



Long-Term Load Forecasting for the 330 kV Nigerian Network using Artificial Neural Network

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ABSTRACT

The availability of reliable, consistent, and sufficient electricity is crucial for the economic, infrastructural, and overall development of any society or country. As the population and socio-economic activities increase, the demand for electricity also rises. To ensure that the supply meets the required demand, it is essential to prioritize early planning, accurate forecasting, and regular maintenance of the utility system. Numerous researchers have highlighted the superiority of artificial intelligence, particularly artificial neural networks, over other methods and models for load forecasting and optimization. This is due to their ability to learn from historical data and identify patterns in electricity consumption. In this study, a long-term load demand forecasting technique was developed using artificial neural networks (ANN) with the Nigerian power system as a case study. Historical load data, gross domestic product (GDP), population figures, and long-term climatic changes (temperature) from 2005 to 2019 were utilized to train and simulate the neural network for long-term load forecasting on the 330 kV Nigerian network. The MATLAB software was employed for modeling, with the data divided into training (70%), validation (15%), and testing (15%) sets. Through simulations conducted on the predicted data, the Mean Average Percentage Error (MAPE) was determined to be 0.71%. This value is lower compared to previous works, indicating the effectiveness of the developed technique in accurately forecasting long-term load demand. By leveraging artificial neural networks and historical data, this approach provides a reliable tool for optimizing electricity supply planning and management, thereby contributing to the sustainable development of the Nigerian power system.

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INTRODUCTION

The Electricity sector in Nigeria generates, transmits and distributes megawatts of electric power that is significantly less than what is needed for meeting the basic household and industrial needs. This deficit is also exacerbated by load shedding, partial and total system collapse and power failure as a result of improper predictions and planning which has hindered industrial growth.

Power supply difficulties cripple the agricultural, industrial and mining sector and impede the Nigeria's ongoing economic development. The energy supply crisis is complex, stems from a variety of issues and has

been ongoing for decades. Most Nigerian businesses and households that can afford to do so run one or more diesel-fueled generators to supplement the intermittent supply.

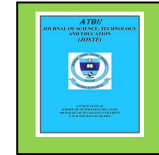
The Nigerian power sector continuously failed to provide adequate electricity supply to domestic households and industrial producers despite a rapidly growing economy, being some of the world's largest deposits of coal, oil and gas and the country's status as the Africa's largest oil producer. Currently only 40% of Nigeria's population is connected to the energy grid whilst power supply difficulties are experienced around 60% of the time (Aliyu *et al.*, 2013).

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The power generating stations of Nigeria power system are strategically located across the geopolitical zones in Nigeria with different generating capacity. The increase in rural to urban migration and insecurity, has led to an excessive demand of electricity due to the increasing population in some cities which has resulted to epileptic power supply, power failure, fluctuation and total power outage, thereby causing loss of energy utilization by the consumers and utility companies (Dikio *et al.* 2018). Global electricity demand is projected to increase by 85% in 2040 as living standards rise, economies expand and the need for electrification of society continues.

Electricity demand forecasting plays an important role in load allocation and planning for future generation facilities and transmission augmentation. Load demand in a given season is subject to a range of uncertainties, including underlying population growth, climate change and economic conditions. In addition, historical data are of importance in demand forecasting (Phuangpornpitak & Promme, 2016). Load forecasting succour an electric utility to make conclusions regarding decision on generating and purchase electric power, load switching, voltage control, network reconfiguration and infrastructure development. Electric load forecasting is the process used for forecasting future electric load, given historical load and weather information and current and forecasted weather information (Anwar *et al.* 2018).

Electrical load forecasting has always been essential for power systems operations, planning, and control problems; and it plays a significant role in economic and financial development. Nigeria has always been lagging behind in terms of industrial and infrastructural development and thus there is need for timely and adequate planning to ensure improved and sufficient electricity supply to meet the nation's electric load demand. The aim of this research is to predict the long-term future load demand on the Nigerian 330 kV power network.

LITERATURE REVIEW

Long term load forecasting plays an important role in terms of load flow analysis, scheduling, contingency analysis, planning and maintenance of electrical power system. This research work will fill the knowledge gap that is in the previous work conducted.

Theoretical Background

One of the fundamental challenges of an electric utility company is to forecast load requirement at various times. The foremost reason behind this task is that power demand in a given place does vary with growth in population and economic activities. Outcomes obtained from load forecasting progressions are used in different endeavours in power sector such as planning, system expansion, maintenance and operational schedule. For example, long-term load forecasting for at least a period of ten years ahead based on monthly and yearly values can be applied for resolution of some basic power sector challenges. Some of the problems can be expansion planning, inter-tie-tariff setting and long-term modelling of capital investment. Short-term load forecasting domino effect of few days to months ahead are considered necessary in unit commitment analysis, maintenance schedule and diagnosis of economic dispatch (Caleb *et al.* 2013).

