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Tabu Search algorithm based general regression neural network for long term wind speed predictions

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ABSTRACT

Accurate prediction of wind speed is needed as the wind power directly depends upon the wind speed. Because of the complex non-stationary and nonlinear characteristics of wind speed, it is difficult to achieve good prediction accuracy. Compared to the prediction models that use single algorithms, hybrid models always have higher accuracy. The decomposition algorithm called Empirical Mode Decomposition (EMD) is combined with the optimization algorithm named Tabu Search (TS) and General Regression Neural Network (GRNN) to achieve high precision and is proposed in this study. The performance of the proposed approach is evaluated using wind speed datasets of different cities in India. The detail of the proposed model is given as follows: EMD (Empirical Mode Decomposition) decomposes the original datasets of wind speed into intrinsic mode functions (IMFs). A partial autocorrelation function determines the number of neurons in the input layer of GRNN. An intelligent algorithm namely Tabu Search is used to optimize the neural networks globally. The proposed model has better prediction accuracy in long term wind speed forecasting.

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Wind speed forecasting; general regression neural network; Tabu Search algorithm; empirical mode decomposition; partial auto-correlation function; intrinsic mode functions

1. Introduction

Economic development and energy consumption has a strong relationship with each other. The rural economy is uplifted and the rural employment is supported by wind energy. The biggest advantage of wind energy is that the fuel is free, and also it doesn't produce CO_2 emission. Wind energy is becoming the largest source of electricity in a number of countries. India has one of the largest growing energy markets and is expected to be the second largest contributor by 2035. Hence, it has to decrease the dependence of fossil fuels and increase the usage of renewable energy [1]. Among renewable energy sources, wind energy is becoming one of the important sources of power generation as wind power plants require no fuel consumption and, have low operating costs [2]. The basic wind speed map of India is shown in Figure 1.

In recent years India's Wind power generation capacity has been significantly increased. By 2022, the target of Renewable Energy is 175 GW out of which 60 GW will be coming from wind power. At 50 m hub-height, the National Institute of Wind Energy (NIWE) estimates the Wind Potential in India that is 49 GW but at 80 m hub height, the potential is high as 102 GW and at a 100 m height the potential is 302 GW. As of 31 March 2019, India ranks 4th in the world after Germany, Spain, and the USA in wind power generation. Renewable Energy Sources currently account for 22% of India's overall installed power capacity of 356100.19 MW with an installed capacity of 35625.97 MW (March 2019) of wind energy. Wind Energy is the largest supplier of clean energy and it occupies 45.5% of total RE capacity (78316.39 MW). The state-wise installed capacity of wind power is shown in Table 1 [3]. Compared to other forms of renewable energy, Wind energy is cost effective as it serves the dual purpose that is the wind farm can be built fast and the wind farm land can be used for farming. India is emerging as the fastest growing supply chain hub and the Capital cost in India is the lowest in the world [4].

The electric power system must be secure from the effects caused by the sudden cut of wind turbines. This can be done by installing the efficient wind speed forecasting system in the grid-connected wind farms by which a schedule can be made for generator operation. The construction and operation of a wind power prediction system is guaranteed by an accurate wind speed forecasting system. Long term wind speed forecasting is done to support decisions on the electricity market and to optimize cost in the planning of maintenance.

Among the low carbon energy technologies, wind energy is an important energy resource [6]. Wind speed is an important attribute for wind turbine operation so the forecasting of wind speed can be done by statistical methods such as Auto-Regressive Moving Average (ARMA) model [7], Auto-Regressive Integrated

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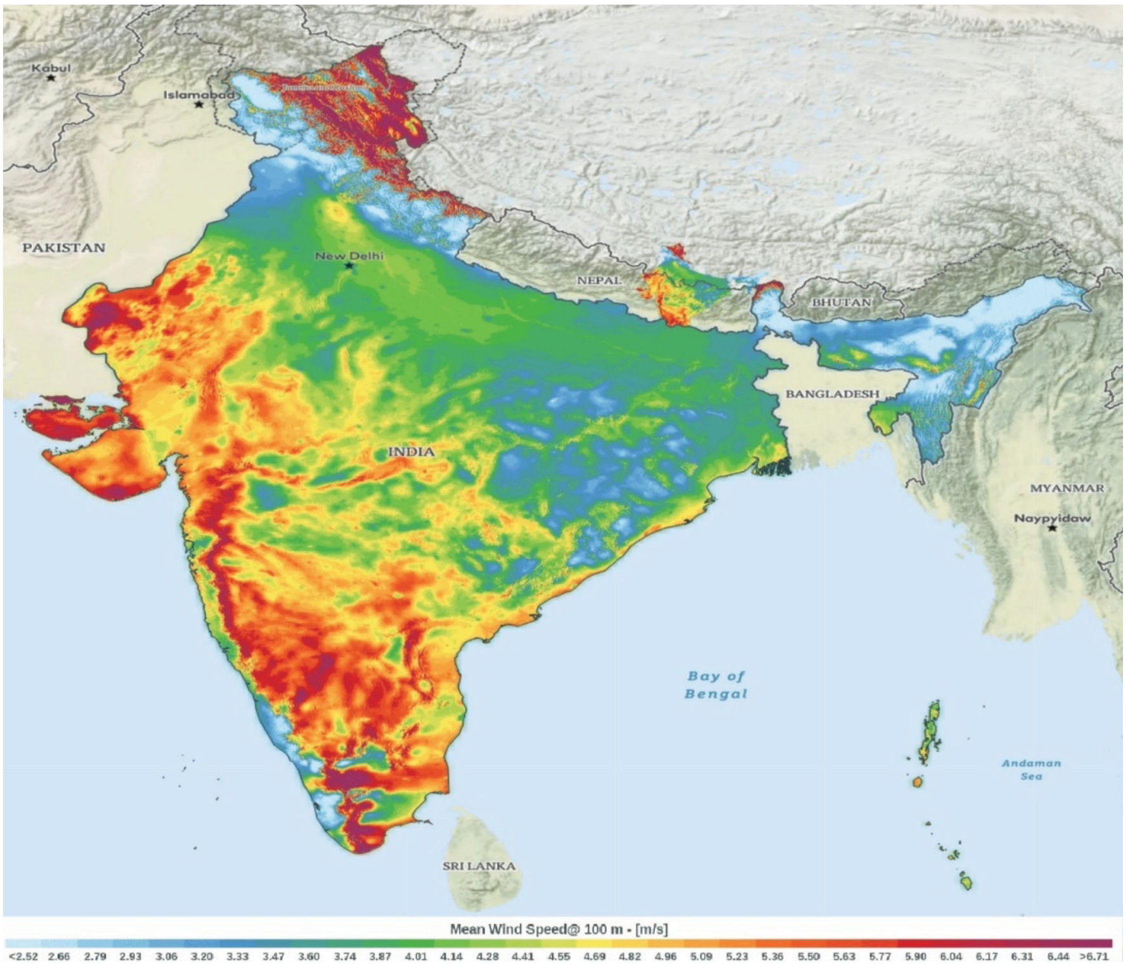

Figure 1. Basic wind speed map of India [5].

