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A COMPARATIVE STUDY OF DIFFERENT TECHNIQUES FOR SHORT TERM LOAD FORECASTING

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ABSTRACT

Load forecasting, this involves estimation of future load according to the previous load. This paper focuses on hybrid technique of load forecasting, which is essential for developing power supply method to improve the reliability of the power line and provide optimal load scheduling for many developing countries where the demand can be increased day by day. Load forecast is an important factor for various fields such as electric energy generation, transmission, distribution and markets. This paper investigates the comparative study of artificial neural network (ANN) and hybrid technique (Neural-Wavelet) as forecasting tools for predicting load in short term category. Load data of the month of DECEMBER, 2015 is taken to perform the proposed work and also used to train the neural network. In this case the forecasting is day ahead and it is observed that Neural-Wavelet represents the more accurate prediction in comparison to non-wavelet (ANN) technique for the same set of data of the same utility.

Index Terms- Load Forecasting, Wavelet Analysis, Neural Networks.

I INTRODUCTION

Load forecasting is sort of planning and it is said that “To work with plan is to work with accuracy”. Load forecasting refers to the prediction of the load in large power system. It is technique used by power or energy provided that companies to predict the power or energy looked-for to meet the demand and supply equilibrium. Due to deregulation and competition there are several changes going on in the structure of the utility industry and the need for accurate load forecasts will enlarge day by day. The accuracy of forecasting is of great implication for the operational and managerial loading of a utility company. It helps electric utility to make important decisions on purchasing and generating electric power, and also in prediction of next day, weeks or year’s load. Timely implementations of such decisions lead to improvement of network reliability and to the reduced occurrences of equipment failures and blackouts.

Load forecast can be divided into following categories: Very short term load forecasting (VSTLF), forecasting horizon ranging from a few minutes ahead to a few hours ahead. Time period for short term load forecasting (STLF) is one day to one month. Medium term load forecasting (MTLF), which forecast within of one month to one year. Long term load forecasting (LTLF) with a time period of more than one year. For short- term load forecasting numerous factors should be considered like time factors, data of weather, and data of possible customer's classes. Time factors include time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. Historical load and weather data, unusual class of customers, age of the appliances in the area and their characteristics, forecast of the economic and demographic data, the appliance sales data, and other factors are taken into account for medium and long-term forecasts.

Short term load forecasting is used to approximate load flows and to make decisions that can avoid overloading. Load flows are also based on the outcome of the short term load forecasting. There are varieties of methods, which include the so-called similar day approach, various regression models, time series, wavelet method, neural networks, expert system, fuzzy logic, and statistical learning algorithms etc. are used for short term load forecasting and sometimes it is also used for medium term load forecasting. For medium and long term load forecasting there are two methods: so-called end use and econometric approach [1].

There are numerous methods which are used for load forecasting. Artificial Neural Network method is an efficient technique gives minimum error forecasting. In ANN model historical load data taken as input and forecasted day is taken as output of ANN. ANN gives linear and non-linear mathematical function of its input values. Sometimes load is divided into two separate patterns: week day and weekend day pattern and backpropagation learning algorithm used to train ANN for forecasting [2]. Another method based on appropriate training data selection is used in ANN for capable approach for load forecasting and minimum forecasting error is achievable. [3]

Artificial Neural Network (ANN) based short term load forecasting technique that consider electricity price is one of the main characteristics of the system load, representing the importance of considering price when predicting load in present day electricity market [4]. ANN is suitable to interpolate among the load and temperature pattern data of training sets to provide the future load pattern [5]. Combination of Artificial Network (ANN) method and Fuzzy Logic method is also used for short term load forecasting, ANN method is found to be more efficient than fuzzy logic method [6].

