Wind Speed forecasting using emperical mode decomposition with ANN and ARIMA models

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***Abstract*—Wind power generation directly depends on wind speed. Wind Speed forecasting is important for unit commitment, economic load dispatch planning, turbine active control and optimal planning for wind farms maintenance. In this paper 30 wind speed samples has been forecasted by Empirical Mode Decomposition (EMD) using Artificial Neural Network(ANN) and Auto Regressive Integrated Moving Average Model (ARIMA). The EMD decomposes the wind speed data into Intrinsic Mode Functions (IMF) and a residue. Non-linear IMFs are given to ANN and linear IMFs and a residue are given to ARIMA model. The result obtained by proposed method has given less mean absolute percentage error (MAPE).wind speed data is collected from National Renewable Energy Laboratory (NREL) website for the year 2014 at site 7263 in the Midwest ISO region is taken for analysis.**

Keywords—forecasting; wind speed;auto regressive integrated movingaverage(ARIMA);empericalmodedecomposition(EMD);artificial neural network(ANN);intrensic mode function(IMF).

I. Introduction

Wind energy sources are abundant in nature and they produce clean energy. Power system instability problem occurs when wind energy sources are connected to the power grid due to its intermittent nature. Therefore, accurate forecasting of wind energy sources are important for wind energy integration into the grid. Wind power output is direct function of cube of wind speed. Accurate wind speed forecasting is important for unit commitment, economic dispatch planning, turbine active control and optimal planning of wind farms maintenance.

Wind speed forecasting may be considered in different time scales based on its application. Wind speed forecasted for milliseconds to a few minutes ahead can be used for turbine active control and it is usually referred to as very short term forecasting, 48-72 hours ahead forecasting can be used for unit commitment and economic dispatch planning and it is usually referred as short term forecasting. 5-7 days ahead forecasting can be used for optimal planning of wind farms maintenance.

Many forecasting models have been developed in past two decades. Physical models like Numerical weather prediction (NWP) [4-6] uses meteorological data for future prediction with the help of mathematical model. Modeling of numerical weather prediction is difficult. But, long term forecasting accuracy of this model is quite good. Statistical methods like multi regressions, exponential smoothing, and auto regressive integrated moving average (ARIMA), Fractional Auto-Regressive Integrated Moving Average (FARIMA), Seasonal Auto-Regressive Integrated Moving Average (SARIMA) [7-11] uses past time series data to forecast with the help of mathematical models. These models are good for linear time series data and for short term forecasting. These methods are not suitable for forecasting non-linear time series data. Computational intelligence based methods such as artificial neural network (ANN), adaptive wavelet neural network (AWNN) [1], support vector regression (SVR) could approximate nonlinear time series data accurately. But, for a big network structure, these are constrained by large training time and possibility of getting trapped in local minima. Re-searchers applied methods like, genetic algorithm (GA),particle swarm optimization (PSO) and hybrid GA-PSO to obtain the optimal set of weights with less computational time and global optimality. On the other hand, empirical mode decomposition (EMD) [2-3] and wavelet transforms provide frequency of signals and time associated with those signals, which makes these methods suitable for wind speed forecasting.

II. EMPERICAL MODE DECOMPOSITION

Empirical Mode Decomposition is very much suitable for non-linear and non-stationary signals and it is an efficient method for decomposition of signal. This method is efficient for decomposing wind speed signal, because it is nonlinear and non stationary. EMD decomposes the given signal into series of IMFs and a residue. IMF is a function that should satisfy the following two conditions 1) In the given data, the number of extrema and number of zero crossing points must either be equal or differ at most by one. 2) At any point, mean of upper and lower envelope must be zero.

The EMD procedure is as follows

1) Find out the local maxima and minima points of original data Y(t), interpolate all maxima by cubic line to get upper envelope U(t) and similarly connect all minima by cubic line to get lower envelope L(t).
2) Take mean of upper U(t)and lower envelope L(t), m=(U(t)+L(t))/2.
3) Subtract mean ‘m’ from original data Y(t) to get H(t), H(t)=Y(t)-m.
4) IMF component C1(t) is separated from original data Y(t) and the residual component is obtained as R1(t).

5) Repeat the above steps to get remaining IMFs by taking R1(t) as original data. the results are as follows

$$R1(t) - C2(t) = R2(t)$$

$$R2(t) - C3(t) = R3(t)$$

$$Rn - 1(t) - Cn(t) = Rn(t)$$

6) In this paper, the termination condition of the EMD proposed by Rilling [11] is used, which is the improvement of the limited standard deviation criterion proposed by Huang.

