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Short-Term Load Forecasting Using The Time Series And Artificial Neural Network Methods

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***Abstract*:** *Forecasting of electrical load is very crucial to the effective and efficient operation of any power system. This is achieved by obtaining the most accurate forecast which help in minimizing the risk in decision making and reducesthe costs of operating the power plant. Therefore, the comparative study of time series and artificial neural network methods for short term load forecasting is carried out in this paper using real time load data of Covenant University,withthe moving average, exponential smoothing (time series method) and the Artificial Neural Network (ANN) models. The work was done for the day-to-day operation of the soon-to-be-completed power station of the university. For each of the methods, models were developed for the load forecast. The Artificial Neural Network proved to be the best forecast method when the results are compared in terms of error measurementswith amean absolutedeviation(MAD) having 0.225, mean squared error (MSE) having 0.095 and the mean absolute percent error(MAPE)having 8.25.*
Keywords:*Artificial neural network, Error measurement, Exponential smoothing, Load forecasting, Moving average.*

I. Introduction

A power system serves a major function of supplying its customers, (large and small) with economical and reliableelectrical energy as much as possible. For adequate electricity to be supplied to the customers, their load demand must be known[1], [2]. The process of making these evaluations of future demand of load is called 'Load forecasting'. Load forecasting is the projection of electrical load that will be required by a certain geographical area considering previous electrical load usage in the said area [3].Loadforecasting helps to make vital decisions concerning the system, therefore, load forecasting is very crucial for successful effective and efficient operation of any energy system. If the system load forecast is overestimated, the system may overcommit the generation of powerwhich will inadvertently lead to costly operation of the power system. On the other hand, if the system load forecast is underestimated, the reliability and security of the system may be compromised, resulting in power interruptions and customer dissatisfaction [1]. 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 and is from a year upwards, is useful for planning operations [3].

This paper focuses on the short term load forecasting (STLF) which is used for prompt load scheduling and determines the most economic load dispatch with operational constraints and policies, environmental and equipment limitations [4].

Over the years, different methods have been developed and improved upon to forecast load demands.These methods of load forecasting are classified into two categories: classical approaches and artificial intelligence (AI) based techniques. Classical approaches are based on various statistical modeling methods.These approaches forecast future values of the load by using a mathematical combination of previous values of the load and other variable such as weather data. This includes the use of regression exponential smoothing, Box-Jenkins, autoregressive integrated moving average (ARIMA) models and Kalman filters. Recently several researchers have studied the use of artificial neural networks (ANNs) models and Fuzzy neural networks (FNNs) models for load forecasting[4].

This paper is organized as follows. Section II briefly discusses electrical load forecasting, while section III,presents the methods used to carry out the load forecasting, and in section IV results are discussed. Section V concludes the paper.

II. Electrical Load Forecasting

There is a need for the development of models for electrical load forecasting. The models to be developed depend on the relative information about the past load data available and how long into the future the forecast will be. Forecasting models merely identify patterns in the load data being analyzed and use these patternsto forecast what will be the future load.Load forecasting holds a lot of benefits for electric power system management and is important for the electricity industry in the deregulated economy. It has many applications which includes energy purchasing, generation, load switching, contract evaluation and infrastructure development. A large variety of mathematical methods have been developed for load forecasting [5]. An accurate load forecast can be very helpful in developing a power supply strategy, finance planning, market research and electricity management [6]. For every forecast, there are different factors to be put into consideration. These factors to a great deal determine how accurate the forecast will be, as well as determine the load demand and hence, affect the load curve. These factors include calendar effects, seasonal variations, weekday variations, weekend-days variation, weather and temperature amongst others. Calendar effects include the effects of working days or trading days and holidays. Growth in the economy, population, extreme weathers may also contribute to annual variations. These variations need to be considered in forecasting energy intended for domestic use [7].

Accurate load forecasting holds a great saving potential for electric utility corporations [8]. The goal of any forecast is to obtain the forecast with the least error. During forecasting, an underestimation in energy demand may result in a limited supply of electricity at the consumer end, which leads to energy quality reduction in system reliability. On the other hand, an overestimation may cause unnecessary investments to the establishments therefore resulting in uneconomical operating conditions [9].

