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Ensemble empirical mode decomposition based adaptive wavelet neural network method for wind speed prediction

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ABSTRACT

Wind energy is one of the emerging sustainable sources of electricity. Wind is intermittent in nature. The typical grid operation of wind energy is complex. The significance of wind energy generation and integration with the grid is increasing day by day. An accurate wind speed forecasting method will help the utility planners and operators to meet the balance of supply and demand by generating wind energy. In this paper, a statistical-based wind speed prediction is implemented without utilizing the numerical weather prediction inputs. This analytical study proposes a hybrid short-term prediction approach that can successfully preprocess the original wind speed data to enhance the forecasting accuracy. The most efficient signal decomposition algorithm, Ensemble Empirical Mode Decomposition is used for preprocessing. This ensemble empirical mode decomposition technique decomposes the original wind speed data. Each decomposed signal is regressed to forecast the future wind speed value by utilizing the Adaptive Wavelet Neural Network model. The proposed hybrid approach is subsequently investigated with respect to the wind farm of South India. The results from a real-world case study in India are reported along with comprehensive comparison. The prediction performance delivered high accuracy, less uncertainty and low computational burden in the forecasts attained. The developed hybrid model outperforms the six other benchmark models such as persistence method, back propagation neural network, radial basis function neural network, Elman neural network, Gaussian regression neural network, and wavelet neural network.

1. Introduction

Renewable sources must play a vital part in reaching the goals set by Paris agreement in December 2015. And the year 2016 was one of the best years for wind energy production field. In this year, global wind power industry installed 54.6 GW with 12.6% growth in cumulative capacity. As per the Global Wind Energy Council (GWEC) report, the new worldwide total wind installed capacity was 486.8 GW by the end of 2016 [1]. Distributed energy resources (DER) technologies are helpful in reduction in greenhouse gas emissions, reduction in damages to human health, and conservation of resources [2]. And the large-scale grid integration of renewable energy sources like wind and solar imposes challenges to the electric power utility industry in terms of technical and economical point of view [3]. In order to address these challenges, an accurate and reliable forecasting is regarded as one of the best ways. This accurate wind speed prediction is useful for bundled generation and transmission expansion planning under wind generation and demand uncertainties[4]. While considering the non-linear features of the generator such as prohibited operating zone and non-smooth functions, an accurate prediction of wind speed is essential for optimal economic load dispatch planning in power systems [5]. It is very significant to determine the proper uncertainty level of the wind forecast for operational security in the day-ahead electricity market [6]. For effective unit commitment decisions with wind energy integration is possible only by optimizing the utilization of the forecast error and reserve decision [7]. Further, spatio-temporal forecasting approaches are useful for regulation actions, and maintenance scheduling for acquiring optimal operating cost [8].

Presently, many researchers and utilities have zeal for wind speed prediction investigations. These wind speed forecasting techniques are classified into three types as follows: physical approach, statistical approach, and hybrid approach [9]. Physical approach utilizes the historical data obtained from weather stations such as power and Numerical Weather Predictions (NWP). It is suitable for long-term predictions as modeling of these are complex. Statistical approach such as autoregressive moving average (ARMA) model, variants of ARMA [10] and artificial neural network (ANN) models will employ historical time-series data for modeling and forecasting the future values. These

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approaches are most accurate for short-term forecasting. And hybrid approaches are combinations of two or more of the forecasting approaches [11].

The fast growth in artificial intelligence techniques has been promoting ANN models [12]. These ANN models have been extensively used in wind speed time-series prediction due to their capability to deal with non-linearities, predominantly including back propagation neural network (BPNN) [13]. Further, the learning ability of the neural network and fuzzy system's expert knowledge is utilized for accurate forecasting using fuzzy neural network (FNN) [14]. The neural networks require a number of neurons to tackle the various problems [15]. To overcome this problem, wavelets are incorporated into them [16]. Currently, hybrid approaches such as wavelet neural networks (WNN) that combines the wavelet transforms (WT) and artificial neural networks (ANN) have drawn a lot of attention and have been extensively employed for wind speed forecasting [17]. The principal difficulty of WNN is that of the selection of wavelet transforms [18]. The translation and dilation parameters of the wavelet basis are fixed and only weights are adjustable during the training of WNN [19]. But with proper selection of wavelet transforms one can improve the forecasting accuracy and computational complexity [20]. Many other hybrid approaches have been implemented to address these problems of WNN. In [21], a hybrid approach which combines the wavelet transform (WT), radial basis function (RBF), multi layer perceptron (MLP) neural networks and imperialist competitive algorithm (ICA) for wind power production forecasting. An RBF network has been utilized for primary prediction with different learning algorithms are used for optimizing three MLP networks. The ICA was employed to optimize the weights and biases of the three MLP networks. The main demerit of this approach is that the ICA has the problem of convergence to a local minima that affects training accuracy and speed. For another case study, optimization algorithm like improved clonal selection algorithm is utilized with wavelet neural networks for future 6-h ahead wind power forecasting [22]. The problem with this is that improved clonal selection algorithm has low accuracy and slow convergence rate. Further, a hybrid model consists of singular spectrum analysis and general regression neural network with CG-BA (SSA-CG-BA-GRNN) employed to acquire 1-h and 3-h ahead forecasting [23]. Furthermore, a hybrid approach as reported in [24] is the combination of kalman Filter (KF), artificial Neural Network (ANN) and autoregressive integrated moving average (ARIMA) model. This model can effectively handle nonlinearity and uncertainty problems. The MAPE values of Iraq and Malaysia testing forecasts are 37.17% and 11.29% respectively. In [25], the authors proposed new hybrid models by integrating the best features of Support Vector Regression (SVR) with seasonal index adjustment (SIA) and Elman recurrent neural network (ERNN) model to forecast the daily wind speed values. These hybrid models are validated by utilizing the three different wind farms data of the Xinjiang region of China. Authors in [26] considered another hybrid method that is employed to achieve high accuracy of the short-term wind power forecasting (48-h-ahead) based on the adaptive neuro-fuzzy inference system (ANFIS). And a hybrid evolutionary-adaptive (HEA) approach for short-term wind power prediction (3-h-ahead) is presented in [27], which combined the wavelet transform, mutual information and evolutionary particle swarm optimization with the adaptive neuro-fuzzy inference system. This HEA approach was successfully tested on Portuguese system and the MAPE and NRMSE values were 3.75% and 2.66% respectively. The review of various hybrid models can be referred in [28].

To enhance the prediction accuracy, improved WNN is employed in this study that is adaptive wavelet neural network (AWNN). This AWNN is a combination of adaptive learning algorithm [29] and conventional WNN. Due to this adaptive learning rate, this developed hybrid model delivers rapid convergence rate and also accuracy of forecasting performance is improved [30]. For further improving the prediction accuracy, there is a need of data preprocessing technique which is significant because it eliminates the noise from data. Wavelet transforms (WT) and empirical mode decomposition (EMD) technologies can be employed to eliminate the noisy data [31]. The hybrid model for multiresolution analysis and for the future time-series prediction is developed by employing WT and ANN [32].

EMD is another decomposition method of original wind data series other than wavelet transforms. This EMD technique decomposes the time-series into intrinsic mode functions (IMFs) and a residue. Then each IMF and residue is easy to examine by SVR to forecast the 1 h, 3 h, and 5 h ahead wind speed [33]. Not only SVR there are so many models such as ANN, ARMA etc. used for wind speed forecasting in combination with EMD. For instance, authors in [34] employed two hybrid models which combines EMD, feature selection with ANN and SVM to forecast future value of wind speed. In [35], authors developed hybrid forecasting tool which combines the EMD, feed-forward neural network (FNN). Partial autocorrelation function (PACF) is utilized for selecting the inputs for EMD-FNN model. Short-term wind speed can be forecasted using a hybrid method of EMD and recursive autoregressive integrated moving average (RARIMA) algorithm [36]. This method was applied for the real-time railway strong wind warning system. However, WT is sensitive to the choice of threshold, and The main disadvantage of EMD is the phenomenon of mode mixing problem.

