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# RESIDENTIAL ELECTRICAL LONG-TERM LOAD FORECAST USING ARTIFICIAL NEURAL NETWORK; WOJI ESTATE 11/0.415 KV FEEDER PORT HARCOURT, NIGERIA

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**ABSTRACT:** *The essentiality of electric load forecast for the effective design and management of electric power systems has been achieved in this study. PHEDC may plan for infrastructure construction, resource allocation, and energy management by using accurate long-term load forecasts of this study. In the context of the Woji Estate 11/0.415 kV Feeder in Port Harcourt, Nigeria, we have discussed the use of artificial neural networks (ANNs) for a long-term of ten (10) years load forecasting in this paper starting from January 2020- December 2029. However, curve fitting feed-forward artificial neural network has been employed for the simulation on MATLAB 2020 environment, with six (6) input datasets obtained from Transmission Company of Nigeria (TCN), Oginigba and Port Harcourt Electricity Distribution Company, and average temperature dataset from NIMET-Abuja all in Nigeria from January, 2015-December, 2019. The regression plot of epoch 11 with training; R=1 and validation of 0.9999 have been achieved which indicates how efficient the training of the dataset was. The Levenberg-Marquardt (LM) algorithm is used as an optimization technique in this study. In addition, training, test, validation, and error analysis have been used to examine the effectiveness of the LM algorithm; it has been found optimal with ANN. The general observation shows that ANN provides effective results on long-term electrical load forecasting of the Woji Estate Feeder with a total forecasted value of 29734.4 MWHR and an average value of 24778.67 MWHR at the end of the tenth year.*

**KEYWORDS**: Artificial Neural Network (ANN), Long-Term Load Forecast (LTLF), Levenberg-Marquardt (LM), Curve Fitting Feed Forward Neural Network (CFFFNN), PHEDC.



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## INTRODUCTION

The increase in development; geographically, politically, and in social amenities has contributed immensely to exponential growth in the nations of the world. However, this growth has equally to a large extent increased electrical demands from the users of different categories in both cities and rural areas of any major town of any nation. Of course, this increase in electrical load demand from the users of energy produced and supplied by any utility company has brought serious concern to the utility providers, because of the unquenchable nature of energy demands by the users. It is on this note that energy providers need a robust system that can articulately take care of all this sudden increase in load demand without causing much disturbances to the large networks, and power grid at large. It is worth saying accurate load forecast is of high necessity to all power systems management, operation, and planning units, in a situation where power consumptions increase steeply and reserved energy becomes inadequate to meet the unpredicted demand for energy [2].

An electrical load forecast is an advanced estimate of electrical energy demand using previous load consumption history as data to justify the resonance of the method employed. Moreover, electrical load forecasts are in three categories, namely: Long-term, mid-term, and shut-term load forecasts. All these three categories mentioned have their respective advantages and disadvantages. And their need is based on the system each is to represent in power system operation and planning objectives. For instance, long-term load forecast ranges from one (1) year to twenty (20) years and above. Objectively, long-term and mid-term load forecasts are useful in determining power generation consequentially, load consumption capacity, and power facilities expansion, namely: substations, generators, and transmission lines. The mid-term load forecast is between one (1) week to one month. While the shut-term load forecast is within one hour to one week. However, through short-term load forecasting power systems generation’s schedule and control are achieved, it can also be used to calculate load flow and make necessary decisions that have the potential to prevent power facilities from overloading [1].

Artificial neural network (ANN) simulation tools have been widely accepted as an efficient tool for formidable electrical load forecasts recently by so many researchers. Because it can interact with complex and nonlinear relationships of the previous load history that traditional techniques cannot capture accurately. Moreover, so many articles on load forecasts have contributed enormously to the understanding of the sudden increase in electrical load forecast on electrical power networks concerning time and suggested methods to engage to overcome disturbances that this sudden increase introduces to the power networks. They have also populated several limitations encountered during training due to limited available data-set for load forecasts that have been carried out. However, this article proposes a two-layer curve fitting feed-forward artificial neural network (CFFFANN) to ensure accurate forecast using an existing network on MATLAB 2020 simulation environment.


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## REVIEW OF PREVIOUS STUDIES

A quiet number of researchers have made serious input to provide an efficient power system grid with enough energy on the respective feeders. However, an energy storage system (ESS) has provided economic benefits and has also improved distributed generation equipment over renewable energy utilization [3] and this author also mentioned that an in-depth analysis of the ESS under a unique life-cycle has geometrically reduced the volume of error posed by long-term gray forecasting model. [4] used data-driven linear clustering to solve long-term system load forecasting problems posed by load instability in some well-developed cities. This author achieved random forecasting error reduction theoretically and practically through the proposed data-driven clustering model. [5] proposed a medium and long-term load forecasting model with the consideration of policy factors in which power load various policies' influence were analyzed. However, the generic algorithm is utilized to ensure the configuration of an optimized architectural model for the proposed stacked long Short-term memory network [6]. The five-ecosystem CSTEP framework and evaluation of neural networks for residential load forecasting [7]: The forecasting of the power load in Danish residential areas is the main goal of this study. Recurrent neural networks (RNN), long-short-term memory networks (LSTM), gated recurrent units (GRU), and feed-forward networks (FFN) are just a few of the neural network types that are evaluated in this study. The results show that these models perform similarly, with an adjusted R2 score of about 0.96 and a 4-5% absolute percentage error for predictions made within an hour. The corrected R2 score for 24-hour forecasts is around 0.91, with an increased absolute percentage inaccuracy of 6–7%. The models are affected by the systematic approach to data identification, with the FFN displaying the biggest rise in error when supporting variables are removed. A systematic approach to electricity load forecasting study" [8]: This review talks about how crucial precise load forecasting is to efficient grid management. Different computational and statistical methods, including correlation, extrapolation, and a mix of the two, have been used to improve load forecast models. While extrapolation approaches use trend analysis to capture the growing tendency, correlation techniques entail comparing the system load to economic and demographic factors. The review emphasizes that there is no one technique that is always better and that the choice of technique depends on the particular circumstance. The article "A scoping review of deep neural networks for electric load forecasting" [9]: This review examines the application of deep neural networks for predicting electric load while taking grid control on the supply side and demand-side management into account. Using a hybrid deep learning multivariate model, which combines neural networks with convolution and recurrence. The suggested input factors include past consumption, climate, and day characteristics. Deep learning models can be used to discover recurring patterns and characteristics in data. In conclusion, the analysis of the literature shows that studies on load forecasting have used neural networks, such as recurrent neural networks (RNN), long-short-term memory networks (LSTM), and gated recurrent units (GRU).

