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A hybrid model for wind speed prediction using empirical mode decomposition and artificial neural networks

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ABSTRACT

Wind speed forecasting is one of the most important technologies to guarantee the wind energy integrated into the whole power system smoothly. In this paper a hybrid model named EMD–ANN for wind speed prediction is proposed based on the Empirical Mode Decomposition (EMD) and the Artificial Neural Networks (ANNs). To choose the best training algorithm for the ANN model, several experimental simulations with different training algorithms are made. To estimate the performance of the EMD–ANN model, two forecasting cases are completed and the results are both compared with the ANN model and the Autoregressive Integrated Moving Average (ARIMA) model respectively. To avoid the randomness caused by the ANN model or the ANN part of hybrid EMD–ANN model, all simulations in this study are repeated at least 30 times to get the average. The results show that: (1) the performance of the proposed model is highly satisfactory; and (2) the proposed EMD–ANN hybrid method is robust in dealing with jumping samplings in non-stationary wind series.

1. Introduction

Wind energy has been developing fast in recent decade years. As a burgeoning renewable energy, it has been a focus of many scientists and researchers [1–6] and supported by almost every government all over the world. Just in China, the current total capacity of wind farms is approximately 13242.2 MW, with a growth rate of 108.4% in 2008 [5]. With the increased integration of wind energy into traditional power networks, it is becoming more important for power utilities to plan the daily distribution of integration and reduce the reserve capacity, so an accurate and reliable forecasting method of non-stationary wind speed is desired [7]. However, wind speed is generally considered as one of the most difficult weather parameters to be forecasted due to its chaotic and random fluctuations [6–8]. To achieve the wind speed prediction, many methods have been reported, which can be classified into four categories [8]: (a) physical models; (b) statistical models; (c) artificial intelligence models; and (d) spatial correlation models.

Each category of prediction models has its own characteristics. Physical models can employ the physical parameters, such as temperature, pressure and topography, to establish multi-variable wind speed prediction model with advantages in long-term forecasting. So it is usually developed by meteorologists and is applied in large-scale area weather prediction [9–11]. And the statistical model always utilizes statistical equations to describe the potential changing law from wind speed samplings to make prediction [12–16]. With the development of artificial technique, some artificial intelligent prediction methods have been mushrooming, including Artificial Neural Networks [17–22], fuzzy logic methods [23,24], support vector machine [25], etc. As for the spatial correlation model, the spatial relationship of wind speed in different sites is taken into account. So in some conditions, it can have a higher accuracy. But it is more complicated compared with the other kinds of models because it needs the detailed records of sampling time and location information to establish a model [24,26].

To attain better performance, most proposed models are combinations of several kinds of the upper methods [23–26]. According to our review [1–26], a hybrid model based on the EMD and the ANN can be an effective way in wind speed prediction. The EMD methodology was first proposed by Huang et al. [27]. As one of the popular signal processing methods, the main advantage of the EMD is that it can decompose a signal into a set of completely

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List of abbreviations

EMD	empirical mode decomposition
IMF	intrinsic mode functions
ANN	artificial neural networks
ARIMA	autoregressive integrated moving average model
AR	autoregressive model
ACF	autocorrelation function
PACF	partial autocorrelation function
FPE	final prediction error
BP	back propagation
QBP	quick back propagation
RBP	resilient back propagation
BFGS	Broyden–Fletcher–Goldfarb–Shanno quasi-newton back propagation
MAE	mean absolute error
MSE	mean square error
MAPE	mean absolute percentage error
SM	simple model

List of symbols

$\{X(t)\}$, $(t=1,2,\ldots,m)$	original wind speed series
$\{C_i(t)\}$, $(t=1,2,\ldots,m;\ i=1,2,\ldots,n)$	Gotten IMFs after EMD decomposition
$\{X_{up}(t)\}$, $(t=1,2,\ldots,m)$	upper cubic spline envelop series
$\{X_{low}(t)\}$, $(t=1,2,\ldots,m)$	lower cubic spline envelop series
$\{M(t)\}$, $(t=1,2,\ldots,m)$	mean cubic spline envelop series
$\{Z(t)\}$, $(t=1,2,\ldots,m)$	process series extracted by the mean cubic spline envelop series$\{M(t)\}$
$\{R(t)\}$, $(t=1,2,\ldots,m)$	residual series extracted by all the Gotten IMFs
δ	terminated parameter of EMD calculation
$\{\rho_i\}$, $(i=1,2,\ldots,n+1)$	aggregate coefficient series for integration of the sub-series predictions
m	length of the original wind speed series
n	numbers of the Gotten IMFs

adaptive basis functions called *Intrinsic Mode Functions* (IMF). In this study, the research on hybrid modeling of the EMD and the ANN has been conducted for wind speed forecasting. The purpose of this work is to find a simple and reliable hybrid intelligent forecasting model for the small wind farms.

This paper is organized as follows: Section 2 states the framework of the EMD–ANN hybrid model; Section 3 presents the detailed modeling steps of the EMD method; Section 4 demonstrates the detailed modeling steps of the ANN; Sections 5 and 6 display two forecasting cases; and Section 7 concludes some important results of this work.

2. Framework of EMD–ANN hybrid model

The framework of an EMD–ANN model is demonstrated in Fig. 1. The detailed calculation steps are described as follows.

(1) Apply the EMD to decompose an original time series into a set of different sub-series which can be identified, separately predicted, and recombined to get aggregate forecasting.
(2) Use the ANN to build a forecasting model for the each sub-series, and make the multi-step forecasting in the each sub-series. To choose the best training algorithm for the ANN, an experimental simulation is made with different kinds of training algorithms.
(3) Conduct aggregate calculation for the predicting results in the sub-series to attain the final forecasting for the original time series.
(4) Compare the performance of the EMD–ANN hybrid model with an ANN model and an Autoregressive Integrated Moving Average (ARIMA) model.

3. Modeling steps of EMD

Given an original wind speed series $\{X(t)\}$, it can be described as the following equation after the EMD calculation.

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

Where $\{C_i(t)\}$, $(i = 1,2,\ldots n)$ is the IMF in different decompositions and $\{R_n(t)\}$ is the residue after n numbers of IMFs are derived. In the EMD, an IMF is defined as a function satisfying the following properties: (a) in the whole data series, the number of extrema (sum of maxima and minima) and the number of zero crossing must be equal or different at most by one, and (b) at any point, the mean value of the envelop defined by the local maxima and minima must be zero. A sifting alterative process is employed to extract the separate components IMFs. The detailed steps of the sifting calculation can be demonstrated as follows [27–30]:

Step 1 Identify all the local extrema of series $\{X(t)\}$, including local maxima and local minima.

Step 2 Connect all the local maxima by a cubic spline line to generate its upper envelop $\{X_{up}(t)\}$. Similarly the lower envelop $\{X_{low}(t)\}$ is made with all the local minima.

