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RESEARCH ARTICLE

Hybrid Forecasting Model Based Data Mining and Cuckoo Search: A Case Study of Wind Speed Time Series

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Abstract: Wind energy has been part of the fastest growing renewable energy sources that is clean and pollution-free, which has been increasingly gaining global attention, and wind speed forecasting plays a vital role in the wind energy field, however, it has been proven to be a challenging task owing to the effect of various meteorological factors. This paper proposes a hybrid forecasting model, which can effectively make a preprocess for the original data and improve forecasting accuracy, the developed model applies cuckoo search(CS) algorithm to optimize the parameters of the wavelet neural network (WNN) model. The proposed hybrid method is subsequently examined on the wind farms of eastern China and the forecasting performance shows that the developed model is better than some traditional models.

1. INTRODUCTION

Along with the continuous increase in world energy consumption and vigorous development in traditional energy resources, the storage of fossil fuel is on the decrease, and the worldwide energy crisis is gradually becoming significant. Wind energy has been part of the fastest growing renewable energy sources that is clean and pollution-free, which has been successfully adopted in many countries, and wind energy represents about 10% of energy consumption in Europe, over 15% in America and Germany [1]. In China, the installed wind power capacity was 75324 MW in 2012, with year on year growth rate of 24.1%, and in 2013, the installed wind power capacity was 91413 MW, with year on year growth rate of 21.4%, ranking first in the world [2].

In recent years, the wind speed forecasting becomes more and more important for the wind energy application and many researchers are attracted to do studies on wind speed forecasting, according to the time scopes of wind speed forecasting, which can be divided into short-term forecasting (from 30 min to six hours ahead), medium-term forecasting (from six hours to one day ahead) and long-term forecasting (from one day to one week or more ahead). While short-term wind speed forecasting has made a great influence on grid reliability [3], medium-term and long-term forecasting is mainly used for system maintenance, planning of windmills and provide important references for site location [4]. According to the computational mechanism, the wind speed forecasting methods can be divided into four categories [5]: (a) artificial intelligence methods; (b) statistical methods; (c) spatial correlation methods; (d) physical methods, while artificial intelligence methods are the most popular in wind speed forecasting field.

The artificial intelligence methods adopt the artificial intelligence theories or evolutionary algorithms to do the wind speed forecasting and with the rapid development of artificial technique, some artificial intelligent forecasting methods

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have been growing fast, artificial neural networks have been widely applied in the wind speed time series due to their ability to deal with nonlinearities, which mainly including back propagation neural network, fuzzy neural network, support vector machine [6 - 12], *etc*. However, the fact they need many neurons to solve the mixed problems is the main trouble with neural networks. To remedy these problems, wavelet technology is introduced into neural networks.

Recently, wavelet neural network (WNN) based on the combination of wavelet decomposition and feed-forward neural networks has attracted much attention and WNN has grown up to be a popular tool for function learning [13]. The selection of wavelet transforms is the main problem of WNN with fixed wavelet bases because the translation and dilation parameters of the wavelet basis are fixed and just the weights are adjustable. The suitable wavelet transforms will lead to the accuracy of improvement and there are several different methods proposed solving the problems [14 - 16] and their algorithms are given.

Recently, a cuckoo search (CS) has been a new meta-heuristic approach proposed by Yang and Deb in 2009 [17]. Recent studies show that CS is potentially far more efficient than PSO and GA [18, 19]. Moreover, the number of parameters in CS to be tuned is less than GA and PSO, and thus it is potentially more generic to adapt to a wider class of optimization problems. In the light of the advantages of CS technique, in the presented paper the five benchmark problems of reliability-redundancy allocation have been solved and it has been observed that the results of the new approach are all superior to the existing results in the literature.

As we all know, removing the noise of data, as an important method of data preprocessing, is significant and meaningful. The methods such as empirical mode decomposition [20 - 26] and wavelet decomposition [27 - 29] can be used to remove noisy data. But, wavelet decomposition technology is sensitive to the choice of the threshold and empirical mode decomposition will appear the phenomenon of mode mixing in the general case. Luckily, fast ensemble empirical mode decomposition can overcome the deficiency of empirical mode decomposition. The basic idea of fast ensemble empirical mode decomposition is to use the statistical characteristic of noise to effectively avoid the phenomenon of mode mixing.