## METHODOLOGY AND MATERIALS

This section emphasizes the design and method employed in this study with the following steps: the proposed feeder (Woji-Estate) was selected among so many 11/0.415 kV feeders of PHEDC's networks, together with the feeder historical data set, the data set collected were updated, development of an algorithm for long-term load forecast, development of ANN model for LTLF, training of the data-set on MATLAB simulation environment, evaluating


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performance on the model used. The data used in this study were obtained from the Transmission Company of Nigeria (TCN), Oginigba and Port Harcourt Electricity Distribution Company (PHEDC), Moscow Road Port Harcourt, and Nigerian Meteorological Agency (NIMET). The data set used in this study is five years historical load of 11/0.415 kV Woji-Estate residential feeder, from January 2015 through December 2019, with previous years average weather temperature data of the same year's frame. The data set was used for ten years of electrical load forecast from 2020 through 2029. The terminology of the data set used in this study is listed below concerning their role during training and testin

**Estimation (Definition) of Input and Output Parameters and their Model Distinguish Measurement (TRAINING AND TESTING PHASE)**

i) Time = Hours of the Year, Hour (Hr).

ii) Pylrsh = Previous Year Hourly Load reading (MW).

iii) Pyhtemp = Previous Year Hourly Temperature, Degree-Celsius (°c)

iv) Pylrmax = Previous Year Hourly Maximum Load Reading (MW).

v) Pylrmin = Previous Year Hourly Minimum Load Reading (MW).

vi) Pylrav = Previous Year Hourly Average Load Reading (MW).

vii) Target = Target (Expected Output), Mega-Watts (MW).

**Error Analysis Measurement**

Root Mean Squared Error (RMSE) = $\sqrt{MSE}$ (1)

Mean Square Error (MSE) = $\sum \frac{(et)^2}{N}$ (2)

Where (et) = forecast error of an individual,

(yt) = Actual Value,

N = Terms error’s number

% Error = $\frac{Actual\ Load - Forecast\ Load}{Actual\ Load} * 100$ (3)

N/B The above equations have been used to evaluate the correctness and reliability strength of the forecasted residential electrical load of Woji-Estate, in which minimal error has been recorded as shown in Table 3.


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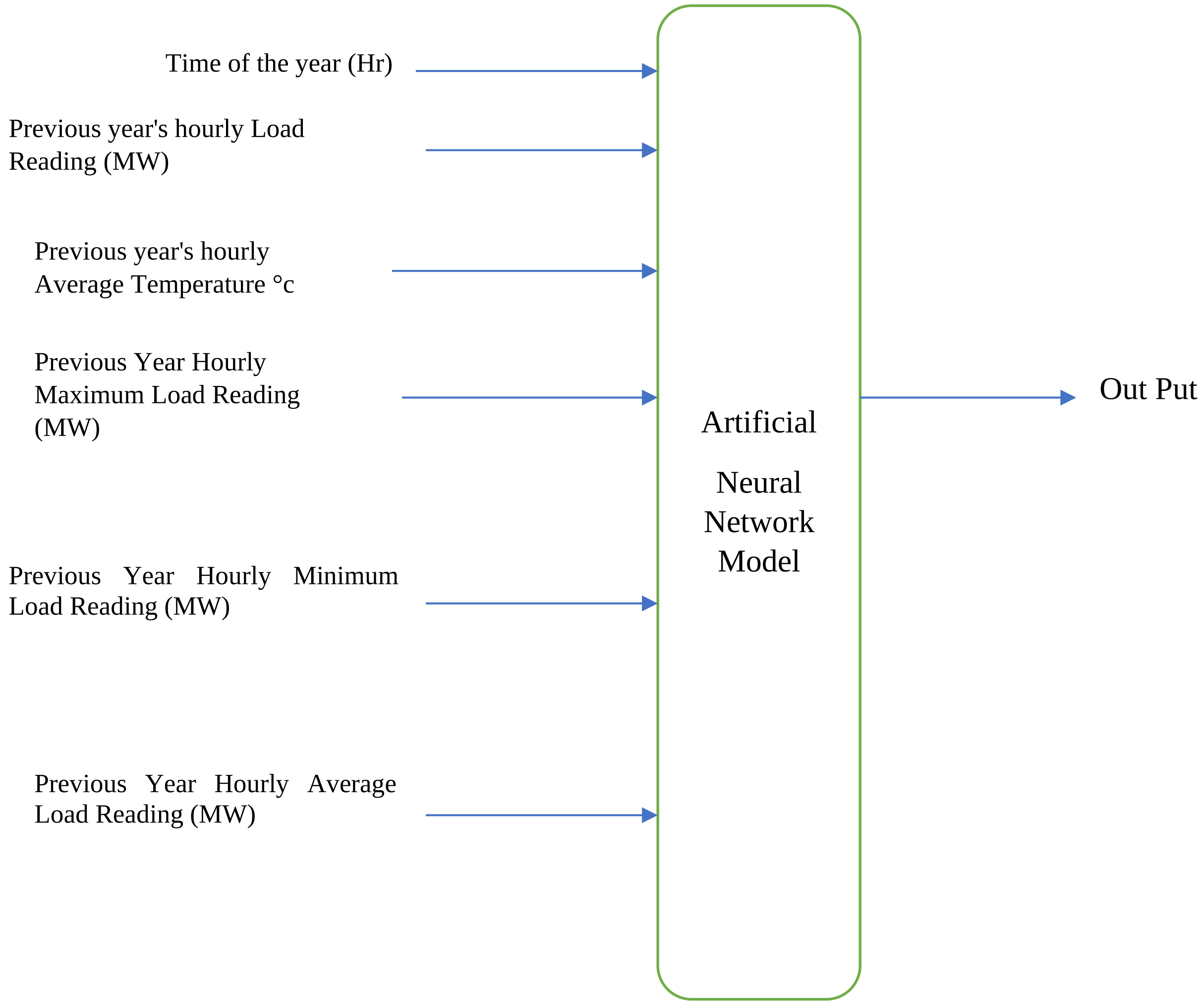


**Fig. 1 ANN Model for Ten (10) Years Load Forecast of Woji-Estate Residential Feeder**

**Residential Load Selection and Analysis**

Currently, Woji-Estate Feeder is being fed by the Woji injection station having her incoming radiating from the transmission station situated at Oginigba, and her injection-station transformer with the tagged name T1 15MVA, and 12MVA for redundancy purposes. However, the historical load readings from January 2015 – December 2019 were obtained from PHEDC head office (Moscow) and TCN station Oginigba. This paper presents Woji-Estate Feeder for residential electrical LTLF of ten (10) years.


