# ARTIFICIAL NEURAL NETWORK-BASED MODELING AND FORECASTING OF ELECTRICITY GENERATION IN NIGERIA

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***Abstract*— This paper presented artificial neural network (ANN)-based modeling and forecasting of electricity generation in Nigeria. The emphasis was on developing an ANN model that can forecast the electric power generation in Nigeria with minimal error. Two climatic variables (rainfall and temperature) were used as the explanatory variables. The prediction performance of the ANN model was compared to that of four regression models which are exponential regression model, multiple linear regressions, Cobb-Douglas model and Box Jenkins' autoregressive model of order 1. The comparative analysis of the prediction accuracy was carried out using the coefficient of determination (R), sum of square error (SSE) and root mean square error (RMSE). From the result, the ANN model had the best prediction performance with the R square value of 0.9807, SSE value of 175020 and RMSE value of 61.6833. As such it was used to forecast the power generation in Nigeria from 2016 to 2020.**

***Keywords*— *Artificial Neural Network, Forecasting, Electricity Generation, Cobb-Douglas Model, Regression Model, Multiple Linear Regressions, Box Jenkins' Autoregressive Model, Exponential Regression Model***

## I. INTRODUCTION

Presently, Nigeria mostly employs gas-fired and hydroelectric turbines for bulk generation, oil being too expensive and coal-fired stations having gone moribund [1,2,3,4,5]. In all, the Nigerian power sector has persistently been erratic and running with great shortfall [6,7,8,9]. The country is faced with acute electricity problems, which is hindering its development notwithstanding the availability of vast natural resources in the country. The electricity demand in Nigeria far outstrips the power generated [10,11,12,13]. The effective total operating capacity of the power generation systems for the national grid is grossly inadequate to meet the demand of an ever increasing population. This is largely due to inadequate planning. The whole scenario lies on the absence of more informative and detailed data on electricity generation in the country.

Importantly, there is a need to understudy the electric power generation in Nigeria using some of the factors that could be responsible for the variation in power generation and also there is need to forecast future power generation for effective planning. Hence, this paper seeks to provide appropriate intelligent and statistical model for electricity generation in Nigeria based on the available data for the year 1970 to 2015. The model uses rainfall and temperature as the explanatory variables. Specifically, artificial neural network (ANN) model is developed along with four statistical models, namely; exponential regression model, multiple linear regressions, Cobb-Douglas model and Box Jenkins' autoregressive model of order 1. The prediction performance of the models is compared and the best model is used to forecast the power generation in Nigeria from 2016 to 2020 [14,15,16,17,18].

## II. METHODOLOGY

In this research, intelligent and statistical models are developed for analyzing and forecasting electricity generation in Nigeria. Specifically, five different statistical models are used in this research. The statistical models are exponential regression model, multiple linear regression model, Cobb-Douglas model and Box Jenkins' autoregressive model of order 1 . The intelligent model is the artificial neural network (ANN).

First, data on power generation in Nigeria as well as data on rainfall and temperature from 1970 to 2015 were collated. The source of data collection for this study is secondary. The data on electricity generation in Nigeria between 1970 and 2015 were obtained from the Central Bank of Nigeria (CBN) statistical bulletin [19], while data on rainfall and temperature were extracted from the National Bureau of Statistics (NBS) abstract [20].

The four different statistical models were specified and then the ANN model was developed. Simulation was done based on each of the model and the data obtained using Matrix Laboratory (MATLAB) software. Furthermore, correlation between power generation and explanatory variables was carried out to show whether the explanatory variables affect electricity generation significantly or not. Test of model fitness and prediction accuracy of the five models was done using generic statistical approach which includes sum of square error, coefficient of determination and root mean square error (RMSE). The prediction accuracy of the five competing models was compared and the best model was selected and then used to forecast the electric power generation in Nigeria up to 2020.

