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Short Term Prediction of Electric Load Demand of University of Benin Using Artificial Neural Network

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Abstract

Electricity load demand prediction is an integral part of Power System Management. The importance cannot be over-emphasized in Electricity Generation, Transmission, Distribution and Marketing. Accurate electric power load forecasting is essential to the operation, expansion and planning of a utility company. In this work short term load demand prediction of University of Benin, Ugbowo Campus, was carried out for a period of one week using 30 days data between 1st to 30th September, 2019. The forecasting technique used in actualizing this task is the artificial neural network (ANN) which was modeled using the MATLAB R2013a toolbox. The actual load demand predicted value are presented in graphical form. It was observed that the ANN architecture 5-35-1 gave the optimal performance of 0.0021% Average Mean Absolute Percentage Error (MAPE). Considering the effect of time delay vector, the time delay vector of [01] also gave the optimal performance of 0.0021% MAPE with a time delay of 123 seconds and two length of vectors which validates the correctness of the simulation using MAPE. Consideration of the ratio parameter indicator in the model prediction, it was observed that the ratio parameter of 0.01 also gave an optimal performance with 0.0021% MAPE. Model adequacy is achieved since the same optimal result was achieved in all the various constraints applied.

1. Introduction

Electric load demand prediction or forecast is an important part of energy management system which involves load estimation for a given period in the future and for a given population [1]. Load forecasting helps Electricity suppliers to make useful decisions including decisions on purchasing and generating electric power, load switching and infrastructure development. Load forecasting has been in existence for decades to forecast the future load demand. Electricity demand forecasting is considered as one of the critical factors for economic operation of power systems. The daily operation and planning activities of an electric utility requires the prediction of electricity demand of its customers [2].

Accurate load forecasting holds a great saving potential for electric utility companies. The maximum savings can be achieved when load forecasting is used to control operations and decisions like economic dispatch, unit commitment and fuel allocation [3]. An accurate load forecast can be very helpful in developing a power supply strategy, finance planning, market research and electricity management. The forecasts for different time horizons are important for different operations within a utility company and the natures of these forecasts are different as well. For example, for a particular region, it is possible to predict the next day load with an accuracy of approximately 1-3% [4]. However, it is impossible to predict the next year peak load with the similar accuracy since accurate long-term weather forecasts are not available. For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations. It is also possible, according to the industry practice, to predict the so-called weather normalized load, which would take place for average annual peak weather conditions or worse than average peak weather conditions for a given area [4].

The time period in which the forecast is carried out is fundamental to the results and use of the forecast. Short-term forecast, which spans a period of one hour to one week, helps to provide a great saving potential for economic and secured operation of power system, medium-term forecast, which ranges from a week to a year, concerns with scheduling of fuel supply and maintenance operation and long-term forecast which span from one year upward is useful for planning operations [5].

[6] stated that various techniques have been implemented by researchers to solve the load forecasting problems, but regression and time series techniques are widely used, this was corroborated by [7] who performed a long term peak load forecasting for the city of Kutahya with the least squares regression based methods and artificial neural networks (ANN) using the load, temperature and population growth data. [8] informed that as compared to traditional statistical algorithms, the neural network approach has a number of unique characteristics, including nonlinear approximation of complex dependencies, flexibility and universality, which allows one to apply ANNs to more complex models.

[9] stated that the main reason while artificial neural networks (ANN) is so popular lies in its ability to learn complex and nonlinear relationships that are difficult to model with conventional techniques but further stressed that there exist large forecasting errors using ANN when there are rapid fluctuations in load and temperatures. [10] presented a study of load demand based on quantitative forecasting model using a time Series Stochastic method for long term.

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts. Various weather variables could be considered for the load forecasting. Temperature and humidity are the most commonly used load predictors. An electric load prediction survey published by [11] indicated that of the twenty-two (22) research report considered, thirteen (13) made use of temperature only, three (3) made use of temperature and humidity, three (3) utilized additional weather parameters and three (3) used only load parameters. In this work, only load parameters are used for the electric load prediction and the technique used is artificial neural networks.

This work employed experimental approach to determine network architecture and parameter setting that would give better prediction results. In each case of choice of network architecture, the network performance was evaluated using mean absolute percentage error (MAPE). For the measurement of the forecast accuracy, the Mean Absolute Percentage Error (MAPE), Mean absolute deviation (MAD) and Mean Squared Error (MSE). The research focuses on the short term load demand forecast for a period of one week using 30 days data between 1st to 30th September 2019 of

University of Benin, Ugbowo Campus. The forecasting technique used is the artificial neural network model, shown in Figure 1.