Table 1. State wise Installations in India.

s.no.	State	Capacity added during 2018–19 (MW)	Cumulative wind power capacity (as on 31st March 2019) (MW)
1.	Andhra Pradesh	123.5	4090.45
2.	Gujarat	459.65	6073.07
3.	Karnataka	86.5	4694.9
4.	Kerala	0	52.5
5.	Madhya Pradesh	0	2519.89
6.	Maharashtra	10.2	4794.13
7.	Rajasthan	2	4299.72
8.	Tamilnadu	771.82	8968.91
9.	Telangana	27.3	128.1
10.	Other	0	4.3
	Total	**1480**.97	**35625**.97

Moving Average model (ARIMA) [8–9]. The machine learning technique such as Artificial Neural Network (ANN) is used to predict wind speeds for 11 locations of Himachal Pradesh and has high prediction accuracy [10]. Adaptive Neural Fuzzy Inference System (ANFIS) and ANN are combined for wind speed forecasting [11]. The Muppandal area of Tamil Nadu in India ANN is implemented by giving wind speed, relative humidity and generation hours as input and the prediction is highly accurate [12]. Least-squares support vector machines outperforms the persistence model [13]. Long term wind speed forecasts are more efficient in the combination of a well known artificial neural network predictor called extreme learning machine as an artificial neural network algorithm and the Grey model [14]. Unscented Kalman filter (UKF) is integrated with support vector regression (SVR) based state-space model [15].

To improve the accuracy of wind speed forecasting Back Propagation Neural Network (BPNN) is combined with seasonal exponential adjustment to reduce greenhouse gas emissions by proper planning of power grids [16]. BPNN is combined with flower pollination algorithm which improves the non-stationary wind speed forecasting [17]. BPNN provides a better prediction performance than Radial Basis Function Neural Network (RBFNN) and ANFIS [18]. The hybrid model of Empirical Mode Decomposition (EMD) and Artificial Neural Networks (ANN) is suitable for jumping samplings in non-stationary wind series. The model is better than ANN and ARIMA [19]. The hybrid model Wavelet Packet Decomposition (WPD) – Convolution Neural Networks (CNN) – Convolution Neural Network Long Short Term Memory (CNNLSTM) is robust and effective compared with eight other models [20]. Two different approaches such as statistical and neural network based approaches provide very small mean absolute error regarding the long term wind speed forecasts [21]. General Regression Neural Network (GRNN) is a memory oriented network as it always depends on memory. It is used to predict long term wind speed in major wind power potential states in India [22]. The hybrid model combining GRNN and EMD and Fruit fly Optimization Algorithm (FOA) decomposes the wind speed series into Intrinsic Mode Functions (IMFs) and the spread parameter is optimized to predict each sub-series and this model outperforms other models and provides a guide for future wind speed forecasting [23]. GRNN is a learning algorithm with a highly parallel structure and it does not require an iterative training procedure and it is highly suitable for long term wind speed forecasting [24]. Thus GRNN is taken as a forecasting model in this paper.

The selection of the parameters for the forecasting model and the spread parameter is done by intelligent optimization algorithms. Based on optimization algorithms, there are many hybrid models in wind speed forecasting. The parameters of BPNN are optimized by Particle Swarm Optimization (PSO) to improve the prediction accuracy of wind speed [25]. A new hybrid model is proposed based on the first definite season index method and the Autoregressive Moving Average (ARMA) models or the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) forecasting models for long term wind speed forecasting [26]. The subseries are trained by Criss Cross Optimization Algorithm (CSO) [27]. The Multi-Layer Perceptron (MLP) Networks are optimized by Mind Evolutionary Algorithm/Genetic Algorithm (MEA/GA) [28]. BPNN is optimized by GA [29]. The above optimization algorithms have problems with local mining, balancing global search and premature convergence. Therefore, Tabu Search (TS) is proposed to solve these problems. The probability of finding global solutions can be increased by increasing the number of neighbourhoods searched [30]. Global optimization is achieved and diversification is assured by the TS algorithm [31]. The heuristic-based optimization algorithm, TS improves prediction precision optimization [32]. A flexible storage structure is introduced and circuitry search is avoided by TS [33]. The local minima are avoided by the iterative search algorithm TS [34] and therefore it is concluded to use TS algorithm for solving wind speed forecasting problems.

The accurate prediction of wind speed is difficult due to its stochastic and intermittent nature. The wind speed series is formed by the combination of sub-series with different frequency and regularities. EMD (Empirical Mode Decomposition) is an adaptive, data-driven and time decomposition method that decomposes the original time series into multiple empirical modes. As EMD is computationally efficient, it can be applied to a larger class of scientific and engineering problems [35]. Based on the local characteristic time scale of the data, the decomposition is done by EMD and it is highly efficient. It eliminates the need for the spurious harmonics [36]. EMD decomposes the signal with a pre-specified tolerance and does not need the mother wavelet. It extracts smooth high-order and symmetry-like low-order IMF (Intrinsic Mode Functions) [37]. EMD is a multi-scale signal decomposition method. Its central idea is to shift the non-stationary signal until the signal is stationary. The contribution of the EMD part is more in increasing the accuracy of the hybrid model when compared with other parts in the hybrid model and it improves the forecasting performance [38]. It has the self-adaptive ability to remove stochastic volatility. Therefore in this study, EMD is taken as the decomposition method to decompose the original datasets.

The performance of wind speed forecasting is better for hybrid methods than the single ones [39]. In this paper, the proposed hybrid model is EMD-TS-GRNN that is GRNN is combined with TS and EMD. This hybrid model is a new one and never used before in wind speed forecasting. The effectiveness of the proposed hybrid model is validated by comparing it with several methods.

The paper is organized as follows: Section 2 presents the methodology of EMD and GRNN optimized by Tabu Search. Section 3 introduces the criteria to evaluate the performance of forecasting. Section 4 presents a case study to know the efficiency of the proposed model. Section 5 presents the conclusion of the paper.

2. Methodology

2.1. Empirical mode decomposition

EMD is an adaptive, non-stationary time domain decomposition method. This method was proposed by Norden E. Huang. The original wind speed is decomposed into many layers by EMD. The simple sublayers are easy to predict [40]. It is used to extract the fluctuation features of wind speed data. It decomposes the time series into simple oscillatory functions called Intrinsic Mode Functions (IMFs). IMFs have varying amplitude and frequency. Each IMF contains lower frequency oscillations than its previous one. IMFs have two properties which are depicted below:

Throughout a single IMF, the number of local extrema and the number of zero-crossings must be equal or the maximum difference is one. There are two envelopes. One envelope is defined by local maxima and the other envelope is defined by local minima. The mean value of these two envelopes should be zero at any data location.

