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Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and GA-BP neural network method

Shouxiang Wang [a, *], Na Zhang [b], Lei Wu [c], Yamin Wang [c]

[a] Key Laboratory of Smart Grid of Ministry of Education (Tianjin University), Tianjin 300072, China
[b] Hulunbuir University, Hailaer 021008, China
[c] Electrical and Computer Engineering Department, Clarkson University, Potsdam, NY 13699, USA

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ABSTRACT

Wind speed is the major factor that affects the wind generation, and in turn the forecasting accuracy of wind speed is the key to wind power prediction. In this paper, a wind speed forecasting method based on improved empirical mode decomposition (EMD) and GA-BP neural network is proposed. EMD has been applied extensively for analyzing nonlinear stochastic signals. Ensemble empirical mode decomposition (EEMD) is an improved method of EMD, which can effectively handle the mode-mixing problem and decompose the original data into more stationary signals with different frequencies. Each signal is taken as an input data to the GA-BP neural network model. The final forecasted wind speed data is obtained by aggregating the predicted data of individual signals. Cases study of a wind farm in Inner Mongolia, China, shows that the proposed hybrid method is much more accurate than the traditional GA-BP forecasting approach and GA-BP with EMD and wavelet neural network method. By the sensitivity analysis of parameters, it can be seen that appropriate settings on parameters can improve the forecasting result. The simulation with MATLAB shows that the proposed method can improve the forecasting accuracy and computational efficiency, which make it suitable for on-line ultra-short term (10 min) and short term (1 h) wind speed forecasting.

1. Introduction

Wind energy, being economically competitive and environmentally friendly, has become the fastest growing renewable energy resource for electricity generation. The wind speed forecast is of great importance for predicting the power output of wind energy systems.

However, the biggest challenge in forecasting wind speed is its intermittency and uncertainty. Many forecasting methods have been proposed recently to predict wind speeds over different timescales. They include physical models, time series method, grey model method, artificial neural network, support vector machine (SVM) method, the wavelet transform method, empirical mode decomposition method, etc. Each method has its own advantages and limitations. For instance, the complex physical models always rely on the numeric weather prediction (NWP) system and the required input data are usually difficult to obtain [1,2]. Statistical forecasting models, such as autoregressive moving average (ARMA) models, were described in Ref. [3]. The parameters could be a function of time and the performance of ARMA forecast models would vary when applied to different time periods. A grey model GM (1, 1) based technique was presented in Ref. [4] for one hour ahead wind speed forecasting. However, this model may be suitable for certain sites with specific wind characteristics, but would not be generalizable to other locations. Artificial neural network was applied in wind speed forecasting in Refs. [5,6]. Three different neural networks including BP, adaptive linear element, and RBF for 1-h ahead wind speed forecasting were compared in Ref. [7]. These methods could approximate complex nonlinear functions, but with a complex network structure, the training time would be very long and more liable to fall into local minimum value. In order to improve the performance of artificial neural network, some researchers applied genetic algorithm to update its learning rule and the network weights, which improves the learning rate and the ability to approach to global optimality. On the other hand, the wavelet transform can provide the frequency of signals and the time associated with those frequencies, which makes it very convenient for the application in forecasting fields, but the forecasting accuracy depends on the choice of base functions [8,9].

* Corresponding author.
E-mail address: sxwang@tju.edu.cn (S. Wang).

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Based on SVM-enhanced Markov model, the short-term distributional forecasts and point forecasts were also derived in Ref. [10]. Hybrid methods, such as the combined fuzzy logic and artificial neural network approach, were established in Ref. [11], which may outperform individual methods.

Empirical mode decomposition (EMD) has been applied extensively for analyzing nonlinear stochastic signals. Compared with wavelet transformation and Fourier transformation, it has many advantages such as good multi-resolution and wide applicability. However, the most significant drawback of EMD is mode mixing. To overcome this problem, a new noise-assisted data analysis method called ensemble empirical mode decomposition (EEMD) was proposed. The superiority of EEMD has been tested in many fields [12–15].

This paper proposes a novel wind speed forecasting method based on a hybrid EEMD and GA-BP neural network method. The original wind speed data is decomposed into certain signals by EEMD. Then, each signal is taken as an input data to establish the GA-BP neural network forecasting model. The final wind speed forecast is obtained by aggregating the predicted data of individual signals. The applicability of the proposed hybrid method for different time-scale wind speed forecasting is also discussed.

The paper is organized as follows. Section 2 presents the principles of EMD and EEMD. Section 3 introduces the GA-BP neural network. The proposed hybrid model is described in Section 4. Case studies and conclusions are drawn in Section 5 and Section 6, respectively.

2. Principles of empirical mode decomposition and ensemble empirical mode decomposition

2.1. Empirical mode decomposition

Hilbert-Huang transform, developed by Huang et al., in 1998, is an adaptive and efficient method for analyzing nonlinear and non-stationary signals and its key part is EMD [16]. Since the wind speed is a kind of nonlinear and non-stationary signal, this method is efficient to analyze the wind speed signal. A series of intrinsic mode functions (IMFs) is extracted from the original signal by sifting stage by stage. An IMF is a function that satisfies the following two conditions: (1) in the entire data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one; and (2) at any point, the mean value of the envelopes defined by the local maxima and the local minima must be zero.

