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Artificial Neural Network for Long-term Industrial Load Forecast: Trans-Amadi Industrial Layout, Nigeria

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ABSTRACT

This paper presents an Artificial neural network (ANN) based approach for long-term load forecasting (LTLF) of the Trans-Amadi industrial feeder under Port Harcourt Electricity Distribution Company (PHEDC) network from 2020 to 2029. Two-layer feed forward neural networks (FFNN) Curve Fitting simulation tool was used for training of the historical load reading with temperature that summed up data collected from PHEDC-Head- office, TCN-Regional Office and Nimet-Office Abuja respectively are examined and have been used in training and testing the proposed neural networks. The simulation results show that Curve Fitting neural networks (CFNN) show quite good performance for long-term load forecasting period. The performance of accuracy of CFNN is evaluated in terms of the mean square error (MSE) and root mean square error (RMSE). However, the forecasting results of the proposed CFNN approach shows that performance of the CFNN is reliable and efficient for the future plans for the respective units of the power system to plan for the future load of Trans-Amadi industrial feeder.

Keywords: Load Forecasting; Artificial Neural Networks; PHEDC; Multi-layer Neural Network.

1. INTRODUCTION

Availability of Electrical energy is one of the major factors that shows the level of the development that a country has reached in their fundamental scopes of achievement and growth. The need for electricity is of high increase on daily basis, as nation's pants for growth socially and infrastructurally. On this same manner of unavoidable increase of electric power demand on daily basis the power utility companies are saddled with responsibilities to put all hands on desk to ensure that there is constant availability of power on their network to meet up with increase in demand that cannot be avoided as nations continues to experience growth and development in all facets of life. However, technology has contributed and still contributing to the easiest method or means of putting structures in place so as to plan for inevitable increase in power demand as loads consuming energy transmits on power system network increases on daily basis. In electrical power system structure, planning and operation, even for optimization of power system control integration; there is always need for awareness of likely load demand before hands (in advance) for all power utility companies and this can only be achieved by taking to the method of technologies to get the accurate expected load demand, this method is called load forecasting.

However, it has become imperative for the electric power utility company of Port Harcourt Electricity Distribution Company who supplies electrical power to Trans-Amadi Industrial Feeder (TAIF) that the load on the network should be estimated in advance, therefore, 'accurate models for electrical power load forecasting is required of power system planning and operation units, because power system expansion planning begins with a forecast of expected future load demands [2].

Review of related searches

Quiet number of publications have been reviewed on the various aspect of electrical load forecast as the growth in load demand has become undeniable scenario in the power industry from customers which has in turned and continually confronting all the sectors in the power industry. From generation, transmission, and distribution with high demand on management planning and operations of the network [9]. Several vital decisions which involves decisions on purchasing and generating electric power, load switching and development of infrastructures have been made through load forecasting, because this subject of load forecasting has been existing for so many years. To forecast the expected load demand; it involves accurate assumption of both the magnitudes and geographical locations of electric load on an un-similar period of the planning horizon [1]. Load forecasting can be categorized into three: Long-term load forecasting (LTLF) which is from five (5) to twenty-five (25) years with a fundamental role in economic planning of new generating capacity and transmission networks for future expansion; Mean-term load forecasting (MTLF) which is usually from one(1) week to one (1) year that's used mainly for the scheduling of fuel supplies, maintenance programme, financial planning and tariff formulations; and Short-term load forecast (STLF) which is also usually from one(1) hour to one(1) week 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.

Out of several forecasting approaches developed so far for LTLF, MTLF and STLF are these broad two classification in their unique categories: Parametric and non-parametric approaches [5]. Load forecasting parametric approach used include mathematical approach such as statistical regression techniques and time series approaches which includes mathematical models such as Autoregressive (AR), Moving Average (MA), and Autoregressive integrated Moving Average (ARIMA). However, non-parametric are artificial intelligence-based algorithms; e.g fuzzy logic (FL), artificial neural networks (ANNs), and generic algorithms (GAs), Box-jenkins ARIMA, support vector machines (SVM) and expert system (ES) [5].

In this study ANN approach is the model used for the long-term electrical load forecast of Trans-Amadi Industrial Layout Feeder, of course this model has proven to be reliable and efficient on electrical load forecast in the past and presently as it's worth is discovered in the results produced so far. ANN works like the neurons in the human brain which 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.

