EJSIT
European Journal of Science, Innovation and Technology
ISSN: 2786-4936
www.ejsit-journal.com
Volume 5 | Number 1 | 2025

Long Term Electricity Demand Forecasting in Nigeria

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ABSTRACT

This study focuses on forecasting long-term electricity demand in Nigeria using three distinct methods: Nonlinear Autoregressive with Exogenous Input Neural Network (NARX), Support Vector Regression (SVR), and Exponential Smoothing - Holt Winters (ES-HW). Over eight years of data from the National Control Centre were utilized to develop and compare these models. The ES-HW model, despite its reliance on limited input data, demonstrated ability to replicate the seasonal patterns and trends in electricity demand, even though it resulted in a higher relative root mean square error (RRMSE) than the other method. While SVR showed slightly better performance metrics, ES-HW provided a more accurate depiction of demand fluctuations over time. The study identified key insights, such as the critical impact of data availability on forecasting accuracy and the comparative effectiveness of different modeling approaches. The research highlights the challenges posed by limited historical data in the Nigerian electricity sector, which constrained the accuracy and scope of the forecasts. Overall, this work contributes valuable knowledge to energy modeling and policy-making, offering a foundation for sustainable energy planning in Nigeria.

Keywords: electricity demand, forecasting, NARX, SVM

INTRODUCTION

Electricity plays an important role in our world today. Electricity is a secondary energy source because it depends on other energy sources (renewable and non-renewable). Electricity is a cleaner, more reliable, easier to transport more efficient energy source and can be easily adapted to suit different applications. Electricity demand forecasting is the method whereby the demand for electricity in future timeframe is estimated by making use of past electricity demand data and some of the factors which affect electricity demand (Atanane, Benabbou, & El Ouafi, 2023). The timeframe of the forecast plays a role in how the factors impacting electricity demand are selected thereby influencing the outcome of the forecast. For example, for short term electricity demand forecasting, human hourly temperature, working hours of the population in the location can be used, while for long term electricity demand forecasting factors like weather, population growth, amount of rainfall can be used. Electricity demand forecasting is divided into various categories determined by the timeframe of the forecast, referred to as forecasting ranges (Nti et al., 2020). Achieving accurate forecast can be crucial for the planning and management of electric power systems, facilitating maintenance, scheduling, system expansion, and other key activities. The specific objective of the forecast dictates the timeframe over which it was conducted. These factors are selected based on the forecast's scope and nature. Research has explored the relationship between these factors and electricity generation, revealing a strong correlation between ambient temperature and hourly electricity consumption, employing methodologies like Pearson's correlation and Spearman's rank correlation to demonstrate these relationships (Dedinec,

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2016). Nigeria has faced significant power supply issues over the years, affecting the quality of life for its citizens. These challenges include insufficient power plants, technical problems, gas supply shortages, lack of government policies, poor planning, and political issues, among others. The country's electricity industry relies on a mix of energy sources, including thermal plants and renewable resources like hydro, solar, and wind. Due to this diverse energy mix, multiple factors influence electricity generation in Nigeria. Accurate electricity demand forecasting is crucial for planning future electricity supply in the country.

Ozveren and King (2007) carried out a study on short-term electricity demand prediction for South Sulawesi Island, Indonesia, using multiple linear regression analysis and collecting data across both rainy and dry seasons. Their findings indicated multiple sources of error, including modeling mistakes, system disturbances, and inaccuracies in temperature forecasting. According to Hsu and Lin (2002), a successful forecast exhibits Mean Absolute Percentage Error (MAPE) below 10%. The direct approach, leveraging actual past data, outperformed the iterative method, yielding a MAPE of 3.2% compared to 5.36% for the iterative approach. Granger causality tests and co-integration analyses are two methods used to evaluate correlation between time series datasets. Granger causality tests ascertain whether one variable in a linear relation is dependent on another variable, determining if the relationship is unidirectional, bidirectional, or nonexistent. Conversely, co-integration analyses assess causal relationships among variables by examining if trends in a group of variables are shared by the series (Stern, 2004). Yukseltan, Yucekaya, and Bilge (2017) presented a novel approach to forecasting electricity demand on an hourly basis across annual, weekly, and daily horizons without relying on climatic or econometric data. Instead, the method utilizes a linear model that incorporates the harmonics of daily, weekly, and seasonal variations, alongside the modulation of diurnal periodic variations by seasonal harmonics. Applied to the Turkish electricity market for 2012–2014, the model achieved a MAPE of 3% for daily and weekly demand forecasts.

Şişman (2017) sought to forecast future electricity demand in Turkey by comparing the accuracy of Provide the full meaning (ARIMA) and grey prediction (GP) models. The ARIMA and GP models demonstrated lower error rates (4.9% and 5.6%, respectively) compared to Provide the full meaning (MAED) (14.8%), indicating their superior accuracy for long-term forecasts. Andoh et al. (2021) employed the SARIMA model (Seasonal Auto-Regressive Integrated Moving Average) to predict electricity demand in the western region of Ghana. Mirasgedis et al. (2006) conducted a study on electricity demand forecasting in Greece, employing two multiple regression models incorporating autoregressive structures. Their models demonstrated high accuracy in forecasting over a one-year period and yielded error rates of 4.6% and 2.8%, respectively. Taylor and Buizza (2003) examined the role of weather forecasts in electricity demand forecasting models, focusing on lead times ranging from 1 to 10 days. Their approach offered an enhanced method for predicting electricity demand by incorporating a range of weather scenarios. Bedi and Toshniwal (2019) proposed a deep learning framework to forecast electricity demand by considering long-term historical dependencies. The proposed method was tested on electricity consumption data from the Union Territory of Chandigarh, India, and its performance was evaluated against Artificial Neural Network (ANN), Recurrent Neural Network (RNN), and Support Vector Regression (SVR) models, demonstrating its effectiveness and applicability. Abdulsalama and Babatunde (2019) proposed an Artificial Neural Network based method for forecasting electrical energy demand, using Lagos state, Nigeria, as a case study. Their results highlighted the potential of ANN in effectively handling the complexities associated with non-linear data in electrical energy demand forecasting.

Mati et al. (2009) in a study highlighted the importance of demand forecasts for optimizing power system operations and minimizing costs, even during local failures. Their study noted the limitations of time series models for long-term forecasting due to uncertainties in future trends. It recommended combining time series models with end-use modeling strategies to overcome these limitations. Okakwu et al. (2019) carried out a study which focused on the complexities of the Nigerian power sector and the importance of accurate electricity demand forecasting due to industry deregulation, fluctuating demand, and population growth. Their study concluded with a recommendation for future research to optimize the Harvey model for even better prediction accuracy. Ezennaya et al. (2014) performed a study addressing the critical importance of accurately forecasting electricity demand in Nigeria due to the country's increasing reliance on stable electric supply for agriculture, industry, and household comfort. This research focused on predicting Nigeria's electricity demand from 2013 to 2030, aligned with the nation's Vision 2025 goals, using Time Series Analysis based on historical load data. Ebakumo (2021) performed a study on forecasting Nigeria's electricity demand from 2020 to 2040, using time series analysis based on historical load data. Their average mean square error, indicating the forecast's accuracy, was approximately 0.52%.