2. Methodology

The following were procedures used in carrying out the research work;

Real time hourly recording of load demand data for 24 hours each day for 30 days between 1st to 30th September 2019 at the University of Benin Substation A, Ugbowo campus as shown in Table 1. This work employed experimental approach to determine ANN Network architecture and parameter setting that would give better prediction results as shown in Table 2. The data collected was entered into Microsoft Spreadsheet and then copied into the MATLAB R2013 software for simulation. The first step in the simulation process is the training of ANN using ANN training tools shown in Figure 2. The input data was divided into two sets; the ANN was trained using the first twenty-thee (23) days load data while the remaining seven (7) days data was used to test the network which is the main prediction period.

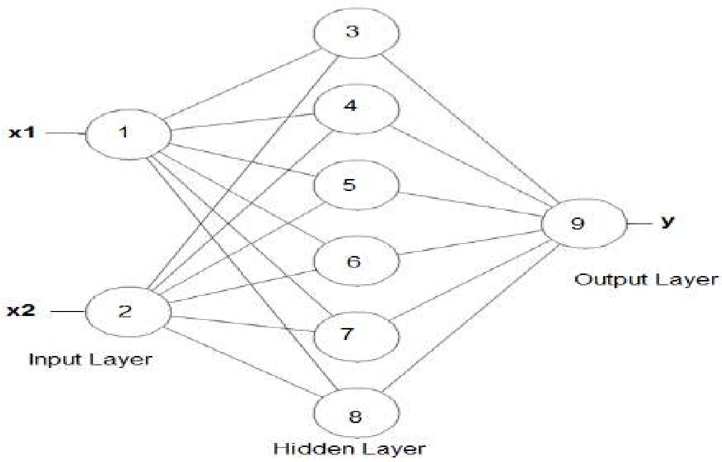

Figure1: A Three Layer Neural Network

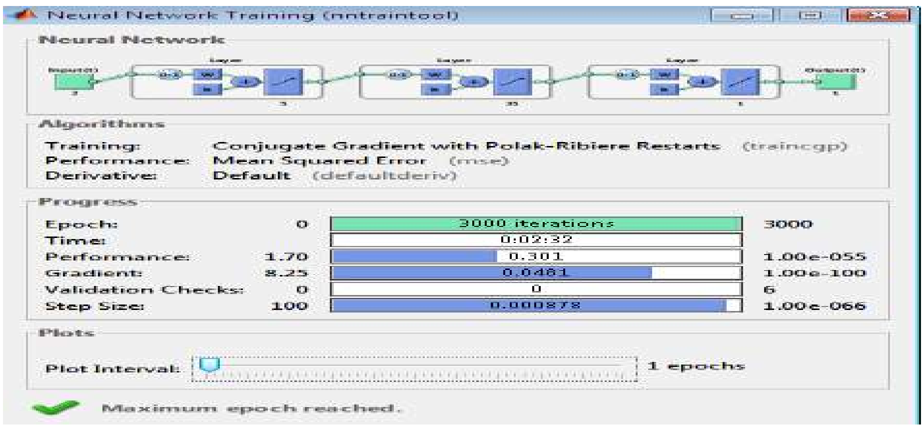

Figure 2: Screenshot of Artificial neural network training tool used for the predictions

2.1 Model Formulation

Mean Absolute Percentage Error (MAPE)

In each choice of network layer architecture, the network performance was evaluated using MAPE. It measures the amount of the error in terms of percentage and calculated as the average of the absolute error. It is calculated using Equation 1.

$$MAPE = \frac{\sum \left| \text{Actual}_t \text{ - forecast}_t \right| / \text{Actual}_t}{n} \times 100\% \quad (1)$$

Mean absolute deviation (MAD) is the measure of the overall forecast error. MAD represents the average difference between our forecast and actual load data. It can be calculated using Equation 2.

$$MAD = \frac{\sum \left| \text{Actual}_t \text{ - forecast}_t \right|}{n} \quad (2)$$

Mean Squared Error (MSE) is an average of the squares of the difference between the actual values of data and the predicted. It can be computed using Equation 3

$$\text{MSE} = \frac{\sum (\text{Actual}_t - \text{forecast}_t)^2}{\text{n-1}} \quad (3)$$

3. Results and Discussion

3.1 MAPE obtained using different network architecture and their performance.

The Mean Absolute Performance Error values obtained are shown in Table 2 which is a reflection of the load demand values as input and varying with the network layer architecture as required constraints for the test simulation of the artificial neural network.