Steps of EMD for the original signal k(t):

(1) Sifting process is defined as the procedure of extracting an IMF. In the test data, all the local extrema are identified. The combination of both maxima and minima is said to be extrema. A cubic spline is used to connect the local maxima and the upper envelope ($k_{max}(t)$) is formed. This procedure is repeated for local minima and lower envelope ($k_{min}(t)$) is formed. The data between the upper and lower envelopes should be covered. The mean value is calculated using Equation (1).

$$Mean\ value\ m(t) = \frac{k_{\max}(t) + k_{min}(t)}{2} \quad (1)$$

(2) Subtract the mean value m(t) from the original signal k(t), to obtain the first IMF q(t) in Equation (2).

$$q(t) = k(t) - m(t) \quad (2)$$

where q(t) is the first IMF and m(t) is the mean value.

(3) Consider q(t) be the data and steps (1) and (2) are repeated iteratively and the final q(t) is p(t) if q(t) satisfies the two properties of IMF.

(4) The residue $r_1(t)$ yields the second IMF and the procedure continues until the residual has no turning points and it is done by using Equation (3). The overall data is represented by the final residual.

$$r_1(t) = k_1(t) - p(t) \quad (3)$$

where p(t) is the final q(t) obtained from step 3.

(5) The sifting process above will be repeated n number of times until no IMF can be extracted and the original signal k(t) can be reconstructed as in Equation (4).

$$k(t) = \sum_{j=1}^{n} p_j + r_n \quad (4)$$

where p_j are IMFs and r_n is final residue.

The main variables of EMD are listed in Table 2.

Table 2. Main variables involved in empirical mode decomposition (EMD).

Variable	Meaning
k(t)	Raw signal
p_j	IMFs
r_n	Residue

2.2. General regression neural network

General Regression Neural Network (GRNN) was suggested by D.F. Specht in 1991 [41]. It is a good solution to solve prediction problems. It represents non-parametric regression, an improved technique in which all samples have a mean to a radial basis neuron. Back propagation is not required since it memorizes every unique pattern so that the training approach is also quick. Gaussian functions are used to have a high accuracy prediction. When a pattern is given input to GRNN, it compares the input with all other patterns in the training set based upon the distance from each other. The structure of GRNN is shown in Figure 2.

It consists of four layers namely input, pattern, summation, and output layer. Consider the input of the network is $I = [I_1, I_2, I_3, I_4, \ldots \ldots \ldots \ldots, I_n]^T$ and output is $O = [O_1, O_2, O_3, O_4, \ldots \ldots ., O_k]^T$, $[pt_1, pt_2 \ldots pt_n]$ is the pattern layer and $[S_D, S_{N1}, \ldots .. S_{NT}]$ is the summation layer.

Input layer:

The input variables are passed to the pattern layer by each neuron. The values are standardized by input neuron by means of subtracting the median and the interquartile range is divided.

(1) Pattern layer:

Hidden nodes have one neuron from each data in the training set. The target value and the predictor variables are stored in the neuron. The Euclidean distance is calculated by a hidden neuron and then radial basis function is applied using the sigma value. The number n of learning samples is equal to the number of neurons in the pattern layer. Each neuron is associated with different learning sample. The transfer function of the neuron is calculated using Equation (5).

$$pt_i = \exp\left[-\frac{(I - I_i)^T (I - I_i)}{2\sigma^2}\right], i = 1, 2 \ldots, n \quad (5)$$

Where pt_i is the output of the i^{th} neuron in the pattern layer, I is the network input variable and I_i is the corresponding learning sample of neuron i, and σ is the spread parameter.

(2) Summation layer:

There are two neurons in this layer. There are two parts of the calculation. One is the denominator part and the other one is the numerator part. The weight values from hidden neurons are added up by the denominator part. The numerator part finds the sum of weighted values multiplied by the target value of each hidden neuron. The transfer function is calculated by Equation (6).

$$A_D = \sum_{i=1}^{n} pt_i \quad (6)$$

Where A_D is the denominator summation unit. The jth element of ith output sample $\mathbf{O}_i$ is the jth neuron in the

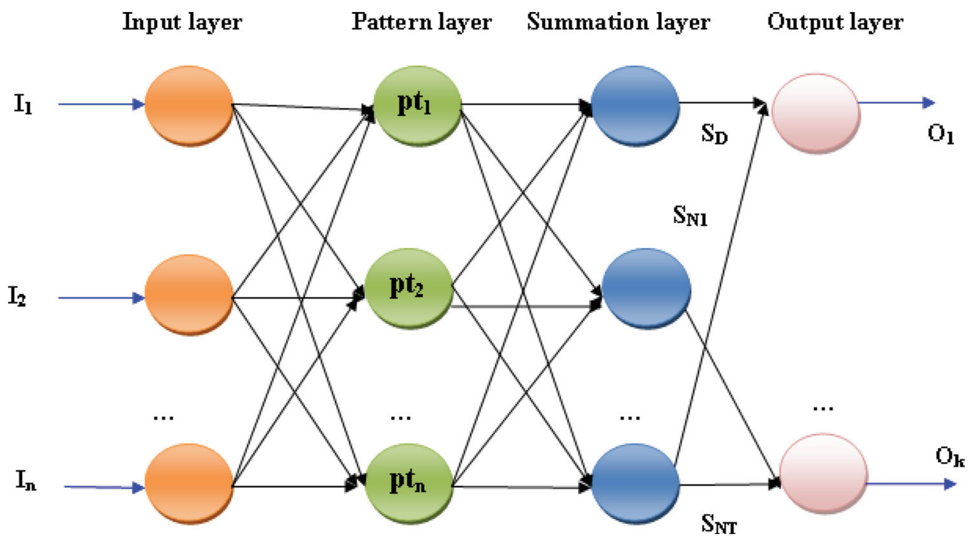

Figure 2. Structure of General Regression Neural Network.

summation layer and the ith neuron in the pattern layer. The transfer function is shown in Equation (7).

$$A_{Nj} = \sum_{i=1}^{n} o_{ij} pt_i, j = 1, 2, \ldots\ldots, k \qquad (7)$$

Where A_{Nj} is numerator summation unit.

(3) Output layer:

The predicted target value is obtained by dividing the values in the numerator part by the values in the denominator part as in Equation (8).

$$o_j = {}^{A_{Nj}}/_{A_D}, j = 1, 2, \ldots\ldots, k \qquad (8)$$

Where k is the number of neurons.

Depending on the selection of the spread parameter, accurate function approximation is done. The GRNN is powerful when the Probability Density Function on a sample is accurately estimated. If the value of the spread parameter is large, the interesting variations in the functional relationship are smoothed as GRNN generalizes too much. If the value of the spread parameter is small, the modelled function is the same as the training data as GRNN is too specific. If the value of the spread parameter is moderate, then a large weight is added to the forecasting point distance. Hence the spread parameters must be estimated in a good manner then only GRNN can model any function with variables distributed in any form. The accurate forecasting results of GRNN depend upon the value of σ and Tabu Search (TS) is used to find the optimal value of σ.

