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New wind speed forecasting approaches using fast ensemble empirical model decomposition, genetic algorithm, Mind Evolutionary Algorithm and Artificial Neural Networks

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ABSTRACT

Wind speed high-precision prediction is one of the most important technical aspects to protect the safety of wind power utilization. In this study, two new hybrid methods [*FEEMD-MEA-MLP/FEEMD-GA-MLP*] are proposed for the wind speed accurate multi-step predictions by combining FEEMD (*Fast Ensemble Empirical Mode Decomposition*), MEA (*Mind Evolutionary Algorithm*), GA (*Genetic Algorithm*) and MLP (*Multi Layer Perceptron*) neural networks. In these two hybrid methods, the FEEMD algorithm is adopted to decompose the original wind speed series into a number of sub-layers and the MLP neural networks optimized by the MEA algorithm and the GA algorithm are built to predict the decomposed wind speed sub-layers, respectively. The innovation of the study is to investigate the promoted percentages of the MLP neural networks by the FEEMD decomposition and the MEA/GA optimization, respectively. The involved forecasting models in the performance comparison in the study include the hybrid FEEMD-MEA-MLP, the hybrid FEEMD -GA-MLP, the hybrid FEEMD-MLP, the hybrid MEA-MLP, the hybrid GA-MLP and the single MLP. Two experimental results show that: (a) among all the involved methods, the hybrid FEEMD-MEA-MLP model has the best forecasting performance; (b) the FEEMD algorithm promotes the performance of the MLP neural networks significantly while the MEA/GA algorithms do not improve the performance of the MLP neural networks significantly; and (c) the hybrid FEEMD-MEA-MLP method and the hybrid FEEMD-GA-MLP method are both effective in the wind speed high-precision predictions.

1. Introduction

In recent years, the wind speed prediction becomes more and more important for the wind energy applications. The accurate wind speed forecasting results can decrease the possibilities of the wind power breakdown and protect the security of the wind power conversion [1].

Scientists have presented some important results in the wind speed prediction. Shukur et al. [2] proposed a new hybrid method to predict the wind speed by combining the ARIMA (*Auto Regressive Integrated Moving Average*) and the KF (*Kalman Filter*). In the proposed method, the ARIMA was adopted to determine the inputting structure of the KF, and the optimized KF was employed to realize the wind speed forecasting computation with the ANN (*Artificial Neural Networks*). The performance of the proposed method was validated by using daily wind speed data from Iraq to Malaysia. Haque et al. [3] presented a new hybrid wind speed forecasting method by based on the WT (*Wavelet Transform*) and the FART (*Fuzzy Adaptive Resonance Theory*). The WT was exploited to decompose the raw wind speed data, the FART was built to do the real forecasting computation. The presented hybrid method had been validated by using some real data measured from North Cape wind farm in Canada. Liu et al. [4] designed a new hybrid wind speed predicting approach by combining the EMD (*Empirical Mode Decomposition*) and the ANN. The EMD was utilized to decompose

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Abbreviations

ARIMA	Auto Regressive Integrated Moving Average
ANN	Artificial Neural Networks
BP	Back Propagation
BM	Bayesian Model
CRO	Coral Reefs Optimization
EMD	Empirical Mode Decomposition
ERNN	Elman Recurrent Neural Networks
ELM	Extreme Learning Machine
FART	Fuzzy Adaptive Resonance Theory
GA	Genetic Algorithm
HSA	Harmony Search Algorithm
KF	Kalman Filter
MLP	Multi Layer Perceptron
MLR	Multiple Linear Regression
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
NARX	Nonlinear Autoregressive Model with Exogenous Inputs
OFM	Organizing Feature Maps
PA	Polynomial Algorithm
PSO	Particle Swarm Optimization
PM	Persistent Model
RBF	Radial Basis Functions
RT	Regression Tress
SVR	Support Vector Regression
SIA	Seasonal Index Adjustment
WT	Wavelet Transform
WDF	Weibull Distribution Function

the original non-stationary wind speed data into a series of sub-layers and the ANN was used to build the best forecasting models for all the sub-layers. The results showed that the proposed method forecasted the extremely jumping samplings successfully. Petković et al. [5] provided a comparison of the wind speed distribution prediction using various soft computing methodologies. The PA (*Polynomial Algorithm*) and RBF (*Radial Basis Functions*) neural network were applied as the kernel function to optimize the SVR (*Support Vector Regression*) to estimate the parameters of the WDF (*Weibull Distribution Function*). Liu et al. [6] investigated an experiment comparing the Wavelet-GA (*Genetic Algorithm*)-MLP (*Multi Layer Perceptron*) with the Wavelet-PSO (*Particle Swarm Optimization*)-MLP for realizing the wind speed high-precision multi-step predictions. Troncoso et al. [7] evaluated the forecasting performance of different RT (*Regression Tress*) in the short-term wind speed prediction. Their experimental results showed that the RT based forecasting methods were able to obtain very satisfactory results. Palomares-Salas et al. [8] compared eight models for the wind speed one-hour ahead forecasting. In the study, the PM (*Persistent Model*), the ARIMA model, the MLR (*Multiple Linear Regression*) and five different types of neural networks were estimated. The comparing results indicated that the BP (*Back Propagation*) neural network had the best performance. Su et al. [9] presented a hybrid wind speed predicting framework by adopting the PSO, the ARIMA and the KF. In the hybrid framework, the PSO was employed to optimize the parameters of the ARIMA model, and then the optimized ARIMA model was utilized to build the initial equations for the KF predictor. Actually the ARIMA-KF algorithm in the proposed PSO-ARIMA-KF format had been published before in Ref. [10]. Baran et al. [11] put forward a BM (*Bayesian Model*) based statistical wind speed forecasting approach. The results provided in the paper showed that the BM was suitable for the wind speed high-precision predictions. Gnana Sheela et al. [12] studied the ANN based computing models for the wind speed predictions. The OFM (*Organizing Feature Maps*) and the MLP were adopted in the proposed models. Their results validated that the hybrid OFM-MLP model had higher accuracy than the single MLP, BP and RBF. Wang et al. [13] designed a new wind speed forecasting strategy. In the strategy, the SVR was employed to detect and preprocess the outliers of the raw wind speed data and the ERNN (*Elman Recurrent Neural Networks*) optimized by the SIA (*Seasonal Index Adjustment*) was built to perform the wind speed prediction. It had been proved in the paper that the proposed strategy was good at the medium-term wind speed forecasting situation. Salcedo-Sanz et al. [14] adopted a new hybrid bio-inspired solver to select the best parameters of meteorological variables for the ELM (Extreme Learning Machine) based wind speed predictor. The bio-inspired solved was generated by the recently proposed CRO (*Coral Reefs Optimization*) and the HSA (*Harmony Search Algorithm*). Two experiments indicated that the optimized ELM obtained satisfactory wind speed forecasting performance. Azad et al. [15] investigated the performance of the long-term wind speed forecasting by the NARX (*Nonlinear Autoregressive Model with Exogenous Inputs*) neural networks. Two groups of real wind speed samples from two meteorological stations in Malaysia were adopted to validate the built NARX forecasting models. The results proved that the built models were satisfactory. From the upper reviewed literature, it can be seen that: (a) the hybrid forecasting methods always can have better performance than the single ones in the wind speed predictions; (b) in the proposed hybrid methods, the signal processing algorithms (e.g., wavelet decomposition [3,6], empirical mode decomposition [4], etc) are adopted to decrease the instability of the raw wind speed data to decrease the high-precision forecasting difficulty and the intelligent optimizing algorithms (e.g., genetic algorithm [6], particle swarm optimization [9], coral reefs optimization [14], etc) are utilized to promote the computational capacity of the built forecasting models for the accurate results; and (c) the neural networks have been generally applied in the wind speed predictions.