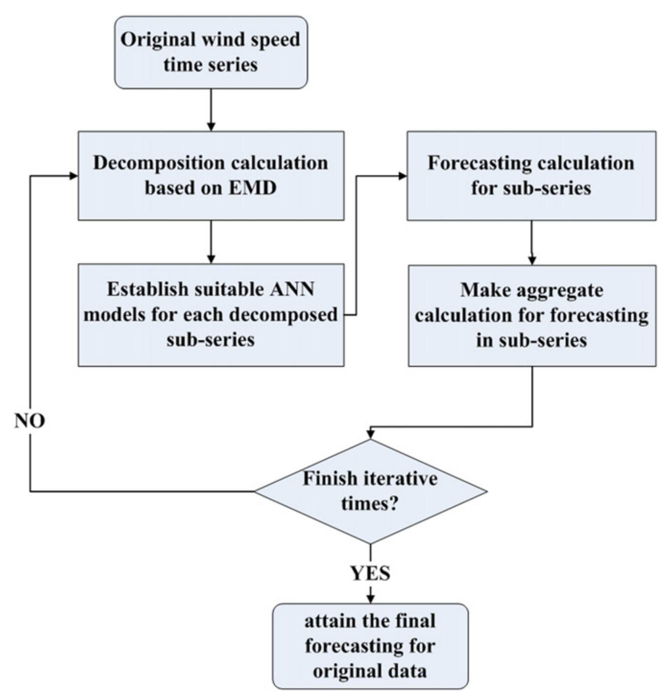

Fig. 1. Flow diagram of the hybrid EMD–ANN model.

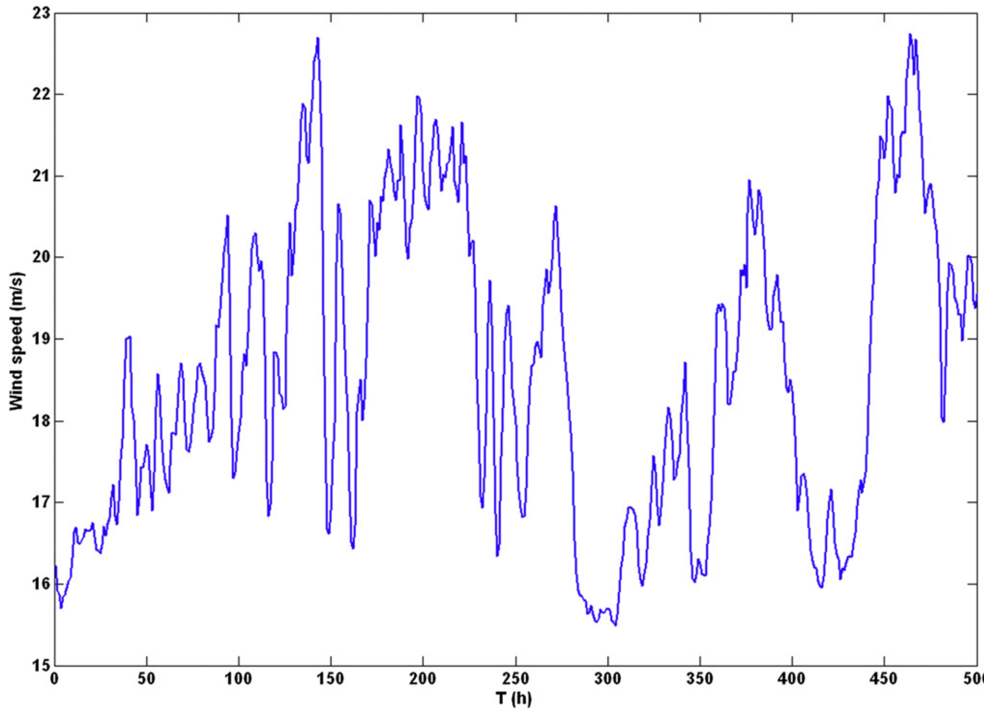

Fig. 2. Original wind speed series (1).

Step 3 Compute the mean envelop $\{M(t)\}$ from the upper and lower envelops as follows:

$$M(t) = [X_{up}(t) + X_{low}(t)]/2 \tag{2}$$

Step 4 Extract the details as follows:

$$Z(t) = X(t) - M(t) \tag{3}$$

Step 5 Check whether $\{Z(t)\}$ is an IMF: (a) if $\{Z(t)\}$ is an IMF then set $C(t) = Z(t)$ and meantime replace $\{X(t)\}$ with the residual $R(t) = X(t) - C(t)$; (b) if $\{Z(t)\}$ is not an IMF, replace $\{X(t)\}$ with $\{Z(t)\}$ then repeat Steps 2–4 until the termination criterion is satisfied. The following equation can be regarded as the termination condition of this iterative calculation:

$$\sum_{t=1}^{m} \frac{[Z_{j-1}(t) - Z_j(t)]^2}{[Z_{j-1}(t)]^2} \le \delta(j = 1, 2, \ldots; t = 1, 2, \ldots, m) \tag{4}$$

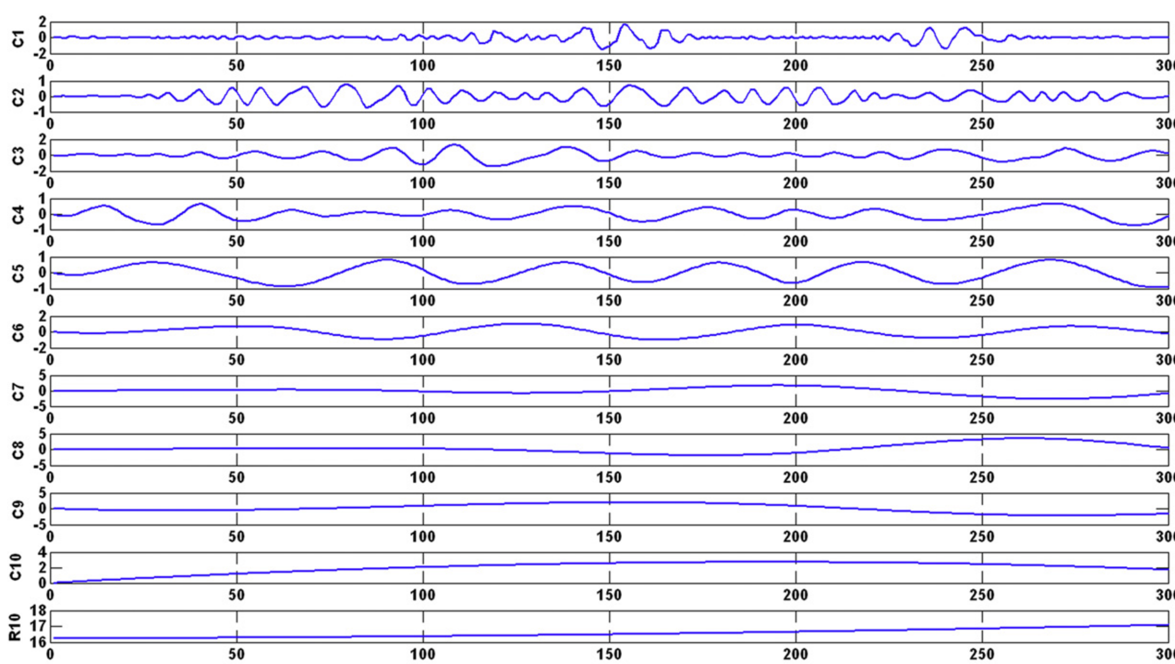

Fig. 3. Decomposition results of the original series by EMD (1).

Table 1
Calculation results of the descriptive statistical analysis (1).

N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
500 5000	15.48025	22.74300	18.5763225	1.85641153	0.227	0.109	−1.041	0.218

where m is the length of signal, δ is the terminated parameter which is usually set as 0.2–0.3, and j denotes the times of iterative calculation. The δ is usually determined by the requirements of application areas. In this study the trial simulations are done to decide it before modeling.

Step 6 The procedure of Steps 1–5 is repeated until all the IMFs are found.