2.3. *Grnn based Tabu Search (TS)*

In 1986, Fred.W.Glover has proposed a meta-heuristic algorithm called Tabu Search (TS). The term Tabu (prohibition) comes from Tongan that means certain things cannot be touched because they are sacred. Here Tabu Search is previously visited solutions should not be visited again. Global optimization is achieved by Tabu Search and the optimization depends on the number of neighbourhoods, neighbourhood structure, tabu list size, and stopping rule. Adjacent solutions are identified by constructing the neighbourhood. Tabu moves are the forbidden moves that are in the tabu list. A flexible storage structure is used and diversification is assured by this algorithm. Local minimal is avoided by using global search capability. Because of its adaptability, it is a very effective optimization methodology. The procedure of the Tabu Search method is shown in Figure 3.

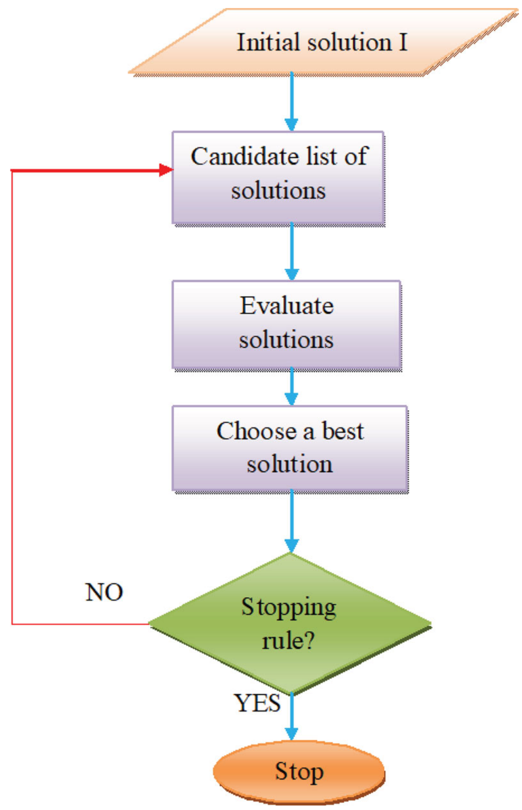

Figure 3. Flowchart of Tabu Search.

Faster convergence is achieved by calculating the batch of solutions in a single iteration so that computational cost is also minimized. The current solution for the next iteration is obtained by taking the best solution with the lowest cost of the last iteration. The search in new regions is done by means of diversification which uses the long term memory. Repetition is avoided by maintaining the last visited solutions in the tabu list. Time is saved by avoiding the cyclic search.

2.4. Steps of wind speed forecasting

The wind speed forecasting model combining the GRNN, TS, and the EMD is illustrated in Figure 4.

Step 1:

A collection of IMFs are obtained by decomposing the original wind series using EMD. The elements of the training set are selected by applying the Partial Auto-Correlation Function (PACF) to each of the IMFs so that a proper input can be chosen. PACF refers to the correlation between o_{t-m} and o_t for m-order lag under the condition of middle random variable $o_{t-1}, o_{t-2}, \ldots, o_{t-m+1}$ for the stationary time series $\{O_t\}$.

Step 2:

Generate an initial solution s in P (set of solutions) and that is taken as Orig-Sol.

The solution is a vector h of size n. The content of h is the list L_i $(1 \leq s \leq n)$. The new positions are in the k^{th} list which is L_k. Take,

$s^* = s$

$j = 0$

$T = 0$

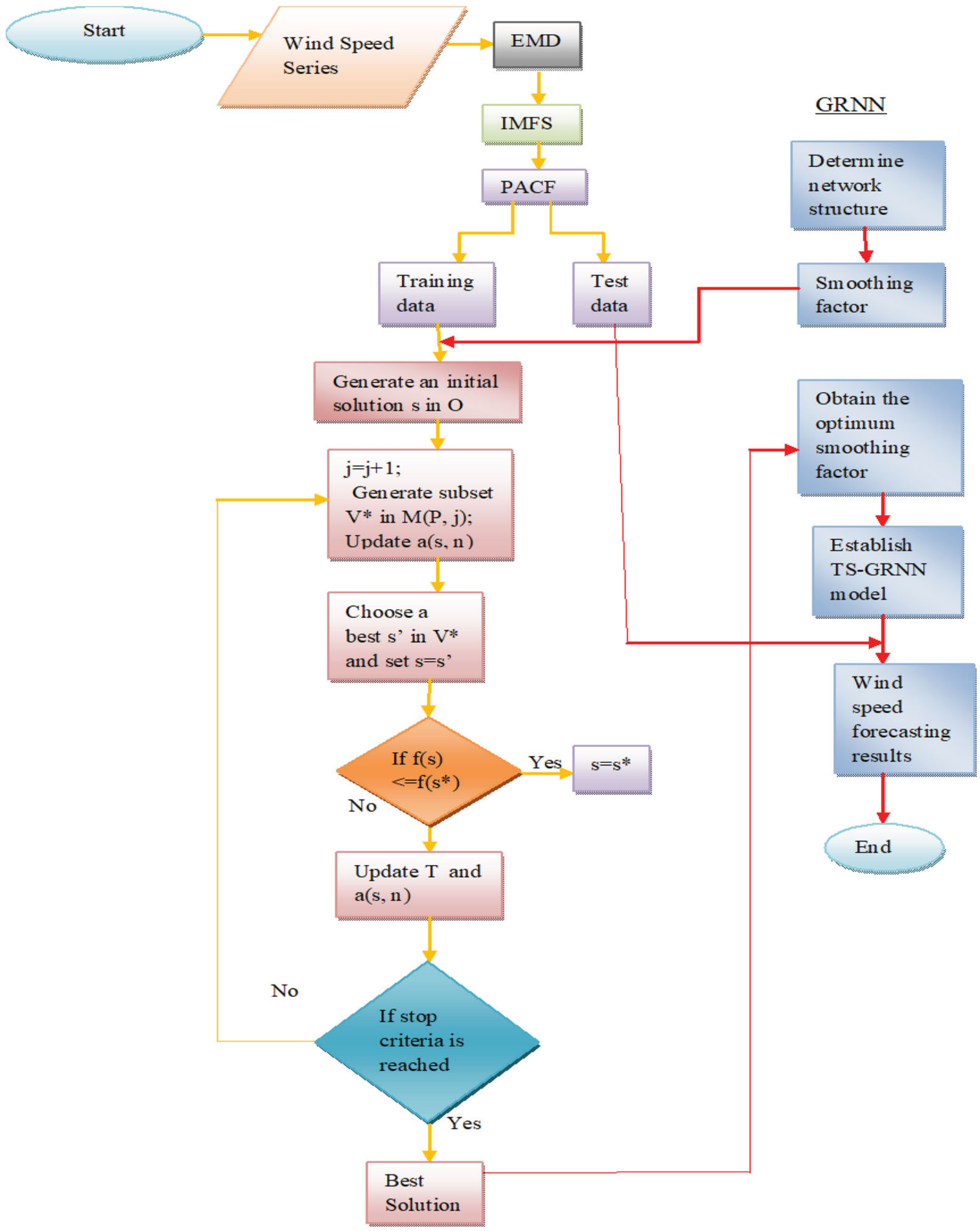

Figure 4. Flowchart of the proposed model combining EMD, TS, and GRNN.

