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Comparison of two new intelligent wind speed forecasting approaches based on Wavelet Packet Decomposition, Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and Artificial Neural Networks

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ABSTRACT

The wind speed forecasting is an important technology for the management of the wind energy. In this study, a new hybrid framework using the WPD (*Wavelet Packet Decomposition*), the CEEMDAN (*Complete Ensemble Empirical Mode Decomposition*) and the ANN (*Artificial Neural Network*) is proposed for wind speed multi-step forecasting. In the proposed framework, the WPD is employed to decompose the original wind speed series into a series of sub-layers, while the CEEMDAN is adopted to further decompose all the obtained sub-layers into a number of IMFs (*Intrinsic Mode Functions*). Finally, three types of ANN models, including the BP (*Back-propagation Neural Network*) models, the RBF (*Radial Basis Function Neural Network*) models and the GRNN (*General Regression Neural Network*) models, are utilized to complete the predicting computation for the decomposed wind speed series, respectively. To investigate the prediction performance of the presented framework, nine models are included in the comparisons as: the BP model, the WPD-BP model, the WPD-CEEMDAN-BP model, the RBF model, the WPD-RBF model, the WPD-CEEMDAN-RBF model, the GRNN model, the WPD-GRNN model and the WPD-CEEMDAN-GRNN model. Two experimental results indicate that: the proposed WPD-CEEMDAN-ANN models have better performance than the involved corresponding ANN models and WPD-ANN models in three-step predictions.

1. Introduction

With the increasing demand for electricity, wind energy, which is clean and abundant, has drawn widespread attention [1]. In the past years, wind energy has rapidly developed. However, since the wind power is intermittent and non-stationary, it is difficult to enable reliable guidance for the wind energy management [2]. To overcome this problem, many technologies are used. One of the main technologies is wind forecasting [3].

Over the past few decades, numerous research studies on wind predictions have been presented by using the physical methods [4]. Howard et al. [5] presented the physical model based on the correction and down-scaling method. Pelikan et al. [6] designed the empirical model by using the physical parameters. Kavasseri et al. [7] built the wind speed forecasting models based on the f-ARIMA methods. Erdem et al. [8] investigated the wind speed and direction prediction performance of some ARMA based approaches. Zhou et al. [9] proposed the improved SVM (*Support Vector Machine*) models for short-term wind speed forecasting. Shrivastava et al. [10] adopted the SVM models for interval forecasts. Sun et al. [11] established the hybrid model based on the FEEMD (*Fast Ensemble Empirical Mode Decomposition*) and RELM (*Regularized Extreme Learning Machine*). Among these models, the

Abbreviations: ANN, Artificial Neural Network; AR, Auto Regressive; ARIMA, Auto Regressive Integrated Moving Average; BA, Bat Algorithm; BP, Back-propagation Neural Network; CEEMDAN, Complete Ensemble Empirical Mode Decomposition; CG, Conjugate Gradient; CLSFPA, Flower Pollination Algorithm with Chaotic Local Search; CNN, Convolutional Neural Network; CS, Compressive Sensing; CSA, Cuckoo Search Algorithm; EEMD, Ensemble Empirical Mode Decomposition; ESM, Exponential Smoothing Method; FA, Firefly Algorithm; FAC, First-order Adaptive Coefficient; GA, Genetic Algorithm; GRNN, General Regression Neural Network; HBSA, Hybrid Backtracking Search Algorithm; HWM, Holt-Winters Model; IMFs, Intrinsic Mode Functions; IS, Input parameter Selection; KF, Kalman filter; LSSVM, Least Square Support Vector Machine; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; MLP, Multilayer Perceptron Neural Network; MOBA, Multi Objective Bat Algorithm; NNCT, No Negative Constraint Theory; NSGA, Non-dominated Sorting Genetic Algorithm; OVMD, Optimized Variational Mode Decomposition; PSO, Particle Swam Optimization; PSOSA, Particle Swarm Optimization based on Simulated Annealing; PSR, Phase Space Reconstruction; RBF, Radial Basis Function Neural Network; RMSE, Root Mean Square Error; SAC, Second-order Adaptive Coefficient; SAM, Seasonal Adjustment Method; SDA, Secondary Decomposition Algorithm; SEA, Seasonal Exponential Adjustment; SOM, Self-Organizing feature Maps; SSA, Singular Spectrum Analysis; SVR, Support Vector Regression; VMD, Variational Mode Decomposition; v-SVM, v-Support Vector Machine; WD, Wavelet Decomposition; WPD, Wavelet Packet Decomposition

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Table 1
Summary of the previous research on the wind speed decomposition algorithms.

Decomposition algorithms	Researchers
WD	Qin et al. [16], Kiplangat et al. [17], Wang et al. [19], Tascikaraoglu et al. [21]
WPD	Wang et al. [20], Meng et al. [22]
EEMD	Wang et al. [15]
FEEMD	Sun et al. [11]
CEEMDAN	Zhang et al. [18],
OVMD	Zhang et al. [23]
SSA	Xiao et al. [24], Wang et al. [25]
WPD-FEEMD	Liu et al. [26]
FEEMD-VMD	Wang et al. [27]

hybrid methods often have better prediction performance than the single models [12], therefore they have attracted increasing attention [13]. Generally, the hybrid methods contain decomposition algorithms and prediction algorithms [14].

Since the decomposition algorithms can reduce the non-stationary characteristics of the time series, they are widely adopted in the hybrid methods for the wind predictions. Wang et al. [15] investigated a novel wind speed forecasting method using the EEMD (*Ensemble Empirical Mode Decomposition*), the GA (*Genetic Algorithm*) and the BP. The cases study validated that the proposed model was more accurate than the GA-BP model. Qin et al. [16] established a hybrid wind speed interval forecasts approach based on the WD (*Wavelet Decomposition*), the CSA (*Cuckoo Search Algorithm*) and the BP. The WD was applied to reduce the high-frequency components, the CSA was incorporated into BP for parameters optimization and the BP was used to forecast the lower and upper bounds. The results demonstrated that the established approach could obtain high quality interval forecasts. Kiplangat et al. [17] demonstrated a hybrid method based on the WD and the simple linear models. The numerical results confirmed that the WD-AR model had higher prediction accuracy than the AR model. Zhang et al. [18]

Table 2
Summary of the previous research on the wind speed prediction algorithms.

Prediction algorithms	Researchers
NWP	Howard et al. [5], Pelikan et al. [6]
AR/ARMA/AMIMA/f-ARIMA	Kavasseri et al. [7], Erdem et al. [8], Kiplangat et al. [17], Maatallah et al. [36]
BP/RBF/GRNN/CNN/ELM/RELM/Elman/ANFIS/ESN/Adaboost	Salcedo-sanz et al. [1], Wu et al. [2], Liu et al. [3], Zhang et al. [4], Sun et al. [11], Liu et al. [12], Liu et al. [14], Wang et al. [15], Qin et al. [16], Zhang et al. [18], Wang et al. [19], Meng et al. [22], Zhang et al. [23], Xiao et al. [24], Wang et al. [25], Liu et al. [26], Wang et al. [27], Ren et al. [29], Sheela et al. [34], Feng et al. [35]
SVM/v-SVM/LSSVM	Zhang et al. [4], Zhou et al. [9], Shrivastava et al. [10], Liang et al. [13], Wang et al. [20], Santamaría-Bonfil et al. [30], Jiang et al. [31], Zhang et al. [33], Feng et al. [35]
KF	Shukur et al. [38]
Chaotic time series model	Tascikaraoglu et al. [21], Guo et al. [32]
SAM/ESM/SEA/SAC	Wang et al. [28], Zhang et al. [37]