In this study, two new hybrid forecasting methods [*i.e., the hybrid FEEMD-MEA -MLP method and the hybrid FEEMD-GA-MLP method*] are proposed by combining the FEEMD (*Fast Ensemble Empirical Mode Decomposition*), the MEA (*Mind Evolutionary Algorithm*), the GA (*Genetic Algorithm*) and the MLP (*Multi Layer Perceptron*) neural networks. The originality of the proposed hybrid methods is explained as follows: (a) the processing of the raw wind speed data and the optimization of the forecasting models are both adopted in this study. In the proposed hybrid forecasting framework, the FEEMD algorithm is used to decompose the raw wind speed signals to decrease the non-stationarity of the original data, the MLP neural networks are established to predict various decomposed wind speed sub-layers, and the MEA/GA algorithms are employed to select the optimized initial parameters for the built MLP models. It can be imagined that by the utilization of the FEEMD decomposition and the MEA/GA optimization, the forecasting performance of the MLP neural network can be promoted considerably; (b) the contribution percentages of various components (*i.e., the FEEMD, the MEA and the GA*) to promote the MLP based wind speed predictors will be fully investigated. Since the formats of the hybrid FEEMD-MEA-MLP and FEEMD-GA-MLP methods have not be presented before, it is the first time to study the contribution percentages of these algorithms for promoting the performance of the MLP models in the wind speed multi-step predictions; and (c) to verify the real performance of the proposed FEEMD-MEA -MLP and FEEMD-GA-MLP methods, a series of comparisons are provided in this paper. The comparing models include the FEEMD-MEA-MLP model, the FEEMD -GA-MLP model, the FEEMD-MLP model, the MEA-MLP model, the GA-MLP model and the single MLP neural network.

This paper is organized as follows: Section 2 presents the wind speed decomposition; Sections 3 shows the MLP neural networks optimized by the MEA/GA algorithms, Section 4 provides and discusses the wind speed multi-step forecasting results; and Section 5 concludes this paper.

2. Wind speed decomposition

2.1. Empirical mode decomposition

The EMD (*Empirical Mode Decomposition*) is a time domain signal decomposing method, proposed by scientist N. E. Huang in 1998 [16], which can decrease the non-stationary of the raw jumping signals by converting them into several locally narrow band components, named Intrinsic Mode Functions (IMFs).

In the theory of EMD, any signal series $X(t)$ can be decomposed and described using the following equation as:

$$X(t) = \sum_{i=1}^{n} IMF_i(t) + R_n(t) \tag{1}$$

where $\{IMF_i(t)\},(i = 1,2,\cdots,n)$ are the EMD decomposed IMFs and $\{R_n(t)\}$ is the residue. The computational steps of the EMD algorithm are explained as follows [4]:

Step1: Identify all the local extrema of the raw series$\{X(t)\}$.
Step2: Connect all the local maxima and the local minima by two cubic spline lines to generate the corresponding upper envelop series $\{X_{UP}(t)\}$ and down envelop series $\{X_{DOWN}(t)\}$, respectively.
Step3: Calculate the mean envelop series $\{X_{MEAN}(t)\}$ as:

$$X_{MEAN}(t) = [X_{UP}(t) + X_{DOWN}(t)]/2 \tag{2}$$

Step4: Execute the extracting computation as:

$$Y(t) = X(t) - X_{MEAN}(t) \tag{3}$$

Step5: Examine whether the extracted series$\{Y(t)\}$ is an IMF component: if yes, set $IMF(t) = Y(t)$ and replace the series$\{X(t)\}$ with the residual $R(t) = X(t) - IMF(t)$; if no, replace the series $\{X(t)\}$ with the extracted series$\{Y(t)\}$ and repeat the steps described in 'Step2–4' until the following terminating threshold is reached.

$$\varsigma_{TERMINATE} = \sum_{t=1}^{m} \frac{\left[Y_{j-1}(t) - Y_j(t)\right]^2}{\left[Y_{j-1}(t)\right]^2} \le \delta \tag{4}$$

where 'm' is the length of the data in the original series$\{X(t)\}$,'δ' is the terminating threshold, and j is the number of the iterative computation.

Step6: The procedure in the '**Step1–5**' will be continued until all the IMFs have been obtained.

