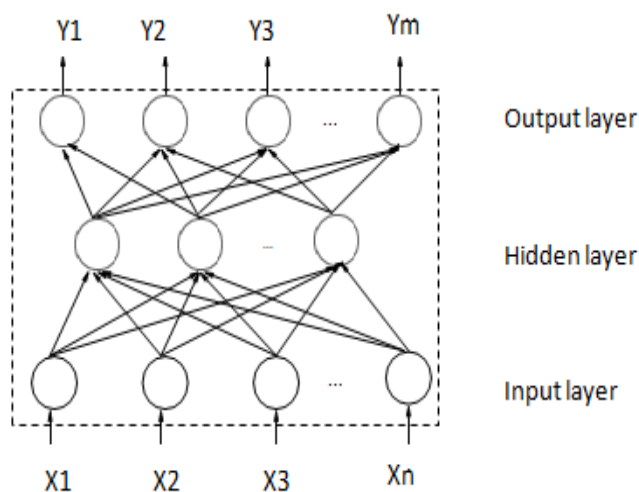
O_j is the output of a neuron;

f_j is a transfer function, which is differentiable and non-decreasing, usually represented using a sigmoid function, such as a logistic sigmoid, a tangent sigmoid, etc.;

w_{jk} is an adjustable weight that represents the connection strength;

x_k is the input of a neuron.

Forecasted Load



Load affecting factors

Figure 3: Schematic of the three layer feed-forward ANN for STLF

2. Network Architecture

The three-layer fully connected feed-forward neural network depicted in Fig. 3.2 is used here; it includes an input layer, one hidden layer and an output layer Schalkoff (1997). Signal propagation is allowed only from the input layer to the hidden layer and from the hidden layer to the output layer. Input variables come from historical data corresponding to the factors that affect the load. The outputs are the desired forecasting

results, which in this case are $m = 24$, i.e., one for each hour of the day. The number of inputs, the number of hidden nodes, transfer functions, scaling schemes, and training methods affect the forecasting performance and hence need to be chosen carefully.

3. General ANN Training

ANN training basically consists on determining the network parameters such as weights and others, that allow achieving the desired objective based on the available training sets. Usually, multi-layer feed-forward neural networks are trained in a supervised manner. Back-propagation is used as the training method here, Lau (1992), which is an iterative procedure that has three steps during each iteration:

1. Forward: The outputs are calculated for given inputs.
2. Backward: The errors at the output layer are propagated backwards toward the input layer, with the partial derivatives of the performance with respect to the weights and biases calculated in each layer.
3. Weight adjustment: A multivariate nonlinear numeric optimization algorithm finds the weights that minimize the error based on the gradient. Training stops when the performance has been minimized to the goal, the performance gradient falls below a minimum gradient, the maximum number of epochs is reached, or the maximum amount of time has been exceeded. The error function used in the back-propagation training process is the sum-squared error, i.e.,

$$E = \frac{1}{2} \sum_p \sum_j (t_{pj} - O_{pj})^2 \quad (3.2)$$

where t_{pj} and O_{pj} are the target output and the actual output j for input pattern p , respectively.

D. Neural Network Training

The NN models developments were performed using the Matlab Neural Networks Toolbox (Matlab 7.7.0 (R2008b)). The initial NN models were trained for the data using 5 input variables: Time in Hours of the day, Hour, Previous day hourly load reading in Mega-watts (MW), Previous week hourly temperature in Degree-Celsius ($^{\circ}C$), Previous week maximum load reading in Mega-watts (MW), Previous week minimum load reading in Mega-watts (MW). While the output is the load. Different NN topologies were trained using back propagation training algorithm and tested in order to find the best network structure that gives the best modelling accuracy. The NN topologies were selected as: Linear, Multi Layer Perceptron (MLP) and Radial Basis Functions (RBF). A maximum two hidden layers were selected (Haykin (1998), MacKay (1992) and Foresee, et al (1997)). The MLP activation functions were sigmoid for the hidden layer and linear for the output layer. The data were selected as 60% for training, 20% for validation, and 20% for testing. Two measures were selected; the performance of the network (standard deviation) and the prediction error (root mean square). Both were evaluated for the training, validation and testing.