The wavelet transform is introduced to preprocess the load data in order to enhance the accurateness of forecasting. Wavelet method splits raw signal into two frequencies i.e. low frequency and high frequency signal and remove high frequency signal and smoothened data [7]. Wavelet and its combination with other techniques are efficient for short term load forecasting and the result has been come in the form of forecasting error. Error should be least for good forecasting. Wavelet decomposition has been integrated successfully with neural networks showing more accurate and acceptable results as compared to conventional methods [8]. Use of pre-processed data through wavelet technique not only improves the performance of the forecasting models but at the same time takes lesser time for training. Wavelet approaches are always much advanced than non-wavelet approaches [9]. Multilevel wavelet decomposition with data pre filtering gives very good results for short term load forecasting [10].

In this paper, load data from of the month of DECEMBER, 2015 is taken to perform Short Term Load forecasting. Wavelet decomposes the input load data, removes non-linearity of data and again reconstructs the load data. This reconstruct data apply to ANN. Comparative approach represents Neural-Wavelet is much superior to non wavelet techniques (ANN).

II ARTIFICIAL NEURAL NETWORK TECHNIQUE [ANN]

Neural networks are essentially non-linear circuits that have the demonstrated capability to do non linear curve fitting. Neural networks is information processing model encouraged by biological nervous systems (such as our brain), in which large number of highly interconnected elements working together to perform a particular task. When a given set of cells (inputs) are stimulated, the signal are passed through the network from node to node and lastly exit the network through another set of simplified nodes. The simple Node sums 'N' weighted inputs are multiplied with a weight of neural network and then passed through the activation function. It is usually used in training the nonlinear function. Feedback paths are sometimes used in ANN method. One of the major features of the neural networks is its learning capability. They can also adjust the weights to improve the performance for a given task. Feed forward ANN model is shown in Fig.1.

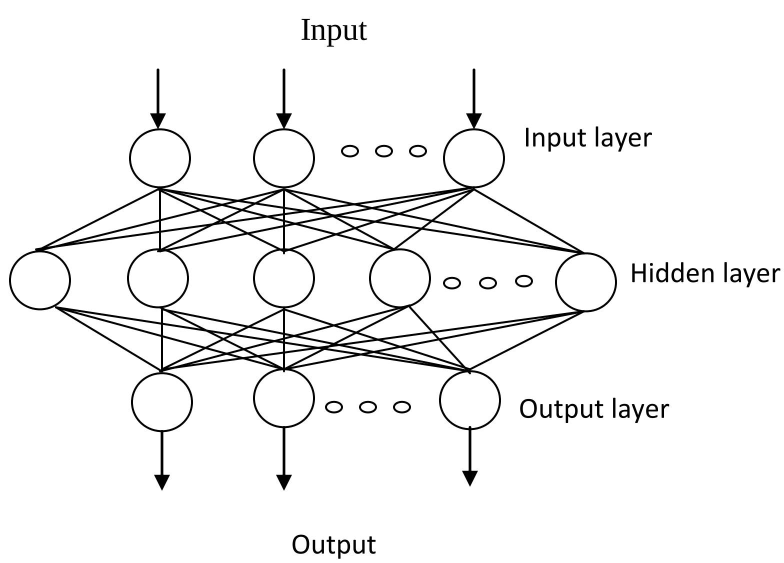

Fig.1 Feed Forward ANN model

Main elements of ANN are: Input layer, Hidden layer and Output layer. Speech processing, image recognition, machine vision, etc. are the different fields where neural networks are better suitable for achieving human-like performance. Processing elements in an ANN are also known as neurons. Each neuron have multiple inputs, while there can be only one output. A neural network consists of four main parts:

1. Processing units.
2. Weighted interconnections between the various processing units.
3. An activation rule which acts on the set of input signals at a unit to produce a new output signal, or activation.
4. Optionally, a learning rule that specifies how to adjust the weights for a given input/output pair [11].