In [10], two time series models (multiplicative decomposition model and the smoothing techniques) were used for the short term load forecast. Moving Average and Exponential Smoothing Techniques were used for the load forecast of UniversitiTeknologi PETRONAS (UTP), Malaysia. In [11]an ANN model was developed for the short term load forecast of the 132/33KV sub-Station, Kano, Nigeria. The Levenberg-Marquardt optimization technique which is one of the best for training the network was used as a back propagation algorithm for the Multilayer Feed Forward ANN model. In [12], the short-term load pattern for the University of Ibadan was investigated and a multi-layered feed-forward artificial neural networks (ANN) model was developed to forecast the time series half-hourly load pattern of the system.

III. Methods And Implementation

The methods of load forecasting used in this work are the time series, the moving average(MA) and exponential smoothingand the Artificial Neural Network (ANN) models.

In this paper, the case study is Covenant University, Canaan land, Ota, Ogun state, Nigeria. This study will show the results obtained from the short-term load forecast that was carried out for the next one hour culminating into next-day (24hours ahead) using the time series and artificial neural network methods. The results of which 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 base station of Canaan land. The variables taken are the historical load demand and time. Table 1 shows the actual data for Monday, 15-Tuesday 16,from 22hrs to 00hrs Oct. 2012. The load forecast is slated for 1to 24hours (1AM -23.59PM) and the moving average points are 3,4, and 5, hence the use of the three last hours of the previous day (15/12/2012).

Table 1 Actual Load Data

S/N	Time	MW	Date
22	22	2.7	15/10/12
23	23	2.5	
24	24	2.2	
1	1:00	2.1	16/10/12
2	2:00	2.1	
3	3:00	1.8	
4	4:00	2.3	
5	5:00	2.5	
6	6:00	2.8	
7	7:00	3	
8	8:00	2.6	
9	9:00	3.6	
10	10:00	3.2	
11	11:00	2.8	
12	12:00	2.5	
13	13:00	2.6	
14	14:00	2.9	
15	15:00	2.8	
16	16:00	2.8	
17	17:00	2.8	
18	18:00	2.8	
19	19:00	2.8	
20	20:00	3.1	
21	21:00	2.9	

22	22:00	2.8	
23	23:00	2.6	
24	0:00	2.5	

1. Time Series

A time series is a set of data generated sequentially in time. The time series models assume that in the absence of major disruptions to critical factors of a recurring event, the data of this event in the future will be related to that of the past events and can be expressed via models developed from the past events [13]. Time-series forecasting are made on the assumption that future values of the series can be estimated from historical data. Time series are well suited for short term load forecasting provided sufficient and accurate past data are available. The four components of a time series are the trend, the cyclical variation or fluctuation, the seasonal variation, and the irregular variation [14].

1.1 Moving Averages

A moving average uses the average of a number of the most recent actual data values in generating a forecast. The term 'moving' is used because each time a new data value becomes available for the time series, it replaces the oldest data value in the equation of the moving average and a new average is computed. Therefore, the average will change as new data is made available.To use moving averages, we have to select the number of time series values to be used for the computation of the moving average. If only the most recent values of *n* are considered as most relevant, a small value of *n* is used and conversely, if more past values are considered relevant, a larger value of *n* is used. The moving average forecast can be computed using the following equation:

$$F_t = MA_n = \frac{\sum_{i=1}^{n} A_{t-i}}{n} = \frac{A_{t-n} + \dots + A_{t-2} + A_{t-1}}{n} \qquad (1)$$

where,
F_t= Forecast for time period t, MA_n =period moving average and A_{t-i} =Actual value in period t - i
n = Number of periods (data points) in the moving average.

The order of the moving average refers to the number of time points to be considered for the average. It i can also be referred to as the 'period' of the moving average. For this work, three (3) different orders were chosen for the moving average. They are 3-point, 4-point and 5-point moving averages.

1.2Exponential Smoothing

The exponential smoothingis a complex weighted averaging method that is relatively easy to use and understand. Every new forecast is based on the previous forecast plus a percentage of the difference between that forecast and the actual value of the series at that point. That is:

$$W_{t+1} = \alpha Y_t + (1- \alpha)\, W_t \qquad (2)$$

Where, W_{t+1} is the forecast of the time series for period t + 1
Y_t is the actual value of the time series in period t
W_t forecast for the time series for period t
α is the smoothing constant with values between 0 and 1

For this work, three (3) different values of the smoothing constant (α) were chosen and used for the forecast. They are 0.1, 0.2 and 0.3.