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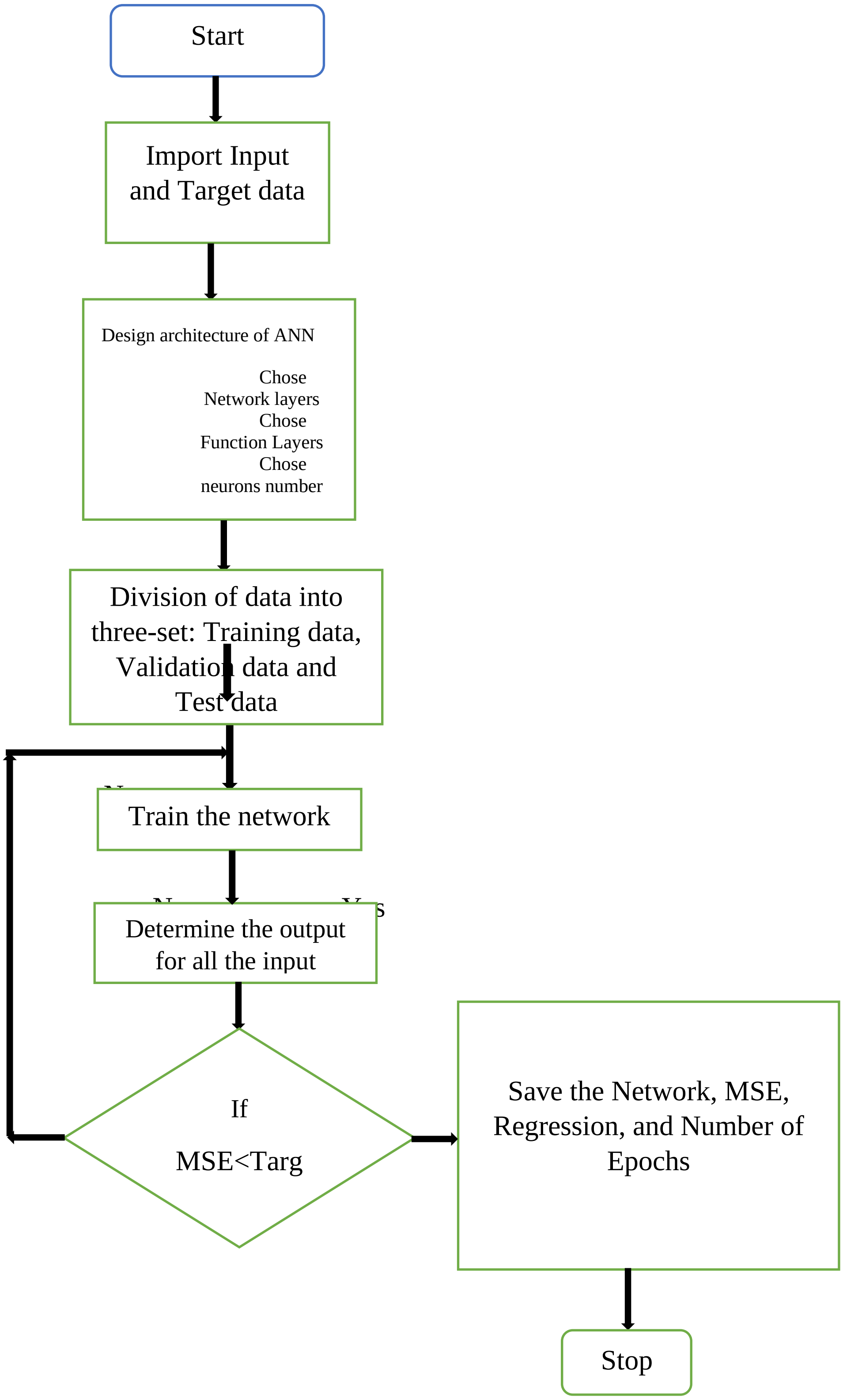


***Figure.2. Flow Chart of the residential ANN Model***



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**Description of Residential ANN Flow Chart Model**

The data set of six input parameters was imported from the excel-sheet to the MATLAB simulation environment with target data in a separate sheet for the selected (Woji-Estate) feeder, moreover, the curve-fitting artificial neural network was selected from the applications pool of the MATLAB simulation environment and the network architecture design was developed by choosing network layers; function Layers; neurons number. After this data were divided into three data set: training data, validation data, and test data, then the network was trained, and outputs for all the inputs were determined, nevertheless, the evaluation was carried out by examining the value of each output value if it's greater than mean square error value then the output can be saved as forecasted load with the used network; regression plot; and number of Epochs, if otherwise go back to train the network section to change your setting.

## ARTIFICIAL NEURAL NETWORK DIAGRAMS

Figures 3,4, and 5 show the Artificial Neural Network diagram, Algorithms, and Progress during training using input parameters shown in Figure 1 for ten years of electrical load forecast. From Figure 4, it is obvious that the neural network diagram for the Woji-Estate's feeder has two hidden layers comprised of weight (W) and bias (b) both at the input of the hidden layer and at the input of the output layer with fifteen (15) neurons each at the hidden layers in figure 4. The ANN architecture performed eleven (11) iterations to achieve the forecasted load in this study.

