



LONG TERM LOAD FORECAST USING ARTIFICIAL NEURAL NETWORK METHOD: RAINBOW-ELEKAHIA COMMERCIAL 33KV FEEDER IN PORT HARCOURT, NIGERIA

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Keywords: Long-Term Load Forecasting; Artificial Neural Networks; Curve-Fitting Neural Networks; PHEDC; Multilayer Neural Networks.

ABSTRACT: This paper presents the Long-term Commercial Electrical Load Forecast of the Rainbow-Elekahia feeder under the Port Harcourt Electricity Distribution Company (PHEDC) network using Artificial Neural Network (ANN) from 2020 to 2029. The data were trained with the instrumentality of a two-layer feed-forward neural networks curve fitting (FFNNCF) simulation tool within the MATLAB 2020 simulation environment. The historical load consumption of the mentioned feeder and Average Temperature was obtained from PHEDC Head Office Moscow Road, Transmission Company of Nigeria (TCN), Oginigba, and NIMET-Office Abuja; the summation of all these formed the data utilized for Training, Validation, and Testing of the proposed neural networks architecture. The forecasted results obtained prove that Curve-Fitting Neural Network (CFNN) is highly efficient for the commercial long-term load forecast as the justification of low error was investigated (evaluated) using Percentage Error combined with Root Mean Square Error (RMSE) and Mean Square Error (MSE) and the results obtained for the number of years shows that error is minimal. Generally, the forecasted load value for ten (10) years is 7354.3 MWhr which has shown a realistic and genuine forecast process that has been carried out through a reliable ANN application.

1 INTRODUCTION

Load forecasting is the advance estimation (expectation) of future electrical demand. Since electrical power generation needs adequate management [8]. The reason is that the power

generated requires to be the same as that consumed. Generally, energy-generating companies are expected to meet these requirements, therefore, it is highly needed to

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estimate the electrical load required in the future. An electrical load forecast is also the process of estimating electrical load in advance on a particular Network in a power system with the help of Mathematical Models, Statistical Models, and Artificial Intelligent Models. The electricity demand depends on several socio-economic factors such as Economic growth, Industrial production, New technological developments that influence lifestyles, Governmental policies, etc [10]. Moreover, Power utility companies supply energy to the load centre via their network for final distribution to the loads, these loads vary based on consumers and the level of voltages receives, the followings are the category of consumers utilizing generated electrical energy from generating stations, transforms by the transformers, from the receiving voltage from the generating plants to different distribution voltages depends on the category of the customers, this transformed voltage will be wheeled or carry to the load centre by the transmission lines for final distribution: such customers includes Domestic or Residential Consumers, Industrial Consumers, Commercial Consumers, Agricultural Consumers, Municipal (Street Lights loads) and Traction [9]. The loads taken by each group has a specialty and their peaks do not generally occur at the same time or instant because of this globally there are different ways of carrying out the forecast on different distribution network these list of classifications have been employed by researchers all the globe; Long-Term Load Forecasts is a load forecast that covers from

one(1) – twenty(20) years and Plays a fundamental role in the economic planning of new generating capacity and transmission networks. While, Mean-Term Load Forecasts covers from one(1) week - one(1) year and its used mainly for the scheduling of fuel supplies, maintenance program, financial planning, and tariff formulations; and Short-Term Load Forecasts. covers one(1) hour-one(1) week as it provides the basis for planning start-up and shut-down schedules of generating units, spinning reserve planning, and the study of transmission constraints used in economic load dispatching and security assessment,[10]. However, for the reason of specialty, this study will use Long-Term load forecasts with the application of Artificial Neural Networks since long-term load forecast can cover one (1) – twenty (20) years, it is suitable for this study which is (10) Ten years from the year 2020 through the year 2029. This study among many classifications and methods of forecasting employed long-term load forecasting as classification and Artificial Neural Network application as a Method on the Rainbow-Elekiah 33 kV commercial feeder under the Port Harcourt Electricity Distribution Company network for ten (10) years.

2. REVIEW OF RELATED SEARCHES:

Several studies have been reviewed on electrical load forecast across different electrical load categories ranging from shut-term to long-term load forecast among them are Forecasting of Electrical Energy Demand in Nigeria Using a Modified Form of the Exponential Model, this study indicates that mismatch is a major problem