In this paper, the hybrid fast ensemble empirical mode decomposition-cuckoo search-wavelet neural network(FEEMD-CS-WNN) model is developed, which combines fast ensemble empirical mode decomposition method, CS algorithm and WNN model. The fast ensemble empirical mode decomposition method is utilized to decompose the original wind speed time series into one residual series and a group of intrinsic mode function, and then establish WNN model and use the CS algorithm to optimize the parameters of WNN, finally apply the CS-WNN model to forecast the data that have excepted the highest frequency and the obtained consequences show that the proposed FEEMD-CS-WNN model can effectively improve the forecasting accuracy.

This paper is structured as follows. Section 2 summarizes our contribution. Section 3 outlines a detailed discussion of required mathematical tools. The proposed model is presented in Section 4. Experimental results in three real case studies and comparison with previous methods is provided in Section 5. Section 6 contains conclusions.

2. OUR CONTRIBUTIONS

An effective hybrid approach which is named after FEEMD-CS-WNN model is proposed to forecast wind speed. Based on the intrinsic characteristics of WNN, a series of suitable concepts, which include data de-noising, data selection and optimized algorithms, were used to improve forecasting accuracy. A case study shows that hybrid FEEMD-CS-WNN model performs better than single models and other hybrid models. Finally, we analyzed the forecasting errors based on statistical theory, which showed that hybrid model is a suitable forecasting model of wind speed in eastern China from Shan Dong province Penglai city.

3. METHODOLOGY

Before the hybrid FEEMD-CS-WNN forecasting model, it is quite necessary to describe the required mathematical tools.

3.1. Brief Reviews of WNN

WNN based on the wavelet transform theory is effective as an alternative to feed forward neural networks for approximating arbitrary nonlinear functions [14]. The WNN is designed to be a three-layered structure with an input layer, a hidden layer and an output layer.

The network output of hidden layer is expressed as:

$$\Psi_i = \Psi_i \left[\frac{\sum_{i=1}^{N} w_{ji} x_i - b_j}{a_j} \right]$$

(1)

where N is the number of hidden nodes, $x_i \left(1 \leq i \leq N\right)$ is the input to the network, w_{ji} and w_{kj} are the weights, and the basis function $\Psi_i \left(1 \leq i \leq N\right)$ chosen to be the Morlet wavelet activation function, a_j and b_j are the dilation and translation factor of wavelet activation function. Morlet wavelet is widely utilized as the activation function, which is expressed by Equation 3.

$$\Psi(x) = \cos(1.75x) \exp(-\frac{x^2}{2})$$

(2)

Therefore, the network output is described as:

$$y_k = \sum_{j=1}^{h} w_{kj} \Psi_j \left(x\right)$$

(3)

Thus, substituting (3) into (4), we may formulate input-output mapping realized by WNN as follows:

$$y_k = \sum_{j=1}^{h} w_{kj} \cos(1.75x) \exp(-\frac{x^2}{2})$$

(4)

3.2. Fundamental Concepts of Ensemble Empirical Mode Decomposition

Ensemble empirical mode decomposition can overcome the deficiency of empirical mode decomposition, which is proposed by Wu and Huang [30]. The basic principle of ensemble empirical mode decomposition is to use the statistical characteristic of noise to effectively avoid the phenomenon of mode mixing. The observed data are mixed noise and true time series, therefore, white noise is added into the raw data to help extract the real signals.

An evaluating experiment was carried out by scientist Y. Wang in 2014 [31] to prove that the time complexity of the EEMD is almost equivalent to that of the Fourier transform and a group of parameters were compared to validate the fast ensemble empirical mode decomposition, which will be actually adopted to do the raw wind speed time series.

3.3. Cuckoo Search Algorithms

Cuckoo search (CS) [17] is one of the latest optimization algorithms and was developed from the inspiration that the obligate brood parasitism of some cuckoo species lay their eggs in the nests of other host birds which are of another species.