If U(t)and L(t)are the upper and lower envelope respectively, then δ(t) is given by $\delta(t) = \frac{|U(t)+L(t)|}{|U(t)-L(t)|}$

We set three threshold values θ1, θ2 and α, and there are two corresponding termination conditions:

Condition 1): $\frac{s\{t \in D / \delta(t < \theta 2)\}}{s\{t \in D\}} \geq 1-\alpha$

where D is the duration range of the signal, s(A) is the number of the elements in the set A, θ1=0.05, α=0.05.

Condition 2): for every moment there are

$$\delta(t) < \theta 2, \theta 2 = 10 * \theta 1$$

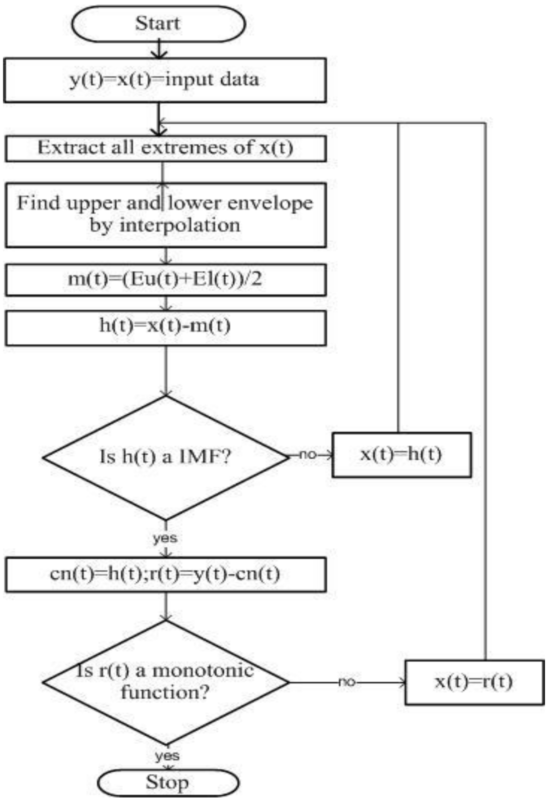


Figure 1 shows the flow chart describing various steps of EMD model.

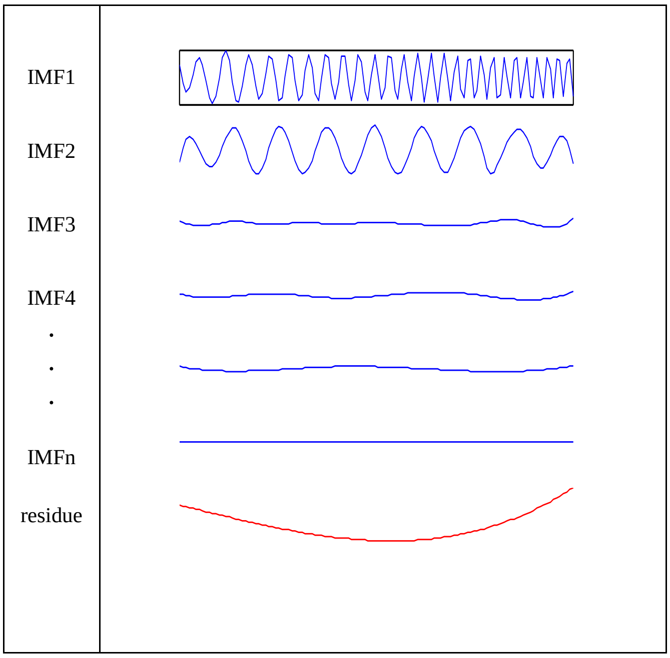


Figure 2 Decomposed signals using EMD

In this paper, EMD decomposes the wind speed signal into IMFs and residue as shown in figure 2. Non-linear IMFs are applied to ANN to forecast wind speed data which is explained in section 3. Linear IMFs and residue are applied to ARIMA to forecast wind data which is explained in section 4. Finally all IMFs and residue forecasted data are combined, Which gives actual forecasted data. Table I and Table II represents the decomposed components of wind speed data and the corresponding model used for forecasting in case study 1 and case study 2

III. Artificial neural network

A. ANN has natural propensity for storing knowledge in the form of weights and making it available for use. BPA is one of the training algorithm of artificial neural networks to train and test the network. BPA starts with random set of weights and transfers information in forward direction, error in backward direction and correspondingly the weights will be updated, This training is carried out until the error reduces to as small value as possible. In this paper, an accuracy of 0.0001 is considered.

Error= (T-O)^2 T=target output O= actual output

ANN is widely used for function approximation and classification. Common structure of ANN is three layer feed forward neural network. ANN has mainly three layers input layer, hidden layer and output layer. BPA requires target output, because the algorithm is based on supervised learning. Mainly BPA training has three stages, namely feed forward stage, back propagation of the error, and weights updating stage. In both hidden and output layers, sigmoidal activation function is used. Wji, Wkj are weights between input(i), hidden(j) layers and hidden(j), output(k) layers.