2.2. Ensemble empirical mode decomposition

To overcome the existent mode-mixing phenomenon of the EMD algorithm, an optimized decomposing method named the EEMD (*Ensemble Empirical Mode Decomposition*) had been proposed by scientists Z. Wu and N.E. Huang in 2009 [17, 18]. The EEMD algorithm adds different realizations of white noise series to the original signal $X(t)$ then adopting the standard EMD procedures to obtain the IMFs without the mode-mixing. The computational steps of the EEMD algorithm are given as follows:

Step1: Calculate $X^k(t) = X(t) + \omega^k(t)$,where$\{\omega^k(t)\}$,$(k = 1,2,3,\cdots,N)$ are the different realizations of white Gaussian noise series, 'N' is the times to add the noise series inside the original signal $X(t)$.
Step2: Decompose the series $\{X^k(t)\}$,$(k = 1,2,3,\cdots,N)$ by executing the standard EMD to obtain their corresponding IMF modes $\{IMF_m^k(t)\},(m = 1,2,3,\cdots,M)$, where '$M$' is the number of the decomposed IMF modes in the 'k' round.
Step3: Compute the average of the corresponding series $\{IMF_m^k(t)\}$ as:

$$\overline{IMF_m}(t) = \frac{1}{N}\sum_{k=1}^{N} IMF_m^k(t) \tag{5}$$

Step4: Repeat the upper average procedure to complete the whole EEMD decomposition. The original signal series $X(t)$ will be formatted as below:

$$X(t) = \sum_{m=1}^{p} \overline{IMF}_m(t) + R_p(t) \tag{6}$$

where $\{\overline{IMF}_m(t)\},(m = 1,2,\cdots,p)$ are the EEMD decomposed IMFs, $\{R_m(t)\}$ is the corresponding residue and 'p' is the number of the final EEMD based IMFs.

To prove that the time complexity of the EMD/EEMD is almost equivalent to that of the Fourier transform, an evaluating experiment was carried out by scientist Y. Wang et al. in 2014 [19]. In this time-complexity investigation, a group of parameters were compared to validate the fast ensemble empirical mode decomposition. The EEMD algorithm using these parameters presented in Ref. [19] is named as the FEEMD in this study, which will be actually adopted to do the raw wind speed signal decomposition for the multi-step forecasting purpose.

3. Optimization of MLP neural networks

3.1. Standard MLP neural networks

The MLP (*Multi Layer Perceptron*) is a feed forward artificial neural network [20]. The modeling process of the MLP network can be seen in Refs. [21,22]. In this study, a three-layer MLP network is established as shown in Fig. 1 and the main parameters of the MLP network are selected as:

- Network Training Algorithm: BFGS Quasi-Newton Algorithm.
- Number of Input Neurons: 6.
- Number of Hidden Layer Neurons: 12.
- Number of Output Neurons: 1.

- Number of Iterations: 200.

3.2. MLP neural networks optimized by GA

In this study, the GA (*Genetic Algorithm*) is used to optimize the initial weights and thresholds of the MLP neural networks. The GA algorithm simulates the activities of biological evolution [23]. The flow diagram of the GA-MLP optimizing process is illustrated in Fig. 2.

As shown in Fig. 2, the computational process of the GA algorithm can be explained as follows:

(a) Employ the GA to search for the optimal weights and thresholds for the MLP.

The length 'N_w' of a chromosome is calculated as:

$$\begin{aligned} N_w &= N_i \times N_j + N_j \times N_k + N_j + N_k \\ &= 6 \times 12 + 12 \times 1 + 12 + 1 \\ &= 97 \end{aligned} \tag{7}$$

where 'N_i' is the number of the inputting neurons of the MLP neural network, 'N_j' is the number of the hidden neurons of the MLP neural network, and 'N_k' is the number of the outputting neurons of the MLP neural network.

The fitness function is adopted as:

$$\begin{cases} F(t) = 1/E(t) \\ E(t) = \sum\limits_{m=1}^{N_l} \sum\limits_{n=1}^{N_k} \left(S_n - S_n^{'}\right)^2 \end{cases} \tag{8}$$

where 't' is the number of the whole chromosomes, 'm' is the number of the learning samples, 'n' is the number of the outputting neurons of the MLP network, 'S_n' is the forecasting wind speed signals, '$S_n^{'}$' is the guiding wind speed signals. In this study, the following parameters are selected for the GA searching.

- Size of chromosomes: *200*.
- Probability of Crossover: *0.25*.
- Probability of Mutation: *0.01*.
- Algorithm of Selection Operation: Roulette Wheel Algorithm.
- Number of Iterations: *50*.

The crossover operation is employed as: suppose '*chrom1*' and '*chrom2*' are two original chromosomes, and 'r_1' is an independently distributed random variance with the range [0, 1], then two new chromosomes will be generated by equation (9).

$$\begin{cases} chrom1' = r_1 \times chrom1 + (1 - r_1) \times chrom2 \\ chrom2' = r_1 \times chrom2 + (1 - r_1) \times chrom1 \end{cases} \tag{9}$$

The mutation operation of a gene 'g_{ij}' position in a chromosome is executed as:

$$g_{ij}' = \begin{cases} g_{ij} + \left(g_{ij} - g_{\max}\right) \times f(g), & r > 0.5 \\ g_{ij} + \left(g_{\min} - g_{ij}\right) \times f(g), & r \le 0.5 \\ f(g) = K \times (1 - g/G_{\max})^2 \end{cases} \tag{10}$$

where 'g_{max}' and 'g_{min}' are the upper limit and the lower limit of the gene 'g_{ij}', 'g' is the current iterative step, 'G_{max}' is the number of the whole iterations, and 'r' and 'K' are both a random value in the range [0, 1].

(b) Complete the wind speed forecasting computation by using the MLP neural network whose parameters have been selected.

3.3. MLP neural networks optimized by MEA

The MEA (*Mind Evolutionary Algorithm*) is used to select the initial weights and thresholds for the MLP neural networks. The MEA is an evolutionary algorithm, presented by Scientist C. Sun in 1998, which emulates the activities of human mind [24]. Actually the MEA is typically proposed to overcome the intrinsic flaws of the GA. As commented in Ref. [24], the MEA is always better than the GA in the convergent speed and the optimizing performance. In the