Fortunately, Ensemble empirical mode decomposition (EEMD) technique can overcome the limitation of EMD. And EEMD is the most powerful and enhanced signal decomposition technique used for nonlinear or intermittent time-series analysis [37]. The wind speed forecasting tool which combines the EEMD technique, feature selection, and error correction is utilized for short-time horizon prediction in [38]. And unlike other reported methodologies the authors implemented big multi-step wind speed forecasting. But this big multi-step wind speed forecasting is more difficult and complicated due to the complexity of mapping relationships. Whereas authors in [39] used fast EEMD and multilayer perceptron (MLP) neural networks for prediction. The mind evolutionary algorithm (MEA) and Genetic algorithm (GA) are employed for optimizing the MLP neural networks. These algorithms do not improve the performance of the MLP neural networks notably due to their limitation of trapping in local minima. The hybrid prediction model was built using EEMD, back propagation NN, and genetic algorithm to forecast the 10 min ahead (very short-term) and 1 h ahead (short-term) wind speed [40]. The performance of this hybrid model is not that good because the parameters such as amplitude of noise and ensemble number are not properly chosen for decomposition. An approach used for multi-step ahead forecasts which is mainly mix of the wavelet packet decomposition (WPD), fast EEMD, and Elman neural networks [41]. The forecasting performance is satisfactory in comparison with other hybrid models. The main outcomes of all the reviewing literature and comparisons, hybrid models are superior than individual forecasting models. The main idea behind combining different individual models is to utilize the superior qualities of each individual model and to optimize the developed hybrid model. As this EEMD is able to overcome the problem of mode-mixing and decomposes the raw wind time-series data into more stationary signals with different frequencies.

In this paper, the hybrid EEMD-AWNN approach is developed, which combines the EEMD technique and AWNN model. The EEMD technique is employed to decompose the raw wind speed into a finite and often small number of intrinsic mode functions (IMFs) and one residue. Then based on the forecasting horizon the Adaptive Wavelet Neural Network (AWNN) model is built. Finally, the hybrid EEMD-AWNN model is used for forecasting the future values of wind speed and analysed results proves that the proposed EEMD-AWNN model can achieve the desired result with enhanced forecasting accuracy. The principal objectives of this paper are as follows:

1. To propose a hybrid model for short-term wind speed prediction.
2. To enhance the prediction accuracy by comprehensive comparison.
3. To reduce the uncertainty in forecasting the future wind speed time-

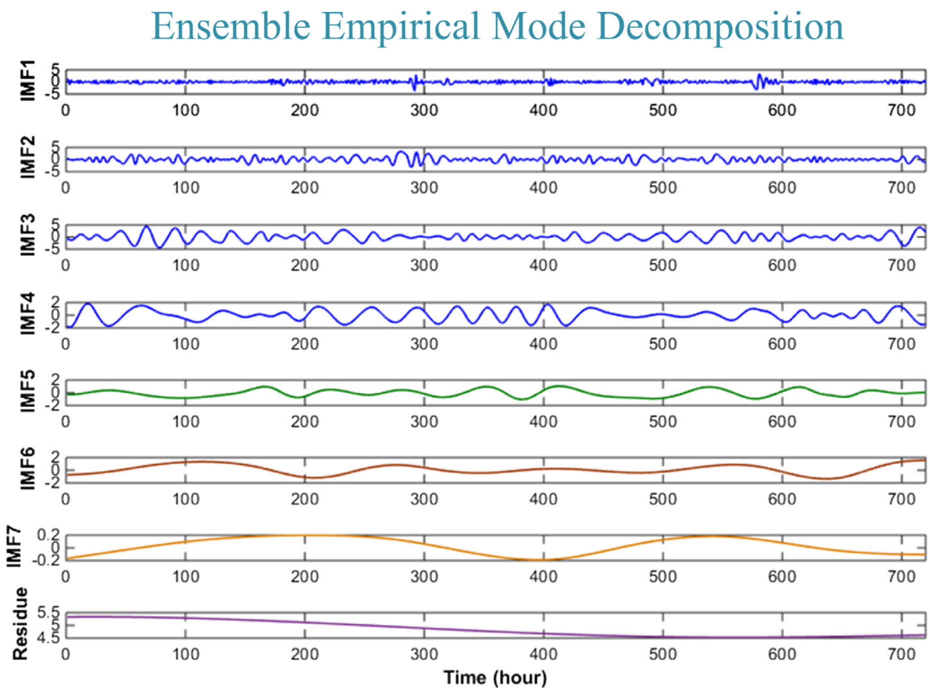

Fig. 1. Decomposed results of the original wind speed data [43] by the EEMD technique.

series.

4. To minimize the computational burden for practical short-term wind speed prediction.

The key technical contributions of this paper are as follows:

1. **Development of a new robust hybrid prediction approach:** An effective hybrid EEMD-AWNN model is developed to predict the wind speed in South India. This proposed model is based on the EEMD technique to remove the uncertainty nature of data and the AWNN model is employed due to localized properties of wavelets and the concept of adapting the wavelet shape according to the training data set instead of adapting the parameters of the fixed shape basis function.
2. **Focusing on statistical model without numerical weather prediction inputs:** A statistical-based wind speed prediction is implemented without utilizing the numerical weather prediction (NWP) inputs.
3. **Focusing on data preprocessing and adaptive learning:** This analytical study proposes a hybrid short-term prediction approach that can successfully preprocess the original wind speed data to enhance the forecasting accuracy. The most efficient signal decomposition algorithm, Ensemble Empirical Mode Decomposition (EEMD) is used for preprocessing. This ensemble empirical mode decomposition technique decomposes the original wind speed data. Then each decomposed signal is regressed to forecast the future wind speed value by utilizing the Adaptive Wavelet Neural Network (AWNN) model.
4. **Focusing on scientific and reasonable model validation system:** The proposed hybrid approach is subsequently investigated with respect to the wind farm of South India. The results from a real-world case study in India are reported along with comprehensive comparison in terms of performance measures.
5. **Focusing on accuracy and computational time simultaneously:** The prediction performance delivered high accuracy, less uncertainty and low computational burden in the forecasts attained. This hybrid EEMD-AWNN model can performs better than both the individual models and other hybrid models.

This paper presents the effective approach for one-step ahead wind speed prediction. And the remaining paper structure is as follows: Section 2 explains in detail about principles of wind speed decomposition techniques and the AWNN model. Section 3 briefs about the architecture of hybrid EEMD-AWNN method. Section 4 presents the analytical study of results obtained and the final conclusions were summarised in Section 5.

2. Principles of wind speed decomposition techniques and Adaptive Wavelet Neural Network model

Before formally introducing the hybrid EEMD-AWNN prediction approach, it is essential to outline the needed fundamental concepts.

2.1. Empirical mode decomposition

This EMD (Empirical mode decomposition) method is adaptive and highly efficient for analysing non-linear and non-stationary time series data. It is employed for extracting several IMFs and one residue from the raw wind speed data signal [42]. It is easy to analyse the IMFs (IMF_i) and residue (R_N) separately than analysing the original time series data directly. But this EMD experiences the frequent appearance of mode mixing problem and this problem can be solved by employing ensemble EMD (EEMD).

The original time-series ($\mathbf{x}$(t)) can be decomposed as shown in Eq. (1) by using EMD technique

$$\mathbf{x}(t) = \sum_{i=1}^{N} IMF_i(t) + R_N(t) \tag{1}$$

2.2. Ensemble empirical mode decomposition

EEMD (Ensemble empirical mode decomposition) technique is a truly noise-assisted data analysis approach and is used for overcoming the disadvantages of EMD. Mainly, there are oscillations of very dissimilar amplitudes in a mode or very similar oscillations in different modes. This phenomenon is known as mode mixing problem. EEMD [37] takes the full benefit of the statistical characteristics of Gaussian white noise to successfully avoid the mode mixing problem of EMD. Fig. 1 presents the decomposed IMFs of raw data.

The procedure of EEMD is as follows:

1. From the given raw data signal ($\mathbf{x}$(t)), produce the new noise-added signal using Eq. (2)

$$\mathbf{x}^i(t) = \mathbf{x}(t) + \varepsilon^i(t) \tag{2}$$

where $\varepsilon^i(t)$ is a Gaussian white noise.

2. Then decompose the new noise-added signal, $\mathbf{x}^i(t)$ into several IMFs and one residue using Eq. (3).

$$\mathbf{x}^i(t) = \sum_{j=1}^{N} IMF_j^i(t) + R_N^i(t) \tag{3}$$

3. Reiterate steps 1 and 2 with distinct Gaussian white noise every time.
4. Finally, take the average of all the corresponding IMFs and arrive at the final result.

2.3. Adaptive Wavelet Neural Network

ANNs are knowledge-based systems and these will learn from experience utilizing data in order to show their generalizing capabilities. These ANNs are data-driven learning approaches and are also called as Artificial Intelligence (AI) approaches [44]. In order to resolve complex problems, they can embrace the ability of the human brain's cognitive process. The ANNs are trained by employing historical wind sample values to acquire knowledge about the relation between predicted output and input samples. Besides these ANNs are capable of training, adaptation and self-organising property [45]. Therefore, they are the flexible and robust tool to forecast the wind speed. In ANNs, historical data is fed to the Input layer for training. Hidden layer(s) and output layer forecasts wind speed and power.

Wavelet is a mathematical function employed for image processing and analysing time series data [46]. Length and breadth of a wavelet are represented by translation parameter a and dilation parameter b respectively. In this paper, the Mexican hat wavelet as shown in Fig. 2 is used as mother wavelet in AWNN.