There are many variables contributing to the electric load makes accurate prediction of electric load a difficult process. These variables involve "uncertainty" and have no direct relation with the final load. Moreover, the load is characterized to be nonlinear and non-stationary process that can undergo rapid changes due to weather, seasonal and macroeconomic variations. (Rishav P. *et al.*, 2015).

There are several factors that should be taken into consideration for load forecasting, which can be classified as time factor, economic factor, weather condition and customer factor (Hong and Fan (2016), Clements *et al.* (2016). The utility company seeks to operate the power system such that a match is achieved between the electric energy demand and supply. This implies that the more accurate the forecast, the more efficient the operation and management of the power system. (Rishav *et al.*, 2015).

Other significant benefits of load forecasting are:

- i) Required to determine the optimal releases from the reservoirs and generation levels in the power houses in hydro-electric power plants.
- ii) Required by thermal systems to determine the minimal-cost hourly strategies for the start-up and shutdown of units.

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- iii) This information permits the dispatchers to prepare the necessary corrective actions (load shedding, power purchases).

A 1% reduction in the average forecast error can save hundreds of thousands or even millions of Naira (Rishav *et al.*, 2015).

Types of Load Forecasting

On the basis of the time period, load forecasting technique can be classified into three categories (Shelly *et al.*, 2016); Short-Term Load Forecasting (STLF), Medium Term Load Forecasting (MTLF) and Long-Term Load Forecasting (LTLF).

Short Term Load Forecasting (STLF)

In the STLF, daily or hourly values were covered for giving the necessary information of the system management in order to achieve the daily operations. This information was used for allocating the spinning reserve, planning the operation, committing the units and for scheduling the maintenance. The basic quantity of interest in STLF is, typically, the hourly integrated total system load. In addition to the prediction of the hourly values of the system load, an STLF is also concerned with the forecasting of the daily peak system load, the values of system load at certain times of the day, the hourly or half-hourly values of system energy, the daily and weekly system energy (Rishav *et al.*, 2015).

Medium Term Load Forecasting (MTLF)

This covers a time span of (1 – 12 months). This type of forecasting depends mainly on growth factors, i.e. factors that influence demand such as main events, addition of new loads, seasonal variations, demand patterns of large facilities, and maintenance requirements of large consumers (Rishav *et al.*, 2015).

In this type for forecasting, data from few days or few weeks was covered. That forecasting data was generally used for the fuel supply and unit maintenance scheduling. It is less time consuming than the long-term forecasting and consumes more time than the short-term load forecasting. The basic application of the MTLF is to plan the seasonal

peak load in the winter and summer seasons (Rishav *et al.*, 2015).

Long-Term Load Forecasting (LTLF)

Long-term load forecasting (LTLF) plays an important role in power systems for system planning, scheduling expansion of generation units by construction and procurement of generation units. It spans from a few years (> 1 year) to 10-20 years. Because it takes several years and requires a huge investment for construction of power generation and transmission facilities, accurate and error-free forecasting is necessary for an electric utility. Accuracy of LTLF has a direct impact on development of future generation and transmission planning, and hence it is a crucial instrument for planning and forecasting future conditions of the electricity network. Based on the forecast, electric utilities coordinate their resources to meet the forecasted demand using a least-cost plan. In general, LTLF is subjected to a large number of uncertainties and ample amount of research indicates that load prediction in presence of uncertainties is required for future capacity resource needs and operation of existing generation resources. (Khuntia *et al.*, 2016). They also mentioned that the various reasons for inaccuracy are:

- i) Peak demand is very much dependent on temperature
- ii) Some of the necessary data for LTLF including weather data and economic data (vital ones) are not available
- iii) It is very difficult to store electric power with the present available technology
- iv) It takes several years and requires a great amount of investment to construct new power generation stations and transmission facilities

Long-term demand forecasts span from eight years ahead up to fifteen years. They have an important role in the context of generation, transmission and distribution network planning in a power system. The objective of power system planning is to determine an economical expansion of the equipment and facilities to meet the customers' future electric demand with an acceptable level of reliability and power quality (Rishav *et al.*, 2015).

This forecasting method has its period which is longer than a year. It is used to supply electric utility company management with predicted prediction of future needs for expansion, equipment purchased or staff hiring (Anwar *et al.*, 2018).