There are several activation function used in ANN, such as step function, signum function, sigmoid function, linear function, bipolar and unipolar function, logsig function, tansig function. In this paper tansig activation function is used for nonlinear input and one month hourly load (in MVA) works as input variables and forecasting day is output of ANN model. Activation function for nonlinear load data is given as

$$tansig(n) = \frac{2}{(1+\exp(-2*n))} - 1$$

2.1 Training of ANN

ANN training mostly used for determining weights and others, that permit to achieving the desired objective, based on existing training sets. In this paper Five days hourly load data is used as training data for forecasting. Back-Propagation is used as training method which is an iterative procedure that has three steps during iteration:

1. Forward: The outputs are calculated for given inputs.
2.Backward: The errors at the output layer are propagated backwards in the direction of the input layer, with the partial derivatives of the performance with respect to the weights and biases are calculated in every layer.
3. Weight adjustment: A nonlinear numeric optimization algorithm is used to find out the weights that minimize the error based on the agreement.

2.2 Mathematical Model of ANN

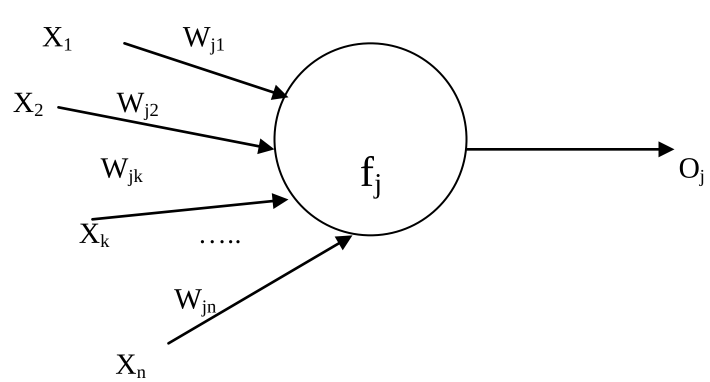

Fig. 2 Mathematical Model of ANN

The output of the given model is

$$O_j = f_k \sum \left(W_{jk} X_k \right)$$

Where, O_j = output of neuron

W_{jk} = adjustable weight

X_k = input of neurons

The Error function used in back propagation training process can be given as

$$E = 0.5 \sum_p \sum_j \left(t_{pj} - o_{pj} \right)^2$$

Where t_{pj} and o_{pj} are the target output and actual output j for input pattern p, respectively. If neuron j is one of the output neurons, error is given as

$$\delta_j = \left(t - O_j \right) O_j \left(1 - O_j \right)$$

Adjusting weights are given as

$$\Delta W_{ij} \left(n+1 \right) = \eta \delta_{pj} O_{pi} + \alpha \Delta W_{ij} (\mathrm{n})$$

Where η is learning rate parameter and α is the momentum constant to determine the effect of past weight changes [2] [5] [4].

III WAVELET ANALYSIS

Wavelet is the extend concept of Fourier Transform. Fourier Transform gives frequency signal information but wavelet provides time-frequency representation of any signal. It uses the Fourier Transform in the form of Short Time Fourier Transform, in which signal is multiplied by window function and then Fourier Transform of signal is taken. Output depends on window’s size. Narrow window provides good time resolution and poor frequency resolution. Wide window provides good frequency resolution and poor time resolution. It is used in load forecasting for smoothing the non-linear load signal.

Wavelet is a powerful tool that can be efficiently utilized for the prediction of short term loads. The expensive information is not easily available from raw signal or original signal. To accurately captured load features at multiple frequencies, wavelet technique is used to decompose the loads into several frequency components. Wavelet transform can be divided into two categories i.e. discrete wavelet transforms (DWT) and continuous wavelet transforms (CWT). DWT algorithm is able of producing coefficients of fine scales for capturing high frequency information, and coefficients of coarse scales for capturing low frequency information.