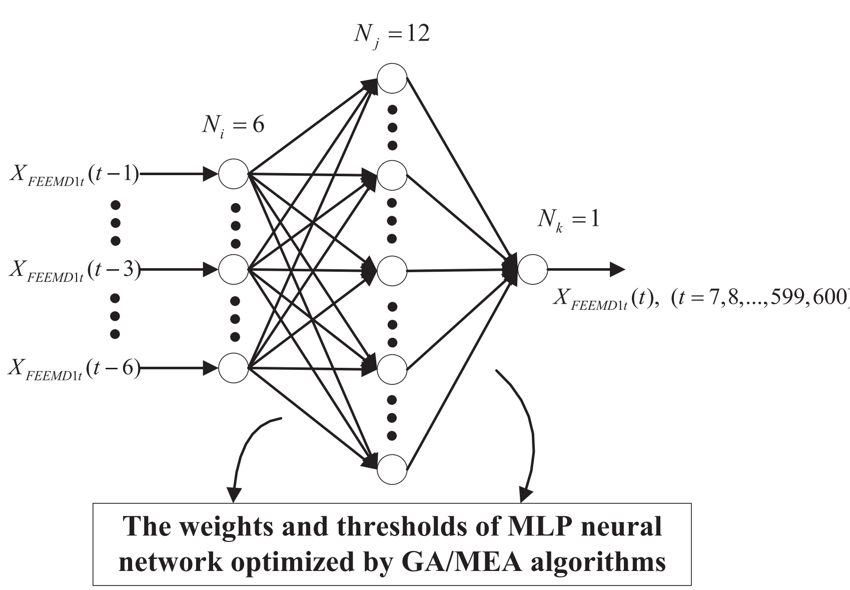

Fig. 1. The built three-layer MLP neural network.

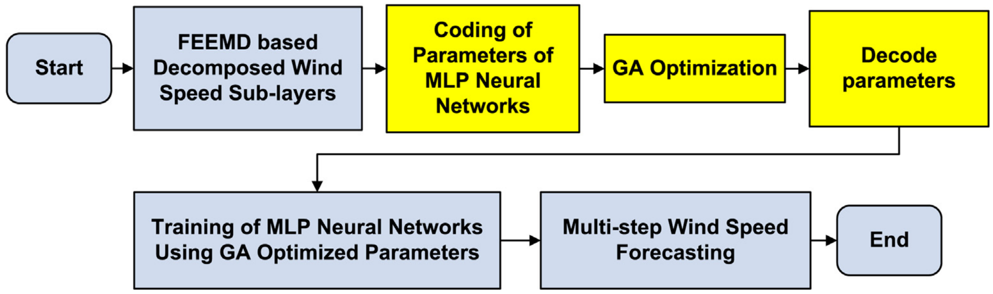

Fig. 2. The flow diagram of the GA-MLP optimizing process.

MEA, two important operations (*i.e., the similar-taxis and the dissimilation*) are put forward to replace the crossover and mutation operations of the GA. The structure of the MEA is illustrated in Fig. 3.

From Fig. 3, the contents of the MEA algorithm can be explained as follows:

(a) The population of the MEA consists of a number of groups in the searching environment. Each group owns a local billboard while the whole search environment has a global billboard. Inside a group, there are a set of individuals. Every individual has a score which is similar to the fitness value in the GA for guiding the group evolutionary process;
(b) In the step of initialization, all the groups are generated at random. Several groups among them are selected as the superior groups and the others are retained as the temporary groups. The selecting criterion is the score rank of all groups. In other words, groups with higher scores are chosen. The superior groups will be recorded in the global billboard.
(c) In the step of local competition, the similar-taxis operation will be adopted. The individuals in every group will compete with each other to get the local optimum. The wining individual will be recorded in the local billboard. In a new generation, all individuals will be re-arranged around the latest winner using the normal distribution and a new internal competition will be re-started to search for a new winner. If the score of the new winner is higher than that of the old winner, the new winner's score will be considered as the new score of the group and recorded in the local billboard. This process of the similar operation will be repeated until the group becomes mature.
(d) In the step of global competition, the dissimilation operation will be used. If the score of a temporary group is higher than that of any superior group being recorded in the global billboard, the corresponding temporary group will replace the position of the superior group in the global billboard. Oppositely, if the score of a temporary group is lower than that of any superior group, it will be dismissed and discarded. At the same time, a new temporary group will be generated to replace the dismissed one. In any case, the total number of the groups will not change.
(e) Repeat the Step (a)-(d) until the predefined number of iterative steps is reached or the best score of the all superior groups cannot be further promoted, then the MEA algorithm is considered convergent and the best winner of the superior groups is the expected global optimum.

The flow diagram of the MEA-MLP optimizing process is given in Fig. 4.

From Fig. 4, the computational process of the MEA algorithm can be given as follows [25]:

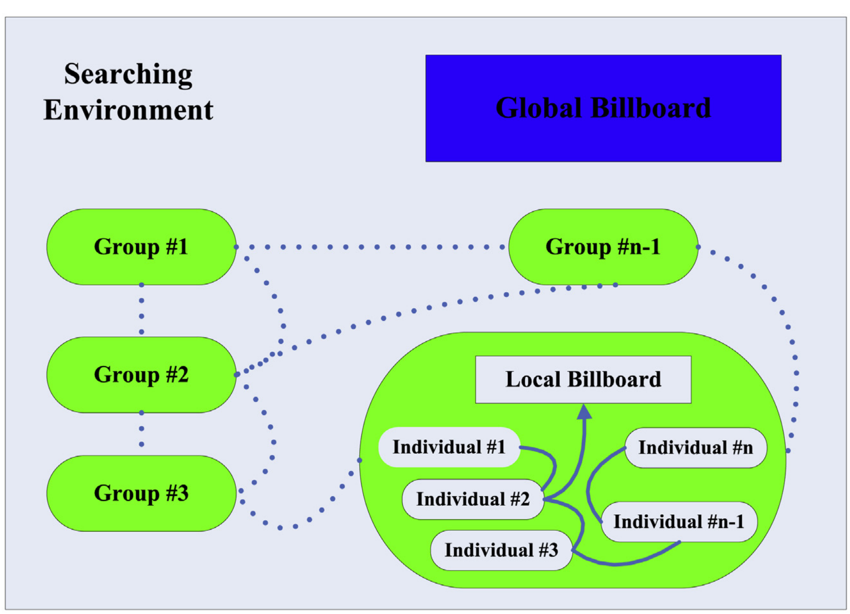

Fig. 3. The mechanism of the MEA algorithm.

(a) Employ the MEA to search for the optimal weights for the MLP network.

The same to that of the GA searching, the length of an individual in the MEA is also equal to 97, which exactly includes the all weights and thresholds of the MLP neural network. The equation (8) presented in the GA is also adopted as the fitness function in the MEA. The other detailed parameters of the MEA searching are listed as follows:

- Size of Population: 200.
- Number of Superior Groups: 5.
- Number of Temporary Groups: 5.
- Size of Superior/Temporary Groups: 20.
- Number of Iterations: 50.