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in power system planning and operation as the Modified Exponential Regression analysis was adopted which is very expensive in terms of cost of data,[4]. Moreover, A Comparative Study of Time Series Analysis for Forecasting Energy Demand in Nigeria was also conducted, Average and Peak Load forecasting were modeled used in conjunction with Harvey, Autoregressive, Moving Average, and Exponential Smoothing Time Series Models, meanwhile, Weather data were not considered in this study and being the major factor of long-term load forecast,[6]. Load Forecasting for HESCOM Using Linear Regression and Artificial Neural Networks has been investigated as well as Linear Regression and Artificial Neural Networks were applied to the Dharwad and Hubli locations of HESCOM even though the regression plot of the study did not prove forecast accuracy,[3]. Artificial Neural Network for Energy Demand Forecast has been conducted this study used a multilayer time-delayed Feed-forward ANN to train with an error backpropagation algorithm. Weather data were not considered in this study and is the major factor of long-term load forecast,[1]. However, having gone through many publications of many researchers on electrical load forecast with the different approaches applied it's worth noting that this paper will make use of the Artificial Neural Network approach to forecast Rainbow-Elekahia 33 kV commercial feeder under Port-Harcourt Electricity Distribution Company Plc's Network, and the result obtained in this study will take its comparison with Short-Term load forecast for Port Harcourt Metropolis using Artificial Neural Network,[7]. In this study, the ANN approach is

the model used for the long-term electrical load forecast of Rainbow-Elekahia 33 kV Commercial Feeder, of course, this model has proven to be dependable and efficient on electrical load forecast in the past and present as its value is discovered in the results produced so far. ANN works like the neurons in the human brain which are capable of using historical data to learn patterns and relationships, in which output can be predicted when a new set of data are supplied to the input of the ANN.

3.1 Methods and Materials

In this section following steps have been taken to achieve the design model and methodology of this paper: Collection of data, Update of the data collected, Development of a strategic method for long-term load forecast, Training of the data using ANN in Matlab simulation environment, Test of performance of the model used. The data that were used for training and testing of the model performance in this research are yearly historical electrical load readings of Rainbow-Elekahia 33 kV Commercial Feeder which was obtained from Port Harcourt Electricity Distribution Company (PHEDC), Moscow Road, Port Harcourt and Transmission Company of Nigeria (TCN), Oginigba, Port Harcourt regional Office. From January 2015 through December 2019 with previous years' weather average temperature of this same year frame gotten from the NIMET office in Abuja both data were used for analysis in this chosen model for ten (10) years of electrical load forecast from January 2020 through December 2029. The details of the data used in their respective terminologies are shown below which are

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- i. The previous year's hours of energy were on the network
- ii. Previous year's hourly load reading
- iii. Previous year's average temperature
- iv. Previous year's maximum load reading
- v. Previous year's minimum load reading
- vi. Previous year's average load reading
- vii. Target.

Load Forecasting Model

The load forecast Model for this study shall be carried out in an ANN Simulation environment using **Multi-Layer Perceptron** (MLP) which is a Network topology configuration that forms connection patterns, formation of linkage elements of neural activation, and strategical training patterns for data process methodology are the characteristics that drive the artificial neural network. MLP is generally an ANN model that is most common; in that, it's known for its ability to perform as a supervised network which requires a desired output to learn, to create a correct model [2]. By latching the input to the output to produce (generate) a model that can invariably be useful to produce future expectations. A Multi-Layer Perceptron is made of several layers of nodes as shown in figure 3.4. the first layer is generally called the input layer, through which information/data from the external world are being inputted into the network between the lowest layer and the highest layer known as the output layer is the hidden layer that consists of one or more intermediate layer as it was mentioned before the data computation occurs in the hidden layer of multi-layer perceptron of ANN [2]. The highest layer is known as the output layer; this is

where the solution to all the problems and computation done in the network is received. The connection of cyclic arc from a lower to a higher layer is a function of their adjacent nodes in their respective layer's characteristics [7]. The artificial neuron function is revealed in fig.3.3 there is the existence of non-linearity vectors that are binary, bipolar, and hard limited in nature, in the case of analogy vectors, thrashing functions like unipolar sigmoid function (0 to 1), hyperbolic, tan, Gaussian, Logarithmic and exponential functions are used, [1].

ANN Modelling for Commercial Long-Term Load Forecasting of Rainbow-Elekahia 33 kV Feeder

ANN has much uniqueness among all other AI methods used for simulation, as its long-term load forecast network design has been a very repetitive task, therefore, modelling issues that determine the result of an ANN were seriously considered. However, appropriate and specific architecture are vital decisions to make which comprise; the number of nodes that each layer consists layers specifically number, and the number of arcs that connect with the nodes as shown in Fig.2

Network Architecture:

This paper presents ANN architecture design for long-term commercial load forecast which includes: The input parameters: 6; Number of iterations: 11; Hidden layers: 2; Output layer: 1.

Commercial Load Selection and Analysis:

Rainbow-Elekahia 33/0.415 kV feeder has been selected as a commercial feeder for this study as its currently being fed by Port Harcourt Mains

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from Transmission Station, Oginigba. Note, the commercial feeder selected in this research has its customers(loads) being Schools, Banks, Oil Servicing Companies Land Based Operation Facilities, Hospitals, Petrol Stations, Hotels, and Commercial Functioning Facilities (CFF) e.t.c which make up ninety-five percent (95%) of its loads.