CS algorithm is based on three idealized rules:

(1) Each cuckoo lays one egg at a time, and dumps its egg in a randomly chosen nest.

(2) The best nests with high quality of eggs will carry over to the next generations

(3) The number of available host nests is fixed and the egg laid by a cuckoo is discovered by the host bird with a probability in the range 0–1. In this case, the host bird can either throw the egg away or abandon the nest, and build a completely new nest.

Based on the above mentioned rules, the basic steps of the Cuckoo search can be summarized as the pseudo code as follows [17]:

Algorithm: CS

1. Objective function: $f(x)$, $x = (x_1, x_2, ... x_n)$
2. Generate an initial population of n host nests $x_i(i = 1,2,...n)$;
3. /*Get the current best solution*/;
4. [fmin,bestnest,nest,fitness]=get_best_nest(nest,nest,fitness);
5. N_iter=0;
6. **FOR** iter=1:N_IterTotal
7. /*Generate new solutions (but keep the current best)*/;
8. new_best=get_cuckoos(nest,bestnest);
9. [fnew,best,nest,fitness]=get_best_nest(nest,new_best,fitness);
10. /*Update the counter*/;
11. N_iter=N_iter+1;
12. /*Discovery and randomization*/;
13. new_nest=empty_nests(nest,pa);
14. /*Evaluate this set of solutions*/;
15. [fnew,best,nest,fitness]=get_best_nest(nest,new_best,fitness);
16. /*Update the counter again*/;
17. N_iter=N_iter+1;
18. /*Find the best objective so far*/;
19. **IF** fnew<fmin
20. fmin=fnew; bestnest=best;
21. **END**
22. **END**

4. HYBRID FEEMD-CS-WNN MODEL

The proposed FEEMD-CS-WNN approach for predicting short-term wind speed was based on fast ensemble empirical mode decomposition method, CS algorithm and WNN model and the process of the proposed model is illustrated as follows. Firstly, fast ensemble empirical mode decomposition decomposes the raw data into a number of independent intrinsic mode function. Remove the first intrinsic mode function and aggregate into the new data. Secondly, establish WNN model and use the CS algorithm to optimize the parameter of WNN. Finally, apply the CS-WNN model to forecast the data that have removed the highest frequency.

The process of the algorithm is described below and flow diagram of the FEEMD-CS-WNN model is shown in Fig. (**1**).

Step 1: De-noising. Utilize fast ensemble empirical mode decomposition to decompose the raw wind speed time series into a number of the intrinsic mode function and one residual series. Then remove the highest frequency and aggregate into the new data.

Step 2: Building model. Establish WNN model and use the CS algorithm to optimize the parameter of WNN.

Step 3: Forecasting. Apply the CS-WNN model to forecast the new data that have removed the highest frequency.

5. EXPERIMENTATION DESIGN AND RESULTS

In this section, three sites of wind speed will be predicted by the proposed model and it is necessary to introduce the source of data, then the evaluation criteria of forecast performance are introduced.