*A. THE STATISTICAL MODELS (MODEL 1): EXPONENTIAL REGRESSION MODEL*

The exponential regression model can be expressed mathematically as:

$$\ln G_i = \ln \beta_0 + \beta_1 R + \beta_2 T + e_i \quad (1)$$

Let g = $\ln G_i$ and $\beta_0 = \ln \beta_0$ where G = Electricity generation (MWh), R = Amount of rainfall (mm), T = Temperature ($^0$C) and $e_i$ is the residual term. The residual term is assumed to be normally distributed with mean 0 and variance $\sigma^2$. After solving for the regression coefficient based on the case study data set, the model exponential regression model used to predict the electricity generation in Nigeria is given as;

$$\ln G = 1.6501 + 0.0164R + 0.1466T \quad (2)$$

$$G = e^{1.6501+0.0164R+0.1466T} \quad (3)$$

*B. THE STATISTICAL MODELS (MODEL 2): MULTIPLE LINEAR REGRESSION*

The multiple linear regression can be represented mathematically as:

$$G_i = \beta_0 + \beta_1 R_i + \beta_2 T_i + e_i \quad (4)$$

After solving for the regression coefficient based on the case study data set, the multiple linear regressions model used in predicting electricity generation in Nigeria is given as;

$$G = 270.6813 + 23.8859R - 30.7189T \quad (5)$$

*C. THE STATISTICAL MODELS (MODEL 3): COBB - DOUGLAS MODEL*

Cobb-Douglas Model can be represented as:

$$G_i = aR_i^b T_i^c + e_i \quad (6)$$

Where R is the yearly mean rainfall, T is the yearly mean temperature. Linearize equation (6) above by taking the logarithm of both sides of the equation gives;

$$\log(G_i) = \log(a) + b\log(R_i) + c\log(T_i) + e_i \quad (7)$$

Let $G_i^1 = \log(G_i)$, $R_i^1 = \log(R_i)$, $T_i^1 = \log((T_i)$ . Then, the Cobb - Douglas model in Equation (7) becomes;

$$G_i^1 = a + bR_i^1 + cT_i^1 + e_i \quad (8)$$

After solving for the regression coefficient based on the case study data set, the Cobb-Douglas model used in predicting electricity generation in Nigeria is given as;

$$lnG = -12.4233 + 1.8017lnR + 3.4600lnT \quad (9)$$

$$G = e^{-12.4233+1.8017lnR+3.4600lnT} \quad (10)$$

*D. THE STATISTICAL MODELS (MODEL 4): BOX JENKINS' AUTOREGRESSIVE MODEL OF ORDER 1*

The Box Jenkins' autoregressive model of order 1 can be expressed mathematically in the form:

$$G_t = \gamma_0 + \gamma_1 g_{t-1} + e_i \quad (11)$$

After solving for the regression coefficient based on the case study data set, the Box Jenkins' autoregressive model of order 1 used in predicting electricity generation in Nigeria is given as;

$$G_t = 646.3208 + 0.6464G_{t-1} \quad (12)$$

## III. DEVELOPMENT OF THE ARTIFICIAL NEURAL NETWORK MODEL

The ANN is based on the Levenberg-Marcquart back propagation network which is depicted in Figure 1. The inputs to the ANN comprises of time and the explanatory variables (temperature and rainfall). The inputs, keyed in shown in Figure 2, are channeled straight to the hidden layers which comprises of the hidden neurons with the weights and biases. The data points are 46 and as shown in Figure 3, about 70% of the data points is used for the training, 15% of the data points is used for validation and 15% of the data points is used for testing.