## RESULTS AND DISCUSSION

**Table 1a: shows the actual load of the Woji-Estate feeder for ten (10) years using trained ANN as residential electrical load in this study.**

**WOJI ESTATE FEEDER ACTUAL LOAD DEMAND (MWHR)**

| **Month** | **2015** | **2016** | **2017** | **2018** | **2019** | **2020** | **2021** | **2022** | **2023** | **2024** |
|---|---|---|---|---|---|---|---|---|---|---|
| January | 929.1 | 1349.8 | 1764.6 | 2632.7 | 2948.4 | 938.6 | 1358.9 | 1775 | 2643 | 2955.5 |
| February | 926.2 | 1871.1 | 1741.1 | 1715.9 | 2255.7 | 936.3 | 1881.3 | 1763.9 | 1726.1 | 2258.5 |
| March | 564.1 | 1898.9 | 1898.9 | 2315.7 | 2392.5 | 580.4 | 1904.2 | 1921.6 | 2340.6 | 2408.7 |
| April | 646.5 | 1261.1 | 1627.5 | 2317 | 2430.8 | 657.2 | 1272.6 | 1638 | 2327.9 | 2445.1 |
| May | 1065.1 | 1039.9 | 1893.5 | 2236.4 | 2480.3 | 1075.9 | 1049.2 | 1908.8 | 2246.2 | 2489.7 |
| June | 1071.3 | 934.7 | 1451.8 | 2392.8 | 2491.8 | 1081.8 | 932.5 | 1463.3 | 2409.1 | 2507.8 |
| July | 1165.7 | 1132.8 | 1005 | 2272.1 | 2443.9 | 1175.1 | 1145.9 | 1017.6 | 2283.1 | 2455 |
| August | 1166.7 | 1105.3 | 1422.8 | 2267.8 | 2288.8 | 1120.6 | 1116.1 | 1432.4 | 2148.6 | 2299.9 |


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| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| September | 1159.4 | 1587.9 | 1054.6 | 2239.3 | 2296.5 | 1169.4 | 1597.3 | 1066.1 | 2249.5 | 2314.1 |
| October | 1160.6 | 1796.1 | 1195.6 | 2768.7 | 2356.7 | 1170.5 | 1805.7 | 1206.8 | 2780.5 | 2366.7 |
| November | 970.4 | 1961.9 | 1477.6 | 2630.5 | 2432.2 | 980.7 | 1971.8 | 1488.1 | 2644.9 | 2445.8 |
| December | 998.6 | 1796 | 2103.6 | 2985.5 | 2654 | 1012.3 | 1800.9 | 2119.3 | 2993.1 | 2666.4 |
| **Total** | **11823.7** | **17735.5** | **18636.6** | **28774.4** | **29471.6** | **11898.8** | **17836.4** | **18800.9** | **28792.6** | **29613.2** |
| **Average** | **985.3083** | **1477.958** | **1553.05** | **2397.867** | **2455.967** | **991.5667** | **1486.367** | **1566.742** | **2399.383** | **2467.767** |

**Table 1b shows the forecast load of the Woji-Estate feeder for ten (10) years forecast using trained ANN as a residential electrical load of this study.**

**WOJI-ESTATE FEEDER FORECASTED LOAD DEMAND (MWHR)**

| **Month** | **2020** | **2021** | **2022** | **2023** | **2024** | **2025** | **2026** | **2027** | **2028** | **2029** |
|---|---|---|---|---|---|---|---|---|---|---|
| **January** | 938.6 | 1358.9 | 1775 | 2643 | 2955.5 | 950.6 | 1370.2 | 1786 | 2652.8 | 2961.8 |
| **February** | 936.3 | 1881.3 | 1763.9 | 1726.1 | 2258.5 | 947.5 | 1892.2 | 1775.1 | 1739.2 | 2269.9 |
| **March** | 580.4 | 1904.2 | 1921.6 | 2340.6 | 2408.7 | 591.8 | 1914.3 | 1932.5 | 2351.2 | 2418.8 |
| **April** | 657.2 | 1272.6 | 1638 | 2327.9 | 2445.1 | 669.7 | 1284 | 1648.8 | 2339.7 | 2455.9 |
| **May** | 1075.9 | 1049.2 | 1908.8 | 2246.2 | 2489.7 | 1087.3 | 1060.7 | 1919.2 | 2257 | 2499.7 |
| **June** | 1081.8 | 932.5 | 1463.3 | 2409.1 | 2507.8 | 1093.4 | 944.5 | 1474.9 | 2419.5 | 2518.2 |
| **July** | 1175 | 1145.9 | 1017.6 | 2283.1 | 2455 | 1187.7 | 1158 | 1029.4 | 2293.3 | 2465.9 |
| **August** | 1120.6 | 1116.1 | 1432.4 | 2148.6 | 2299.9 | 1132.3 | 1128.1 | 1443.9 | 2158.3 | 2310.7 |
| **September** | 1169.3 | 1597.3 | 1066.1 | 2249.5 | 2314.1 | 1179.1 | 1608.7 | 1078.1 | 2259.9 | 2324.5 |
| **October** | 1170.5 | 1805.7 | 1206.8 | 2780.5 | 2366.7 | 1181.4 | 1817 | 1218 | 2789.3 | 2376.9 |
| **November** | 980.7 | 1971.8 | 1488.1 | 2644.9 | 2445.8 | 990.6 | 1982.4 | 1499.5 | 2654.5 | 2455.7 |
| **December** | 1012.3 | 1800.9 | 2119.3 | 2993.1 | 2666.4 | 1020.5 | 1811.5 | 2129.9 | 2998.2 | 2676.4 |
| **Total** | **11898.6** | **17836.4** | **18800.9** | **28792.6** | **29613.2** | **12031.9** | **17971.6** | **18935.3** | **28912.9** | **29734.4** |
| **Average** | **991.55** | **1486.367** | **1566.742** | **2399.383** | **2467.767** | **1002.658** | **1497.633** | **1577.942** | **2409.408** | **2477.867** |


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**N/B:** Table 4.2a and Table 4.2b show the result of the actual and forecasted load reading in Megawatt Hour (MWHR) gotten from the trained Artificial Neural Network using the input parameters in Appendix B for Woji-Estate Feeder for ten (10) years