Ezenugu, Nwokonko, and Markson (2017) conducted a statistical analysis of residential electricity demand in Nigeria using annual data from 2006 to 2014 resulting in quadratic regression model with higher coefficient of determination (93.87) and a lower Root Mean Square Error (RMSE) of 52.77, compared to the multiple regression model's coefficient of determination of 93.50 and RMSE of 53.16. Idoniboyeobu, Ogunsakin, and Wokoma (2018) studied long-term electric power load forecasting for Nigeria, researchers projected a 20-year period from 2013 to 2032 using a modified exponential regression model implemented on the Matlab platform. In their study, the modified exponential regression model provided the most accurate results, with a percentage error of 1.37%, as opposed to 1.67% for the existing model. Mir et al. (2020) investigated the growing global electricity demand and the associated uncertainties, emphasizing the necessity for accurate load forecasting techniques to inform business and policy decisions identifying research gaps and recommended areas for further exploration, highlighting the need for region-specific forecasting approaches to better address the complexities of electricity demand in diverse economic contexts. Vasquez, Rodriguez, and Dayupay (2020) conducted a study focusing on predicting energy consumption within the Puerto Rico distribution system from 2019 to 2028, employing multi linear regression. Their energy forecast for 2028 projected consumption at 566,078,019.1 kWh. The regression outcomes exhibited error rates of 0.995 and 0.991, with a mean average percentage error of 0.74%, indicating the model's strong alignment with the dataset. Saravanan, Kannan, and Thangaraj (2012) investigated electricity demand forecasting for India over a 19-year period (2012-2030 resulting in principal component artificial neural network (PC-ANN) achieving a MAPE of 0.430%, outperforming Principal Component Regression (PCR) at 0.597% and traditional regression analysis at 0.969%.

Various types of exponential smoothing exist, including first-order, second-order, higher-order exponential smoothing, and the Holt-Winters method (Montgomery, Jennings, & Kulahci, 2015). Bindiu, Chindris, and Pop (2009) conducted a study on a fittings manufacturer in Cluj-Napoca, aiming to forecast day-ahead load using the Holt-Winters method. Their study modeled load forecasts for an industrial client with a predictable operational cycle, leading to repeated load consumption similar to historical data. While the mean square error (MSE) yielded satisfactory results within acceptable limits, MAPE values exceeded acceptable thresholds, indicating insufficient accuracy for dependable forecasting. Contreras-Salinas et al. (2020) applied Holt's method to predict electricity demand in Colombia, considering parameters such as energy consumption, per capita GDP, and purchasing power parity, which directly influence energy demand. Using data spanning 2007 to 2017 from the national interconnected system (NIS) and World Bank, they forecasted energy consumption for 2018, 2019, and 2020, showing a slight 0.1% increase if per capita values remained between 14880 to 15525. Abd Jalil, Ahmad, and Mohamed (2013) conducted a short-term electricity demand forecast using one-year data from Malaysia. They applied Standard Holt-Winters Exponential Smoothing, HWT Exponential Smoothing, and the Modified Holt-Winters method, demonstrating the superiority of the HWT exponential smoothing method given the available data. Nafil et al. (2020) employed different forecasting methods, including ARIMA, temporal causality modeling, and exponential smoothing, to forecast energy demand in Morocco for 2020. Al-Farttoosi and Mansouri (2019) predicted electricity consumption in Misan, Iraq, by analyzing monthly consumption data from 2009 to 2019. They utilized Box-Jenkins methods, exponential smoothing, and state-space classes, with model evaluation identifying the SARIMA (0,1,1) model as the most suitable for the dataset.

Erdogdu (2007) conducted a study on electricity demand in Turkey, employing co-integration analysis and ARIMA modeling for estimation and forecasting. Their results indicated electricity demand growth from 2005 to 2014 at an annual rate of 3.3%, with limited customer response to electricity price changes and income fluctuations. Almeshaiei and Soltan (2011) introduced a pragmatic methodology for constructing Electric Power Load Forecasting (EPLF) models, which is essential for planning electricity production and network operations. Akay and Atak (2007) addressed the challenge of electricity configuration planning and estimation in Turkey, given the country's increasing energy demand and uncertain economic structure. The Model of Analysis of Energy Demand (MAED), officially used by the Turkish Ministry of Energy and Natural Resources (MENR), is the current method for energy planning. Dudek (2015) explored a method utilizing the Random Forest model for short-term electricity load forecasting. This technique, along with Artificial Neural Networks, exhibited superior performance compared to other methods like ARIMA and exponential smoothing. Aprillia, Yang, and Huang (2019) investigated a novel approach termed Whale Optimization Method, Discrete Wavelet Transforms, and Multiple Linear Regression (WOA-DWT-MLR) for high-accuracy short-term load forecasting. The method combines whale optimization algorithm (WOA) with discrete wavelet transformation and multiple linear regression, showcasing improved accuracy compared to traditional methods. Additionally, fuzzy logic methods such as Interval Type-2 Fuzzy Logic, as proposed by Dharma, Robandi, and Purnomo (2011), have been effective in short-term load forecasting. Self-Organizing Maps (SOM), introduced by Hernández et al. (2014), have also shown promise in providing accurate short-term load forecasts.

METHODOLOGY

Different methods can be used for carrying out electricity demand forecasting ranging from soft computational methods to traditional forecasting methods. Three methods were used to carry out long term electricity demand forecast in this work; Nonlinear Autoregressive with exogenous input (NARX), Support vector machines (SVM) and exponential smoothening Holtz Winters methods (ES-HW). Data for the study was collected from National control center (NCC) from the period between January 2015 to December 2022. There are many factors affecting the outcome of a long-term electricity demand forecast. The factors which will be considered in developing the forecasting models are population, days of rainfall in a month and average temperature in a month collected for the period between January 2015 to December 2022 (Nigeria Climate, 2024). Two methods were used to measure the error for the different forecasting models developed; relative root mean square error (RRMSE) and relative mean absolute error (RMAE).

Nonlinear Autoregressive with Exogenous Inputs

Nonlinear autoregressive with exogenous inputs (NARX) is a type neural network known as a recurrent dynamic network. It consists of connections which encloses several layers of networks having feedback connections. The structure of a NARX is made up of three layers; input layer, hidden layer and an output layer. The NARX is suited for this study due to its ability to model nonlinear dynamic systems.

The NARX network is expressed mathematically in Equation (1),

$$y(t) = f\left(x(t-1), x(t-2) \dots x(t-D_x), y(t-1), y(t-2) \dots y\left(t-D_y\right)\right) \quad (1)$$

Where f represents the nonlinear function which is approximated by the multi-layer perceptron (Sum, Kan, & Young, 1999). x(t) and y(t) represent the input and output of the neural network at different time steps *t* respectively. The predicted data *y(t)* is regressed using the available target input values.

The Non-linear autoregressive with external input neural network (NARX) is built with 2 input delays, 2 feedback delays and 14 hidden layers. Historical data was split into 75% train data, 10% validation data and 15% test data. Figure 1 displays the NARX network showing the two hidden layers in the neural network model which was used to carry out the electricity demand forecast.