Wavelet processing has two stages: decomposition and reconstruction. Wavelet reconstruction provides a signal to break into many lower resolution components, recognized as wavelet decomposition hierarchy. Wavelet decomposition hierarchy can yield a signal to get valuable information. The decomposition can carry on only until the individual details consist of a signal sample or pixel. Wavelet decomposition will break the load data into low and high frequency terms. In this paper mother wavelet based on Daubechie3 (Db3), Discrete wavelet transform is used for filter's coefficients. Db3 are asymmetric, orthogonal, biorthogonal in nature. In first step Db3 gives approximated and detailed coefficients. Approximations are high scale, low frequency components of the signal and details are low scale, high frequency components. In second level decomposition these approximated coefficients further decomposed into approximated and detailed coefficients. Wavelet decomposition is shown in Fig.3. In preprocessing stage, Db3 decomposes original signal into three levels:

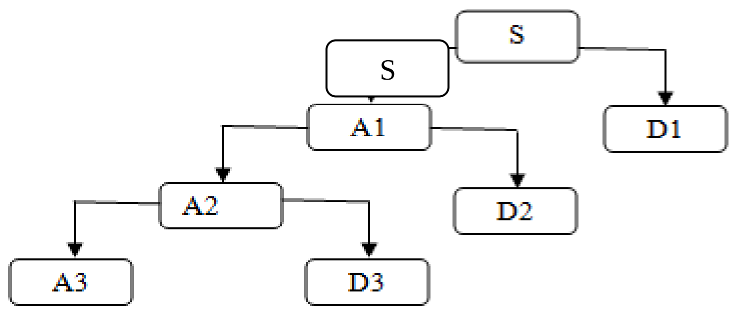

Fig.3 Wavelet Decomposition

Where S is original signal and A, D are coefficient vectors. The length of the wavelet (or scaling) filter is two times of that number (Db3) .The higher the number of vanishing moments, smoother the wavelet (and longer the wavelet filter). Decomposed components of wavelet can be assembled back into the original signal without loss of information. This process is called reconstruction. The signal is reconstructed by combining its wavelet coefficients as shown in Fig.4. Up sampling is the process of broadening a signal component by inserting zeros between samples. The down sampling of the signal components is performing during the decomposition. There are two types of filters to decompose or reconstruct the signal. The low and high pass filters (L and H), together with their associated reconstruction filters form a system.

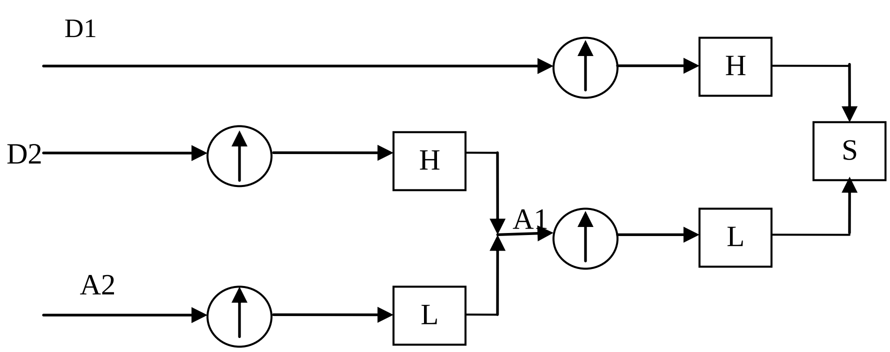

Fig. 4 Wavelet Reconstruction

Where H and L are represents High pass and Low pass filters respectively. The reconstruction details and approximations are true of the original signal:

S = A1 +D1 (Level 1)

= A2 + D2 +D1 (Level 2)

= A3 + D3 + D2 + D1 (level 3)

The coefficients vectors A1 are D1 created by down sampling and are half of the original signal. Therefore, they cannot directly merge to reproduce the signal. It is compulsory to reconstruct the approximations and details before combining with each other [12] [7].

IV HYBRID MODEL

A single neural network however may not be proficient to precisely capture complicated load features because the load data have multiple frequency components, and each may have unique pattern. Furthermore, spikes are erratically distributed over time and have different magnitudes and widths. They influence neural network training, and result in degraded predictions. The wavelet method is dominant tool which is used for load forecasting. Consequently, wavelet decomposition method in this research is developed and combined with the neural network for increasing the reliable forecast.