E. Using Neural Network Model

The Neural Network Function Fitting is the process of training a neural network based on a set of inputs for the purpose of generating an associated set of target outputs.

Once the neural network fit the data well, it will establish an input-output relationship used to generate outputs from new inputs that are not trained previously. This dataset can be used to train a neural network to estimate the energy consumption in

terms of time and power consumption. To realize the fitting model, these two variables are loaded into MATLAB workspace: Input is a 5x168 matrix used to define 5 attributes for 168 different datasets. The input data is described as shown below:

1. Hour of the Day: hour from 1 to 24. '1' represents 01:00 am while '13' represent 1:00 pm.
2. Dayofweek: it represents the date. '1' represents Monday and '7' represents Sunday.
3. Hourly Load: the present hourly load data of the day on focus.
4. PrevDaySameHourLoad: the present hourly load data replaced by the same hour data of the same day in the previous week
5. PrevWeekMaxHourlyLoad: the present hourly load data replaced by the same maximum hourly data of previous weeks in the same month.
6. Target: Average of Previous Day Same Hourly Load and Previous Wks Max Hourly Load.

Table: 1 Sample of Hourly Load Supplied Data for Choba Community.

INPUT DATA FOR MONDAY						
Date	Day of the Week	Hour of the Day	Hourly Load (MW)	Previous Day Same Hrly Load (MW)	Previous Wk Max Load (MW)	Target Load (MW)
22/02/2016	1	1	6.1	11.3	13.3	12.3
22/02/2016	1	2	6.2	11.3	13.3	12.3
22/02/2016	1	3	6.4	10.6	13.3	11.95
22/02/2016	1	4	6.4	10.6	13.3	11.95
22/02/2016	1	5	6.4	10.6	13.3	11.95
22/02/2016	1	6	6.3	10.3	13.3	12.3

IV. SIMULATION RESULTS AND DISCUSSION

A. Validation and Data Testing

The data used in training the neural network has the following input:

Training data: In order to perform this training program, 70% of the sample was used to train the neural network. These data are presented to the network during training and the network is adjusted according to its error.

Validation data: These data are used to measure network generalization, and to halt training when generalization stops improving. In these work, 15% of the sample was used to validate the neural network.

Testing data: These data has no effect on the training and so provides an independent measure of network performance during and after training. In these work, 15% of the sample was used to test the neural network.

B. Simulation interface of Choba Electricity demand prediction with Matlab;

The Matlab neural network training interface of Choba electricity demand is shown below, the training is done in epoch. Prediction training recorded sixty-nine iterations in two seconds to complete the training. The training recorded the root mean square of 5.2e-04 which is almost equivalent to zero.

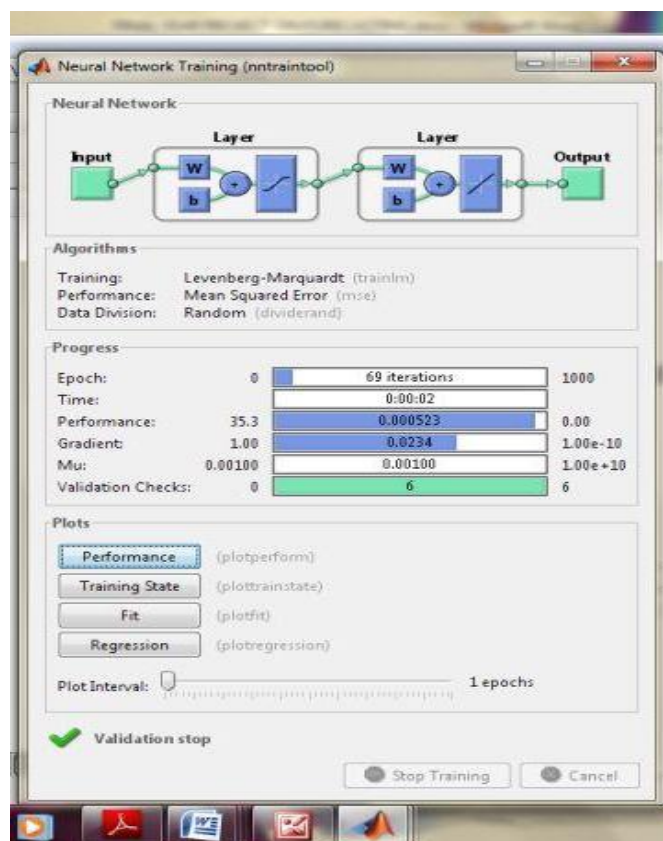


Figure 4: Graphical User Interface for Neural Network Training Tool

The Matlab neural network Fitting tool interface for Choba, Rivers State is shown below. Root mean square value and the regression value of the training, validation and testing are shown. It also shows the number of sample data used for the training, validation and the testing.