Commercial Load Reading Pre-treatment & Target of Rainbow–Elekahia Feeder

Electrical historical load consumption of Rainbow-Elekahia commercial feeder was obtained from PHEDC head office, Moscow Road, Port Harcourt, and Transmission Company of Nigeria (TCN) Port Harcourt regional office Oginigba, combined with the weather; Temperature Average of the previous five(5) years from Nigerian Metrological Agency(Nimet), the combination of these data shows the load reading in Mega-Watt Hour

(MWHR) of the six (6) input parameters and expected target explained in page 38, used in training the artificial neural network (ANN) for the Ten (10) years electrical Load forecast

Error Analysis

Measurement of ANN Algorithm Performance

There are a lot of methods to evaluate the performance of an ANN in load forecast such as the modeling time and training time since the level of accurate prediction is the main reason for performance measurement [7]. Which can be achieved through the training data. However, accuracy measurement has been informed of the difference between the actual and the target value [7]. These under-listed equations would be employed for this paper's measurement of accuracy in evaluating the performance of the proposed neural network.

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{MSE} \dots\dots\dots (3.5)$$

$$\text{Mean Square Error (MSE)} = \sum \frac{(et)^2}{N} \dots\dots\dots (3.7)$$

Where (et) = forecast error of an individual,

(yt) = Actual Value,

N = Terms error's number

$$\% \text{ Error} = \frac{\text{Actual Load} - \text{Forecast Load}}{\text{Actual Load}} * 100 \dots\dots\dots (3.9)$$

RESULTS AND DISCUSSION

4.1 ACTUAL AND FORECASTED COMMERCIAL FEEDER OF ELECTRICAL LOAD

The actual versus a forecast of electrical load demand of Rainbow-Elekahia commercial feeder as explained on pages 5 and 6 under commercial load selection analysis in Megawatt hours are shown below.

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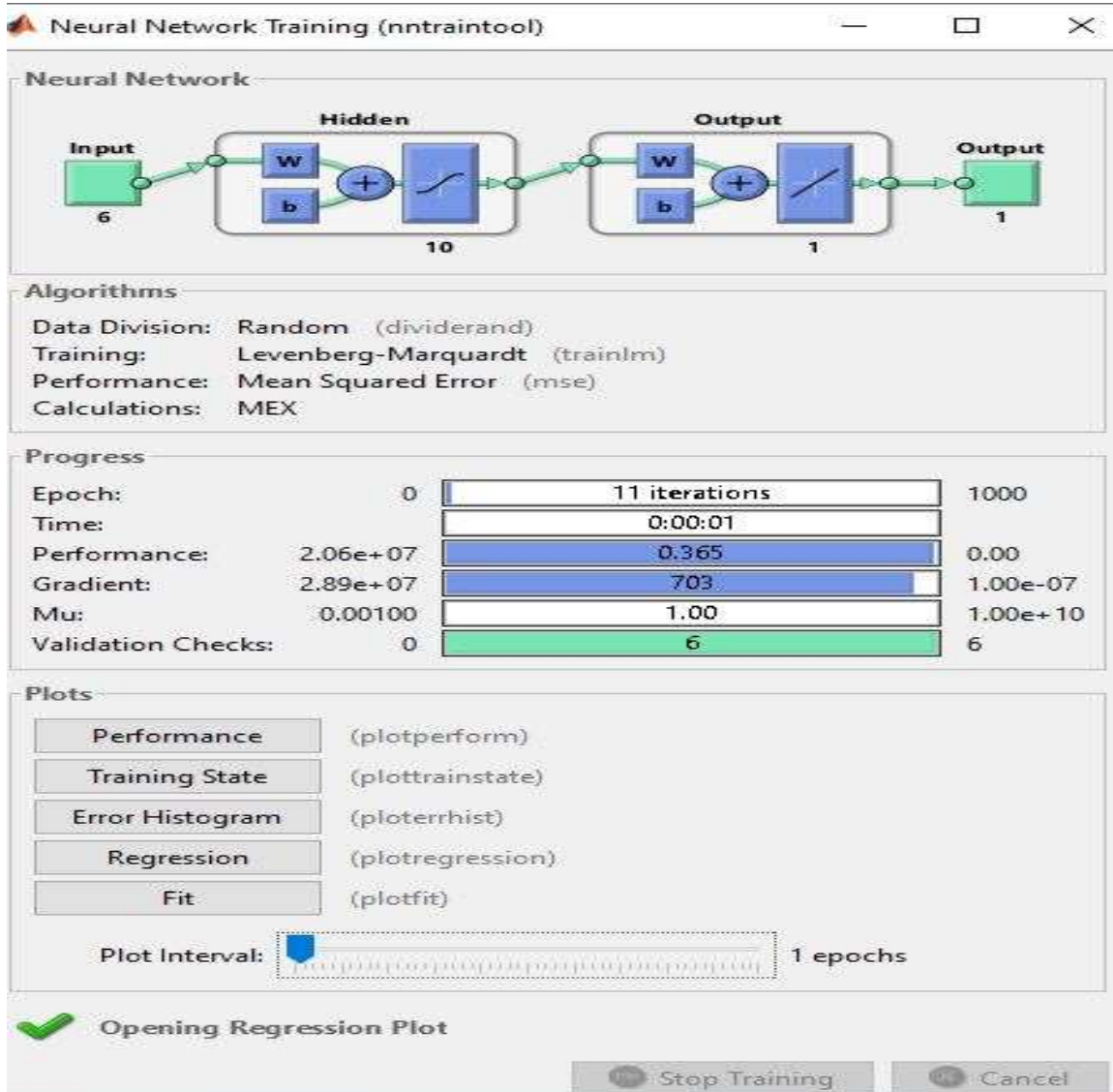