3.2 MAPE obtained for different time delay vector.

In achieving this, the different time delay was used to obtain the MAPE. However, the time delay value corresponding to the lowest Mean Absolute Percentage Error was used for the analysis which is shown in Table 3.

3.3 MAPE Value using Performance Ratio Parameters.

Performance ratio parameter is one of the constraints used in finding the Mean Absolute Performance Error in the simulation process and the results are presented in Table 4.

Table 2: MAPE Network Architecture and their Performance.

Layer Architecture	MAPE (%) on the Test Result							
	1	2	3	4	5	6	7	Average MAPE (%)
3-2-1	0.0024	0.0021	0.0024	0.0021	0.0021	0.0020	0.0020	0.0022
5-7-1	0.08	0.0805	0.0799	0.0417	0.081	0.081	0.081	0.075
5-11-1	0.2413	0.2405	0.2414	0.121	0.2405	0.2405	0.2405	0.2237

5-17-1	0.0431	0.0437	0.043	0.0234	0.0437	0.0437	0.0437	0.0406
5-35-1	**0.0022**	**0.002**	**0.0022**	**0.002**	**0.002**	**0.002**	**0.002**	**0.0021**
15-35-1	0.3822	0.3815	0.3895	0.1904	0.3765	0.3765	0.3764	0.3533
22-38-1	0.0236	0.0227	0.0193	0.0168	0.0392	0.04	0.0385	0.0286
27-45-1	0.6495	0.65	0.6499	0.3258	0.633	0.6338	0.633	0.5964
35-50-1	0.0573	0.0572	0.0575	0.0289	0.0551	0.0552	0.0551	0.0523
30-48-1	0.3669	0.3652	0.3662	0.1841	0.3732	0.373	0.3732	0.3431
28-38-1	0.1793	0.1797	0.1744	0.0949	0.2288	0.2272	0.2292	0.1876
35-45-1	0.0914	0.1136	0.1379	0.0322	0.4072	0.4018	0.4021	0.2266
22-42-1	0.0365	0.0358	0.0366	0.0196	0.035	0.035	0.349	0.0333
40-60-1	0.0029	0.0021	0.0028	0.0077	0.06	0.059	0.0639	0.0283

Table 3: Effect of Time Delay Vector

S/N	Time delay vector	Length of Vector	Time Elapsed (Sec)	Model Performance MAPE (%)							Average MAPE(%)
				1	2	3	4	5	6	7	
1	1	1	57.84	0.0586	0.0592	0.0586	0.0592	0.0592	0.0592	0.0592	0.059
2	0	1	178.30	0.0023	0.0026	0.0023	0.0027	0.0027	0.0026	0.0026	0.0025
3	**[0 1]**	**2**	**123.48**	**0.0022**	**0.002**	**0.0022**	**0.002**	**0.002**	**0.002**	**0.002**	**0.0021**
4	[0:1]	5	54.65	0.0532	0.0538	0.0532	0.0396	0.0538	0.0538	0.0538	0.0516
5	[0:10]	11	33.23	0.0448	0.0454	0.0448	0.0632	0.0449	0.0449	0.0449	0.0476

Table 4: Difference in Performance Ratio Parameters

γ	Daily MAPE(%) values							Average MAPE (%)
	1	**2**	**3**	**4**	**5**	**6**	**7**	
0.5	0.0335	0.0348	0.0338	0.0206	0.0313	0.0314	0.0313	0.0309
0.2	0.0032	0.0038	0.0032	0.0039	0.0039	0.0039	0.0039	0.0037
0.1	0.0022	0.0025	0.0024	0.0026	0.002	0.0031	0.0027	0.0023
0.09	0.0999	0.0982	0.098	0.0511	0.0113	0.0112	0.0113	0.0979
0.6	0.0318	0.0337	0.0303	0.0186	0.0356	0.0357	0.0325	0.0312
0.01	**0.0022**	**0.002**	**0.0022**	**0.002**	**0.002**	**0.002**	**0.002**	**0.0021**
0.9	0.0175	0.0181	0.0175	0.0104	0.0181	0.0181	0.018	0.0168
0.001	0.0026	0.0021	0.0027	0.0109	0.0021	0.0021	0.0021	0.0035
0.05	0.0279	0.0266	0.0279	0.0143	0.0272	0.0272	0.0272	0.0255

Figure 3 to Figure 9 shows the load curves of the actual and predicted output results of the daily load demand of University of Benin, Ugbowo campus for the month of September 2019 between 24th September to 30th September 2019 using the Artificial Neural Network MATLAB simulation model which are represented in graphical diagrams.