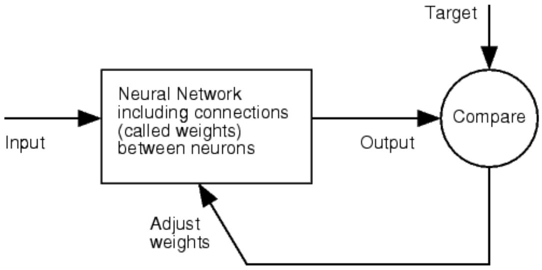


**Figure 1: The ANN model procedures (Ermiset *al*., 2007)**


**Figure 2: The input dialogue box for keying in the input data and the target data**

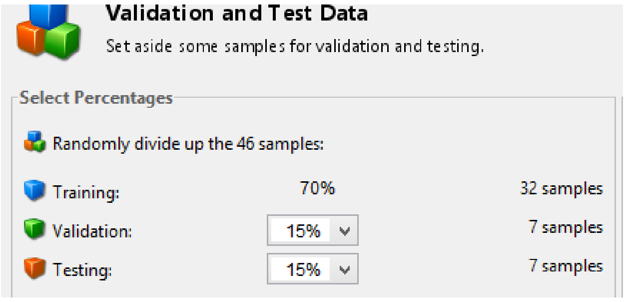


**Figure 3 : Selecting the percentage of data points for training, validation and testing**

During training, the weights and bias are adjusted automatically to ensure that the output is as close to the targets as possible (where the target is the actual power generated). The output of the hidden layer are channeled to the output layer and then to the output. The output was compared with the actual power generated and the error is fed back to the hidden layer after adjusting the weights. This simulation was carried out with the ANN toolbox in MATLAB. In all, the ANN has about thee input, one output, 20 hidden layer neurons, one neuron at the output layer, as shown in Figure 4 and the schematic diagram is in Figure 5.

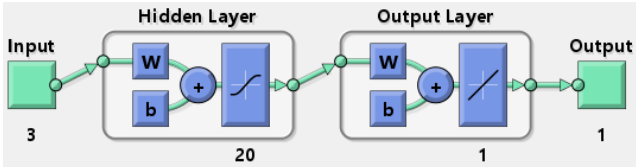


**Figure 4: Selecting number of the hidden neurons**

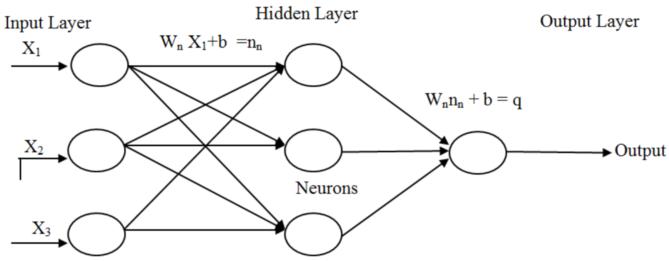


**Figure 5: Schematics of the ANN model**

Where X is the input, W are the weights, b are the biases and q is output. a

The power generation data and the explanatory variables data are normalized with respect to the respective maximum value in the data set using the expression given as follows;

$$x_{norm} = \frac{x}{x_{max}} \quad (13)$$

Where $x_{norm}$ is the normalized data, x is the data to be normalized and $x_{max}$ is the maximum value of x in the data set. The normalized data for the explanatory variables and the actual power generated are presented in Figure 6. In order to convert the normalized data to the real data, the following expression is used;

$$x = x_{norm} * x_{max} \quad (14)$$

## IV. RESULTS AND DISCUSSION

The normalized data for the explanatory variables and the actual power generated are shown in Figure 6.