Step 3:

j = j+1 and neighbourhood of solutions are generated by applying permutations on the positions of the current solution in M(s,j). An aspiration criteria a(s,n) is updated.

Step 4:

From the set of neighbouring solutions M(s,j), the best solution s' is chosen.

s = s'

Let s' be a solution of M(s,j) in which the lists are $L'_{i1}, L'_{i2}, \ldots \ldots, L'_{in}$, and let f be the evaluation function on the set of solutions s' by:

$$f(s') = -\sum_{i=1}^{n} |card(L'_{is}) - card(L_s)| \tag{9}$$

Step 5:

Update the aspiration criteria and the list of tabu movements T. The Tabu list is added with the best solution.

Step 6:

If the stopping criteria is reached then stop otherwise, return to step 3.

Step 7:

Now optimization is stopped and prediction is started and the GRNN model takes the best value of the spread parameter.

3. Statistical criteria to evaluate the forecasting performance

The statistical criteria such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) are used to evaluate the performance of the forecasting models. If the values of the above criteria are small then the performance of the forecasting is better.

For MAPE,

$<$ 10% – high prediction accuracy,

10% to 20% – good prediction

20% to 50% – acceptable prediction

$\geq$ 50% – inaccurate prediction

The above indexes can be calculated by using the Equations (10), (11), (12):

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |o_t - o_t^*| \tag{10}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N} \left|\frac{o_t - o_t^*}{o_t}\right| X100\% \tag{11}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N} (o_t - o_t^*)^2} \tag{12}$$

Where o_t is the original wind speed and o_t* is the predicted wind speed at time period t. The period of forecasting is represented by N.

4. Case study

4.1. Wind speed dataset collection

In India, 47 cities are selected and the wind speed data of these cities are collected. Then this data is divided into training and testing. The wind speed data of 26 cities are used as the training set and the remaining 21 cities are used as the testing set. The wind speed dataset of training and testing is collected from NASA [42]. The input variables used are atmospheric pressure, heating degree-days, cooling degree-days, elevation, earth temperature, relative humidity, air temperature, latitude and longitude. Monthly average values for a year of these variables are recorded and long term wind speed prediction is done. The latitude and longitude of the training and testing cities are shown in Tables 3 and 4 respectively. The non-stationary and nonlinear characteristics of the original wind speed monthly mean values is shown in Figure 5. in which x- axis has the months in the training set and y-axis has monthly mean wind speed values.

4.2. Steps of forecasting

Step 1:

Non- stationary of the data is eliminated by decomposing the original wind speed series by EMD into IMFs so that the prediction accuracy can be increased. Figure 6. shows that the condition of the EMD is satisfied by decomposing the wind speed time series until six independent IMFs and one Residue.

Step 2:

PACF is used to select the input variables for wind speed forecasting. The PACF is applied to IMFs and residual. Wind speed data is taken as input for GRNN.

Table 3. Latitude and Longitude of Training Cities.

S.N.	City	Lat.	Lon.	S.N.	City	Lat.	Lon.	S.N.	City	Lat.	Lon.
1	Ahmadabad	23.05	72.66	10	Deoli	25.75	75.38	19	New Delhi	28.35	77.12
2	Ahmednagar	19.09	74.74	11	Dhandhuka	22.35	72.03	20	Padra	22.25	73.11
3	Ajanta	20.55	75.70	12	Dhrangadhra	22.98	71.51	21	Palanpur	24.2	72.44
4	Thiruvanth puram	8.5	76.9	13	Hingoli	19.71	77.14	22	Palitana	21.51	71.88
5	Amreli	21.6	71.25	14	Jamnagar	22.45	70.11	23	Rajkot	22.3	70.93
6	Anand	22.53	73.0	15	Jasdan	22.06	72.51	24	Ranchi	23.35	85.33
7	Anklesvar	21.63	73.03	16	Jodhpur	26.18	73.01	25	Rapar	23.53	70.06
8	Dabhoi	22.18	73.41	17	Junagadh	21.51	70.6	26	Shillong	25.34	91.53
9	Srinagar	34.08	74.79	18	Junnar	19.20	73.87				

Table 4. Latitude and Longitude of Testing Cities.

S.N.	City	Lat.	Lon.	S.N.	City	Lat.	Lon.	S.N.	City	Lat.	Lon.
1	Bangalore	12.57	77.38	10	Kolkata	22.39	88.27	19	Tharad	24.38	71.61
2	Bansda	20.75	73.46	11	Limbdi	22.56	71.88	20	Akalkot	17.52	76.20
3	Bharuch	21.68	73.01	12	Lucknow	26.45	80.56	21	Vishakhap atnam	17.43	83.14
4	Bhavnagar	21.77	72.15	13	Panjim	15.49	73.81				
5	Dholka	22.73	72.48	14	Patan	23.86	72.01				
6	Dhoraji	21.75	70.61	15	Patna	25.61	85.13				
7	Godhra	22.75	73.66	16	Petlad	22.48	72.08				
8	Hamirpur	31.68	76.52	17	Dehradun	30.19	78.02				
9	Kheralu	23.9	72.66	18	Taranga Hill	24.05	72.73				

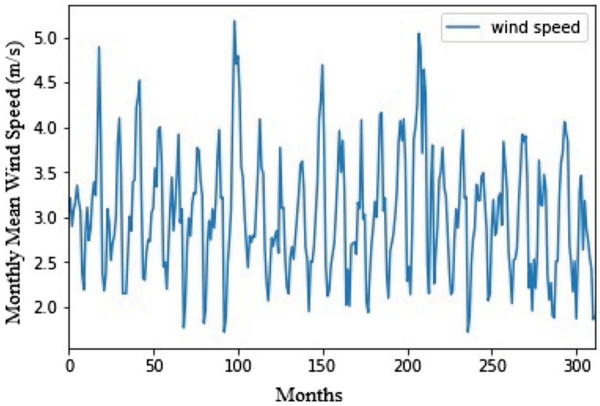

Figure 5. Original Wind Speed Series.

The results of the Partial Auto Correlation Function of each IMF are shown in Figure 7. At lag m, if the PACF is out of the 95% confidence interval then i_j is the output variable for each decomposition wind speed time series and i_{j-m} is applied as one of the input variables.

