Wind Speed Prediction Using Wavelet transform and Artificial Neural Network

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Abstract **-** In last two decades, machine learning models have drawn attention and have established themselves as serious contenders to classical statistical models in the forecasting community. Accurate wind speed forecasting, i.e., an estimate of the expected production of one or more wind turbines in the near future can relieve the pressure of peaking power system by improving the ability to include wind power in the grid. In this paper, prediction of wind speed has been made by using a hybrid model using a back propagation trained ANN and wavelet transform. The wind speed data has been collected from the official site of national renewable Energy Laboratory (NREL) & the performance of the model is evaluated on the basis of statistical indicators such as RMSE (Root mean square error) and MAE (mean absolute error).

Keywords **-** Wind speed prediction, Wavelet transform, Artificial neural network (ANN), Numerical weather prediction (NWP).

I. INTRODUCTION

Wind power generation is the fastest growing energy conversion system since last few decades, mainly, due to the growing concerns about global warming, financial incentives from governments and advancement in power electronic design and manufacturing. With the increasing involvement of wind power in the rising power system, an accurate prediction method of wind power is very much essential for the system operator, to include wind generation into economic scheduling, unit commitment and reserve allocation problem. The prediction also helps the wind power producer to increase their benefits by bidding in the electricity market. An accurate tool for wind power prediction is useful to reduce the undesirable effect in the growing wind power. In pool-based electricity markets, a short term wind prediction tool is essential for a wind power producer to participate in day-ahead adjustments and balancing market. For many wind energy applications, it is necessary to predict the energy data from available meteorological data. Overall efforts by various researchers for wind power prediction can be divided into three main categories depending on the model used as described in the following sub-sections:

A) Physical Models

This method is based on the (NWP) numerical weather prediction using weather forecast data like surface roughness, temperature, pressure etc. This method is used for long term prediction. The NWP system usually provides wind speed forecasts for a grid of surrounding point around the wind generator. According to the type of NWP system, these forecasts are given with a spatial resolution. Many researchers have used these models for wind power/speed prediction [1-5], however collecting information of terrain condition is one of the main difficulties in the implementation.

B) Statistical Models

The aim of statistical methods is to find the relationship of on-line measured power data. For this purpose, historical data of the wind energy conversion system (WECS) may be used [6]. In comparison to other models, the statistical models are easy to model, cheaper to develop and good for short term prediction. Many researchers have used some of these models for the purpose of wind power/speed prediction, e.g., Autoregressive (AR) model [7,8], Autoregressive conditionally heteroscedastic (ARCH) model [9], Auto regressive moving average (ARMA) method [10,11], vector auto regression (VAR) models [10], Autoregressive integrated moving average (ARIMA) model [12], Persistence method [13, 14], etc.

C) Hybrid Models

The main aim of hybrid models is to get benefit from the advantages of each model and obtain a globally optimal forecasting performance [15]. Since the information contained in the individual forecasting method is limited, hybrid method is able to maximize the available information, integrate individual model information and make the best use of the advantages of multiple forecasting methods thus improving the prediction accuracy [16-29].

Many classical models have been proposed in literature for improving the accuracy and efficiency of wind prediction. But, intelligent models like artificial neural networks (ANNs) can have superior features over conventional methods in forecasting as they perform well even with an incomplete data due to their capability of generalization [30-31]. In this work, an artificial neural network is trained for forecasting of wind speed by using Levenberg-Marquardt optimization (generally the quickest backpropagation learning algorithm in the MATLAB toolbox). Wind speed data has been collected from the official site of national renewable Energy Laboratory (NREL) [6], for a period from July 2015 to June 2016. Method of wavelet decomposition is used to generate the training data for ANN. To evaluate prediction accuracy, two performance measures, viz. MAE (mean absolute error) and RMSE (root mean square error) have been used.

Rest of the paper is organized as follows: An introduction to the artificial neural networks and wavelet analysis has been given in sections II and III respectively. Overall prediction algorithm is explained in section IV. Section V gives the simulation results followed by conclusion and list of references.

II. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network (ANN) is an interconnected assembly of simple processing elements, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to (or learning from) a set of training patterns. An ANN has three types of layers as shown in Fig. 1.