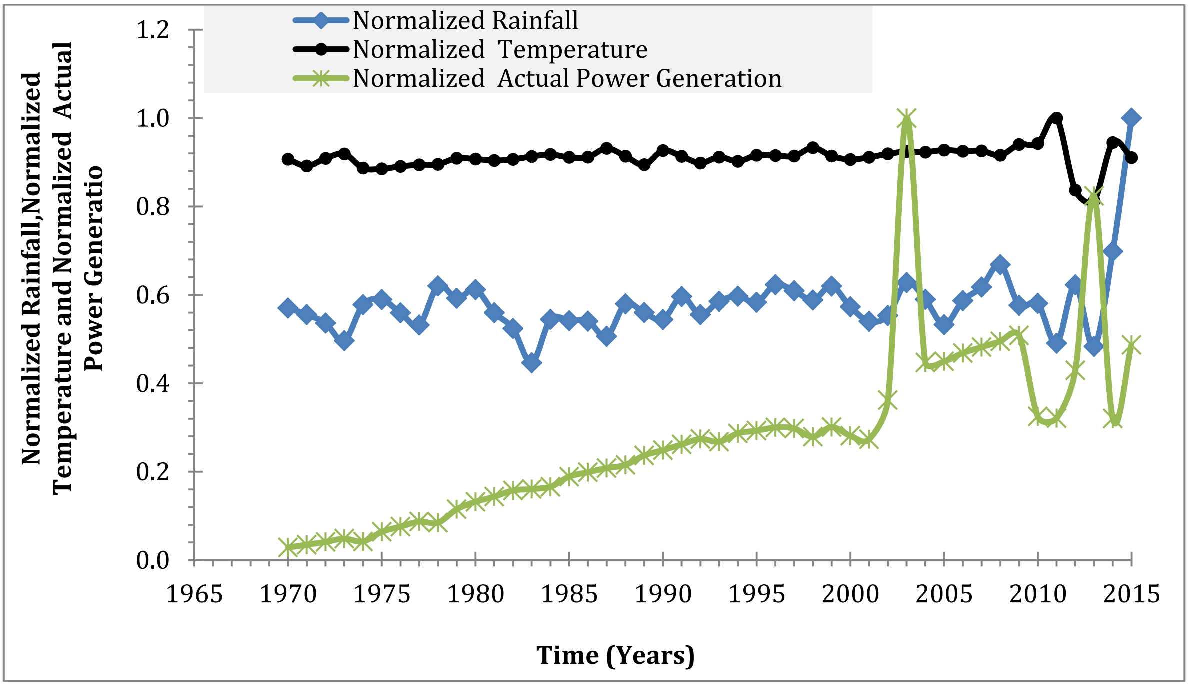


Figure 6 : The normalized data for the explanatory variables and the actual power generated

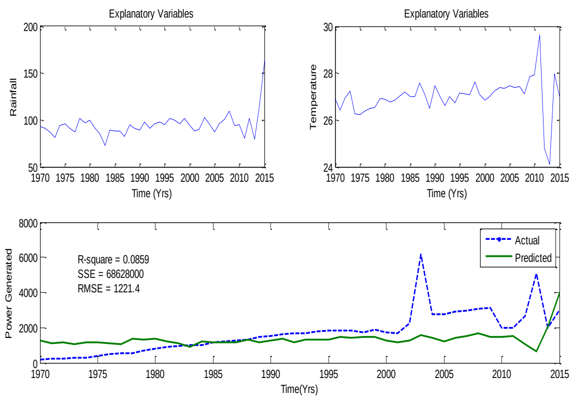


**Figure 7: Graph of actual and predicted power generation in Nigeria with exponential regression model**

The prediction of power generated in Nigeria from 1970 to 2015 with the exponential regression model is shown in Figure 7. The regression coefficient R is 0.0859 (8.59%), the sum of square error (SSE) is 68628000and root mean square error (RMSE) is 1221.4. The low R value of 0.0859 means that the exponential model is not suitable for estimating the power generation in Nigeria.