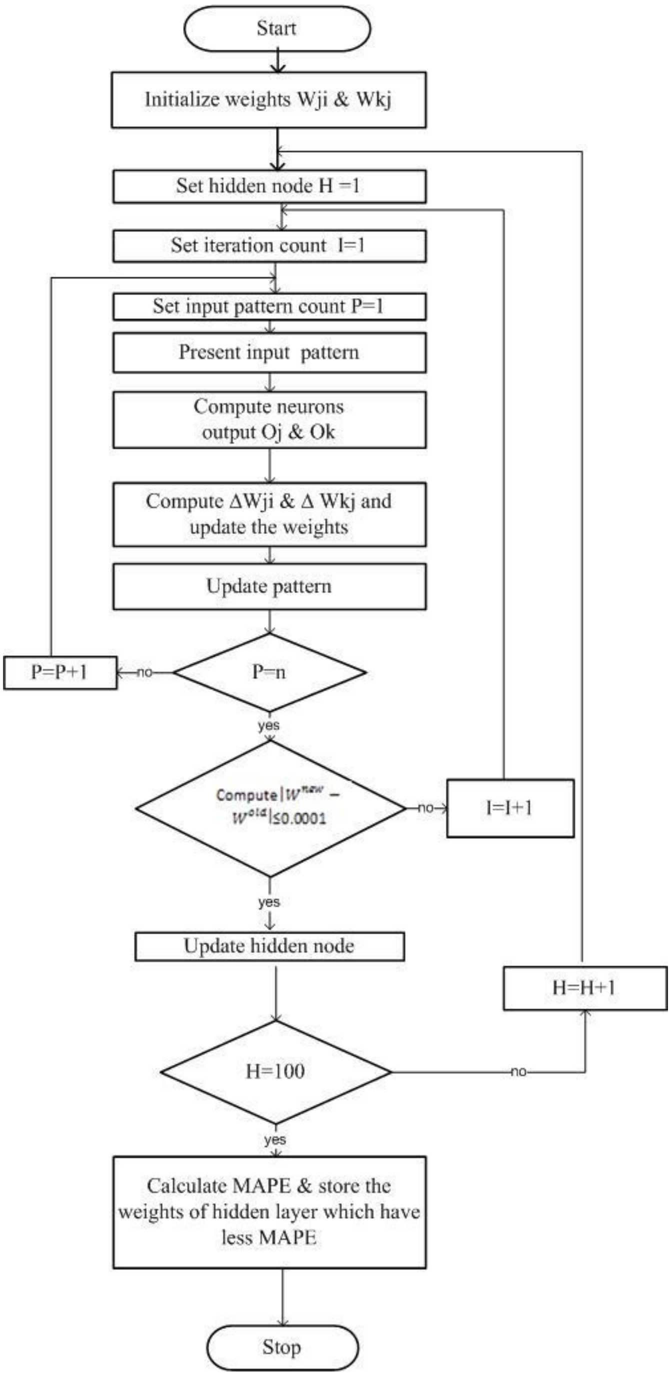


Figure 3 shows the flow chart describing various steps of ANN model.

B. Various steps of ANN is as follows:

1. Normalize the wind speed samples which are selected as input.
2. Randomly initialize the weights [Wji], [Wkj] between input to hidden layer and hidden to output layer respectively.
3. To train the network, 50 wind speed samples are considered for one pattern and likewise 20 patterns have been considered.
4. Sigmoidal activation function is used in both hidden and output layers.
5. For training, 1-50 wind speed samples have been taken as input vector and 51st as target element and error has been calculated and this error is used to update the weights [Wji] and [Wkj].
6. Next 2-51 (here 51st is forecasted wind speed sample in 1st pattern) wind speed samples have been given as input to the network and 52nd wind speed sample is the target.
7. Similarly repeat for next 20 patterns to train the network.
8. Update the number of iterations and repeat until the error is less than or equal to 0.0001.
9. Perform validation check for the data 90-120 for different number of hidden nodes and calculate MAPE for case study 1 and case study 2.
10. The weights at particular number of hidden nodes which give less MAPE are stored in a file and are used for testing.
11. For testing the network inputs are given as 71-120 and 121st signal is forecasted and after that output is used recursively and forecasted upto 150th signal. This way forecasting has been done from 121 to 150 that is total 30 samples in case study 1.For case study 2, 1610-1660 is the input and 1661st is forecasted signal. After that output is used recursively and forecasted upto 1690.

IV. AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL(ARIMA)

A. ARIMA model: ARIMA model known as Box Jenkins model, is a combination of autoregressive (AR), integration(I) and moving average(MA) models. ARIMA model is stated as ARIMA(p,d,q) and this represents the order of the autoregressive terms (p), the number of differencing operators (d), and the order of the moving average terms(q). ARIMA model has mainly three stages that are model identification, parameter estimation and diagnostic checking followed by forecasting.