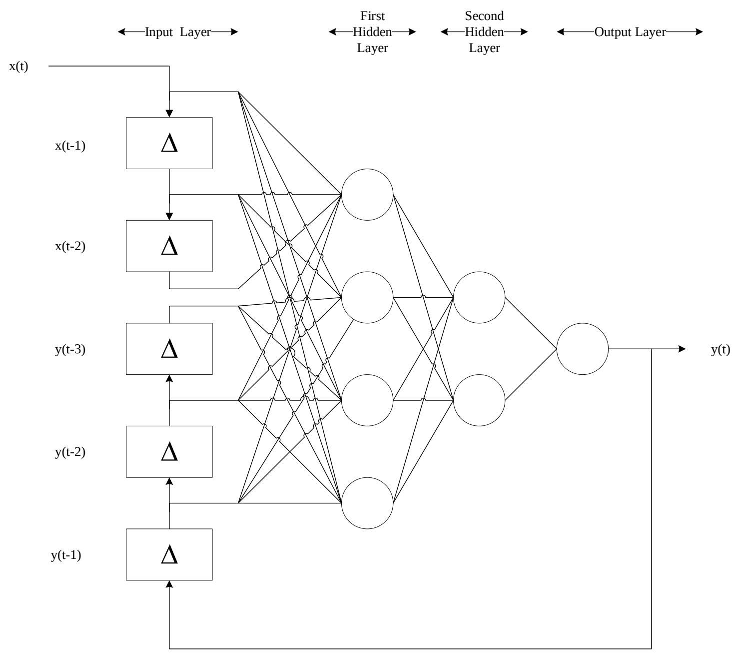

Figure 1: Two layered NARX neutral network model

The first and second hidden layers is made up of several neurons M in the first layer and N in the second layer which can be tweaked during training of the model until a satisfactory performance is attained by the model which minimizes the error between the output and the electricity consumption data. To train the network, Levenberg-Marquardt Method (LMA) is applied. LMA is an algorithm which is used to find the minimum function in a space of parameter by first picking a region of an objective function and modeling it, then another function such as a quadratic function and compared. Once an adequate fit is found, the region is expanded (Farber, 2011). Figure 2 shows a flow chart for the NARX algorithm.

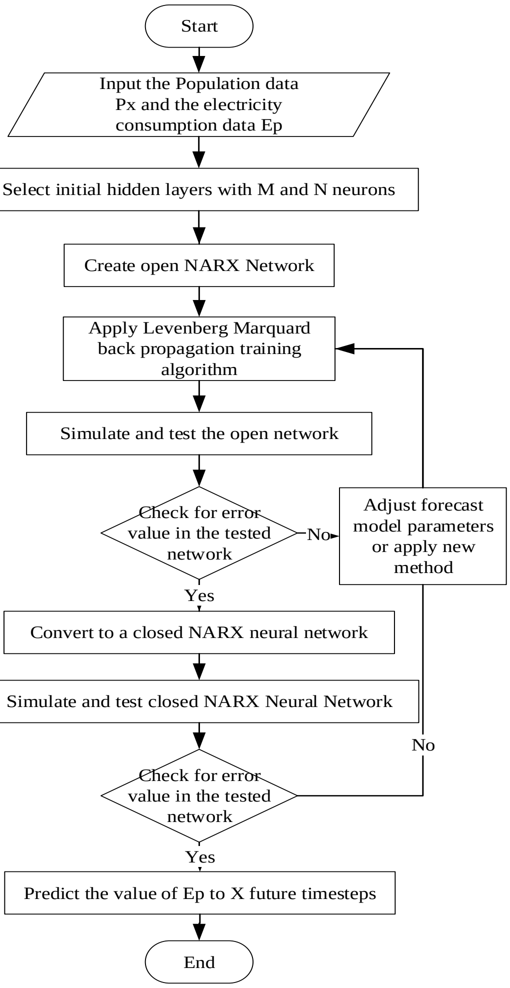

Figure 2: Flowchart for NARX neural network method

Support Vector Machine

Support vector machines (SVM) is a type of supervised learning which is based on statistical learning which can be resolved for classification and regression problems. This can be applied to time series prediction as regression analysis. When it a support vector machine is used to solve a regression problem, it is known as support vector regression (SVR).

SVM's are used to find a hyperplane (a separating line) between two different classes of data. After the hyperplane is identified, the SVM algorithm finds the points which are closest to the lines from both classes of data which are called support vectors. The distances in between the two support vectors are known as a margin. The purpose of an SVM is to maximize this distance between the support vectors. The hyperplane which has the maximum margin is known as the optimal hyperplane.

For a regression problem, the ε-tube is equivalent to the margin in a classification problem as shown in Figure 3. While the support vectors represent data that are at the outside of the ε-tube (Rodriguez-Perez & Bajorath, 2022).

Regression problems can be linear or non-linear and SVR can be applied to solving both forms of problems. A brief introduction of SVR is given below. Figure 3 shows a support vector regression for linear equations.

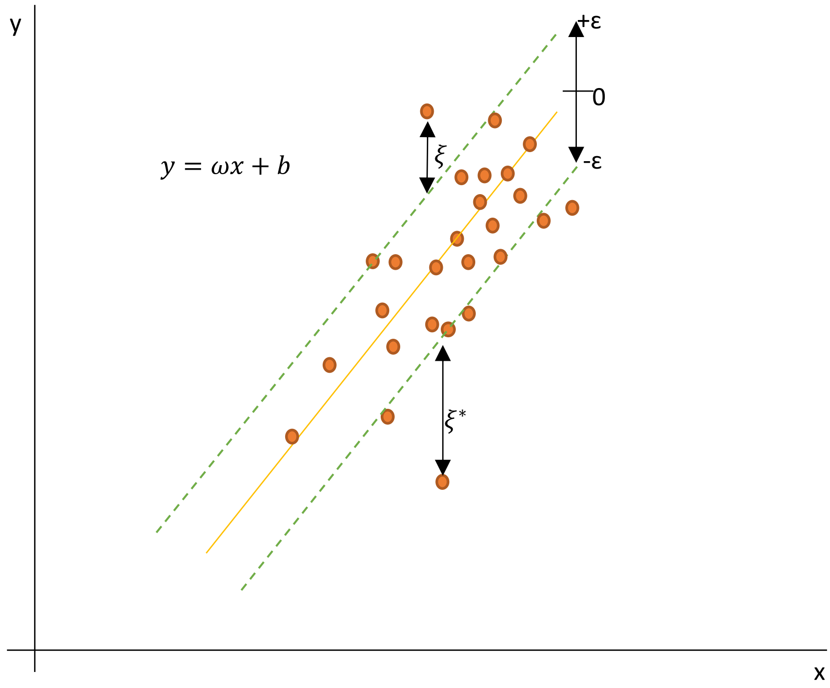

Figure 3: Linear Support Vector Regression (SVR) showing errors

Given a dataset with training data $((x_1, y_1)\ldots\ (x_l, y_l)$, SVR is used to solve the optimization problem where x_i represents the input vectors and y_i are the output values of x_i (Chen, Chang, & Lin, 2004).

$$(min_{\omega,b,\xi,\xi^*}\ \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{l}(\xi_i + \xi_i^*)) \tag{2}$$

Subject to

$$y_i - (\omega^T\phi(x_i) + b)\ \leq \epsilon + \xi_i, \tag{3}$$

$$(\omega^T\phi(x_i) + b) - y_i\ \leq \epsilon + \xi_i^*, \tag{4}$$

$$\xi_i, \xi_i^* \geq 0, i = 1, \ldots, l \tag{5}$$

From equation (2) above, x_i is mapped by the function ϕ to a higher dimensional space, ξ_i is the upper training error while ξ_i^* is the lower error subject to $|y_i - (\omega^T\phi(x_i) + b)| \leq \epsilon$. C is the quality of cost error, ϵ the width of the tube and ϕ is the mapping function.

For a non-linear SVR, a kernel is used to select the type of hyperplane which is used in separating the data. For our studies, a Gaussian RBF kernel is used.

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{6}$$

Where σ represents the standard deviation.