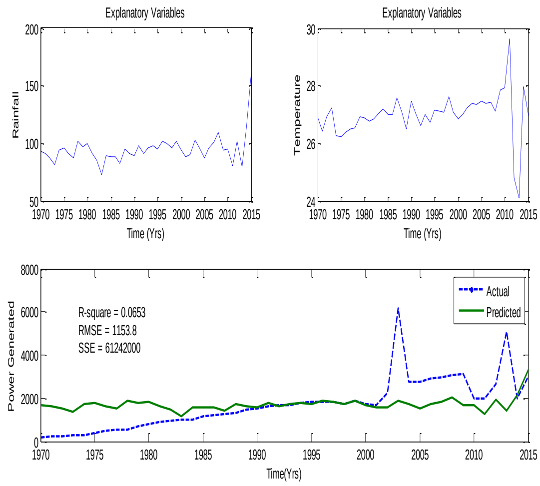


**Figure 8: Actual and predicted power generation in Nigeria with multiple linear regression model**

The prediction of power generated in Nigeria from 1970 to 2015 with the multiple linear regression model is shown in Figure 8. The regression coefficient R is 0.0653 (6.53%), the sum of square error (SSE) is 61242000 and root mean square error (RMSE) is 1153.8. The low R value of 0.0653 means that the multiple linear regression model is not suitable for estimating the power generation in Nigeria.

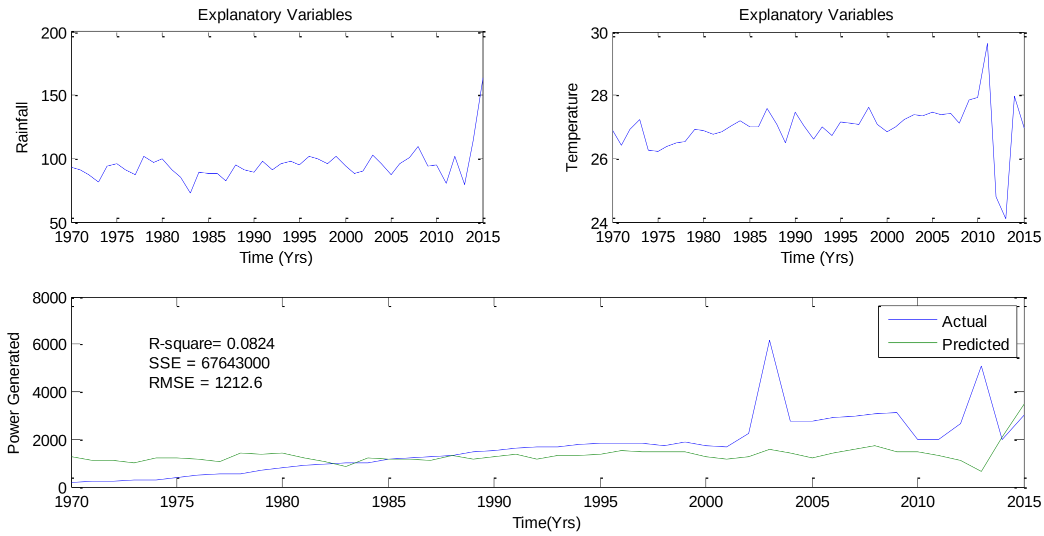


**Figure 9: Graph of actual and predicted power generation in Nigeria with Cobb-Douglas Model**

The prediction of power generated in Nigeria from 1970 to 2015 with the **Cobb-Douglas** model is shown in Figure 9. The regression coefficient R is 0.0824 (8.24%), the sum of square error (SSE) is 67643000 and root mean square error (RMSE) is 1212.6. The low R value of 0.0824 means that the Cobb-Douglas model is not suitable for estimating the power generation in Nigeria.