2. METHODS AND MATERIALS

In this case 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 the 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 reading of Trans-Amadi Industrial Feeder as obtained from Port Harcourt Electricity Distribution Company (PHEDC), Moscow Road, Port Harcourt and Transmission Company of Nigeria (TCN), Oginigba, Port Harcourt. From January, 2015 through December, 2019 with previous years weather average temperature of this same year frame gotten from NIMET office Abuja both data were used for analysis in this chosen model for ten (10) years electrical load forecast from January, 2020 through December, 2029. The details of the data used in their respective terminologies are shown below which are

i. Previous year hours energy was on the network (Hr)
ii. Previous year hourly load reading (Pylrsh)
iii. Previous year temperature (Pyhtemp)
iv. Previous year maximum load reading (Pylrmax)
v. Previous year minimum load reading (Pylrmin)
vi. Previous year average load reading (Pylrav)
vii. Target.

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Conceptual Frame Work of ANNS

ANNs are known as nonlinear statistical data modelling tools where the complex relationships between inputs and outputs are modelled or patterns are found. An ANN has several advantages but one of the most well-known of these is the ability to learn from observing data sets, in this manner, [3] ANN is used as a random function approximation tool. These types of tools enhance the most cost effective and ideal methods of estimates so as to arrive at solutions, which will eventually save time and money simultaneously. ANNs are considered fairly simple mathematical models to enhance existing data analysis technologies.

ANNs have three layers that inter connected; the first layer consists of input neurons, those neurons send data on to the second layer, which in turn sends the output neurons to the third layer. Training an artificial neural network involves choosing from allowed models for which there are several associated algorithms [3]. The ANN network has processing elements (PEs) that are differential equations by interpretation [6]. The processing elements are interrelated and connected layer by layer and also interconnected. The artificial neuron function is revealed in fig.3.3 there is existence of non-linearity vectors that are binary, bipolar and hard limited in nature, in case of analogy vectors, thrashing functions like unipolar sigmoid function (0 to 1), hyperbolic tan, Gaussian, Logarithmic and exponential functions are used, [6].

ANN Modelling for Long-Term Load Forecasting

ANN has number of 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 determines the result of an ANN were seriously considered. However, appropriate and specific architecture are vital decisions to make which comprise; number of nodes that each layer consist, layers specific number, and the number of the arcs that connect with the nodes as shown in Fig.1.

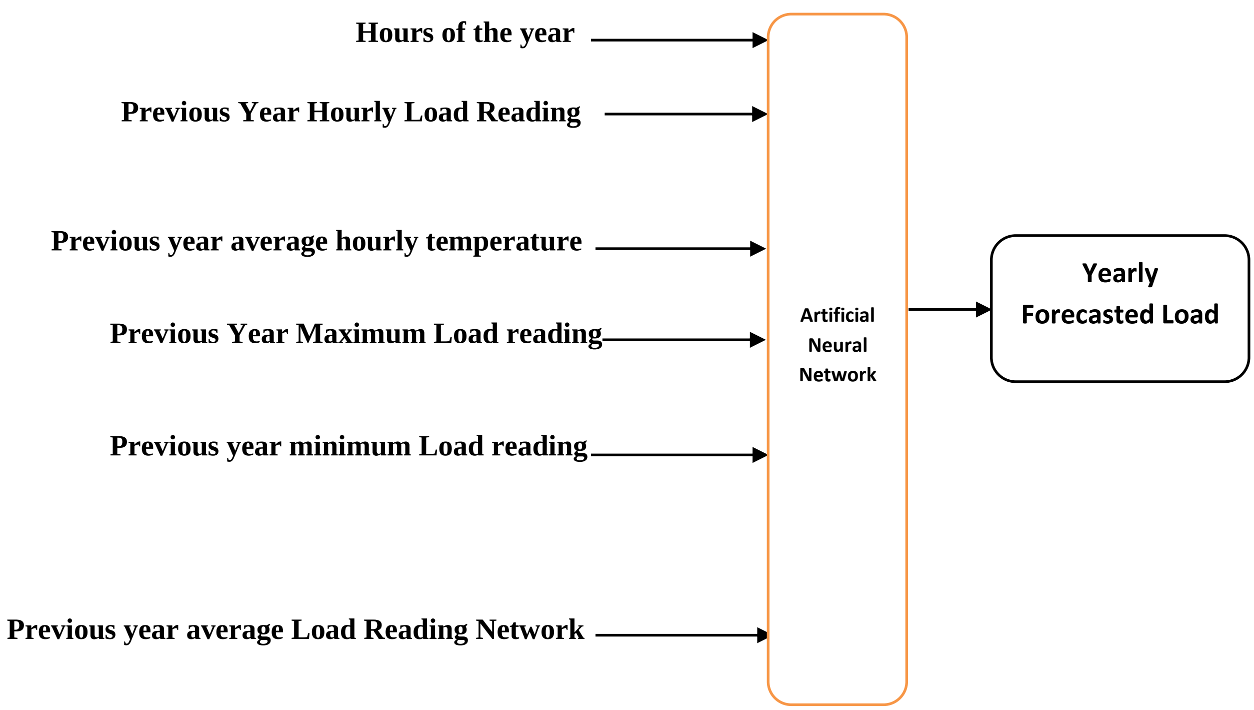

Figure 1 Inputs-Output Block of the Proposed ANN System

Network Architecture

In the network architecture of ANN of the MLP, which consist of nodes, in the input layers confinement, hidden nodes are also assigned into one or more intermediately hidden layers. To design the proposed multi-Layer Perceptron of long-term load forecast using neural network the following parameters were considered [7].

i. Specific number of output nodes/target nodes
ii. Actual number of hidden layers and hidden nodes
iii. Specific number of input nodes.

