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Artificial Neural Network Base Short-term Electricity Load Forecasting: A Case Study of a 132/33 kv Transmission Sub-station

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ABSTRACT

Forecasting of electrical load is extremely important for the effective and efficient operation of any power system. Good forecasts results help in minimizing the risk in decision making and reduces the costs of operating the power plant. This work focuses on the short-term load forecast of the 132/33KV transmission sub-station at Port-Harcourt, Nigeria, using the artificial neural network (ANN). It provides accurate week-ahead load forecast using hourly load data of previous weeks. ANN has three sections namely; input, processing and output sections. There are four input parameters for the input section which are historical hourly load data (in MW), time of the day (in hours), days of the week and weekend while the output parameter after the processing (i.e. training, validation and test) is the next week hourly load predicted for the entire system. The technique used is the ANN with the aid of MATLAB software. It was proven to be a good forecast method as it resulted in R-value of 0.988 which gives a mean absolute deviation of 0.104 and mean squared error of 0.27.

Keywords: Load Forecast, Transmission Substation, Artificial Neural Network, Power System

JEL Classifications: C63, L94, L98, Q48

1. INTRODUCTION

The process of predicting future electric load given historical load and sometimes weather information is known as electricity load forecasting (Samuel et al., 2017). Load forecasting is very important to the planning and running of electricity companies. Basically, load forecast is very essential to the entire power sector in order to meet load demands for a given period of time (Samuel et al., 2017; Samuel et al., 2014). It improves the energy-efficiency, reliability and effective operation of a power system as it helps in decision-making process and overall security of the system (Feinberg and Genethliou, 2004; Samuel et al., 2016). The prediction is therefore based on a study of regularity in patterns

such that a data set of consumed loads over a period of time is obtained and processed in order to estimate the amount of load that would be consumed at a future time. According to the time span, load forecasting methods are classified into short-term, mid-term and long-term models (Baliyan et al., 2015). This paper focuses on the short-term load forecasting (spanning from a few hours to days) which is used for timely load scheduling and also in determining the most economic load dispatch, equipment limitations and operational constraints. In this work, one of the most prominent transmission substations was considered. On this station, short-term load forecast was carried out using daily hourly load readings of the preceding weeks in the month of September, 2017 to predict the following week load demand. The results

derived from proposed method were compared with the actual values recorded within the period of the forecast.

1.1. Electric Load Forecasting: Brief Review

In a bid to efficiently supply electric energy to the consumers in a secure and eco-nomic manner, electric utility companies face numerous economic challenges and technical difficulties in operation. Among these challenges are load scheduling, load flow analysis, control and planning of the electric energy system are most eminent (Taylor, 2013). Load forecasting has therefore been found to be one of the most emerging and challenging fields of research over the past few years. Furthermore, the need for accurate load forecasting cannot be overemphasized as accurate load forecasts aid electric companies in making relevant decisions including decisions on generating and purchasing electricity, load switching, facility maintenance and also contract evaluations. Some factors are considered when carrying out electricity load forecasting, these factors are; economic, time, weather and a number of random factors (Hong et al., 2010; Santos et al., 2004). Economic factors comprise investment in the company’s infrastructure via the building of new structures, laboratories and experiments/facilities that add to the overall load of the electric system while time factors could be subdivided into seasonal effects, holidays and weekly daily cycles that affect the load profile (Lee et al., 1992).

Accurate load forecasting holds a great saving potential for electric utility corporations as the goal of any forecast is to obtain the forecast with the least error. Artificial neural network (ANN) model is very versatile and superior in solving load forecast problems when compared with other methods (Samuel et al., 2016; Samuel et al., 2017; Samuel et al., 2014; Srivastava et al., 2016). In this work, the backpropagation algorithm for the multilayer feed forward ANN model is deployed for the short-term load forecast of 132/33KV sub-Station, Port-Harcourt, Nigeria.

2. METHODOLOGY AND IMPLEMENTATION

The 132/33 kV transmission substation Port-Harcourt, Nigeria is selected as a case study in this work. The 132/33 kV transmission substation is modelled by ANN. This work shows the results obtained from the short-term load fore-cast that was carried out for the next week using load data of previous weeks. The results were then compared with the actual values recorded within the forecasted period. The data required for the study were collected on an hourly basis from the transmission substation selected. The load data were inspected to ensure error free result.