Model identification: model identification of ARIMA(p,d,q) is nothing but estimation of the values of p,d and q. The value of d is obtained by carrying the number of differences. If the wind speed data is non stationary, then to make it stationary, differencing is done until stationary data is achieved. Differencing once to a wind speed data, means the data has been ‘’first differenced’’ and ‘d’ value is 1. This process is done essentially to remove the trend present in wind speed data. After differencing, if trend is present in data then do one more difference, then data would be ''second differenced'', and 'd' value is 2. 'd' value can also be found by another method augmented dickey-fuller(ADF) test. In this paper, d's value found out based on augmented dickey-fuller (ADF) unit root test. The values of p and q are found based on auto correlation function (ACF) and partial auto correlation function (PACF). If ACFs tails off to 0 and PACFs has some nonzero values at AR terms in the model and zero values elsewhere then the model represents Auto Regressive AR(p). If PACFs tail off to 0 and ACFs have some nonzero values at MA terms in the model and zero values elsewhere then the model represents Moving Average MA(p). If both ACFs and PACFs tail off to 0,then model represents ARMA(p.q) and this model was trickiest because the order will not be particularly known. Basically, one has to guess one or two terms of each type and then find the estimated model.

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots\ldots + \phi_p y_{t-p} + \in_t$$

$$y_t = \theta_1 \in_{t-1} + \theta_2 \in_{t-2} + \ldots\ldots + \theta_p \in_{t-p} + \in_t$$

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots\ldots + \phi_p y_{t-p} + \theta_1 \in_{t-1} + \theta_2 \in_{t-2} + \ldots\ldots + \theta_p \in_{t-p} + \in_t$$

Parameter estimation and diagnostic checking: In this paper, parameters have been estimated based on maximum likelihood method. After estimating the parameters do the following

1) Checkout for significance of the coefficients. For each coefficient calculate Z=estimated coefficient/standard error coefficient. If Z>1.96 the estimated coefficient is significant else coefficient is not significant and remove that term.
2) For a good model, all ACFs for residuals series should be non-significant. If this is not the case, try for another model.

Sometimes more than one model can seem to work for the same dataset. Then following steps be used to decide the models:

1) Choose the model with fewest parameters.
2) Choose the model which has lowest standard errors for prediction of the future.
3) Choose the model which has low values of Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Forecasting: ARIMA model forecasts the values based on its previous values and previous errors and Forecasting has been done with the best suitable model.

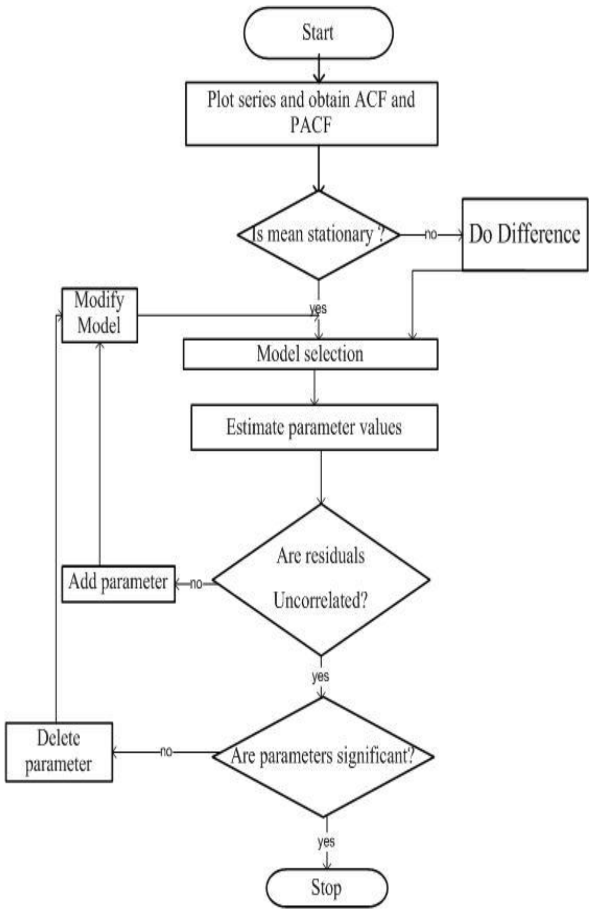


Figure 4 shows the flow chart describing various steps of ARIMA model.