The input variables for the TS-GRNN are

(i_{t-1}) of IMF1,

$(i_{t-1}, i_{t-2}, i_{t-3}, i_{t-4})$ of IMF2,

$(i_{t-1}, i_{t-2}, i_{t-3}, i_{t-4}, i_{t-5})$ of IMF3,

$(i_{t-1}, i_{t-2}, i_{t-3}, i_{t-4}, i_{t-5}, i_{t-6}, i_{t-7})$ of IMF4,

(i_{t-1}) of IMF5,

(i_{t-1}) of IMF6,

(i_{t-1}) of Residual

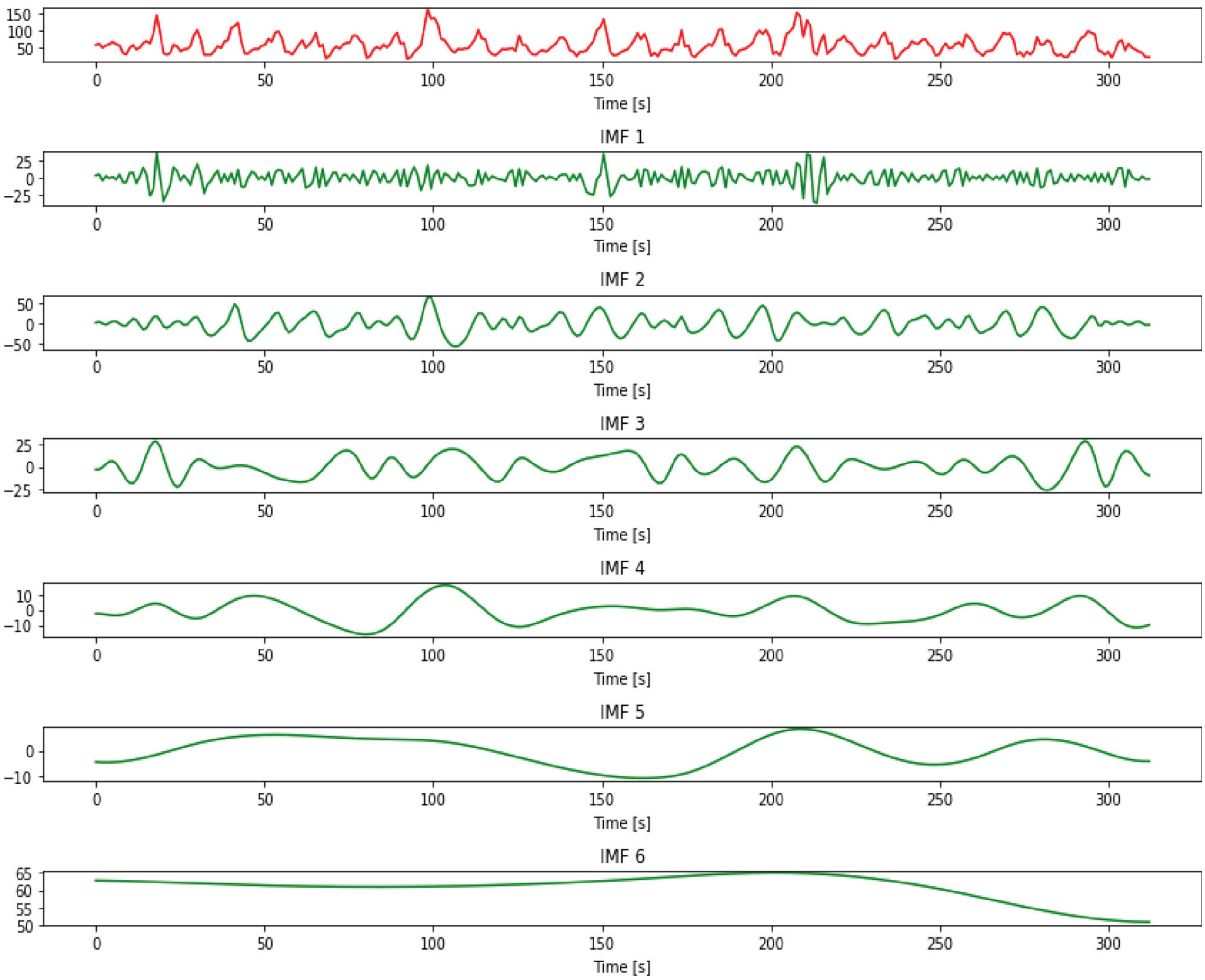

Figure 6. The EMD results of the original wind speed series.