Figure 4.1 Shows the Rainbow-Elekahia Commercial Feeder ANN diagram, Algorithms & Progress during training from year One (1) to year Ten (10)

Figure 4.2 Shows the Regression plots (graph) after training the neural network using input parameters in table 1. for ten (10) years of

electrical load forecast. From the regression plot, four (4) graphs are gotten which include; the Training phase plot; Testing phase plot;

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Validation phase plot; and a Summation (Average) of the entire phase plot also called 'All'. The closer the data plotted to the dotted straight line passing through the origin, the more accurate the forecast of the trained ANN. Therefore, a graph where all the plotted data are on the dotted straight line from the origin

results in an R-value of 1, this shows that the relationship between the input and target was well learned and understood by the trained (ANN), [7]. Consequently, such a neural network can give a hundred percent accurate forecast for that phase plot, and the same follows for all other phase plots.

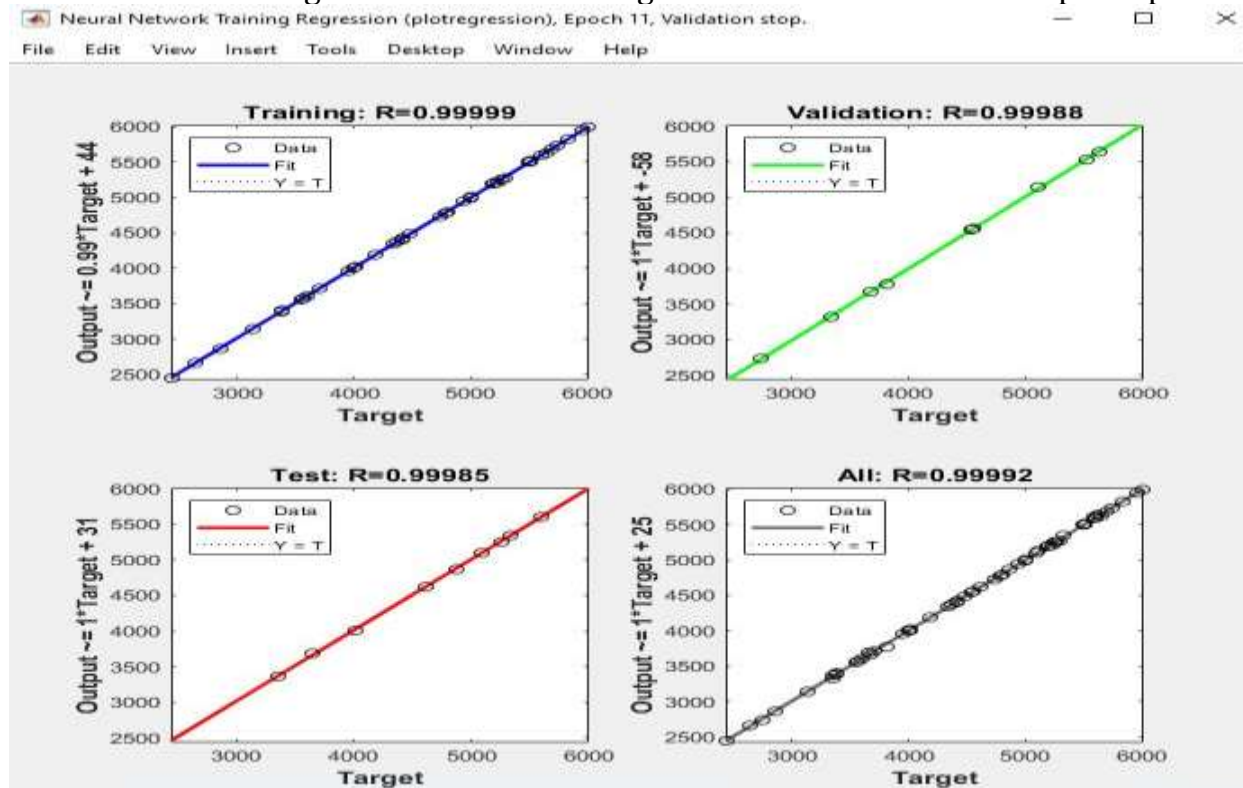


Figure 4.2
Shows the Rainbow-Elekahia Commercial Feeder Regression plot after training from year One (1) to year Ten (10).