Forecasting Methods

Over the last few decades, a number of forecasting methods have been developed. Two of the methods, so-called end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, expert systems, fuzzy logic, and statistical learning algorithms, are used for short-term forecasting. The development, improvements, and investigation of the appropriate mathematical tools will lead to the development of more accurate load forecasting techniques.

Statistical approaches usually require a mathematical model that represents load as function of different factors such as time, weather, and customer class. The two important categories of such mathematical models are: additive models and multiplicative models. They differ in whether the forecast load is the sum (additive) of a number of components or the product (multiplicative) of a number of factors. Chen *et al.* (2005) presented an additive model that takes the form of predicting load as the function of four components:

$$L = L_n + L_w + L_s + L_r \dots\dots(1)$$

Where, L is the total load, L_n represents the 'normal' part of the load, which is a set of standardized load shapes for each 'type' of day that has been identified as occurring throughout the year, L_w represents the weather sensitive part of the load, L_s is a special event component that create a substantial deviation from the usual load pattern, and L_r is a completely random term, the noise.

Chen *et al.* (2001) also suggested electricity pricing as an additional term that can be included in the model. Naturally, price decreases/increases affect electricity consumption. Large cost sensitive industrial and institutional loads can have a significant effect on loads. The study used Pennsylvania-New

Jersey-Maryland (PJM) spot price data (as it related to Ontario Hydro load) as a neural network input. The authors report that accurate estimates were achieved more quickly with the inclusion of price data.

A multiplicative model may be of the form:

$$L = L_n \times F_w \times F_s \times F_r \dots\dots(2)$$

Where L_n is the normal (base) load and the correction factors F_w , F_s , and F_r are positive numbers that can increase or decrease the overall load.

These corrections are based on current weather (F_w), special events (F_s), and random fluctuation (F_r). Factors such as electricity pricing (F_p) and load growth (F_g) can also be included. Rahman (1990) presented a rule based forecast using a multiplicative model. Weather variables and the base load associated with the weather measures were included in the model.

Medium-Term and Long-Term Load Forecasting Method

The end-use modelling, econometric modelling, and their combinations are the most often used methods for medium- and long-term load forecasting. Descriptions of appliances used by customers, the sizes of the houses, the age of equipment, technology changes, customer behaviour, and population dynamics are usually included in the statistical and simulation models based on the so-called end-use approach. In addition, economic factors such as per capita incomes, employment levels, and electricity prices are included in econometric models. These models are often used in combination with the end-use approach. Long-term forecasts include the forecasts on the population changes, economic development, industrial construction, and technology development.

End-Use Models

The end-use approach makes load forecasts based on the statistical information about customers along with dynamics of change of loads. This model requires extensive information on end users, for instance, customer size, size of houses and so on. End-use models divide customers for several sectors (residential, commercial, and industrial) and

they are based on the principle that electricity demand is derived from customer's demand for light, heating, cooling, etc. Ideally, end-use approach is very accurate but it is very sensitive to the quality and amount of the end user's data. The disadvantage of this method is that "most end-use models assume a constant relationship between electricity and end-use (electricity per appliance)" (Ghods & Kalantar, 2008).

Ideally this approach is very accurate. However, it is sensitive to the amount and quality of end-use data. For example, in this method the distribution of equipment age is important for particular types of appliances. End-use forecast requires less historical data but more information about customers and their equipment.

Econometric Models

The econometric approach estimates the relationship between energy consumption and factors influencing consumption by the least square method or time series methods. To forecast electricity demand, it uses economic theory and statistical techniques. In the econometric models the dependent variable, in our case it is a demand for electricity, is expressed as a function of various economic factors. These could be various parameters such as population, income per capita or value added or output, price of power, prices of alternative fuels, proxies for penetration of appliances/equipment etc. Thus, we have a formula for electricity demand:

$$ED = f(Y, P_i, P_j, Pop, T) \quad \dots(3)$$

Where, ED is electricity demand, Y is output or income, P_i -own price, P_j – price of related fuels, POP – population and T is technology.

The econometric approach combines economic theory and statistical techniques for forecasting electricity demand. The approach estimates the relationships between energy consumption (dependent variables) and factors influencing consumption. The relationships are estimated by the least-squares method or time series methods. One of the options in this framework is to aggregate the econometric approach, when consumption in different sectors (residential, commercial, industrial, etc.) is calculated as a function of weather, economic

and other variables, and then estimates are assembled using recent historical data. Integration of the econometric approach into the end-use approach introduces behavioural components into the end-use equations (Ghods and Kalantar, 2011).

This method incorporates statistics, economics and mathematical theory in order to forecast the electricity demand. *The approach estimates the relationships between energy consumption and factors influencing consumption* (Feinberg *et al.*). It is a combination of the end-use and trend analysis methods but it does not take on the assumption used in trending that future demand can be predicted based on past demand. Unlike the end-use model, it allows the variation of the relationships between the end-use and the amount of electrical power received by consumers.