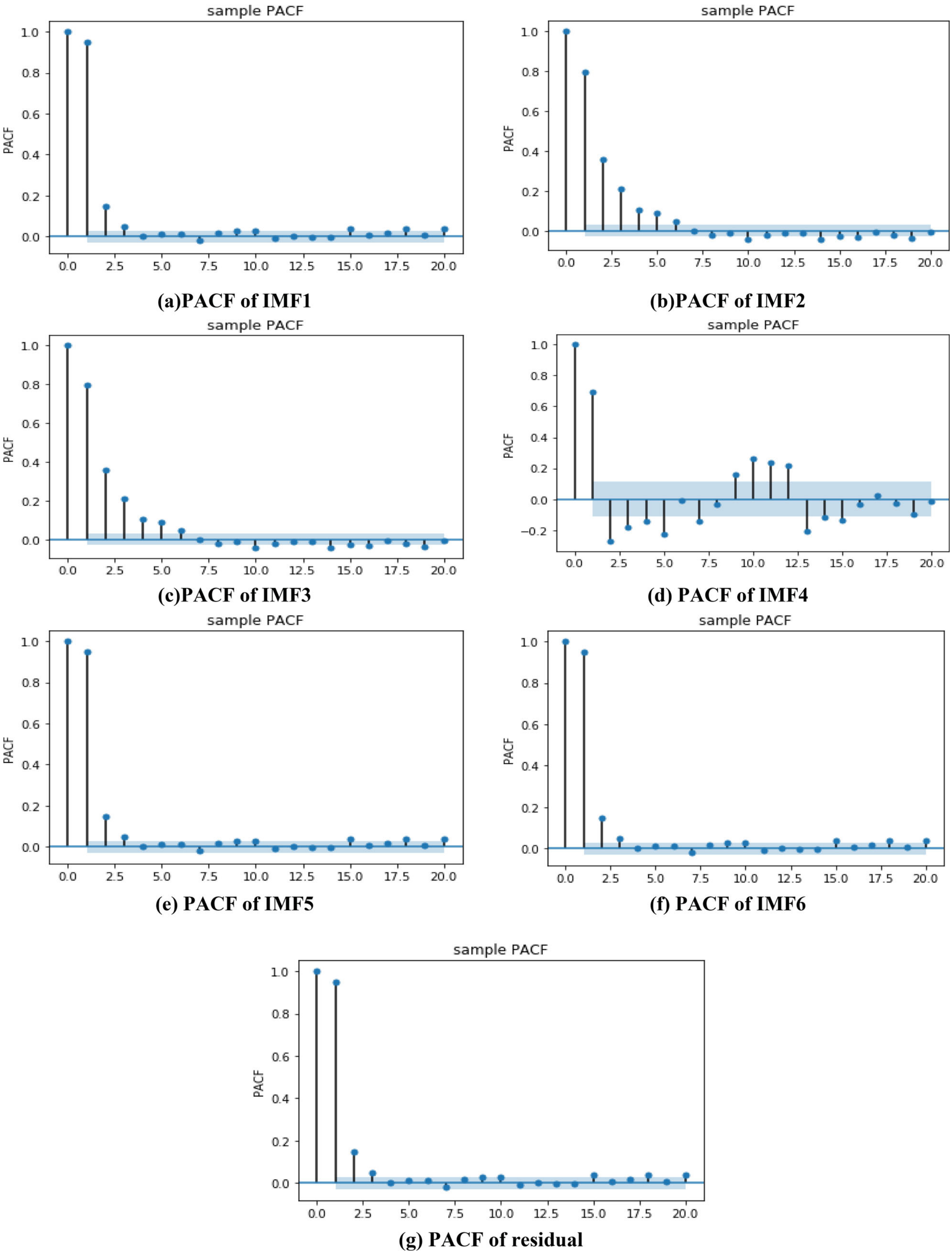

Figure 7. PACF of each IMF and one residual.

Step 3:

With the selected input variables in Step 2, the corresponding sub-series are predicted by utilizing the TS-GRNN. By combining the prediction results of each sub-series, the final forecasting results are obtained. Tabu Search optimizes the values of the spread parameter in GRNN and it is shown in Table 5.

Step 4:

Figure 8. shows the hybrid models of wind speed decomposition and optimization models. The wind

Table 5. Values of the spread parameter.

IMFs	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	R0
Spread parameter	0.0636	0.0206	0.0883	0.0539	0.0054	0.00381	0.00381

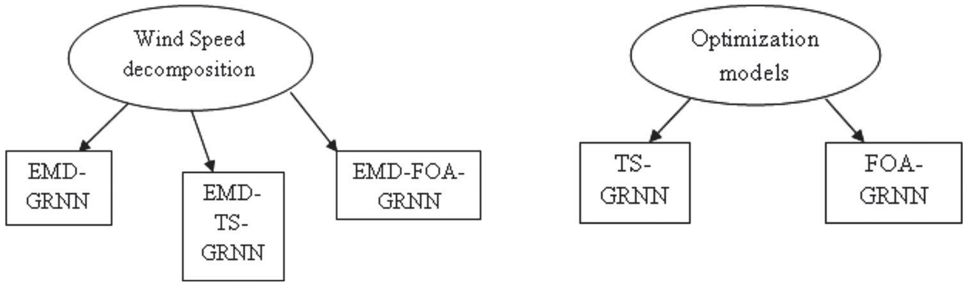

Figure 8. Comparison Framework of wind speed forecasting model.

speed decomposition method EMD is combined with neural network GRNN and optimization algorithms such as Tabu Search and Firefly Optimization algori thm. In order to know the effectiveness of EMD, the predicted values obtained from the hybrid methods such as EMD-GRNN, EMD-TS-GRNN, EMD-FOA-GRNN are compared with the actual value of wind speed data. Similarly, the optimization algorithms such as TS and FOA are combined with GRNN to know the effectiveness of optimization. The predicted values obtained from the hybrid models such as TS-GRNN and FOA-GRNN are compared with the actual value of wind speed data in predicting the wind speed.

Figure 9. shows the actual and forecasting values of wind speed for different models. The optimized spread parameter value for GRNN obtained from Tabu Search is 0.05. The accuracy of prediction is tested by comparing the various hybrid models such as EMD-TS-GRNN, EMD-FOA-GRNN, EMD-GRNN, TS-GRNN, FOA-GRNN with the actual value of wind speed data. This figure shows that the hybrid model EMD-TS-GRNN closely matches with the actual value of wind speed data when compared with other models. Since the optimized spread parameter is achieved from Tabu Search for GRNN, it is recommended to use EMD-TS-GRNN for accurate wind speed forecasting when compared with other hybrid models. The variation between the actual data and the other hybrid models is

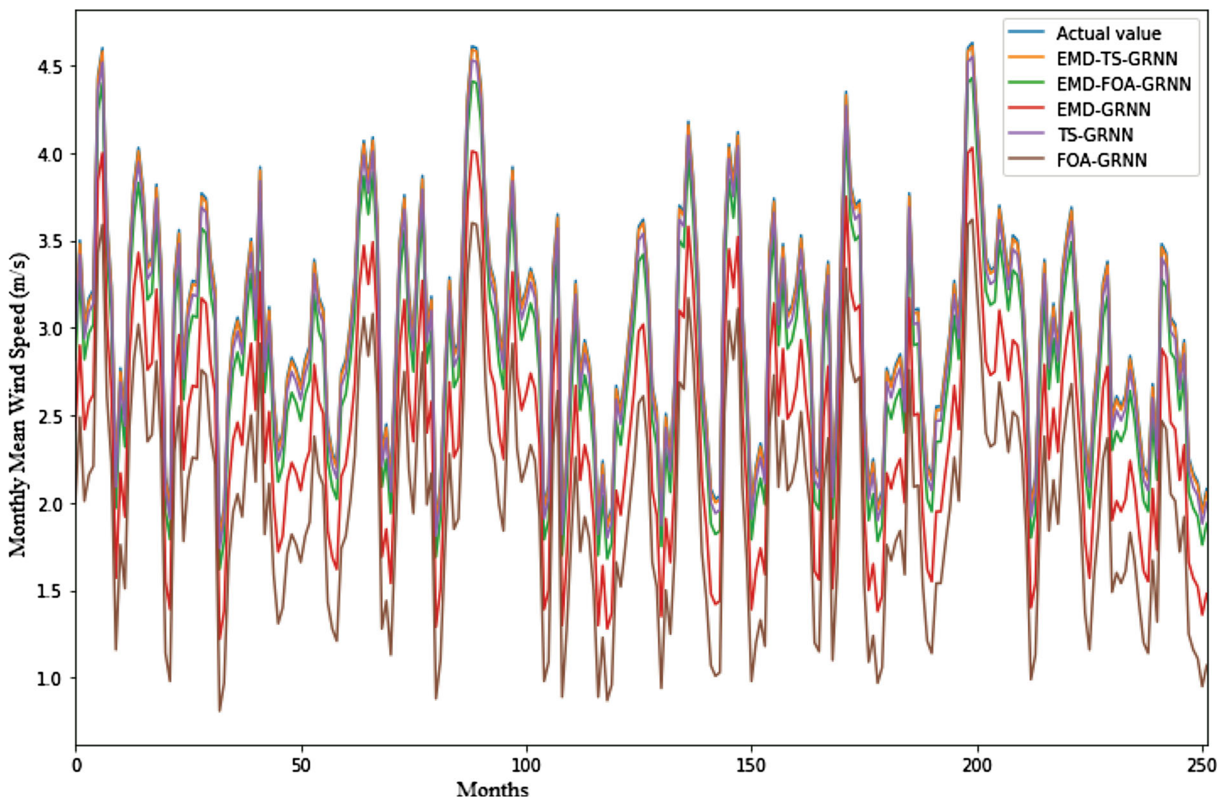

Figure 9. Prediction results of wind speed.

large when compared with EMD-TS-GRNN. Thus the accurate wind speed forecasting can be done by using EMD-TS-GRNN model.