(b) In the similar-taxis operating process, the new individuals will be generated among the group winner using a normal distribution with a variance 'δ'. In the study, the following adaptive equation is used to calculate the 'δ' in every iteration as:

$$\begin{cases} F(k+1)/F(k) < \zeta, & \delta(k+1) = \alpha \times \delta(k), \quad \alpha > 1; \\ F(k+1)/F(k) \geq \zeta, & \delta(k+1) = \beta \times \delta(k), \quad \beta \leq 1; \end{cases} \tag{11}$$

where 'F' is the fitness function of the similar-taxis operator, 'k' is the current iterative step, 'ζ' is the controlling factor of the similar-taxis operator, 'α' and 'β' are both reference values. Here the 'ζ' is equal to 0.2.

(c) In the dissimilation operating process, if the best score of all superior groups cannot be further promoted in ten iterations, the iterative process will be terminated then the best score is the finally expected optimum. The following equation is utilized to decide the step to terminate the searching process as:

$$\begin{cases} \varphi(k) = \sum_{i=1}^{10} F(k-i+1) \\ |\varphi(k+1) - \varphi(k)| < \mu \end{cases} \tag{12}$$

where 'μ' is the terminating factor. Here the 'μ' is equal to 0.3.

4. Wind speed forecasting computation

4.1. Hybrid architecture

The architecture of the proposed hybrid methods is given in Fig. 5.

As shown in Fig. 5, the contents of the proposed methods include:

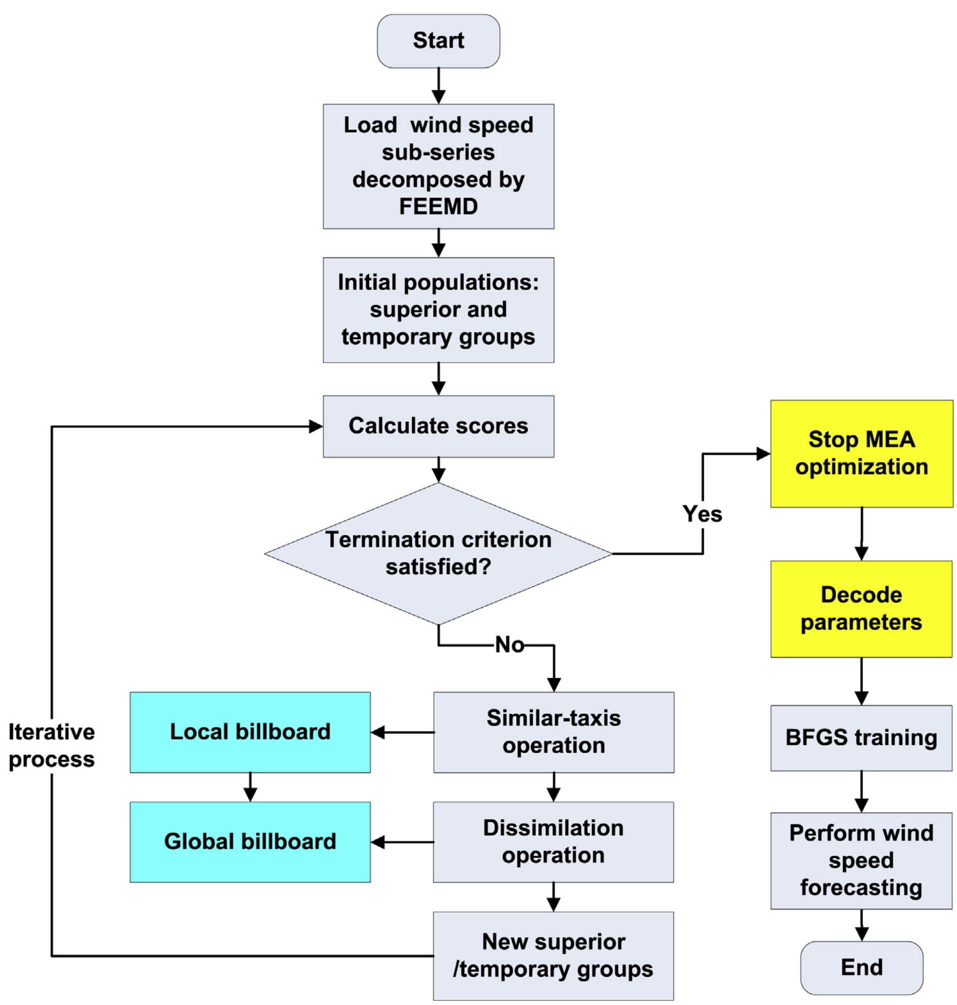

Fig. 4. The flow diagram of the MEA-MLP optimizing process.

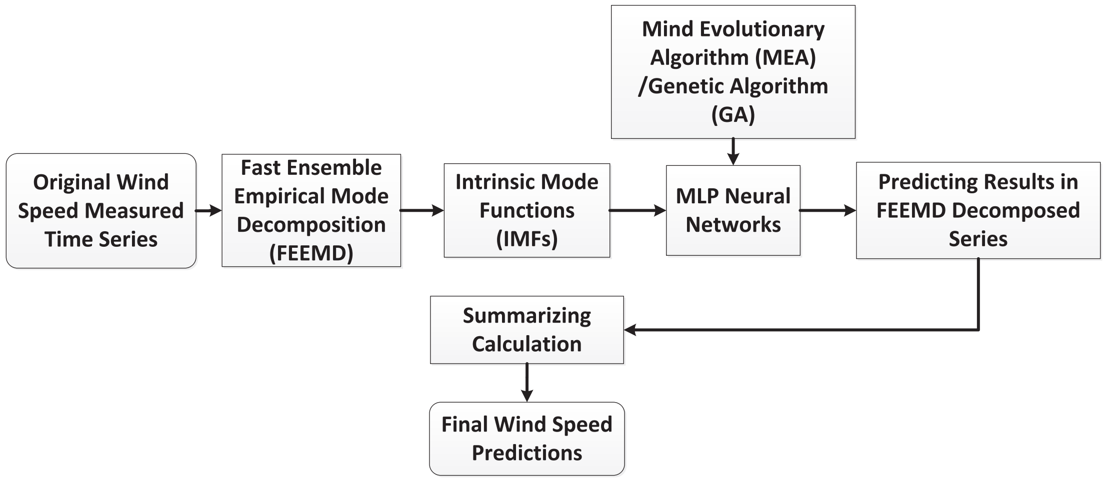

Fig. 5. Framework of the proposed hybrid methods.