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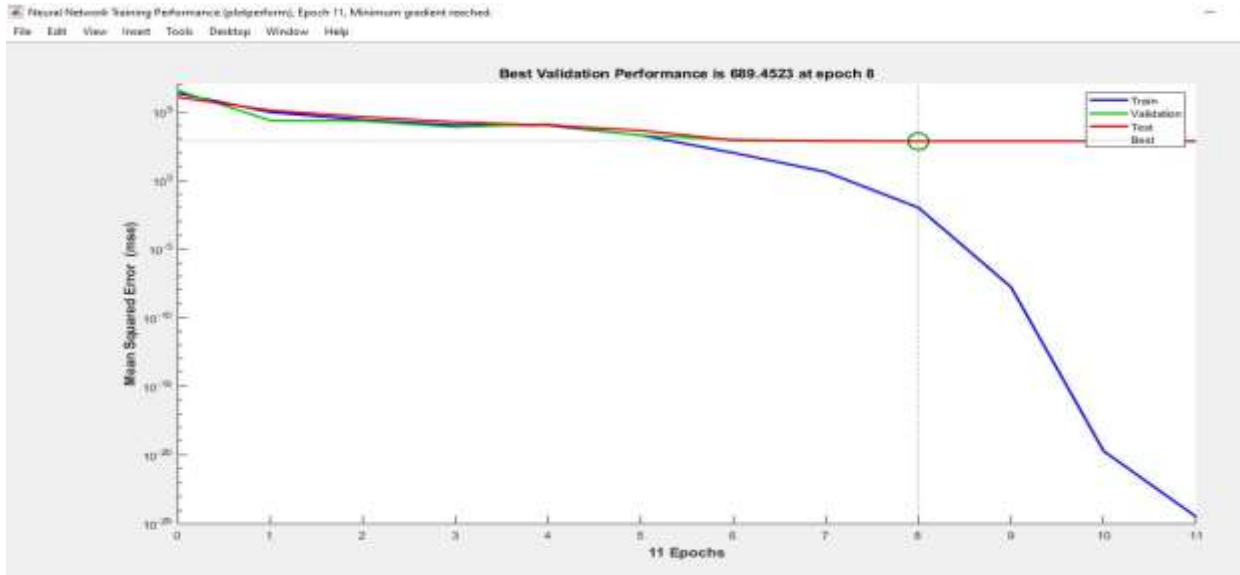


Figure 4.3

Shows Rainbow-Elekahia Commercial Feeder ANN Performance Graph during training for years one (1) to ten (10)

Table 4a shows an actual electrical load of the Rainbow-Elekahia Commercial feeder for ten

(10) years forecast using trained ANN in this study.

RAINBOW-ELEKAHIA COMMERCIAL FEEDER ACTUAL LOAD DEMAND (MWHR)

Months	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
January	2417.8	4392.8	4167.3	5828.0	5615.9	2444.5	4422.3	4182.3	5824.5	5640.4
February	2634.8	4470.0	3803.0	4602.5	5083.1	2667.3	4487.7	3779.1	4627.3	5103.1
March	4325.8	4720.1	4769.4	5589.2	6002.3	4346.5	4738	4783.2	5601.1	6002.1
April	4325.8	3116.6	4932.6	5243.7	5493.1	4342.5	3145.2	4943.5	5249.6	5498.7
May	4003.1	5197.6	3361.0	5504.8	5503.9	4022.7	5212.1	3390	5512.9	5506.3
June	4003.8	4522.4	3375.1	5321.7	5507.5	4003.6	4550.4	3396.7	5346	5523.4
July	3983.2	3645.4	3558.8	5633.4	5278.0	4005.4	3693.3	3574.1	5634.5	5277.8
August	3591.4	2836.0	4400.8	4986.2	4858.6	3609.5	2862.5	4411.6	4989	4869
September	3341.9	3690.5	3665.7	5256.9	5209.4	3363.5	3709.5	3667.6	5258.8	5216.6
October	3935.2	4357.6	4543.5	5581.1	5184.3	3960.7	4375.6	4562.2	5605.5	5190
November	2727.9	3536.9	5181.6	4795.9	5685.2	2737.4	3559.5	5187	4798.3	5691.7
December	3338.3	4988.3	5727.4	5095.4	5954.1	3321.8	5011.4	5735.7	5135.8	5951.8
Total	42629.0	49474.2	51486.2	63438.8	65375.4	42825.4	49767.5	51613.0	63583.3	65470.9
Average	3552.4	4122.9	4290.5	5286.6	5448.0	3568.8	4147.3	4301.1	5298.6	5455.9

Table 4b Shows the forecasted electrical load of Rainbow-Elekahia Commercial Feeder for ten (10)

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RAINBOW-ELEKAHIA COMMERCIAL FEEDER FORECASTED LOAD DEMAND (MWHR)