4.3. Result analysis

Compared with the TS-GRNN and EMD-GRNN models, the predicted wind speed by the EMD-TS-GRNN model matches with the actual wind speed. At each sampling instant one step ahead the forecast is being made. The proposed model by one step ahead can serve as a valuable assistant to researchers, policy makers, industry and system planners in performing their wind speed before wind turbine is sited.

The absolute value of error is shown in Figure 10. and it is seen that only very few error points are there out of 4 m/s which shows that the proposed model has better forecasting results.

The accuracy estimation of the forecasting models using relative errors is shown in Table 6. Relative errors are categorized as less than 10%, 10–20%, and greater than 20%. For better accuracy prediction, hybrid models focus on the category of less than 10% relative errors. In the proposed hybrid model EMD-TS-GRNN, 165 data samples have relative error less than 10% and the percentage is 65.47% (out of 252 testing samples), 72 data samples in 10–20% and the percentage is 28.57% (out of 252 testing samples) and 15 samples in greater than 20% and the percentage is 5.95% (out of 252 testing samples). Compared to other hybrid models, the proposed hybrid model EMD-TS-GRNN has the highest number of samples that is 165 samples have a relative error less than 10%. It is concluded that the proposed hybrid model has better forecasting strategy and can be installed in grid connected wind farms to have an accurate prediction.

Table 7. Analysis based upon statistical criteria.

Prediction models	MAE	MAPE	RMSE
EMD-TS-GRNN	0.37	6.489	0.0299
EMD-FOA-GRNN	0.56	8.95	0.0409
EMD-GRNN	0.85	10.99	0.198
TS-GRNN	0.96	11.3	0.107
FOA-GRNN	1.06	11.69	0.3929

Table 7 shows that

Compared with the other models, the proposed model based on EMD and GRNN optimized by Tabu Search (TS) shows better forecasting performance based on the evaluation criteria MAE, MAPE, and RMSE. The MAE, MAPE, RMSE values obtained by EMD-TS-GRNN are 0.37, 6.489, 0.0299 respectively.

The forecasting results are better for intelligent models when compared with statistical models. To forecast non-stationary and nonlinear wind speed series, GRNN is more suitable with only one parameter to be optimized.

Comparing with other hybrid models, the forecasting performance of the proposed model is improved by

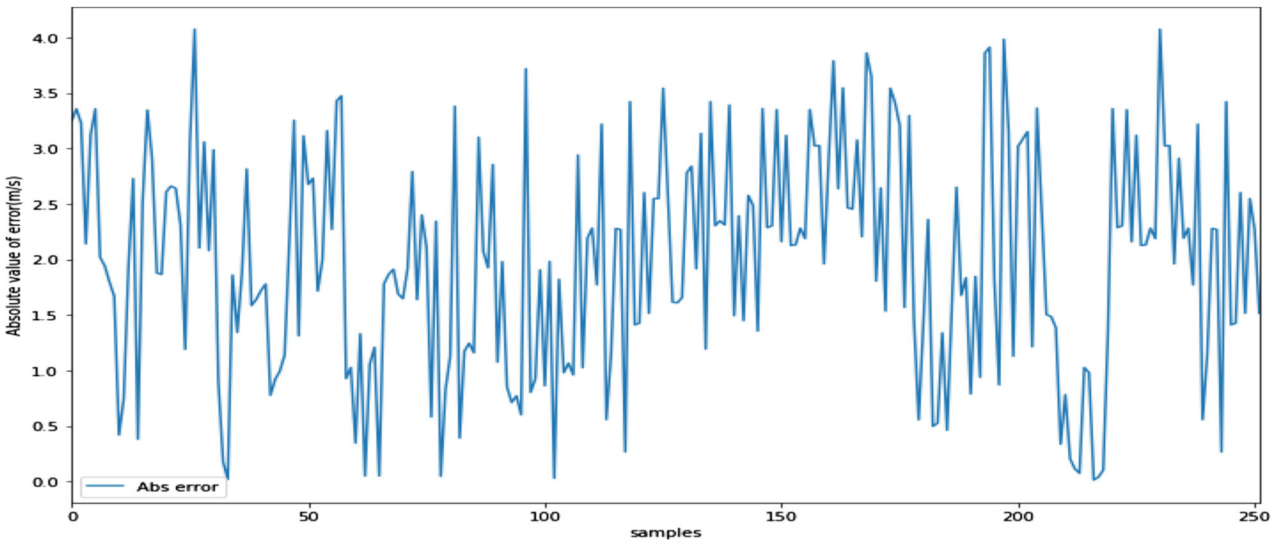

Figure 10. The absolute value of error.

Table 6. Estimation of Accuracy.

	Less than 10%		10–20%		Greater than 20%	
Prediction models	Samples	%	samples	%	samples	%
EMD-TS-GRNN	165	65.47%	72	28.57%	15	5.95%
EMD-FOA-GRNN	160	63.49%	74	29.36%	18	7.14%
EMD-GRNN	147	58.33%	71	28.17%	34	13.49%
TS-GRNN	137	54.36%	69	27.31%	46	18.25%
FOA-GRNN	122	48.41%	80	31.74%	50	19.84%

EMD and this proves that EMD can decompose the signal effectively so that the forecasting capacity can be improved.

The optimized model TS-GRNN produces better results. To select the appropriate value of the spread parameter for the GRNN, TS algorithm is utilized. This optimization algorithm TS improves the global searching ability of the GRNN, avoids the local optimum and enhances the training and learning process. TS made a better optimal performance and its optimization mechanism is verified from these three indexes (MSE, MAPE, RMSE). The proposed model is simple and efficient forecasting method for long term wind speed forecasting and is necessary and highly desirable for the development of the wind energy systems.

5. Conclusion:

A hybrid model is presented in this paper for long term wind speed forecasting. To convert the non-stationary signal to stationary signal, Empirical Mode Decomposition (EMD) is proposed and the random fluctuations of the wind speed data are also eliminated by EMD. Then, the set of Intrinsic Mode Functions (IMFs) obtained by the EMD are forecasted by the Generalized Regression Neural Network (GRNN), which is improved by Tabu Search (TS). The lags of the historical speeds are chosen by the Partial Auto-Correlation Function (PACF). The conclusions are summarized as:

The performance of the forecasting is effectively improved by EMD.

The global searching capability of the proposed model is strongly increased by the optimization algorithm TS and it shows better performance.

The accuracy of the EMD-TS-GRNN model is increased by the EMD and the TS.

From the error measures, it is seen that the proposed model EMD-TS-GRNN is an efficient method to forecast the long term wind speed.

The future study is the application of more advanced models to predict wind speed with the development of signal processes and intelligent algorithms.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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