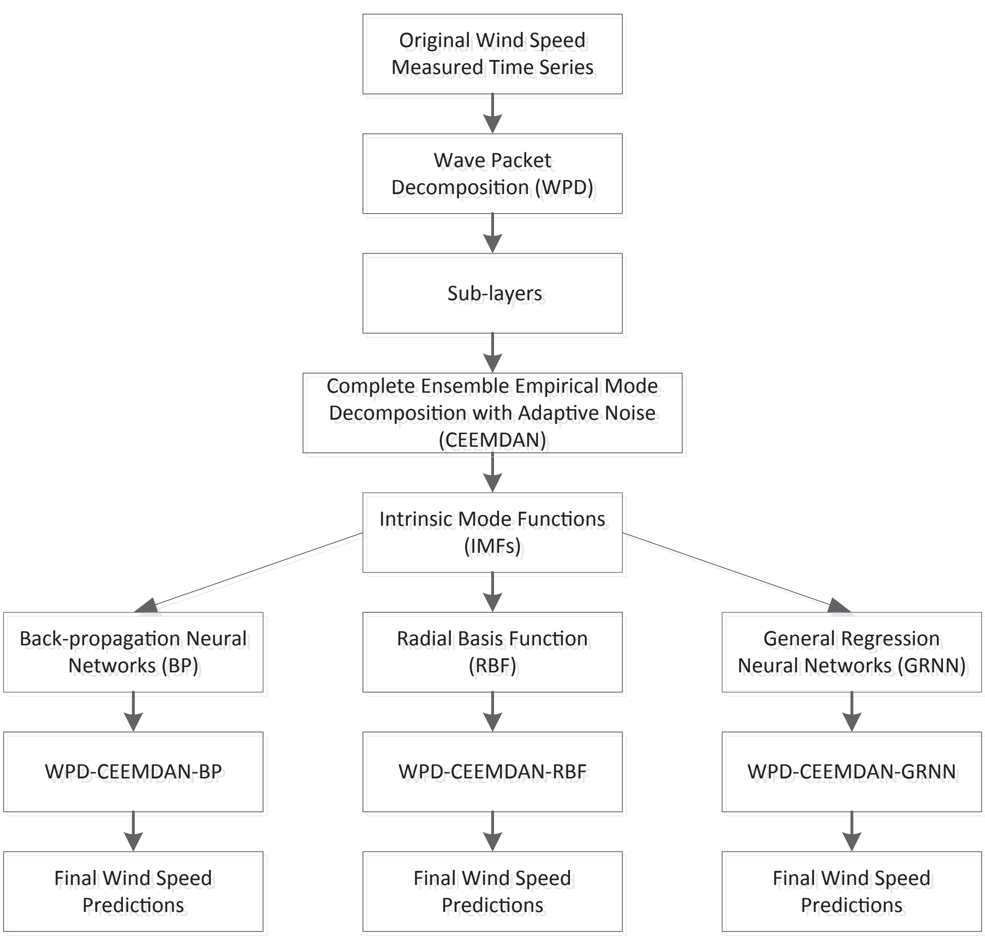


Fig. 1. The proposed hybrid prediction framework.

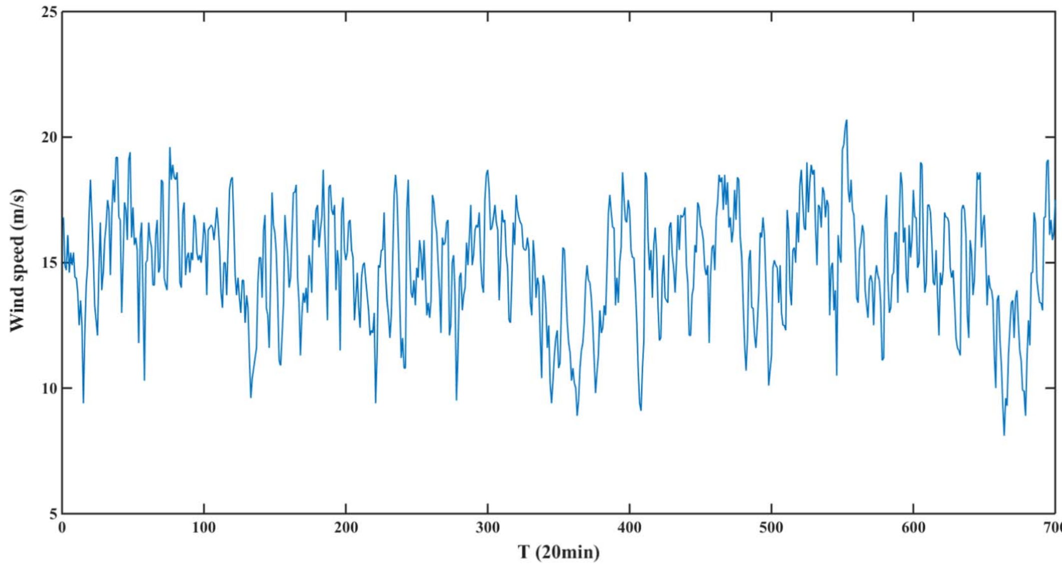


Fig. 2. Original wind speed time series #1.

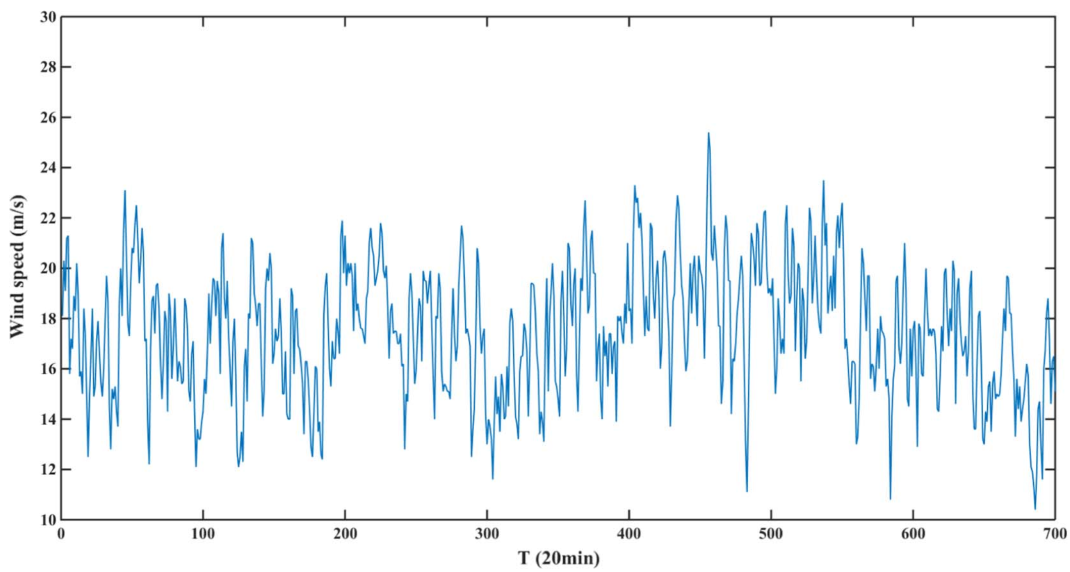
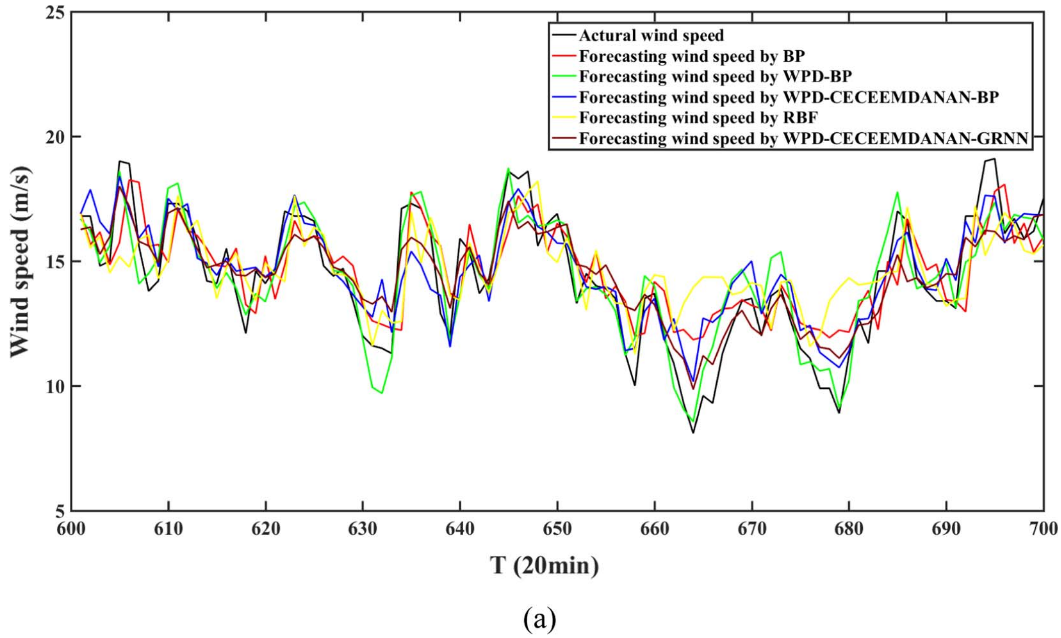


Fig. 3. Original wind speed time series #2.