The general schematic structure of AWNN [30] with three layers is as depicted in Fig. 3. It is almost same as that of FFNN. Here in FFNN hidden layer comprises sigmoidal function. This AWNN structure consists of input layer, the hidden layer with Mexican hat as mother wavelet and output layer. The detailed and smooth signals are individually applied to AWNN model to forecast the day-ahead wind speed.

The second derivative of Gaussian function is called Mexican hat

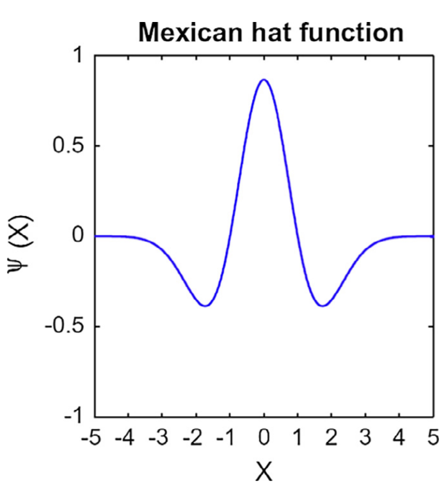

Fig. 2. Mexican Hat Wavelet adopted from [22].

wavelet which is given by Eq. (4)

$$\psi(x_i) = (1-x_i^2)e^{-0.5x_i^2} \tag{4}$$

This wavelet is considered as mother wavelet in the hidden layer of the network because of its special properties like symmetry in shape due to this it allows exact time-frequency analysis. The input pattern vector to train AWNN is $U = [u_1,u_2,...,u_n]^T$ where n is wind speed sample number. By using translation and dilation parameters of Mexican hat, wavelet family is produced as given in Eq. (5)

$$\psi_{a,b}(u_i) = \left(1-\left(\frac{u_i-b}{a}\right)^2\right)e^{-0.5\left(\frac{u_i-b}{a}\right)^2} \tag{5}$$

$i \in n; a,b \in \Re; a > 0$

The input wind speed sample data is directly passed on to wavelon (hidden layer with Mexican hat wavelet). The hidden layer output z_j is equal to the tensor product of all 1-D wavelets as depicted in Eq. (6)

$$z_j = \prod_{i=1}^{n} \psi_{a_{ij},b_{ij}}(u_i) \tag{6}$$

The output of AWNN can be calculated as the sum of three terms of which the first term is representing hidden layer to output layer, the second term is direct input and is mapped to output layer and the third one is external bias. It is given as below in Eq. (7)

$$y = \sum_{j=1}^{m} w_j z_j + \sum_{j=1}^{n} v_i u_i + g \tag{7}$$

where w_j is connecting weight from j^{th} hidden neuron to output neuron, v_i is connecting weight from i^{th} input neuron to output neuron, and g is bias signal.

The standard back-propagation (BP) technique is employed for training the AWNN [45]. This BP algorithm is based on the gradient descent technique. The calculated output function by using AWNN is differentiable w.r.t. translation and dilation coefficients, all unknown coefficients, weights, and biases. As shown in Eq. (8) the minimization of Mean Square Error (MSE), which acts as a cost function is a primary goal of training the network

$$E = \frac{1}{2N}\sum_{p=1}^{P}[e(p)]^2 \tag{8}$$

where $e(p) = y^d(p) - y(p)$ and y(p), $y^d(p)$ are predicted and actual values for the p^{th} input pattern, respectively. And a free parameter can be updated using Eqs. (9) and (10)

$$f(p+1) = f(p) + \eta\Delta f(p) + \alpha\Delta f(p-1) \tag{9}$$

$$\Delta f = \frac{\partial E}{\partial f} \tag{10}$$

where η is the learning rate and α is the momentum factor. Then the changes in the free parameters can be calculated employing all equations from (11)–(16)

$$\Delta w_j = e z_j \tag{11}$$

$$\Delta v_i = e u_i \tag{12}$$

$$\Delta a_{ij} = -\frac{\partial E}{\partial a_{ij}} \tag{13}$$

$$= e w_j z_j \left[\frac{1}{a_{ij}}\right]\left[\left[\frac{x_i-b_{ij}}{a_{ij}}\right]^2\left[3-\left[\frac{x_i-b_{ij}}{a_{ij}}\right]^2\right]e^{-0.5\left[\frac{x_i-b_{ij}}{a_{ij}}\right]^2}\right] \tag{14}$$

$$\Delta b_{ij} = -\frac{\partial E}{\partial b_{ij}} \tag{15}$$

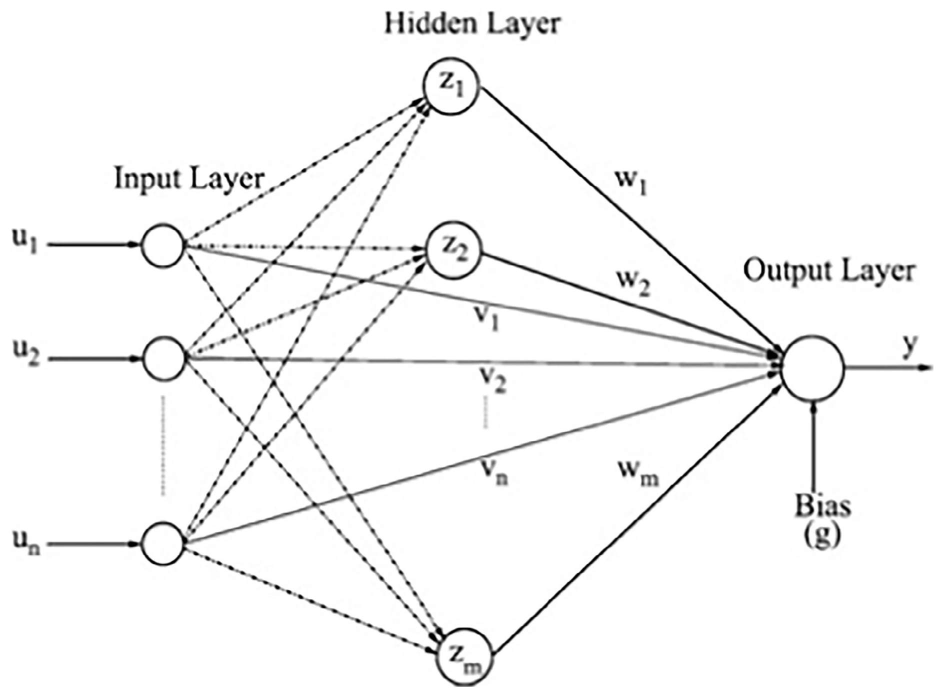

Fig. 3. General structure of AWNN [30].

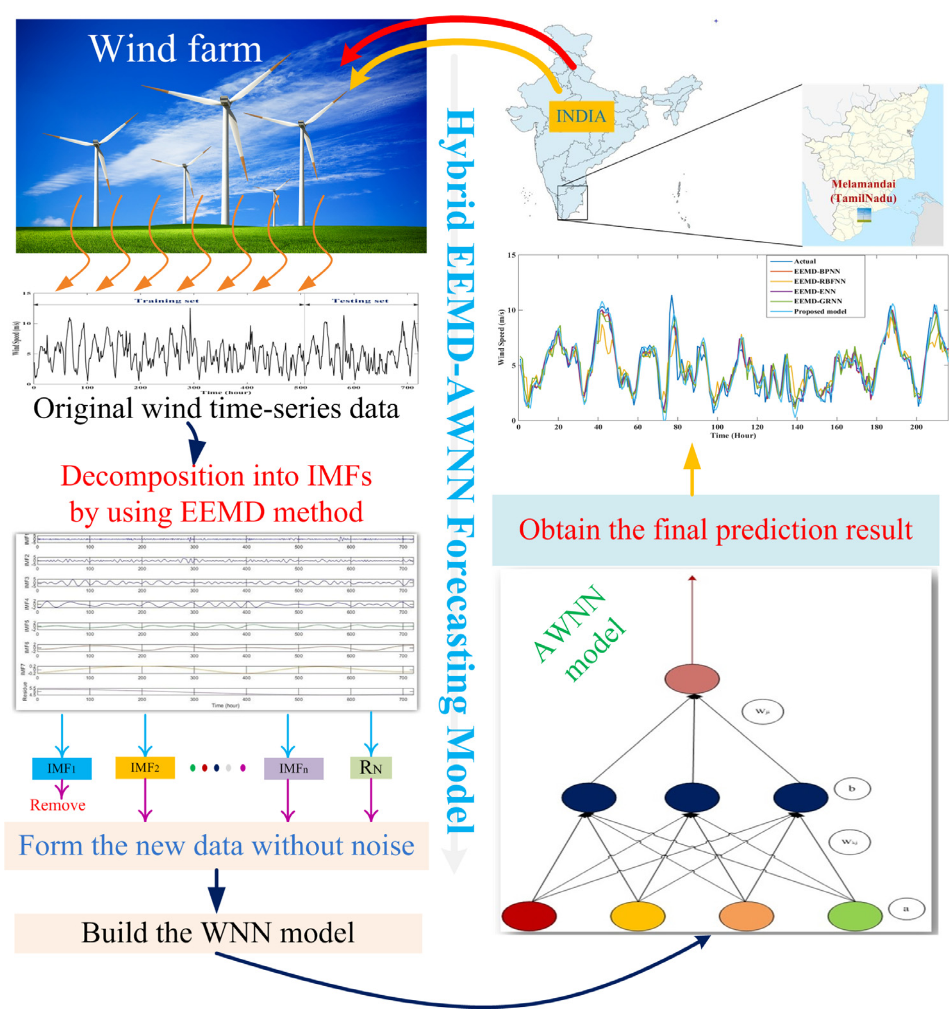

Fig. 4. Framework of the hybrid EEMD-AWNN method.