4. Modeling steps of ANN

4.1. Network structure

Nowadays, the ANN has been generally used in signal processing due to its nonlinear capacity and robust performance. The structure of the ANN is very important for its performance. Some results [8,13,19–21,24] showed that three-layer network is enough to fit any non-stationary signal. In this study the decided ANN will be used in a real-time wind power system which has to do the wind speed prediction for several wind stations at the same time, so the training and predicting time of the ANN is emphasized. When considering the condition, the structure with three layers is chosen.

4.2. Training data organization

In ANN theory, apart from the structure of network, the training data format also can affect the performance of network directly. Once the calculation of the EMD is finished, several IMFs can be attained. How to use those sub-series data to train a neural network is another important work. In this study, the time series models such as the Auto Regressive (AR) model and the ARIMA model are used to find the potential existing relation between the wind sub-series and their lags. During the calculation process of time series modeling, the Autocorrelation Function (ACF), the Partial Autocorrelation Function (PACF) and the Final Prediction Error (FPE) criterion will be adopted.

4.3. Training algorithm

ANN usually uses Back Propagation (BP) as its training algorithm. To improve the performance of the neural network with BP, more training algorithms have been reported in recent years, including Quick Back Propagation (QBP), Resilient Back Propagation (RBP), Broyden–Fletcher–Goldfarb–Shanno Quasi-Newton Back Propagation (BFGS), etc. To choose the best one among them for wind speed prediction in this study, an experimental simulation will be made by using the original wind speed series.

4.4. Aggregate calculation of sub wind speed series

Equation of aggregate calculation for sub-series is given by

$$\hat{X}(t) = \sum_{i=1}^{n} \rho_i \times \hat{C}_i(t) + \rho_{n+1} \times \hat{R}_n(t), \quad t = 301, 302, \ldots, 499, 500 \tag{5}$$

where $\{\rho_i\}$ is the aggregate coefficient of the prediction of each sub-series, $\{\hat{C}_i(t)\}$ is the forecasting series in the different IMFs, $\{\hat{R}_n(t)\}$ is forecasting series in the residue layer, and $\{\hat{X}(t)\}$ is the final forecasting wind speed series. Here $\rho_i = 1$, $(i = 1,2,3,\ldots)$.

5. Case one

The real wind speed data is obtained from a wind station in the wind farm. The wind station is comprised of two anemometers, two solar power plates, two batteries, a control box and a set of braces. The locations of wind stations are determined by considering both the local historical wind data and the requirement of power departments.

5.1. EMD of wind speed series

Fig. 2 shows an hourly actual time series (including 500 samplings) of the wind speed in certain station which have many jumping samplings. To verify the performance of the proposed hybrid EMD–ANN model in this study, the 1s–300th ones of this original series is utilized to establish models, the 301st–500th ones to check the validity of the established models. Fig. 3 shows the calculation results of the descriptive statistical analysis for the data in Fig. 2.

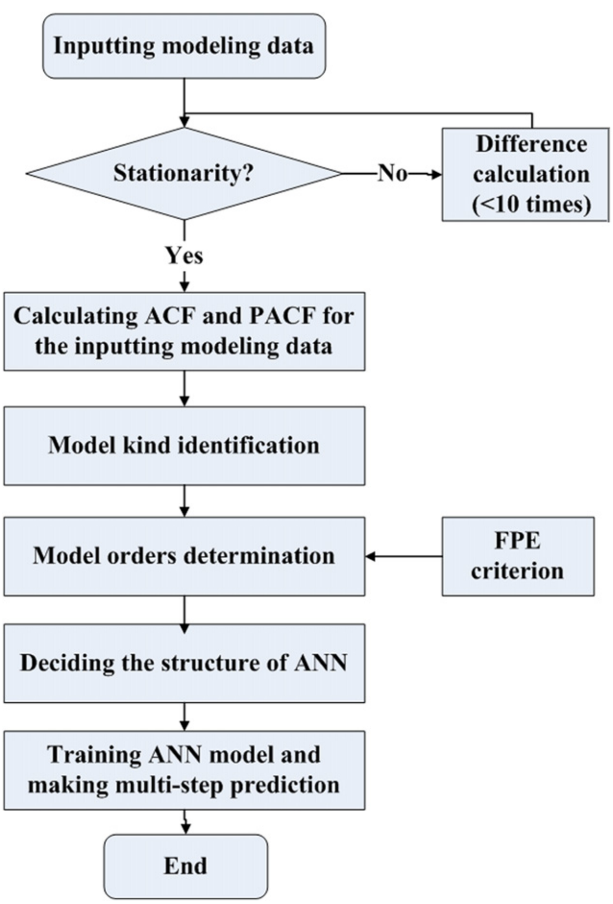

Fig. 4. Flow diagram of the Box–Jenkins methodology.

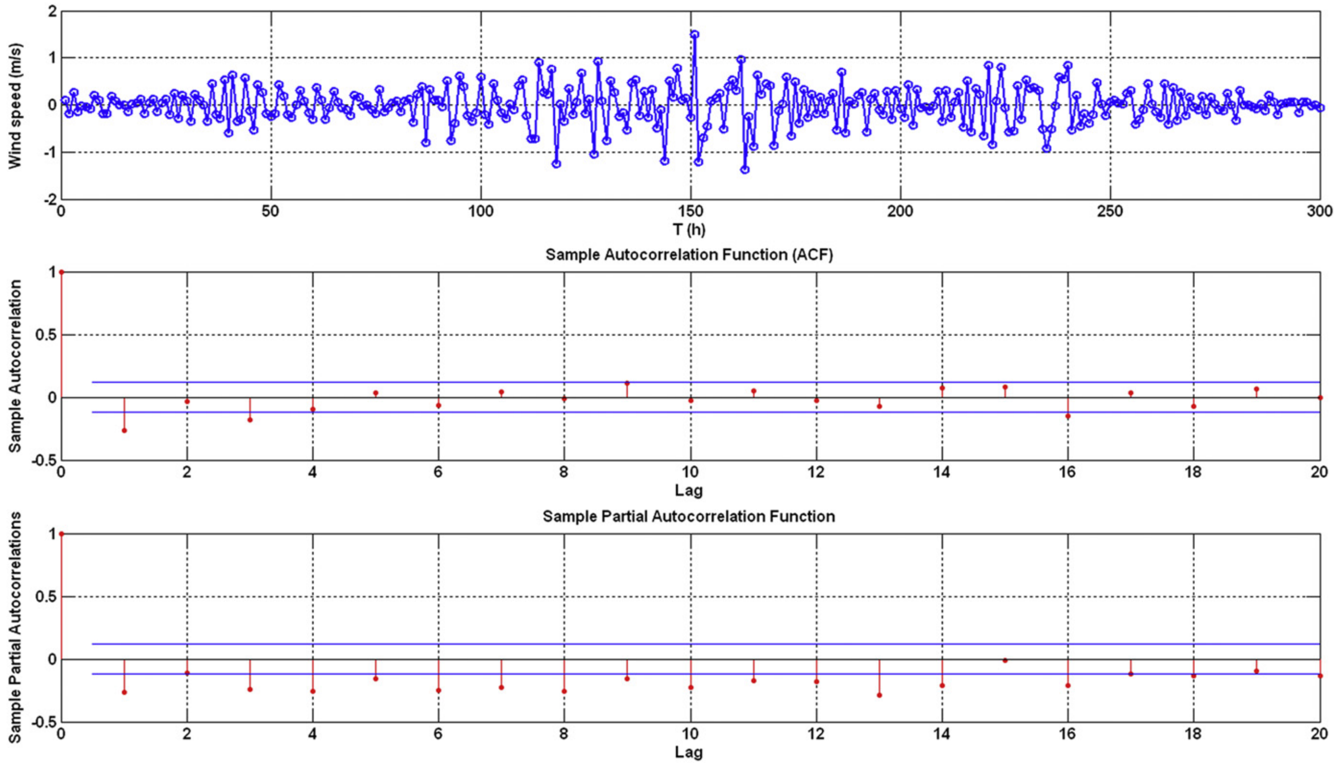

Fig. 5. The 1st–300th ones of the $\{C_1(t)\}$ series after second difference transformation.