5.1. Data Sets

Hybrid FEEMD-CS-WNN algorithm is examined using three case studies of forecasting wind speed times series. The wind speed data which are collected from Shan Dong province Penglai city in China were gathered in just ten minutes. The locations of the three selected stations (Site 1: N37.48 E120.45, Site 2: N38.46 E118.5, Site 3: N36.75 E119.34) located offshore are shown in Fig. (**3**).
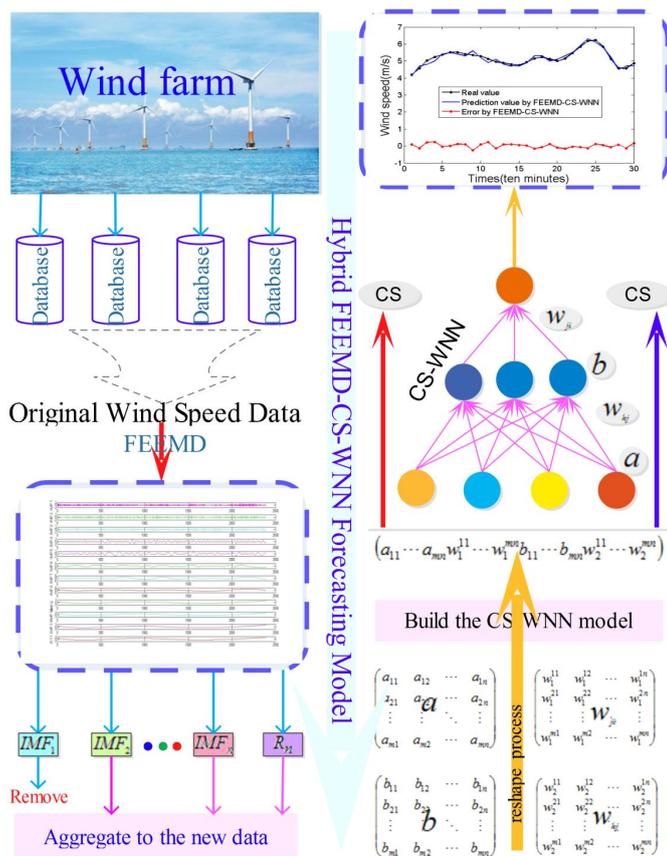
Fig. (1). Flow diagram of the FEEMD-CS-WNN model.

In this paper, there are three sites, and we select 2930 observation values and the initial 2900 values were used as the training sample, and the remaining 30 values were used as the test sample for each site. The data sample is illustrated in Fig. (**3B**), as seen from Fig. (**2B**), it presents the fluctuation, irregularity and instability (Fig. **2**).
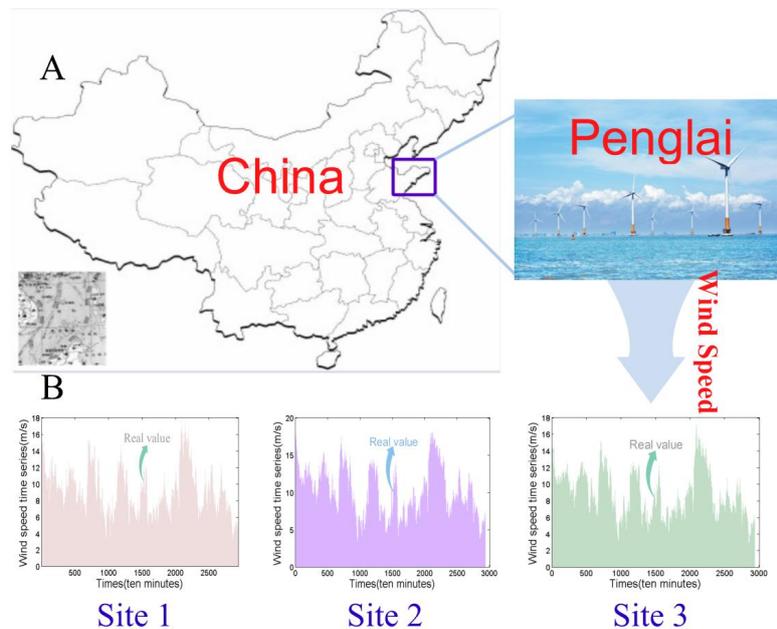

Fig. (2). The geographic location of the study area and real values of three sites.

5.2. Evaluation Metrics

The mean absolute error (MAE), mean absolute percentage error (MAPE) and mean square error (MSE) are used to assess the forecasting performance of the proposed model. The three indices are defined as follows:

$$MAE = \frac{1}{T} \sum_{t=1}^{T} \left| a_t - \hat{a}_t \right|$$

(5)

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \frac{\left| a_t - \hat{a}_t \right|}{a_t} \times 100\%$$

(6)

$$MSE = \frac{1}{T} \sum_{t=1}^{T} \left(a_t - \hat{a} \right)^2$$

(7)

where a_t is the actual value and $\hat{a}_t$ is the forecast value. *T* means the total number of the data-set. Smaller values of these measures indicate more accurately forecasting consequences.