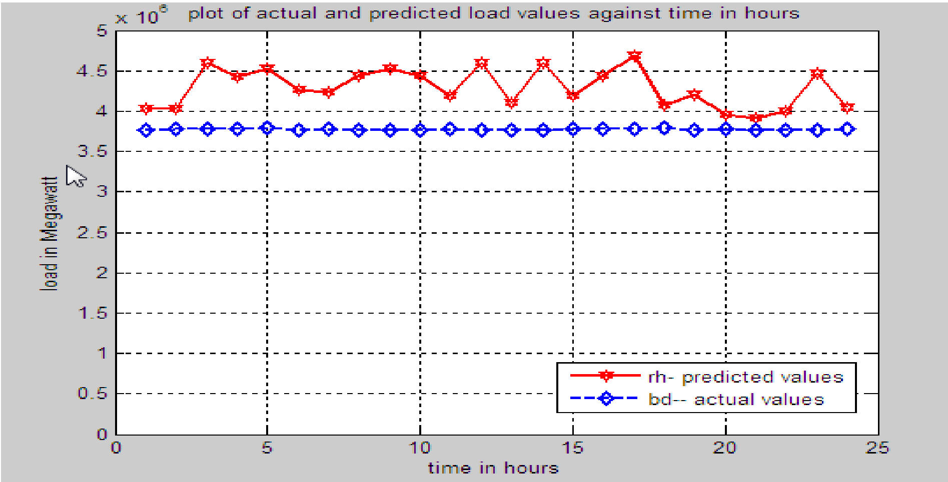

Figure 3: Shows the graphical representation of the result of actual load demand and prediction value (MW) against time (hours) for 24th September, 2019

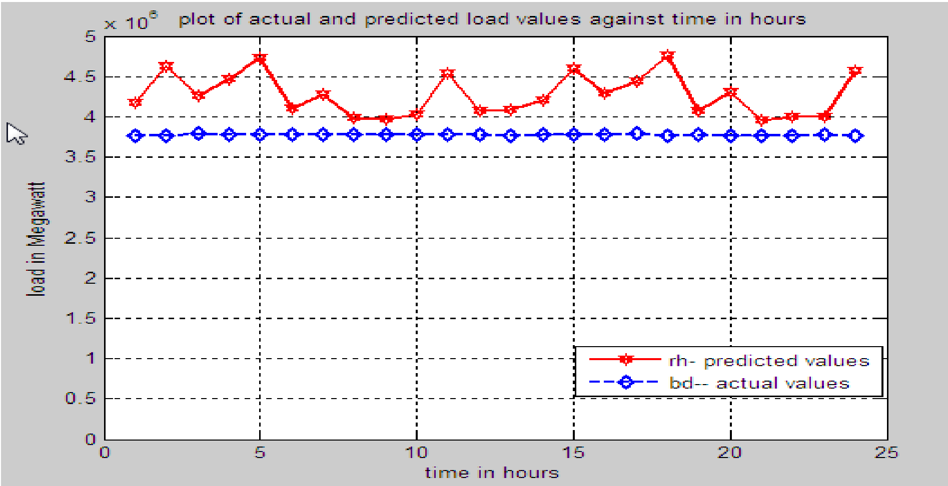

Figure 4: Shows the graphical representation of the result of actual load demand and prediction value (MW) against time (hours) for 25th September, 2019