Fig. 2 and Table 1 show that: (1) the wind speed series have non-stationary character, which range from 15.480 m/s to 22.743 m/s; and (2) the distribution of the wind speed series is not Gaussian distribution.

IMFs are extracted from the original wind speed by the EMD. Fig. 3 shows that the original wind speed series are decomposed into a series of relatively stationary wind speed datasets, which can be readily modeled. The decomposed wind speed data in each IMF

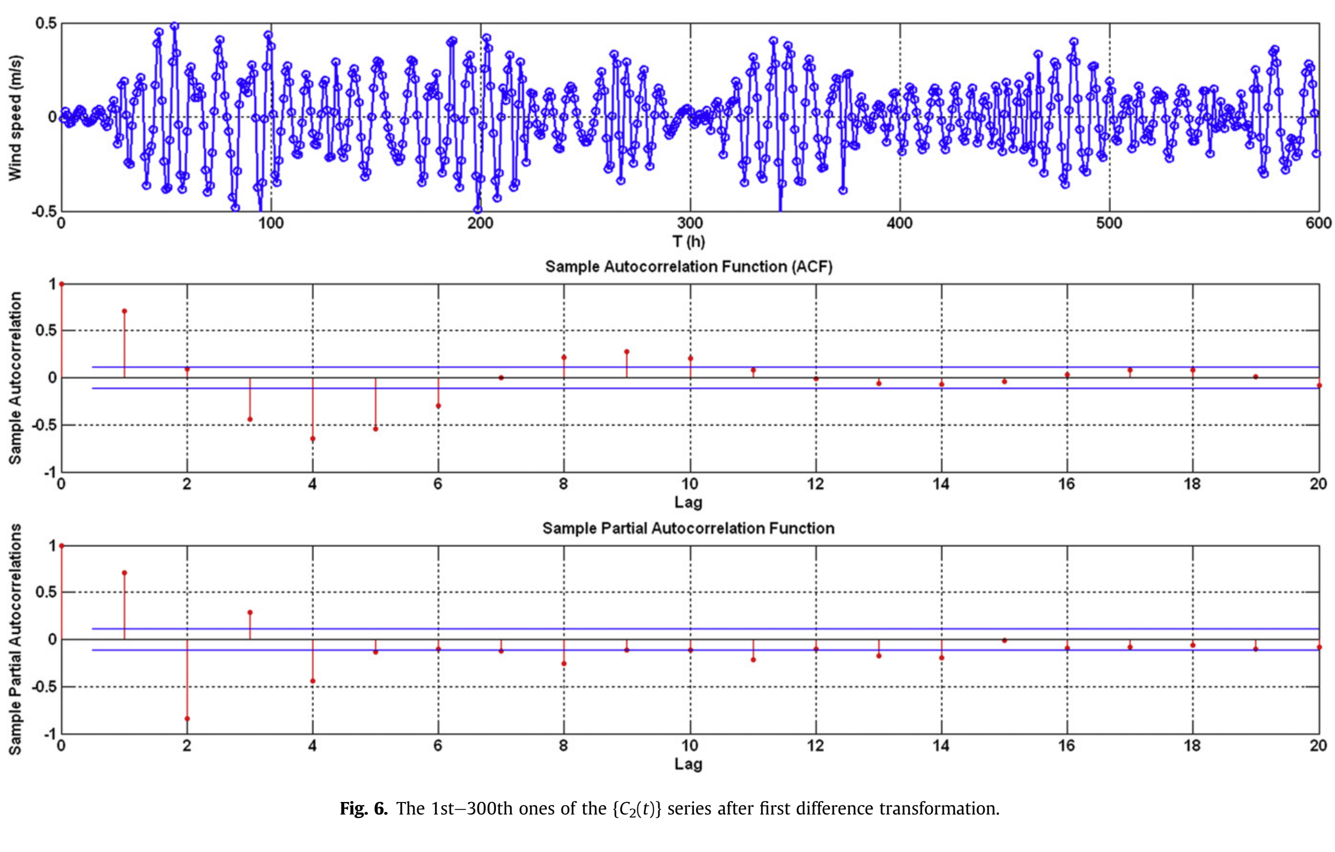

Fig. 6. The 1st–300th ones of the $\{C_2(t)\}$ series after first difference transformation.

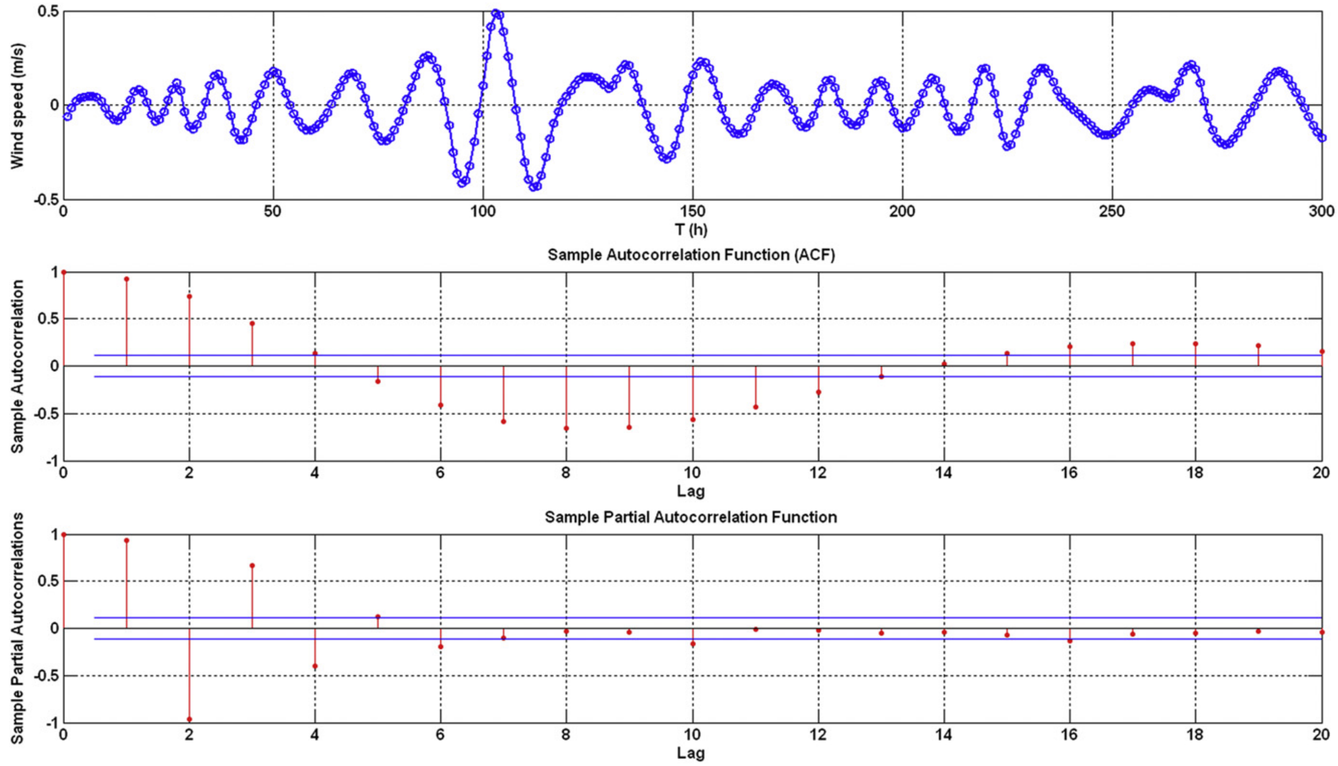

Fig. 7. The 1st–300th ones of the $\{C_3(t)\}$ series after first difference transformation.

sub-series will be used to build their corresponding ANN predicting models, respectively. The Box–Jenkins methodology [14,15] of the time series theory will be used to identify the inputting data structure of the ANN models.