5.3. Study Cases

In this paper, there are three cases and each study case was divided into two parts, experiment 1 and experiment 2. Experiment 1 used the original wind speed data and experiment 2 used data decomposed by the fast ensemble empirical mode decomposition technique. Two group data were predicted by single WNN, GA-WNN, PSO-WNN, and CS-WNN model, respectively. Experiment 1 aims to compare the CS-WNN with the other three models, single WNN, GA-WNN, and PSO-WNN and the purpose of experiment 2 illustrates the effectiveness of fast ensemble empirical mode decomposition method.

We performed our experiments on a standard workstation based on an Intel Xeon W3680 CPU with 6 cores, 24 GB of memory and 12 MB of cache, and is denoted 'C1'. We run 64 bit Linux OS; Matlab R2014b (8.4.0.150421) on C1. To avoid OS noise and caching effects, all tests were performed 20 times and the results were determined as the arithmetic mean.

5.3.1. Study of Case 1

In this case, each step will be clearly presented by tables and figures to show the performance of all models. Firstly, wind speed forecasting consequences of three sites are shown in Table **1**.

Table 1. MSE, MAE and MAPE of three sites for the hybrid forecasting model.

Site	Model error	Model	Model	Model	Model
		WNN	GA-WNN	PSO-WNN	CS-WNN
Site 1	MAE	0.2859	0.2556	0.2652	0.214
	MAPE(%)	5.48	4.89	5.1	4.14
	MSE	0.1185	0.1101	0.1033	0.0648
Site 2	MAE	0.2925	0.2628	0.2652	0.2249
	MAPE(%)	6.02	5.48	5.48	4.91
	MSE	0.1389	0.1183	0.1207	0.0831
Site 3	MAE	0.3593	0.2936	0.2903	0.2639
	MAPE(%)	4.77	3.79	3.77	3.6
	MSE	0.2203	0.1294	0.1251	0.1129
Site	Model error	Model	Model	Model	Model
		FEEMD-WNN	FEEMD-GA-WNN	FEEMD-PSO-WNN	FEEMD-CS-WNN
Site 1	MAE	0.1663	0.1365	0.1326	0.1128
	MAPE(%)	3.15	2.68	2.58	2.22
	MSE	0.0438	0.0278	0.0246	0.0167

(Table 1) contd.....

Site	Model error	Model	Model	Model	Model
		WNN	**GA-WNN**	**PSO-WNN**	**CS-WNN**
Site 2	MAE	0.2162	0.1689	0.1727	0.1479
	MAPE(%)	4.53	3.58	3.65	3.15
	MSE	0.0659	0.0472	0.0482	0.0402
Site 3	MAE	0.3041	0.2381	0.1972	0.1143
	MAPE(%)	3.72	3.2	2.66	2.24
	MSE	0.1408	0.0894	0.0782	0.0176

Forecasting effectiveness for site 1 is shown in Fig. (**3A**). The left of the figure is the performance of experiment 1, which is predicted by models without utilizing ensemble empirical mode decomposition method, we can see that the WNN,GA-WNN, PSO-WNN, especially CS-WNN model follows the real values; the right of the figure is the performance of experiment 2, which is predicted by models utilizing ensemble empirical mode decomposition method, we can see the FEEMD-WNN,FEEMD-GA-WNN,FEEMD-PSO-WNN, especially FEEMD-CS-WN N model is succeeded to follow the real values. When comparing experiment 1 and experiment 2, as seen from Table **1** and Fig. (**3**), the latter has improved the performance of the former obviously.