The proposed hybrid method (neural wavelet method) consists of wavelet decomposition, smoothening of decomposed data and again reconstructs the data. Historical load data was divided into low and high frequencies. Historical load data was smoothened by deleting high frequency components. Reconstruct data apply to the Neural Network model and minimum error forecasting is done. Wavelet approach is much superior to non-wavelet methods and minimum error is found with the help of wavelet method. Forecasting process of hybrid method is shown in Fig.5. [9].

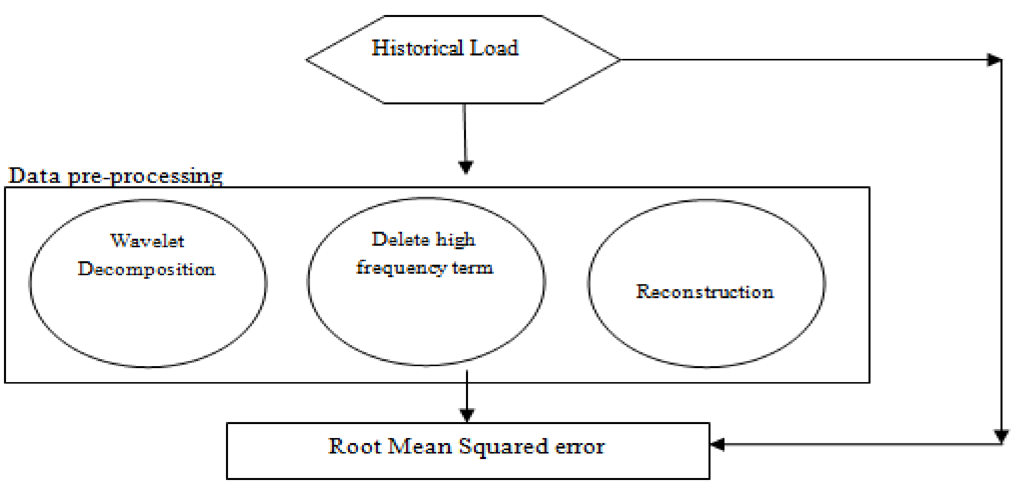

Fig.5 Forecasting Process

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V FORECASTING MODEL ACCURACY

Error is defined as the difference between the actual value and the forecasted value for the corresponding period.

$$\varepsilon_t = A_t - F_t$$

Where, ε_t is the error for the period T, A_t is the actual value for the period T, F_t is the forecasted value for the period T. Following are the errors calculated for the load forecasting:

1. Mean Absolute Error:

$$MAE = \frac{\sum_{t=1}^{N} |\varepsilon_t|}{N}$$

2. Mean Absolute Percentage Error:

$$MAPE = \frac{\sum_{t=1}^{N} \left|\frac{\varepsilon_t}{A_t}\right|}{N}$$

3. Root Mean Squared Error:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} \varepsilon_t^2}{N}}$$

Where N represents the number of observations used for analysis.

VI TEST RESULTS

i)ANN results or Input load data,

Fig. 6 shows one month hourly load data used as ANN input.