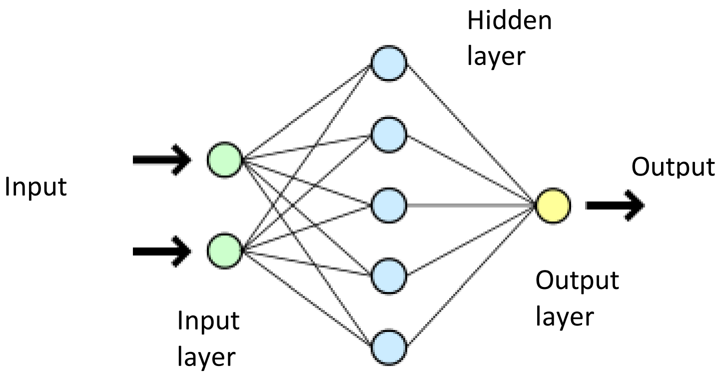
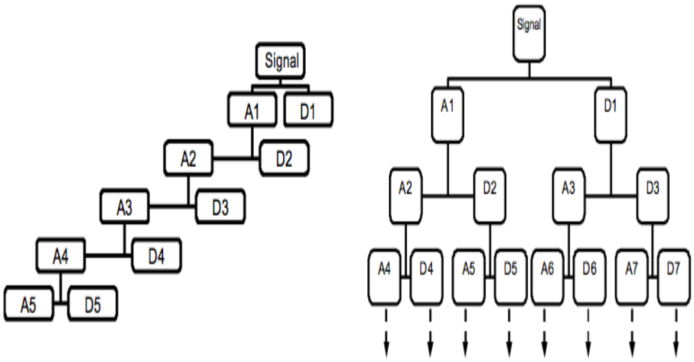


Fig. 1. Structure of ANN

In this work, method of back propagation is used in which the gradient of the loss function is calculated with respect to the weights in an artificial neural network. The optimization algorithm repeats two phase cycle, i.e., propagation and weight update. When an input vector is presented to the network, it is propagated forward through the network, layer by layer, until it reaches the output layer. The output of the network is then compared to the desired output, using a loss function, and an error value is calculated for each of the neurons in the output layer. The error values are then propagated backwards, starting from the output, until each neuron has an associated error value which roughly represents its contribution to the original output. Back propagation uses these error values to calculate the gradient of the loss function. In the second phase, this gradient is fed to the optimization method, which in turn uses it to update the weights, in an attempt to minimize the loss function. The importance of this process is that, as the network is trained, the neurons in the intermediate layers organize themselves in such a way that the different neurons learn to recognize different characteristics of the total input space [30-31].

III. WAVELET ANALYSIS

Wavelet analysis is similar to Fourier analysis in the sense that it breaks a signal down into its constituent parts for analysis. Whereas the Fourier transform breaks the signal into a series of sine waves of different frequencies, the wavelet transform breaks the signal into its "wavelets", scaled and shifted versions of the "mother wavelet". Discrete wavelet transform (DWT) provides a sparse representation for many natural signals. In other words, the important features of many natural signals are captured by a subset of DWT coefficients that is typically much smaller than the original signal. This "compresses" the signal. With the DWT, one ends up with the same number of coefficients as the original signal, but many of the coefficients may be close to zero in value. As a result, one can often throw away those coefficients and still maintain a high-quality signal approximation. Wavelet packet decomposition is similar to the DWT (wavelet tree decomposition). Here, in addition to the decomposition of the wavelet approximation component at each level, the wavelet detail component is also decomposed to obtain its own approximation and detail components as shown in Fig. 2. Wavelet packet analysis provides better control of frequency resolution for the decomposition of the signal in contrast with DWT.



(a) (b)

Fig. 2. Wavelet tree(a) and wavelet packet decomposition(b)

IV. IMPLEMENTATION OF WIND FORECASTING SCHEME USING BP TRAINED ANN

The steps used for the the implementation of forecasting scheme are as follows:

A. <u>Step: 1 wind speed data series</u>

The wind speed data has been collected from the official site of national renewable Energy Laboratory (NREL) [6], for a period from July 2015 to June 2016. Thus, hourly data series consists of 8759 entries.