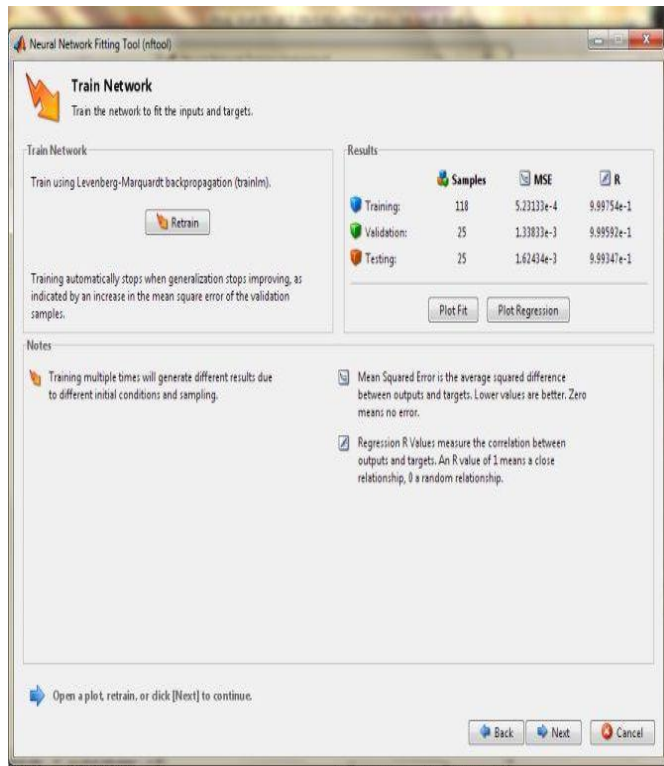


Figure 5: Graphical User Interface for Neural Network Training Tool

The Matlab neural network training performance interface for Choba electricity demand is shown in the figure below. In this graph we can see that the training phase registered the minimum amount error, followed by the validation phase then the testing phase. The best fit for the training was shown in the graph. With this graph one can easily see the performances of both the training, validation and the testing phases. The graph also shows that the training was done in 13 epoch.

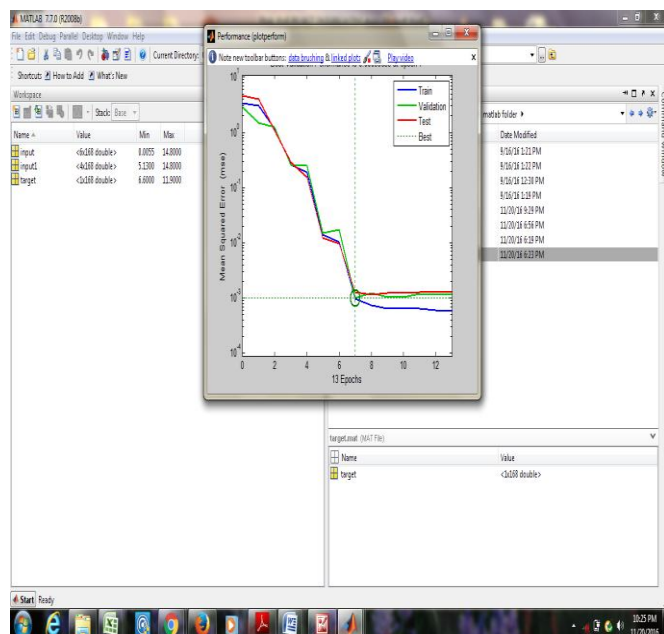


Figure 6: Graphical User Interface for Training Performance Tool.