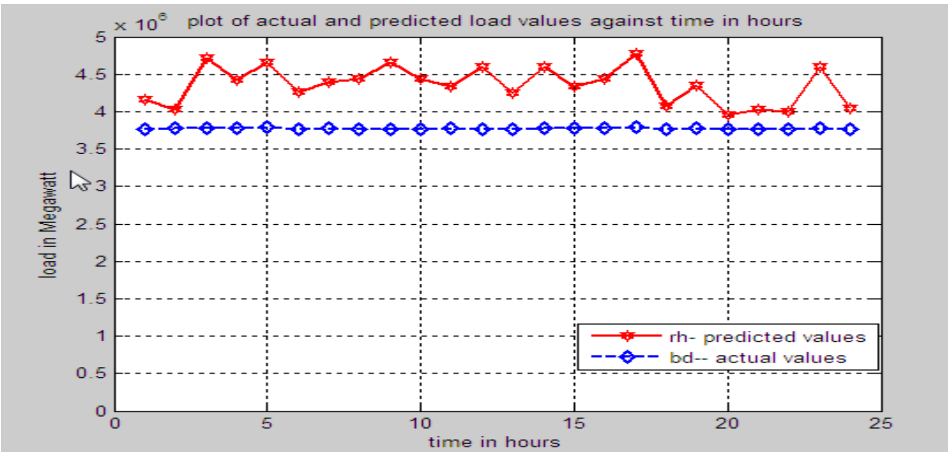

Figure 5: Shows the graphical representation of the result of actual load demand and prediction value (MW) against time (hours) for 26th September, 2019

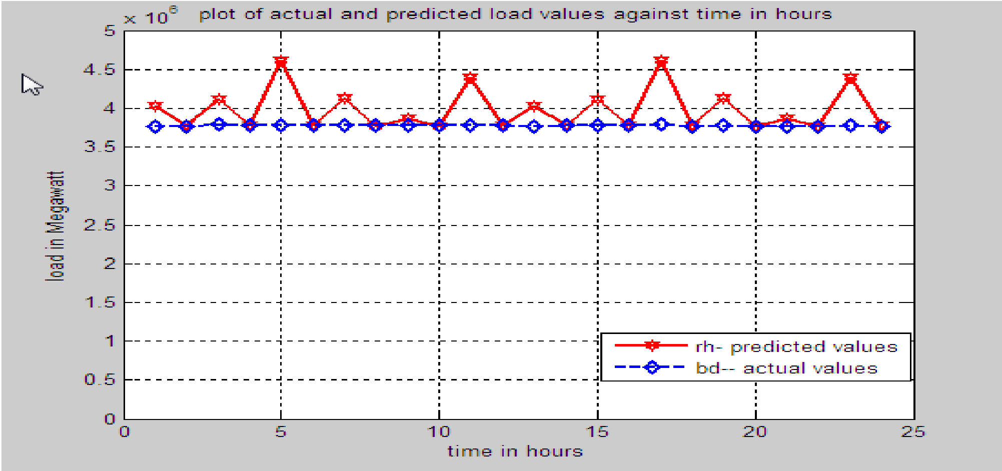

Figure 6: Shows the graphical representation of the result of actual load demand and prediction value (MW) against time (hours) for 27th September, 2019

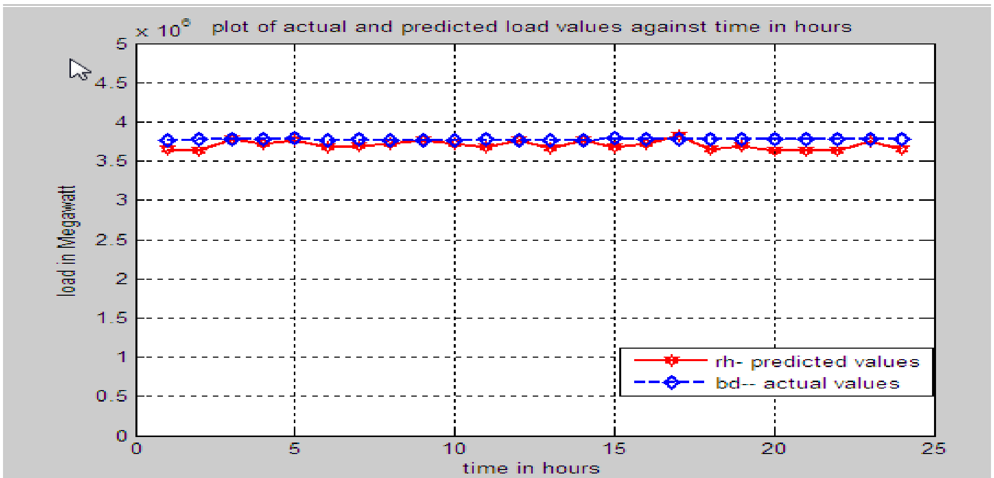

Figure 7: Shows the graphical representation of the result of actual load demand and prediction value (MW) against time (hours) for 28th September, 2019