- Using the FEEMD algorithm to decompose the original wind speed time series into a number of Intrinsic Mode Functions (IMFs). The purpose of this step is to decrease the difficulty of the MLP neural networks for the high-precision predictions.
- Building the MLP neural networks for all the FEEMD decomposed wind speed sub-layers. In this step, the built MLP neural networks are optimized by the MEA algorithm and the GA algorithm, respectively. The MEA and GA algorithms select the best initial weights and thresholds for the MLP neural networks to improve the network global searching capacity.
- Calculating the multi-step predictions for all the decomposed wind speed sub-layers by using the optimized MLP neural networks. Summarizing the obtained forecasting results of all the sub-layers to get the final predictions for the original wind speed series.
- Making comparisons of the forecasting performance generated by the proposed different models. The involved models include the hybrid FEEMD-MEA-MLP model, the hybrid FEEMD-GA-MLP model, the hybrid MEA-MLP model, the hybrid GA-MLP model and the single MLP neural network.
- The hybrid models proposed in this study realize the wind speed forecasting computation based on the wind speed historical data. To really verify the nonlinear tracking and forecasting capacity of the proposed models, the multi-step predictions are provided in the comparison of the forecasting performance as below. In the multi-step iterative process, the previously forecasted results will be further used to calculate the future-step results.
  - ✧ One-step predictions: The forecasted wind speed value $\widehat{X}(t+1)$ will be calculated based on the historical wind speed series$\{X(1),X(2),X(3),\cdots,X(t-1),X(t)\}$, where '*t*' is the sampled time of the wind speed series.
  - ✧ Two-step predictions: The forecasted wind speed value $\widehat{X}(t+2)$ will be calculated based on the historical wind speed series$\{X(2),X(3),X(4),\cdots,X(t-1),X(t)\}$ and the previously forecasted value $\widehat{X}(t+1)$, where '*t*' is the sampled time of the wind speed series.
  - ✧ Three-step predictions: The forecasted wind speed value $\widehat{X}(t+3)$ will be calculated based on the historical wind speed series$\{X(3),X(4),X(5),\cdots,X(t-1),X(t)\}$ and the previously forecasted wind speed series $\{\widehat{X}(t+1),\widehat{X}(t+2)\}$, where '*t*' is the sampled time of the wind speed series.

4.2. *Wind speed forecasting results*

4.2.1. *Accuracy estimating errors*

To investigate the performance of the proposed FEEMD-MEA-MLP and FEEMD-GA-MLP methods, six forecasting models are established to realize the three-step wind speed predictions. To estimate the forecasting performance, three error criterions are adopted, including the MAE (*Mean Absolute Error*), the MAPE (*Mean Absolute Percentage Error*) and the RMSE (*Root Mean Square Error*). The detailed equations of these three error criterions are given as follows:

- MAE:

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|X(t)-\widehat{X}(t)\right| \tag{13}$$

- MAPE:

$$MAPE = \frac{1}{M}\sum_{t=1}^{N}\left|\frac{X(t)-\widehat{X}(t)}{\widehat{X}(t)}\right| \tag{14}$$

- RMSE:

$$RMSE = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}\left[X(t)-\widehat{X}(t)\right]^2} \tag{15}$$

where $\{X(t)\}$ is the raw wind speed data series, $\{\widehat{X}(t)\}$ is the forecasted wind speed data series and '*N*' is the number of the sample in the$\{X(t)\}$ series.

To compare the performance difference between two forecasting models, three percentage error criterions are also used in the study as follows:

- P_{MAE}:

$$P_{MAE} = \left| \frac{MAE_1 - MAE_2}{MAE_1} \right| \tag{16}$$

- P_{MAPE}:

$$P_{MAPE} = \left| \frac{MAPE_1 - MAPE_2}{MAPE_1} \right| \tag{17}$$

- P_{RMSE}:

$$P_{RMSE} = \left| \frac{RMSE_1 - RMSE_2}{RMSE_1} \right| \tag{18}$$

Fig. 6 shows the multi-step predicted results at the 601^{st}-700^{th} samples of the original wind speed data using the different involved models (*the 1^{st}-600^{th} samples are used to build models*). Fig. 7 displays the absolute errors of every wind speed sampling point in the multi-step forecasting results. The estimated results of these predictions are given in Table 1. Based on the results given in Table 1, the improved percentages of the built MLP neural network by different algorithms are computed as shown in Tables 2 and 3.

From Table 1, it can be seen that: (a) all the proposed hybrid forecasting models forecast the wind speed effectively; (b) among all involved models, the hybrid FEEMD-MEA-MLP model has the best performance; (c) there are two levels of forecasting accuracy provided by these various models. In the high accuracy level, the models include the hybrid FEEMD-MEA-MLP model, the hybrid FEEMD-GA-MLP model and the hybrid FEEMD-MLP model. In the normal accuracy level, the models include the hybrid MEA-MLP model, the hybrid GA-MLP model and the single MLP model. The models in the high level have better forecasting performance than those in the normal level; and (d) both of the hybrid FEEMD-MEA-MLP model and the hybrid FEEMD-GA-MLP model have satisfactory forecasting performance.

From Table 2, it can be analyzed that:

(a) When comparing the hybrid FEEMD-MEA-MLP model with the single MLP model, the former has improved the performance of the latter obviously. The MAPE promoting percentages of the single MLP model by the proposed FEEMD-MEA-MLP from one-step to three-step predictions are 68.69%, 77.40% and 80.32%, respectively.
(b) When comparing the hybrid FEEMD-GA-MLP model with the single MLP model, the former has also improved the performance of the latter considerably. The MAPE promoting percentages of the single MLP model by the proposed FEEMD-GA-MLP model from one-step to three-step predictions are 66.96%, 76.37% and 79.89%, respectively.
(c) The reason of the phenomenon shown in (a) and (b) is that: in both the hybrid FEEMD-MEA-MLP model and the hybrid FEEMD-GA-MLP model, the combination of the FEEMD algorithm and the MEA/GA algorithms has promoted the forecasting capacity of the single MLP model effectively. Since the FEEMD algorithm decreases the jumping character of the original wind speed and the MEA/GA algorithms select the best initial weights and thresholds for the built MLP model, the optimized MLP model can achieve high-precision forecasting results.