The Matlab neural network training regression graph interface for Load demand in Choba, Rivers State is shown in the figure below. The Regression (R) value measure the correlation between outputs and targets. A Regression (R) value of 1 means a close relation, 0 a random relationship. From the graph we can see that both the output and the input are closely related.

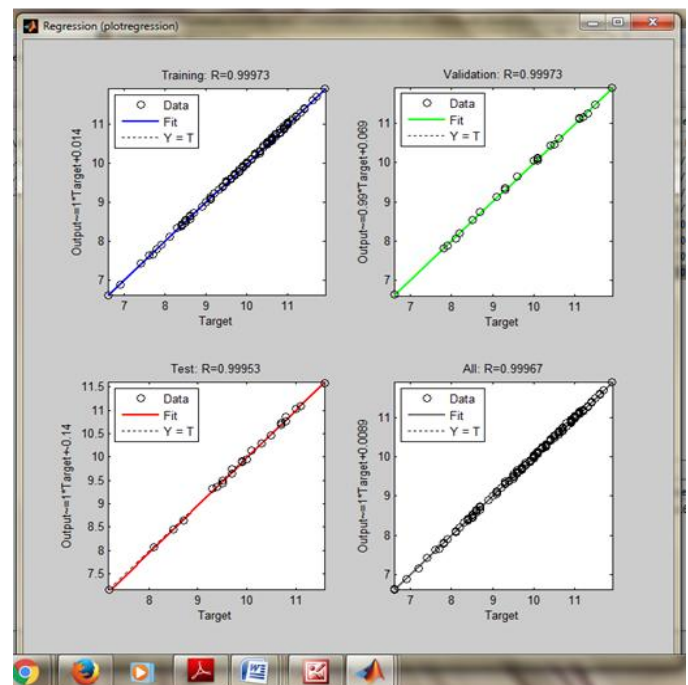


Figure 7: Result presentation of Choba Electricity Demand Prediction

C. Result presentation of the Choba Electricity demand prediction

The performance analysis of the load demand prediction in Choba was analyzed using the Mean Squared Error (MSE) and Regression (R) Values. The result is shown in the table 4.1. The Mean Squared Error values (5.23133e-4 from the Training, 1.33833e-3 from the validation and 1.62434e-3 from the testing) shows that the prediction was done with minimum amount of error and it can be seen from the table. The Regression (R) value measure the correlation between outputs and targets. A Regression (R) value of 1 means a close relation, 0 a random relationship. The regression values (0.999754 from the Training, 0.999592 from the validation and 0.99347 from the testing) show that the output has a close relationship with the targeted prediction.

Table 2: The Performance Analysis of the Choba Electricity demand prediction

	No of Samples	Mean Squared Error (MSE)	Regression R Values
Training	118	5.23133e-4	0.999754
Validation	25	1.33833e-3	0.999592
Testing	25	1.62434e-3	0.999347

D. The graphical representation of the Actual and the Predicted values

Normally, graphs are used to aid our understanding; the different Actual values are compared with the predicted values using line graphs. The graph is shown below in figure 4.5. The graph demonstrates the direction of the State's load prediction. From the graph one can see that the predicted value follows the actual value.

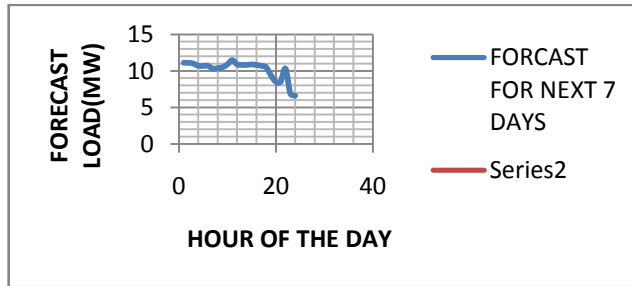


Figure 8: The Graphic Representation Of The Predicted Value of Load Vs Time in Choba Community

The daily sample of the supply load prediction for Choba, Rivers State is shown in Table 4.3. Predicted values with different Neural Network predictive models is presented below in the table. When compared with the actual value it was observed that the predictive model of 5-16-1 gives the best prediction for the area in view.

