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Wind speed prediction using the hybrid model of wavelet decomposition and artificial bee colony algorithm-based relevance vector machine

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ABSTRACT

In this paper, the hybrid model of wavelet decomposition and artificial bee colony algorithm-based relevance vector machine (WABCRVM) is presented for wind speed prediction. Here, wind speed can be regarded as a signal and decomposed into four decomposed signals with different frequency range, which can be obtained by 2-layer wavelet decomposition for wind speed data, and the prediction models of the four decomposed signals can be established by RVM with their each appropriate embedding dimension. Artificial bee colony algorithm (ABC) is used to select the appropriate kernel parameters of their RVM models. Thus, each decomposed signal's RVM model of wind speed has appropriate embedding dimension and kernel parameter. Finally, the experimental results show that it is feasible for the proposed combination scheme to improve the prediction ability of RVM for wind speed.

Introduction

It is well-known that wind power has been increasingly regarded as a significant source of renewable energy as its clean and pollution-free [1–3]. In the Inner Mongolia of China, abundant wind energy resources exist, especially in the Hohehot, which is one of the most wind energy reserve areas in China. Thus, the analysis and estimation of wind energy in this area is very significant. Accurate wind speed prediction is helpful for wind farm operation control, wind power prediction, and more [4,5]. As is known to all, one of the primary reasons for the low utilization rate of wind power is the volatility of wind speed, which makes it hard to predict. The time series-based method is a popular method to forecast wind speed as it uses only historical wind data and can obtain the suitable short-term prediction results for wind speed.

Recently, some time series-based intelligent prediction methods have been presented for wind speed, such as artificial neural networks and support vector machine. Li and Shi [6] presented the application of different artificial neural networks in 1-h ahead wind speed forecasting. Ren et al. [7] presented a wind speed method by combining the PSO-BP neural network with input parameters selection, and the experiment results indicate that the proposed method achieves much better forecast performance than the basic back propagation neural network and ARIMA model. However, application of artificial neural networks is limited due to the shortcomings of over-fitting and falling into local extremum easily [8,9]. Support vector machine is a kind of machine learning method based on the statistical learning theory. Compared with artificial neural networks, support vector machine (SVM) has the better generalization performance [10]. Sancho et al. [11] presented an evolutionary-SVM algorithm for short-term wind speed prediction, and applied the evolutionary-SVM algorithm to wind speed prediction in wind turbines of a Spanish wind farm.

Relevance vector machine (RVM) is an intelligent learning technique based on sparse Bayesian framework, the number of relevance vectors in RVM is much smaller than that of support vectors in SVM, which makes RVM have a sparser representation compared with SVM [12,13]. Moreover, there is no need to set the penalty parameter in RVM, which makes RVM more convenient to use than SVM. Thus, RVM has a better application prospect in wind speed prediction. As it is difficult to obtain an appropriate embedding dimension in creating directly the prediction model of wind speed by RVM, the hybrid model of wavelet decomposition and artificial bee colony algorithm-based RVM (WABCRVM) is presented for wind speed prediction in this paper. Here, wind speed can be regarded as a signal and decomposed into several sub-signals with different frequency range, we perform 2-layer wavelet decomposition for wind speed data, the four decomposed signals with different frequency range can be obtained, and the prediction models of the four decomposed signals can be established by RVM with their each appropriate embedding dimension. Artificial bee colony algorithm (ABC) is used to select the appropriate kernel parameters of their RVM models, artificial bee colony algorithm is a swarm-based meta-heuristic technique, which is inspired by the foraging behavior of honey bees. In the last few

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years, the ABC algorithm has been widely applied to various research fields including clustering analysis [14], image processing [15], optimal filter design [16], numerical optimization [17], and so on. Recently, artificial bee colony algorithm has been extended for parameters optimization of some popular intelligent learning algorithms, such as artificial neural networks [18] and support vector machine [19]. In some researches, artificial bee colony algorithm has been proved to be more effective than some other evolutionary algorithms, such as genetic algorithm (GA) and particle swarm optimization (PSO) [20–22]. Thus, each decomposed signal's RVM model of wind speed has appropriate embedding dimension and kernel parameter. In order to show the superiority of the proposed WABCRVM method, the RVM models with several different embedding dimensions and Gaussian RBF kernel parameters are used to compare with the proposed WABCRVM method. Finally, the experimental results show that it is feasible for the proposed combination scheme to improve the prediction ability of RVM for wind speed.