2. Artificial Neural Network

Artificial Neural Network (ANN) has been applied to short term loads forecasting. An Artificial Neural Network (ANN) is a mathematical or computational model based on the structure and functional aspects of biological neural networks. It consists of a group of artificial neurons interconnected together, and it processes information using a connectionist approach to computation. The foundation of every artificial neural network is the artificial neuron. The neuron has three simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron, the inputs are weighted what means that every input value is multiplied with an individual weight. In the middle section of artificial neuron is the sum function that finds the sum of all the weighted inputs and bias. At the exit of artificial neuron is the sum of the previously weighted inputs and bias that have passed through an activation function which is also referred to as the transfer function [15]. Fig. 1. shows a Neural network model.

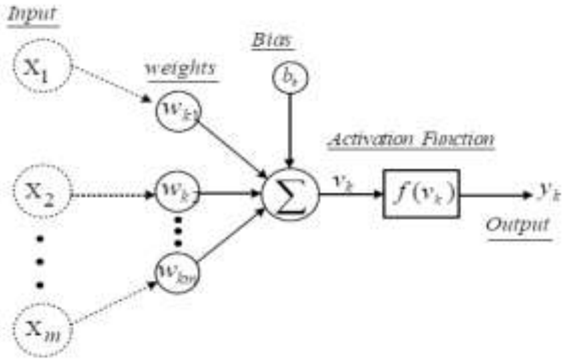

Fig. 1A Neural network model

There are several types of artificial neural networks. They include: the feed-forward artificial neural network, the recurrent artificial neural networks, Hopfield artificial neural network, Elman and Jordan artificial neural networks, self-organizing map artificial neural networks, radial basis function (RBF), stochastic artificial neural networks and so on [16][17]. The two main types are the feed forward artificial neural networks (FFNN) and the recurrent artificial neural networks (RNN) [17].

As for the STLF problem, the back propagation network is the most widely used. It has the ability to approximate any continuous nonlinear function. An ANN has to be designed and implemented in a way that the set of input data results into a desired output. Training of the neural network is often referred to as 'learning'. The network learns (updates its weights) from the given data in a bid to minimize some cost function of the 'error' between the training set data (output) and its own output [17]. For this work, the supervised learning is used. Supervised learning involves feeding the network with inputs and corresponding outputs for each input. The network now learns the relationship between the input and output which can now be used to forecast.

The neural network had three layers- input, hidden and output. The inputs to the neural network are the multiplied by the weights and acted upon by the transfer or activation function. The output which is the forecasted hourly load data is obtained from the output layer. The network chosen for the purpose of this work is the Multilayer-Layer perceptron (MLP). There were four inputs to the input layer of the network. They are:

1. Previous hour load (in MW)
2. Time of the day (in hours).
3. Day of the week.
4. 'Weekday' or ' weekend'.

The days of the week were assigned numerical values from 1-7 from Monday to Sunday. The 'weekdays' are given the number code 1 and the 'weekends', 0. The time of the day in hours were also assigned numbers from 1-24 representing 1am to 12midnight.The forecast model was then designed and trained using the MATLAB software R2012b. Adjustments were now made to the network till the best performance was gotten. To get the best network, the number of epochs, hidden layers, activation functions, the network architecture and so on can be adjusted. The process of training is essentially done by trial and error. The model with the best performance had two neurons in the hidden layer and one neuron in the output layer. The sigmoid transfer function was used as the activation function. The neural network architecture used for this forecast showing table 1.

Table 2: Showing The Neural Network Architecture

Number of Inputs	Number of Hidden Layer Neurons	Number of Output Neuron	Activation Function
4	2	1	Sigmoid

Training of the Network: This is just a process of weight adjustments with respect to the targeted output by the neural network. The training of the network is carried out using the MATLAB software. The load data collected is the input data to the neural networks. 50% 0f this data was used for the training of the neural network, 25% was used for the validation and the remaining 25%, for the forecast. The neural network was trained using different activation functions and number of layers till the best performance was obtained. Figure

2shows the neural network being trained and Figure 3 shows the training process of the network and the number of layers.