V. RESULTS AND DISCUSSIONS

In this section, the results have been analyzed and compared. The methods are BPA based Artificial Neural Network (ANN), Adaptive Wavelet Neural Network (AWNN), Empirical Model Decomposition (EMD) using ANN, EMD using ANN and ARIMA. In these methods 30 hours ahead wind speed forecasting has been done for case study 1 and case study 2

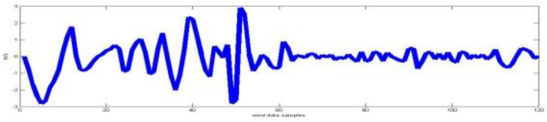
Parameters for BPA:

- Tolerance ($\mathcal{E}$) = 0.0001,
- Momentum coefficient ($\propto$) = 0.05,
- Learning rate (η) = 0.95
- Number of input nodes = 50,
- Maximum number of iterations = 10000.

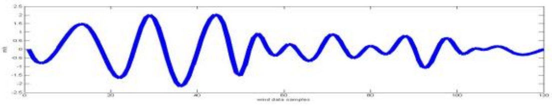
CASE STUDY 1

In this section, Data is used up to 120 samples and forecast has been done for 121-150(30 samples). After applying signal to EMD it decomposes the signal into four IMFs and one residue which we can observe from figure V. First two IMFs have been forecasted by ANN due to more non linear nature in signal and remaining two IMFs and one residue have been forecasted with ARIMA due to less non linearity in signal. Results and errors have been compared in table II&III.

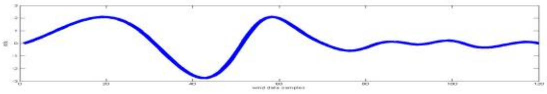
IMF1



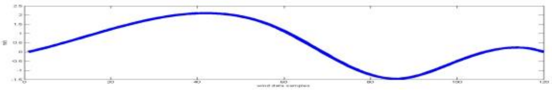
IMF2



IMF3



IMF4



Residue

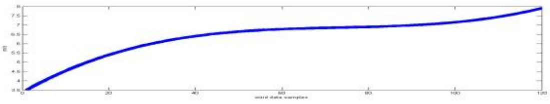


Figure 5 Decomposed signals by EMD

Table I
Application of ANN and ARIMA to decomposed signals

EMD	IMF1	IMF2	IMF3	IMF4	Residue
MODEL	ANN	ANN	ARIMA	ARIMA	ARIMA

Table I

Comparison and Results

S.NO	**WD[1]**	**ANN[1]**	**AWNN[1]**	**EMD ANN**	**EMD ANN ARIMA**
1	7.0110	6.6131	7.4087	7.0598	7.0607
2	7.2873	6.4874	6.9206	7.3294	7.3328
3	7.4658	6.7812	7.3209	7.5083	7.5151
4	7.9883	6.6859	8.1822	7.9015	7.9112
5	7.7893	6.4618	8.1997	8.0705	8.0827
6	8.0975	6.5327	8.3780	8.2952	8.3099
7	8.4141	6.6025	8.5304	8.3715	8.3894
8	8.7466	7.5222	7.9495	8.8484	8.8720
9	8.8940	8.1024	8.4616	8.8484	8.9172
10	8.6585	8.4887	6.5218	8.5107	8.5586
11	8.2191	8.3215	7.9631	8.4115	8.4809
12	8.7643	8.2705	9.1483	8.6782	8.7767
13	9.7380	8.3447	8.9059	9.2090	9.3444
14	9.4075	8.3937	8.7878	9.7091	9.8889
15	9.3118	7.6980	8.8873	9.6967	9.9279
16	9.5955	7.5913	8.8315	9.9078	10.1955
17	10.5816	8.1625	9.9526	9.7474	10.0949
18	11.4038	8.7206	9.8613	9.4371	9.8452
19	11.7030	9.2684	9.9597	9.4468	9.9139
20	12.0218	8.9887	11.8906	9.5377	10.0592
21	12.2175	8.8807	11.3510	10.0091	10.5782
22	12.3300	9.1108	11.8290	10.5471	11.1542
23	12.2646	9.0810	10.8723	10.4302	11.0640
24	11.8018	9.0638	10.8646	10.7410	11.3890
25	11.8845	9.3049	10.6999	10.6034	11.2519
26	11.2417	9.3953	10.3391	10.2172	10.8529
27	10.2478	9.3817	9.7010	9.9924	10.6022
28	9.4651	9.3983	8.2123	10.2811	10.8532
29	10.3000	9.4439	8.1137	10.8512	11.3756
30	10.8408	9.4930	9.7083	11.1219	11.5909

Table II
Comparison of Errors

ERRORS	ANN	AWNN	EMD-ANN	EMD-ANN-ARIMA
MAPE	15.27	7.904	6.412	5.609
MAE	1.577	0.783	0.714	0.606
RMSE	2.645	1.357	1.275	1.020