5.2. Box–Jenkins methodology

To establish ARIMA model, the steps of the Box–Jenkins methodology are shown in Fig. 4.

5.2.1. Model kind identification

The original wind speed series shown in Fig. 2 are non-stationary. The differencing approach [16] recommended by Box and Jenkins is employed in this study. The 1st–300th ones of $\{C_1(t)\}$, $\{C_2(t)\}$ and $\{C_3(t)\}$ series after difference transformation are given in Figs. 5–7. The terminal iterative times of the difference transformation in this study is the augmented Dickey–Fuller univariate unit root test.

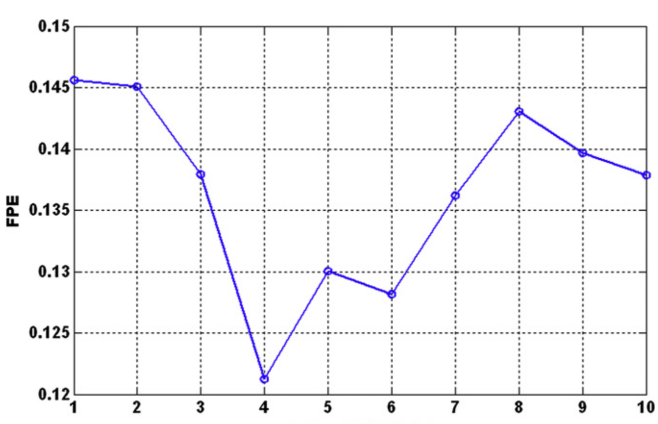

Fig. 8. The FPE result of $\{C_1(t)\}$ series.

5.2.2. Model-order determination

Both the ACF and the PACF are utilized to decide which (if any) autoregressive or moving average component should be included in models in this stage. From the ACF and PACF results of $\{C_1(t)\}$ series displayed in Fig. 6, one can see that (a) the data satisfies AR model because the ACF has the trailing character while the PACF has the decreasing and oscillating component; and (b) the suitable order of the AR model for those section of data is four.

In time series modeling theory, apart from the ACF and PACF determination method, the information-based criteria such as FPE have been preferred and used. These criteria can help automate the model identification process and verify the initial determination. The FPE results of $\{C_1(t)\}$ series are shown in Fig. 8, which further verify that the suitable order of AR model for $\{C_1(t)\}$ series is four.

5.2.3. Inputting data structure for ANN model

Based on the analysis of Fig. 8, the 1st–300th ones of the $\{C_1(t)\}$ series can be divided as AR kind training data format as follows:

$$X(t) = f[X(t-1), X(t-2), X(t-3), X(t-4)] \tag{6}$$

Based on Eq. (6), the training parameters of network for the 1st–300th ones of the $\{R_{10}(t)\}$ series also can be easily determined as follows.

Table 2
Calculation result of experimental simulation (1).

Training algorithm	Estimation indexes		
	MAE (m/s)	MSE (m/s)	MAPE (%)
BP	0.2929	0.3862	1.56
QBP	0.2557	0.3466	1.36
RBP	0.2379	0.3186	1.26
BFGS	0.1887	0.2453	1.00

Table 3
Parameters and performance test results of the developed neural networks for all the IMFs (1).

IMFs	Numbers of neurons			Performance test results of the One-step ahead forecasting		
	Input neurons	Hidden neurons	Output neurons	MAE (m/s)	MAPE (%)	MSE (m/s)
C1	4	9	1	0.1262	29.67	0.1684
C2	5	9	1	0.0370	9.52	0.0509
C3	7	10	1	0.0090	3.21	0.0137
C4	6	10	1	0.0037	1.61	0.0073
C5	7	10	1	0.0063	0.35	0.0093
C6	8	11	1	0.0124	0.20	0.0256
C7	8	11	1	0.0998	0.11	0.0739
C8	7	10	1	0.0857	0.10	0.0366
C9	8	11	1	0.0021	0.053	0.0021
C10	7	10	1	0.0260	0.09	0.0173
R10	4	9	1	0.0853	0.03	0.0831

(a) Number of input neurons: 4.
(b) Number of output layer: 1.
(c) Number of hidden neurons: 9.

(This value is chosen by empirical equation in Refs. [20–22])

(d) Number of iterative steps: 500.
(e) Value of the learning rate: 0.01–0.25.

The experimental simulation for choosing the best training algorithm is made by using the 1st–200th series of the original wind speed series, as shown in Fig. 2. To estimate the performance of each run of the experimental simulation, three error measures, the MAE, MSE, and MAPE, are used. Each simulation is run at least 30 times to obtain the mean values. The results of the experimental simulation are listed in Table 2, which shows that BGFS algorithm

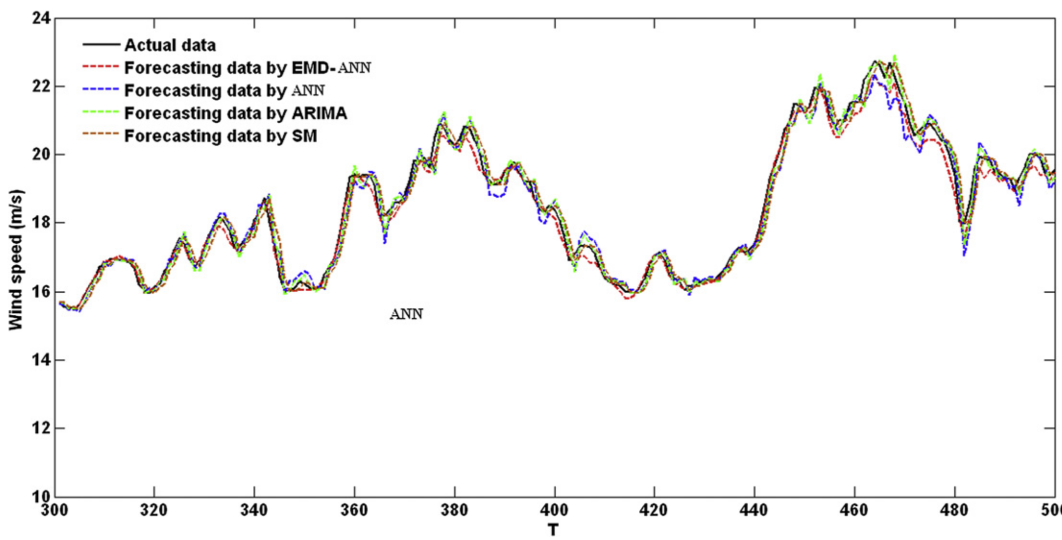

Fig. 9. One-step ahead forecasting results (1).