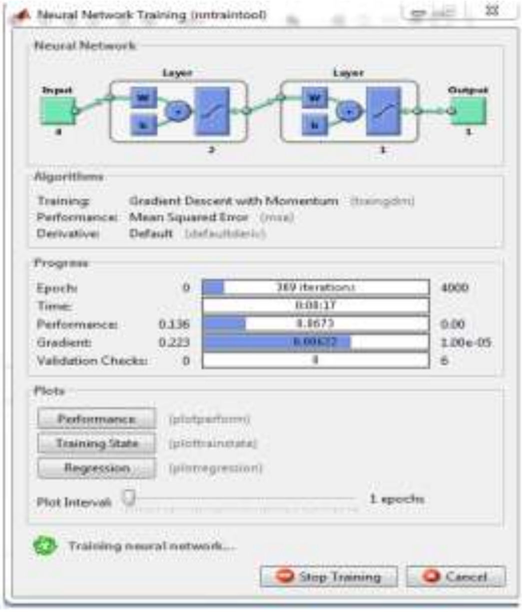

Figure 2. A neural network being trained

The training performance of the model is as shown in figure 3.

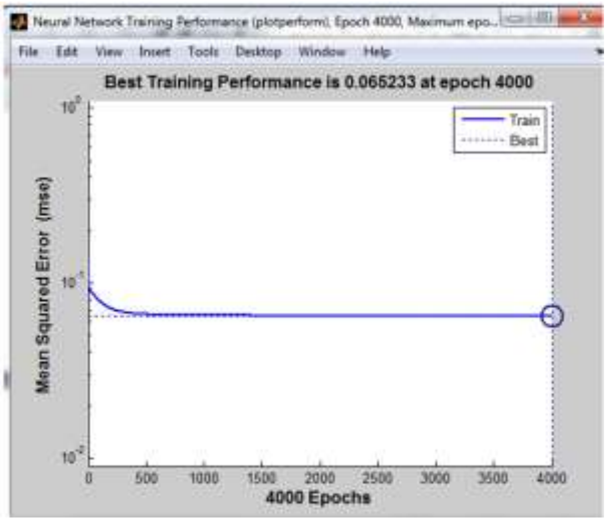

Figure 3. Plot showing the training performance of the model.

3. Accuracy (Error) Measurement

For the measurement of the forecast accuracy, the Mean Absolute Percentage Error (MAPE), Mean absolute deviation (MAD) and Mean Squared Error (MSE) were used. MAPE measures the amount of the error in terms of percentage. It is calculated as the average of the absolute percentage error. It can be calculated using the formula:

$$\text{MAPE} = \frac{\sum \frac{|\text{Actual}_t - \text{Forecast}_t|}{|Actual_t|}}{n} * 100 \qquad (3)$$

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 the formula:

$$\text{MAD} = \frac{\sum |\text{Actual}_t - Forecast_t|}{n} \qquad (4)$$

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 the formula:

$$\text{MSE} = \frac{\sum(\text{Actual}_t - Forecast_t)^2}{n-1} \tag{5}$$

IV. Results

(i) Moving Average (MA):the forecast of the next time period in the 3-point moving average is the average of the three most recent data values in the time series and same for the 4 and 5 point. Table 3 shows the result for the three point considered.Figure4 shows the graph that compares the forecast and actual values of the 3-pointMoving Average (MA).Figure5 shows the graph that compares the forecast and actual values of the 4-point MA and Figure 6 shows the graph that compares the forecast and actual values of the 5-point MA

