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Comparative Study of Load Demand Forecast Using Non-Linear Regression and Neural Network Techniques: A case Study

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Abstract

Demand load forecasting is the estimation of electrical load that will be required by a certain geographical area with the use of previous electrical load data in the said geographical area. This has become necessary due to the increasing number of prospective power users around the world to address for likely shortage of electricity and to further plan for resources budgeting and power real time availability. However, this research work carried out a short term comparative study of electric load demand forecast of the University of Benin, Ugbowo campus between 1st to 30th September, 2019. The forecasting approaches used in realizing this task are the non-linear regression and artificial neural network (ANN) approaches which was analyzed using MATLAB 2015 software. The current load demand was presented and modeled using the two approaches, the ANN gave an optimal result of 0.0021% mean absolute percentage error (MAPE) for all the days and all the constraint parameters used for the training of the model. Following the validation of the ANN model with the non- linear regression (NLR) model, it was observed that the artificial neural network gave the best optimal result of 0.0021% MAPE for all constraints applied while the non-linear regression model gave an optimal result of 0.0448% MAPE. Therefore, the artificial neural network (ANN) model is considered to produce a more accurate result than the non-linear regression model as confirmed by the result of validation clearly confirming model suitability for the analysis.

1. Introduction

Forecasting is an important aspect of making decision that will affect the future. Power load forecasting is the estimation of electrical load that will be required by some certain distribution network users by making use of the previous electrical load usage within the distribution networks.

There is a growing tendency towards unbundling the electricity system. This is continually confronting the different sectors of the industry (generation, transmission, and distribution) with increasing demand on planning management and operations of the network. The operation and planning of a power utility company requires an adequate model for electric power load forecasting [1]. With the increasing penetration of large-scale intermittent energy such as wind and solar as well as energy storage station, it has given rise to new characteristics of peak load and a more challenging task for demand forecast. In such a context, it is evident that accurate load demand forecast becomes a necessary element to the power grid operations and its planning [2]. [3] established that electrical load forecasting has a lot of applications which includes energy purchasing and generation, load switching, contract evaluation and infrastructure development.

Basically, there are three terms of forecasting which includes; short term load forecast (STLF) is normally carried out for a duration of one hour to one week. When the duration is more than one week to one year, then the forecasting is called medium term load forecasting (MTLF). MTLF is mostly used to estimate fuel prices. While long term load forecasting (LTLF) is the forecasting that spans more than one year [4]. Short-term load forecasting is crucial for the operations and planning of an electrical grid which means that forecasting the next day electrical load in a grid allows operators to plan and optimize their resources [5]. The time period in which the forecast is carried out is fundamental to the results and use of the prediction. Short-term forecast which spans from 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 [6].

Various techniques have been developed for electricity demand forecasting during the past few years. Statistical models are widely adopted for the load forecasting problem, which include linear regression models, stochastic process models, exponential smoothing and ARIMA models. To incorporate the non-linearity of electricity demand series, artificial neural networks (ANNs) have also received substantial attentions in load forecasting with good performance [7]. Regression models have been deployed in load forecasting which make the relationships between input and output variables easy to comprehend [8], but artificial neural networks have been widely used in load demand forecasting which have gained considerable attention due to its evident design, straightforward execution, and good performance [9].

The electric power load forecast is highly related to the economy's development, and it is also related to national security and the daily operation of the larger society. Therefore, the accuracy of electric load forecasting has great importance for energy generating capacity, scheduling and power system management, as these accurate forecasts lead to substantial savings in operating and maintenance costs [10]. [11] reported that the development of an exact, fast and robust electrical load demand forecasting approach is of importance to both the electric utility and its customers stressing that a forecast that is too low or high can result in revenue loss. However, an expensive or over estimation of load demand will result in substantial investment for the construction of excess power facilities, while under estimation will result in customer dissatisfaction. Unfortunately, it is difficult to forecast load demand accurately over a planning period of several years. This fact is due to the uncertain nature of the forecasting process [12].

The proposed research employed methodologies (Non-Linear Regression and Neural Networks) which has been introduced for experimental approach comparison in determining the network architecture and parameter setting that would give an enhanced prediction results by evaluating the mean absolute percentage error (MAPE). This research focuses on the short term load demand forecast for a period of one week using 30 days real-time data between 1st to 30th September 2019 of University of Benin, Ugbowo Campus. The forecasting techniques used in this study are the artificial neural network and the non-linear regression techniques.

2. Methodology

The real time data was collected on an hourly basis from the University of Benin, Ugbowo Campus substation. The load demand data was collected hourly for 24 hours daily from the 11kV digital output diplay of the 11kV panel and recorded on a log book this was done within a duration of one month from 1st to 30th September, 2019. The collected data was further processed and arranged into days using Microsoft Excel worksheet.