With the above definitions for IMF, a signal could be decomposed through the following steps [16]:

For wind speed signal $x(t)$, identifying all local maxima and minima. Connect all maxima by a cubic spline line to produce the upper envelop, and connect all minima by another cubic spline line to produce the lower envelop. The mean value of the upper and the lower envelops is defined as m, and the difference between $x(t)$ and m is defined as h.

$$h = x(t) - m \tag{1}$$

Take h as the new original signal $x(t)$, and repeat Step (a) k times until h is an IMF. The criterion (2) is used to determine whether h is an IMF.

$$D_k = \frac{\sum_{t=0}^{T} \left| h_{(k-1)}(t) - h_k(t) \right|^2}{\sum_{t=0}^{T} \left| h_{(k-1)}(t) \right|^2} \tag{2}$$

Here, if D_k is smaller than the predetermined value, h_k can be considered as an IMF. Designate the first IMF as $c_1 = h_k$.

Once c_1 is determined, the residue r_1 can be obtained by separating c_1 from the rest of the data (3). Then, take r_1 as the new original signal $x(t)$, repeat the operations in Step (a) and Step (b) until the second IMF c_2 is obtained. In order to get all IMFs, the above operations should be taken j times until r_j is smaller than the predetermined threshold or r_j becomes a monotone function. Finally, a series of IMFs and the residue r can be obtained.

$$r_1 = x(t) - c_1 \tag{3}$$

2.2. Ensemble empirical mode decomposition

Mode mixing is the most significant drawback of EMD, which implies that a single IMF consists of signals with dramatically disparate scales or a signal of the same scale appears in different IMF components. This usually causes intermittency when using EMD to analyze signals.

To solve the mode mixing problem in EMD, a new noise-assisted data analysis method EEMD is proposed. In EEMD, the true IMF components are defined as the mean of an ensemble of trails. Each trail consists of the decomposition results of the signal plus a white noise of finite amplitude [17]. EEMD benefits from recent studies on white noises, which showed that EMD is an effective self-adaptive dyadic filter bank when applied to white noises [18,19]. The results demonstrate that noise can help data analysis in the EMD method. The EEMD algorithm is described as follows:

1) Add a white noise series to the original wind speed signal.
2) Decompose the signal with added white noise into IMFs using EMD.
3) Repeat Steps (1) and (2) with different white noises and obtain the corresponding IMF components. The number of repeated procedures is called the ensemble number.
4) Take the mean of all IMF components and the mean of residue components as the final results.

In EMD, the combination of all IMFs and the residue r is the original data. However, in EEMD, the combination is no longer the original data because of added white noises. When applying EEMD, one may argue that the forecasting results will become worse because the original data have been changed. On the contrary, the truth is that as better decomposed IMFs can be obtained by EEMD and the signals of IMFs become smooth, the accuracy of forecasting results has been significantly enhanced. More detailed discussion on this is provided in Section 4.

2.3. Comparison between EMD and EEMD

To better illustrate the superiority of EEMD over EMD, a simple example is shown below. In Fig. 1, signal y_1 denotes a sinusoid signal $y_1 = \sin(20\pi t)$, y_2 denotes an intermittent signal $y_2 = \begin{cases} 0.4\sin(100\pi t) & 0.05 \le t \le 0.15 \\ -0.2\sin(300\pi t) & 0.2 \le t \le 0.25 \\ 0 & others \end{cases}$, and y denotes $y = y_1 + y_2$. signal y in Fig. 1 is decomposed by EMD and EEMD. The first and the second IMFs of EMD are shown in Fig. 2 and those of EEMD are shown in Fig. 3. In Fig. 2, it is obvious that signals with different frequencies exit in IMF1. However, in Fig. 3, it is observed that this mode mixing problem is solved by EEMD and the two signals with different frequencies have been successfully separated.

3. The GA-BP neural network

Genetic Algorithm (GA) is a powerful stochastic algorithm based

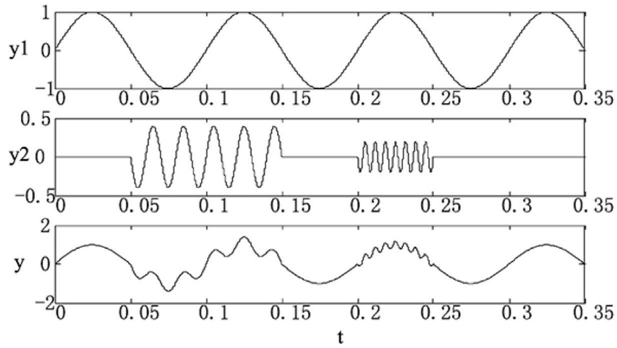

Fig. 1. Synthesized signal y to be analyzed.