2.1. ANN

ANN is a model that is broadly used to understand different data for several applications (Adetiba et al., 2014). It is modelled after the basic working principle of a human brain (Uzubi et al., 2017) and it consists of several neurons. All neurons process in-formation in the same way and information within neurons are transmitted in the form of electrical impulses

(Daramola et al., 2011). A neuron receives information over its input nodes and aggregates the information. It then determines its activation and propagates its response over the output node to other neurons. ANN has the competence to arrest the auto-correlative relations in a time series even when the substrate laws are not known or too complex to define. It is preferred for the task since quantitative fore-casting is based on deriving patterns from observed past events and extrapolating them into the future (Takiyar and Singh, 2015).

In order to generate an accurate forecast, information on a daily basis were used. The forecast was carried out by inputting all the daily data as candidates to be trained by ANN in order to create an individual model for each day.

The following are the three basic stages involve in short term load forecasting pro-posed in this work.

1. Model training: The ANN imitates the working of a human brain. This, therefore, implies that training is an important requirement for an accurate forecast. The training is done by feeding the network with inputs corresponding to the targeted outputs. The network is then simulated and adjustments until least error is achieved. Usually, a trial and error approach is adopted in adjusting the number of epochs, activation functions, and network architecture
2. Model validation: Here, the targeted outputs and inputs are introduced into the developed algorithm and simulated. Comparisons are made between the outputs generated by the ANN and the desired output to show the accuracy of the ANN model
3. Forecasting with the trained model: The network carries out its predictions based on the relationship observed from the training stage. Figure 1 shows the diagram of an ANN.

The ANN model used in this work is the multilayer perceptron with back-propagation. The network consisted of 3 layers; the input layer, six (6) hidden layers and the output.

There are four parameters that made up the input layer of the network. They are:

1. Previous week hourly load (i.e., historical load data in MW)
2. Time of the day (in hours)

Figure 1: The Artificial Neural Network

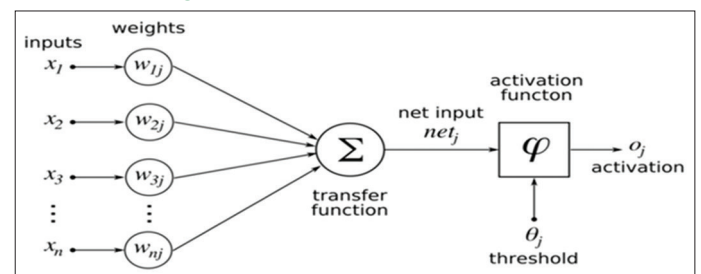


Table 1: Numerical values assigned to each day of the week

Mon	Tue	Wed	Thur	Fri	Sat	Sun
1	2	3	4	5	6	7

- 3. Working days (i.e., Monday, Tuesday, Wednesday, Thursday and Friday)
 - 4. Weekend (i.e., Saturday and Sunday).
- The days of the week (from Monday to Sunday) are assigned certain numerical values. Table 1 shows the assignment of numerical values to the days of the week.

Figure 2: Architecture for the forecast

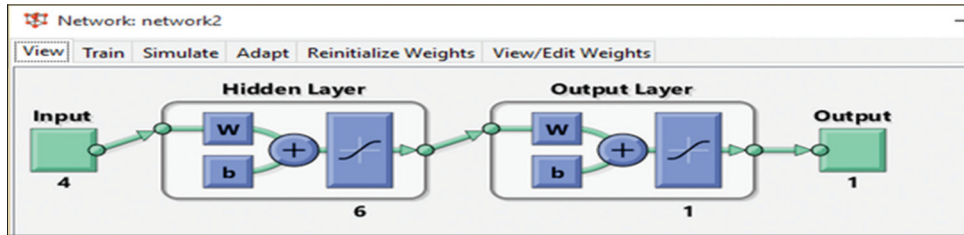


Figure 3: A trained neural network

The screenshot shows the 'Neural Network Training (ntraintool)' window. It displays the neural network architecture (4 input, 6 hidden, 1 output) and various training parameters and progress indicators.

Neural Network

- Input: 4
- Hidden Layer: 6
- Output Layer: 1
- Output: 1

Algorithms

- Data Division: Random (dividerand)
- Training: Gradient Descent with Momentum (traingdm)
- Performance: Mean Squared Error (mse)
- Calculations: MEX

Progress

Epoch:	0	3000 iterations	3000
Time:		0:00:08	
Performance:	10.4	0.0341	0.00
Gradient:	3.91	0.0145	1.00e-05
Validation Checks:	0	2519	3000

Plots

- Performance (plotperform)
- Training State (plottrainstate)
- Regression (plotregression)

Plot Interval: 1 epochs

Opening Regression Plot

Buttons: Stop Training, Cancel

The “weekdays” are given the number code 1 and the “weekends” 0. The time of the day in hours from 1 am to 12 midnight were also assigned numbers from 1 to 24.