Exponential Smoothing

Exponential smoothing is a method used to predict a future load using the load from the past. The procedure for exponential smoothing puts into consideration recent experiences in its future forecasts by assigning exponentially decreasing weights to more recent observations. The model is suitable for univariate time series data where the future data is a weighted linear sum of past data. Exponential smoothing works on prior assumptions like seasonality and trend in the time series which are defined during modeling. Seasonality refers to a periodicity while trend is a repeated pattern within periods.

There are different exponential smoothing methods single, double and triple exponential smoothing, however their applications depend on the nature of dataset available.

Simple exponential smoothing assumes the data fluctuates around a mean and it is applied usually for short range forecasting. Double exponential smoothing can be used in a case where there is an identifiable trend in the time series. This model considers the trends by analyzing periods in the data set and applying a smoothed estimated of the average growth by each period. Triple exponential smoothing applicable when the time series developed from the dataset exhibits both trend and seasonality. There are two types of seasonality a dataset can exhibit: additive and multiplicative.

Holts-Winters multiplicative method is an extension of the Holts exponential smoothing method which considers seasonality. This method expresses the seasonal component in percentages and the series is divided through to create the seasonal component (Emmanuel, Adebanji, & Labeodan, 2014).

Equation (7) is the model equation for Holt winters multiplicative method.

$$y_t = (b_1 + b_2 t)S_t + \epsilon_t \tag{7}$$

Where b_1 is known as the permanent component or base signal, b_2 is the linear trend component. S_t is the multiplicative seasonal factor and ϵ_t is the random error component.

L represents the length of the periods. The seasonality factor is therefore the sum of the length of the seasons i.e.

$$\sum_{1 \le t \le L} S_t = L \tag{8}$$

The forecasting equations used for Holts winters multiplicative methods are shown in equations (9) to (11).

Overall smoothing is represented by $\underline{R}_t$ and defined by Equation (9) below.

$$\underline{R}_t = \alpha \frac{y_t}{s_{t-L}} + (1 - \alpha) * (\underline{R}_{t-1} + \underline{G}_{t-1}) \tag{9}$$

Where α is a smoothing constant and varies between 0< α<1. Dividing y_t by s_{t-L} de-seasonalizes the data such that trend factor and previous value of the permanent component is updated in $\underline{R}_t$.

Smoothing of the trend factor is the second equation in the model represented by $\underline{G}_t$.

$$\underline{G}_t = \beta\left(\underline{S}_t - \underline{S}_{t-1}\right) + (1 - \beta) * \underline{G}_{t-1} \tag{10}$$

Where β is a smoothing constant that varies between 0 and 1.

Smoothing of the seasonal index is the final equation represented by $\underline{S}_t$ in Equation (11)

$$\underline{S}_t = \gamma_{es} \frac{y_t}{\underline{S}_t} + (1 - \gamma_{es}) s_{t-L} \tag{11}$$

Where γ_{es} is the third smoothing constant varying from 0 to 1. y_t. represents the most recent observed seasonal factor.

To carry out a forecast for the next period, the three equations are applied. Equation (12) is the expression for forecasting the next period.

$$y_t = (\underline{R}_{t-1} + \underline{G}_{t-1}) * \underline{S}_{t-L} \tag{12}$$

For a multi-step ahead forecast, the value of the forecast T periods is given by

$$y_{t+T} = (\underline{R}_{t-1} + T * \underline{G}_{t-1}) * \underline{S}_{t+T-L} \tag{13}$$

The seasonal factors were initialized using historical data. However, to estimate the initial values of the models, the following equations (14) to (16) are used.

$$\underline{G}_0 = (\underline{y}_m - \underline{y}_1)/(m - 1)L \tag{14}$$

$$\underline{R}_0 = \underline{x}_1 - \frac{L}{2}\underline{G}_0 \tag{15}$$

$$\underline{S}_t = \frac{x_t}{\underline{x}_i - \left[\frac{L+1}{2} - j\right]\underline{G}_0} \tag{16}$$

Where $\underline{x}_i$ is the average for the season which corresponds to the index t. *j* represents the position of the period *t* within the season. *J*=1, 2, …. *mL* denotes the average number of the observations made during the j^{th} season.

Holts-Winters multiplicative method is an extension of the Holts exponential smoothing method which considers seasonality.

The input data (Nigerian population) was prepared by scaling process before it is applied to the SVR model. Data scaling is a process whereby the values in a data set are rescaled to fit into a certain range. In Min-max scaling, the dataset is rescaled to fit into a range of 0 – 1.

After successful development of the forecasting models, the performance of the models was tested using two standard performance measurement methods; relative root mean square error (RRMSE) and relative mean absolute error (RMAE) methods. Equations (17) and (18) are expresses mathematical formula for RRMSE.

$$RMSE = \sqrt{\sum_{i=1}^{n}\left(\frac{(A_i - F_i)^2}{2}\right)} \quad (17)$$

$$RRMSE = RMSE\ x\ \frac{100\%}{F_{avg}} \quad (18)$$

Equation (19) represents formula for RMAE:

$$RMAE = \frac{\sum_{i=1}^{n}|A_i - F_i|}{n}\ x\ \frac{100\%}{F_{avg}} \quad (19)$$

Where A_i represents the actual data, F_i represents the predicted data and F_{avg} represents the average of predicted data.

RESULTS AND DISCUSSION

The results from the study are presented in this section. The training error and fitting diagram when developing the NARX is presented in Figure 4 and Figure 5.

Forecasted electricity demand and actual historical electricity demand is plotted in a line chart with Y-axis representing electricity demand and x-axis representing time-steps (months) as shown in Figure 6. Forecasted electricity demand from January 2023 to December 2050 is shown in Figure 7.

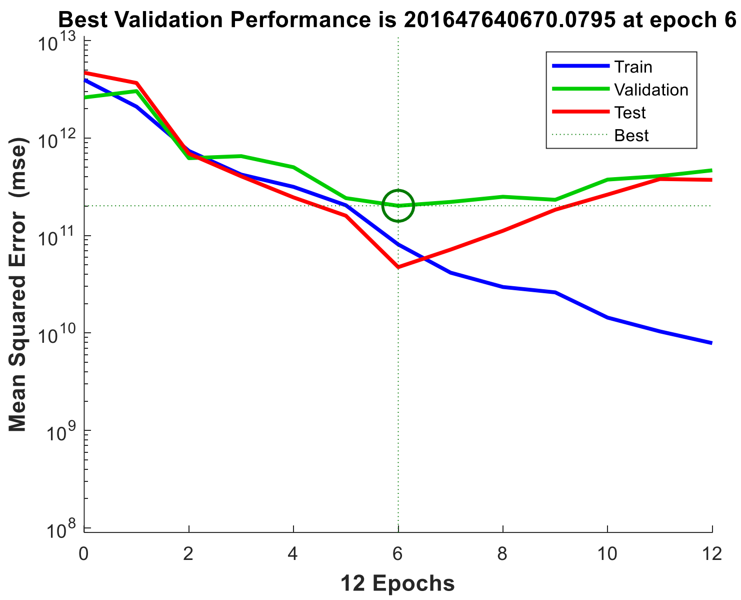

Figure 4: NARXNET training error using Mean Squared Error (MSE)