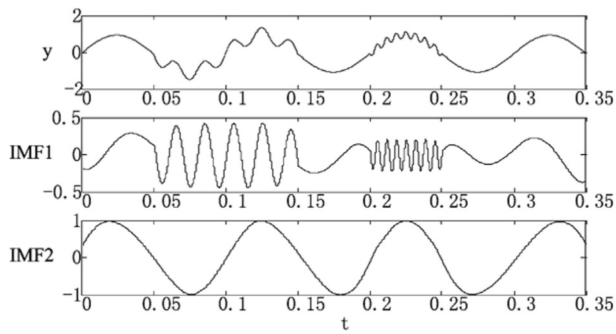

Fig. 2. IMF1 and IMF2 obtained by EMD.

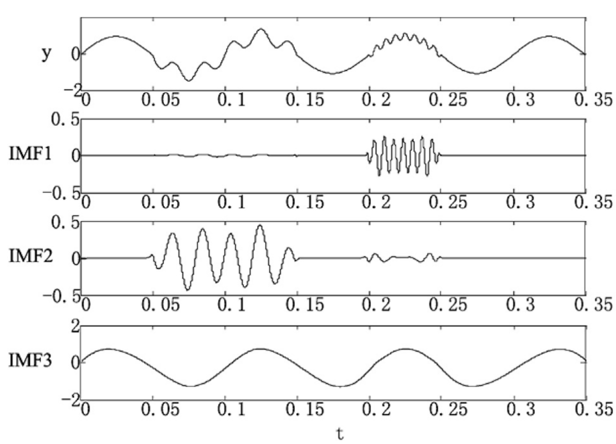

Fig. 3. IMF1 and IMF2 obtained by EEMD.

on natural selection mechanisms and Darwin's main principle: survival of the fittest. This algorithm has been successfully applied in optimization problems. GA starts with an initial set of random solutions called population, and each individual in the population is called a chromosome. The fitness of each chromosome is evaluated according to the objective function. After a series of operations including selection, crossover, and mutation, chromosomes with lower fitness are eliminated and a new population is obtained. These operations are repeated until the chromosome can satisfy certain criteria.

Artificial Neural Network (ANN) is an information processing approach based on the biological neural network. ANN, which, in theory, can imitate any complex and non-linear relationship through non-linear units (neurons), has been widely used in the forecasting area. The structure of ANN is composed of input layers, hidden layers, and output layers. One of the most extensively used ANN model is BP neural network model based on the BP algorithm. The neural network is determined when all the weights among different layers are decided. Thus, the neural network is trained to set all weights before it can be used for forecasting. The initial weights are randomly set and during the forward direction of the training process, output data can be obtained by certain rules. The weights are modified according to the differences between output data and desired data in the backward process. Forward and backward processes repeat until the difference between output data and desired data is small enough. When applied to wind speed forecasting, the input data are wind speed in previous hours and the output data are predicted wind speed data. The desired data for comparison is the observed actual wind speed.

Although BP neural network can obtain the final convergence of the network learning course, the weakness is that the time of learning and training is too long and most likely it will converge to local optimal values. To solve this problem, BP neural network has been improved by adding genetic algorithm technique (GA) [20], which is called GA-BP neural network. The training starts with GA, which performs a global search on weight ranges and finds out the best initial weights for BP neural network. Then, the BP algorithm starts the training process with the best initial weights provided by GA and approaches the optimum solution.

4. Wind speed forecasting model based on EEMD and GA-BP algorithm

The proposed wind speed forecast model includes three steps as follows.

First, original wind speed data are decomposed into certain more stationary signals with different frequencies by EEMD. Second, GA-BP neural network is used to forecast each IMF and the residue *r*. A rolling forecasting process is studied. The prediction is made using the previous data for one step ahead. Finally, the forecasting results of each IMF and the residue *r* are aggregated to obtain the final wind speed forecasting results. The flowchart is shown in Fig. 4.

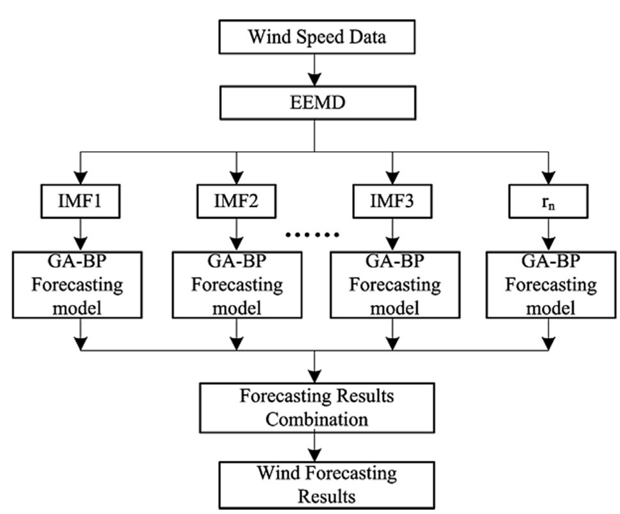

Fig. 4. The flowchart of wind speed forecasting model based on EEMD and GA-BP algorithm.