B. <u>Step: 2 Normalization</u>

The input and output data for the neural network may have different ranges if actual yearly data is directly used. This may cause convergence problem during the learning process. To avoid such problem, the input and output data are scaled by using eqns. 1-3 such that they remain within the range of (0.1-0.9). The lower limit is 0.1, so that during testing it could not go far beyond lower extreme limit, which is 0. Similarly, the upper limit is taken as 0.9, so that the data could go up to upper extreme limit, which is 1.0, in testing. These margins of 0.1 on both sides are called safe margins.

xmax=max(x) (1)
xmin=min(x) (2)
x=(x(ii))/xmax (3)

Where, x = the actual data, ii = length of wind series, xmax= maximum value of wind series, xmin=minimum value of wind series.

C. **Step: 3Auto Correlation Function(ACF)**

ACF is one of the tools to find pattern in the data. Specifically the ACF tells the correlation between points separated by various time lags. The ACF of a sample wind series over 500 lag hours is calculated to check daily, weekly, & seasonal pattern available in wind series, which make it difficult to identify any inputs for the forecasting model.

D. **Step: 4 Wavelet Decomposition**

Wavelet decomposition use wavelet scales to turn the current layer into a set of layers with each holding a different type of pattern that is visible within the image. In present work, seventh level decomposition of the wind series is performed using db4 wavelet. Decomposed signal has two levels of frequency i.e. low level and high level. The low levels are approximation signals and high levels are detailed signals.

E. **Step:5 Auto Correlation Function of Decomposed Signals**

Auto correlation function of each detailed signal (D1, D2……, D7) and approximation signal (A7) is calculated & is checked for some pattern.

F. **Step: 6 Selections of Input Variables**

The selection of input variables depends upon the auto correlation function of decomposed signals. In case, it is symmetrical with respect to x-axis, then the training data for ANN is generated by using step 6 & step 7. Input lag hours for each decomposed signal are selected by taking highly positive and negative correlation terms of first 3-4 cycles.

G. **Step: 7 Decomposed Signals training By Neural Network**

The Neural Network Toolbox software uses the network object to store all of the information that defines neural network. After a neural network has been created, it needs to be configured and then trained. Configuration involves arranging the network so that it is compatible with the problem we want to solve, as defined by sample data. After the network has been configured, the adjustable network parameters (called weights and biases) need to be tuned, so that the network performance is optimized. This tuning process is referred to as training the network. Once the network weights and biases are initialized, the network is ready for training. The multilayer feed-forward network can be trained for function approximation (nonlinear regression) or pattern recognition. The training process requires a set of examples of proper network behavior. In incremental training the weights and biases of the network are updated each time an input is presented to the network.

In batch training the weights and biases are only updated after all the inputs are presented. The batch training methods are generally more efficient in the MATLAB environment, and they are emphasized in the Neural Network Toolbox software, but there some applications where incremental training can be useful, so that paradigm is implemented as well. Using Levenberg back propagation learning algorithm, the neural network is trained.

H. **Step:8 Composition of Signals**

All the normalized signals are composed together to determine the overall predicted wind speed series.

I. **Step: 9 Error Calculation & Comparisons of Predicted and Actual Wind Series**

The measures of errors used in this work are mean absolute error (MAE) and root mean square error (RMSE), which are defined by eqns. 4 & 5 respectively.

$$MAE(k) = 1/N(\sum_{t=1}^{N} |e(t+k\ |t)\ |) \quad (4)$$

$$RMSE(K) = [1/N(\sum_{t=1}^{N} e^2(t+k\ |\ t))]^{0.5} \quad (5)$$

The predicted denormalised series is compared to the actual wind series on the basis of these error measures.

V. SIMULATION RESULTS

The implementation and simulation results from the proposed prediction models are as follows:

Step 1: Wind Speed Data Series

The real data of wind speed is collected from official site of NREL[6]. The chosen time period from 1 July 2015 to 30 June 2016. The data is analyzed in MATLAB16 software by using an hp laptop with Intel core i5 processor. Graph of wind speed data against time is given in Fig. 3. After normalization of data, the graph of wind data against time is represented in Fig. 4.