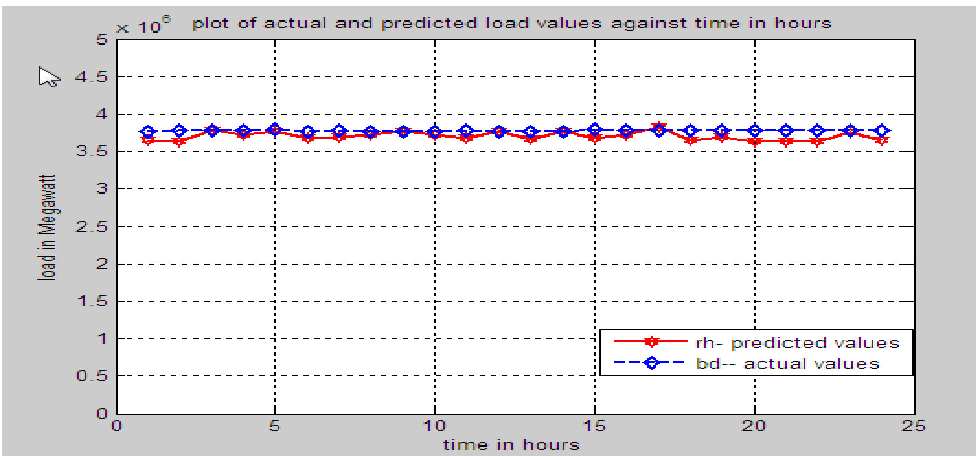

Figure 8: Shows the graphical representation of the result of actual load demand and prediction value (MW) against time (hours) for 29h September, 2019

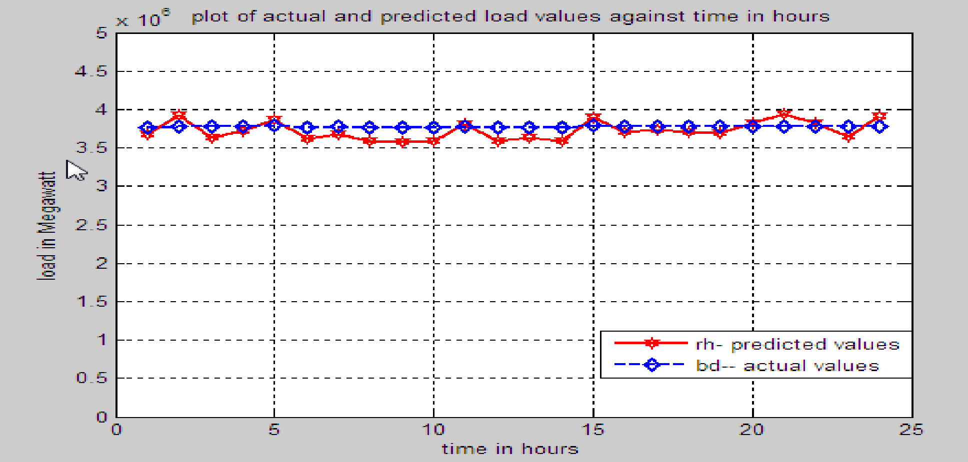

Figure 9**:** Shows the graphical representation of the result of actual load demand and prediction value (MW) against time (hours) for 30th September, 2019

The result analyses of this research using the artificial neural network (ANN) models are presented in the tables above. In Table 2, it is observed that the layer architecture **5-35-1** gave the optimal performance of **0.0021%** MAPE in terms of the forecast error. This architecture is defined as three layer network architecture with the input layer as 5 neurons, the hidden layer as 35 neuron and the output layer as 1 neuron. It is important to point out that increasing or decreasing the numbers of neurons in a layer by one or more neurons does not affect the performance of the models. However, in some cases, some layer architecture of different neurons can give same result. From Table 3, considering the effect of time delay vector, the time delay vector of **[0 1]** also gave the optimal performance of **0.0021%** MAPE with a time delay of **123.48 seconds** and two length of vectors which validates the correctness of the simulation using Mean Absolute Percentage Error (MAPE). Following the consideration of the ratio parameter indicator in the model prediction as depicted in Table 4 above, it was observed that the ratio parameter of 0.01 also gave an optimal performance with **0.0021%** MAPE. Model adequacy is achieved since the same optimal result was achieved in all the various constraints applied.