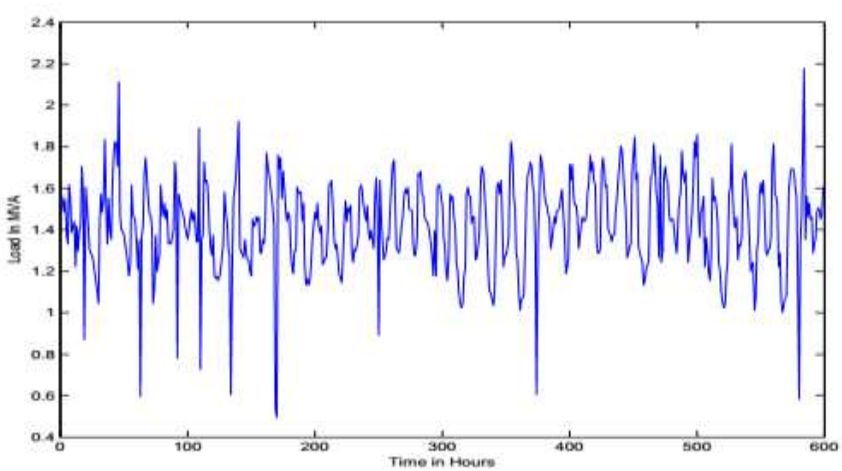

Fig. 6 Input Load Data

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ii)ANN output or predicted load

Day ahead prediction of DECEMBER month load is shown in Fig. 7. Five days load data is used as training data for ANN.

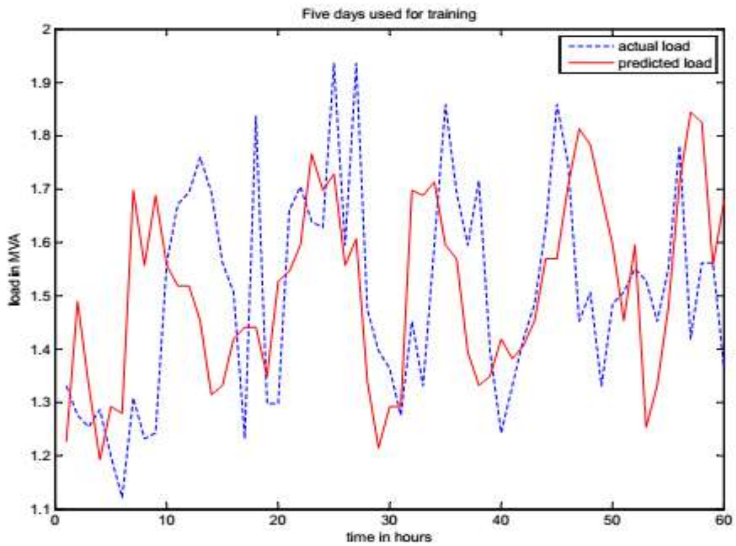

Fig.7 ANN Predicted Load

iii)Best Training Performance for ANN

Fig. 8 shows the performance of ANN Technique. The RMSE for ANN technique is 6.342%.

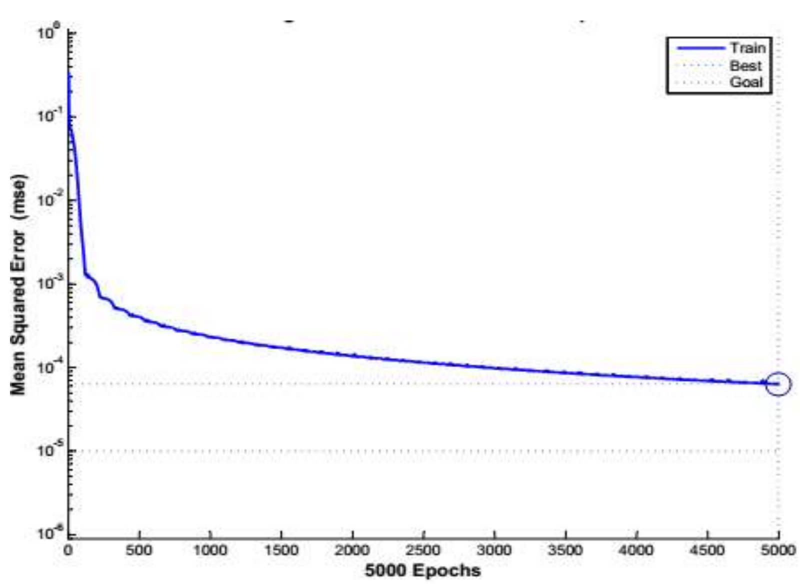

Fig.8 Performance of ANN

NEURAL-WAVELET RESULTS

i) Wavelet decomposition of input load

Fig. 9 shows the decomposition of input load data using Db3 and removes non-linearity or spikes from raw signal.