proposed a hybrid model by combining the CEEMDAN, the CLSFPA (*Flower Pollination Algorithm with Chaotic Local Search*), five neural networks and the NNCT (*No Negative Constraint Theory*). The proposed model was effective in wind speed forecasting. Wang et al. [19] provided a hybrid model based on the WD and CNN (*Convolutional Neural Network*). The WD was adopted to decompose the original wind power data into several sub-layers, while the CNN was adopted to complete the forecasting. The simulated results indicated that the proposed model had accurate and robust prediction performance. Wang et al. [20] established a hybrid wind speed forecasting model using the WPD, LSSVM (*Least Square Support Vector Machine*), PSOSA (*Particle Swarm Optimization based on Simulated Annealing*) and PSR. The WPD was used to decompose the raw wind speed series, while the LSSVM was adopted to model those series. In addition, the PSOSA was built to tune the parameters of the LSSVM, and the PSR was applied to determine the input form of the LSSVM. The results indicated that as compared to the ARIMA model, the LSSVM model, the LSSVM-PSOSA model, the WD-LSSVM-PSOSA model, the proposed could obtain higher accuracy predictions. Tascikaraoglu et al. [21] presented a hybrid method for short-term wind speed forecasting based on the WD, CS (*Compressive Sensing*) and structured-sparse recovery algorithms. The case studies proved that the proposed method had high accuracy forecasts. Meng et al. [22] proposed a hybrid wind speed forecasting model using the WPD, crisscross algorithm and ANN. The crisscross algorithm was used to optimize the neural networks. Their results indicated that the hybrid model could significantly improve the prediction accuracy of the traditional ANN. Zhang et al. [23] proposed a compound model using the OVMD (*Optimized Variational Mode Decomposition*), the ELM and the HBSA (*Hybrid Backtracking Search Algorithm*). The OVMD was adopted to reduce the noise and decompose the wind speed series into several modes, while the ELM was used as the predictor, besides the HBSA was exploited to select the inputs, weights and bias of the ELM. The results indicated that the proposed model could obtain satisfactory prediction performance. Xiao et al. [24] developed a hybrid model for multi-step wind speed predictions based on the SSA (*Singular Spectrum Analysis*), the CG (*Conjugate Gradient*), the BA (*Bat Algorithm*) and the GRNN. The numerical experiments showed that proposed model could provide accurate forecasting results. Wang et al. [25] presented a combined architecture for wind speed forecasting consisting of the SSA, the MOBA (*Multi Objective Bat Algorithm*) and the ANNs. The SSA was used to



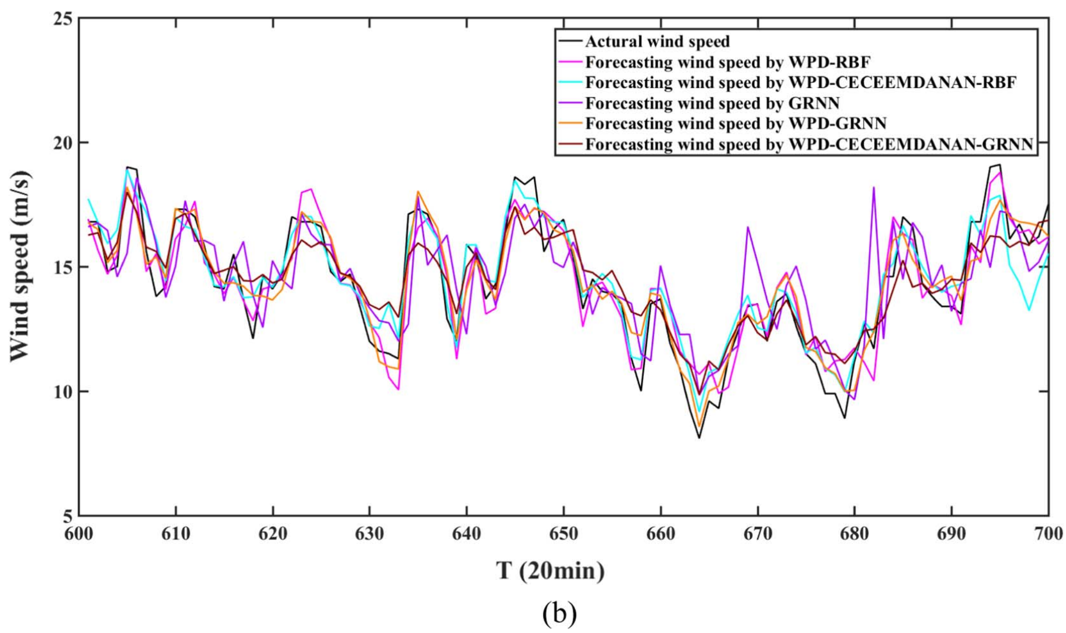


Fig. 4. The results of one-step predictions for the original wind speed series #1: (a) the algorithm group #1 and (b) the algorithm group #2.

decompose the wind speed series, while the ANNs optimized by the MOBA were used to achieve the forecasting. The results indicated that the proposed architecture was both accuracy and robust.

The aforementioned reviewing shows that the decomposition algorithms can significantly improve the prediction performance of the hybrid models for wind series. To further improve the prediction performance, the SDA (*Secondary Decomposition Algorithm*) has been proposed. Liu et al. [26] presented a hybrid approach using the WPD, FEEMD and Elman neural network. The WPD was used to decompose the original wind speed series into a number of sub-layers, and the FEEMD was used to further decompose the high frequency sub-layers. The results showed that the proposed model outperformed the WPD-ELM model. Wang et al. [27] presented a hybrid model based on the FEEMD (*Fast Ensemble Empirical Mode Decomposition)*, VMD (*Variational Mode Decomposition*), BP and FA (*Firefly Algorithm*). The FEEMD was used to decompose the original series into several IMFs, while the VMD was used to further decompose high frequency IMFs. The results showed that the proposed model outperformed the FEEMD-FA-BP model and the VMD-FA-BP model.

The prediction algorithms, which mainly include the ARIMA, the SVM and the ANN, are the core parts of the hybrid methods. Recently, a lot of research on the prediction algorithms has been presented. Wang et al. [28] proposed a hybrid model based on the SAM (*Seasonal Adjustment Method*), the ESM (*Exponential Smoothing Method*) and the RBF. Two experimental results showed that the built model numerically outperformed the HWM (*Holt-Winters Model*), the MLP (*Multilayer Perceptron Neural Network*), the ESM, the RBF, the hybrid SAM-ESM, the hybrid SAM-RBF, and the hybrid ESM-RBF. Ren et al. [29] developed an IS-PSO-BP model constructed by the IS (*Input parameter Selection*), the PSO (*Particle Swam Optimization*) and the BP. The experiment results indicated that the built model obtained better forecast performance than the BP model and the ARIMA (*Auto Regressive Integrated Moving*