5. Case study

Two case studies are analyzed in this section to illustrate the effectiveness of the proposed method. The wind speed data in a wind farm of Inner Mongolia in China is used. Case 1 utilizes the proposed method for the ultra-short term (10 min) wind speed forecasting, and in Case 2, a short term (1 h) wind speed forecasting is discussed.

5.1. Case I-ultra short term forecasting

Ten-minute wind speed data from 6:00 January 4, 2011 to 6:00 January 9, 2011 in the wind farm of Inner Mongolia in China are used in this case study. In this example, a rolling forecasting process is studied in which the first six wind speed data points are used to forecast the seventh data. That is, prediction is done using the previous one-hour data for one step ahead (i.e., ten minutes). All requisite experiments are implemented in MATLAB on an Intel (R) Core(TM)2 Duo CPU 2.99 GHz personal computer.

The original wind speed data are decomposed by EEMD into 8 different IMFs and the residue r as shown in Fig. 5. In this case study, the amplitude (standard deviation) of the white noise is 0.5 and the ensemble number is set as 200.

As shown in Fig. 5, different IMFs present distinct features. The frequencies of IMF1 and IMF 2 are much higher and they mainly reflect the random information of the original wind speed signal. The periodic trends of IMF3 to IMF6 are more significant than IMF1 and IMF2, which are the periodic components of the original signal. IMF7, IMF 8, and r are called the trend components.

After the wind speed signal is decomposed by EEMD, the wind speed forecasting is converted into the forecasting of each IMF and the residue r. GA-BP neural network is used for the forecasting of each IMF and the residue r. Each IMF and the residue r include 721 data points. The first 450 data are selected as the training data for GA-BP neural network and the rest 271 data are selected as the test data. As a result, in the test process, 265 forecasted data are obtained when using the first six wind speed data to predict the seventh. In the rolling process, the second to the seventh data are used to forecast the eighth data and so on. In this paper, numbers of input layers, hidden layers, and output layers of GA-BP neural network are 6, 10, and 1, respectively. The forecasting results of IMF4 to IMF8 and r by GA-BP neural network are perfect because their frequencies are low and the periodic trend is obvious. The forecasting result of IMF1 is the worst because the signal has strong random information.

Forecasting wind speed data can be obtained by adding up forecasting results of individual IMFs and the residue r. The forecasting result of the hybrid EEMD and GA-BP neural network method is shown in Fig. 6. For comparison, forecasting results of the traditional GA-BP neural network method, the EMD and GA-BP neural network method, and the wavelet neural network prediction method (WNN) are shown in Fig. 7, Fig. 8, and Fig. 9, respectively.

Root mean square error ($RMSE$) and mean absolute percentage error ($MAPE$) are used as metrics to assess the performance of different methods.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - f_t)^2} \tag{4}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - f_t}{y_t}\right| \tag{5}$$

Where y_t and f_t denote the observed and the forecast values, and

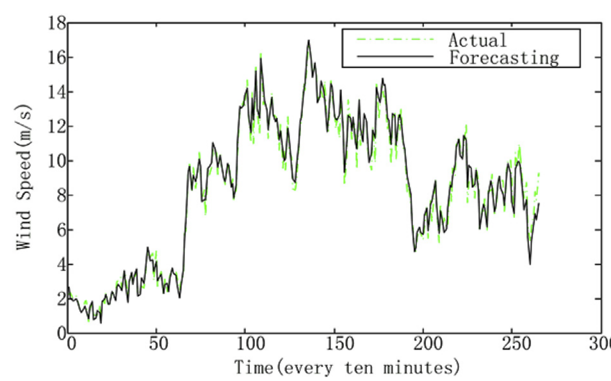

Fig. 6. Wind speed forecasting results of the hybrid EEMD and GA-BP neural network method in Case I.