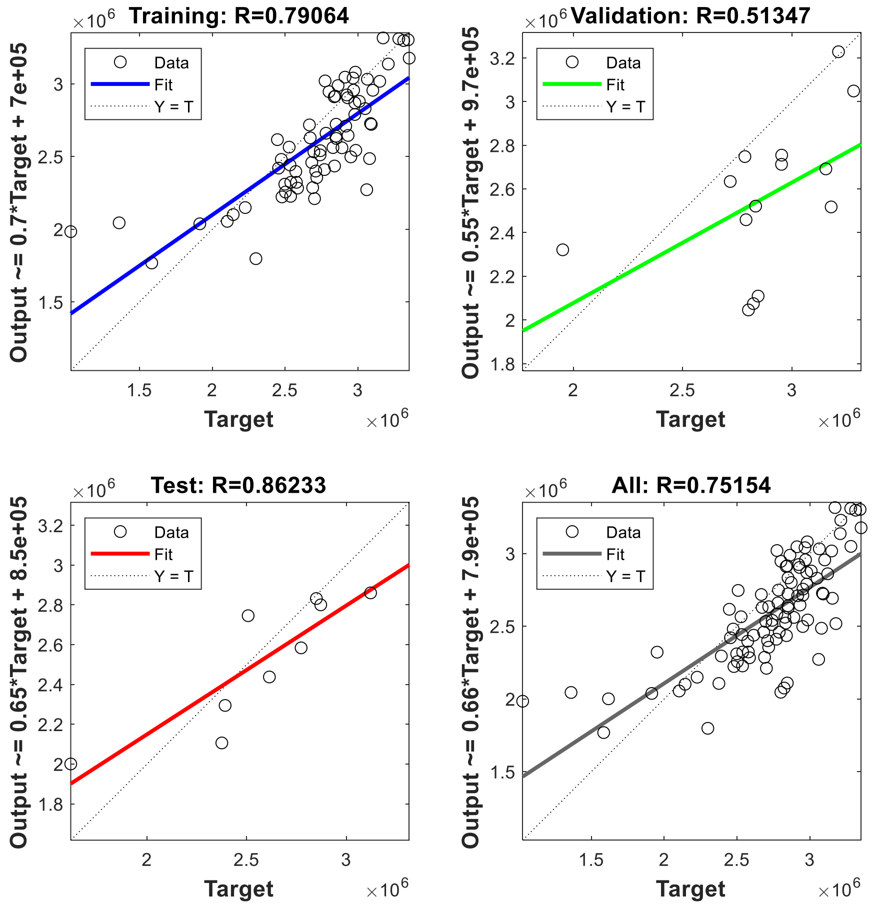

Figure 5: NARXNET fitting diagrams

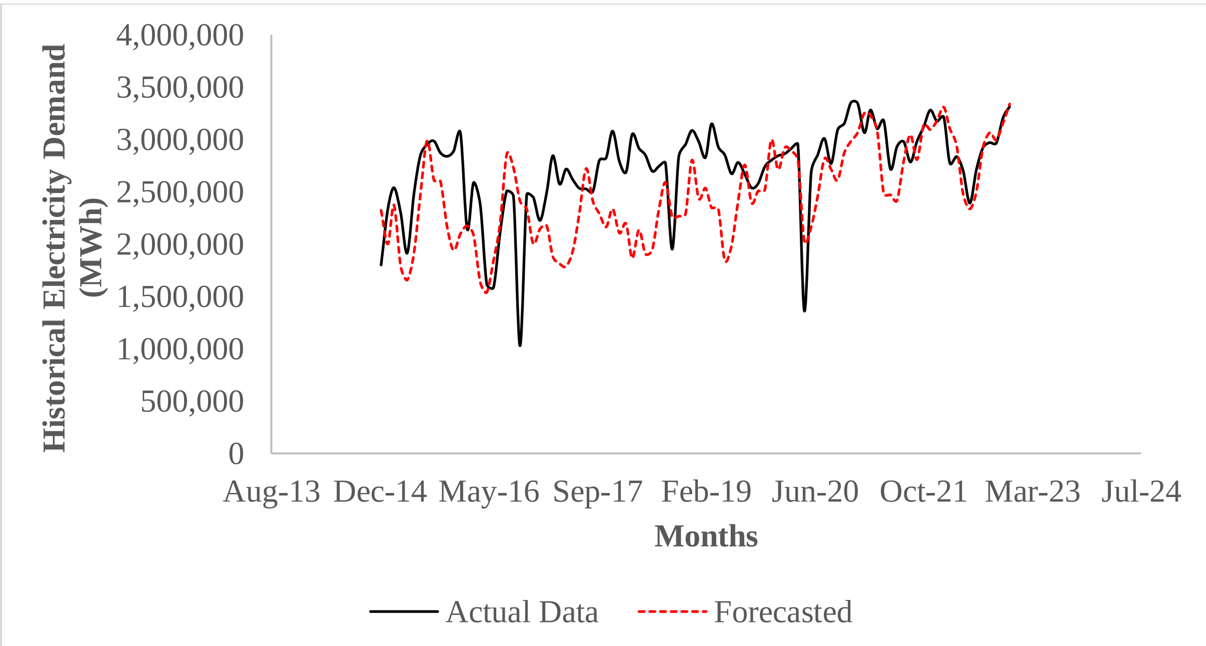

Figure 6: Actual historical monthly electricity demand versus forecasted electricity demand using NARX neural network

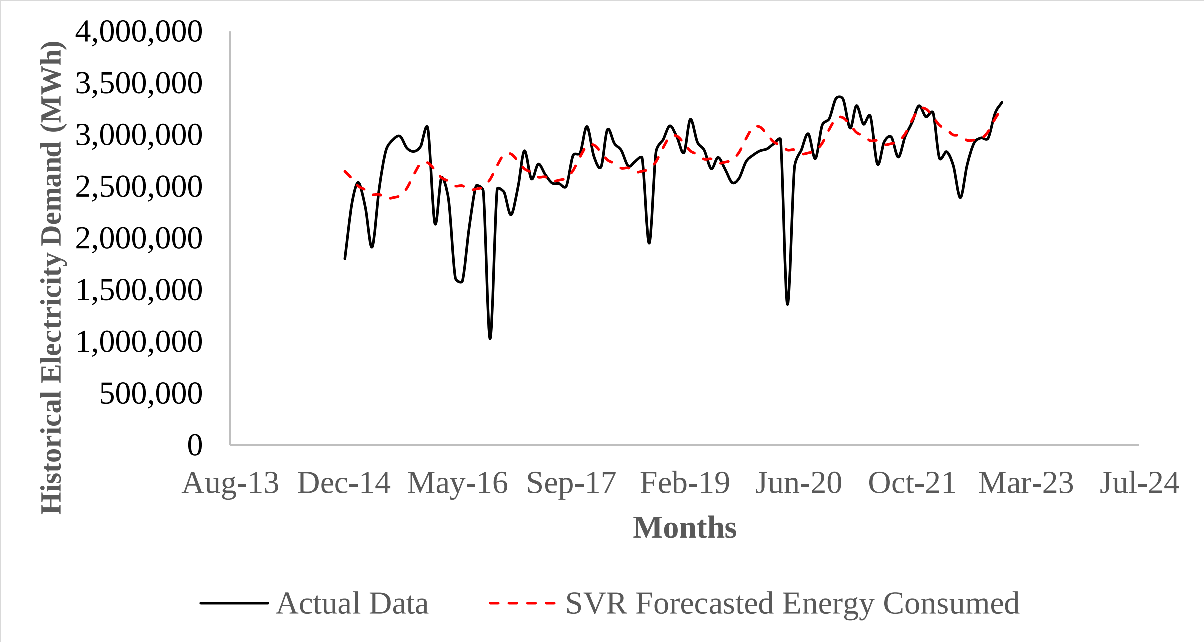

Figure 7: Actual historical monthly electricity demand versus forecasted electricity demand using Support Vector Regression