Statistical Model-Based Learning

The end-use and econometric methods require a large amount of information relevant to appliances, customers, economies, etc. Their application is complicated and requires human participation. In addition, such information is often not available regarding particular customers and a utility keeps and supports a profile of an 'average' customer or average customers for different type of customers. The problem arises if the utility wants to conduct next-year forecasts for sub areas, which are often called load pockets. In this case, the amount of the work that should be performed increases proportionally with the number of load pockets. In addition, end-use profiles and econometric data for different load pockets are typically different. The characteristics for particular areas may be different from the average characteristics for the utility and may not be available.

The focus of the study was the summer data. After comparison of several load models, it was concluded that the following multiplicative model is the most accurate

$$L(t) = F(d(t), h(t)) \cdot f(w(t)) + R(t) \quad \dots(4)$$

Where, $L(t)$ is the actual load at time t , $d(t)$ is the day of the week, $h(t)$ is the hour of the day, $F(d, h)$ is the daily and hourly component, $w(t)$ is the weather data that include the temperature and

humidity, $f(w)$ is the weather factor, and $R(t)$ is a random error.

In fact, $w(t)$ is a vector that consists of the current and lagged weather variables. This reflects the fact that electric load depends not only on the current weather conditions but also on the weather during the previous hours and days. In particular, the well-known effect of the so-called heat waves is that the use of air conditioners increases when the hot weather continues for several days.

To estimate the weather factor $f(w)$, we used the regression model

$$f(w) = \beta_0 + \beta_j X_i \dots\dots\dots(5)$$

Where, X_j are explanatory variables which are nonlinear functions of current and past weather parameters and β_0, β_j are the regression coefficients.

REVIEW ON LOAD FORECASTING METHODOLOGIES

Based on the various types of load forecasting techniques, there are three major groups of techniques used for load forecasting; Traditional Forecasting technique, Modified Traditional Technique and Soft Computing Technique (Arunesh *et al.* (2012)).

Short Term Load Forecasting Methods

Many methods which include the so-called similar day approach are various regression models, time series, neural networks, expert systems, fuzzy logic, and statistical learning algorithms, are used for short-term forecasting (Arunesh *et al.* (2012)).

Artificial Intelligence Based Methods

An Artificial Neural Network (ANN) is an information processing model. It is a type of machine learning system whose method of processing is inspired from the biological nervous system. A simple explanation of ANN is that it is a set of connected input/output units that has a weight attached/associated with every connection. It consists of a pool of simple processing elements which communicate by sending signals to each other over a large number of weighted connections.

Research on the artificial neural networks ANN has experienced three periods of extensive activity. The first peak in the 1940s

was due to McCulloch and Pitts' pioneering work. The second occurred in the 1960s with Rosenblatt's perceptron convergence theorem and Minsky and Papert's work showing the limitations of a simple perceptron. Minsky and Papert's results dampened the enthusiasm of most researchers, especially those in the computer science community. The resulting lull in neural network research lasted almost 20 years. Since the early 1980s, ANNs have received considerable renewed interest. The major developments behind this resurgence include Hopfield's energy approach in 1982 and the backpropagation learning algorithm for multilayer perceptrons (multilayer feedforward networks) first proposed by Werbos, reinvented several times, and then popularized by Rumelhart in 1986 (Rishav *et al.*, 2015).

Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear network are some linear or nonlinear mathematical function of its inputs (Taylor and Buizza, 2003). The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used. 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 bi-directional or unidirectional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally. The most popular artificial neural network architecture for electric load forecasting is back propagation.

ANN finds its usefulness in different industries e.g. the aerospace, defense, electronics, manufacturing, medical, robotics, speech and transportation amongst other industries in areas of classification, pattern recognition, data mining, control, optimization, etc. The areas of application of ANN in power system include load forecasting, fault diagnosis/fault location, economic dispatch, security assessment and transient stability.

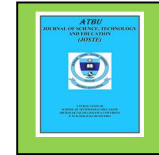
Artificial Neural Network (ANN) is a machine learning approach inspired by the way in which the brain performs a particular learning task [Sivanandam *et al.* (2006) and Haykins

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(1999)]. ANNs are modelled on human brain and consists of a number of artificial neurons. Neurons in ANNs tend to have fewer connections than biological neurons. Each neuron in ANN receives a number of inputs. A function called activation function is applied to these inputs which results in activation level of neuron. Three different classes of network architectures: Single-layer feed-forward, Multi-layer feed-forward, Recurrent.