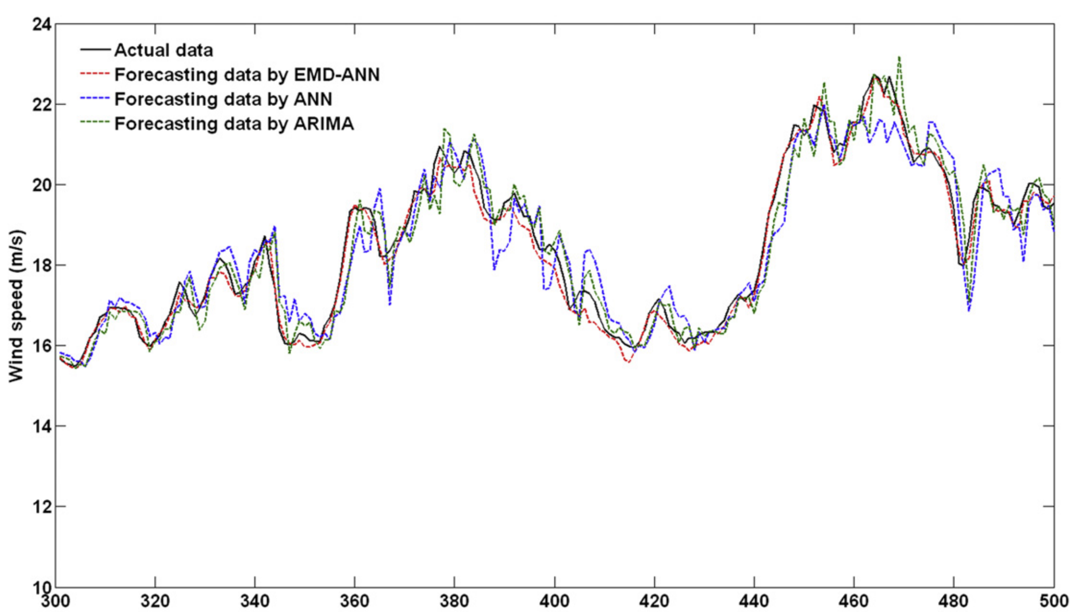

Fig. 10. Two-step ahead forecasting results (1).

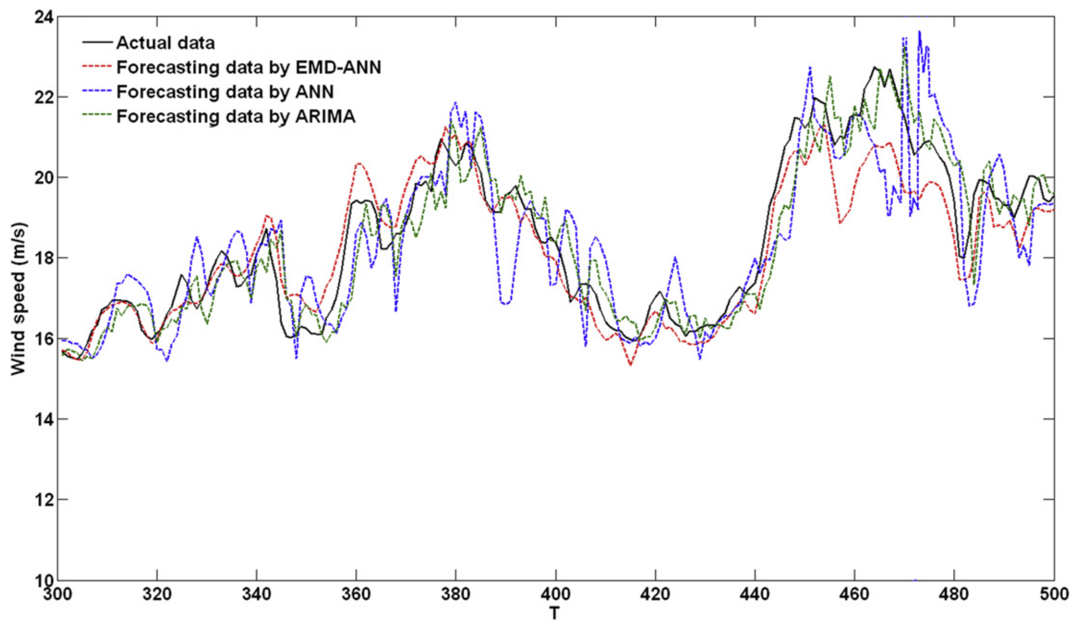

Fig. 11. Three-step ahead forecasting results (1).

Table 4
Estimation result of multi-step ahead prediction shown in Figs. 9–11.

Indexes	EMD–ANN model			ANN model			ARIMA model			SM model		
	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step
MAE (m/s)	0.1293	0.1850	0.5614	0.2238	0.4233	0.6069	0.2954	0.5448	0.8151	0.3228	–	–
MAPE (%)	0.69	1.00	2.29	1.19	2.26	3.26	1.57	2.39	4.35	1.61	–	–
MSE (m/s)	0.1576	0.2069	0.6865	0.2982	0.5500	0.7817	0.3905	0.7557	1.0568	0.4468	–	–

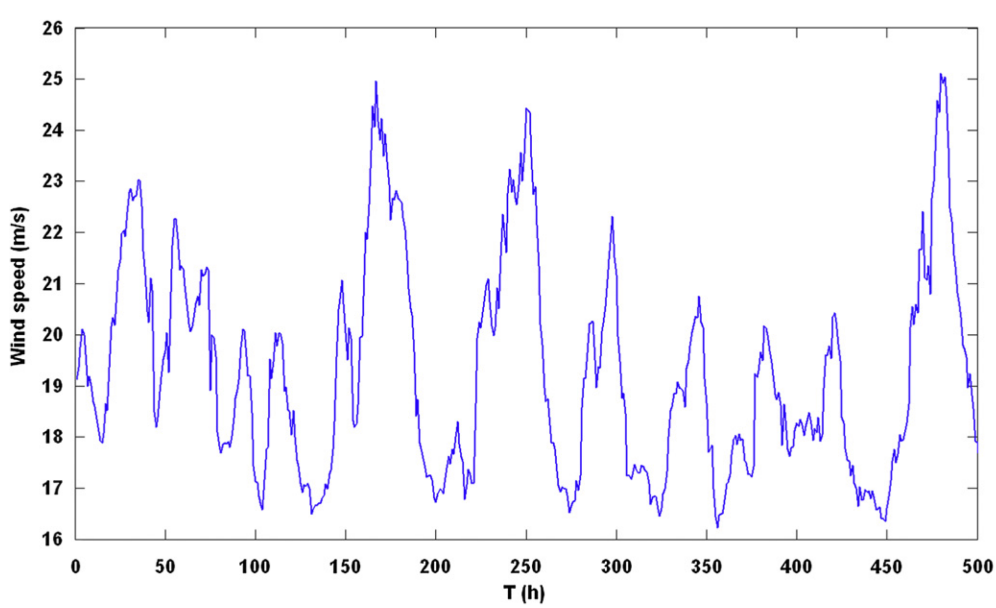

Fig. 12. Original wind speed series (2).

Table 5
Calculation results of the descriptive statistical analysis (2).