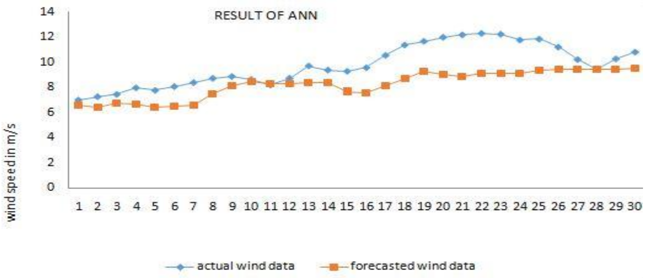


Figure 6 Forecasted wind speed and actual wind speed of ANN

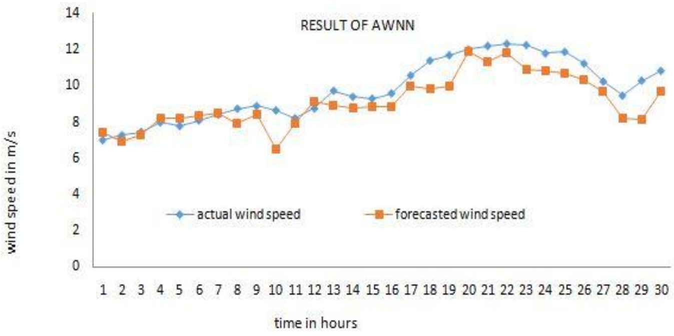


Figure 7 Forecasted wind speed and actual wind speed of AWNN

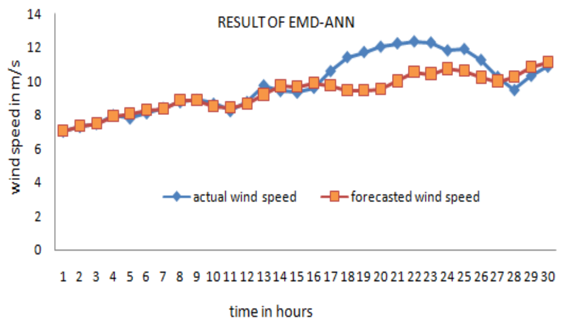


Figure 8 Forecasted wind speed and actual wind speed of EMD-ANN

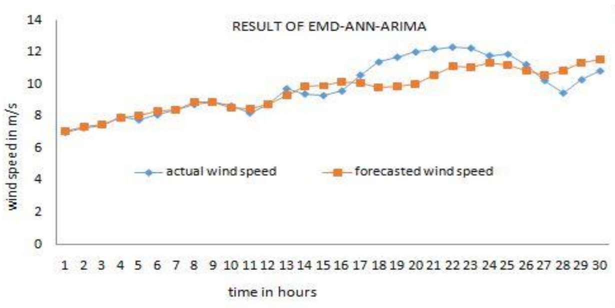


Figure 9 Forecasted wind speed and actual wind speed of EMD-ANN-ARIMA

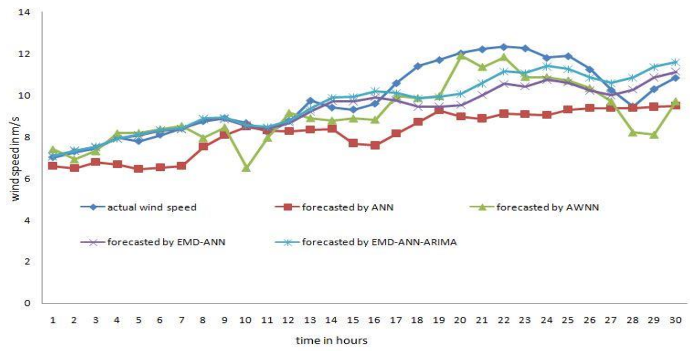
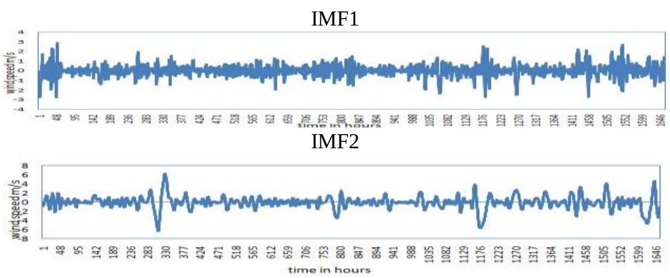


Figure 10 Forecasted wind speed and actual wind speed of ANN, AWNN, EMD-ANN, EMD-ANN-ARIMA

From the Table III, we have been observed that ANN has given MAPE as 15.27%, AWNN has given MAPE as 7.90%, EMD using ANN has given 6.41% and EMD using ANN and ARIMA has given 5.60%. Among the above four models, EMD using ANN and ARIMA model gave less MAPE for wind speed forecasting. From the figure 10, the graph of EMD-ANN-ARIMA model is closer to actual wind speed graph compared to remaining models which were done in this case study. This is because of combination of ANN and ARIMA with EMD which produces low frequency and high frequency intrinsic mode functions and a residue, a residue component has more magnitude compared to IMFs components magnitude which has been forecasted accurately by ARIMA model.