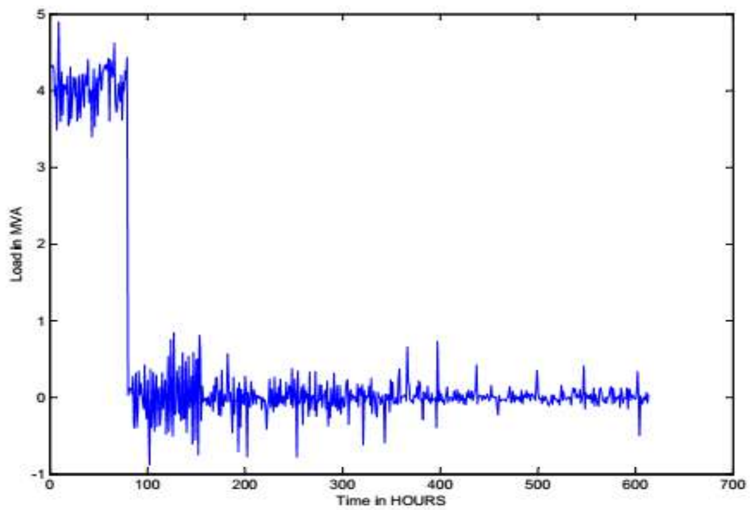

Fig. 9 Wavelet Decomposition

ii) Wavelet Reconstruction or ANN input

Fig. 10 shows the reconstruction process of decomposed data and original signal achieved without losing any information from signal.

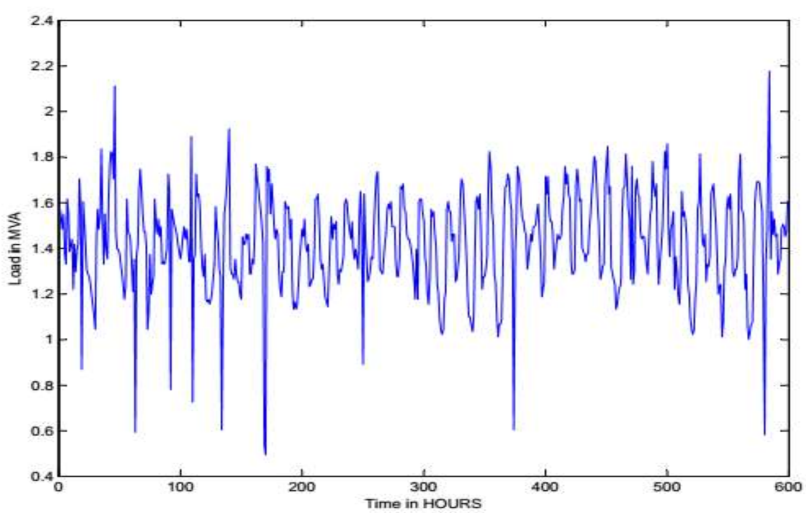

Fig.10 Wavelet Reconstruction

iii) Neural-Wavelet output or predicted load data

In this step, Wavelet reconstructs data used as input data for ANN. Predicted data and actual data of Neural-Wavelet technique is shown in Fig. 11