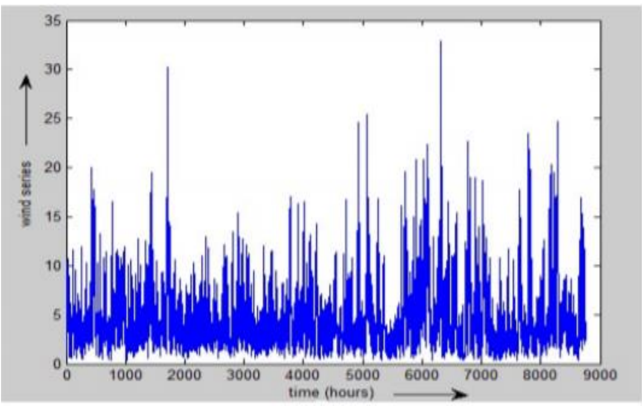


Fig. 3. Wind speed data series

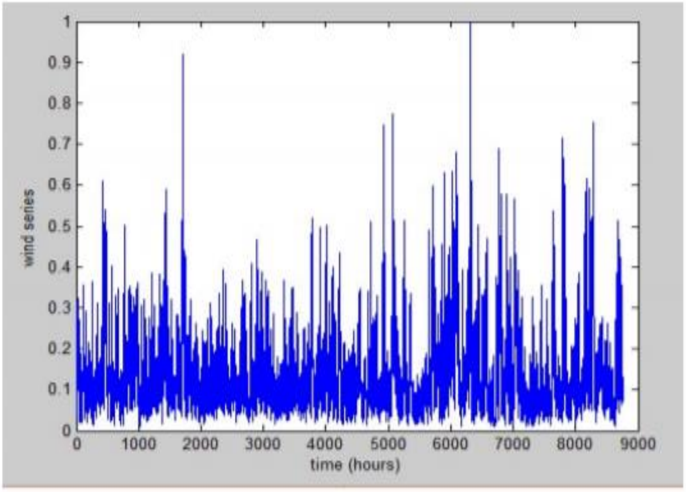


Fig. 4. Normalized wind speed data series

A. Step 2: Auto Correlation function

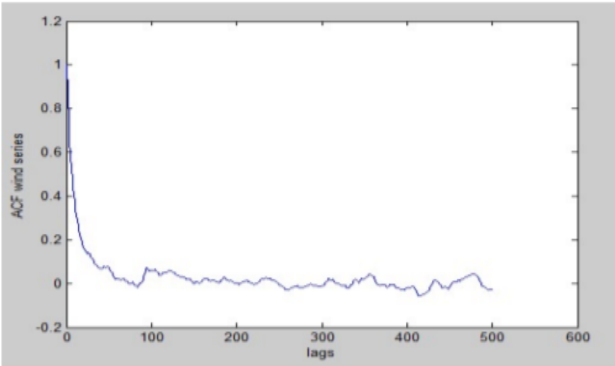


Fig. 5. Auto Correlation Function

Fig. 5 shows the auto correlation function of wind time series against no. of lags. It is clear that this curve is not symmetrical hence wind series data is not predictable directly.

Step 2: Wavelet Decomposition

For the purpose of prediction, normalized wind data is decomposed by using wavelet tool box of MATLAB. Using db4 wavelet, various detailed (D1, D2, D3……, D7) and approximation signal (A1, A2, A3……., A7) component so obtained are shown in Fig. 6.

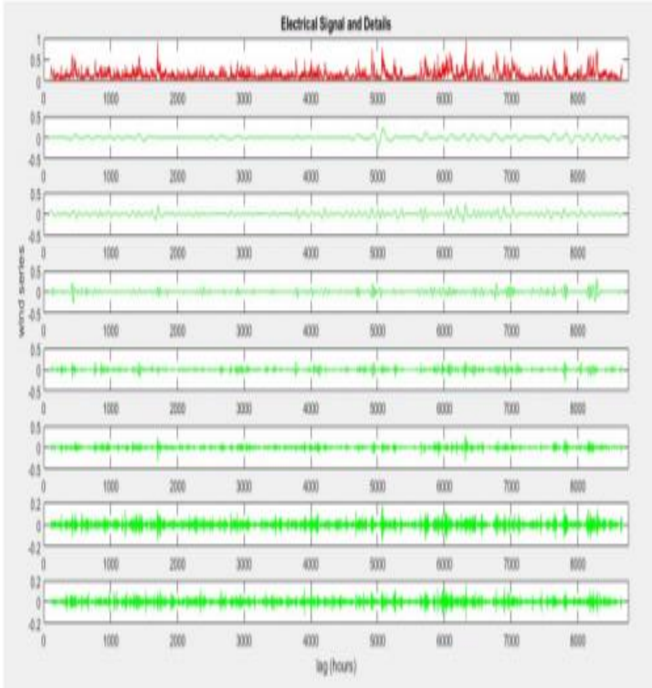


Fig. 6. Decomposition of Detailed and Smooth Signal.