Table 3. The Forecast Result For The Moving Average

		3 Point MA	4 Point MA	5Point MA
Time(hrs)	**Actual(MW)**	**Forecast(MW)**	**Forecast(MW)**	**Forecast(MW)**
1	2.1	2.47	2.55	2.76
2	2.1	2.27	2.38	2.46
3	1.8	2.13	2.23	2.32
4	2.3	2	2.05	2.14
5	2.5	2.07	2.08	2.1
6	2.8	2.2	2.18	2.16
7	3	2.53	2.35	2.3
8	2.6	2.77	2.65	2.48
9	3.6	2.8	2.73	2.64
10	3.2	3.07	3	2.9
11	2.8	3.13	3.1	3.04
12	2.5	3.2	3.05	3.04
13	2.6	2.83	3.03	2.94
14	2.9	2.63	2.78	2.94
15	2.8	2.67	2.7	2.8
16	2.8	2.77	2.7	2.72
17	2.8	2.83	2.78	2.72
18	2.8	2.8	2.83	2.78
19	2.8	2.8	2.8	2.82
20	3.1	2.8	2.8	2.8
21	2.9	2.9	2.88	2.86
22	2.8	2.93	2.9	2.88
23	2.6	2.93	2.9	2.88
24	2.5	2.77	2.85	2.84

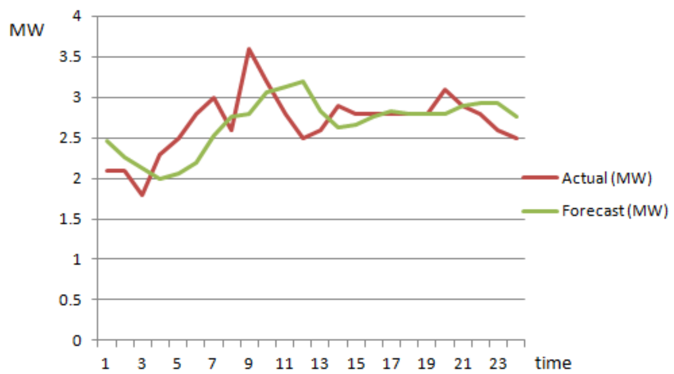

Fig.4. The graph that compares the forecast and actual values of the 3-point MA

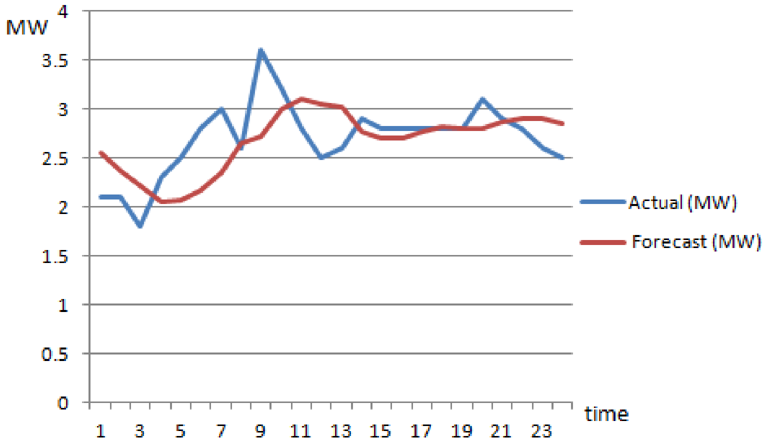

Fig.5. The graph that compares the forecast and actual values of the 4-point MA

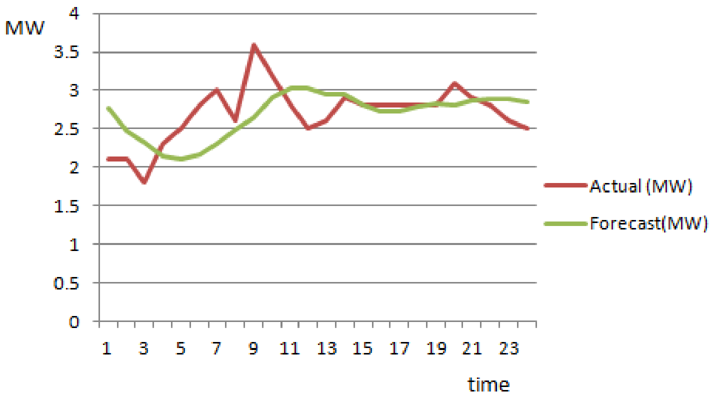

Fig.6. The graph that compares the forecast and actual values of the 5-point MA

(ii) Exponential Smoothing: Table 4 shows the result of the forecast for smoothing constant value, αof 0.1, 0.2 and 0.3considered. Figure7 shows the graph that compares the forecast and actual values of α= 0.1, Figure8 shows the graph that compares the forecast and actual values of α= 0.2 and Figure 9shows the graph that compares the forecast and actual values α= 0.3.