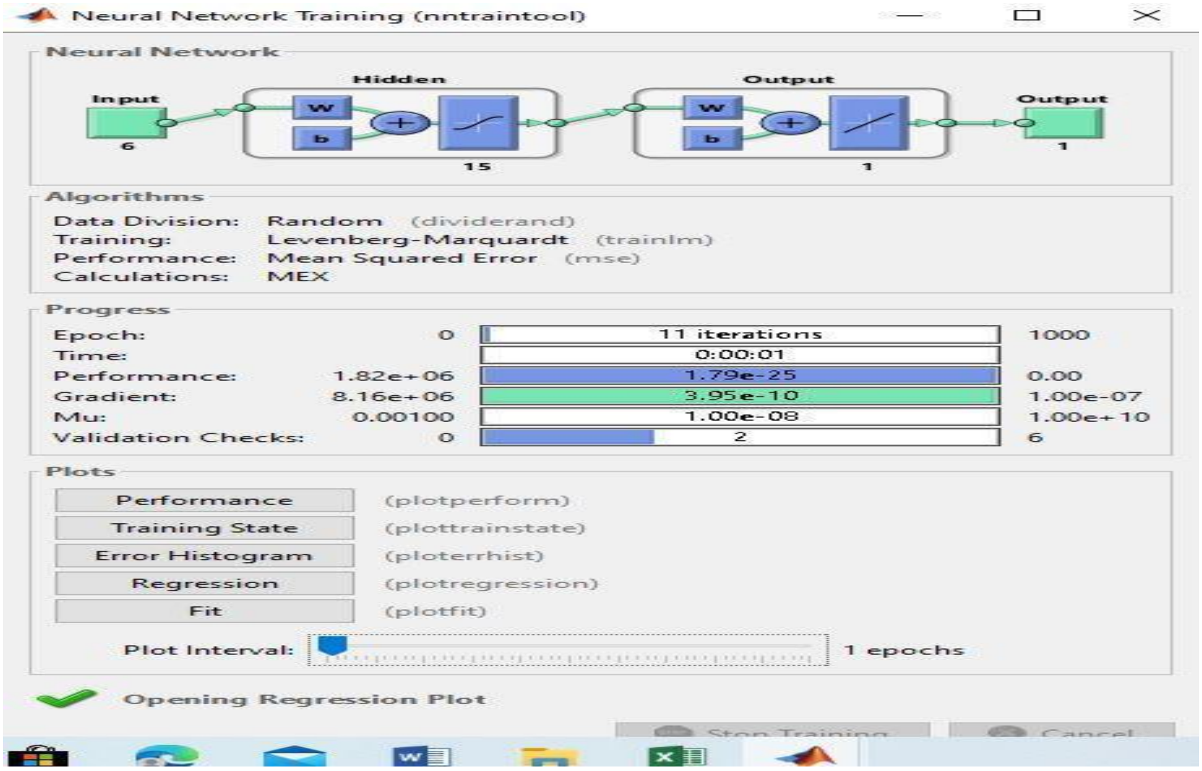


***Figure 3. Shows Woji-Estate Feeder ANN diagram, Algorithms & Progress during training from year One (1) to Ten (10).***


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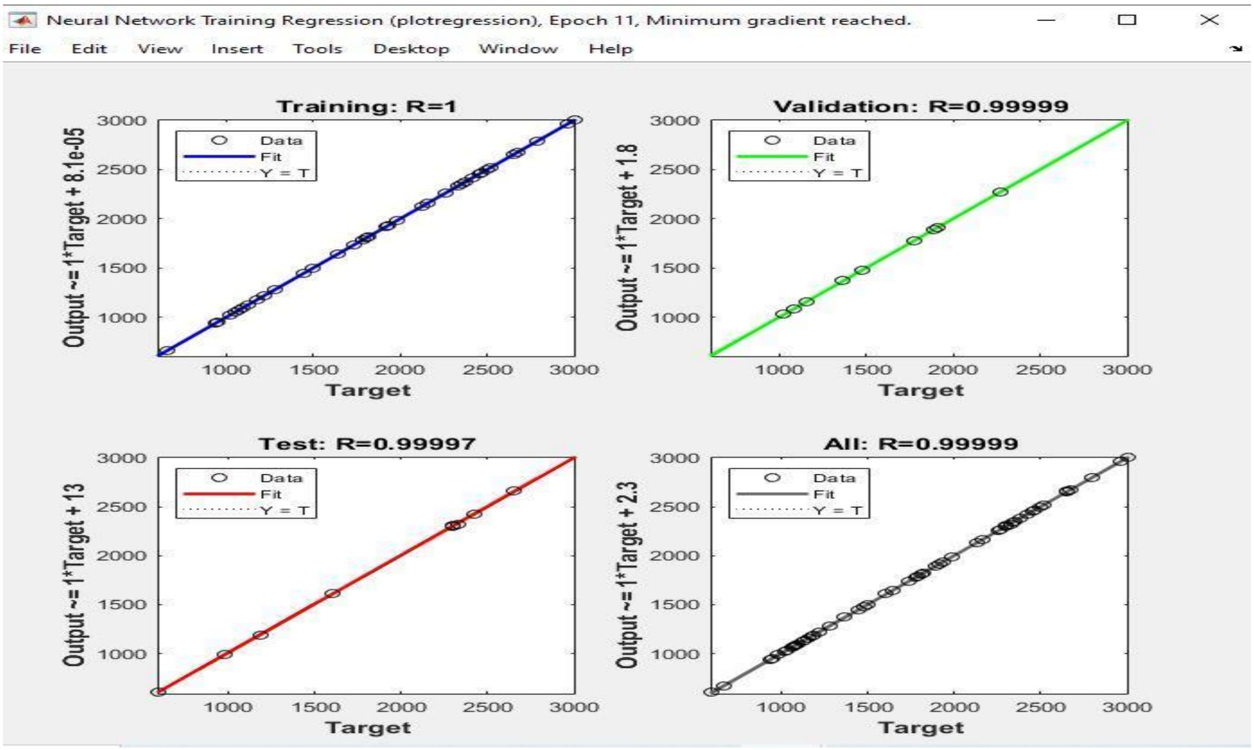


*Figure 4. Shows the Woji-Estate Regression plot after training from year one (1) to year (10).*