50% of the data collected was used in training the neural network, 25% was used for the validation and the remaining 25%, was used for the forecast.

Figure 4: A graph showing the line of best fit

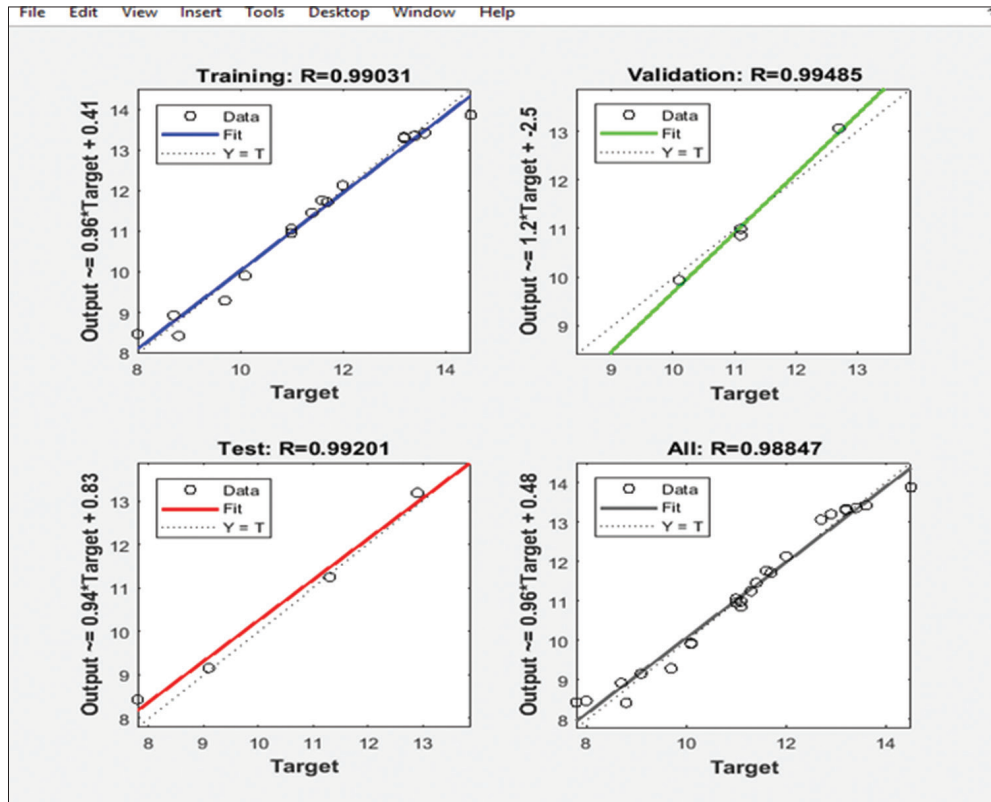


Table 2: The daily actual and forecasted load values from 24th to 30th September 2017