From Table 3, it can be found that:

(a) When comparing the hybrid FEEMD-MEA-MLP model with the hybrid FEEMD-GA-MLP model, the performance of the hybrid FEEMD-MEA-MLP model is better than that of the hybrid FEEMD-GA-MLP model. The MAPE promoting percentages of the hybrid FEEMD-GA-MLP model by the hybrid FEEMD-MEA-MLP model from ones-step to three-step are 5.24%, 4.36% and 2.16%, respectively. This indicates that the MEA algorithm is more powerful than the GA algorithm to optimize the hybrid FEEMD-MLP model. The reason of the phenomenon is that the MEA algorithm does not have the local optimization and prematurity problems but the GA algorithm sometimes has these problems. In addition, the MEA algorithm has a considerable algorithm advantage that it can remember the optimum in every iterative step so that the fast global results always can be obtained.
(b) When comparing the hybrid FEEMD-MEA-MLP and FEEMD-GA-MLP models with the hybrid FEEMD-MLP model, the hybrid FEEMD-MEA-MLP and FEEMD-GA-MLP models have not improved the performance of the FEEMD-MLP model significantly. The MAPE promoting percentages of the hybrid FEEMD-MLP model by the hybrid FEEMD-MEA-MLP model from one-step to three-step are only 8.00%, 11.36% and 17.06%, respectively. The MAPE promoting percentages of the hybrid FEEMD-MLP model by the hybrid FEEMD-GA-MLP model from one-step to three-step are only 2.91%, 7.32% and 15.23%, respectively.
(c) When comparing the hybrid FEEMD-MLP model with the single MLP model, the former has improved the performance of the latter significantly. The MAPE promoting percentages of the single MLP model by the hybrid FEEMD-MLP model from one-step to three-step are up to 65.97%, 74.50% and 76.27% respectively.
(d) When comparing the hybrid MEA-MLP model and the hybrid GA-MLP model with the single MLP model, the hybrid MEA-MLP and GA-MLP models both have not improved the performance of the single MLP model considerably. The MAPE promoting percentages of the single MLP model by the hybrid MEA-MLP model from one-step to three-step are only 0.50%, 6.89% and 15.41%, respectively. The MAPE promoting percentages of the single MLP model by the hybrid GA-MLP model from one-step to three-step are only 0.12%, 6.63% and 13.63%, respectively.
(e) The phenomenon showed in (b)-(d) validates that the FEEMD based decomposition makes much more contribution than both the MEA based optimization and the GA based optimization in the performance improvement to the single MLP model. On the other hand, the promoted percentages of the single MLP model by the FEEMD algorithm are much more than those obtained by either the MEA algorithm or the GA algorithm.

5. Conclusions

In this paper, two new hybrid methods [*i.e., the FEEMD-MEA-*

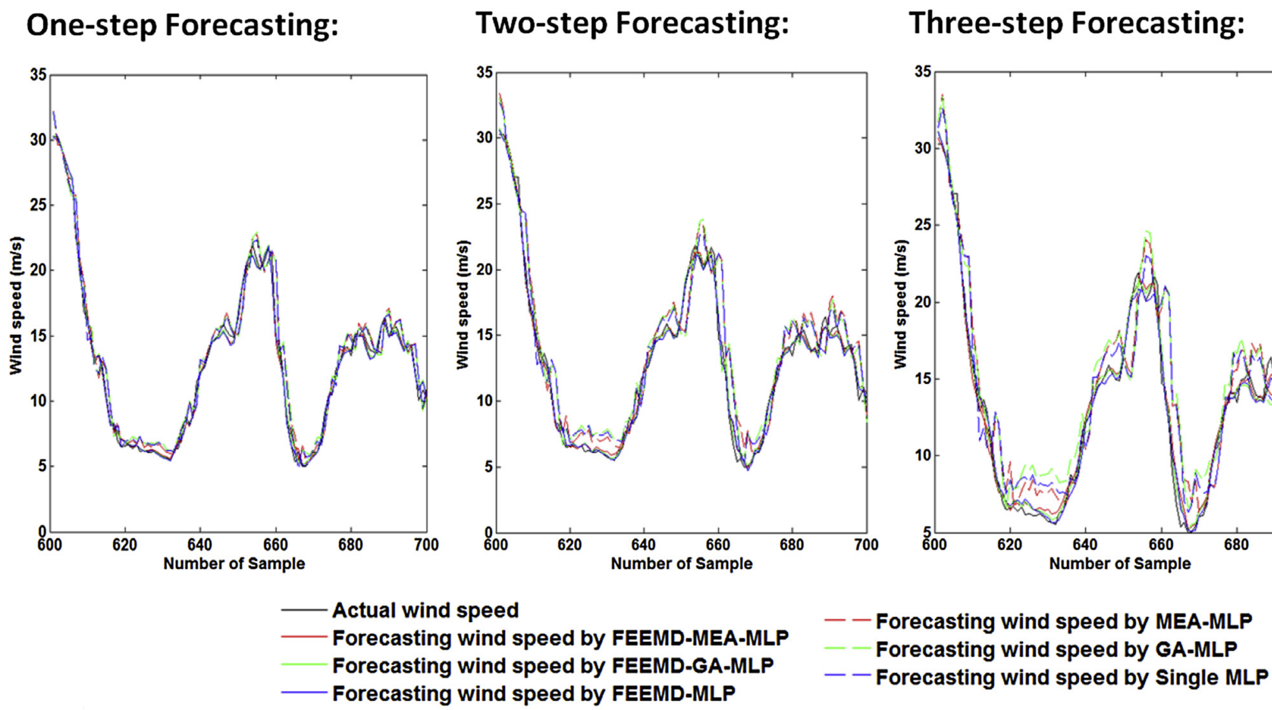

Fig. 6. Results of the multi-step wind speed predictions.