Fuzzy Logic

Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. Under fuzzy logic an input has associated with it a certain qualitative range. For instance, a transformer load may be low, medium or high. Fuzzy logic allows one to deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs. Among the advantages of fuzzy logic is the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise or even noise free inputs (Miranda & Monteiro, 2000).

Danladi *et al.* (2016), worked on "Long-term load forecast modelling using a fuzzy logic approach". In their work, a fuzzy logic model was developed based on the weather parameters (temperature and humidity) and historical load data for the town of Mubi in Adamawa state to forecast a year-ahead load. The fuzzy logic model forecast a year-ahead load with a MAPE of 6.9% and efficiency of 93.1%. The result obtained reveal that the proposed model is capable of predicting future load.

Expert Systems

Expert systems are known to apply rules which have been generated by experts in the field. These procedures and rules are then transformed into software, which can automatically make forecasts about electricity demand. However, in order for the software to be efficient, expert forecasters will have to work hand in hand with software developers to include all expert information into the software. Here, software developers will be involved in coding all the information obtained from experts in forming software rules. The advantage of utilizing this method is that it is fast, accurate

and easy to use when forecasting information about electricity demand. This is because it involves the use of software applications, which usually run at the click of a button.

REVIEW OF RELATED WORKS

Rishav *et al.* (2015) performed load forecasting using Linear Regression and Artificial Neural Networks. Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) have been used for forecasting the loads which has the advantage of learning directly from the historical data. They used data such as past load, weather information like humidity and temperatures. At the end of the research, they concluded that Artificial Neural Network outperforms Linear Regression method.

Oussama & Nadir (2015) presented an article titled Multi-Model Approach for Electrical Load Forecasting at the SAI Intelligent Systems Conference. Their work focused on forecasting medium and long terms of Algerian electrical load using information from past consumption. The article used time series models to forecast, different models have been implemented and tested on a database, which represents ten years of consumption. Three models are implemented in this work. Multiple linear regressions, artificial neural network MLP (multilayer perceptron), SVR (Support Vector Machines Regression), a parallel approach using seasons decomposition is used to have a more accurate result. The results based on the error measurement showed that ANN model outperforms the other approaches.

Gil (2015) presented Forecasting Electricity Demand for Small Colombian Populations. The paper presents an Artificial Neural Network (ANN) for the prediction of daily electricity demand (GWh) in small Colombian populations. The methodology proposed by Kaastra and Boyd is used for the construction, training and validation of the network and the development of the model in the statistical software SPSS. Among the different methods used to predict electricity demand, Artificial Neural Networks (ANN) allow the consideration of variables and external factors difficult to quantify with other methodologies, and suit the behaviour of a data series better. This paper concluded that the predicted values with models constructed with Artificial Neural Networks (ANN) present a greater degree of approach

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with the real values of electricity demand (GWh). Also, it indicates that the values obtained using models developed with other forecasting techniques (game theory, time series, simulation models, and others) allow to include variables and external factors that are difficult to quantify with simple equations.

Jebaraj (2017), studied Electricity Demand Forecasting for Malaysia Using Artificial Neural Network. Their analysis employed regression techniques, double moving average, double exponential smoothing, triple exponential smoothing, Auto Regressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) for the electricity demand forecasting in Malaysia. The model validation was done to select the best forecasting model. It was found that the ANN model gives better results. Hence, the ANN model is used for the electricity demand forecasting in Malaysia. It is also predicted that the total electricity demand for the year 2020 and 2030 is 172,665 and 245,037 GWh respectively. It was concluded that ANN has superior prediction abilities in comparison to other techniques.

An Empirical Study across Techniques and Domains of long-term load forecasting was done by Sujit *et al.* (2017). In their work, more emphasis is given to the methodologies used for long-term forecasting. Parametric methods like trend analysis, end use & econometric technique and computational intelligence-based methods like artificial neural network; fuzzy logic model; wavelet networks and genetic algorithm/programming are explained in detail. The results from the comparative study show that the ANN model is a superior technique for long term electric load forecasting due to its ability to give satisfactory results where the availability of past data is low. It also gives lower error than the other models discussed.

Eyad (2017), presented a neural network (NN) based approach for long-term load forecasting (LTLF) of the Jordanian power system from 2015 to 2029. Two types of feed forward neural networks (FFNN) are examined, namely, the back-propagation and the radial basis function neural networks; (BPNN) and (RBFNN), respectively. Historical data obtained from the National Electric Power Company (NEPCO) have been used in training and testing

the proposed neural networks. The simulation results show that both neural networks show quite good performance over a long forecasting period. The performance accuracy of both NNs is assessed in terms of the mean square error (MSE) and mean absolute error (MAE). Moreover, the forecasting results of the proposed NN approach have been compared with the forecasting results obtained by NEPCO. It was found that the results are comparable and satisfactory. The case study reveals that the proposed NN approach can be effectively applied for forecasting the annual peak loads of the Jordan's system.