Step 3: Auto Correlation function of Decomposed signals

Fig. 7 shows the auto correlation function of detailed signal against no. of lags. It is clear that these curves are symmetrical hence each decomposed signal is predictable.

Step 4: selection of input variables

Table 1 gives the input lag hours selected for each decomposed signal which corresponds to the highly positive and negative correlation terms of first 3 – 4 cycles. From these inputs, 1 hour ahead predictions are made.

TABLE 1

INPUT VARIABLE SELECTED FOR DIFFERENT FORECASTING MODELS

Input Series	(lag hours)	Architecture (FFNN)
A7	1-3, 185-200, 282-285	15 – 2 – 1
D7	1, 2, 73-76, 171-177	13 – 2 – 1
D6	1, 40-44, 100-104	11 – 2 – 1
D5	1-6, 20-22, 48-52	13 – 2 – 1
D4	1-3, 11, 12, 25-27, 38-39	11 -2 – 1
D3	1, 6, 14, 21-22, 31-33,4,49	7- 2 – 1
D2	1, 4, 7, 11	4 – 5- 1
D1	1, 2, 4, 6	4- 2- 1

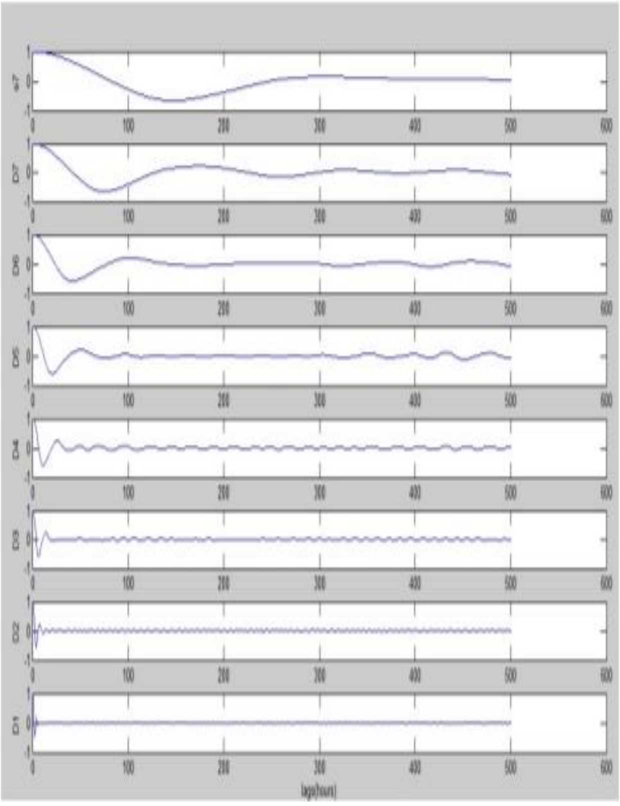


Fig. 7. Auto correlation function of detailed signal against no. of lags.

Step 5: decomposed signal training by neural network

For the purpose of prediction(1 hour ahead) of these eight decomposed signals, eight neural networks are used. As an example, for forecasting of D1, four lag inputs are used as shown in TABLE 1. The network has four input nodes, two neurons in the hidden layer and one neuron in the output layer. Training data for this component is generated by using first 1000 samples of data. The network is trained by using LM back propagation learning algorithm. Mean squared error is chosen to be the performance criteria. Other training parameters are given in TABLE 2.