MLP method and the FEEMD-GA-MLP method] are proposed for the wind speed high-precision predictions by combining the FEEMD algorithm, the MEA algorithm, the GA algorithm and the MLP neural networks. The contribution percentages of the FEEMD algorithm and the MEA/GA algorithms to promote the single MLP model are investigated based on two wind speed forecasting experiments. The results in the two experiments show that: (a) the FEEMD algorithm can improve the forecasting performance of the MLP neural network considerably. It indicates that it is feasible to adopt the signal decomposing algorithms to decrease the non-stationarity of the original wind speed data for the MLP models to obtain high-precision forecasting results; (b) although both of the MEA algorithm and the GA algorithm also can improve the forecasting performance of the MLP neural network but all the contribution is limited compared to that of the FEEMD algorithm; (c) the promoted percentage of the MLP model by the MEA algorithm is better than that of the GA algorithm. The reason is that the MEA algorithm always does not have the local optimization and prematurity problems which the GA algorithm has. Due to this reason, compared to the GA algorithm, the MEA algorithm can find better global optimized parameters for the build MLP model to have more accurate forecasting results; (d) in the proposed various models, the hybrid FEEEMD-MEA-MLP model has the best performance in every forecasting step; and (e) the proposed hybrid

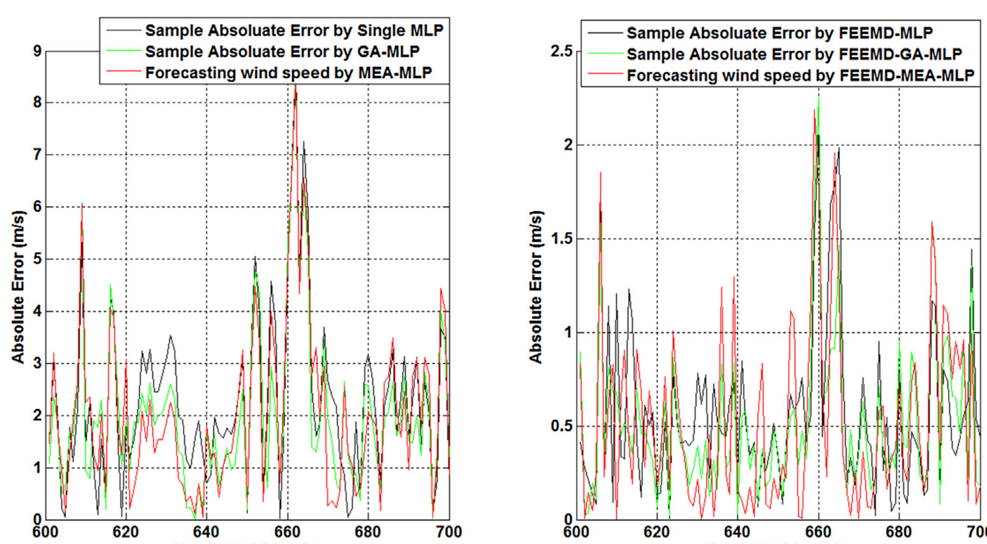

Fig. 7. Absolute errors of every wind speed sampling points in the multi-step forecasted results.

Table 1
Analysis of the predictions given in Fig. 6.

Indexes	Hybrid FEEMD-MEA-MLP			Hybrid FEEMD-GA-MLP		
	1-step	2-step	3-step	1-step	2-step	3-step
MAE (m/s)	0.2944	0.4066	0.5118	0.3020	0.4281	0.5137
MAPE (%)	2.53	3.51	4.52	2.67	3.67	4.62
RMSE (m/s)	0.3884	0.5672	0.6501	0.4019	0.5909	0.7025
Indexes	Hybrid FEEMD-MLP			Hybrid MEA-MLP		
	1-step	2-step	3-step	1-step	2-step	3-step
MAE (m/s)	0.3027	0.4388	0.5605	0.8524	1.5432	2.0553
MAPE (%)	2.75	3.96	5.45	8.04	14.46	19.43
RMSE (m/s)	0.4157	0.6104	0.7287	1.0977	1.7661	2.2196
Indexes	Hybrid GA-MLP			Single MLP		
	1-step	2-step	3-step	1-step	2-step	3-step
MAE (m/s)	0.8924	1.5785	2.0306	0.9117	1.6383	2.2864
MAPE (%)	8.07	14.50	19.84	8.08	15.53	22.97
RMSE (m/s)	1.1577	1.8059	2.2352	1.1958	1.9976	2.3409

Table 2
Improvement percentages of the single MLP models by the proposed hybrid models.

Indexes	Hybrid FEEMD-MEA-MLP vs. Single MLP			Hybrid FEEMD-GA-MLP vs. Single MLP		
	1-step	2-step	3-step	1-step	2-step	3-step
P_{MAE} (%)	67.71	75.18	77.62	66.88	73.87	77.53
P_{MAPE} (%)	68.69	77.40	80.32	66.96	76.37	79.89
P_{RMSE} (%)	67.52	71.61	72.23	66.39	70.42	69.99

Table 3
Improvement percentages of the single MLP model by the proposed hybrid FEEMD-MEA-MLP model.

Indexes	Hybrid FEEMD-MEA-MLP vs. Hybrid FEEMD-GA-MLP			Hybrid FEEMD-MEA-MLP vs. Hybrid FEEMD-MLP		
	1-step	2-step	3-step	1-step	2-step	3-step
P_{MAE} (%)	2.52	5.02	0.37	2.74	7.34	8.69
P_{MAPE} (%)	5.24	4.36	2.16	8.00	11.36	17.06
P_{RMSE} (%)	3.36	4.01	7.46	6.57	7.08	10.79
Indexes	Hybrid FEEMD-GA-MLP vs. Hybrid FEEMD-MLP			Hybrid FEEMD-MLP vs. Single MLP		
	1-step	2-step	3-step	1-step	2-step	3-step
P_{MAE} (%)	0.23	2.44	8.35	66.80	73.22	75.49
P_{MAPE} (%)	2.91	7.32	15.23	65.97	74.50	76.27
P_{RMSE} (%)	3.32	3.19	3.60	65.24	69.44	68.87
Indexes	Hybrid MEA-MLP vs. Single MLP			Hybrid GA-MLP vs. Single MLP		
	1-step	2-step	3-step	1-step	2-step	3-step
P_{MAE} (%)	6.50	5.80	10.11	2.12	3.65	11.19
P_{MAPE} (%)	0.50	6.89	15.41	0.12	6.63	13.63
P_{RMSE} (%)	8.20	11.59	5.18	3.19	9.60	4.52

forecasting methods are all suitable for the wind speed high-precision predictions for the safety of the wind power conversion.

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