N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
500	16.21900	25.11050	19.2935585	2.08075237	0.695	0.109	−0.305	0.218
500								

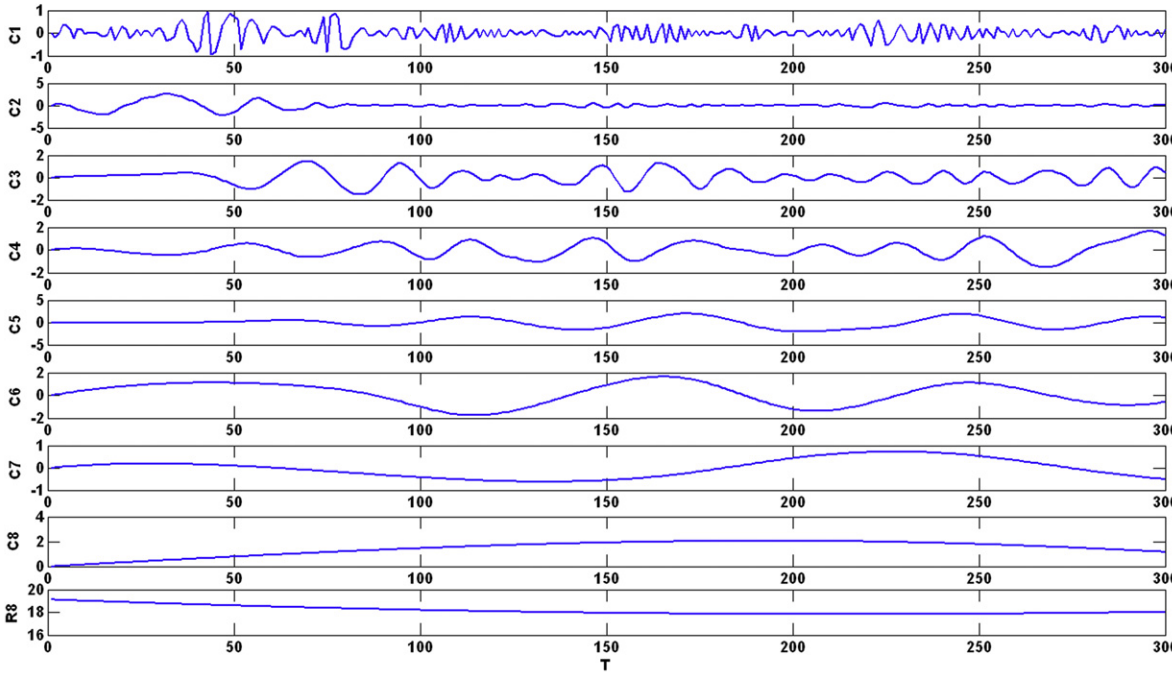

Fig. 13. Decomposition results of the original series by the EMD (2).

Table 6
Calculation result of experimental simulation (2).

Training algorithm	Estimation indexes		
	MAE (m/s)	MSE (m/s)	MAPE (%)
BP	0.2929	0.3862	1.56
QBP	0.2557	0.3466	1.36
RBP	0.2379	0.3186	1.26
BFGS	0.1887	0.2453	1.00

gives the best performance. Hence, BGFS algorithm is chosen as the training algorithm of the ANN model.

As for the other IMF sub-series, their neural networks can also be determined by referring to the upper modeling steps. The detailed parameters and performance test results of the developed neural networks for all IMFs are given in Table 3.

Table 7
Parameters and performance test results of the developed neural networks for all the IMFs (2).

IMFs	Numbers of neurons			Performance test results of the One-step ahead forecasting		
	Input neurons	Hidden neurons	Output neurons	MAE (m/s)	MAPE	MSE (m/s)
C1	6	9	1	0.1420	23.48%	0.2023
C2	7	10	1	0.0534	13.92%	0.0723
C3	6	9	1	0.0127	5.45%	0.0185
C4	7	10	1	0.0558	1.16%	0.1237
C5	7	10	1	0.0024	0.35%	0.0031
C6	7	11	1	0.0842	0.12%	0.0014
C7	6	9	1	0.0501	0.066%	0.0530
C8	7	10	1	0.0335	0.56%	0.0306
R8	4	7	1	0.0699	0.36%	0.1291

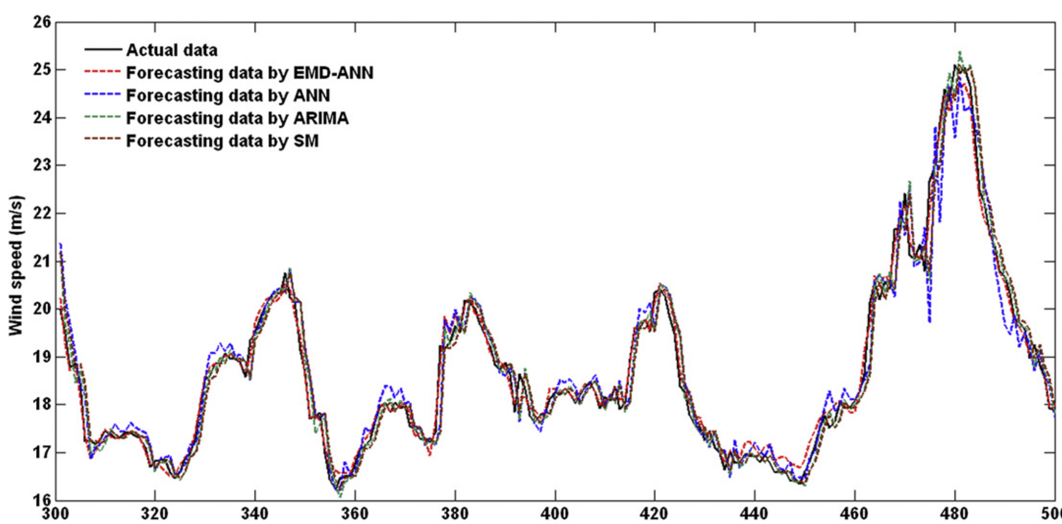

Fig. 14. One-step ahead forecasting results (2).

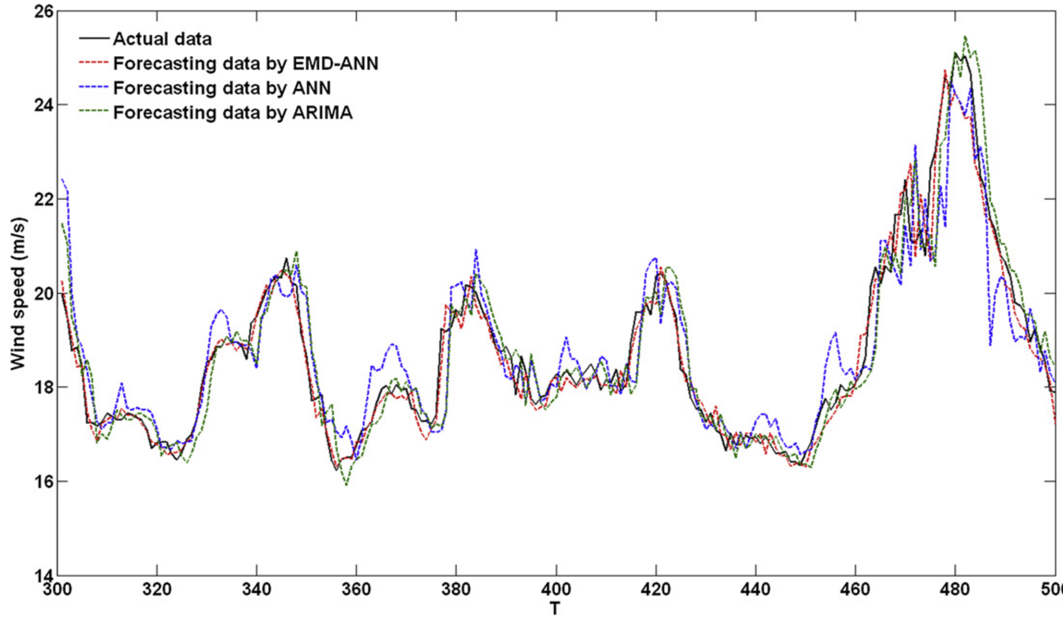

Fig. 15. Two-step ahead forecasting results (2).