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Generally, problem dependent is the factor that defined the choice of all these parameters.

Activation Function

Every activation function (or non-linearity) takes a single number and performs a certain fixed mathematical operation on it. However, the relationship between inputs and outputs of nodes and ANN network is determined by the transfer function which is also known as Activation function. More often than none, the degree of non-linearity is being highlighted by activation function which is applicable to almost ANN algorithm/principle of load forecasting. The below is the used activation function in this paper that one may also encounter in practice [4]:

Sigmoid: takes a real-valued input and squashes it to range between 0 and 1

$$\sigma(x)=\frac{1}{(1+\exp(-x))} \quad \ldots\ldots\ldots\ldots \quad (1)$$

Sigmoid transfer function finds its usefulness in most applications [4] however, Logsig activation function will be used in the hidden layer of this proposed network of course in the output layer linear activation function shall be employed.

Training Algorithm

Lavenberg-Marquardt training method is the training algorithm that suit the need of this proposed network as its nonlinear optimization data efficiency is very high or more; it has convergence rate, very robotic, also find its attractiveness in ANN training as it has capability to sought local minimal since the neural network training is very crucial unconstrained nonlinear minimization problem whereby arc weight of a network are continually adjusted to reduce to its barest minimum, the overall error that can be mean or square error between the forecast and actual output values of all [7].

Training, Testing and Validation Samples

An ANN forecast is built by these two samples; training and testing samples. Of course, the testing sample is used for development of ANN model while the training Sample is employed for determining the forecasting power of the model. In a situation where data sets are small it is of great merit to use same test sample for validation and testing purposes. Adequate consideration has been given to selection and division of the data into training, testing and validation sets, for wrong division and separation process of the training, selection of best ANN structure which will equally affect the evaluation of ANN forecasting performance [7].

Industrial Load Selection and Analysis:

Trans-Amadi Feeder is the only industrial feeder for this study and is radiating from Transmission Company of Nigeria (TCN) Oginigba Port Harcourt Station with the 132/33 kV transformer tagged T2 60 MVA (Z2) which is equally known as RSPU(Rivers State Public Utilities) Feeder, being an industrial populated environment majorly most oil servicing companies and main oil and gas industries land base operation facilities are sited in this area of Port Harcourt Electricity Distribution Network, however, some of these loads are fetched directly from the 33 kV line coming from transmission station which are also known as Line Loads with thirty-nine (39) number of 100 kVA Line Load Transformer installed, Meanwhile, there are other four (4) number of 11/0.415 kV feeders stepped down by 15 MVA transformer situated inside the Alpha Zonal office of PHEDC/ Ordinance office control room. These four feeders are named Water Works, Revoc, Fimie, and Ndahbros to feeds other medium voltage industrial customers within Trans-Amadi environ, supplies by Trans-Amadi 33 kV industrial feeder.

Load Reading Pre-treatment and Target

The electrical energy monthly load reading in mega-watt hour (MWHR) of the six (6) input parameters and expected target consumption from PHEDC and TCN for the mentioned feeder and Simulation targeted from January, 2015 – December, 2019 is used for the simulation of ten (10) years electrical load forecast of the mentioned feeder from January 2020 through December 2029 according to their various terminologies given in fig. 2 and as explained under Data Collection above has been used for training using CFNN and the results obtained is as shown below in table 1 and 2; actual and forcasting tables for this paper.

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3. RESULTS AND DISCUSSION

Actual and forecasted electrical load

The following tables shows the actual versus forecast of electrical load demand of Trans-Amadi Industrial feeder as explained in page 5 and 6 under industrial load selection analysis in Megawatt hour.