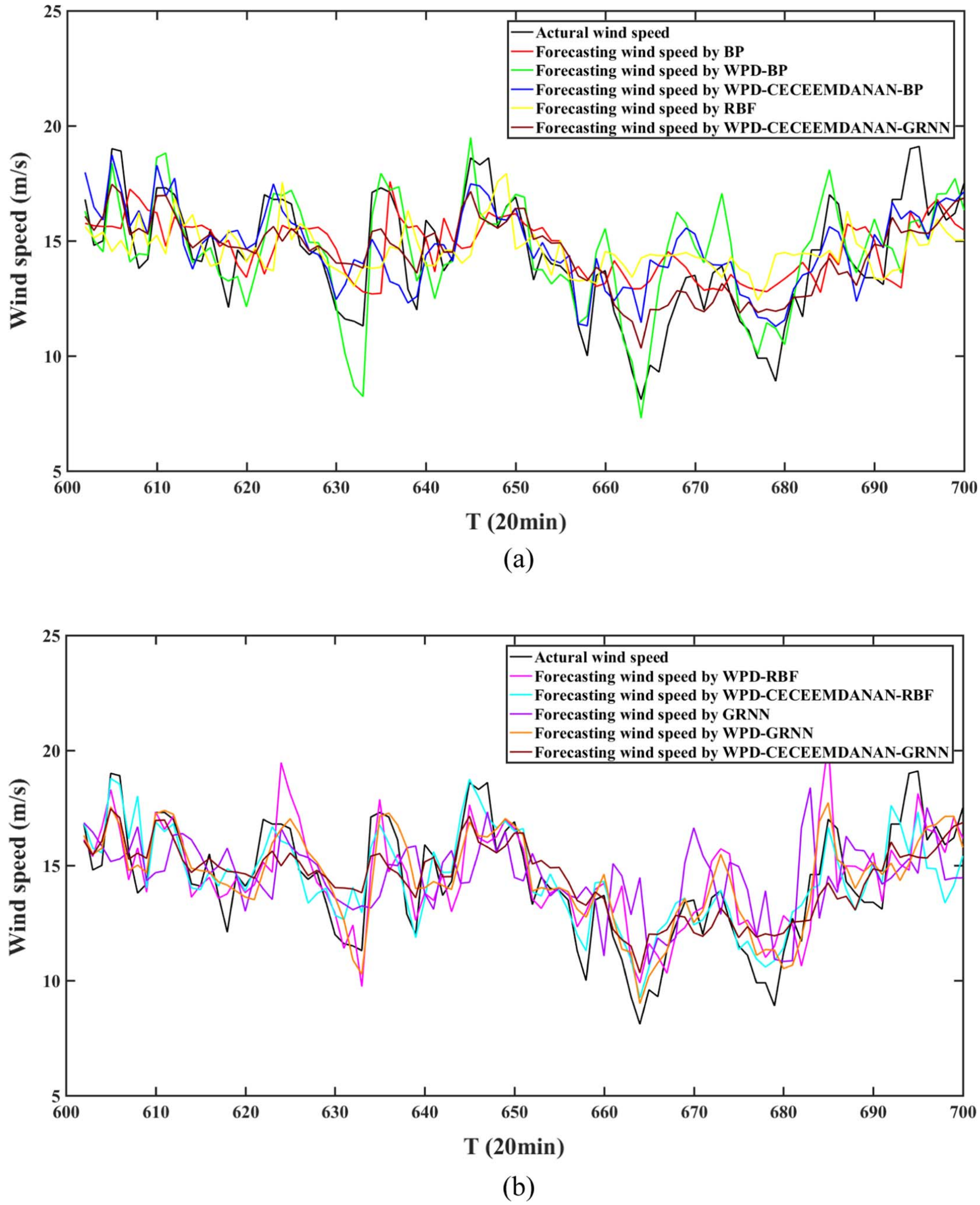
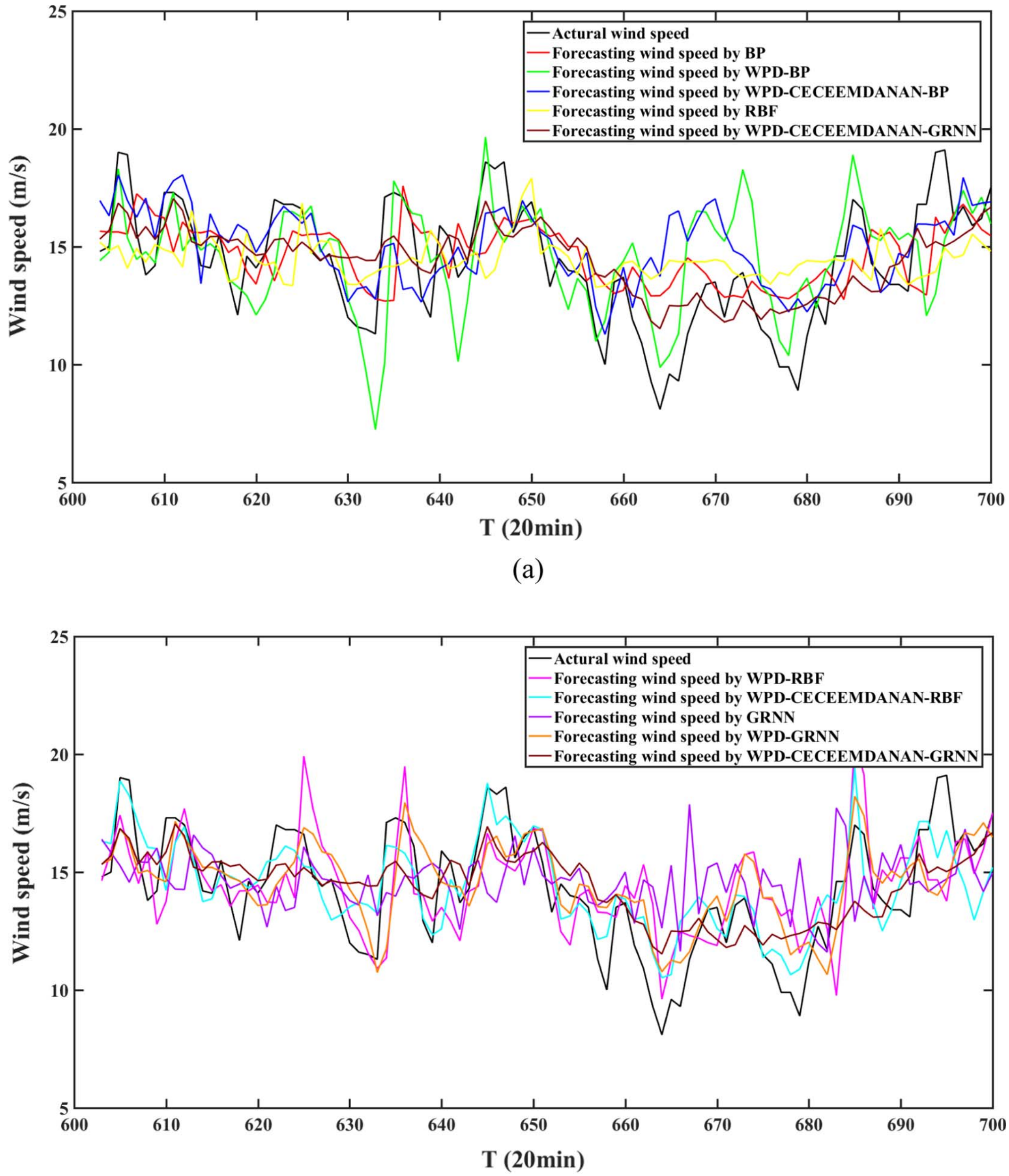


Fig. 5. The results of two-step predictions for the original wind speed series #1: (a) the algorithm group #1 and (b) the algorithm group #2.

Average) model. Santamaría-Bonfil et al. [30] provided a hybrid methodology by combining the PSR (*Phase Space Reconstruction*), the GA and the SVR (*Support Vector Regression*). The simulated results reflected that the provided method had higher prediction accuracy than the persistence models and the auto-regressive models in medium-short term wind speed forecasting. Jiang et al. [31] proposed a hybrid short-term wind speed prediction model by combining the grey correlation analysis, the CSA algorithm and the v-SVM (*v-Support Vector Machine*) model. The grey correlation analysis was used to select the inputs from the wind speed of the neighbouring wind turbine generators and the target wind turbine generators, while the v-SVM model optimized by the CSA algorithm was utilized to conduct the wind speed forecasting. The results indicated that the proposed model produced better wind speed predictions than the ARIMA model and the persistent model. Guo et al. [32] developed a wind speed prediction approach based on the Apriori algorithm and the chaotic time series model. The Apriori algorithm was employed to discover the association rules, while the chaotic time series model was used to complete the wind speed forecasting. The simulation results showed that the proposed approach had excellent prediction performance. Zhang et al. [33] established the RBF to perform wind speed interval forecasting. The k-means clustering algorithm, the least squares algorithm and the NSGA (*Non-dominated Sorting Genetic Algorithm*) were utilized to determine the connection weights of the RBF. The experimental results validated that as compared to the MLP method, the established approach could provide higher quality prediction intervals. Sheela et al. [34] presented a hybrid model integrating the SOM (*Self Organizing feature Maps*) and the MLP, which had satisfactory prediction performance. Feng et al. [35] developed a data-driven multi-model wind prediction methodology using a two-layer ensemble machine learning technique. The first layer was composed of four prediction models: the ANN, the SVM, the gradient boosting machine and the random forest. The second layer used a



(a)

(b)

Fig. 6. The results of three-step predictions for the original wind speed series #1: (a) the algorithm group #1 and (b) the algorithm group #2.

blending algorithm to integrate the predictions produced by the first layer. The numerical results showed that the proposed framework was better than the single ANN model, the single SVM model and the single random forest model. Maatallah et al. [36] developed a wind speed forecasting model by adapting the Hammerstein model to the AR (*Auto Regressive*) model. The results validated that the proposed model outperformed the ANN model and ARIMA model in terms of the prediction accuracy. Zhang et al. [37] designed two hybrid strategies: the SPFAC strategy and the SPSAC strategy, which were based on the SEA (*Seasonal Exponential Adjustment*), PSO, FAC (*First-order Adaptive Coefficient*) and SAC (*Second-order Adaptive Coefficient*). The modified models were validated more accurate than the original FAC and SAC models. Shukur et al. [38] adopted the ARIMA to select the parameters of the KF (*Kalman filter*) and the ANN models. Their experimental results proved that the proposed model had satisfactory prediction performance. The decomposition algorithms and prediction algorithms are summarized in Tables 1 and 2, respectively.

In this study, a novel hybrid wind speed prediction framework is presented based on the SDA and the ANN. The framework can be explained as follows: (a) the WPD is employed to decompose the original wind speed series into a series of sub-layers; (b) the CEEMDAN is adopted to further decompose all the obtained sub-layers into a number of IMFs; (c) three types of ANN models including the BP models, the RBF models and the GRNN models are utilized to complete the predicting computation for the decomposed wind speed series, respectively. To investigate the prediction performance of the presented framework, nine models are included in the comparisons as: the BP model, the WPD-BP model, the WPD-CEEMDAN-BP model, the RBF model, the WPD-RBF model, the WPD-CEEMDAN-RBF model, the GRNN model, the WPD-GRNN model and the WPD-CEEMDAN-GRNN model.

The innovations of this paper are explained as follows: (a) a novel secondary decomposition algorithm is presented using the WPD and CEEMDAN methods. Although either the WPD or the CEEMDAN has been employed to decompose the wind speed time series, their

Table 3
Analysis of the predictions shown in Figs. 4–6.