Time (hours)	Sunday (MW)		Monday (MW)		Tuesday (MW)		Wednesday (MW)		Thursday (MW)		Friday (MW)		Saturday (MW)	
	Actual	Fore-cast	Actual	Fore-cast	Actual	Fore-cast	Actual	Fore-cast	Actual	Fore-cast	Actual	Fore-cast	Actual	Fore-cast
1.00	9.7	13.4	10.1	9.9	9.9	9.8	13.6	13.4	14.4	13.7	12.8	12.9	11.7	7.9
2.00	9.3	13.3	11.3	11.3	9.9	9.7	12.3	12.5	13	13.1	12.6	12.8	11.3	7.9
3.00	9.1	9.9	11	10.9	9.6	9.6	13.4	13.3	12.9	13	5.8	8.6	10.9	7.9
4.00	6.7	9.9	10.9	10.8	9.6	9.5	10.4	10.2	12.9	13.1	6.2	8.6	10.4	7.9
5.00	6.5	9.2	6.6	8.5	7	8.6	11	10.9	13.4	13.4	6.4	8.5	10.4	8
6.00	6.2	8.9	7	8.5	7.1	8.5	11.5	11.6	13.9	13.6	7	8.5	10.6	8.1
7.00	9.6	11.7	11.4	11.4	11.9	12.1	11.7	11.9	10.4	10.1	10.4	10.1	9.4	8.1
8.00	9.7	11.4	14.2	13.7	14.9	13.9	12.3	12.6	14.7	13.9	9.9	9.6	10.5	8.2
9.00	9	10.9	15.4	14	14.3	13.8	10.5	10.2	14.6	13.8	7.3	8.5	8.8	8.2
10.00	6.1	11.2	15.1	14.1	12.7	12.9	11.6	11.6	10.3	9.8	10	9.5	8.8	8.9
11.00	9.3	13.2	14.8	13.9	8.5	8.6	12.7	12.9	12.6	12.8	12.2	12.4	9.2	9
12.00	7.2	13.8	16.4	14	12.7	12.9	12.8	13	11	10.7	10.7	10.3	8.8	9
13.00	7.7	12.1	16	14	15	13.9	10	9.4	6.4	8.3	14.9	13.9	8.8	8.9
14.00	8.1	11.7	16.9	14.1	16.6	14	12.5	12.6	6.5	8.3	10.4	9.9	8.9	8.7
15.00	10.7	10.8	15.8	14.2	13.3	13.3	15.7	14	9.7	9.2	1.5	8.2	12.9	12.7
16.00	10.7	8.4	15.9	14	13.6	13.4	17	14.1	6.5	8.3	14.6	13.8	11.8	12
17.00	8.8	8.4	15.9	13.9	13.3	13.3	13.9	13.6	7.5	8.3	8.9	8.7	11	11.5
18.00	5.7	8.5	13.9	13.5	13.6	13.5	13.7	13.5	7.9	8.4	12	12.2	10.5	10.2
19.00	11.6	9.2	7.8	8.4	10.2	9.8	9.5	9.9	7.4	8.3	12.4	12.7	10	9.9
20.00	10.7	10.9	9	8.8	10.1	9.7	10.3	9.1	7.3	8.4	11	10.9	9.7	9.5
21.00	11.8	11.1	11.1	11.2	10.2	9.9	11	11.1	5.1	8.2	10	9.6	9.5	9.4
22.00	11.6	13.1	12.3	12.7	10.3	10.1	12.9	13.1	11.1	11.3	10	9.7	9.3	9.4
23.00	11.8	13.2	13.6	13.4	3.2	8.2	12.5	12.9	8.9	8.8	13.1	13.2	10.7	10.5
12.00	10.1	13.3	12.3	12.8	12.8	13.2	13.6	13.4	13.3	13.3	12.1	12.7	10.7	10.6

The neural network was trained using different activation functions and a number of layers until the best performance was obtained with six (6) hidden layers. Figure 2 shows the architecture for the forecast with six (6) layers.

However, the training process of the neural network and its respective layers are depicted in Figure 3. Figure 4 shows the training performance of the network in form of a graph showing the line of best fit of the trained network. The validation of the network model is to ensure proper working of the neural network. If the understanding of the non-linear characteristics of the load data by the network is good, the fore-cast inputs are fed to the network and the outputs are gotten. For this research work, the output was the next week’s hourly load. The resulting outputs are then recorded and compared with the actual hourly load readings for each day of the week.