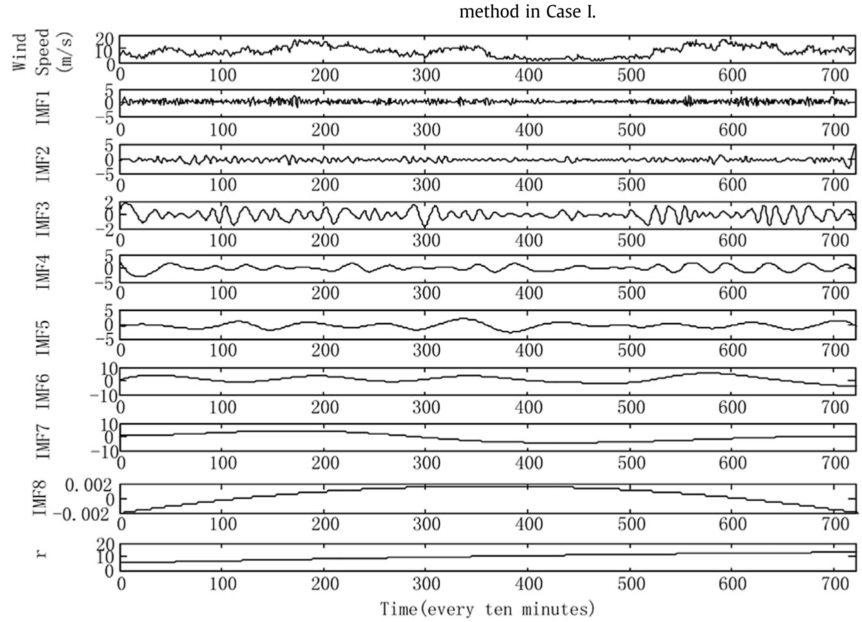

Fig. 5. Decomposed result of wind speed data by EEMD in Case I.

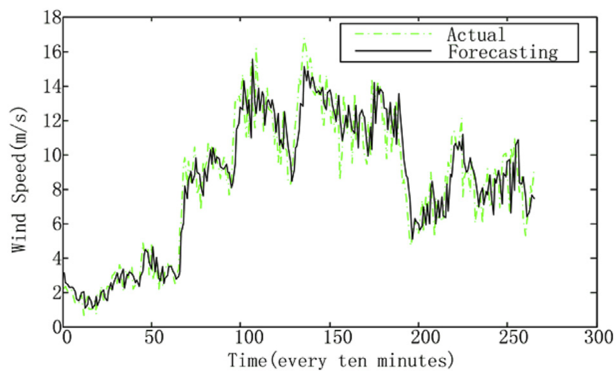

Fig. 7. Wind speed forecasting results of the traditional GA-BP neural network method in Case I.

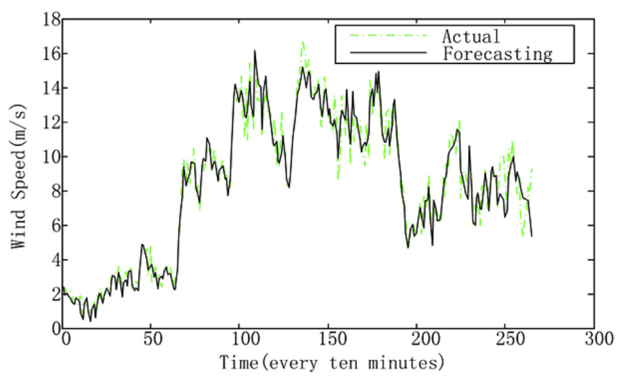

Fig. 8. Wind speed forecasting results of the EMD and GA-BP neural network method in Case I.

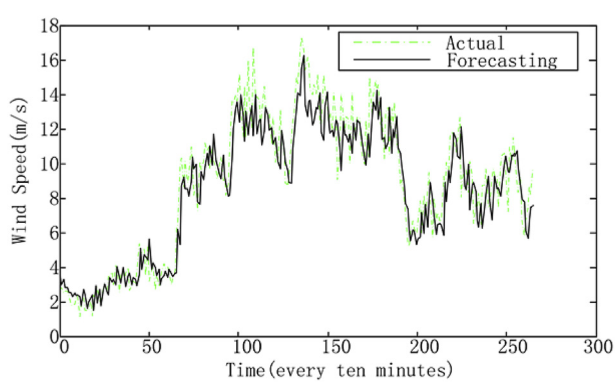

Fig. 9. Wind speed forecasting results of the wavelet neural network method in Case I.

T is the number of data used for the performance evaluation. Results are shown in Table 1.

Table 1 shows that forecasting results of the hybrid EEMD and GA-BP method are ameliorated a lot as compared to the traditional GA-BP direct forecasting method. This is because after EEMD, the original unsteady and nonlinear data are changed into certain components that have fixed frequency and periodicity. When forecasting via GA-BP neural network, results of these certain components are much better than those of the original data. In addition, another conclusion is that the hybrid EEMD and GA-BP method also outperforms the hybrid EMD and GA-BP method. Compared with Fig. 8, forecasting data in Fig. 6 follow the trend of original signals better. Although in EEMD a series of white noises is added into the original data which slightly change the original data (by about 2%), the decomposition results of EEMD are more stable and smooth. In turn, when predicted by GA-BP neural network, the results of individual IMFs are better because GA-BP neural network performs better on stable and smooth data. The total computational time includes training time, testing time, and forecasting time. It is worth noticing that the total computational time is shorter than 5 min, which makes it suitable for ultra-short wind speed forecasting. In addition, wavelet neural network prediction method is also used in this case. In comparison, the proposed hybrid method is much better, and the forecasting results are more accuracy. Generally speaking, the models need to be retrained after a certain time period, which is determined by different situation. This section chooses 2-day as the time interval for retraining the forecasting models.

Table 1
Results analysis of different methods in case I.