Isaac *et al.* (2017), worked on a Comparative Study of Regression Analysis and Artificial Neural Network Methods for Medium-Term Load Forecasting. The work was carried out with load demand data set obtained from Covenant University campus in Nigeria. The regression analysis and Artificial Neural Network (ANN) models were used to show the feasibility of generating an accurate medium-term load forecast for the case study despite the peculiarity of its load data. The statistical evaluation methods used are Mean Absolute Percentage Error (MAPE) and root mean square error. The results from the comparative study show that the ANN model is a superior method for load forecast due to its ability to handle the load data and it has lower MAPE and RMSE of 0.0285 and 1.124 respectively which is far better result than the regression model.

Akpama *et al.* (2018), worked on Artificial Neural Network for Energy Demand Forecast. The data that was used in training and testing of the model proposed in the research are the yearly electric power supplied to Owerri city as obtained from Enugu Electricity Distribution Company (EEDC), Egbu, Owerri 132/33kV station. The historical data for 2007 through 2016 was used for the analysis, and thus, a ten-year forecast from the period of 2007 to 2016 was made. The input data used which include: Historical electric load demand, Gross Domestic Product (GDP), Population and Industrial Index of Production (IIP), were the data for Owerri City for the period of investigation. At the end of their research, the results show that the ANN method of forecasting has a close relationship between the forecasted data and the target data and hence,

artificial neural network (ANN) is suitable for long-term load forecasting.

Olajuyin (2018), worked on long term load forecasting using artificial neural network. He used a historical data from January 2008 to February 2013 obtained from Works and Services Department of Federal University of Agriculture, Abeokuta, Ogun State (FUNAAB) to forecast electric load demand of FUNAAB from 2013 to 2027. The forecasted result indicated that by 2027 the consumption load of FUNAAB would be 1.94×10^5 kwh (10104.1 kVA and 8083.3 kW).

Naji *et al.* (2018), used Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models to analyse historical load data obtained from the Metrological Department of Malaysia. The data sets cover a seven-year period (2009- 2016) on monthly basis. The ANN and ANFIS were used for long-term load forecasting. The performance evaluations of both models that were executed by showing that the results for ANFIS produced much more accurate results compared to ANN model. It also studied the effects of weather variables such as temperature, humidity, wind speed, rainfall, actual load and previous load on load forecasting. The simulation was carried out in the environment of MATLAB software.

Agboola *et al.* (2021) applied Artificial Neural Network for Long-term Industrial Load Forecast: Trans-Amadi Industrial Layout, Nigeria. The result shows that ANN simulation tool is highly reliable for load forecast couple with percentage error result which also proves minimum error of the process as forecasted electrical load results were generated for Trans-Amadi industrial feeder for ten (10) years starting from year 2020-2029. However, from year one (1) to year ten (10) the ANN training architecture maintained eleven (11) iterations with fifteen (15) neurons data set to achieved its forecasted results for the electrical forecasted load to be achieved.

Thus, this study will adopt a long-term load forecasting for adequate planning and critical operational decisions such as installation of FACTS devices, network reinforcements, distributed generators etc.

METHODOLOGIES

The methods used in achieving the aim and objectives of the research from data

acquisition to training and simulation of the data leading to obtaining result are discussed. More details on how the long-term load forecasting for the 330kV Nigerian network was successfully achieved is discussed.

Artificial Neural Network (ANN)

Artificial neural network (ANN) is basically machine learning approach that models human brain and consists of a number of artificial neurons. Their ability to learn by example makes them very flexible and powerful. Neural networks, has its own strength to derive meaning from complicated or imprecise data, and most of the time can be used to detect the pattern and trend in the data, which cannot be detectable easily from human eye or any computer techniques. This section shows the application of neural network in modelling long-term electricity demand of the Nigerian power systems. The input variable of the neural network are the historical data for the population, gross domestic product (GDP) and the temperature whereas the output is the historical load consumption. Figure 2.0 shows the neural network.