Indexes	1-step	2-step	3-step	1-step	2-step	3-step
	BP			WPD-BP		
MAPE (%)	6.91	9.42	9.46	4.25	6.4	8.85
MAE (m/s)	1.3206	1.7997	1.8076	0.8125	1.2217	1.6907
RMSE (m/s)	1.6481	2.1933	2.202	1.037	1.5895	2.2018
	WPD-CEEMDAN-BP			RBF		
MAPE (%)	4.97	6.38	8.31	7.81	9.91	9.99
MAE (m/s)	0.9487	1.2177	1.5876	1.4913	1.8930	1.9081
RMSE (m/s)	1.2204	1.6116	2.1363	1.9783	2.3493	2.4227
	WPD-RBF			WPD-CEEMDAN-RBF		
MAPE (%)	4.06	6.53	8.97	3.58	4.68	6.12
MAE (m/s)	0.7762	1.2481	1.7130	0.6838	0.8937	1.1681
RMSE (m/s)	0.9623	1.5374	2.1452	0.8933	1.1891	1.4708
	GRNN			WPD-GRNN		
MAPE (%)	7.35	10.20	10.89	3.79	5.72	7.68
MAE (m/s)	1.4037	1.9487	2.0795	0.7242	1.0917	1.4672
RMSE (m/s)	1.7769	2.3720	2.5739	0.9058	1.3637	1.8380
	WPD-CEEMDAN-GRNN					
MAPE (%)	4.91	6.34	7.56			
MAE (m/s)	0.9376	1.2103	1.4439			
RMSE (m/s)	1.1765	1.5087	1.7801			

combination in wind speed series secondary decomposition has not been investigated; (b) the wind speed series are predicted by combining the ANN and the proposed secondary decomposition algorithm. The involved ANN algorithms include the BP, the RBF and the GRNN. To study the prediction performance of the proposed framework, several comparing models are presented, including the BP model, the WPD-BP model, the WPD-CEEMDAN-BP model, the RBF model, the WPD-RBF model, the WPD-CEEMDAN-RBF model, the GRNN model, the WPD-GRNN model and the WPD-CEEMDAN-GRNN model.

This paper is organized as follows: Section 2 proposes the hybrid wind speed prediction framework; Section 3 explains the modeling procedure; Section 4 presents two wind speed forecasting experiments; and Section 5 concludes this study.

2. Hybrid prediction framework

The hybrid prediction framework is shown in Fig. 1. From Fig. 1, the proposed framework is explained as follows:

(1) The WPD is employed to decompose the original wind speed series into a series of sub-layers, while the CEEMDAN is adopted to further decompose all the obtained sub-layers into a number of IMFs. *The modeling details of the WPD and CEEMDAN algorithms are shown in Section 3.*
(2) Three types of ANN models, including the BP models, the RBF models and the GRNN models are built to complete the predicting computation for the decomposed wind speed series, respectively. To simplify the modeling, in the hybrid prediction framework, the ANN models for all the wind speed sub-layers have the same parameters. The predicted results of the IMFs are summarized to obtain the final forecasting results for the wind speed series.
(3) The prediction results from the BP model, the WPD-BP model, the WPD-CEEMDAN-BP model, the RBF model, the WPD-RBF model, the WPD-CEEMDAN-RBF model, the GRNN model, the WPD-GRNN model and the WPD-CEEMDAN-GRNN model are analyzed to investigate the prediction performance of the presented framework. *The comparing results are given in Sections 4 and 5.*
(4) To compare the prediction performance of the nine models, the neural networks of the ANN models, WPD-ANN models and WPD-CEEMDAN-ANN models have the same parameters.

3. Modeling procedure

3.1. Wind speed time series

As shown in Figs. 2 and 3, two groups of original wind speed time series including 700 samples are adopted in the investigation of the prediction performance. The 1st–600th samples are employed to build the prediction models, and the leaving 601st–700th samples are employed to evaluate the prediction performance of the built models.

3.2. Wavelet Packet Decomposition

The WPD is a special WD method, which can decompose both of the appropriate components and the detailed components [39]. The WPD is employed to decompose the original wind speed series into a series of sub-layers.

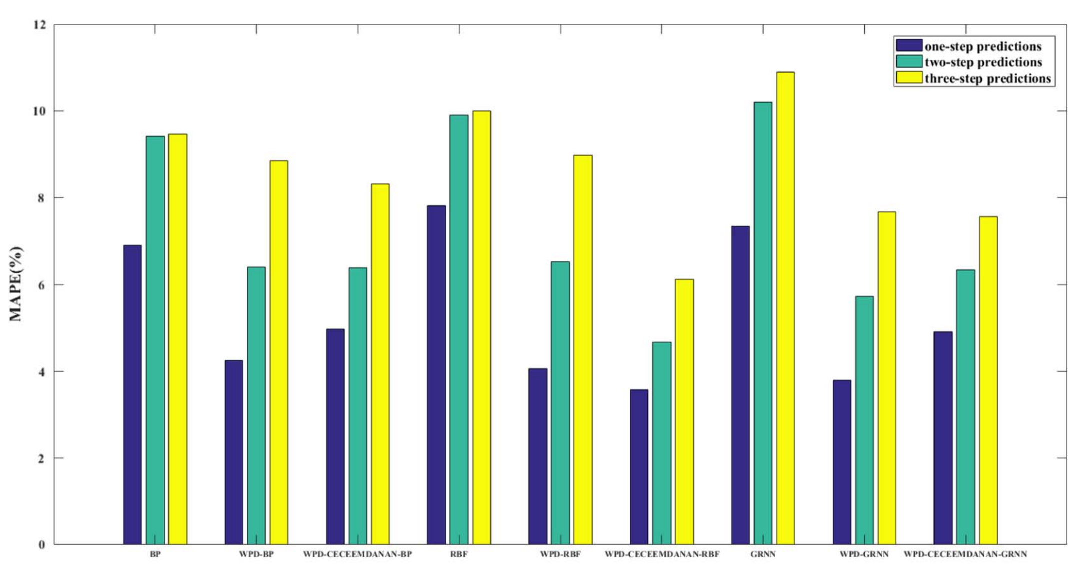


Fig. 7. Forecasting comparison of the nine involved models in case one.

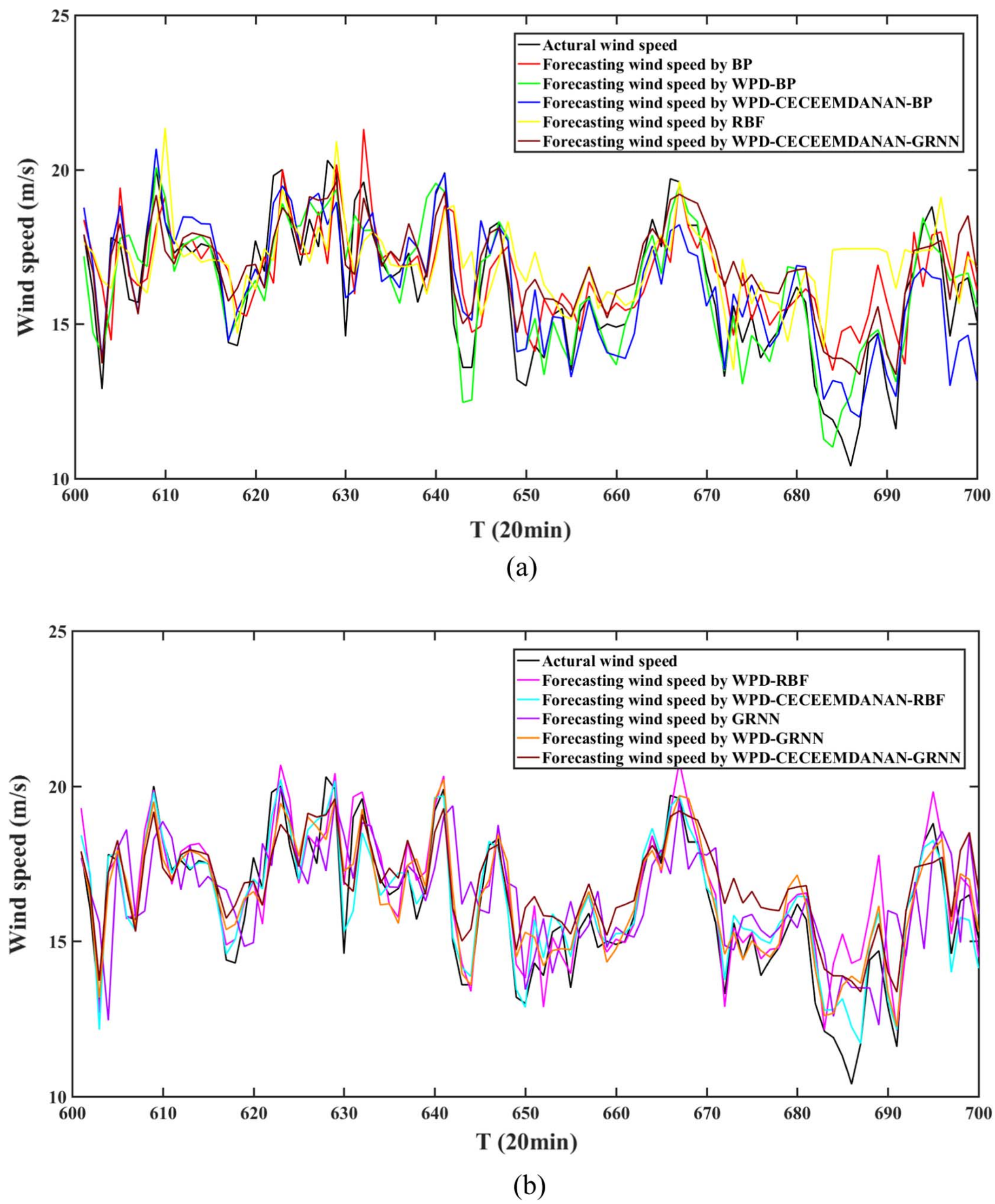


Fig. 8. The results of one-step predictions for the original wind speed series #2: (a) the algorithm group #1 and (b) the algorithm group #2.