Table 1 Shows actual electrical load of Trans-Amadi feeder being the only industrial feeder for a period of ten (10) years forecasted using trained ANN in this study

TRANS-AMADI FEEDER ACTUAL LOAD DEMAND (MWHR)										
Months	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
January	7034.1	5523.6	6858.2	7865.8	8052.8	7041.1	5761.3	6882.9	7915.4	8085.3
February	7210.2	3558.7	6719.8	6489.6	6224.7	7239.8	3795	6772.9	6527.2	6259.5
March	6388.6	2041.1	7588.8	7234.2	6720.9	6441.5	3003.7	7624.1	7274.6	6752.4
April	6388.6	6289.3	7336.8	6803.3	6215.0	6448.7	6313.5	7371.5	6846.1	6249.7
May	5643.4	5771.9	6571.0	7513.1	6599.5	5715.7	5797.7	6622.2	7574.1	6620.4
June	5324.6	5465.0	6441.5	6681.1	6787.7	5394.1	5478.8	6485.3	6714.3	6799.4
July	4532.5	2167.7	6044.6	6941.4	6654.3	4568.1	2599.9	6055.7	6967	6644
August	4345.5	2352.6	6861.2	7188.4	6042.7	4297.2	2467.3	6892.4	7214.4	6039.2
September	4556.5	1766.3	6419.9	6293.9	6286.1	4578.7	2846.5	6426.1	6319.7	6294
October	3986.6	4414.8	6891.0	7469.2	6825.5	3726.9	4422.3	6910	7490.8	6810
November	3539.7	2525.8	7199.6	7725.5	7175.6	3762.9	2473.9	7242.1	7779	7211.5
December	3884.4	6319.5	7579.8	8147.3	7520.1	3873.01	6343.7	7627.9	8164.5	7557.1
TOTAL	**62834.7**	**48196.3**	**82512.2**	**86352.8**	**81104.9**	**63087.7**	**51303.6**	**82913.1**	**86787.1**	**81322.5**
AVERAGE	**5236.2**	**4016.4**	**6876.0**	**7196.1**	**6758.7**	**5257.3**	**4275.3**	**6909.4**	**7232.3**	**6776.9**

Table 2. Shows the result of the forecasted load reading in mega-watt hour (MWHR) gotten from the trained Artificial Neural Network using the six input parameters as shown in figure 2 for ten (10) years.

TRANS-AMADI FEEDER FORECASTED LOAD DEMAND (MWHR)										
Months	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**
January	7041.1	5761.3	6882.9	7915.4	8085.3	7051	5789.4	6940.7	7920.9	8095.3
February	7239.8	3795	6772.9	6527.2	6259.5	7221.5	3819.1	6803.3	6557.1	6287.2
March	6441.5	3003.7	7624.1	7274.6	6752.4	6471.2	3022.5	7653.6	7291.8	6784.5
April	6448.7	6313.5	7371.5	6846.1	6249.7	6467.2	6353.1	7407.3	6864.7	6277.8
May	5715.7	5797.7	6622.2	7574.1	6620.4	5751.7	5826.7	6640.3	7570.2	6641.9
June	5394.1	5478.8	6485.3	6714.3	6799.4	5414.2	5502.5	6505.7	6731.2	6812.2
July	4568.1	2599.9	6055.7	6967	6644	4582.8	2600.6	6072.4	6977.8	6659
August	4297.2	2467.3	6892.4	7214.4	6039.2	4316.1	2739.8	6917.2	7224.7	6050.5
September	4578.7	2846.5	6426.1	6319.7	6294.1	4590.3	2844.6	6438.1	6333.8	6324.6
October	3726.9	4422.3	6910	7490.8	6810	3732	4443.5	6935.6	7465.7	6823.5
November	3762.9	2473.9	7242.1	7779	7211.5	3783.2	2473.7	7263.1	7799.9	7228.9
December	3873	6343.7	7627.9	8164.5	7557.1	3886.9	6378.2	7635.6	8179.2	7567.5
TOTAL	**63087.7**	**51303.6**	**82913.1**	**86787.1**	**81322.6**	**63268.1**	**51793.7**	**83212.9**	**86917**	**81552.9**
AVERAGE	**5257.308**	**4275.3**	**6909.425**	**7232.258**	**6776.883**	**5272.342**	**4316.142**	**6934.408**	**7243.083**	**6796.075**