Methods	*MAPE*(%)	*RMSE*(m)	Computation Time(s)
Traditional GA-BP	16.87	1.56	28.76
EMD and GA-BP	9.21	0.79	258.20
EEMD and GA-BP	6.82	0.59	280.84
WNN	29.01	1.95	101.91

5.2. Case II-short term forecasting

Hourly wind speed data, from 0:00 April 4, 2011 to 19:00 April 21, 2011 in the wind farm of Inner Mongolia in China, are used in this case study, which includes 500 data in total. In this case study, the amplitude (standard deviation) of the white noise is 0.5, and the ensemble number is 200.

The decomposed result is shown in Fig. 10. Each IMF and the residue r include 500 data. The first 350 data are selected as the training data for GA-BP neural network, and the rest 150 data are selected as the test data. That is, there are 147 test samples. In this case, numbers of input layers, hidden layers, and output layers of GA-BP neural network are 3, 5, and 1, respectively. The results of the hybrid EEMD and GA-BP neural network method, the traditional GA-BP neural network method, the EMD and GA-BP neural network method, and the wavelet neural network are shown in Fig. 11, Fig. 12, Fig. 13, and Fig. 14, respectively.

By comparing Figs. 11 and 13 with Fig. 12, it can be seen that forecasting results of the hybrid EMD and GA-BP model and the proposed hybrid EEMD and GA-BP model are better than that of the GA-BP model. The result of GA-BP model lags seriously behind. In addition, the result of the proposed hybrid EEMD and GA-BP model is much better than that of the hybrid EMD and GA-BP model in most times. The wavelet neural network could predict the trend of data, but the result is unsatisfactory.

Table 2 compares the results of the four methods. From the results in Table 2, a similar conclusion as that in Case I can be drawn here, which indicates that the proposed method is also suitable for the short-term wind speed forecasting.

6. Guidelines for graphics preparation and submission sensitive analysis

The proposed method includes two parameters, the ensemble number and the noise amplitude, which need to be predefined. In order to discuss the sensitivity of parameters, several cases are simulated in this section.

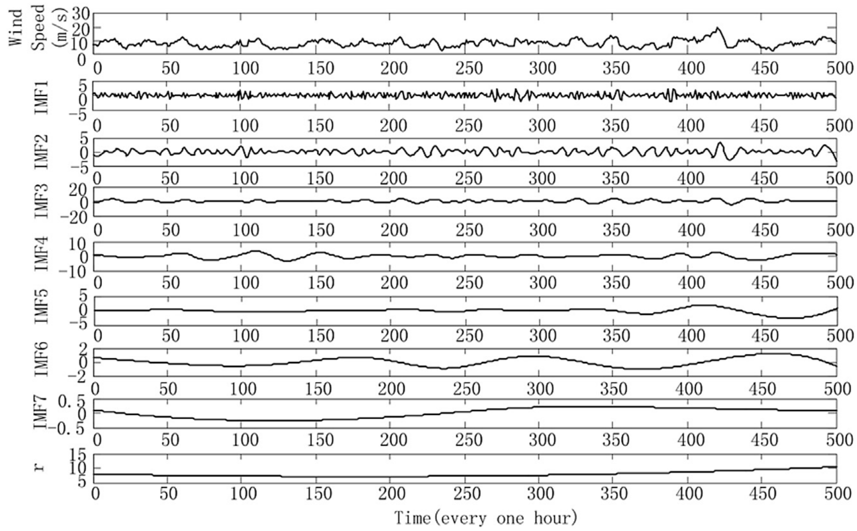

Fig. 10. Decomposed result of wind speed data by EEMD in Case II.

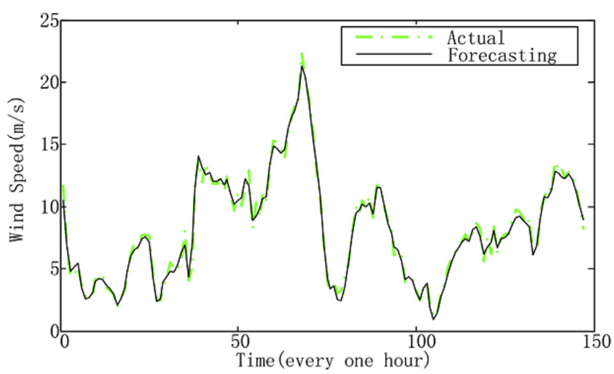

Fig. 11. Wind speed forecasting results of the hybrid EEMD and GA-BP neural network method in Case II.

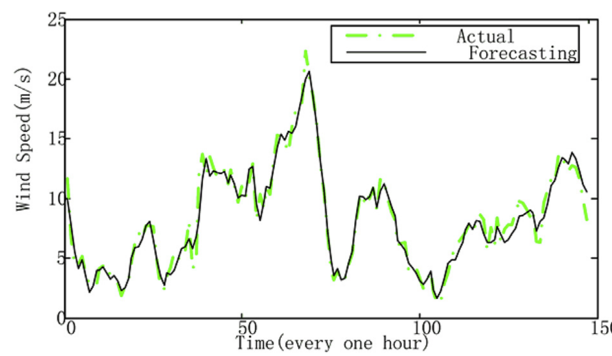

Fig. 13. Wind speed forecasting results of the EMD and GA-BP neural network method in Case II.