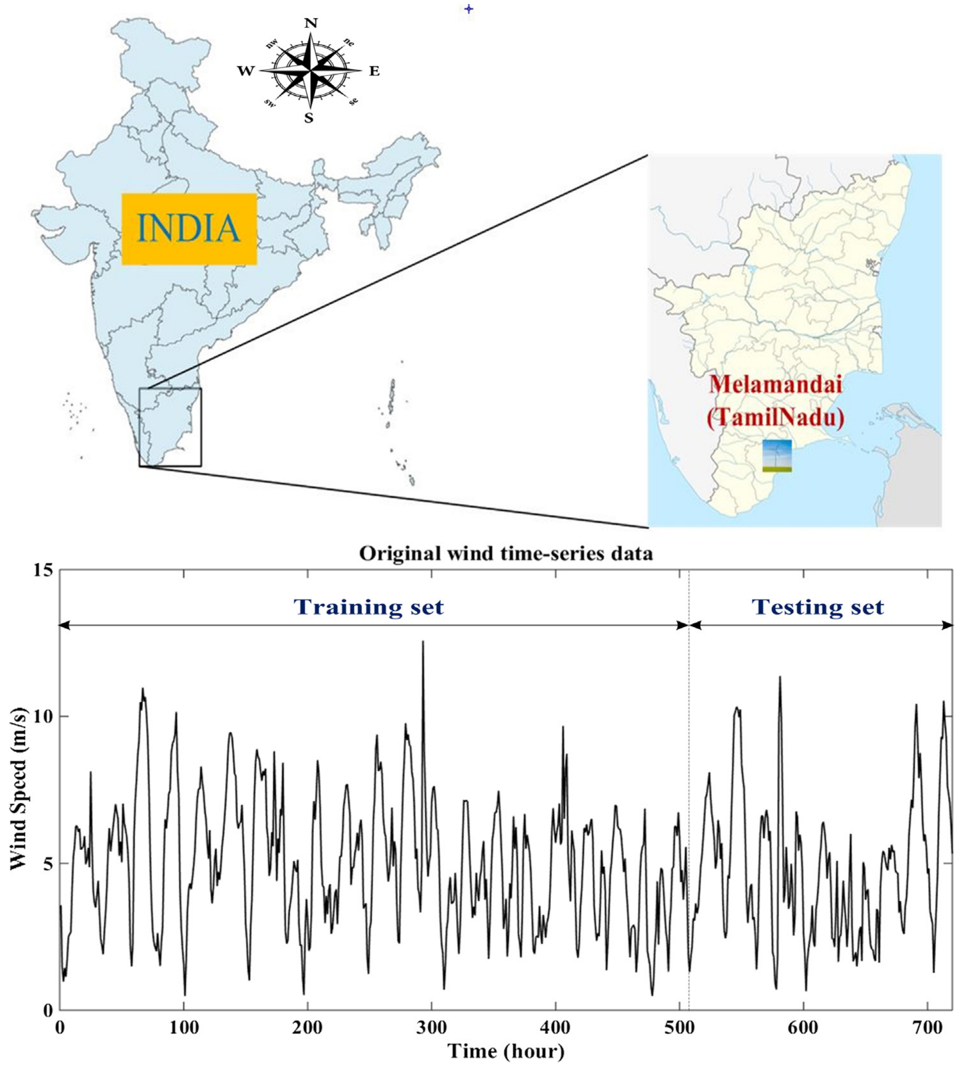

Fig. 5. Geographical location of the study site and original wind time-series [43].

Table 1
Statistical information of original wind time-series data.

Wind input	Minimum (m/s)	Maximum (m/s)	Mean (m/s)	Median (m/s)	Standard Deviation (m/s)
x(t)	0.4845	12.5762	4.9734	4.8805	2.2411

$$= ew_j z_j \left[\frac{1}{a_{ij}}\right]\left[\frac{x_i - b_{ij}}{a_{ij}}\right]\left[3 - \left[\frac{x_i - b_{ij}}{a_{ij}}\right]^2\right] e^{-0.5\left[\frac{x_i - b_{ij}}{a_{ij}}\right]^2} \tag{16}$$

3. Architecture of hybrid wind speed prediction approach

The intermittent nature of wind speed is encouraged to use EEMD technique, which is an efficient data preprocessing algorithm for eliminating the noisy data. The individual AWNN model can predict the wind speed but for enhancing the performance accuracy further this hybrid EEMD-AWNN model is utilized. The framework of the EEMD-AWNN approach is as shown in Fig. 4.

For this statistical-based model, historical wind speed time-series data is collected from wind farm anemometer in southern India. So that one can form original wind time-series data for this analytical study. Then for preprocessing the data, the developed model employs the most efficient signal decomposition algorithm which is Ensemble Empirical Mode Decomposition (EEMD) algorithm is used to decompose the original wind speed data. This EEMD technique decomposes the original data into finite number of independent IMFs and one residue. After obtaining the decomposed sub-series, remove the high frequency IMF that is first IMF to form the new time-series data without noise. Then build the AWNN model to forecast the future wind speed time-series data. Each decomposed signal is regressed to forecast the future wind speed value by utilizing the Adaptive Wavelet Neural Network (AWNN) model. Finally, aggregating all the sub-series predictions will give the final predicted wind speed time-series. This hybrid EEMD-AWNN approach is applied to other fields such as power load forecasting, stream flow forecasting, product sales forecasting, and traffic flow forecasting. And this application of methodology is different compared to other fields because it employs only statistical information without including any NWP inputs for accurate prediction.

The main steps of novel hybrid EEMD-AWNN approach are as follows:

Step 1: De-noising: By employing EEMD technique, first decomposition of raw wind data is carried out to find the several IMFs and a residue.
Step 2: Build model: Establish the AWNN model for future wind speed prediction.
Step 3: Apply the decomposed IMFs and residue sub-series