Wavelet decomposition of wind speed

Wavelet transform is an important mathematical tool for nonlinear and non-stationary signal analysis, which allows the decomposition of a signal into several sub-signals with different frequency range [23,24]. In this study, wind speed can be regarded as a signal and decomposed into several sub-signals with different frequency range, and we perform 2-layer wavelet decomposition for wind speed data, the four decomposed signals are signal 2-1, signal 2-2, signal 2-3 and signal 2-4, which are shown in Fig. 1. Signal 2-1 is a low frequency signal, which reflects the variation trend of wind speed. Other wavelet decomposed signals have higher frequency than wavelet decomposed signal 2-1, which includes the detailed information of wind speed. As the four decomposed signals have different characteristics, we must create four different prediction models to fit and predict them.

Predicting the wavelet decomposed signals by ABCRVM

The regression model of relevance vector machine

The regression model of relevance vector machine can be used to solve the nonlinear regression problems [13]. The output target t_n of the regression model of RVM includes the additive noise, which can be formulated as follows:

$$t_n = y(\mathbf{x}_n, \mathbf{w}) + \varepsilon_n \tag{1}$$

where $\mathbf{x}_n$ is the input vector, and ε_n is assumed to be mean-zero Gaussian noise with variance σ^2.

The regression function of relevance vector machine consists of a linear combination of the weighted kernel functions, which can be described as follows:

$$y(\mathbf{x}, \mathbf{w}) = \sum_{i=1}^{N} w_i K(\mathbf{x}, \mathbf{x}_i) + w_0 \tag{2}$$

where $K(\mathbf{x}, \mathbf{x}_i)$ is kernel function, $\mathbf{w} = [w_1, w_2, \cdots, w_N]$ is the weight vector, and w_0 is the bias.

Gaussian RBF kernel has been used in this RVM, which can be expressed as follows:

$$K_{\mathrm{RBF}}(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{\gamma^2}\right) \tag{3}$$

where γ denotes the kernel parameter of Gaussian RBF kernel.

Artificial bee colony algorithm

In this study, the kernel parameter of Gaussian RBF kernel is selected by artificial bee colony algorithm. Artificial bee colony algorithm is a swarm-based meta-heuristic technique, which is inspired by the foraging behavior of honey bees. The colony of artificial bees consists of three groups of bees: onlooker bees, employed bees and scout bees, among which onlooker bees and