E. Graphical Representation of Hourly Forecasted Load

The sample of daily electricity demand prediction for Choba Community was represented below using Graphs on Predicted Values with the best Neural Network Predictive Model

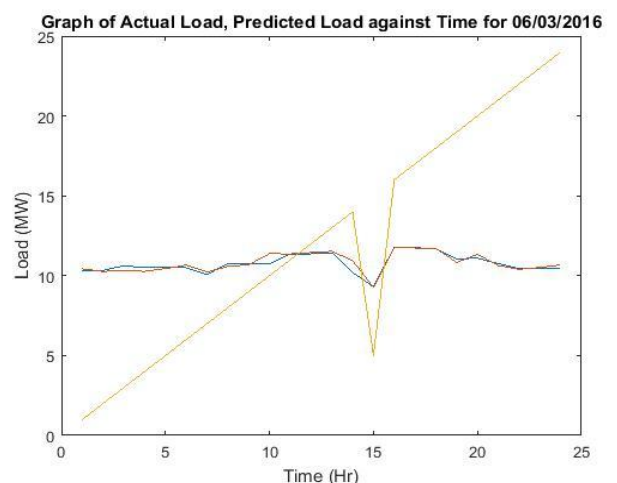
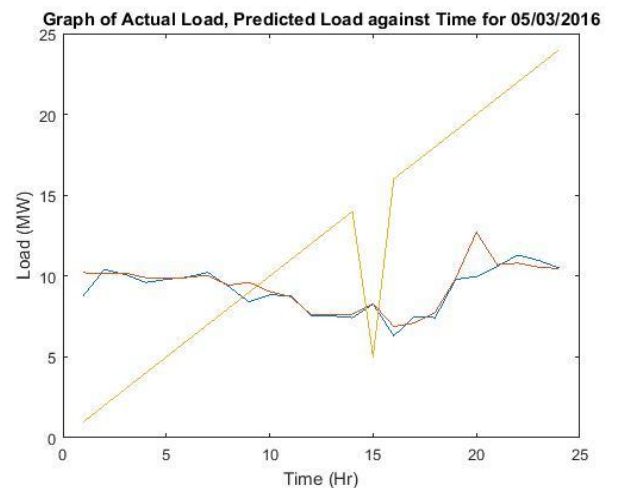
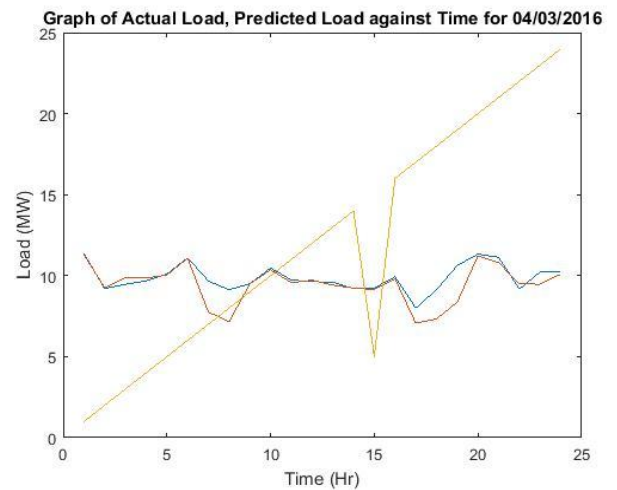
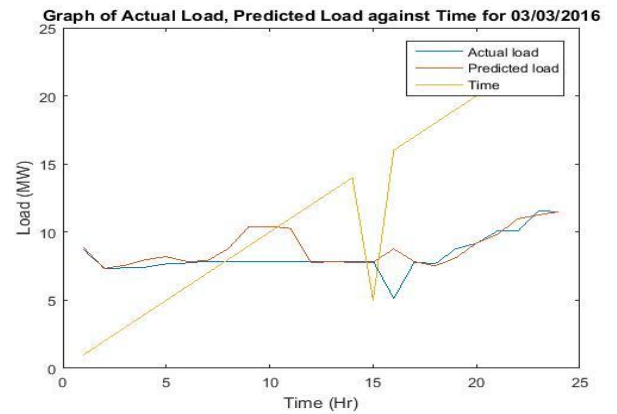
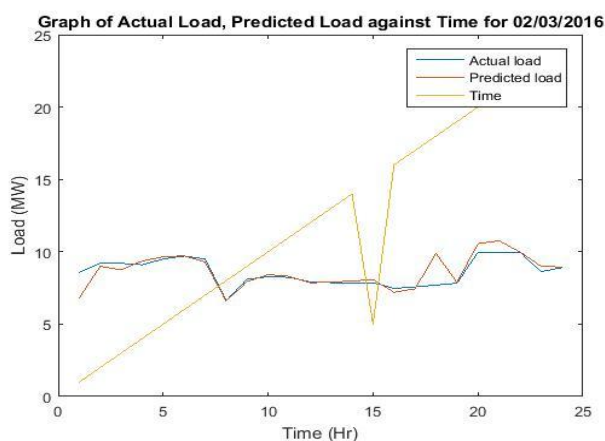
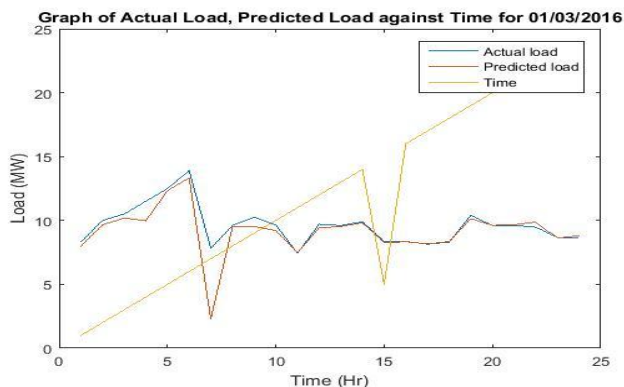
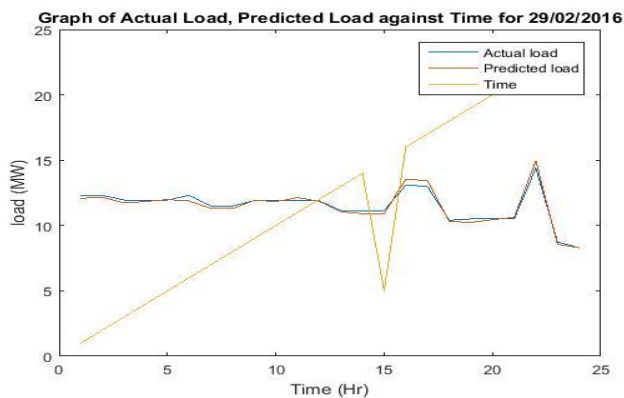