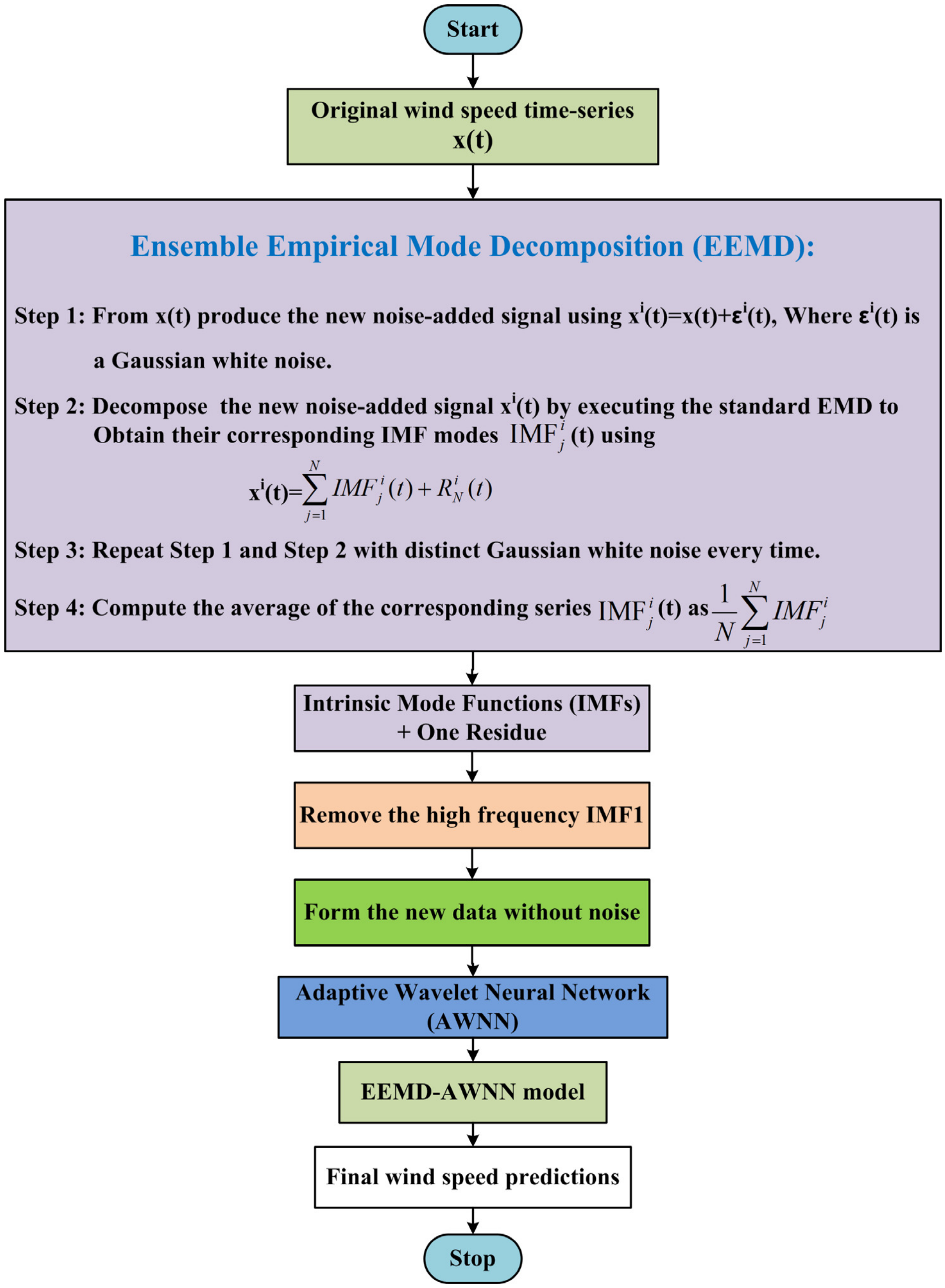

Fig. 6. The detailed flowchart of the hybrid EEMD-AWNN method.

Table 2
Comparison of performance indices between hybrid EEMD-AWNN model and benchmark models.

Performance Metrics	Persistence model [10]	BPNN model [12]	RBFNN model [13]	ENN model [31]	GRNN model [23]	WNN model [22]	Proposed model
RMSE (m/s)	01.2134	01.1938	01.0507	01.1455	01.4794	01.2602	**00.5249**
MAE (m/s)	00.8721	00.8377	00.7521	00.8067	01.1178	00.9130	**00.4176**
MAPE (%)	23.9041	23.6522	21.5713	23.2732	29.2489	24.8214	**14.0188**
Time (s)	–	02.8600	03.1100	03.6500	03.7400	03.9900	**32.1600**

separately to selected AWNN models for forecasting.
Step 4: Addition of all the sub predictions from step 2 will be the final forecast of wind time-series.

4. Analytical study

The wind speed data (Fig. 5) utilized for this work is collected from an anemometer installed at the site located in Melamandai, TamilNadu, India [43]. This data has been captured between April 01, 2015 and April 30, 2015 as 10 min samples of wind time series. The wind speed is averaged over 1-h and the first 70% of the data was utilized for training and remaining 30% of the data was employed for testing the selected AWNN model. The statistical information about the data which is used for this work is as shown in Table 1.

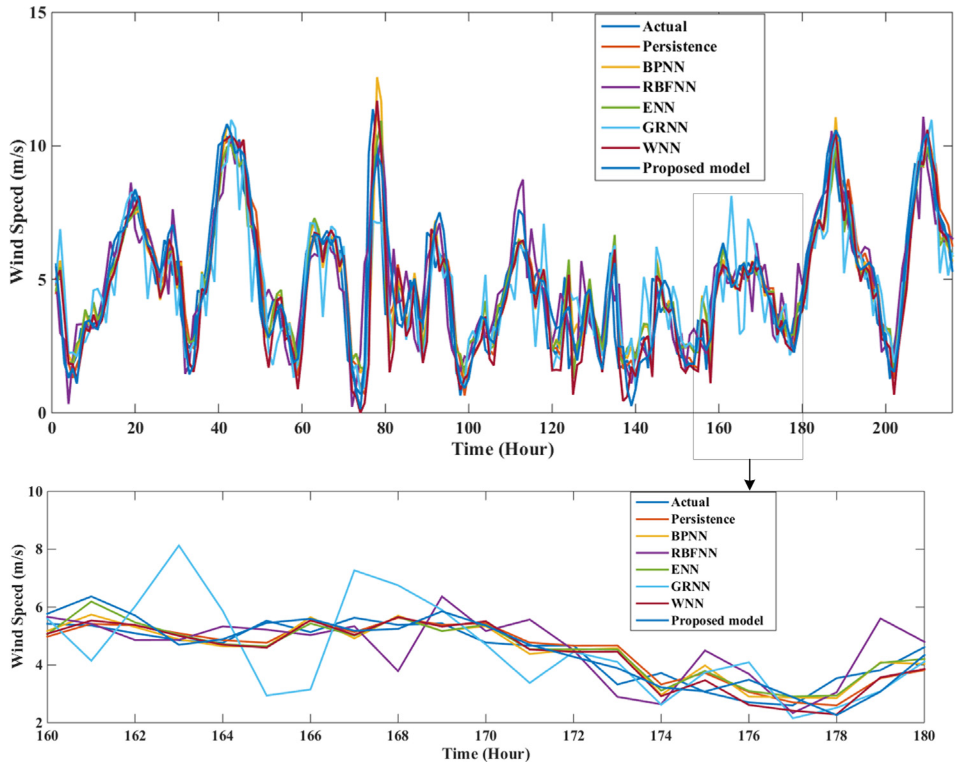

Fig. 7. Comparison of Predicted values with actual wind speed data.

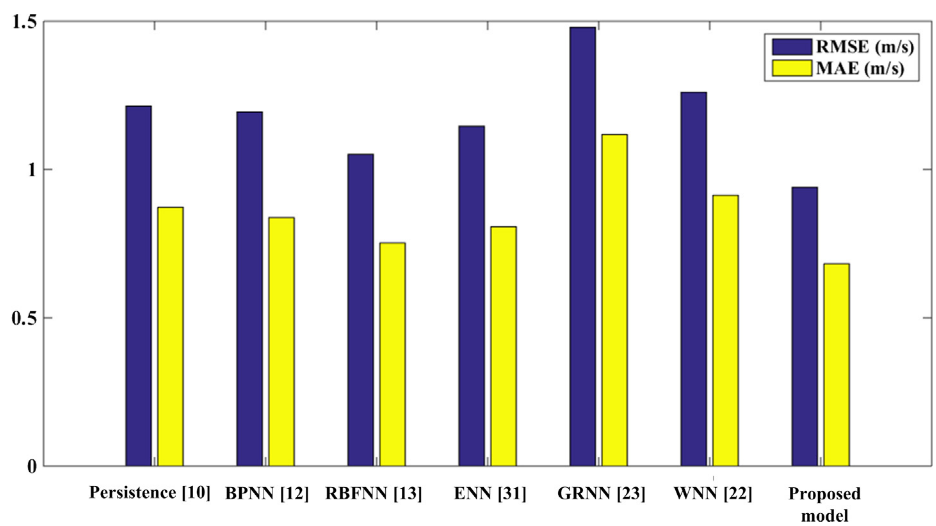

Fig. 8. Comparison of RMSE and MAE values of different prediction models.

The analytical study for predicting the future wind speed is conducted by utilizing the MATLAB R2009b software on an Intel i3-4005U CPU 1.70 GHz, 4 GB RAM computer.

4.1. Performance criteria

For improved renewable energy integration with the grid, the dependable and error-free forecasting approaches have become necessary and important [47]. The amount of data needed for forecasting relies on the approach which is used for prediction. The efficacy of the forecasting depends upon the methodology used and the time-scale of forecasting. The main statistical error parameters employed for assessment of proposed approach accuracy are mean absolute percentage error (MAPE) and root mean square Error (RMSE).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_{forecasted,i} - X_{actual,i})^2 \tag{17}$$

where in Eq. (17), N is wind data sample number, where as $X_{forecasted,i}$ and $X_{actual,i}$ are forecasted and actual values of wind data respectively.