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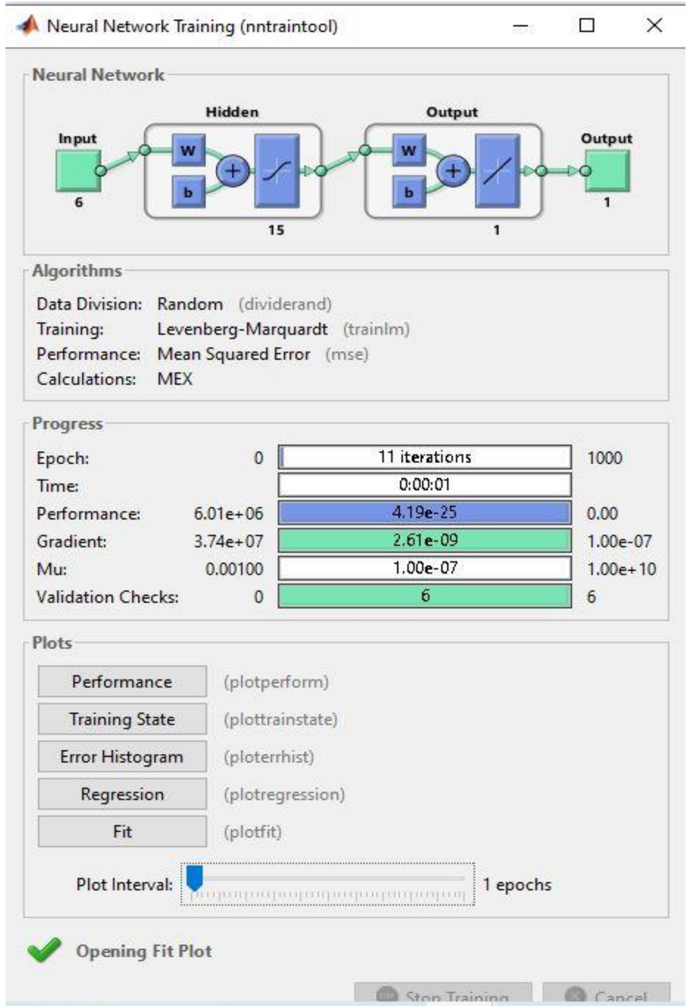

Figure 2. Shows Trans-Amadi Feeder ANN diagram, Algorithms & Progress during training

Figure 3. Shows the Regression plots (graph) after training the neural network using input parameters in table 1. for ten (10) years electrical load forecast. From the regression plot, four (4) graphs are gotten which include; Training phase plot; Testing phase plot; Validation phase plot; and a Summation (Average) of the entire phase plot also call 'All'. The closer the data plotted are 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 origin results to an R value of 1, this shows that the relationship between the input and target were well learnt and understood by the trained (ANN). Consequently, such a neural network can give a hundred percent accurate forecast for that phase plot, and same follows for all other phase plots [7].

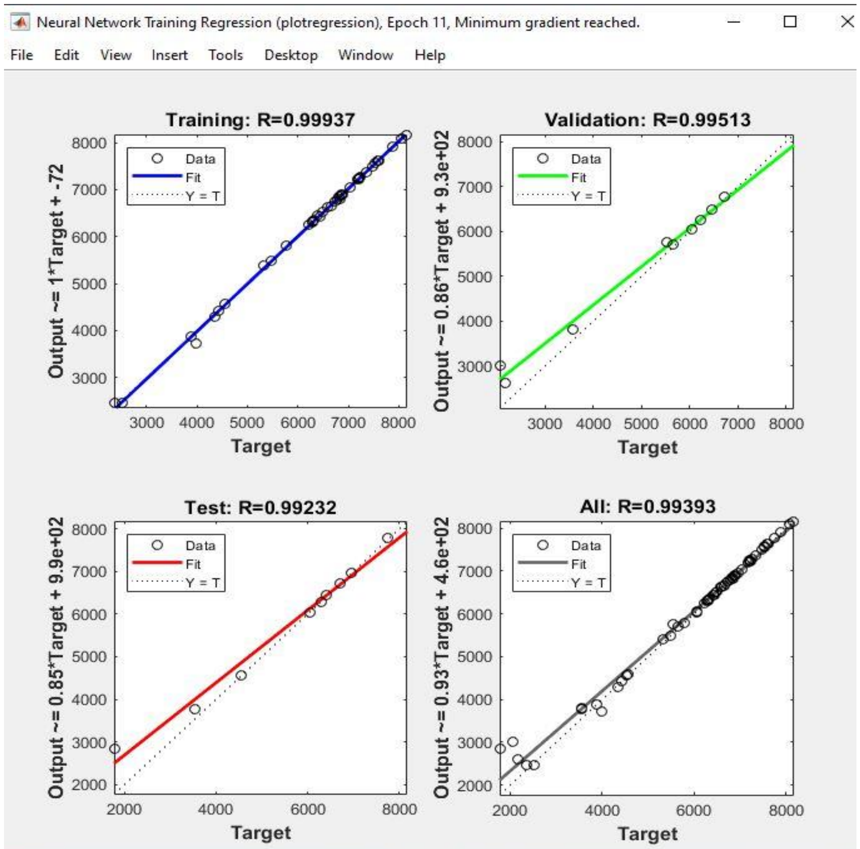

Figure 3. Shows Trans-Amadi Regression plot after training from year one (1) to year ten (10)