Table 4: The Result Of The Forecast For Smoothing Constant Values.

		α= 0.1	α= 0.2	α= 0.3
Time(hours)	**Actual(MW)**	**Forecast(MW)**	**Forecast(MW)**	**Forecast(MW)**
1	2.1	2.2	2.2	2.2
2	2.1	2.19	2.18	2.17
3	1.8	2.18	2.16	2.15
4	2.3	2.14	2.09	2.04
5	2.5	2.16	2.13	2.12
6	2.8	2.19	2.21	2.23
7	3	2.25	2.33	2.4
8	2.6	2.33	2.46	2.58
9	3.6	2.36	2.49	2.59
10	3.2	2.48	2.71	2.89
11	2.8	2.55	2.81	2.98
12	2.5	2.58	2.81	2.93
13	2.6	2.57	2.75	2.8
14	2.9	2.57	2.72	2.74
15	2.8	2.6	2.75	2.79
16	2.8	2.62	2.76	2.79
17	2.8	2.64	2.77	2.79
18	2.8	2.66	2.78	2.8
19	2.8	2.67	2.78	2.8
20	3.1	2.68	2.78	2.8
21	2.9	2.73	2.85	2.89

22	2.8	2.74	2.86	2.89
23	2.6	2.75	2.85	2.86
24	2.5	2.73	2.8	2.79

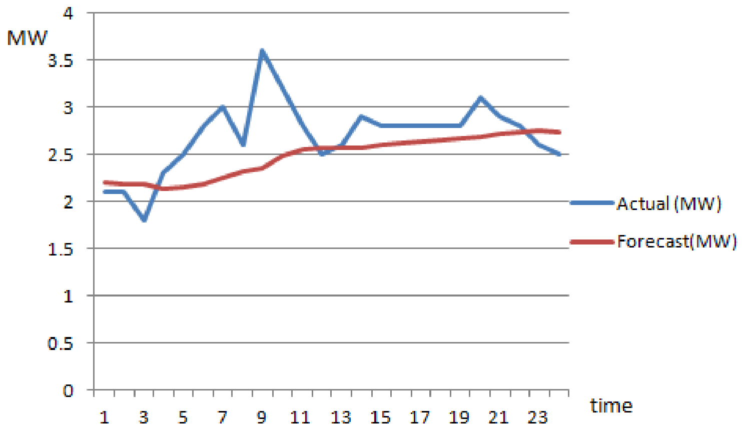

Fig.8. The graph that compares the forecast and actual values of α = 0.1

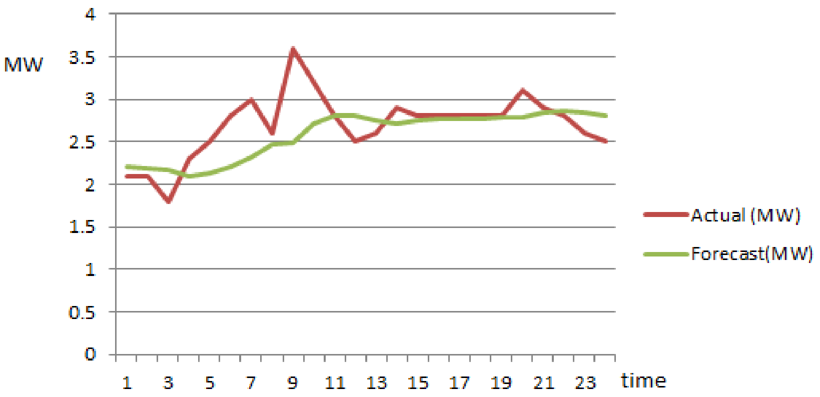

Fig.8. The graph that compares the forecast and actual values of α = 0.2

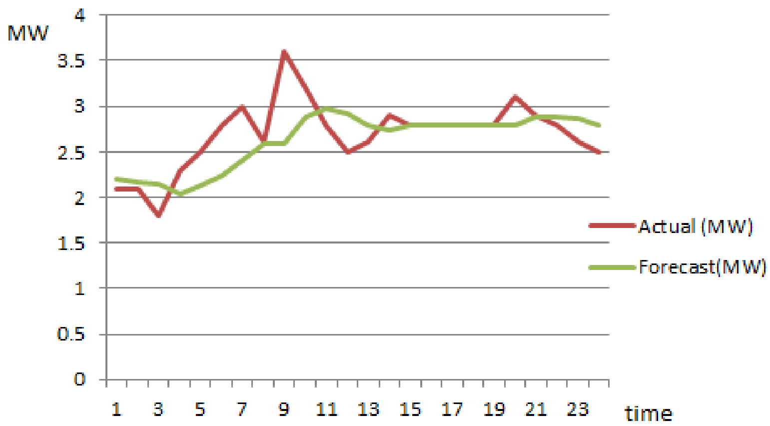

Fig.9. The graph that compares the forecast and actual values of α = 0.3

(iii) ANN Model: Table5 shows the result of the forecast for the ANN model result and figure10 shows the graph that compares the forecast and actual values of the ANN model.

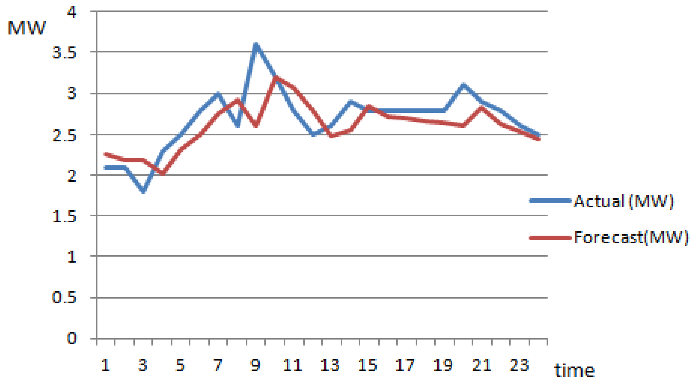

Fig.10. The graph that compares the forecast and actual values of the ANN model

Table 5:The Result Of The Forecast For The Ann Model Result

Time(hrs)	Actual(MW)	Forecast(MW)
1	2.1	2.25
2	2.1	2.19
3	1.8	2.18
4	2.3	2.02
5	2.5	2.31
6	2.8	2.49
7	3	2.76
8	2.6	2.92
9	3.6	2.6
10	3.2	3.19
11	2.8	3.07
12	2.5	2.8
13	2.6	2.47
14	2.9	2.56
15	2.8	2.85
16	2.8	2.72
17	2.8	2.7
18	2.8	2.67
19	2.8	2.64
20	3.1	2.61
21	2.9	2.82
22	2.8	2.63
23	2.6	2.54
24	2.5	2.44