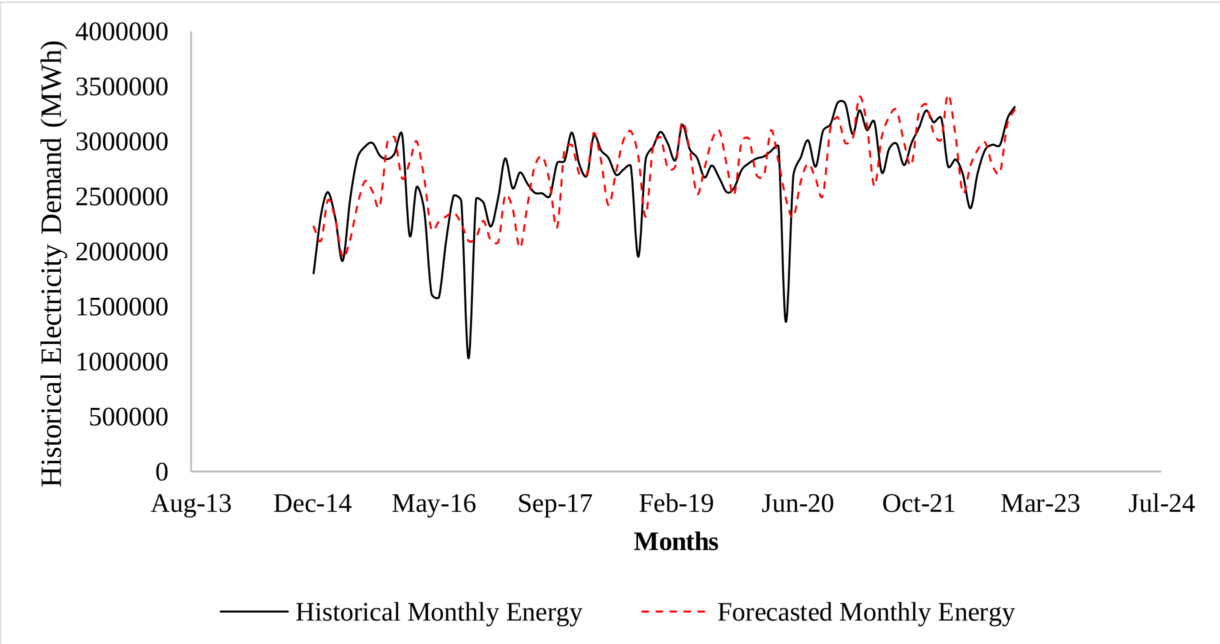

Figure 8: Actual historical monthly electricity demand versus forecasted electricity demand using exponential smoothing Holtz winters method

Figures 6 to 8 show plots of the actual historical electricity demand data and the results of the forecast done by the three forecasting models used. The plot of actual historical data shows very deep troughs which may be indicative of loss of power supply and may not necessarily correlate to seasonality. The result from the NARX neural network, can be seen in figure 6 shown in red dotted lines while the solid black line is the actual historical electricity demand time series chart. From physically assessing the plot, it can be deduced that the neural network was able to closely follow the actual historical data points. From the performance evaluation done on the NARX neural network model, RMAE resulted in 9.6% while RRMSE resulted in 12.6%.

For the Support vector regression method different kernel functions and cross validation folds were used. Cross validation folds are used to partition the dataset in a bid to prevent against overfitting while the kernel functions are what transforms input data into the required processing data. The best model resulted with the use of Linear kernel function. Cross validation did not have much effect on the forecasted results. Similar to the NARX model, monthly population, monthly days of rainfall and monthly average temperature was used as the input data while the output data was historical electricity demand. From the performance evaluation done on the SVR model, RMAE resulted in 8.5% while RRMSE resulted in 13.0%. A review of Figure 7 shows that the forecasted electricity demand from the SVR model shown by red dotted lines replicated the trend of the historical data. However, it was unable to closely match the points from the historical data.

Finally, the performance evaluation done on the ES-HW model, resulted in RMAE of 9.7% and RRMSE resulted in 13.6%. A plot of the actual historical data and results of exponential smoothing – Holtz Winters (ES-HW) is shown in Figure 8. Unlike the NARX and SVR method, ES-HW requires just one independent factor and an output in developing the model. In this case, population was used as the independent factor and the output was historical electricity demand dataset. ES-HW method takes into consideration seasonality and trend when developing its model.

A comparison of the accuracy of the different forecasting models is shown in Table 1. From the three forecasting models, NARX performed best when RRMSE was used while SVR performed best when RMAE was used.

Table 1: Comparison of errors from different models

S/N	Performance	NARX (%)	SVR (%)	ES-HW (%)
1	RMAE	9.6	8.5	9.7
2	RRMSE	12.6	13.0	13.6

The 3 models were used to carry out a long term electricity demand forecast from 2023 until 2050. The results obtained very similar to each other. Figures 9 to 11 show plots of the forecasted electricity demand between 2023 to 2050.

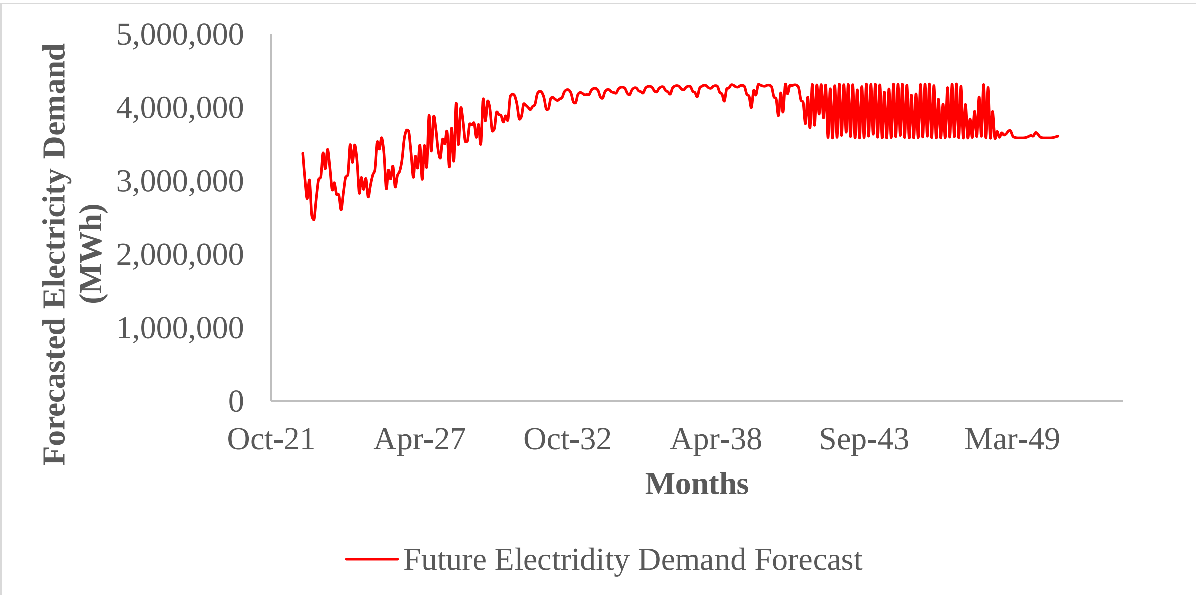

Figure 9: Forecasted energy electricity from January 2023 to December 2030 using NARX-neural network