Figure 9: Graphical Representation of Hourly Forecasted Load from 29/02/2016 -6/03/2016

F. Result Analysis

Based on the result obtained by the models we can compare the model as follows:

Efficiency: The proposed model appears to be more efficient than the existing model because the mean square error values and the regression values of the prediction show that the model is very efficient.

From the results obtained, the forecasted electricity demand recorded a Mean Squared Error (MSE) and Regression (R) Values of $5.23133e-4$ and 0.999754 respectively.

CONCLUSION

It can be concluded that the load forecasting model was successfully designed using Matlab 7.7.0 (R2008b) ANN Toolbox with BP. The implementation of the network architecture, training of the Neural Network with four (4) input and simulation of test results were all successful with a very high degree of accuracy resulting into 24 hourly load output. From the results recorded a Mean Squared Error (MSE) and Regression (R) Values of $5.23133e-4$ and 0.999754 were obtained respectively. The result of this work has shown really that artificial neural network when trained can be used to predict future electricity demand.

RECOMMENDATION

Other forecasting method should always be used for easy comparison with the ANN BP method. Power Engineers in Higher institution should partner with the Utility companies to Carryout research and proffer solution to the incessant nature of power supply in Nigeria. Many developed countries give much consideration to research and technology team in higher Institution.

References

- [1] Alsayegh, O. A., (2003). "Short-term load forecasting using seasonal artificial neural networks," *International Journal of Power and Energy Systems*, 23(3):137-142.
- [2] Baklitzis, A. G., Petrdis, V., Klartzis, S. J., Alexiadis, M. C. and Malssis, A. H., (1996). "A neural network short term load forecasting model for the Greek power system," *IEEE Trans. Power Systems*, 11(2): 858-863.
- [3] Bansal, R.C. and J.C. Pandey (2005). Load forecasting using artificial intelligence techniques: A literature survey. *Int. J. Comput. Appl. Technol.*, 22: 109-119.
- [4] Cancelo, J.R. and A. Espasa, (1991). Forecasting daily demand for electricity with multiple-input nonlinear transfer function models: A case study. Working Paper 91-21, Departamento de Economia, Universidad Carlos III de Madrid, Spain, July 1991, pp: 1-73.
- [5] Chen H, Canizares C.A, and Singh A.(2001). ANN-Based Short-Term Load Forecasting in Electricity Markets. *Proceedings of the IEEE on Power Engineering Society Transmission and Distribution Conference*, 2:411-415, 2001.
- [6] Chen H., (1996). "A Practical On-line Predicting System for Short- Term Load," *East China Electric Power*, Vol. 24, No. 3, March 1996.
- [7] Dash P.K., H. P. Satpathy, A. C. Liew, and S. Rahman, (1997). "A Real-time Short-Term Load Forecasting System Using Functional Link Network," *IEEE Trans. Power Systems*, Vol. 12, No. 2, May 1997, pp. 675-680
- [8] Emmanuel U. Oleka, Samuel N. Ndubis, Gerald K. Ijamaru (2016). Electric Power Transmission Enhancement: A Case of Nigerian Electric Power Grid. *American Journal of Electrical and Electronic Engineering*, Vol. 4, No. 1, 33-39. doi:10.12691/ajeee-4-1-5
- [9] Foresee, D. and Hagan, F., (1997). "Gauss-Newton approximation to Bayesian learning," *International Conference on Neural Networks*, 3: 1930-1935 .
- [10] Haykin, S., "Neural Network: A Comprehensive Foundation," Prentice Hall International, Second edition (1998).
- [11] Hippert, H. S., Pedreira, C. E. and Souza, R. C., (2001). "Neural networks for short-term load forecasting: A review and evaluation," *IEEE Trans. Power Syst.*, 16(1): 44-55.
- [12] Ibe, D. G. (2010). "The overview of Electricity in Nigeria", *Nigeria Tribune*, pp. 4 – 6, (2010).
- [13] Ibe A.O, 2002. Power system Analysis.
- [14] Idoniboyeobu, D.C. and Newman M.A. (2013). Electric load prediction technique using multiple regression method a case study of port harcourt metropolis. *Eur. J. Sci. Res.*, 118: 61-74.
- [15] Khotanzad G.E and English B.C, "A Review of Load Forecasting Methodologies"
- [16] Labruno, M.P., and J.W. Taylor (2001). Short term electricity demand using double seasonal exponential smoothing. *J. Operat. Res. Soc.*, 54: 799-805.
- [17] Lau C., (1992). *Neural Networks Theoretical Foundations and Analysis*, IEEE Press,.
- [18] Lu C.N., H. T. Wu, and S. Vemuri, (1993). "Neural Network Based Short Term Load Forecasting," *IEEE Trans. Power Systems*, Vol. 8, No. 1, Feb. 1993, pp. 337-342.
- [19] MacKay, D. J. C., (1992). "Bayesian interpolation," *Neural Computation*, 4: 415-447.
- [20] Papalexopoulos A. D., S. Hao, and T. M. Peng, (1994). "An Implementation of a Neural Network Based Load Forecasting Model for the EMS," *IEEE Trans. Power Systems*, Vol. 9, No. 4, Nov. 1994, pp. 1956-1962.
- [21] Schalkoff R. J., (1997). "Artificial Neural Networks," McGraw-Hill Inc.,.
- [22] Senjyu, T., Takara, H., Uezato, K. and Funabashi, T., (2002). "One hour-ahead load forecasting using neural network," *IEEE Trans. Power Systems*, 17(1): 113-118.
- [23] Slutsker I., K. Nodehi, S. Mokhtari, K. Burns, D. Szymanski and P. Clapp, (1998). "Market Participants Gain Energy Trading Tools," *IEEE Computer Applications in Power*, Vol. 11, NO. 2, April 1998, pp. 47-52.
- [24] Vermaak j., (1998). "Recurrent Neural Networks for Short-Term Load Forecasting," *IEEE Tran. Power Systems*, Vol. 13, No. 1, Feb. 1998, pp. 126-132.