Fig. (**3B**) displays the comparison of the predicted values by models with the real values and the corresponding errors of site 1. As seen from Fig. (**3B**), the error of the FEEMD-WNN, FEEMD-GA-WNN, FEEMD-PSO-WNN, FEEMD-CS-WNN model are smaller than the error of the WNN,GA-WNN,PSO-WNN,CS-WNN model, particularly, it is clear that the FEEMD-CS-WNN model is succeeded to follow the actual wind speed closely and performs much better than other models, its corresponding error is close to zero.
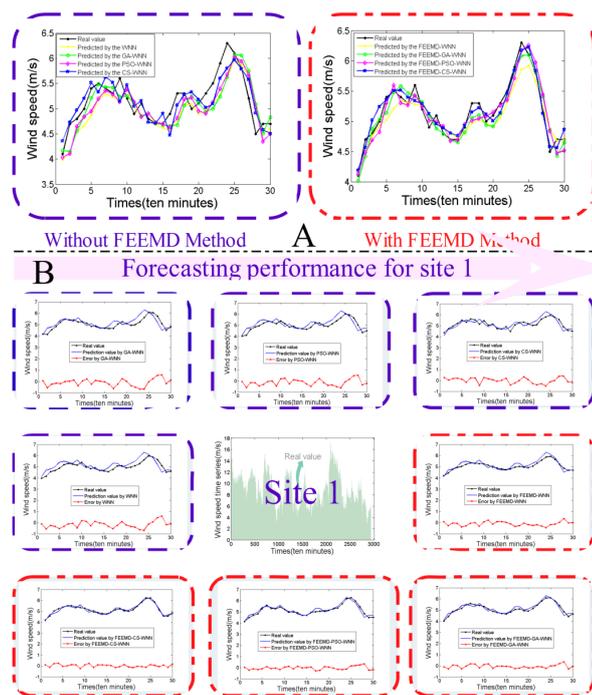

Fig. (3). Forecasting performance for site 1.

5.3.2. Results of Analysis

In this section, the comparison and forecasting effectiveness for another two sites are shown in Figs. (**4A and 5A**) while the comparison of the predicted values by all models with the actual values and the corresponding errors for another two sites are illustrated in Figs. (**4B** and **5B**).

Similarly, as also seen from Figs. (**4A** and **5A**), the WNN, GA-WNN, PSO-WNN, especially CS-WNN model follows the real values while the FEEMD-WNN, FEEMD-GA-WNN,FEEMD-PSO-WNN, especially FEEMD-WNN models are succeeded to follow the real values. We can make a decision that experiment 2 outperforms better than experiment 1; As seen from Figs. (**4B** and **5B**), the error of the FEEMD-WNN, FEEMD-GA-WNN, FEEMD-PSO-

WNN, FEEMD-CS-WNN model are smaller than the error of the WNN,GA-WNN,PSO-WNN,CS-WNN model, particularly, it is very clear that the FEEMD-CS-WNN model agrees with the actual wind speed exceptionally well and performs much better than other models, its corresponding error is close to zero.
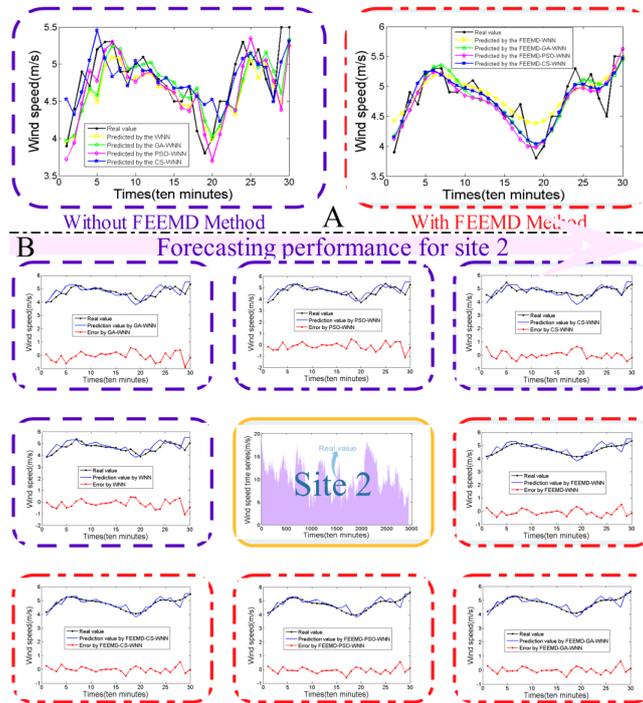