From the results, the ANN was better than all the time series models having very low values of MSE, MAD and MAPE. The results from the Neural network took a longer time to obtain the outputs than the time series because of the time involved in training the network. Table 6 below shows the accuracy comparison of the methods used.

Table 6: Comparing The Accuracies Of The Different Methods Used

MODELS	MAD	MSE	MAPE
3-Point Moving Average	0.272	0.124	10.3
4-Point Moving Average	0.290	0.141	11.02
5-Point Moving Average	0.301	0.162	11.55
Smoothing constant of 0.1	0.299	0.172	10.6
Smoothing constant of 0.2	0.246	0.132	8.89
Smoothing constant of 0.3	0.234	0.116	8.56
Artificial Neural Network	0.225	0.095	8.25

V. Conclusion

The comparative study of time series and artificial neural network methods for short term load forecasting is carried out in this paper using real time load data of Covenant University, with the moving average, exponential smoothing (time series method) and the Artificial Neural Network (ANN) models. The work was done for the day-to-day operation of the soon-to-be-completed power station of the university. For each of the methods, models were developed for the load forecast. The Artificial Neural Network proved to be the best forecast method when the results are compared in terms of error measurements with a MAD having 0.225, MSE having 0.095 and MAPE having 8.25. The Artificial neural network (ANN) model was the best of all the methods showing the robustness of the method to model non-linear load data. The work presented usable and accurate methods for short term load forecasting which is very important to the operation of any power system.

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