3. RESULTS ANALYSIS

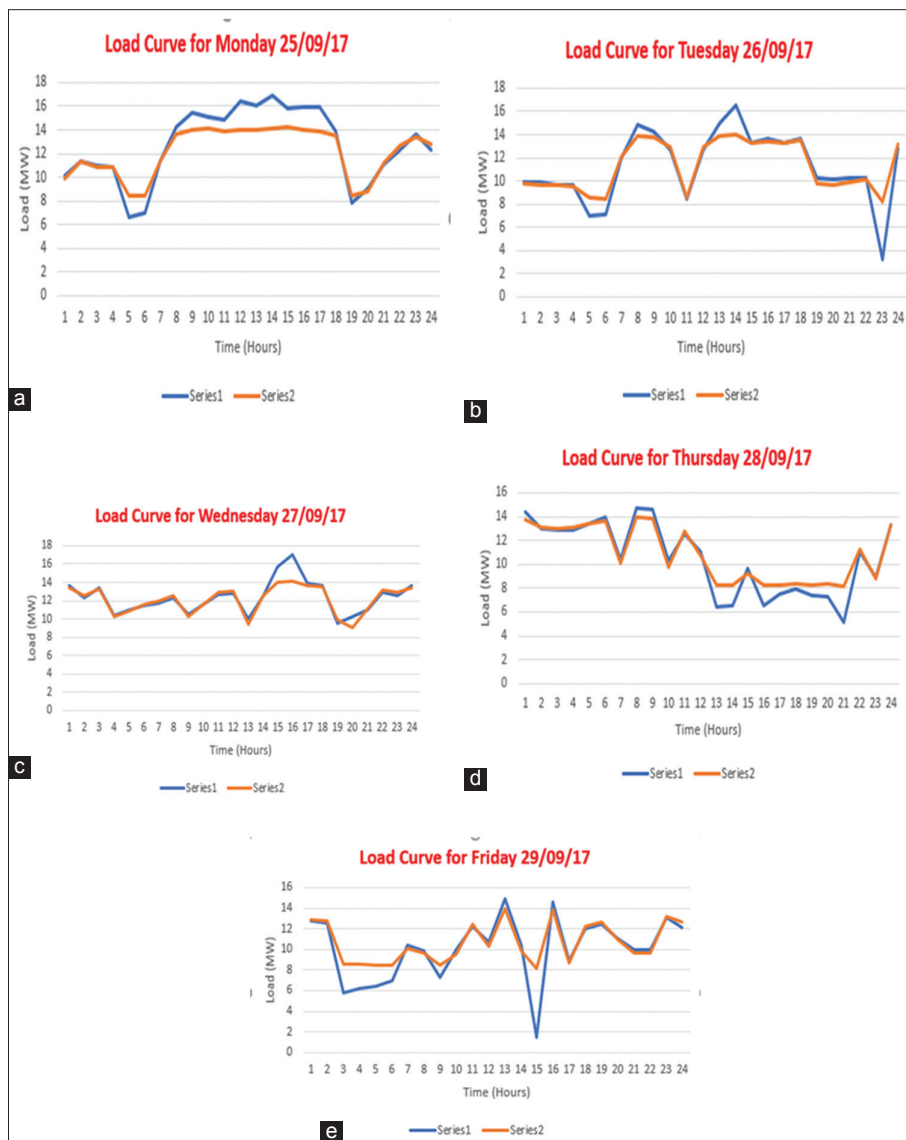
In order to ensure proper comparison and interpretation, the actual daily load and forecasted values are represented in a tabular form

put side by side as shown in Table 2. Consequently, both load values are plotted on the same graph as shown in Figure 5a-e. Table 2 shows the daily actual observed load and forecast load values from 24th to 30th September, 2017.

Figure 5a-e is the graphs showing the relationship between the actual load and the forecasted values. It represents the actual and forecasted load values from Monday to Friday plotted against time of the day. The lines in blue (series 1) represent the actual load values and orange (series 2) represent the forecasted load values.

The accuracy of any forecast is usually dependent on the historical error performance of that forecast. This makes error measurement statistics very critical role in considering forecast accuracy (Samuel et al., 2014). Forecast error is simply the difference between the predicted values and the actual ones over a given time period i.e., $\text{Error} = \text{Actual} - \text{Forecast}$. Two commonly used methods of historical error summaries are the mean squared error (MSE), and the mean absolute deviation (MAD) (Pradeep and Rajesh, 2013).

Figure 5: (a-e) Relationship between the actual load and the forecasted values



MSE is the average of the square of the difference between the actual observed values and predicted ones. It can be computed using the formula:

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

MAD is the measure of the overall fore-cast error. It can be calculated using the formula below:

$$\text{MAD} = \frac{\sum \text{Actual}_t - \text{Forecast}_t}{n} \quad (2)$$

The accuracy of this method was seen to be considerably high with an MSE of 0.27 and MAD of 0.104.

4. CONCLUSION

Understanding of every region of power system such as generation, transmission, substation, distribution, etc. is very important to its design, planning and operation. Hence, designing a model that is commendable to predict the week ahead load de-mand is very pertinent. In this work, ANN model is de-signed and implemented to forecast a week ahead load demand for 132/33KV Port-Harcourt transmission substation in Nigeria based on the available input parameters which are previous hour load (in MW), time of the day (in hours), working days and weekend. The ANN model was designed in MATLAB environment and based on the results obtained, it can be deduced that the ANN model is a very good tool for predicting short-term load forecast considering high R-value obtained.

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