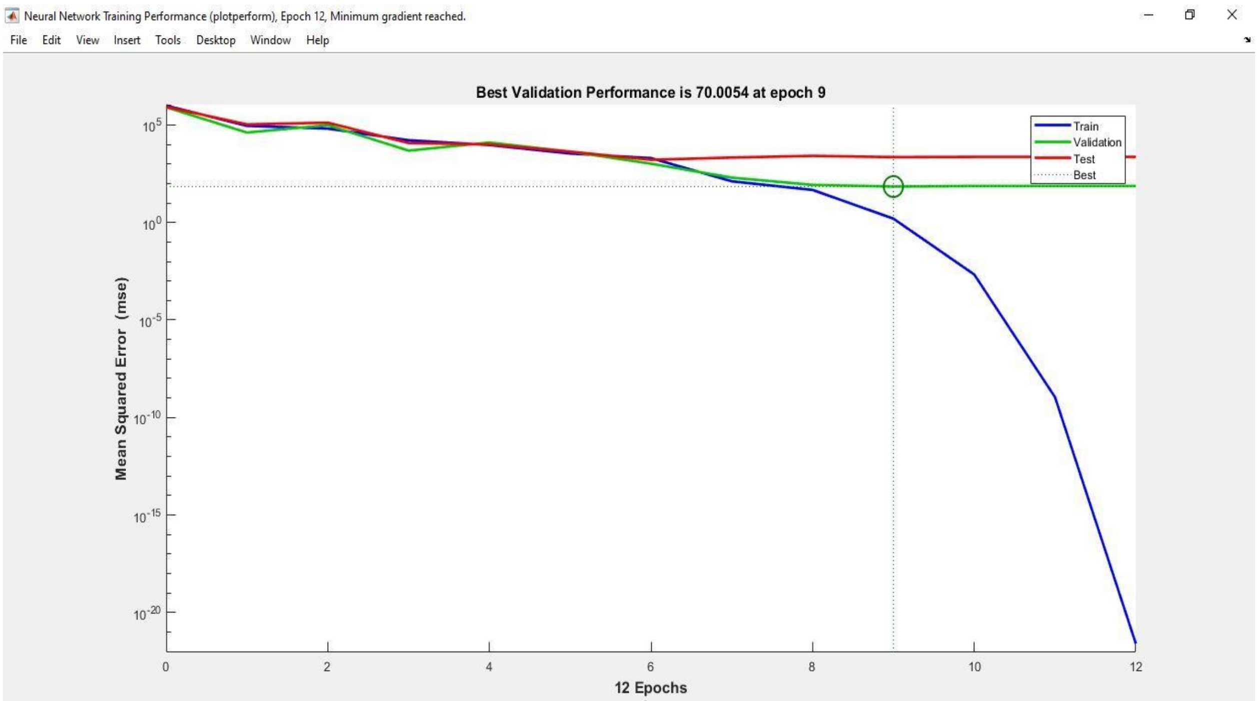


*Figure 4.6b shows Woji-Estate Feeder ANN Performance Graph During Training from Year One (1) to Ten (10).*


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**Graphs of Actual vs Forecast Load of Woji-Estate Residential Feeder**

Figures (4.17a – 4.17e), are the line graphs (plot) of the Actual and forecasted load in Megawatt Hour (MWHR) of trained Artificial Neural Network using results from table 4.1 for ten (10) years (2020-2029) as shown for Woji-Estate residential feeder.

From the graphs, it is seen that the forecast load is within (-2.2, -46.1, and -119.2 MWHR; for the lower side and 4.9 – 22.8 MWHR for the upper side; below and above the actual load which means by August 2020; June 2021 and August 2023 there would be drop in load demand below their respective actual load while there would be increasing in load demand in the remaining months of the forecasted years which depicts a realistic and true forecast. Of course, Maximum load demands of (1166.7 / 1961.9 MWHR, 2103.3 /2985.5 MWHR, 2948.4 /1175.1 MWHR, 1971.8 / 2119.3 MWHR & 2993.1 /2955.5 MWHR) were recorded in (Aug. 2020/Nov. 2021, Dec. 2022/Dec. 2023, Jan. 2024/Jul. 2025, Dec. 2026/Dec. 2027, Dec. 2028/Jan. 2029) respectively from (January-December of each year). While maximum load forecast of (1175 /1971.8 MWHR, 2119.3 /2993.1 MWHR, 2955.5 /1187.7 MWHR, 1982.4 /2129.9 MWHR, & 2998.2 / 2961.8 MWHR) were recorded in (Jul.2020/Nov.2021, Dec.2022/Dec.2023, Jan.2024/Jul.2025, Nov.2026/Dec.2027, & Dec.2028/Jan.2029) respectively from (January-December of each forecasted years). Furthermore, minimum load demand of (564.1 /934.7 MWHR, 1005 /1715.9 MWHR, 2255.7 /580.4 MWHR, 932.5 /1017.6 MWHR, & 1726.1 /2258.5 MWHR) was equally recorded in ( Mar. 2015/Jun.2016, Jul. 2017/Feb.2018, Feb. 2019/Mar. 2020, Jun.2021/Sep. 2022, & Feb.2023/Feb.2024) respectively from (January-December) while minimum load forecast of( 580.4 /932.5 MWHR, 1017.6 /1726.1 MWHR, 2258.5 /591.8 MWHR, 944.5 /1029.4 MWHR, & 1739.2 /2269.9 MWHR) as recorded in ( Mar. 2020/Jun.2021, Jun.2022/Feb.2023, Feb.2024/Mar.2025, Jun.2026/Jul.2027, Feb.2028/Feb.2029) respectively from (January-December).