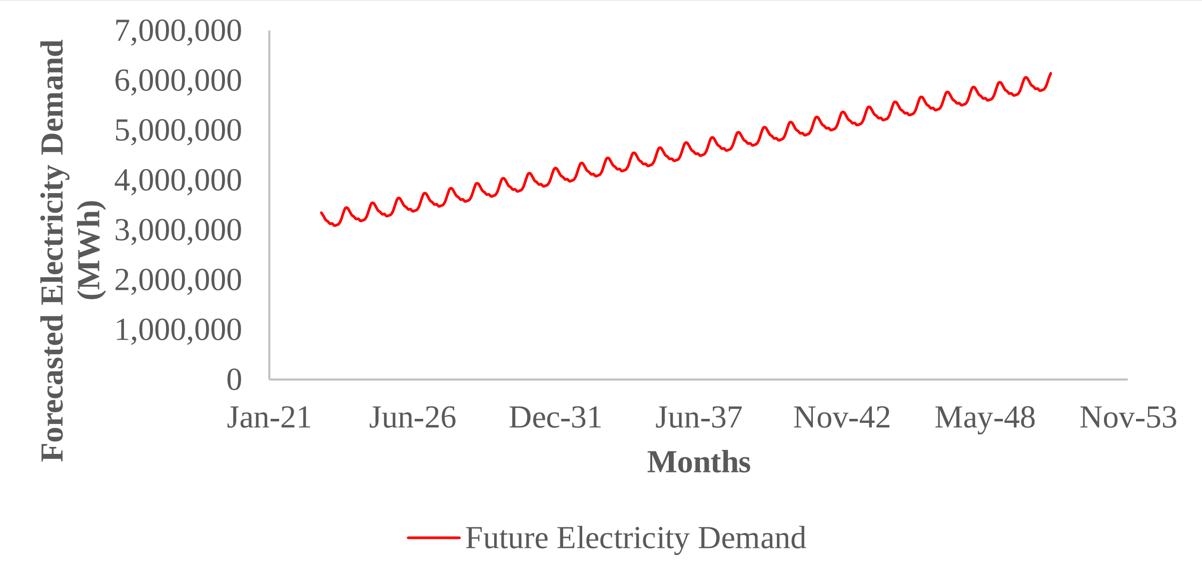

Figure 10: Forecasted electricity demand from January 2023 to December 2050 using SVR method

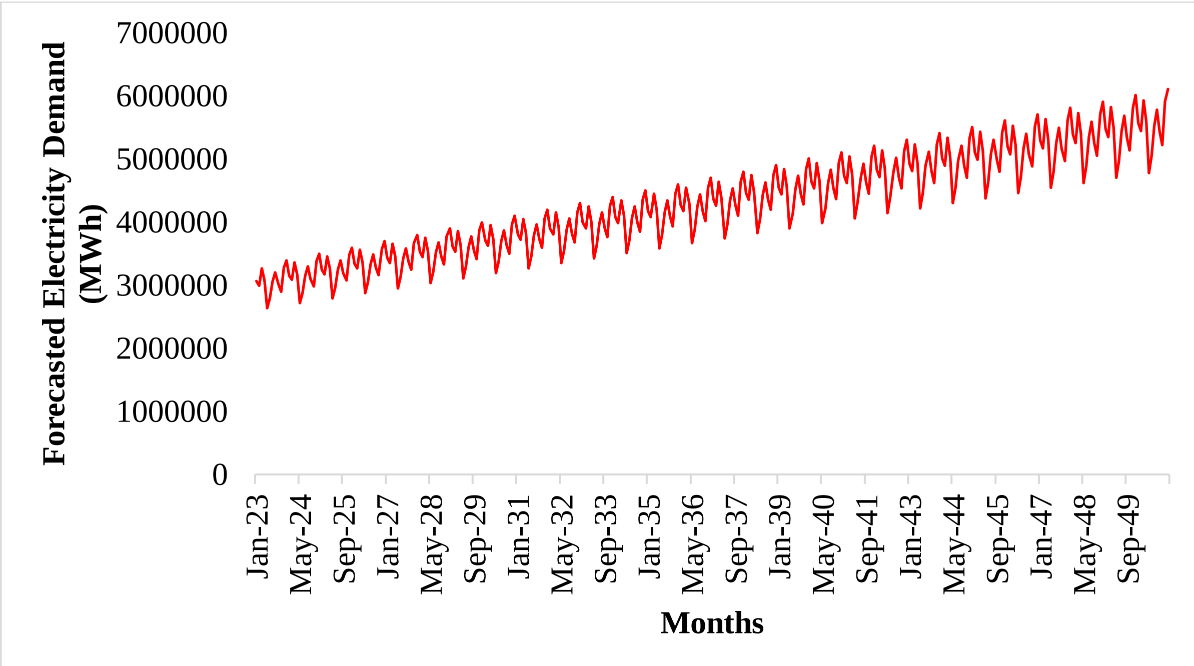

Figure 11: Predicted electricity demand from January 2023 to December 2050 using exponential smoothing - Holtz winters (ES-HW) method

From Figure 7 the results of NARX forecasting model displayed in time series chart shows that the model performed well for the few months (up until around October 2032) due to the presence of a trend, peaks and troughs representing seasons. However, from then the chart smoothens out and then become very noisy which indicates a failure of the model to predict far into the future. Figure 10 shows that the forecast for SVR model replicated the trend and was not successful in tracing the peaks and troughs observed in the actual historical time series. The long term forecasted electricity demand from the ES-HW model was plotted in a chart shown in Figure 11. The time series chart produced from the forecast has an increasing trend and exhibits seasonality which is consistent with the input historical electricity demand data.

CONCLUSIONS

Electricity generation data collected for a period of eight (8) years representing 96 months was collected from National Control Center to forecast a long term electricity demand for Nigeria. Three different methods were used to build the forecasting models for long term electricity demand and the different models were subsequently compared. The methods are nonlinear autoregressive with exogenous input neural network Support vector regression and exponential smoothing – Holtz winters.

Insufficient electricity demand data significantly affects the accuracy of different forecasting models. Among the different forecasting methods applied, the NARX performed least when applied for simulating long term electricity demand forecast. Although the model had the best performance when compared using RRMSE, it succeeded in forecasting only few months ahead successfully. This was due to the limited data available which was used in developing the model. Both SVR and ES-HW models had similar performance results however the ES-HW future electricity demand forecast over the long term period showed better dips and peaks which is a better replication of the actual historical electricity demand time series characteristics. The exponential smoothing Holtz winters model produced a RRMSE of 13.6%, the lowest error among the three-forecasting model. However, it produced the best forecast for long term future electricity demand. Electricity generation in Nigeria can benefit from electricity demand forecasting by application of the results in planning for future electricity needs.

REFERENCES

Abd Jalil, N. A., Ahmad, M. H., & Mohamed, N. (2013). Electricity load demand forecasting using exponential smoothing methods. *World Applied Sciences Journal*, *22*(11), 1540-1543.

Abdulsalam, K. A., & Babatunde, O. M. (2019). Electrical energy demand forecasting model using artificial neural network: A case study of Lagos State Nigeria. *International Journal of Data and Network Science*, *3*, 305-322.

Akay, D., & Atak, M. (2007). Grey prediction with rolling mechanism for electricity demand forecasting of Turkey. *Energy*, *32*(9), 1670-1675.

Al-Farttoosi, S. A., & Mansouri, B. (2019). Predicting Electricity consumption of Misan Province of Iraq Using Univariate Time Series Analysis. *Opción*, *89*, 2899-2921.