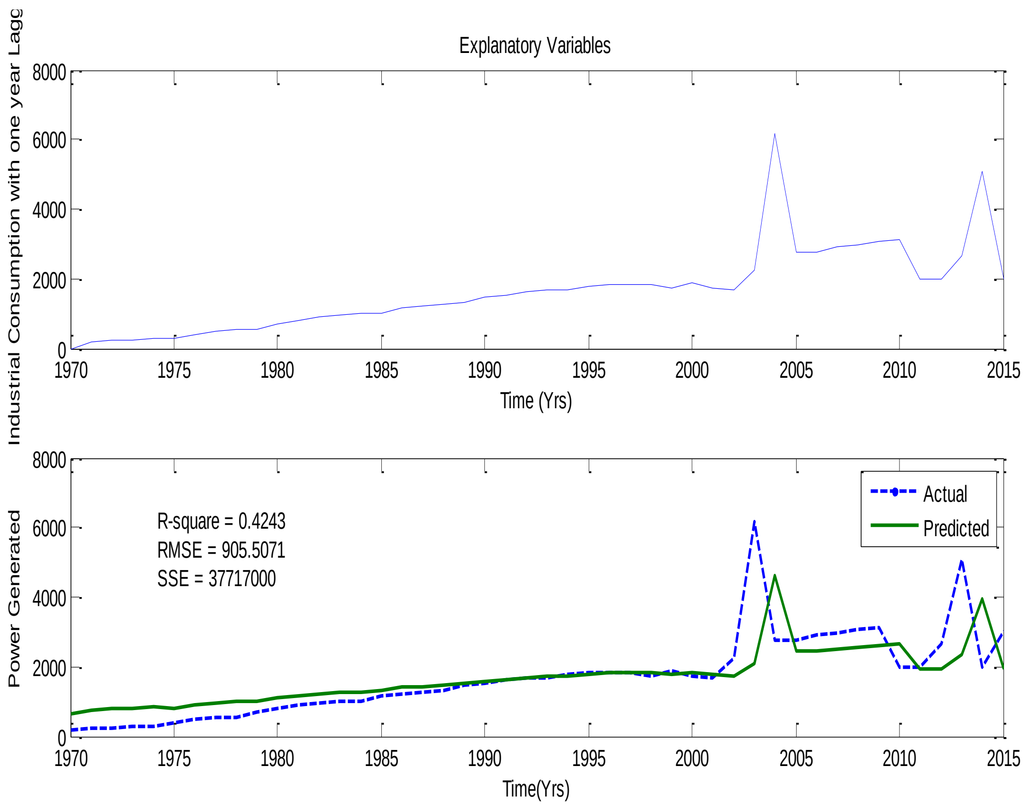


**Figure 10: Graph of actual and predicted power generation in Nigeria with Box Jenkins' autoregressive model**

The prediction of power generated in Nigeria from 1970 to 2015 with the Box Jenkins' autoregressive model is shown in Figure 10. The regression coefficient R is 0.4243 (42.43%), the sum of square error (SSE) is 37717000 and root mean square error (RMSE) is 905.5071. The low R value of 0.4243 (42.43%) means that the Box Jenkins' autoregressive model is not good enough for estimating the power generation in Nigeria.