CASE STUDY 2

In this section, Data is used upto1660 samples for ARIMA model, for ANN model 1-50 samples as input vector likewise 20 patterns are used for training, 90-120 samples are used for validation check and forecast has been done for 1661-1690(30 samples). After applying signal to EMD it decomposes the signal into seven IMFs and one residue which we can observe from figure 11. First four IMFs have been forecasted by ANN due to more non linear nature in signal and remaining three IMFs and one residue have been forecasted with ARIMA due to less non linearity in signal and the application of models to corresponding decomposed signal was given in the table IV. Results and errors have been compared in table V&VI.



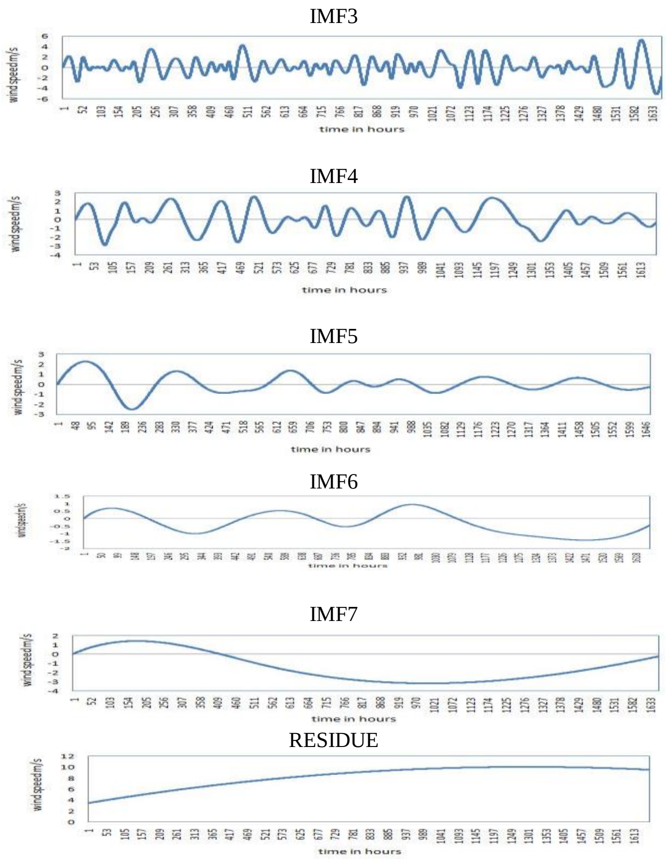


Figure 11 Decomposed signals by EMD

Table IV
Application of ANN and ARIMA to decomposed signals

EMD	IMF1	IMF2	IMF3	IMF4
MODEL	ANN	ANN	ANN	ANN

IMF5	IMF6	IMF7	Residue
ANN	ARIMA	ARIMA	ARIMA

Table III
Comparison and Results

S.NO	**WD[1]**	**ANN**	**EMD ANN**	**EMD ANN ARIMA**
1	7.9263	7.4595	8.2647	7.8746
2	7.9398	7.2002	8.2656	8.3177
3	8.4005	7.6911	7.9553	8.6996
4	8.9546	8.4276	7.4433	9.1060
5	9.4611	7.4844	7.2303	9.5521
6	9.6260	7.0519	7.5258	10.0670
7	10.5443	7.7261	8.3524	10.6044
8	10.9006	8.4233	9.2758	11.0664
9	11.4020	8.7748	10.0598	11.4429
10	11.6103	9.03161	10.8063	11.6973
11	12.0423	9.9448	11.1897	11.8645
12	12.0288	10.9555	11.4009	11.9234
13	11.6498	11.2040	11.3150	11.8430
14	11.1946	11.2399	10.9975	11.7417
15	11.0428	10.7765	11.1088	11.6167
16	11.1283	10.0220	11.1123	11.4729
17	10.8495	9.6599	11.2366	11.2715
18	10.7566	9.15462	10.0324	11.01428
19	11.3361	8.7513	11.3565	10.7658
20	10.7751	8.4519	10.9843	10.5141
21	10.9988	8.1893	10.5905	10.3138
22	11.3256	7.9299	10.1789	10.1692
23	9.6743	7.5334	9.7634	8.8200
24	7.9016	8.1625	9.6978	8.2399
25	9.3985	8.6457	9.7199	10.1733
26	10.3580	8.4398	9.8565	10.3201
27	9.0838	8.5356	8.3567	10.5243
28	8.3408	8.8609	8.4808	10.6570
29	9.1616	9.5164	10.0837	10.7547
30	9.4803	10.2576	9.9210	10.7462