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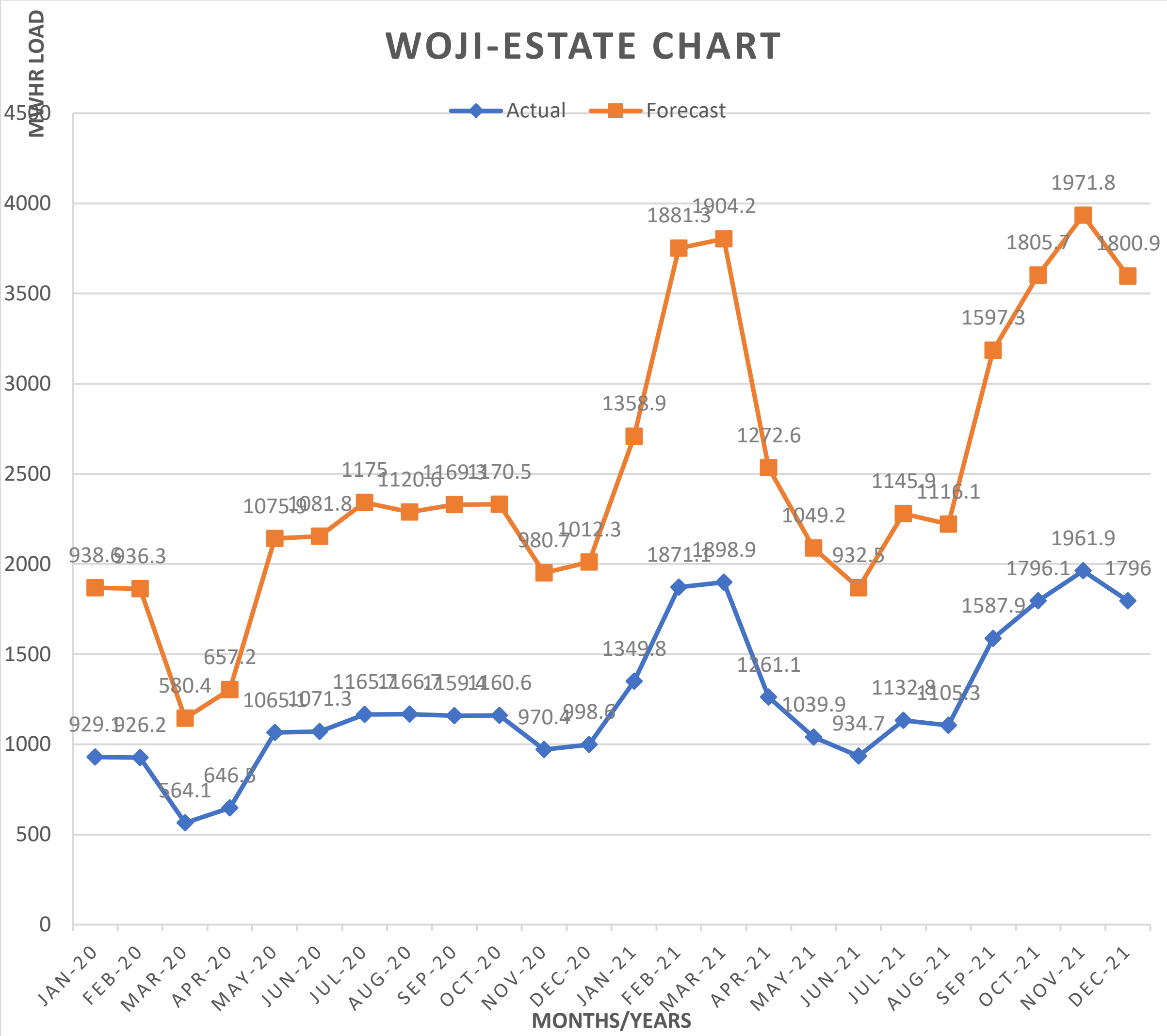


***Figure 4.17a Woji-Estate Feeder graph of Actual VS Forecast Load after the testing phase of years 2020 and 2021***



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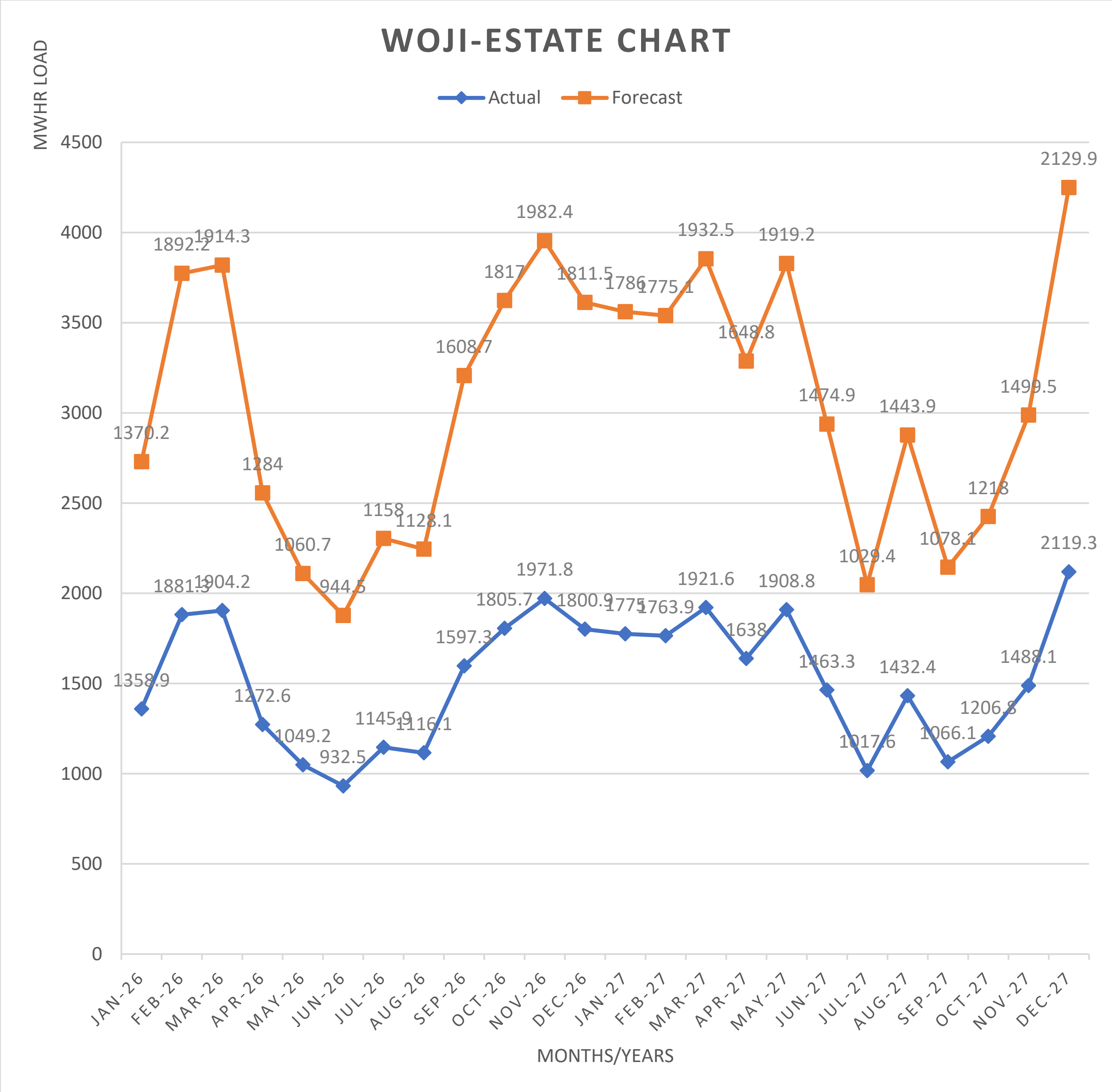


*Figure 4.17d Woji-Estate Feeder graph of Actual VS Forecast Load after testing phase of years 2026 and 2027*