Months	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029
January	2444.5	4422.3	4182.3	5824.5	5640.4	2460.1	4429.7	4189.3	5800.2	5649.6
February	2667.3	4487.7	3779.1	4627.3	5103.1	2680.7	4499.4	3792.1	4638.7	5113.6
March	4346.5	4738	4783.2	5601.1	6002.1	4352.5	4749.2	4793.9	5614.9	6010.4
April	4342.5	3145.2	4943.5	5249.6	5498.7	4356.6	3159.3	4944.3	5259.6	5504.3
May	4022.7	5212.1	3390	5512.9	5506.3	4034	5227.3	3404.3	5522.9	5516.2
June	4003.6	4550.4	3396.7	5346	5523.4	4018.1	4565	3408.8	5356.1	5530.3
July	4005.4	3693.3	3574.1	5634.5	5277.8	4018.7	3691.4	3587.6	5643.6	5284.8
August	3609.5	2862.5	4411.6	4989	4869	3622.4	2878	4423.8	5000	4880
September	3363.5	3709.5	3667.6	5258.8	5216.6	3376.7	3713.3	3675.3	5268.9	5226.6
October	3960.7	4375.6	4562.2	5605.5	5190.1	3975.1	4388.3	4573.6	5614.8	5200.3
November	2737.4	3559.5	5187	4798.3	5691.7	2749.4	3573.5	5197.2	4808.6	5699.5
December	3321.8	5011.4	5735.7	5135.8	5951.8	3336.1	5006.3	5745	5146.4	5947.1
Total	42825.4	49767.5	51613	63583.3	65471	42980.4	49880.7	51735.2	63674.7	65562.7
Average	3568.783	4147.292	4301.083	5298.608	5455.917	3581.7	4156.725	4311.267	5306.225	5463.558

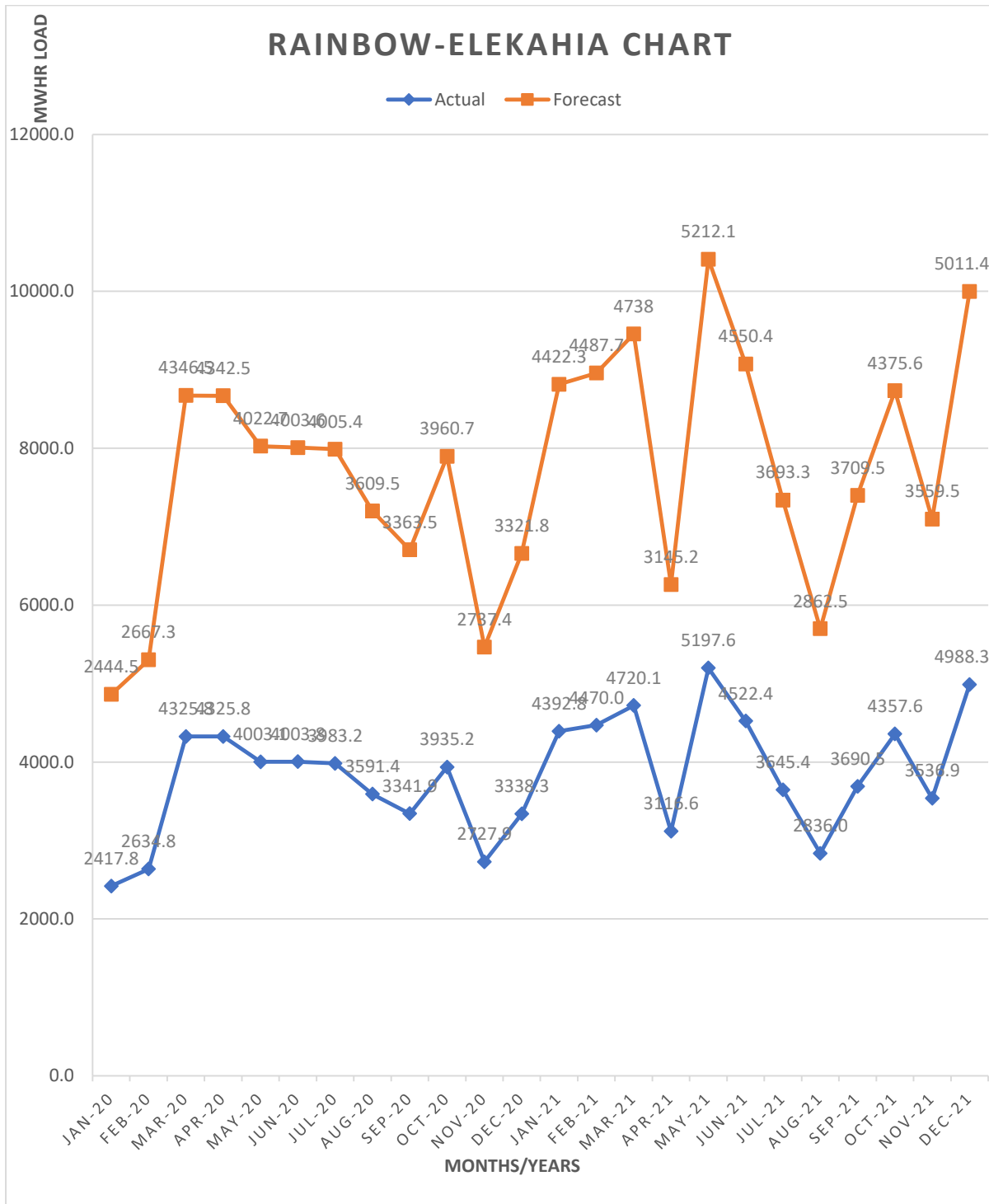
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Graphs of Actual vs Forecast Load of Rainbow-Elekahia Commercial Feeder:

Figures (4a – 4e), are the line graphs (plot) of the Actual and forecasted load in mega-watt hour (MWHR) of trained Artificial Neural Network using results from table 4.1 for ten (10) years (2020-2029) as shown for Rainbow-Elekahia Commercial feeder. From the graphs, it is seen that the forecasted load is within (-0.2, -16.5, -23.9, -3.5, -2.3, -1.9, -5.1, -24.3, and -4.7) MWHR for the lower side and (1.1 - 47.9) MWHR for the upper sides of the forecast which also means by June 2020; December 2020; February 2022; January; 2023; December 2024; July 2025; December 2025; January 2026; and December 2029 there would be load drop in their respective months of actual demand values while there would be an increase in the remaining months of forecasted years which shows a realistic and true forecast. Meanwhile, Maximum load demands of (4325.8 / 5197.6 MWHR, 5727.4 / 5828.0 MWHR, 5954.1 / 4346.5 MWHR, 5212.1 / 5735.7 MWHR & 5824.5 / 6002.1 MWHR) were recorded in (Mar.2020/May.2021, Dec.2022/Jan.2023, Dec.2024/Mar.2025, May.2026/Dec.2027,

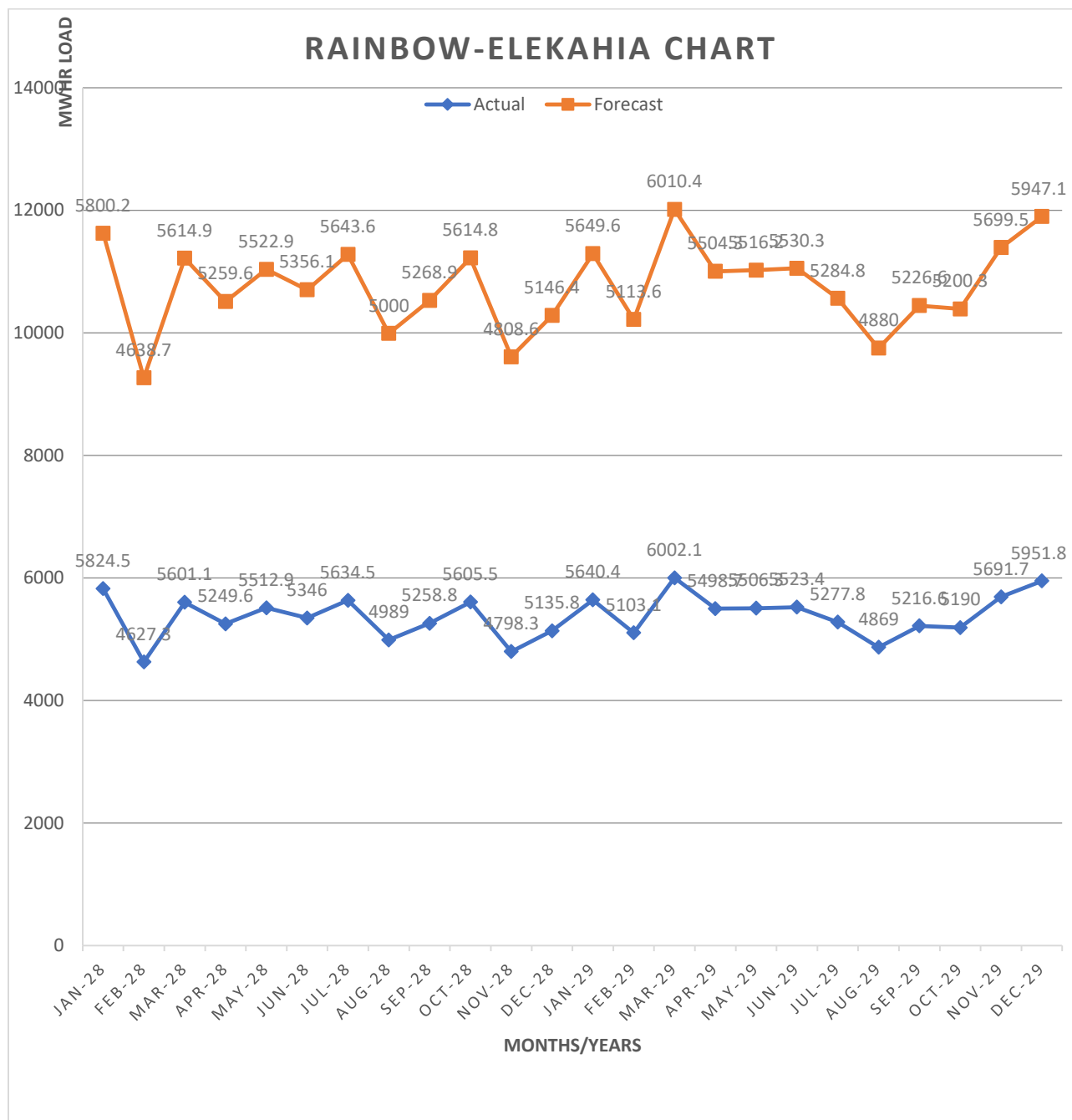
Jan.2028/Mar.2029) respectively from (January-December of each year). While maximum load forecast of (4346.5 / 5212.1 MWHR, 5735.7 / 5824.5 MWHR, 5951.8 / 4356.6 MWHR, 5227.3 / 5745 MWHR, & 5800.2 / 6010.4 MWHR) was recorded in (Mar.2020/May.2021, Dec.2022/Jan.2023, Dec. 2024 / Mar.2025, May.2026/Dec.2027, & Jan.2028/Mar.2029) respectively from (January-December of each forecasted years). Furthermore, minimum load demand of (2417.8 / 2836.0 MWHR, 3361.0 / 4602.5 MWHR, 4858.6 / 2444.5 MWHR, 2862.5 / 3390.0 MWHR, & 4627.3 / 4869 MWHR) was equally recorded in (Jan.2020/Aug.2021, May.2022/Feb.2023, Aug. 2024/Jan.2025, Aug.2026/May.2027, & Feb.2028/Aug.2029) respectively from (January-December) while minimum load forecast of (2444.5 / 2862.5 MWHR, 3390 / 4627.3 MWHR, 4869.0 / 2460.1 MWHR, 2878 / 3404.3 MWHR, & 4638.7 / 4880.0 MWHR) as recorded in (Jan. 2020/Aug.2021, May.2022/Feb.2023, Aug.2024/Jan.2025, Aug.2026/May.2027, & Feb.2028/Aug.2029) respectively from (January-December)