The wavelet transform can be defined as:

$$\mathrm{CWT}_f(a,b) = \langle f(t),\Psi_{a,b}(t)\rangle = \int_{-\infty}^{+\infty} f(t)\Psi^{*}((t-b)/a)/\sqrt{a}\,dt \tag{1}$$

where $f(t)$ is the signal, $\Psi(t)$ is a mother wavelet function, $*$ is the complex conjugate, a and b are the scale and translation coefficient, respectively.

3.3. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise

The CEEMDAN is developed from the EEMD. To alleviate the mode mixing problem, the white Gaussian noise which having a certain standard deviation is adopted. By adding the limited number of the adaptive white noise at the every decomposition, the CEEMDAN needs fewer experiments than the EEMD. In addition, since the decomposition and reconstruction of the CEEMDAN are complete, the CEEMDAN can overcome the mode mixing problem [40].

The computation of the CEEMDAN can be described as [41]:

(1) Add a collection of white Gaussian noise series, the obtained signal can be shown as:

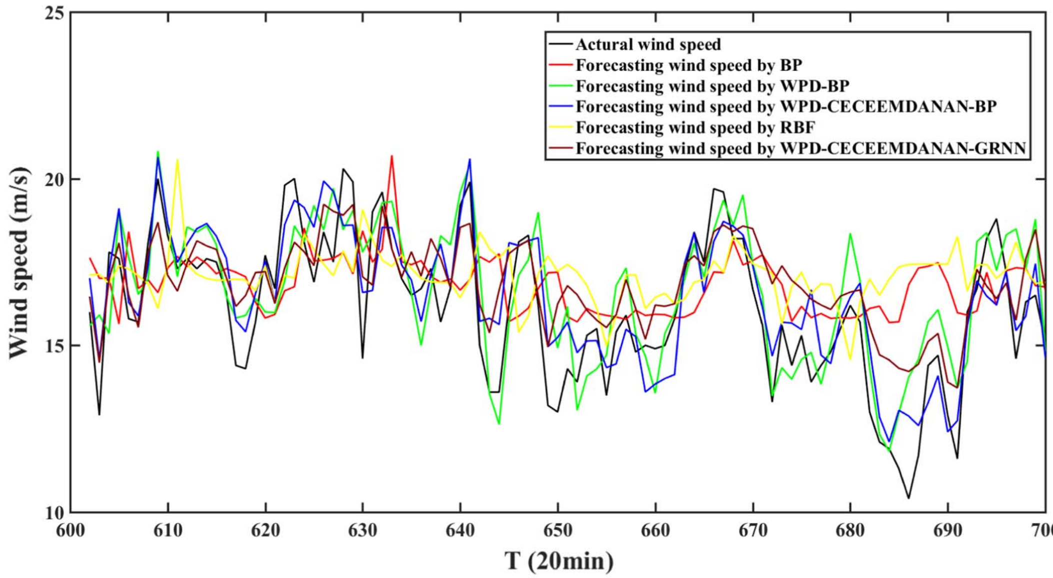
$$s^{i}(n) = s(n) + \varepsilon_0 v^{i}(n) \tag{2}$$

where i is the number of the trials, s(n) is the original signal and $v^i(n)$ is the white Gaussian noise series.

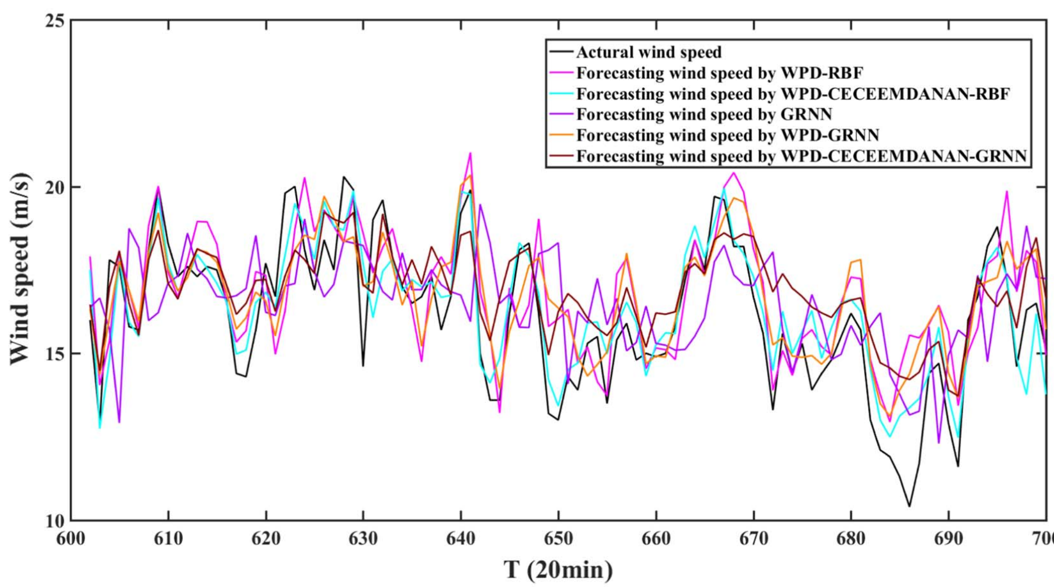
(2) Use EMD to obtain the first IMF as:

$$IMF_1(n) = \left(\sum_{i=1}^{I} IMF_1^{i}(n)\right) \Big/ I \tag{3}$$

(3) Calculate the first residue $r_1(n)$ by:



(a)



(b)

Fig. 9. The results of two-step predictions for the original wind speed series #2: (a) the algorithm group #1 and (b) the algorithm group #2.

$$r_1(n) = s(n) - IMF_1(n) \tag{4}$$

(4) Calculate the k-th residue as:

$$r_k(n) = s(n) - IMF_k(n) \tag{5}$$

(5) Decompose the noise-added residue to obtain the (k + 1)-th IMF of the CEEMDAN as:

$$IMF_{k+1}(n) = \left(\sum_{i=1}^{I} E_1(r_k(n) + \varepsilon_k E_k(v^i(n))\right) \Big/ I \tag{6}$$

where $E_k(\cdot)$ is the k-th mode of the EMD

(6) repeat (4)–(5), until all the IMFs are found.

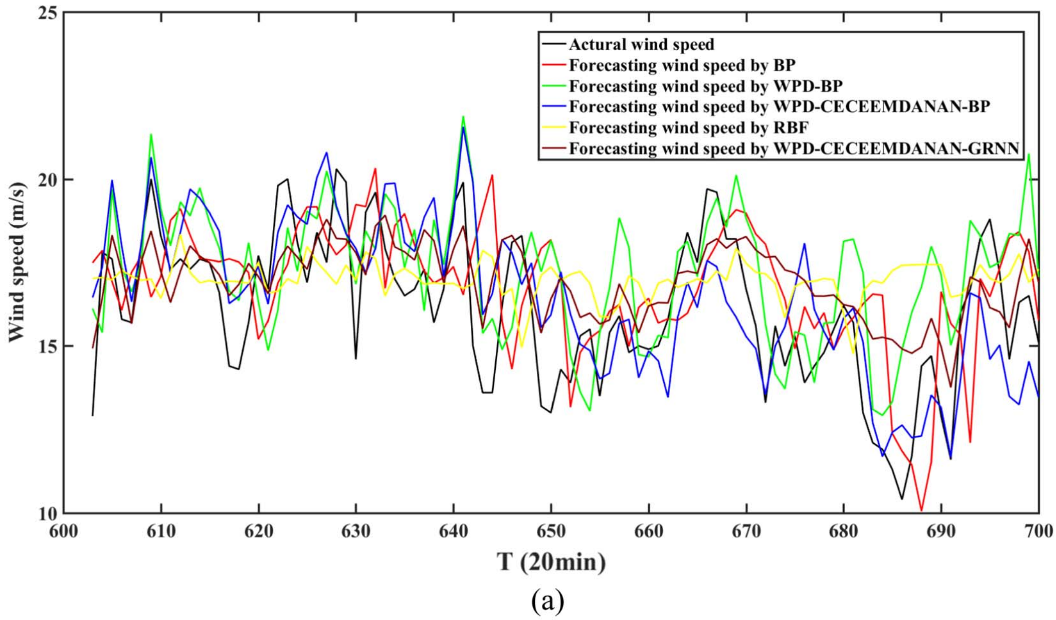
3.4. Artificial Neural Network

In this study, three types of ANN models, including the BP models, the RBF models and the GRNN models are built to complete the predicting computation for the decomposed wind speed series, respectively. The BP, which is based on the gradient descent algorithm, is a multilayer feed forward artificial neural network. The RBF, which is based on the radial activated function, is a three-layer feed forward artificial neural network. The GRNN, which is based on the non-linear regression theory, is a four-layer artificial neural network.