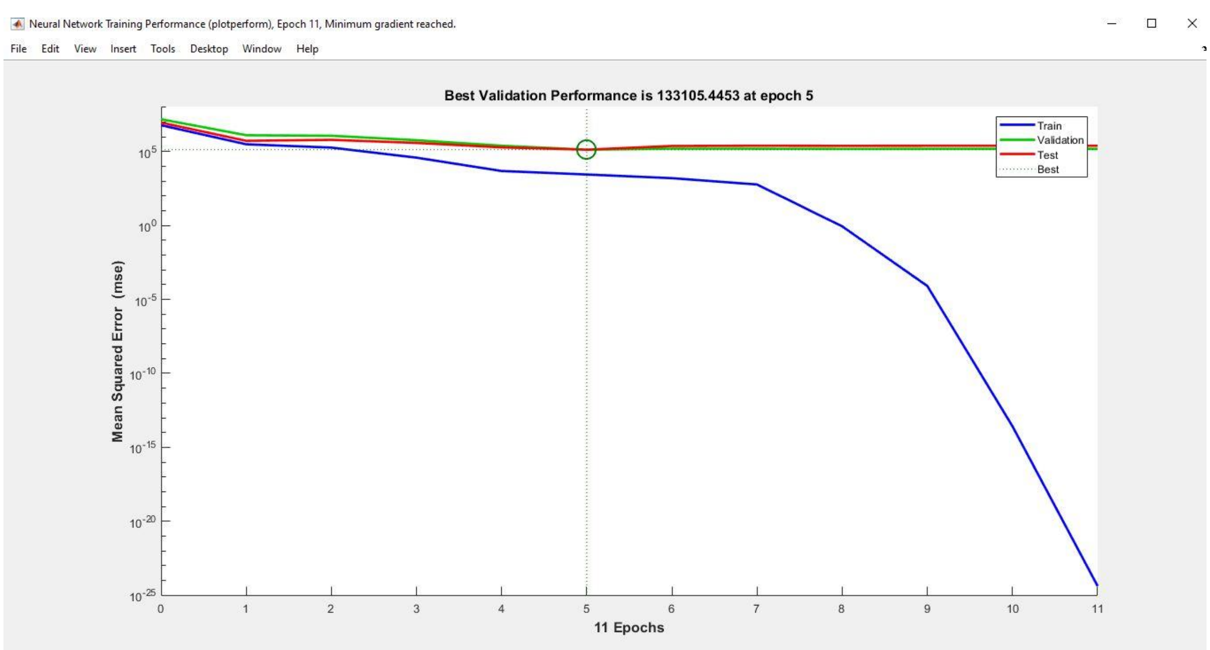

Figure 4. Shows Trans-amadi Feeder ANN Performance Graph during training from year One (1) to yearTen (10)

Graphs of Actual vs Forecasted Load of Trans-Amadi Industrial Feeder:

Figures (5a – 5e), are the line graphs (plot) of Actual and forecasted load in mega-watt hour (MWHR) of trained Artificial Neural Network using results from table 2. for ten (10) years being (2020-2029) as shown for Trans-Amadi Industrial layoutfeeder. Maximum load demands of (7210.2 /6319.5 MWHR, 7579.8 /8147.3 MWHR, 8052.8 /7239.8 MWHR, 6343.7 /7627.9 MWHR& 8164.5 /8085.3 MWHR) were recorded in (Feb.2020/Dec.2021, Dec.2022/Dec.2023, Jan.2024 /Feb.2025, Dec. 2026/Dec.2027,

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Dec.2028/Jan.2029) respectively from (January-December of each year). While maximum load forecast of (7239.8 /6343.7 MWHR, 7627.9 /8164.5 MWHR, 8085.3 /7221.5 MWHR, 6378.2 /7653.6MWHR, & 8179.2 / 8095.3 MWHR) were recorded in (Feb.2020/Dec.2021, Dec.2022/Dec.2023, Jan.2024 /Feb.2025, Dec. 2026/Mar.2027, Dec.2028/Jan.2029) respectively from (January-December of each forecasted year). Furthermore, minimum load demand of (3539.7 /1766.3 MWHR, 6044.6 /6293.9 MWHR, 6042.7 /3726.9 MWHR, 2467.3 /6055.7 MWHR, & 6319.7/6039.2 MWHR) were equally recorded in (Nov.2020/Sep.2021, Jul.2022/Sep.2023, Aug.2024/Oct. 2025, Aug.2026/Jul.2027, & Sep.2028/Aug.2029) respectively from (January-December) while minimum load forecast of (3762.9 /2467.3 MWHR, 6055.7 /6319.7 MWHR, 6039.2/3732 MWHR, 2473.7 /6072.4 MWHR, & 6333.8 /6050.5 MWHR) were also recorded in (Nov.2020/Aug.2021, Jul.2022/Sep.2023, Aug.2024/Oct.2025, Nov.2026/Jul.2027, & Sep.2028/Aug.2029) respectively from (January-December).