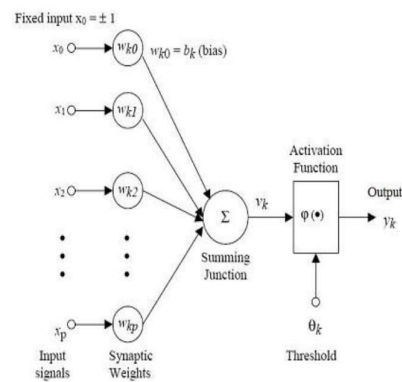


Figure 2: Schematic of an Artificial Neuron

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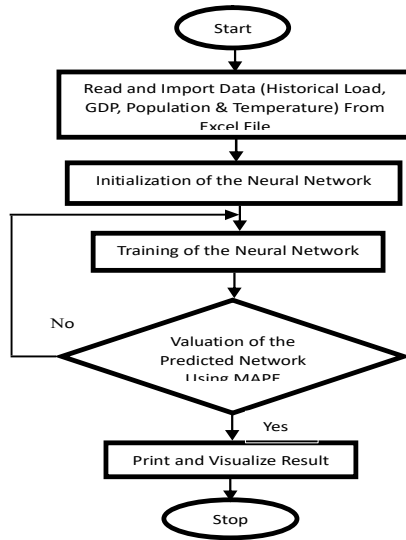


Figure 3: Schematic of an Artificial Neuron

Neural Network Flow Chart

The flow chart shows a sequential or step by step manner in which the program was executed in MATLAB environment until a better result was achieved. Mean average percentage error (MAPE) was used to determine the output with least error and maximum reliability. Figure 3 shows the flow chart of the Artificial Neural Network Algorithm.

Parameters Modelling

The parameters used for the forecasting were modelled into the artificial neural network include: monthly data collected for population, gross domestic products, temperature and the load consumption for a period of 15 years were used to train a neural network using three input which are the temperature, population and the GDP and one output which is the electrical load demand that is needed to be forecasted. The training method is feed-forward back-propagation based on Tran-sigmoidal function using Lavenberg - Marquart training algorithms with 10 hidden neurons. The mean square error was used to evaluate the performance of the network.

Mean Absolute Percentage Error (MAPE)

To validate the accuracy of the model, the mean absolute percentage error (MAPE),

also known as mean absolute percentage deviation (MAPD), being a measure of prediction accuracy of a forecasting. MAPE measure the amount of error in terms of percentage. It is calculated as the average of the absolute percentage error. The formula for calculating it is:

$$MAPE = \left(\frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \right) \times 100\% \quad \dots(6)$$

Where; n is the is number of samples, A_i is the actual value and F_i is the forecasted value

MAPE has several desirable properties including reliability; ease of use and interpretation. It also incorporates all of the information in its calculation, but MAPE has a major drawback, like any average, MAPE is affected by extreme values, but in the case of MAPE, the extreme values most often occur at the high end of the distribution (Swanson, *et al.*, 2011).

RESULTS AND DISCUSSIONS

The results obtained during the training, testing and validation of the ANN based long-term load forecast model were analysed. Tables and graphs for the year's ahead predictions were also presented. The actual load (historical load) was mapped with the predicted load from the MATLAB software during training to obtain Figure 4. The figure shows how the neural network was able to satisfactorily follow the actual load pattern, learn its behaviour and train the network effectively.

Results of the ANN Input Variable Prediction

Three neural networks were trained to individually predict the three-input variable by using their deseasonalization which were in turn used to predict the temperature, population and the GDP respectively.

Load Forecasting Result

Figure 5 and 6 show the architecture and the regression plot of neural network model of the Nigerian power system load demand with three inputs and one output after 6 iterations.