Assessment of forecasting approaches is done by comparing the normalized RMSE of each individual approach. The major advantage with RMSE is that weightage for big variations between forecasted and actual values is more than small variations. Because of this reason, this is appropriate for wind power generation applications.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{forecasted,i} - X_{actual,i})^2} \tag{18}$$

The Mean Absolute Percentage Error (MAPE) and mean absolute error (MAE) are also commonly employed parameters for checking

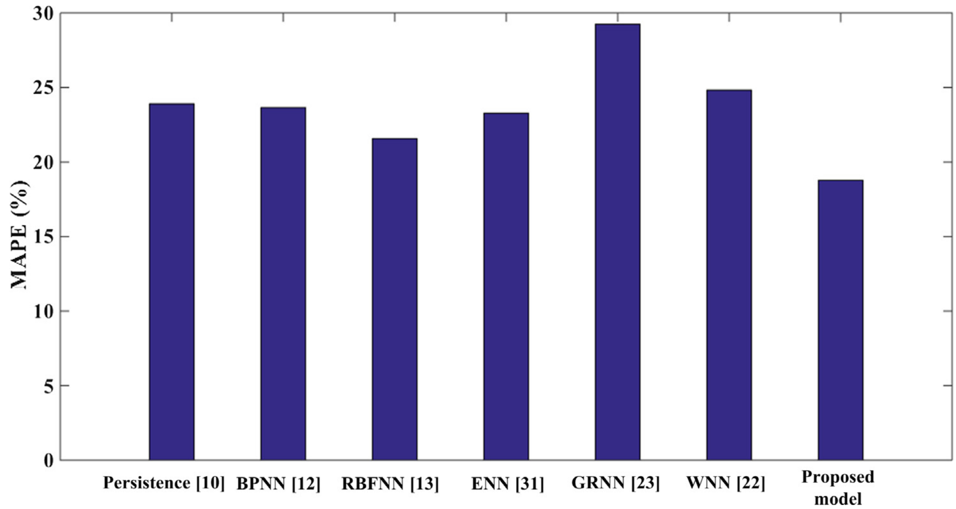

Fig. 9. Comparison of MAPE values of different prediction models.

Table 3
Comparison of performances in percentage of Hybrid EEMD-AWNN model over benchmark models.

Performance metrics	P_{RMSE}(%)	P_{MAE}(%)	P_{MAPE}(%)
Hybrid EEMD-AWNN Vs Persistence [10]	56.7413	52.1156	41.3539
Hybrid EEMD-AWNN Vs BPNN [12]	56.0304	50.1509	40.7294
Hybrid EEMD-AWNN Vs RBFNN [13]	50.0428	44.4755	35.0118
Hybrid EEMD-AWNN Vs ENN [31]	54.1792	48.2374	39.7642
Hybrid EEMD-AWNN Vs GRNN [23]	64.5194	62.6409	52.0707
Hybrid EEMD-AWNN Vs WNN [22]	58.3505	54.2642	43.5212

forecasting accuracy.

$$MAE = \frac{\sum_{i=1}^{N} |X_{forecasted,i} - X_{actual,i}|}{N} \tag{19}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_{actual,i} - X_{forecasted,i}}{X_{actual,i}}\right| *100 \tag{20}$$

In order to assess the forecasting model performance, the following indices are also utilized. Percentage improvement of RMSE, MAE, MAPE errors between two models can be evaluated by using Eqs. ()()() (21)–(23) respectively.

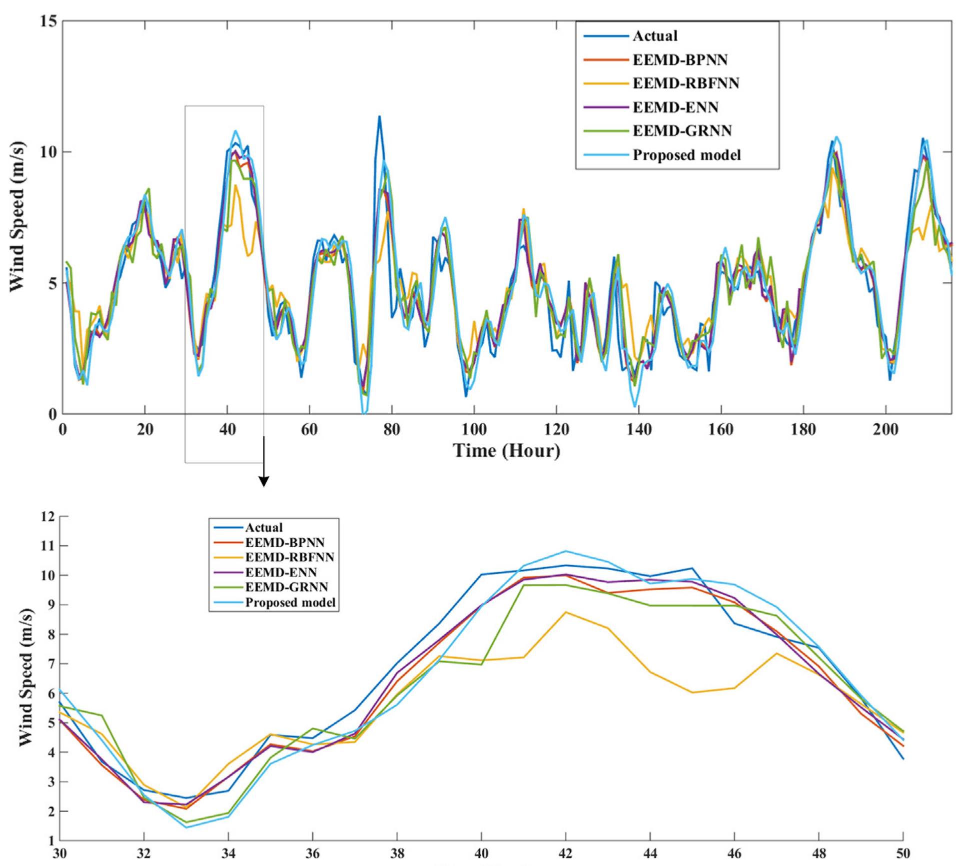

Fig. 10. Comparison of Predicted values using EEMD based hybrid models with actual wind speed data.

Table 4
Comparison of performance indices between hybrid EEMD-AWNN model and EEMD based hybrid models.

Performance Metrics	EEMD-BPNN Model [35]	EEMD-RBFNN Model [23]	EEMD-ENN Model [41]	EEMD-GRNN Model [23]	Proposed model
RMSE (m/s)	00.7695	01.2359	00.7731	00.9811	**00.5249**
MAE (m/s)	00.5726	00.8617	00.5761	00.7244	**00.4176**
MAPE (%)	16.6304	25.1255	16.8295	20.1528	**14.0188**
Time (s)	30.2700	31.5100	31.7800	31.8400	**32.1600**

$$P_{RMSE} = \left|\frac{RMSE_1 - RMSE_2}{RMSE_1}\right| \tag{21}$$

$$P_{MAE} = \left|\frac{MAE_1 - MAE_2}{MAE_1}\right| \tag{22}$$

$$P_{MAPE} = \left|\frac{MAPE_1 - MAPE_2}{MAPE_1}\right| \tag{23}$$

4.2. Forecasting results and discussions

In the proposed hybrid EEMD-AWNN model, the EEMD method is utilized for extracting the decomposed components which are high frequency to low frequency from the raw wind speed time-series as depicted in Fig. 1. Then remove the highest frequency IMF from the number of IMFs obtained by de-noising the original wind speed signal. After that, aggregate the remaining IMFs and one residue to form the new data. Too many IMFs may lead to computational burden and less forecasting accuracy. These difficulties can be solved by simply aggregating the new data.

In the next step, build the appropriate AWNN model. The number of input nodes, hidden nodes and output nodes of this AWNN model are 4, 9, and 1 respectively. The procedure for constructing the AWNN structure and principle of operation is explained in detail in Section 3. For this AWNN model, apply the new data which is obtained by removing the high-frequency IMF. The detailed flowchart of the hybrid EEMD-AWNN forecasting method is shown in Fig. 6.

4.2.1. Performance evaluation through Comparison

For decreasing the intermittent nature of generated wind power, accurate forecasting is the most important technique with growing wind capacity. Validation of forecasting model is very important and this can be achieved by performance evaluation criteria (like RMSE, MAE, MAPE). Adopting distinct criteria for forecasting approach may lead to distinct results every time and this is avoided through validation of the model. The performance evaluation in terms of RMSE (m/s), MAE (m/s), MAPE (%), and computational time (s) of the individual models in comparison with the proposed hybrid EEMD-AWNN model is shown in Table 2. The forecasting results using these individual models such as Persistence method, Back Propagation based Feed Forward NN (BPNN), Radial Basis Function based NN (RBFNN), Elman NN (ENN), General Regression NN (GRNN), and individual WNN are compared with the original wind time-series in Fig. 7. And a zoom section is added, from 160 h to 180 h in Fig. 7 to grasp the small differences between the models.