Table IVI
Comparison of Errors

ERRORS	ANN	EMD-ANN	EMD-ANN-ARIMA
MAPE	13.89	7.237	5.429
MAE	1.456	0.713	0.527
RMSE	2.949	2.058	0.890

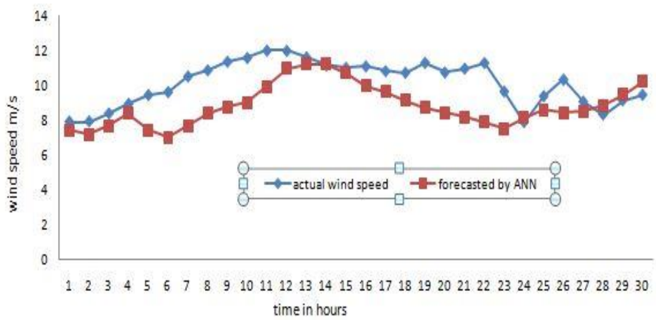


Figure 12 Forecasted wind speed and actual wind speed of ANN

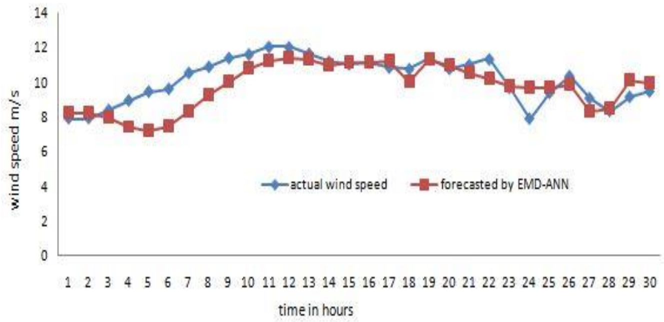


Figure 13 Forecasted wind speed and actual wind speed of EMD-ANN

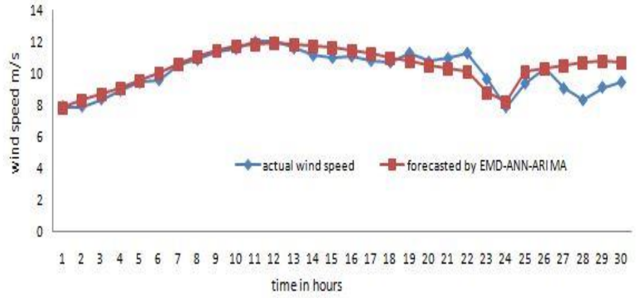


Figure 14 Forecasted wind speed and actual wind speed of EMD-ANN-ARIMA

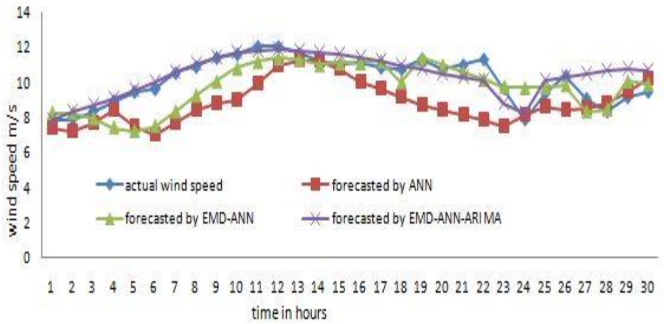


Figure 15 Forecasted wind speed and actual wind speed of ANN, AWNN, EMD-ANN, EMD-ANN-ARIMA

From the Table VI, Forecasting with ANN has given MAPE as 13.89%, EMD using ANN has given 7.237% and EMD using ANN and ARIMA has given 5.429%. Among the above three models, EMD using ANN and ARIMA model gave less MAPE for wind speed forecasting. From the figure 15, the graph of EMD-ANN-ARIMA is closer to actual wind speed graph compared to remaining models which were done in this case study. This is because of combination of ANN and ARIMA with EMD which produces low frequency and high frequency intrinsic mode functions and a residue, a residue component has more magnitude compared to IMFs components magnitude which has been forecasted accurately by ARIMA model.

VI. Conclusion

In this paper, 30 hours ahead wind speed forecasting has been attempted using EMD model. EMD decomposes the data into IMFs and residue. Non-linear (high frequency) IMFs are forecasted using ANN model. In ANN, Hidden node which has least MAPE has been considered for training and testing. Linear (low frequency) IMFs are forecasted using ARIMA model. ARIMA is applied for low frequency IMFs and a residue which were forecasted accurately compared to ANN. so, compared to ANN, AWNN and EMD-ANN, EMD-ANN-ARIMA model gave less MAPE which is better than the other methods

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