4. Forecast results and comparative analysis

4.1. Precision estimating indexes

Three error indexes are employed to evaluate the performance of the built forecasting models. To estimate the performance of the built



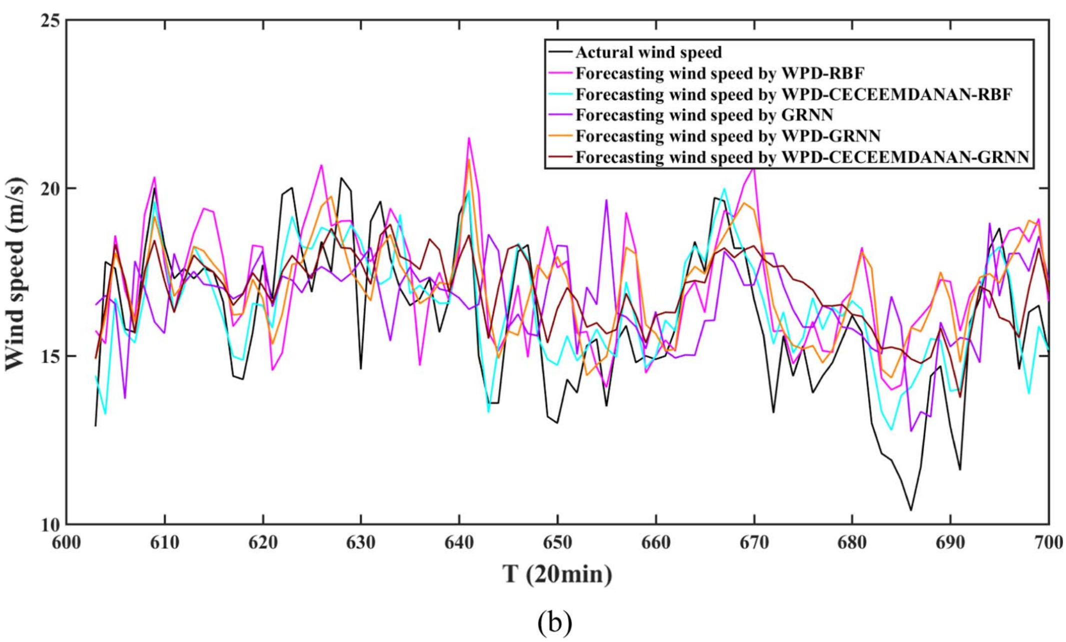


Fig. 10. The results of three-step predictions for the original wind speed series #2: (a) the algorithm group #1 and (b) the algorithm group #2.

models, three error indexes are employed. They are MAPE (*Mean Absolute Percentage Error*), MAE (*Mean Absolute Error*) and RMSE (*Root Mean Square Error*).

Their detailed equations are shown as:

$$MAPE = \left(\sum_{t=1}^{N} |(X(t) - \widehat{X}(t))/\widehat{X}(t)| \right) \bigg/ N \tag{7}$$

$$MAE = \left(\sum_{t=1}^{N} |X(t) - \widehat{X}(t)| \right) \bigg/ N \tag{8}$$

$$RMSE = \sqrt{\left(\sum_{t=1}^{N} [X(t) - \widehat{X}(t)]^2 \right) \bigg/ (N-1)} \tag{9}$$

where $X(t)$ is the original wind speed series, $\widehat{X}(t)$ is the predicted wind speed series, and N is the number of the $X(t)$ series.

To compare the prediction performance of the built models, three percentage error indexes are used. They are the P_{MAE} (*Promoting percentages of Mean Absolute Error*), P_{MAPE} (*Promoting percentages of Mean Absolute Percentage Error*) and P_{RMSE} (*Promoting percentages of Root Mean Square Error*), which are given as:

$$P_{MAE} = |(MAE_1 - MAE_2)/MAE_1| \tag{10}$$

$$P_{MAPE} = |(MAPE_1 - MAPE_2)/MAPE_1| \tag{11}$$

$$P_{RMSE} = |(RMSE_1 - RMSE_2)/RMSE_1| \tag{12}$$

4.2. Forecasting experiments

To compare the performance of the BP model, the WPD-BP model, the WPD-CEEMDAN-BP model, the RBF model, the WPD-RBF model,

Table 4
Analysis of the predictions shown in Figs. 8–10.

Indexes	1-step	2-step	3-step	1-step	2-step	3-step
	BP			WPD-BP		
MAPE (%)	6.55	8.72	9.10	3.78	5.83	8.79
MAE (m/s)	1.3306	1.7707	1.8482	0.7675	1.1834	1.7837
RMSE (m/s)	1.7118	2.271	2.3872	1.0007	1.4763	2.1576
	WPD-CEEMDAN-BP			RBF		
MAPE (%)	4.38	4.70	7.39	8.13	9.38	9.60
MAE (m/s)	0.8901	0.9535	1.5003	1.6510	1.9041	1.9487
RMSE (m/s)	1.0866	1.1778	1.8275	2.1972	2.4387	2.5330
	WPD-RBF			WPD-CEEMDAN-RBF		
MAPE (%)	3.73	6.45	8.77	2.42	3.78	4.82
MAE (m/s)	0.7575	1.3103	1.7808	0.4908	0.7673	0.9782
RMSE (m/s)	1.0668	1.6421	2.2260	0.6889	1.0377	1.317
	GRNN			WPD-GRNN		
MAPE (%)	6.81	8.72	8.95	3.62	5.96	7.87
MAE (m/s)	1.3825	1.7692	1.8177	0.7356	1.2097	1.5984
RMSE (m/s)	1.7949	2.2213	2.2973	0.9736	1.4775	2.0084
	WPD-CEEMDAN-GRNN					
MAPE (%)	5.15	6.1	7.17			
MAE (m/s)	1.0459	1.2383	1.4563			
RMSE (m/s)	1.2841	1.5419	1.7988			

the WPD-CEEMDAN-RBF model, the GRNN model, the WPD-GRNN model and the WPD-CEEMDAN-GRNN model, two experimental cases based on the original wind speed time series (shown in Figs. 2 and 3) are proposed in this section.

4.2.1. Case one

Figs. 4–6 show the multi-step prediction results of the original wind speed time series #1. According to Figs. 4–6, Table 3 provides the error estimated results of the predictions. Fig. 7 gives the prediction performance of the nine models.

4.2.2. Case two

Figs. 8–10 show the multi-step prediction results of the original wind speed time series #2. According to the Figs. 8–10, Table 4 provides the error estimated results of the predictions. Fig. 11 gives the prediction performance of the nine models.

4.2.3. Analysis

According to the two experimental cases, Table 5 provides the comparison results between the WPD-BP model and the BP model; Table 6 provides the comparison results between the WPD-CEEMDAN-BP model and the WPD-BP model; Table 7 provides the comparison results between the WPD-RBF model and the RBF model; Table 8 provides the comparison results between the WPD-CEEMDAN-RBF model and the WPD-RBF model; Table 9 provides the comparison results between the WPD-GRNN model and the GRNN model; Table 10 provides the comparison results between the WPD-CEEMDAN-GRNN model and the WPD-GRNN model.

From Figs. 4–11 and Tables 3–10, it can be found that:

(a) When comparing the WPD-BP model with the BP model, the prediction accuracy of the former is higher than the latter distinctly, especially in one-step and two-step forecasting results. For instance, in case two, the one-step to three-step promoting percentages of the MAPE of the BP model by the WPD-BP model are 42.29%, 33.14% and 3.41%, respectively. The one-step to three-step promoting percentages of the MAE of the BP model by the WPD-BP model are 42.32%, 33.17% and 3.49%, respectively. The one-step to three-step promoting percentages of the RMSE of the BP model by the WPD-BP model are 41.54%, 34.99% and 9.62%, respectively.