4. Conclusion

This research work investigated power load demand and the prediction of future load demand using 30 days data of 33/11kV sub-station A, University of Benin, Ugbowo Campus, Benin City. The forecasting technique used in actualizing this task is the artificial neural network which gave optimal results. The forecasting technique used in actualizing this task is the artificial neural network which was modeled using the MATLAB R2013a toolbox. The research findings gave an optimal value of 0.0021% Average Mean Absolute Percentage Error (MAPE) using the Network Architecture layer, time delay vector and performance ratio as various constraints for the evaluation confirming model adequacy.

Nomenclature/symbols

ANN	Artificial Neural Network
MAPE	Mean Absolute Percentage Error
MAD	Mean Absolute Deviation
MSE	Mean Squared Error
γ	Performance Ratio
MW	Megawatts

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Appendix

Table 1: UNIBEN Load Demand for 1st – 30th September 2019

Daily Load Demand (Megawatts) for September 2019												
Date	1.00hr	2.00hr	3.00hr	4.00hr	5.00hr	6.00hr	7.00hr	8.00hr	9.00hr	10.00hr	11.00hr	12.00hr
1/9/2019	3.363	3.332	3.332	3.363	3.332	3.331	3.451	3.451	3.451	3.452	3.435	3.454
2/9/2019	3.454	3.456	3.454	3.452	3.456	3.456	3.456	3.456	3.456	3.456	3.456	3.456
3/9/2019	3.332	3.332	3.332	3.332	3.332	3.331	3.333	3.332	3.333	3.334	3.335	3.336
4/9/2019	3.332	3.333	3.334	3.335	3.334	3.335	3.334	3.335	3.334	3.334	3.335	3.336
5/9/2019	3.334	3.334	3.335	3.335	3.334	3.335	3.335	3.334	3.335	3.334	3.335	3.335
6/9/2019	3.363	3.332	3.332	3.363	3.332	3.331	3.451	3.451	3.451	3.452	3.435	3.454
7/9/2019	3.363	3.332	3.332	3.363	3.332	3.331	3.457	3.451	3.451	3.452	3.441	3.454
8/9/2019	3.456	3.459	3.457	3.459	3.456	3.456	3.450	3.452	3.451	3.452	3.434	3.454

9/9/2019	3.363	3.332	3.332	3.363	3.336	3.331	3.451	3.451	3.452	3.451	3.447	3.454
10/9/2019	3.425	3.332	3.334	3.363	3.335	3.332	3.452	3.452	3.452	3.452	3.434	3.454
11/9/2019	3.394	3.333	3.332	3.364	3.335	3.331	3.451	3.451	3.451	3.451	3.433	3.454
12/9/2019	3.363	3.333	3.332	3.363	3.334	3.334	3.451	3.452	3.452	3.454	3.447	3.454
13/9/2019	3.375	3.334	3.332	3.363	3.334	3.333	3.452	3.451	3.452	3.452	3.436	3.454
14/9/2019	3.425	3.335	3.332	3.363	3.333	3.332	3.451	3.452	3.452	3.459	3.435	3.454
15/9/2019	3.363	3.335	3.332	3.365	3.332	3.332	3.451	3.451	3.452	3.453	3.434	3.454
16/9/2019	3.332	3.332	3.332	3.369	3.332	3.331	3.451	3.451	3.451	3.452	3.435	3.454
17/9/2019	3.711	3.705	3.711	3.705	3.711	3.705	3.711	3.705	3.711	3.705	3.711	3.705
18/9/2019	3.705	3.703	3.705	3.703	3.705	3.703	3.705	3.703	3.705	3.703	3.705	3.703
19/9/2019	3.699	3.705	3.699	3.705	3.699	3.705	3.699	3.705	3.699	3.705	3.699	3.705
20/9/2019	3.718	3.332	3.718	3.332	3.718	3.332	3.718	3.332	3.718	3.332	3.718	3.332
21/9/2019	3.767	3.765	3.789	3.779	3.786	3.774	3.776	3.780	3.786	3.780	3.774	3.786
22/9/2019	3.771	3.786	3.744	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
23/9/2019	3.767	3.765	3.789	3.779	3.786	3.774	3.776	3.780	3.786	3.780	3.774	3.786
24/9/2019	3.771	3.786	3.774	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
25/9/2019	3.767	3.765	3.789	3.779	3.786	3.774	3.776	3.780	3.786	3.780	3.774	3.786
26/9/2019	3.771	3.786	3.744	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
27/9/2019	3.767	3.785	3.789	3.779	3.786	3.774	3.776	3.780	3.786	3.780	3.774	3.786
28/9/2019	3.771	3.786	3.744	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
29/9/2019	3.771	3.786	3.744	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
30/9/2019	3.771	3.786	3.744	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766