The RMSE, MAE values of individual BPNN model are 1.1938, 0.8721 respectively and these RMSE, MAE values of hybrid EEMD-BPNN model are 0.7695, 0.5726 respectively that means by combining the EEMD technique with this BPNN model one can improve the forecasting accuracy (as shown in Fig. 8). This improvement in prediction accuracy only because of the most efficient signal decomposition algorithm which is EEMD is employed for preprocessing the original wind speed data to remove the noise from the data. The hybrid EEMD-AWNN model is further enhanced the prediction accuracy with 0.5249, 0.4176 values of RMSE, MAE measures. The main reason for this is that the hybrid EEMD-AWNN model uses the best feature of adaptive learning rate. The other statistical metric, MAPE value of proposed hybrid EEMD-AWNN model is 14.0188 which is the best value when compared with the all individual model MAPE values like 23.9041, 23.6522, 21.5713, 23.2732, 29.2489, and 24.8214 (as shown in Fig. 9). But the computational time required for individual models is less than 4 s and in case of the hybrid EEMD-AWNN model this computational time for forecasting the future wind speed is a bit more in comparison with reported individual models. By comparing the performance metrics between the proposed hybrid EEMD-AWNN model and individual approaches, the hybrid approach outperformed all individual approaches for the wind dataset under RMSE, MAE, and MAPE measures. The main reason for this is simply the best features of EEMD are utilized for wind speed forecasting. The proposed approach performance when compared with individual WNN in terms of percentage is improved by 58.3505 % as presented in Table 3. The MAE, MAPE values of the proposed hybrid EEMD-AWNN model are 0.4176, 14.0188 respectively which are the best values when compared with all other individual models. Therefore, it is evident that the proposed approach is very effectively forecasting than any other individual model.

Reliable forecasts play a vital role in the enhanced renewable energy integration into the electrical system. The enhanced approaches like the combination of distinct forecasting methods are employed to utilize the strengths and minimize the weaknesses of each method. The forecasting performance of hybrid approaches such as EEMD-BPNN, EEMD-RBFNN, EEMD-ENN, and EEMD-GRNN have plotted along with

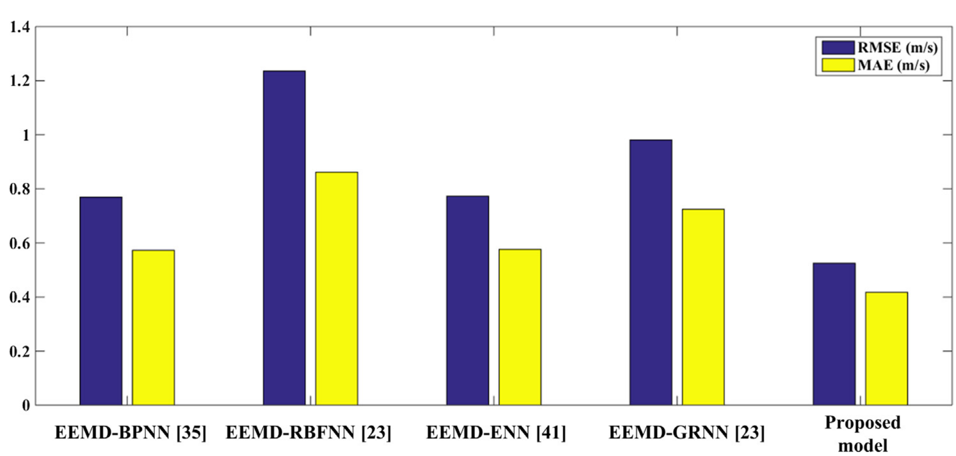

Fig. 11. Comparison of RMSE and MAE values of different EEMD based hybrid prediction models.

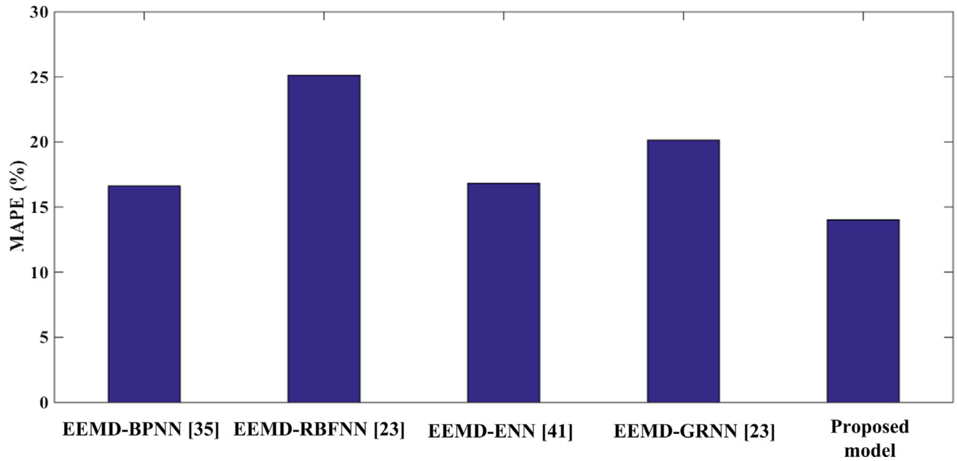

Fig. 12. Comparison of MAPE values of different EEMD based hybrid prediction models.

Table 5
Comparison of performances in percentage of Hybrid EEMD-AWNN model over EEMD based hybrid models.

Performance metrics	Hybrid EEMD-AWNN Vs EEMD-BPNN [35]	Hybrid EEMD-AWNN Vs EEMD-RBFNN [23]	Hybrid EEMD-AWNN Vs EEMD-ENN [41]	Hybrid EEMD-AWNN Vs EEMD-GRNN [23]
P_{RMSE}(%)	31.7829	57.5299	32.1066	46.4967
P_{MAE} (%)	27.0655	51.5402	27.5152	42.3559
P_{MAPE}(%)	15.7035	44.2049	16.7008	30.4374

original wind time-series in Fig. 10. And a zoom section is added, from 30 h to 50 h in Fig. 10 to grasp the small differences between the EEMD based models. The RMSE value of the proposed hybrid EEMD-AWNN model is 0.5249 is the best value when compared with combinational model RMSE values such as 0.7695, 1.2359, 0.7731, and 0.9811 (as shown in Table 4). The developed hybrid EEMD-AWNN model can predict with enhanced accuracy and less uncertainty in future wind speed time-series since it can overcome the disadvantages of mode mixing problem of signal decomposition using EEMD technique and slow convergence by employing the AWNN model. In comparison with four EEMD based combinational models, it is observed that the proposed EEMD-AWNN model has shown best performance for the wind dataset prediction under RMSE, MAE, and MAPE measures as presented in Figs. 11 and 12. And the MAPE error percentage improved by employing proposed hybrid EEMD-AWNN model with 15.7035 % in comparison with hybrid EEMD-BPNN model (as shown in Table 5). Similarly, among all other EEMD based hybrid models, the proposed hybrid EEMD-AWNN model is giving the best performance in terms of MAE, MAPE values. This best performance of the hybrid EEMD-AWNN model is because of the proposed model exploits the merits of the EEMD technique and the AWNN model.

5. Conclusion

The prominence of wind energy generation and integration with the Grid has encouraged reliable and most accurate forecasting approaches. Virtual Power Plants (VPP) and Smart grid concepts have raised the worth of accurate forecasts. Encouraged by this requirement of accurate forecasting techniques, in this paper a statistical-based approach without employing NWP inputs is developed and tested with Indian wind farm data successfully. This hybrid approach which combines EEMD technique and AWNN model to deliver high accuracy, less uncertainty and low computational burden. The most efficient signal decomposition algorithm EEMD is utilized for preprocessing the original wind speed data and enhances the forecasting accuracy by eliminating the noisy data. The AWNN model delivers faster convergence and improved forecasting accuracy by using adaptive learning rate. The developed hybrid model is investigated with regard to the wind farm of southern India. The RMSE, MAE and MAPE values of the hybrid EEMD-AWNN model are 0.5249,0.4176 and 14.0188% are best performance measures in comparison with all individual and hybrid models. This implemented model also reduced the MAPE value by 43.5212% when compared to individual WNN model. Hence, the performance evaluation among the proposed model and all other ten models (individual and hybrid models) have shown that the hybrid EEMD-AWNN approach outperformed all other approaches in terms of performance measures such as RMSE, MAE, and MAPE. This prediction method would be applied to larger power system for better forecasts in terms of robustness and accuracy. This hybrid approach can be applied in other parts of the world as a generalized statistical model in forecasting aspects by incorporating past meteorological and technical characteristics, including wind power, wind direction, temperature, pressure, and air humidity for enhanced accuracy. In the future work, the wind direction can be incorporated in the forecasting method to optimize the proposed hybrid model. The implementation of the proposed hybrid model for very short-term and long term forecasting cases would be investigated. And the proposed hybrid method can be applied in many different fields, such as power load forecasting, product sales prediction, and traffic flow forecasting.