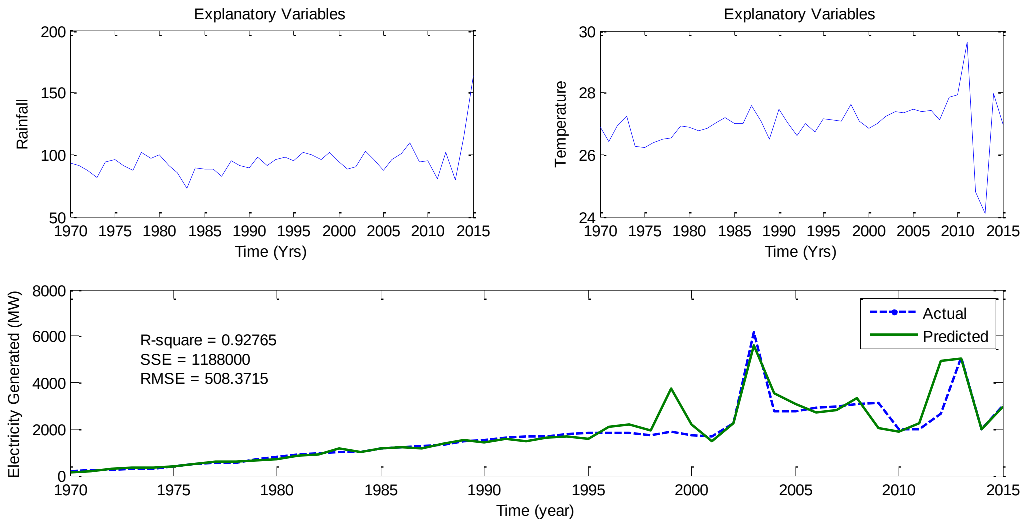


**Figure 11: Artificial neural network model Graph of actual and predicted power generation in Nigeria**

The prediction of power generated in Nigeria from 1970 to 2015 with the ANN model is shown in Figure 11. The regression coefficient R is 0.92766 (92.766%) , the sum of square error (SSE) is 1188000 and root mean square error (RMSE) is 508.3715.

The prediction performance of the five models is given in Table 1 and the results show that the ANN has the best prediction performance followed by the Box Jenkins' autoregressive model. Consequently, the ANN model is used to forecast the power generation in Nigeria from 2016 to 2020 , as shown in Table 2 and Figure 12.

**Table 1 Comparison of the prediction performance of the models**

| Model | R-Square value | SSE | RMSE |
|---|---|---|---|
| Exponential Regression | 0.0859 | 68628000 | 1221.4 |
| Multiple linear Regression | 0.0653 | 61242000 | 1253.8 |
| Cobb-Douglas | 0.0864 | 67643000 | 1212.6 |
| Box Jenkins' Autoregressive | 0.4243 | 37717000 | 905.5071 |
| ANN | 0.92766 | 1188000 | 508.3715 |

**Table 2: Forecast of the electricity generation in Nigeria using the ANN model**

| Time (Yrs) | Temperature | Rainfall | Forecast of Electricity Generation |
|---|---|---|---|
| 2016 | 26.8210 | 96.0532 | 4725.1 |
| 2017 | 27.3320 | 102.4870 | 5231.6 |
| 2018 | 27.1920 | 88.3310 | 5007.2 |
| 2019 | 28.1390 | 109.8310 | 5088.0 |
| 2020 | 27.1330 | 90.6190 | 5021.7 |

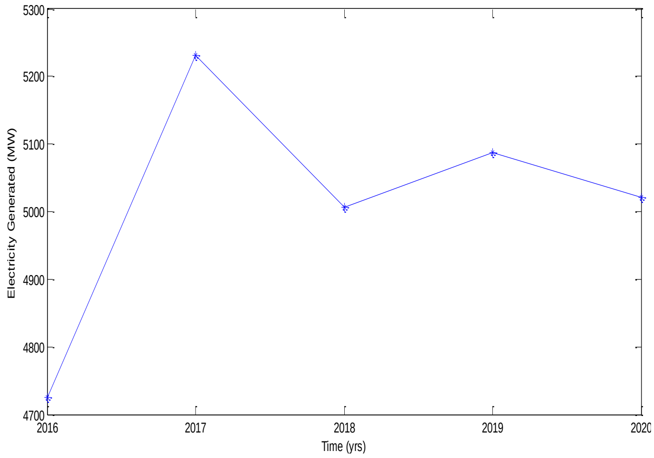


**Figure 12: Power generation forecast in Nigeria using the ANN model**

## V. CONCLUSION

In this work, artificial neural network (ANN) model was compared with four different statistical models used in modeling the power generation in Nigeria using two climatic variables (rainfall and temperature) as the explanatory variables. The 46 years data on electricity generation in Nigeria were obtained from the Central Bank of Nigeria Statistical Bulletin while data on rainfall and temperature were extracted from the National Bureau of Statistics (NBS) abstract**.** The statistical models are exponential regression, multiple linear regression, Cobb-Douglas model, box Jenkins' autoregressive model of order 1. The models' forecasting accuracy was done using generic statistical approach which include coefficient of determination and root mean square error and the best model among the four models was selected. The best model , which was ANN was also used to forecast the electric power generation in Nigeria from 2016 to 2020.

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