(b) When comparing the WPD-CEEMDAN-BP model with the WPD-BP model, the accuracy of the former is higher than the latter in three-step forecasting results. For instance, in case two, the three-step promoting percentage of the MAPE of the WPD-BP model by the WPD-CEEMDAN-BP model is 15.93%. The three-step promoting percentage of the MAE of the WPD-BP model by the WPD-CEEMDAN-BP model is 15.89%. The three-step promoting percentage of the RMSE of the WPD-BP model by the WPD-CEEMDAN-BP model is 15.30%.

(c) When comparing the WPD-RBF model with the RBF model, the prediction accuracy of the former is higher than the latter significantly, especially in one-step and two-step forecasting results. For instance, in case two, the one-step to three-step promoting percentages of the MAPE of the RBF model by the WPD-RBF model are 54.12%, 31.24% and 8.65%, respectively. The one-step to three-step promoting percentages of the MAE of the RBF model by the WPD-RBF model are 54.12%, 31.19% and 8.62%, respectively. The one-step to three-step promoting percentages of the RMSE of the RBF model by the WPD-RBF model are 51.45%, 32.66% and

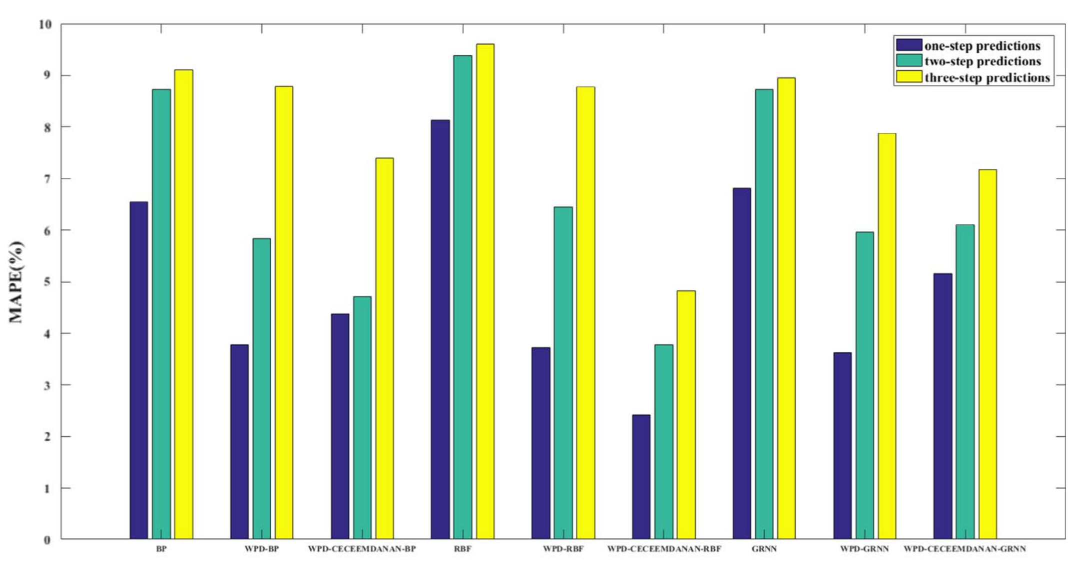


Fig. 11. Forecasting comparison of the nine involved models in case two.

Table 5
Promoting percentages of the BP model by the WPD-BP model.

Indexes	WPD-BP vs. BP					
	Case One			Case Two		
	1-step	2-step	3-step	1-step	2-step	3-step
MAPE (%)	38.49	32.06	6.45	42.29	33.14	3.41
MAE (%)	38.47	32.12	6.47	42.32	33.17	3.49
RMSE (%)	37.08	27.53	0.01	41.54	34.99	9.62

Table 6
Promoting percentages of the WPD-BP model by the WPD-CEEMDAN-BP model.

Indexes	WPD-CEEMDAN-BP vs. WPD-BP					
	Case One			Case Two		
	1-step	2-step	3-step	1-step	2-step	3-step
MAPE (%)	−16.94	0.31	6.10	−15.87	19.38	15.93
MAE (%)	−16.76	0.33	6.10	−15.97	19.43	15.89
RMSE (%)	−17.69	−1.39	2.97	−8.58	20.22	15.30

Table 7
Promoting percentages of the RBF model by the WPD-RBF model.

Indexes	WPD-RBF vs. RBF					
	Case One			Case Two		
	1-step	2-step	3-step	1-step	2-step	3-step
MAPE (%)	48.02	34.11	10.21	54.12	31.24	8.65
MAE (%)	47.95	34.07	10.22	54.12	31.19	8.62
RMSE (%)	51.36	34.56	11.45	51.45	32.66	12.12

Table 8
Promoting percentages of the WPD-RBF model by the WPD-CEEMDAN-RBF model.

Indexes	WPD-CEEMDAN-RBF vs. WPD-RBF					
	Case One			Case Two		
	1-step	2-step	3-step	1-step	2-step	3-step
MAPE (%)	11.82	28.33	31.77	35.12	41.40	45.04
MAE (%)	11.90	28.40	31.81	35.21	41.44	45.07
RMSE (%)	7.17	22.66	31.44	35.42	36.81	40.84

Table 9
Promoting percentages of the GRNN model by the WPD-GRNN model.

Indexes	WPD-GRNN vs. GRNN					
	Case One			Case Two		
	1-step	2-step	3-step	1-step	2-step	3-step
MAPE (%)	48.44	43.92	29.48	46.84	31.65	12.07
MAE (%)	48.41	43.98	28.44	46.79	31.62	12.06
RMSE (%)	49.02	42.51	28.59	45.76	33.48	12.58

12.12%, respectively.

(d) When comparing the WPD-CEEMDAN-RBF model with the WPD-RBF model, the accuracy of the former is higher than the latter significantly, especially in three-step forecasting results. For instance, in case two, the one-step to three-step promoting percentages of the MAPE of the WPD-RBF model by the WPD-CEEMDAN-RBF model are 35.12%, 41.40% and 45.04%, respectively. The one-step to three-step promoting percentages of the MAE of the WPD-RBF model by the WPD-CEEMDAN-RBF model are 35.21%, 41.44% and 45.07%, respectively. The one-step to three-step promoting percentages of the RMSE of the WPD-RBF model by the WPD-CEEMDAN-RBF model are 35.42%, 36.81% and 40.84%, respectively.

Table 10
Promoting percentages of the WPD-GRNN model by the WPD-CEEMDAN-GRNN model.

Indexes	WPD-CEEMDAN-GRNN vs. WPD-GRNN					
	Case One			Case Two		
	1-step	2-step	3-step	1-step	2-step	3-step
MAPE (%)	−29.55	−10.84	1.56	−42.27	−2.35	8.89
MAE (%)	−29.47	−10.86	1.59	−42.18	−2.36	8.89
RMSE (%)	−29.89	−10.63	3.15	−31.89	−4.36	10.44

(e) When comparing the WPD-GRNN model with the GRNN model, the prediction accuracy of the former is higher than the latter significantly, especially in one-step and two-step forecasting results. For instance, in case two, the one-step to three-step promoting percentages of the MAPE of the GRNN model by the WPD-GRNN model are 46.84%, 31.65% and 12.07%, respectively. The one-step to three-step promoting percentages of the MAE of the GRNN model by the WPD-GRNN model are 46.79%, 31.62% and 12.06%, respectively. The one-step to three-step promoting percentages of the RMSE of the GRNN model by the WPD-GRNN model are 45.76%, 33.48% and 12.58%, respectively.

(f) When comparing the WPD-CEEMDAN-GRNN model with the WPD-GRNN model, the accuracy of the former is higher than the latter in three-step forecasting results. For instance, in case two, the three-step promoting percentage of the MAPE of the WPD-GRNN model by the WPD-CEEMDAN-GRNN model is 8.89%. The three-step promoting percentage of the MAE of the WPD-RBF model by the WPD-CEEMDAN-GRNN model is 8.89%. The three-step promoting percentage of the RMSE of the WPD-GRNN model by the WPD-CEEMDAN-GRNN model is 10.44%.

(g) In all the wind speed prediction models involved, the WPD-CEEMDAN -RBF has the best estimated performance.

5. Conclusions

According to the results of the two comparing experimental cases, it can be concluded as: (a) the WPD-BP model, the WPD-RBF model and the WPD-GRNN model have better prediction performance than the BP model, the RBF model and the GRNN model, respectively, especially in one-step and two-step forecasting results; (b) the WPD-CEEMDAN-BP model, the WPD-CEEMDAN-RBF model and the WPD-CEEMDAN-GRNN model have better prediction performance than the WPD-BP model, the WPD-RBF model and the WPD-GRNN model in three-step forecasting results, respectively; (c) In all the wind speed prediction models involved, the WPD-CEEMDAN-RBF has the best estimated performance in one-step to three-step forecasting results.

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