The forecast models of ANN and Non-linear Regression was built in MATLAB 2015 software to carry out the short term load forecasting, these models incorporates various data like time, temperature, load, climate and performance indices e.t.c. In load demand forecast of electrical load, it is imperative to select the model that best suits the data available for forecasting. This work employed experimental approach to determine if ANN Network architecture and the non-linear regression using performance indices as parameter setting in evaluating which model will give better prediction results as shown. The first step in the simulation process is the training of ANN using ANN training tools. 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. The first step in the simulation process is the training of ANN using ANN training tools shown in Figure 1. This process was repeated using the Non-linear Regression model which was modeled to validate the results of the ANN.

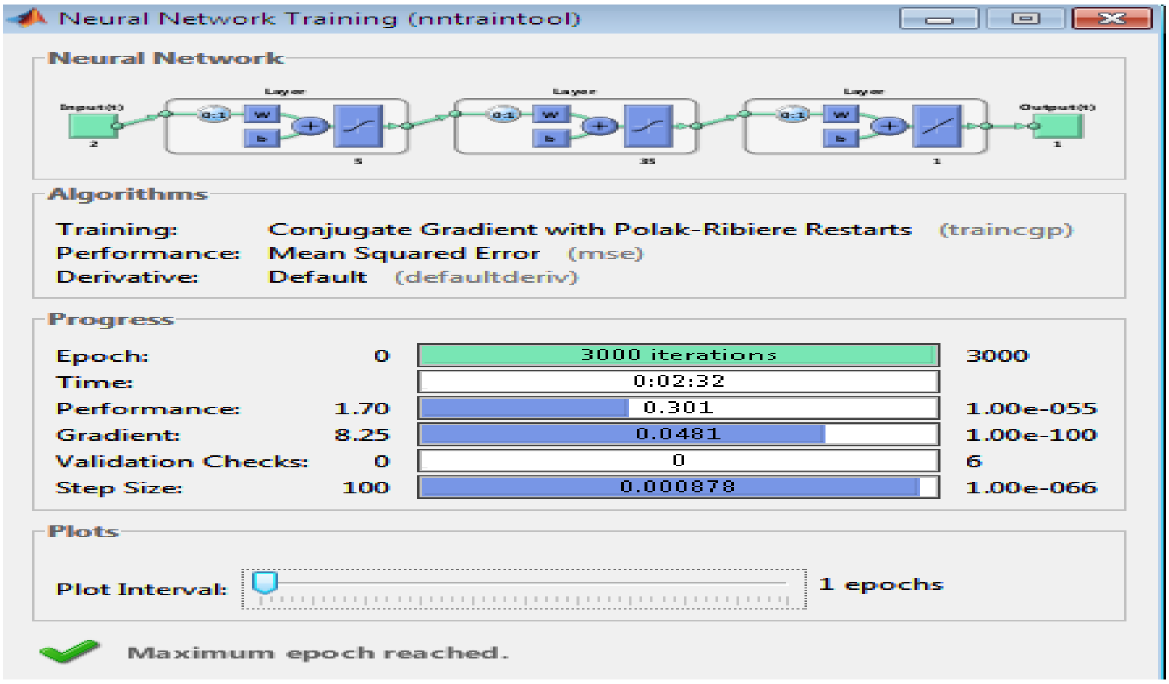

Figure 1: Screenshot of Artificial neural network training tool used for the predictions

2.1 Model Formulation

2.1.1 Mean Absolute Percentage Error (MAPE)

The mean absolute percentage errors are widely used performance evaluation indices in forecasting that are deployed as one of the model performance evaluation indices to determine the difference between the actual and expected results of the prediction. It is used to determine how successful the model is and also used to determine the performance of the model. The MAPE error is the most commonly used constraint by researchers in load demand forecast approach. 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.

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

2.1.2 Mean absolute deviation (MAD)

This 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.

$$MAD = \frac{\sum \left| \mathrm{Actual}_t \text{ - } \mathrm{forecast}_t \right|}{n} \tag{2}$$

The linear and non-linear regression model applied in this work is seen in Equation 3 to 7

$$Y \quad = a + bX \tag{3}$$

Where,
Y is the value of the load demand in Megawatts
X is the number of days.
The values a and b are derived by solving Equations (4) and (5) simultaneously.

$$\sum Y \quad = na + b \sum X \tag{4}$$

$$\sum XY \quad = a \sum X + b \sum X^2 \tag{5}$$

$$B \quad = \frac{n \sum xy - \sum x \sum y}{n \sum x^2 - (\sum \mathrm{x})2} \tag{6}$$

$$A \quad = \bar{Y} - B\bar{X} \tag{7}$$

Upon transformation,
Thus, $y = ab^x$ (8)

3. Results and Discussion

Table 1: Difference in Performance ratio Parameters for the various days

γ	Daily MAPE(%) values							Average MAPE (%)
	24/9/2019	25/9/2019	26/9/2019	27/9/2019	28/9/2019	29/9/2019	30/9/2019	
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