TABLE 2
TRAINING PARAMETERS

Parameters	Range
Show	50
Learning rate (lr)	0.1
Epochs	3000
Max_fail	500
Mean square error (MSE)	0

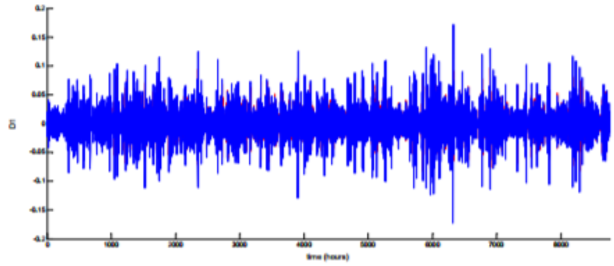


Fig. 8. Prediction of detailed signal D1(Blue)

Fig. 8. shows that the prediction of signal D1 against time in hours (for all values of samples). Fig. 9. shows that the best performance of D1.

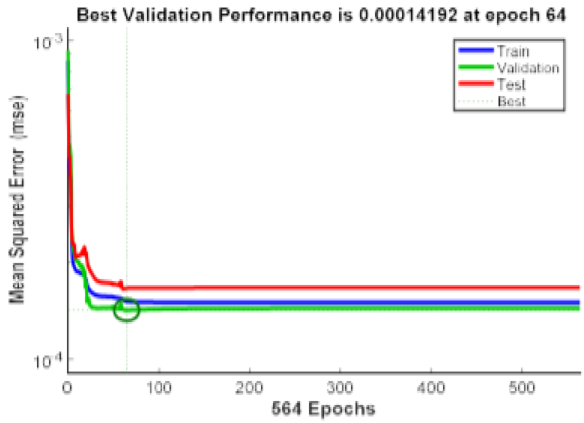


Fig. 9. Best performance of detailed signal D1.

Following the same process, seven other neural networks are constructed to predict seven other components. Figs. 10 – 16 show that the prediction of detailed components D2 to D7 and approximation signal A7 against time in hours (for all values of samples).

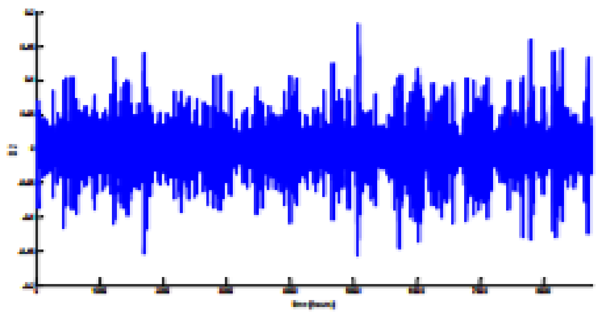


Fig. 10. Prediction of detailed signal D2(Blue)

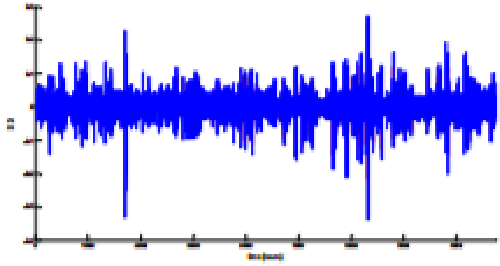


Fig. 11. Prediction of detailed signal D3(Blue) .

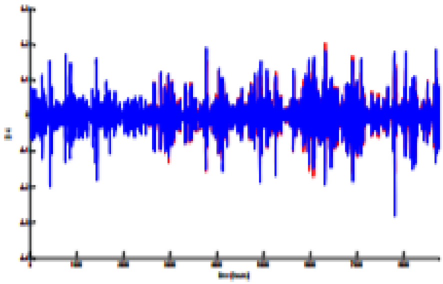


Fig. 12. Prediction of detailed signal D4 (Blue)

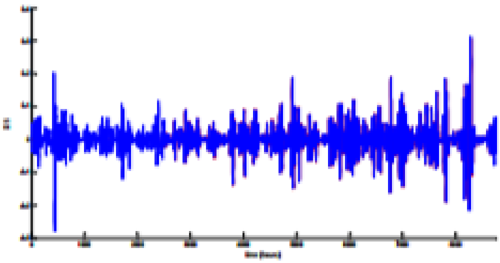


Fig. 13. Prediction of detailed signal D5(Blue)