Table 8
Estimation result of multi-step ahead prediction shown in Figs. 14–16.

Indexes	EMD–ANN model			ANN model			ARIMA model			SM model		
	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step
MAE (m/s)	0.1638	0.2460	0.3722	0.3388	0.5644	0.7807	0.3026	0.4605	0.6340	0.3116	–	–
MAPE (%)	0.85	1.27	1.87	1.76	2.93	4.04	1.58	2.41	3.30	1.62	–	–
MSE (m/s)	0.2213	0.3560	0.6223	0.4935	0.7828	1.0661	0.4397	0.6480	0.8832	0.4519	–	–

A simple model (SM) is also used in this study. The forecasts of the SM model are equal to the last known values. Actually the SM model can be regarded as the AR (1) model deducted the white noise, which does not have non-stationary tracking ability. The SM model is just used in the one-step prediction.

The iterative calculation steps of the proposed EMD–ANN method can be demonstrated as follows: (a) apply the EMD on the first 300 data; (b) train ANN models; (c) use the ANN models to do one-step, two-step and three-step ahead predictions, respectively; (d) apply again the EMD on 301 data; (e) repeat Steps (b) and

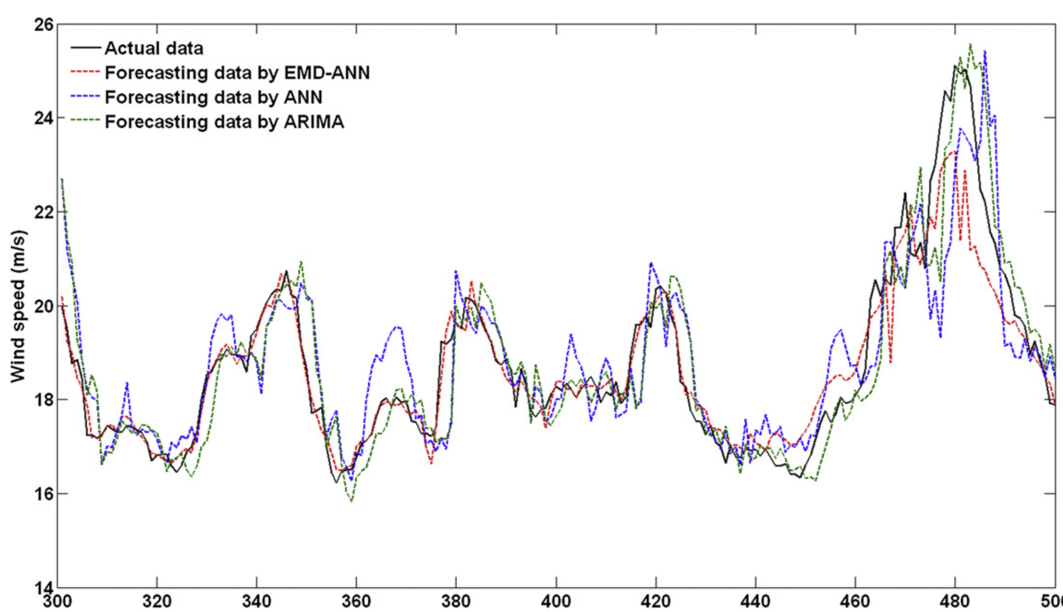

Fig. 16. Three-step ahead forecasting results (2).

(c) to get the predictions; (f) repeat Step (d) with a new EMD calculation and continue until 500 data.

Figs. 9–11 show the multi-step ahead forecasting results of the original wind speed signal $\{X(t)\}$ made by the proposed hybrid model, the ANN with BFGS algorithm, the ARIMA model and the SM model [31], respectively. And their estimation results are given in Table 4.

Figs. 9–11 and Table 4 indicate that: (1) the prediction accuracy decreases as the increase of forecasting steps; (2) the performance of the EMD–ANN model is superior to those of the ANN and ARIMA model, especially for the jumping samplings; (3) the performance of the ANN model is close to that of the ARIMA model; (4) the EMD part of the hybrid model improves the performance of the traditional ANN model significantly, without the obvious increase of the overall computation cost. The presented percentage of the MAE index from one-step to three-step ahead is 42.23%, 56.30% and 7.50%, respectively; The improved percentage of the MSE index from one-step ahead to three-step ahead is 47.15%, 62.38% and 12.18%, respectively; The improved percentage of the MAPE index from one-step ahead to three-step ahead is 42.17%, 55.75% and 29.75%, respectively; (5) when comparing the performance of the EMD–ANN model with that of the ARIMA model, the EMD–ANN has the absolute advantage. Such as, the presented percentage of the MAE index from one-step to three-step ahead is 56.23%, 66.04% and 31.13%, respectively; The improved percentage of the MSE index from one-step ahead to three-step ahead is 59.64%, 72.62% and 35.04%, respectively; The improved percentage of the MAPE index from one-step ahead to three-step ahead is 56.05%, 58.16% and 47.36%, respectively; and (6) when comparing the performance of the EMD–ANN model with that of the SM model, the presented percentage of the MAE, MSE, MAPE index in one-step predictions are 59.94%, 64.73% and 52.14%, respectively.

6. Case two

To further check the performance of the proposed EMD–ANN model, another multi-step ahead forecasting simulation is made in this study. Another hourly actual time series (including 500 samplings) are displayed in Fig. 12 and their descriptive statistical analysis results are demonstrated in Table 5. Fig. 12 and Table 5 show that this section of wind speed series is also non-stationary.

The EMD calculation results of these wind speed series are shown in Fig. 13.

Similar to the case one, the trial simulations are also finished for the case two to determine the best structure of neural networks for each IMF. The results of experimental simulation and the detailed information of the developed ANN models and the performance test for all the IMFs are given in Tables 6 and 7.

Based on Table 7, the EMD–ANN models can be easily established to predict the 301st–500th ones of the wind speed series shown in Fig. 12. To verify the performance of the proposed hybrid method, the single ANN with BFGS algorithm, the ARIMA and the SM are also used to do the prediction for the same wind speed. The final multi-step forecasting results are shown in Figs. 14–16, and the calculation results of estimation indexes are listed in Table 6. As the Figs. 14–16 and Table 8 show, the robust capacity of the EMD–ANN model is retained and some similar conclusions can be made as that presented results in Section 5.

7. Conclusions

A hybrid model consisting of the EMD and the ANN is proposed and developed for the wind speed prediction in two different actual wind speed time series. The results show that (1) the hybrid model achieves highly accurate prediction without the obvious increase of the complexity of model, as both compared to the ANN model and the ARIMA model; and (2) the proposed EMD–ANN hybrid model is suitable for the jumping wind samplings, which can be applied to the real-time wind power systems.

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