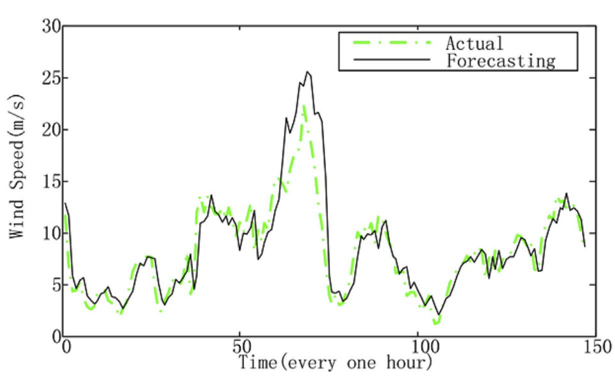

Fig. 12. Wind speed forecasting results of the traditional GA-BP neural network method in Case II.

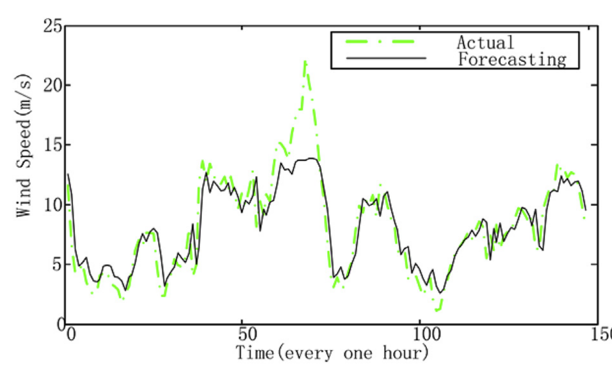

Fig. 14. Wind speed forecasting results of the wavelet neural network method in Case II.

6.1. The ensemble number for EEMD

Keeping the noise amplitude while changing the number of ensembles, the decomposed results are shown in Fig. 15. The ensemble number is set as 50, 100, and 200, respectively. The amplitude of the white noise is 0.5.

It is clearly shown in Fig. 15 that the synchronization among

Table 2
Results analysis of different methods in case II.

Methods	*MAPE*(%)	*RMSE*(m)	Computation Time(s)
Traditional GA-BP	21.59	2.36	23.88
EMD and GA-BP	12.46	1.22	199.34
EEMD and GA-BP	8.08	0.71	207.75
WNN	21.09	1.91	48.17

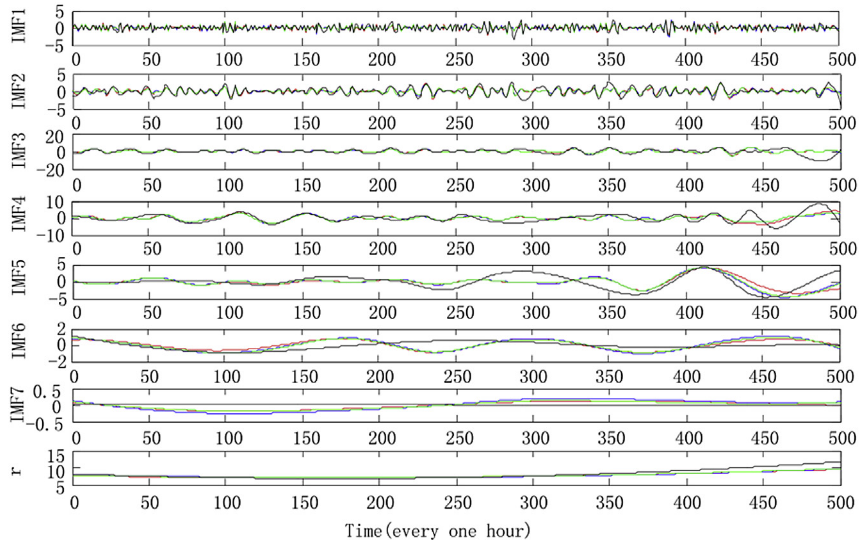

Fig. 15. The decomposed results with different values of the ensemble number for EEMD. Black line corresponds to the standarddecomposition using EMD without any added noise, Red blue and green lines correspond toEEMD decompositionswith added noise of standard deviation of 0.5, the ensemble number is set as 50, 100, 200, respectively.

cases with different values of ensembles is consistent, except the case without noise in which mode mixing produces an unstable decomposition. It is worth noticing that partial decomposed components are almost the same, such as IMF2, IMF3, IMF4, and *r*. In fact, by increasing the value of the ensemble number, the effect of the added white noise can be reduced to a negligibly small level [14].

Table 3compares the forecasting results of the hybrid EEMD and GA-BP method with different values of ensemble. It can be seen that the larger the ensemble number, the higher the accuracy, and the longer the runtime. A series of white noises is added in the original data, which will make the sequence a little different from the original data. However, by increasing the ensemble number, this effect will be reduced, and the decomposition results of EEMD are more stable and smooth. When forecasting by GA-BP neural network, the result is better than others. On the other hand, although the total computational time increases, it is still shorter than 4 min and would be acceptable for practical applications.