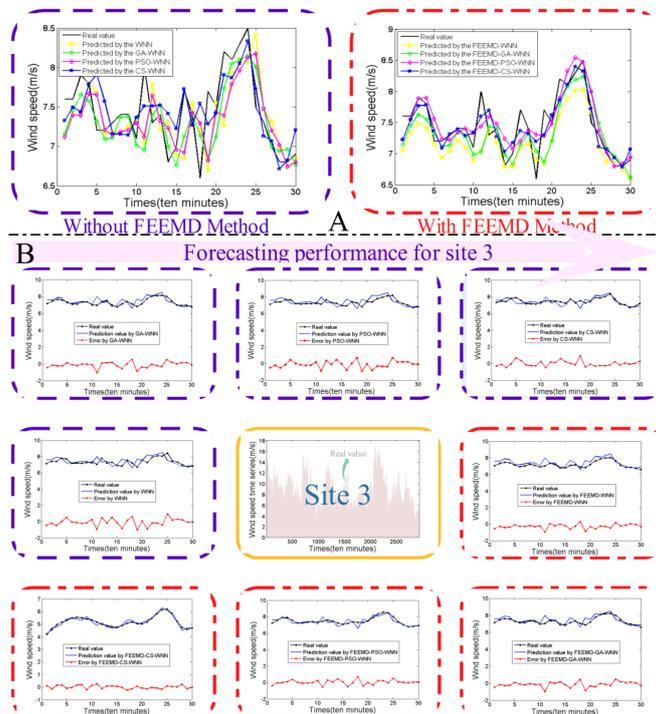
Fig. (4). Forecasting performance for site 2.

Fig. (5). Forecasting performance for site 3.

Overall, it is not difficult to determine that FEEMD-CS-WNN has the best effectiveness among the models of single WNN, GA-WNN, PSO-WNN, CS-WNN, FEEMD-WNN, FEEMD-GA-WNN and FEEMD-PSO-WNN. We can conclude that the proposed FEEMD-CS-WNN model can more accurately forecast the wind speed time series and discussing with these forecasting models will demonstrate in the next part.

5.3.3. Comparison and Discussion

Many different models have been proposed to handle the wind speed forecasting. To reflect the superiority of the proposed model, it is quite necessary to build additional models to compare with the FEEMD-CS-WNN model. In this section, to verify the proposed FEEMD-CS-WNN method, we compared our model with other models and the results of comparison are given in Table **2** and Fig. (**6**).

Table 2. MSE, MAE and MAPE of three sites for the single forecasting models.

Site	Model error	Model	Model	Model	Model	Model	Model
		WNN	BP	RBF	GRNN	FNN	SVM
Site 1	MAE	0.2925	0.2909	0.4436	0.2968	0.2876	0.3361
	MAPE(%)	6.02	6.22	9.13	6.39	6.2	7.06
	MSE	0.1389	0.1232	0.3188	0.1315	0.1232	0.1612
Site 2	MAE	0.2859	0.2714	0.3268	0.3162	0.2836	0.3247
	MAPE(%)	5.48	5.76	6.44	6.26	5.66	6.28
	MSE	0.1185	0.147	0.162	0.1738	0.139	0.1527
Site 3	MAE	0.3593	0.3659	0.5539	0.4765	0.3659	0.4218
	MAPE(%)	4.77	4.94	7.32	6.61	4.92	5.75
	MSE	0.2203	0.2267	0.565	0.3369	0.214	0.237

At first, conventional single model forecasting values are given in Table **2**, as seen from Table **2**, the three sites of MAE, MAPE and MSE of the WNN model are 0.2925, 6.02%, 0.1389 and 0.2859, 5.48%, 0.1185 and 0.3593, 4.77%, 0.2203, respectively and the performance of single WNN model is superior to another single model. As seen from Figs. (**3**-**5**), it is clear that single WNN model can approximately describe the characteristics of the selected wind speed time series and these single forecasting results reveal that selecting single WNN model is a reasonable choice.