Table 1 Cont'd: UNIBEN Load Demand for 1st – 30th September 2019

Daily Load Demand (Megawatts) for September 2019												
Date	13.00hr	14.00hr	15.00hr	16.00hr	17.00hr	18.00hr	19.00hr	20.00hr	21.00hr	22.00hr	23.00hr	24.00hr
1/9/2019	3.456	3.454	3.452	3.456	3.456	3.456	3.456	3.456	3.456	3.456	3.456	3.456
2/9/2019	3.363	3.332	3.332	3.363	3.332	3.331	3.451	3.451	3.451	3.452	3.435	3.454
3/9/2019	3.332	3.335	3.334	3.331	3.332	3.332	3.332	3.333	3.332	3.333	3.335	3.332
4/9/2019	3.332	3.335	3.335	3.331	3.332	3.335	3.332	3.334	3.332	3.334	3.335	3.334
5/9/2019	3.335	3.334	3.335	3.331	3.332	3.335	3.332	3.334	3.332	3.334	3.335	3.334
6/9/2019	3.456	3.452	3.452	3.456	3.456	3.456	3.456	3.456	3.458	3.456	3.456	3.456
7/9/2019	3.457	3.452	3.452	3.456	3.457	3.457	3.456	3.457	3.457	3.457	3.456	3.456
8/9/2019	3.458	3.453	3.452	3.456	3.456	3.457	3.458	3.459	3.456	3.459	3.456	3.456
9/9/2019	3.457	3.454	3.451	3.457	3.458	3.459	3.456	3.456	3.457	3.456	3.456	3.456
10/9/2019	3.456	3.452	3.452	3.456	3.459	3.458	3.457	3.457	3.458	3.457	3.459	3.456
11/9/2019	3.458	3.454	3.454	3.458	3.456	3.456	3.456	3.456	3.456	3.456	3.456	3.456
12/9/2019	3.457	3.451	3.452	3.456	3.457	3.458	3.457	3.458	3.457	3.458	3.456	3.456
13/9/2019	3.456	3.454	3.452	3.457	3.456	3.456	3.456	3.456	3.456	3.456	3.456	3.456
14/9/2019	3.456	3.452	3.452	3.456	3.459	3.459	3.458	3.457	3.457	3.457	3.456	3.456
15/9/2019	3.456	3.454	3.454	3.458	3.456	3.456	3.456	3.456	3.456	3.456	3.456	3.456
16/9/2019	3.457	3.457	3.452	3.456	3.459	3.459	3.459	3.457	3.458	3.457	3.456	3.456
17/9/2019	3.711	3.705	3.711	3.705	3.711	3.705	3.711	3.705	3.711	3.705	3.711	3.705
18/9/2019	3.705	3.703	3.705	3.703	3.705	3.703	3.705	3.703	3.705	3.703	3.705	3.703
19/9/2019	3.699	3.705	3.699	3.705	3.699	3.705	3.699	3.705	3.699	3.705	3.699	3.705
20/9/2019	3.718	3.332	3.718	3.332	3.718	3.332	3.718	3.332	3.718	3.332	3.718	3.332
21/9/2019	3.771	3.786	3.774	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
22/9/2019	3.767	3.771	3.786	3.774	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784
23/9/2019	3.771	3.786	3.774	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
24/9/2019	3.767	3.771	3.786	3.774	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784
25/9/2019	3.771	3.786	3.774	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
26/9/2019	3.771	3.786	3.774	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
27/9/2019	3.771	3.786	3.774	3.780	3.792	3.767	3.774	3.762	3.762	3.764	3.784	3.766
28/9/2019	3.767	3.765	3.789	3.779	3.786	3.774	3.776	3.780	3.786	3.780	3.774	3.786
29/9/2019	3.767	3.765	3.789	3.779	3.786	3.774	3.776	3.780	3.786	3.780	3.774	3.786
30/9/2019	3.767	3.765	3.789	3.779	3.786	3.774	3.776	3.780	3.786	3.780	3.774	3.786