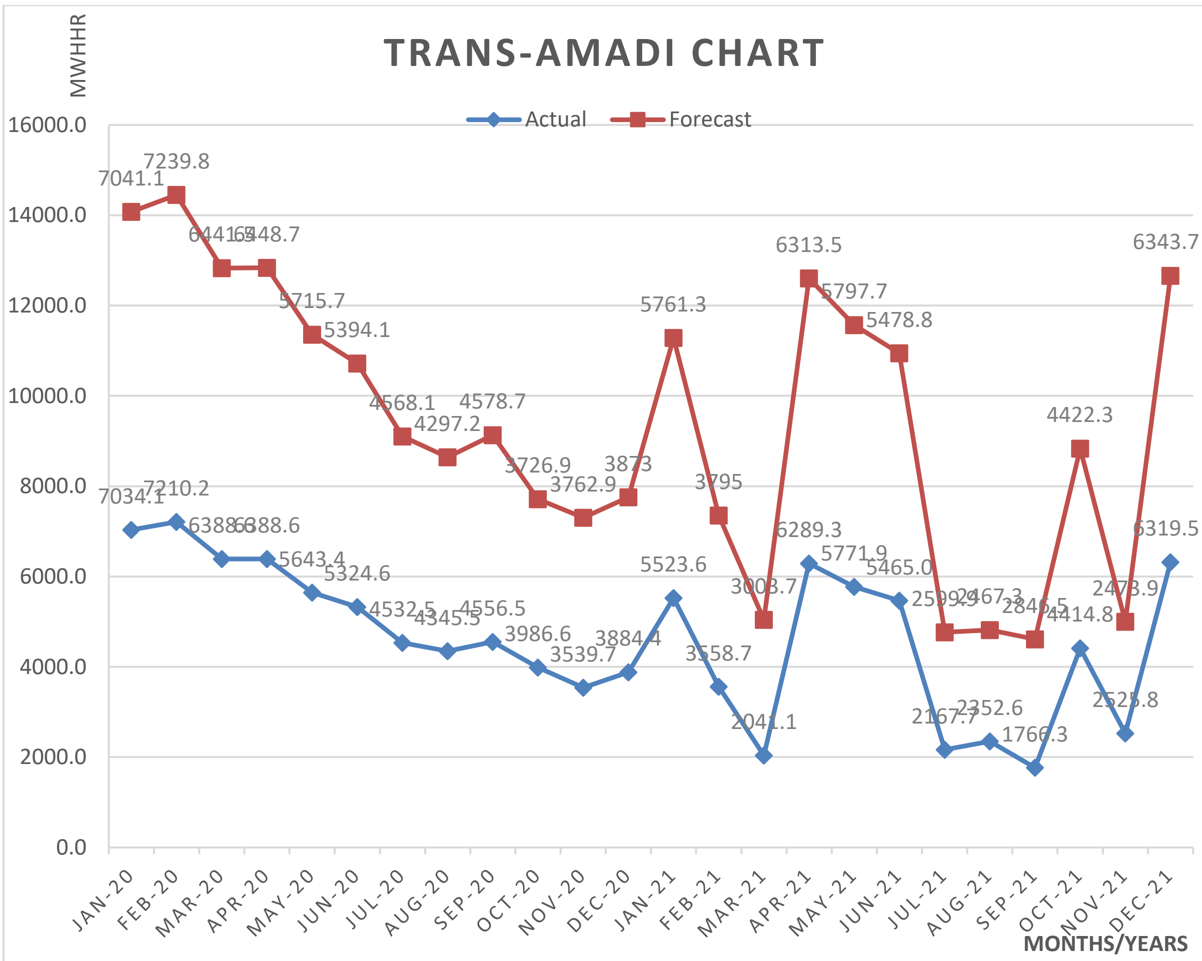

Fig. 5a Trans-Amadi Industrial Feeder graph of Actual VS Forecast Load after testing phase of years 2020 and 2021.

N/B Fig. 5b, 5c and 5d of Trans-Amadi Industrial 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. 5a and 5e.