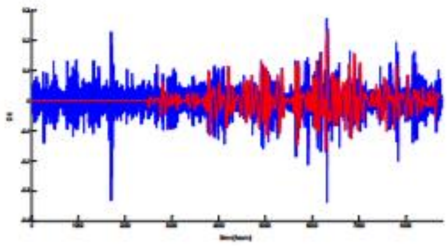


Fig. 14. Prediction of detailed signal D6(Blue)

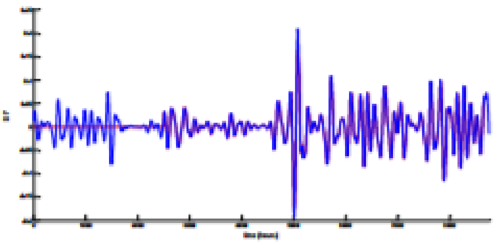


Fig. 15. Prediction of detailed signal D7(Blue)

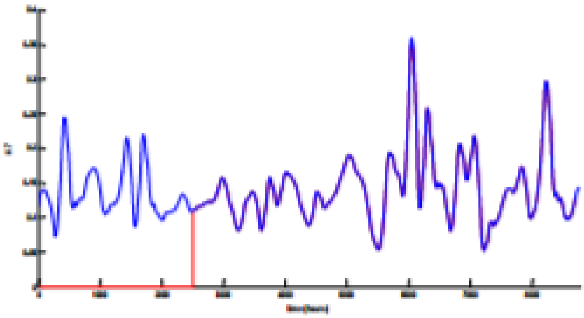


Fig. 16. Prediction of approximation signal A1(Blue)

Step 6: Error Calculation:

Accuracy of prediction is quantified in terms of two error measures, i.e., MAE, RMSE) The corresponding errors of these samples are given in TABLE 3.

TABLE 3
ERROR CALCULATION

Decomposed signal	MAE	RMSE
D1	0.142	0.0200
D2	0.0190	0.0259
D3	0.0254	0.0135
D4	0.0262	0.0400
D5	0.0306	0.0475
D6	0.0265	0.0360
D7	0.0150	0.0134
A7	0.0138	0.1434

Step 7: Composed detailed signal:

After prediction of each decomposed signal, final predicted wind speed data, 'Y' is obtained by composition of these detail (D1, D2,….,D7) and approximation signal (A7) by use of eqn. 6.

$$Y=D1+D2+D3+D4+D5+D6+D7+A7 \qquad (6)$$

Step 8: comparison of actual and predicted wind speed

Prediction accuracy is quantized in term of two error measures i.e. mean absolute error (MAE) and root mean square error (RMSE). Prediction by using ANN is given in Fig. 17. The corresponding errors from this prediction are given in TABLE 4.

TABLE 4

Prediction Errors from ANN

S.No	Performance measure	ANN
1	MAE	0.1217
2	RMSE	0.1576

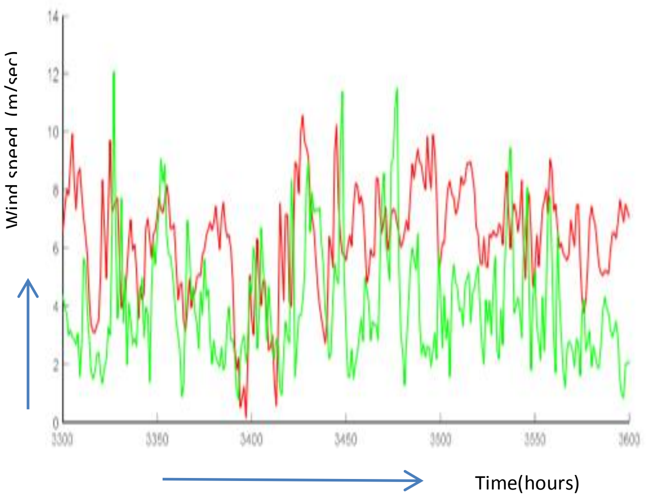


Fig. 17. Predicted wind speed series (red), Actual time series (green)

VI. CONCLUSION

Low values of performance (error) measures i.e. mean absolute error (MAE) and root mean square error (RMSE) indicate that the proposed scheme can be effectively used for short time prediction of wind speed, i.e., one hour ahead prediction. In future, this task can be done with the help of other intelligent technique like particle swarm optimization algorithm, Fuzzy logic controller, ANFIS etc.

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