Table 2: 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 3: Non-Linear Regression Table

x(days)	y(load MW)	Y = logy	X.Y	X^2	Y^2
1	3.7734	6.5767	6.5767	1	43.52291
2	3.7759	6.5770	13.154	4	43.52278
3	3.7733	6.5767	19.7302	9	43.36565
4	3.7759	6.5770	26.3081	16	43.36736
5	3.7759	6.5770	32.8851	25	43.36788
6	3.7759	6.5770	39.4621	36	43.52291
7	3.7759	6.5770	46.0391	49	43.52410
		46.0384	184.1553	140	304.19359

Table 4: Forecasted Load Values Using Non-Linear Regression Model

(days)	Actual load (MW)	Forecasted load (MW)	Error	MAPE (%)
24/9/2019	3.7734	3.7871	0.00781	0.0519
25/9/2019	**3.7759**	**3.7877**	**0.01184**	**0.0448**
26/9/2019	3.7733	3.7883	0.01506	0.0570

27/9/2019	3.7759	3.7889	0.01308	0.0495
28/9/2019	3.7759	3.7896	0.01370	0.0518
29/9/2019	3.7759	3.7902	0.01432	0.0542
30/9/2019	3.7759	3.7908	0.01494	0.0565

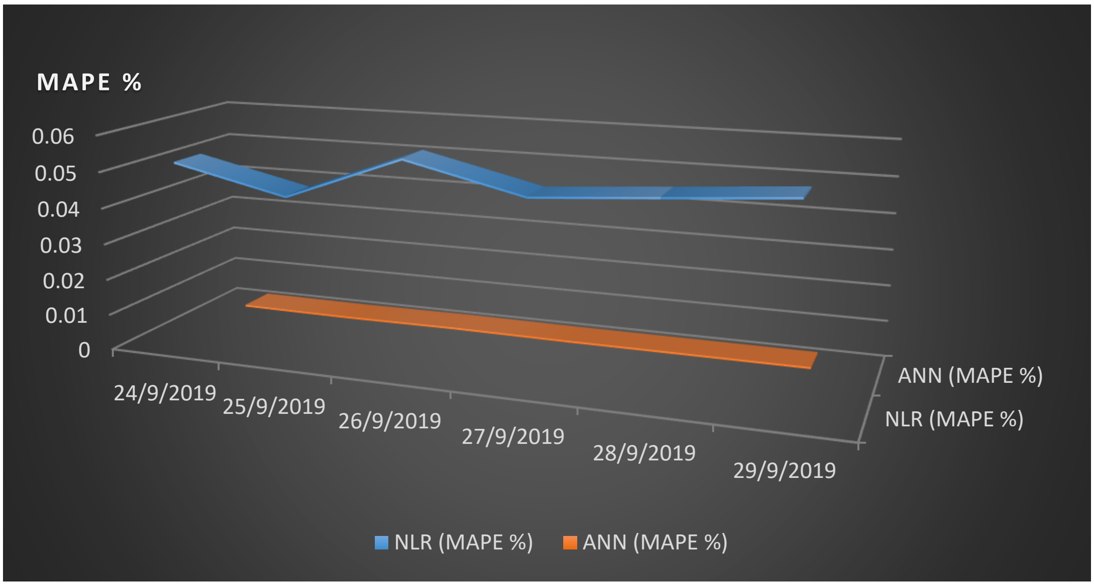

Figure 2: MAPE (%) Chart between ANN and NLR model.

The result of the comparative study using the artificial neural network (ANN) and the non-linear regression models are presented in the tables above. It is observed that the layer architecture gave the optimal performance of **0.0021%** MAPE in terms of the forecast error. However, in some cases, some layer architecture of different neurons can give same result. From Table 2, 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 1 above, it was observed that the ratio parameter of 0.01 also gave an optimal performance with **0.0021%** MAPE. It was observed that the artificial neural network gave the best optimal result of 0.0021% MAPE for all constraints applied while the non-linear regression model gave an optimal result of 0.0448% MAPE. Figure 2 clealy shows that the mean absolute percentage error (MAPE) value for the ANN model is low compare to its corresponding NLR model. Therefore, the ANN model is considered to produce a more accurate result than the non-linear regression model. This confirmed model adequacy is achieved for ANN since the same optimal result was achieved in all the various constraints applied.

4. Conclusion

This study investigated the comparative analysis power load demand and the forecast of future load demand using 30 days data of University of Benin, Ugbowo Campus, Benin City. The forecasting approaches deployed for this task are the non-linear regression and artificial neural network (ANN) approaches which was analyzed using MATLAB 2015 software. . It was observed that the artificial neural network gave the best optimal result of 0.0021% MAPE for all constraints applied while the non-linear regression model gave an optimal result of 0.0448% MAPE. Therefore, the ANN model is considered to produce a more accurate result than the non-linear regression model.

Nomenclature/symbols

ANN	Artificial Neural Network
MAPE	Mean Absolute Percentage Error
MAD	Mean Absolute Deviation
γ	Performance Ratio
MW	Megawatts
NLR	Non-Linear Regression
STLF	Short term load forecast
MTLF	Medium term load forecast
LTLF	Long term load forecast

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