Then, the GA-WNN model, PSO-WNN model and CS-WNN model are also given in Table **1** and performance of all hybrid model of three sites are shown in Fig. (**6**). As seen from Table **1** and Fig. (**6**), the predicted performance of these model is better than the single WNN, What's more, the three criteria of CS-WNN model are the lowest with the MAE, MAPE and MSE which are 0.214,4.14% and 0.0648,0.2249,4.91% and 0.0831,0.2639,3.6% and 0.1129, respectively.
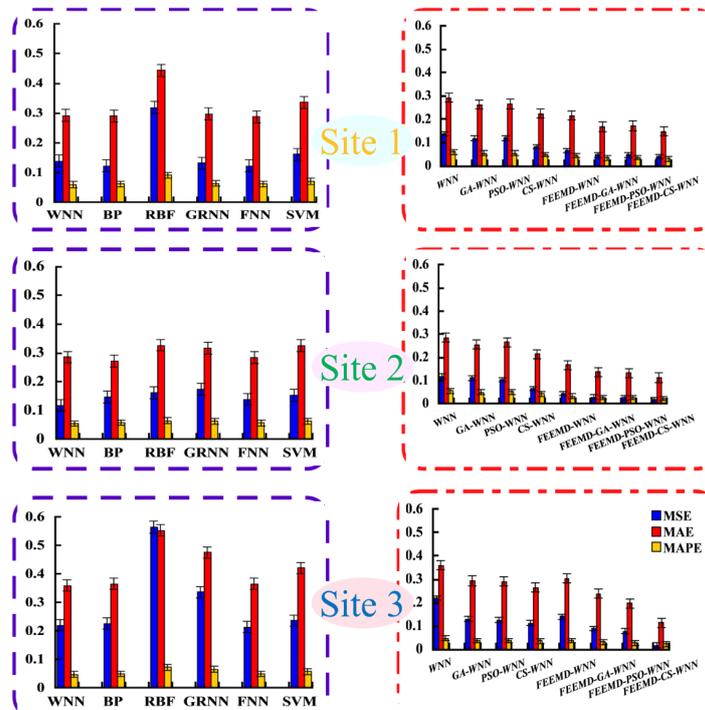

Fig. (6). Performance of three sites.

Finally, comparison between Experiment 1 and Experiment 2, Table **1** and Figs. (**3-5**) indicate that the fast ensemble empirical mode decomposition de-noising processing is necessary to forecast the wind speed and the three sites of MAE, MAPE, MSE of the hybrid FEEMD-CS-WNN model are 0.1128, 2.22%, 0.0167 and 0.1479, 3.15%, 0.0402 and 0.1143, 2.24%, 0.0176, respectively, which are the smallest in the Experiment. Moreover, it is also reported that the FEEMD-CS-WNN model that includes de-noising processing constitutes a noteworthy improvement in wind speed forecasting and the proposed hybrid model adequately makes use of the advantages of the ensemble empirical mode decomposition methods, CS algorithm and WNN model.

CONCLUSION

Wind energy has been part of the fastest growing clean and renewable energy sources and wind speed forecasting plays a vital role in the wind energy field, however, wind speed forecasting has been proven to be a challenging task owing to the effect of various meteorological factors. In this paper, a hybrid approach which combines fast ensemble empirical mode decomposition method, CS algorithm and WNN model is proposed to solve these troublesome problem.

Based on evaluating criteria of forecast performance that include the MAE, MAPE, and MSE, a statistical analysis that refers to a group of tables and figures, the advantages of the proposed model are summarized as follows. Firstly,WNN based on the combination of wavelet decomposition and feed-forward neural networks has become a very popular tool, as seen conventional single forecasting models from Table **2**, the performance of WNN gets a good result and just needs a very short time. Secondly, CS algorithm is proposed to optimize the parameters of WNN,as seen from Table **1** and Fig. (**6**), the results in the two experiments show that: CS algorithm is far more efficient than PSO and GA and the FEEMD algorithm can improve the forecasting performance of WNN considerably, it indicates that fast ensemble empirical mode decomposition as an efficient decomposition method can decrease the non-stationary of the original wind speed data for the WNN to obtain high-precision forecasting results. Finally,the performance of the proposed FEEMD-CS-WNN model get the best results, the three sites of MAE, MAPE, MSE of the hybrid FEEMD-CS-WNN model are 0.1128, 2.22%, 0.0167 and 0.1479, 3.15%, 0.0402 and 0.1143, 2.24%, 0.0176, respectively.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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