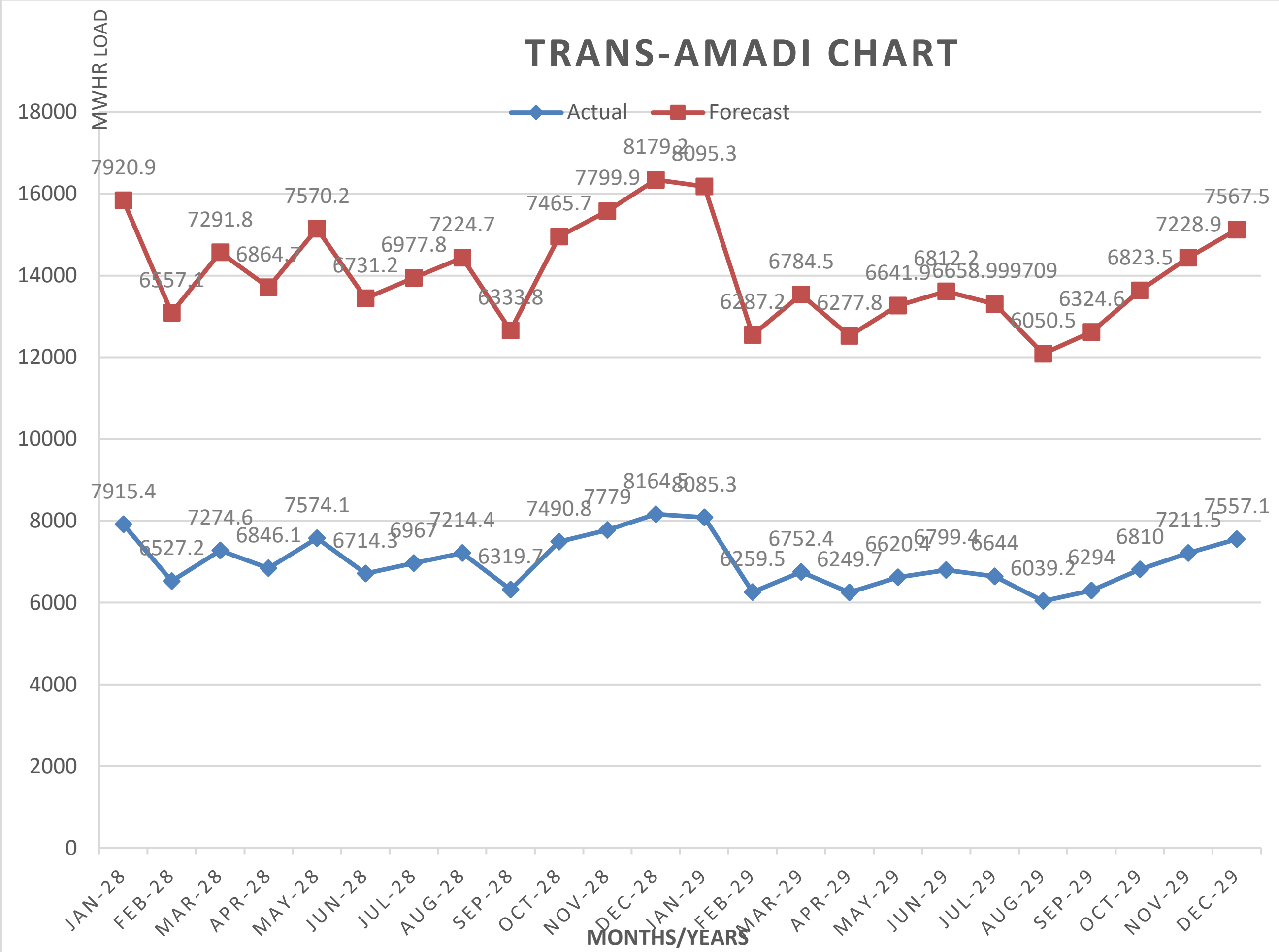

Fig.5e Trans-Amadi Industrial Feeder graph of Actual VS Forecast Load after testing phase of years 2028 and 2029.

Table 3. shows values of percentage error of the forecasted load for Trans-Amadi Feeder network

Trans-Amadi Feeder Percentage Error Values		
Year	MSE%	√MSE%
2020	0.01	0.11
2021	3.45	1.85
2022	0.01	0.13
2023	0.02	0.14
2024	0.01	0.07
2025	0.01	0.08
2026	0.07	0.27
2027	0.01	0.10
2028	0.001	0.04
2029	0.006	0.08

The performance of Artificial Neural Network trained data was examined by Mean Square Error and Root Mean Square Error, the outcomes are shown in the Table above for Trans-Amadi industrial Feeder in which high degree of accuracy has been recorded and ANN strength for electrical load forecast has been highly proved.

4. CONCLUSIONS

A neural network approach for long-term electrical load forecast has been presented in this paper for Trans-Amadi industrial feeder under PHEDC metropolis network, the results of the forecasted load of ten (10) years has been presented in table 2. From ANN trained six (6) inputs data, the result shows that ANN simulation tool is highly reliable for load forecast couple with percentage

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error result which also proves minimum error of the process asforecasted electrical load results were generated for Trans-Amadi industrial feeder for ten (10) years starting from year 2020-2029. However, from year one(1) to year ten (10) the ANN training architecture maintained eleven (11) iterations with fifteen (15) neurons data set to achieved its forecasted results for the electrical forecasted load to be achieved as shown in ANN of figure 5.

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This study has not received any external funding.

Conflict of Interest

The author declares that there are no conflicts of interests.

Data and materials availability

All data associated with this study are present in the paper.

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