6.2. *The amplitude of added noise*

This section explores the impact of white noise amplitude on the forecasting result. That is, the value of the ensemble number remains unchanged, but the added white noise amplitude changes. In Fig. 16, noises with standard deviations of 0.1, 0.2, 0.5, and 1 are added. The ensemble number for each case is 200.

By comparing the curves in Fig. 16, it can be seen that the curve profile between cases with different levels of added noise is similar. The standard decomposition using EMD without any added noise is more different from others.

Table 4 represents the ability of the proposed method in forecasting wind speed with different levels white noises. Considering the root mean square error and mean absolute percentage error, the best prediction is obtained using the proposed method with the amplitude of added noise 0.5. The results indicate that changing noise amplitudes could affect the forecasting result. The appropriate parameters can improve the result. If the added noise amplitude is too small, it may not introduce a series of good stable and smooth data, and in turn the forecasting results with the GA-BP neural network may not be significantly improved. On the other hand, if the added noise amplitude is too large, some frequency components may be buried in noise, and the forecasting error may increase. The computational time of all cases is shorter than 4 min.

Table 3
Results analysis of different numbers of ensemble for EEMD.

White noise is 0.5	The value of ensemble number for EEMD		
	50	100	200
MAPE(%)	8.92	8.32	8.08
RMSE(m)	0.74	0.74	0.71
Computation Time(s)	200.01	205.15	207.75

7. Conclusions

This paper presents a novel wind speed forecasting method based on the hybrid EEMD and GA-BP neural network method. Through EEMD, wind speed data are decomposed into different IMFs and a residue *r*. GA-BP neural network is applied to forecast individual IMFs and the residue *r*. Final result can be obtained by adding the forecasting results of individual IMFs and *r*. In the Case I study, MAPE and RMSE of the proposed method are 6.82% and 0.59, and in the Case II study, MAPE and RMSE of the proposed method are 8.08% and 0.71, which are all much better than the traditional GA-BP forecasting method and the method based on EMD and GA-BP algorithm. In order to illustrate the effectiveness of the proposed approach, wind speed forecasting results from the wavelet neural network is also discussed. In comparison, the proposed hybrid method is much better. The forecasting results are more accuracy. Besides, the sensitivity analysis on parameters shows that appropriate values of the white noise amplitude and the ensemble number can improve the forecasting result. Although the computational time is slightly longer than the EMD method, it is still within 5 min. It shows that the proposed method based on hybrid EEMD and GA-BP neural network performs well in wind speed forecasting, and is suitable for ultra-short term (10 min) and short term (1 h) wind speed forecasting.

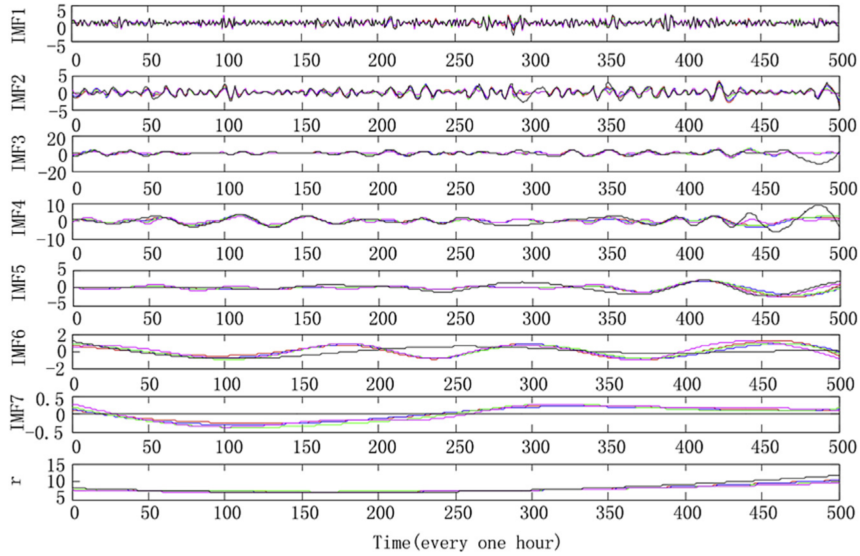

Fig. 16. The decomposed results with added different amplitude noise for EEMD. Black line corresponds to the standard decomposition using EMD without any added noise, Red blue green and pink line correspond to EEMD decompositions with added noise of standard deviation of 0.1, 0.2, 0.5, 1, respectively. The ensemble number for each case is 200.

Table 4
Results analysis of different amplitude of added noise for EEMD.

The value of the ensemble number is 200	The amplitude of added noise			
	0.1	0.2	0.5	1.0
MAPE(%)	10.83	9.30	8.08	8.76
RMSE(m)	0.98	0.91	0.71	0.72
Computation Time(s)	208.06	215.56	207.75	210.78

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