References

[1] GWEC. Global wind report, annual market update, 2016. report, global wind energy council; 2016.
[2] Akorede MF, Hizam H, Pouresmaeil E. Distributed energy resources and benefits to the environment. Renew Sustain Energy Rev 2010;14(2):724–34.
[3] Lunney E, Ban M, Duic N, Foley A. A state-of-the-art review and feasibility analysis of high altitude wind power in northern ireland. Renew Sustain Energy Rev 2017;68:899–911.
[4] Baharvandi A, Aghaei J, Niknam T, Shafie-khah M, Godina R, Catalão JP. Bundled generation and transmission planning under demand and wind generation uncertainty based on a combination of robust and stochastic optimization. IEEE Trans Sustain Energy 2018.
[5] Meyyappan U. Wavelet neural network–based wind speed forecasting and application of shuffled frog leap algorithm for economic dispatch with prohibited zones incorporating wind power. Wind Eng 2018. 0309524X17723208.
[6] Wang Y, Zhou Z, Botterud A, Zhang K. Optimal wind power uncertainty intervals for electricity market operation. IEEE Trans Sustain Energy 2018;9(1):199–210.
[7] Wang C, Li X, Wang Z, Dong X, Liang Z, Liu X, et al. Day-ahead unit commitment method considering time sequence feature of wind power forecast error. Int J Electric Power Energy Syst 2018;98:156–66.
[8] Tascikaraoglu A. Evaluation of spatio-temporal forecasting methods in various smart city applications. Renew Sustain Energy Rev 2018;82:424–35.
[9] Foley AM, Leahy PG, Marvuglia A, McKeogh EJ. Current methods and advances in forecasting of wind power generation. Renewable Energy 2012;37(1):1–8.
[10] Kavasseri RG, Seetharaman K. Day-ahead wind speed forecasting using f-arima

models. Renewable Energy 2009;34(5):1388–93.
[11] Meng A, Ge J, Yin H, Chen S. Wind speed forecasting based on wavelet packet decomposition and artificial neural networks trained by crisscross optimization algorithm. Energy Convers Manage 2016;114:75–88.
[12] Rotich NK, Backman J, Linnanen L, Daniil P. Wind resource assessment and forecast planning with neural networks. J Sustain Dev Energy Water Environ Syst 2014;2(2):174–90.
[13] Chang G, Lu H, Chang Y, Lee Y. An improved neural network-based approach for short-term wind speed and power forecast. Renewable energy 2017;105:301–11.
[14] Sharifian A, Ghadi MJ, Ghavidel S, Li L, Zhang J. A new method based on type-2 fuzzy neural network for accurate wind power forecasting under uncertain data. Renewable Energy 2018;120:220–30.
[15] Liu H, Mi X, Li Y. Comparison of two new intelligent wind speed forecasting approaches based on wavelet packet decomposition, complete ensemble empirical mode decomposition with adaptive noise and artificial neural networks. Energy Convers Manage 2018;155:188–200.
[16] Kiplangat DC, Asokan K, Kumar KS. Improved week-ahead predictions of wind speed using simple linear models with wavelet decomposition. Renewable Energy 2016;93:38–44.
[17] Liu H, Tian H-q, Pan D-f, Li Y-f. Forecasting models for wind speed using wavelet, wavelet packet, time series and artificial neural networks. Appl Energy 2013;107:191–208.
[18] Tascikaraoglu A, Sanandaji BM, Poolla K, Varaiya P. Exploiting sparsity of interconnections in spatio-temporal wind speed forecasting using wavelet transform. Appl Energy 2016;165:735–47.
[19] Azimi R, Ghofrani M, Ghayekhloo M. A hybrid wind power forecasting model based on data mining and wavelets analysis. Energy Convers Manage 2016;127:208–25.
[20] Liu H, Mi X-w, Li Y-f. Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and elman neural network. Energy Convers Manage 2018;156:498–514.
[21] Aghajani A, Kazemzadeh R, Ebrahimi A. A novel hybrid approach for predicting wind farm power production based on wavelet transform, hybrid neural networks and imperialist competitive algorithm. Energy Convers Manage 2016;121:232–40.
[22] Chitsaz H, Amjady N, Zareipour H. Wind power forecast using wavelet neural network trained by improved clonal selection algorithm. Energy Convers Manage 2015;89:588–98.
[23] Xiao L, Qian F, Shao W. Multi-step wind speed forecasting based on a hybrid forecasting architecture and an improved bat algorithm. Energy Convers Manage 2017;143:410–30.
[24] Shukur OB, Lee MH. Daily wind speed forecasting through hybrid kf-ann model based on arima. Renewable Energy 2015;76:637–47.
[25] Wang J, Qin S, Zhou Q, Jiang H. Medium-term wind speeds forecasting utilizing hybrid models for three different sites in Xinjiang, China. Renewable Energy 2015;76:91–101.
[26] Liu J, Wang X, Lu Y. A novel hybrid methodology for short-term wind power forecasting based on adaptive neuro-fuzzy inference system. Renewable Energy 2017;103:620–9.
[27] Osório G, Matias J, Catalão J. Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization wavelet transform and mutual information. Renewable Energy 2015;75:301–7.
[28] Okumus I, Dinler A. Current status of wind energy forecasting and a hybrid method for hourly predictions. Energy Convers Manage 2016;123:362–71.
[29] Ho K-L, Hsu Y-Y, Yang C-C. Short term load forecasting using a multilayer neural network with an adaptive learning algorithm. IEEE Trans Power Syst 1992;7(1):141–9.
[30] Pindoriya N, Singh S. An adaptive wavelet neural network- based energy price forecasting in electricity markets. IEEE Trans Power Syst 2008;23(3):1423–32.
[31] Yu C, Li Y, Zhang M. Comparative study on three new hybrid models using elman neural network and empirical mode decomposition based technologies improved by singular spectrum analysis for hour-ahead wind speed forecasting. Energy Convers Manage 2017;147:75–85.
[32] Doucoure B, Agbossou K, Cardenas A. Time series prediction using artificial wavelet neural network and multi-resolution analysis: application to wind speed data. Renewable Energy 2016;92:202–11.
[33] Ren Y, Suganthan PN, Srikanth N. A novel empirical mode decomposition with support vector regression for wind speed forecasting. IEEE Trans Neural Networks Learn Syst 2016;27(8):1793–8.
[34] Zhang C, Wei H, Zhao J, Liu T, Zhu T, Zhang K. Short-term wind speed forecasting using empirical mode decomposition and feature selection. Renewable Energy 2016;96:727–37.
[35] Guo Z, Zhao W, Lu H, Wang J. Multi-step forecasting for wind speed using a modified emd-based artificial neural network model. Renewable Energy 2012;37(1):241–9.
[36] Liu H, Tian H-q, Li Y-f. An emd-recursive arima method to predict wind speed for railway strong wind warning system. J Wind Eng Ind Aerodyn 2015;141:27–38.
[37] Wu Z, Huang NE. Ensemble empirical mode decomposition: a noise-assisted data analysis method. Adv Adapt Data Anal 2009;1(01):1–41.
[38] Jiang Y, Huang G, decomposition Short-term wind speed prediction: Hybrid of ensemble empirical mode. Short-term wind speed prediction: hybrid of ensemble empirical mode decomposition, feature selection and error correction. Energy Convers Manage 2017;144:340–50.
[39] Liu H, Tian H, Liang X, Li Y. New wind speed forecasting approaches using fast ensemble empirical model decomposition, genetic algorithm, mind evolutionary algorithm and artificial neural networks. Renewable Energy 2015;83:1066–75.
[40] Wang S, Zhang N, Wu L, Wang Y. Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and ga-bp neural network method. Renewable Energy 2016;94:629–36.
[41] Liu H, Tian H-q, Liang X-f, Li Y-f. Wind speed forecasting approach using secondary decomposition algorithm and elman neural networks. Appl Energy 2015;157:183–94.
[42] Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, et al. The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. In: Proceedings of the Royal Society of London A: mathematical, physical and engineering sciences, vol. 454, The Royal Society; 1998. p. 903–95.
[43] NIWE, India. ministry of new and renewable energy, niwe.res.in [accessed on 20.06.2017].
[44] Li D, Du Y. Artificial intelligence with uncertainty. FL, USA: CRC press978-1-4987-7626-4; 2007.
[45] Du L-M, Hou Z-Q, Li Q-H. Optimum block-adaptive learning algorithm for error back-propagation networks. IEEE Trans Signal Process 1992;40(12):3032–42.
[46] Parcival D, Waldeni A. Wavelet methods for time series analysis. NY, USA: Cambridge Univ. Press0-521-64068-7; 2010.
[47] Ahlstrom M, Bartlett D, Collier C, Duchesne J, Edelson D, Gesino A, et al. Knowledge is power: efficiently integrating wind energy and wind forecasts. IEEE Power Energy Mag 2013;11(6):45–52.