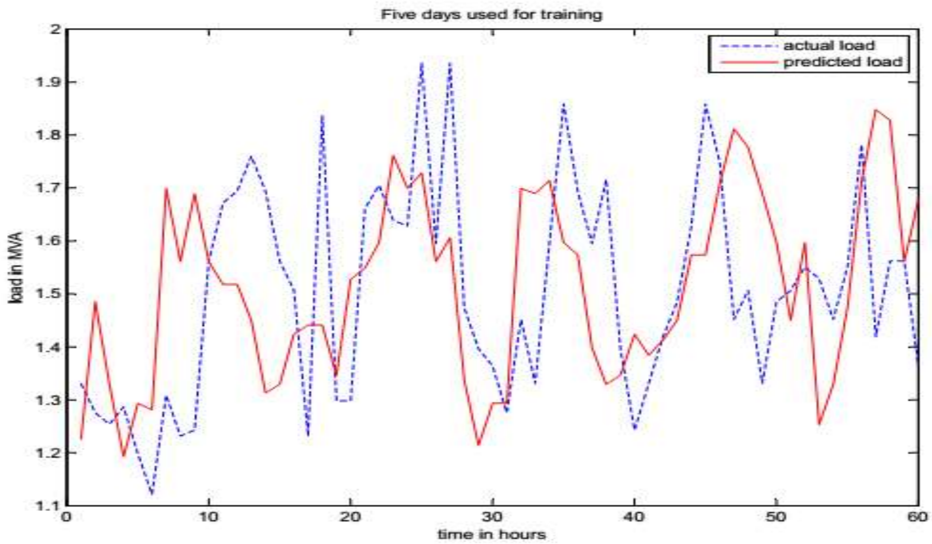

Fig. 11 Neural Wavelet Predicted Load Data

iv) Performance of Neural-Wavelet

Fig. 12 shows Neural-Wavelet performance and minimum RMSE (5.01%) is found in comparison to ANN technique.

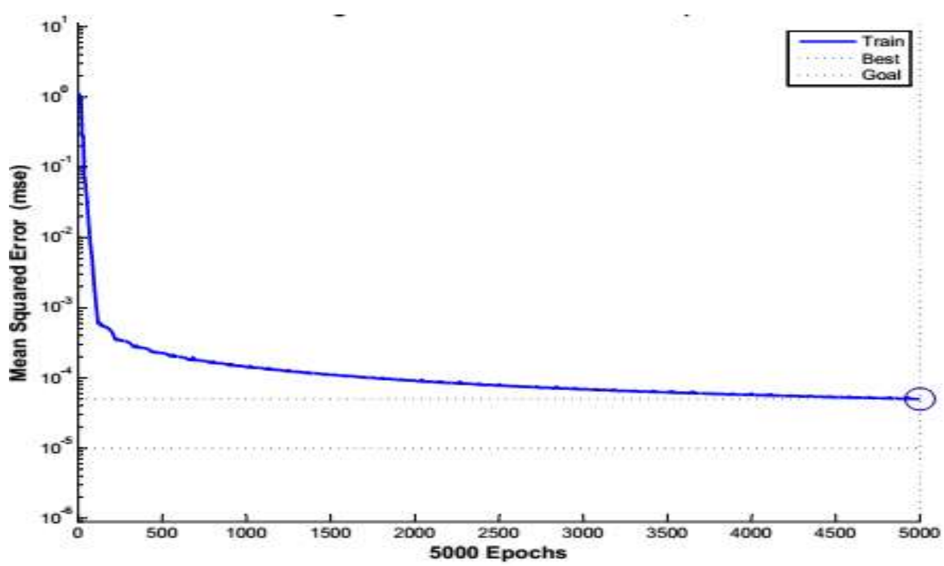

Fig. 12 Performance of Neural Wavelet

Table 1: COMPARISON OF Percentage ERROR

Error (in percentage)	Artificial neural network	Neural Wavelet or Hybrid Method
Root Mean Squared Error (RMSE)	**6.34%**	**5.01%**

Root Mean squared error is minimum incase of Wavelet Neural Method.

VII CONCLUSION

Fig. 8 and Fig. 12 shows the performance of the two technique – ANN and Neural-Wavelet, that indicates the superiority of proposed Neural-Wavelet approach or hybrid method over non-wavelet methods (ANN). It shows that the use of pre-processed data through wavelet technique not only improves the performance of the forecasting models but at the same time takes lesser time for training. By use of Hybrid methods errors are possibly reduced or minimum error (5.01%) is obtained as compared to non wavelet approach (6.34%).

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