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Figure 4a. Shows Rainbow-Elekahia Commercial Feeder graph of Actual VS Forecast Load after testing phase of years 2020 and 2021



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Figure 4e. Shows Rainbow-Elekahia Commercial Feeder graph of Actual VS Forecast Load after testing phase of years 2028 and 2029

N/B Fig. 11b, 11c, and 11d of Rainbow-Elekahia Feeder graph of Actual VS Forecast Load after testing phase of years 2022 and 2023; 2024 and 2025; 2026 and 2027 followed the same trend of Fig. 11a and 11e.

Table 3. shows values of percentage error of the forecasted load for the Rainbow-Elekahia Feeder network

Rainbow-Elekahia Feeder Percentage Error Values

Year	MSE%	$\sqrt{\text{MSE\%}}$
2020	0.017	0.132
2021	0.029	0.170
2022	0.004	0.069
2023	0.004	0.063
2024	0.001	0.040
2025	0.010	0.10
2026	0.004	0.063
2027	0.004	0.066
2028	0.001	0.040
2029	0.001	0.040

The performance of Curve Fitting Artificial Neural Network trained data was investigated by Mean Square Error and Root Mean Square Error, the results are shown in the Table above for Rainbow-Elekahia Commercial Feeder in which a high degree of accuracy has been recorded and ANN strength for electrical commercial load forecasted has been highly proved.

5. CONCLUSIONS

A Curve-Fitting Feed Forward Neural Network method has been used for the long-term electrical load forecast of the Rainbow-Elekahia commercial feeder network under the Alpha Zonal Office of PHEDC network and the results obtained are shown in Table 2. Couple with the plotted graphs of actual versus forecasted load in figure 4a and figure 4e. the obtained results justify the accuracy strength

of Artificial Neural Networks on long-term load forecast with minimum error recorded as shown in table 3 and compared with the result obtained in [7]. However, ten (10) years of electrical load forecast has been carried out from the year 2020 through the year 2029 with eleven (11) iterations and ten (10) neurons used to achieve the stated objectives throughout the training states of this forecast. Moreover, the regression plot shows that the data trained were highly learned and understood by the ANN architecture with six(6) inputs as stated on page two(2) of this paper, all the data used in this study were fetched from the feeder studied except the weather data collected from Nimet which must have given the system the critical reality of what the conditions have been like with load consumption in the next ten years forecasted.

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