Almeshaiei, E., & Soltan, H. (2011). A methodology for electric power load forecasting. *Alexandria Engineering Journal*, *50*(2), 137-144.

Andoh, P. Y. A., Sekyere, C. K. K., Mensah, L. D., & Dzebre, D. E. K. (2021). Forecasting electricity demand in Ghana with the SARIMA model. *Journal of Applied Engineering and Technological Science*, *3*(1), 1-9.

Aprillia, H., Yang, H. T., & Huang, C. M. (2019). Optimal decomposition and reconstruction of discrete wavelet transformation for short-term load forecasting. *Energies*, *12*(24), 4654.

Atanane, A., Benabbou, L., & El Ouafi, A. (2023, November). Electricity demand forecasting: a systematic literature review. In *2023 14th International Conference on Intelligent Systems: Theories and Applications (SITA)* (pp. 1-8). IEEE.

Bedi, J., & Toshniwal, D. (2019). Deep learning framework to forecast electricity demand. *Applied energy*, *238*, 1312-1326.

Bindiu, R., Chindris, M., & Pop, G. V. (2009). Day-ahead load forecasting using exponential smoothing. *Scientific Bulletin of the Petru Maior University of Tirgu Mures*, *6*, 89-93.

Chen, B. J., Chang, M. W., & Lin, C.J. (2004). Load forecasting using support vector machines: a study on EUNITE Competition. *IEEE Transactions on Power Systems, 19*(4), 1821-1830.

Contreras-Salinas, J., López, F., Rondon-Rodriguez, C. A., et al. (2020). Analysis of energy consumption in Colombia using the Holt method. *International Journal of Energy Economics and Policy, 10*(6), 679-683.

Dedinec, A. (2016). Correlation of variables with electricity consumption data. In *International Conference on information society and technology ICIST 2016* (pp. 118-123).

Dharma, A., Robandi, I., & Purnomo, M. H. (2011). Application of interval type-2 fuzzy logic system in short term load forecasting on special days. *IPTEK The Journal for Technology and Science*, *22*(2), 110-115.

Dudek, G. (2015). Short-term load forecasting using random forests. *Intelligent systems, 323*, 821-828.

Ebakumo, O. (2021). Electrical energy demand forecast in Nigeria between 2020-2040 using probabilistic extrapolation method. *International Journal of Engineering Science and Application*, *5*(3), 71-85.

Emmanuel, O. O., Adebanji, A., & Labeodan, O. (2014). Using Holt Winter's Multiplicative Model to Forecast Assisted Childbirths at the Teaching Hospital in Ashanti Region, Ghana. *Journal of Biology, Agriculture and Healthcare, 4*(9), 83-89.

Erdogdu, E. (2007). Electricity demand analysis using cointegration and ARIMA modelling: A case study of Turkey. *Energy Policy*, *35*(2), 1129-1146.

Ezennaya, O. S., Isaac, O. E., Okolie, U. O., & Ezeanyim, O. I. C. (2014). Analysis of Nigeria's national electricity demand forecast (2013–2030). *International Journal of Science and Technology Research*, *3*(3), 333-340.

Ezenugu, I. A., Nwokonko, S. C., & Markson, I. (2017). Modelling and Forecasting of residential electricity consumption in Nigeria using Multiple and Quadratic regression models. *American Journal of Software Engineering and Applications*, *6*(3), 99-104.

Farber, R. (2011). *CUDA application design and development*. Elsevier.

Hernández, L., Baladrón, C., Aguiar, J. M., Carro, B., Sánchez-Esguevillas, A., & Lloret, J. (2014). Artificial neural networks for short-term load forecasting in microgrids environment. *Energy*, *75*, 252-264.

Hsu, C. W. & Lin, C. J. (2002). A comparison of Methods of Multiclass Support vector machines. *IEEE Transactions on Neural Networks*, *13*(2), 415-425.

Idoniboyeobu, D. C., Ogunsakin, A. J., & Wokoma, B. A. (2018). Forecasting of electrical energy demand in Nigeria using modified form of exponential model. *American Journal of Engineering Research*, *7*(1), 122-135.

Mati, A. A., Gajoga, B. G., Jimoh, B., Adegobye, A., & Dajab, D. D. (2009). Electricity demand forecasting in Nigeria using time series model. *The Pacific Journal of Science and Technology*, *10*(2), 479-485.

Mir, A. A., Alghassab, M., Ullah, K., Khan, Z. A., Lu, Y., & Imran, M. (2020). A review of electricity demand forecasting in low and middle income countries: The demand determinants and horizons. *Sustainability*, *12*(15), 5931-5941.

Mirasgedis, S., Sarafidis, Y., Georgopoulou, E., Lalas, D. P., Moschovits, M., Karagiannis, F., & Papakonstantinou, D. (2006). Models for mid-term electricity demand forecasting incorporating weather influences. *Energy*, *31*(2-3), 208-227.

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2015). *Introduction to time series analysis and forecasting*. John Wiley & Sons.

Nafil, A., Bouzi, M., Anoune, K., & Ettalabi, N. (2020). Comparative study of forecasting methods for energy demand in Morocco. *Energy Reports*, *6*, 523-536.

Nigeria Climate. (2024). *Climate Zone and Historical Climate Data*. Retrieved from Weather and Climate: https://weatherandclimate.com/nigeria

Nti, I.K., Teimeh, M., Nyarko-Boateng, O., & Adebayo, F. A. (2020). Electricity load forecasting: a systematic review. *Journal of Electrical Systems and Inf Technol, 7*(13).

Okakwu, I. K., Oluwasogo, E. S., Ibhaze, A. E., & Imoize, A. L. (2019). A comparative study of time series analysis for forecasting energy demand in Nigeria. *Nigerian Journal of Technology, 38*(2), 465-469.

Ozveren C. S. & King, D. J. (2007). Short term load forecasting using Multiple Linear Regression. *Proceedings of the universities power engineering conference, 42,* 1-10. University of Abertay Dundee, UK.

Rodriguez-Perez, R., & Bajorath, J. (2022). Evolution of support vector machine and regression modelling in chemoinformatics and drug discovery. *Journal of Computer-Aided Molecular Design, 36*(5), 355-362.

Saravanan, S., Kannan, S., & Thangaraj, C. (2012). India's electricity demand forecast using regression analysis and artificial neural networks based on principal components. *ICTACT Journal on soft computing*, *2*(4), 365-370.

Şişman, B. (2017). A comparison of ARIMA and grey models for electricity consumption demand forecasting: The case of Turkey. *Kastamonu Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *13*(3), 234-245.

Stern, D. I. (2004). Economic growth and energy. *Encyclopedia of energy*, *2*, 35-51.

Sum, J. P. F., Kan, W. K., & Young, G. H. (1999). A note on the equivalence of NARX and RNN. *Neural Computing & Applications*, *8*, 33-39.

Taylor, J. W., & Buizza, R. (2003). Using weather ensemble predictions in electricity demand forecasting. *International Journal of forecasting*, *19*(1), 57-70.

Vasquez, A. R. G., Rodriguez, M. E. F., & Dayupay, R. C. (2020). Energy Consumption Forecasting Model for Puerto Princesa Distribution System Using Multiple Linear Regression. *International Journal of Innovative Science and Research, 5*(11), 37-40.

Yukseltan, E., Yucekaya, A., & Bilge, A. H. (2017). Forecasting electricity demand for Turkey: Modeling periodic variations and demand segregation. *Applied Energy*, *193*, 287-296.