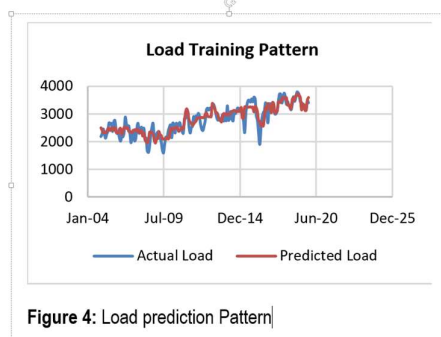


Figure 4: Load prediction Pattern

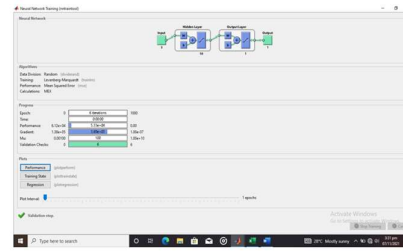


Figure 5: Load Demand Neural Network Model of Nigerian Power System

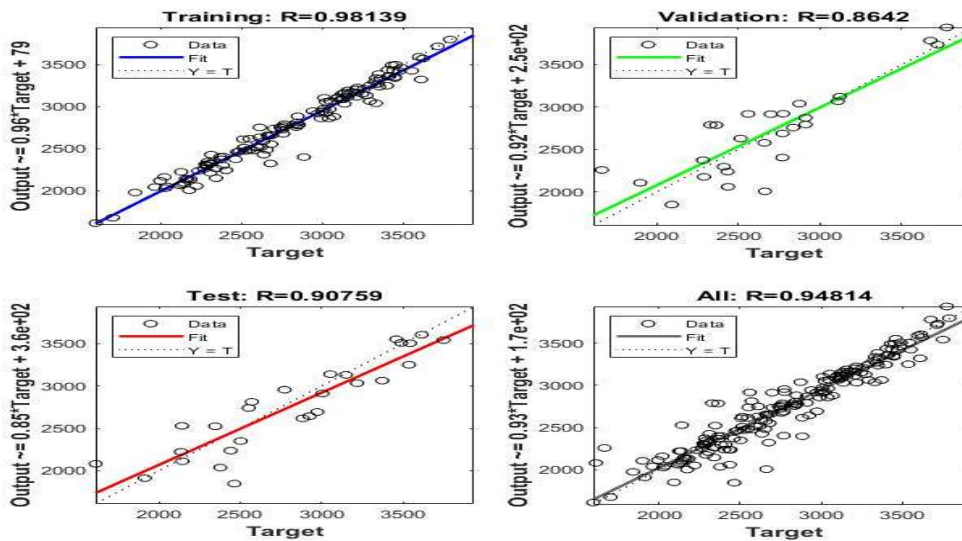


Figure 6: Regression Plot of Neural Network Model

After successfully training the network on MATLAB, the trained network was used to forecast the load demand for the Nigerian network for the years 2020, 2021, 2022, 2023, 2024, 2025 and 2026 as presented in Table 1.

Table 1: Seven Years Load Forecasting of the Nigerian Power System

	Year 2020	Year 2021	Year 2022	Year 2023	Year 2024	Year 2025	Year 2026
January	3480.203	3889.604	3973.638	4131.934	4177.463	4362.831	4469.783
February	3396.554	3889.41	3975.621	4124.185	4230.211	4280.883	4422.178
March	3761.943	3904.009	4024.48	4111.426	4223.64	4253.844	4445.755
April	3791.605	3902.827	4009.871	4128.677	4217.101	4249.38	4457.367
May	3792.526	3898.373	3997.634	4141.766	4216.589	4303.282	4486.788
June	3812.103	3912.527	3961.367	4160.258	4277.358	4394.134	4227.394
July	3821.269	3949.738	4053.316	3904.325	4248.455	4409.734	4253.715
August	3770.801	3966.627	4101.886	3826.273	4294.678	4382.945	4108.952
September	3863.882	3991.715	4084.273	3945.442	4312.146	4387.735	4093.861
October	3877.452	3995.729	4099.824	3816.032	4330.683	4411.514	3889.021
November	3876.833	4003.934	4099.464	3801.152	4344.477	4428.475	4200.536
December	3881.852	4005.955	4122.025	4132.376	4355.541	4460.043	4418.59

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As evident in Figure 7, the load is exponentially increasing due to growth in population and industrial activities among others.

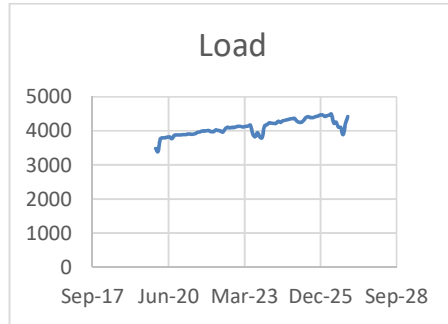


Figure 7: Seven Years Load Forecasting of the Nigerian Power System

Figure 7 further shows a linear pattern of how the forecasted load increases over time, from 3480.2 MW in January 2020 to 4486.7 MW in 2026. The overall performance for the Nigerian load forecasting was measured using the mean absolute percentage error (MAPE). The MAPE result was obtained to be 0.71 which is a good value in comparison to other previous works.

CONCLUSION

In this work, the load demand of the Nigeria power system was modelled using an artificial neural network using three inputs (population, GDP and the temperature) and one output (Load) using 10 hidden neurons in MATLAB software. The modelled network was simulated and the future load demand on the Nigerian utility network was forecasted using Artificial Neural Network (ANN). Measure of the error was calculated using the mean absolute percentage error (MAPE). The MAPE was obtained to be 0.71 which is a good value compared literature with MAPE of 1.67 and 6.90.

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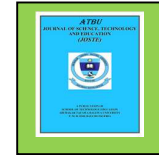
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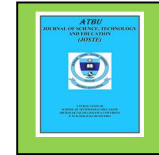
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