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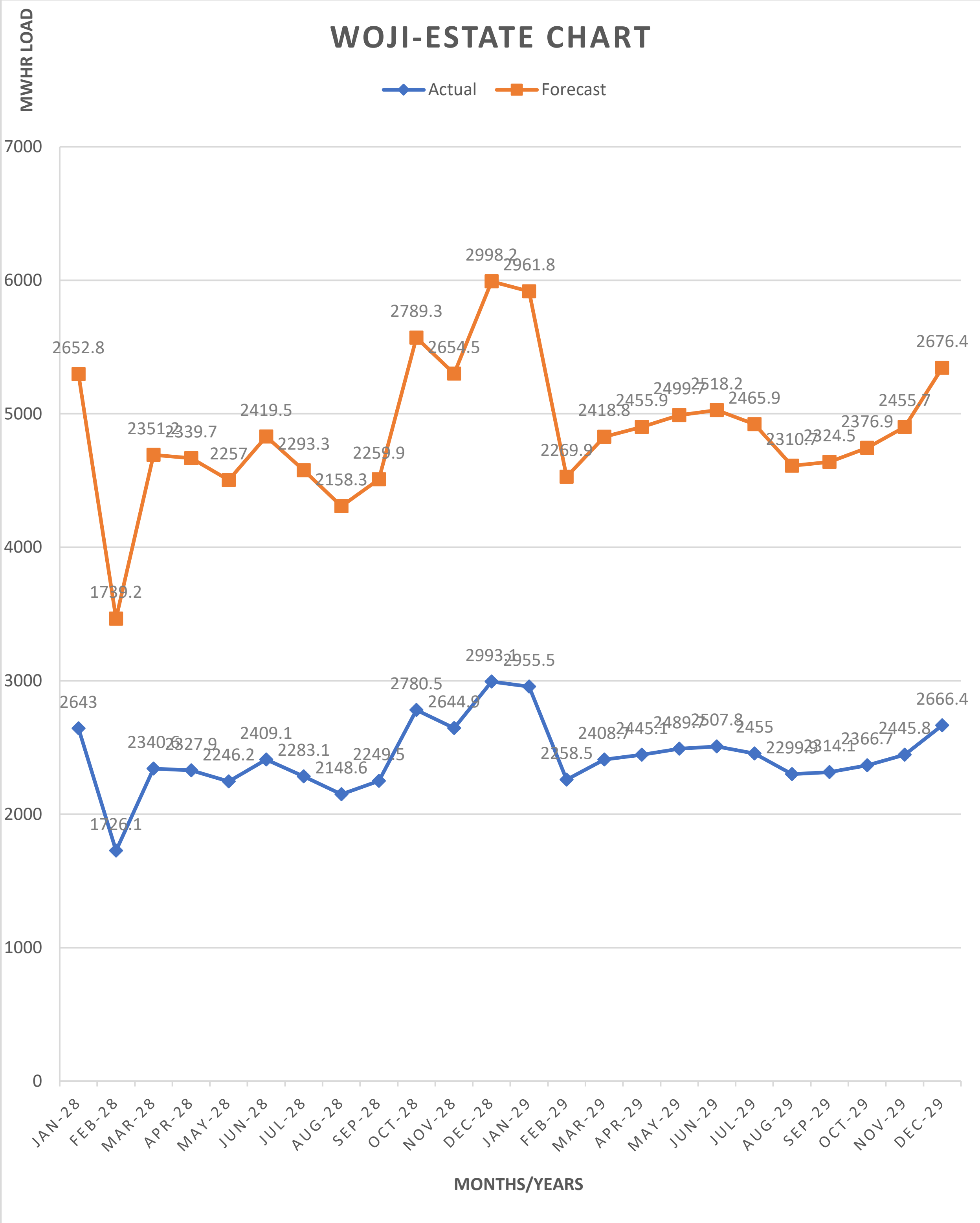


***Figure 4.17e Woji-Estate Feeder Forecast Load after the testing phase of years 2028 and 2029***


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**Table 3 shows values of percentage error of the forecasted load for the Woji-Estate Feeder network**

Woji-Estate Percentage Error Values

| Year | MSE% | √MSE% |
|---|---|---|
| 2020 | 0.03 | 0.18 |
| 2021 | 0.02 | 0.16 |
| 2022 | 0.06 | 0.25 |
| 2023 | 0.0003 | 0.017 |
| 2024 | 0.019 | 0.138 |
| 2025 | 0.102 | 0.320 |
| 2026 | 0.046 | 0.216 |
| 2027 | 0.042 | 0.204 |
| 2028 | 0.014 | 0.118 |
| 2029 | 0.013 | 0.115 |

**Percentage Error Analysis**

In this study percentage error analysis has been carried out using the percentage error of equation (3) and evaluated with the help of root mean square error and mean square error; the result obtained is shown in Table 3. This indicates a minimal error, high accuracy, and efficient performance of ANN feed-forward curve fitting. With great impact on the respective year forecasted.

## CONCLUSION

An artificial neural network has been used for the long-term load forecast of Woji-Estate 11/0415 kV residential feeder in the Port Harcourt metropolis of Rivers state, Nigeria. During this study, the two-layer feed-forward curve fitting architecture of ANN is employed. Six(6) input data-sets were fed into the input of the two-layer feed-forward curve fitting (TLFFCF) and LM algorithm for training purposes with set targets. The data set was divided into 70%, 15%, and 15% for Training, Validation, and Test respectively.

[5] To examine the accuracy and practicality of the method used in this study Statistical tools like MSE, RMSE, and Percentage Error have been used, however, the result shows that the error in the results obtained from the L_M ANN algorithm is very low, this has galvanized the robust forecasted values obtained for each month and the number of years in this study.

The regression plot of Figure 4 justifies the accuracy of the training process because the closer the data points are to the graph curve the more efficient the performance of the ANN [10]. Moreover, figure 4b shows that the performance of ANN and data update were in alignment with a highly significant impact on the result obtained from the ANN algorithm. Meanwhile, in the tenth year December 2029 the total forecasted value of 29734.4 MWHR and the average of 2477.86 MWHR were obtained, this has proved beyond imagination that ANN is a powerful tool to achieve robust long-term electrical load forecast, as the results show how operation and


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planning unit of the concerned utility company is to plan to meet this future load demand on this residential feeder.

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