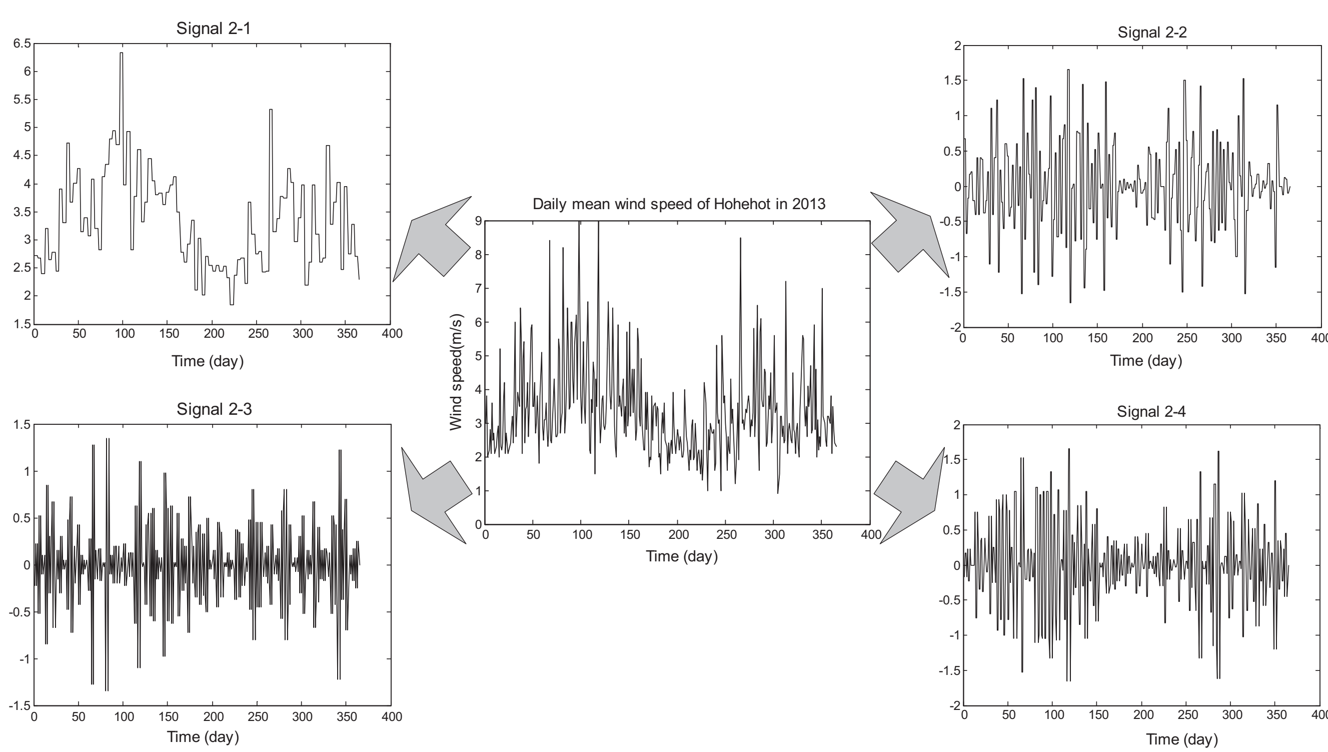

Fig. 1. Wavelet decomposition of wind speed data.

employed bees perform the exploitation process in the search food-source position, and scout bees control the exploration process [25]. In ABC algorithm, a randomly distributed initial population of M solutions (positions) in a certain range can be created, the position of each food source can be generated by the following equation:

$$x_{i,j} = x_{\min,j} + \mathrm{rand}[0,1] \times (x_{\max,j} - x_{\min,j}) \tag{4}$$

where $x_{\max,j}$ is the upper bound of the jth parameter, $x_{\min,j}$ is the lower bound of the jth parameter, rand [0, 1] is a random number in the range [0,1]; $j = \{1, \cdots, D\}$, D is the number of the parameters to be optimized, in this study, $D = 1$.

The nectar amount of a food source is used to measure the quality (fitness value) of the associated solution. The fitness value can be calculated as follows:

$$\mathrm{fitness}_i = \frac{1}{1 + \mathrm{Obj.Fun.}_i} \tag{5}$$

where $\mathrm{Obj.Fun.}_i$ denotes the objective function.

Generate a new food source $x_{i,j}^{\mathrm{new}}$ for each employed bee $x_{i,j}$ in the neighborhood of its present position by using following equation:

$$x_{i,j}^{\mathrm{new}} = x_{i,j} + \mathrm{rand}[-1,1] \times (x_{i,j} - x_{l,j}) \tag{6}$$

where $l \neq i$, rand $[-1, 1]$ is a random number in the range $[-1, 1]$.

After all employed bees complete the search process, they share the information related to the nectar amounts and their position with the onlooker bees on the dance area, onlooker bees evaluate the nectar amounts taken from all employed bees and choose a food source with a probability p_i calculated by using the following equation:

$$p_i = \frac{\mathrm{fitness}_i}{\sum_{i=1}^{M} \mathrm{fitness}_i} \tag{7}$$

where $\mathrm{fitness}_i$ denotes the fitness value of solution i, and M denotes the total number of food-source positions.

Kernel parameter optimization of RVM based on artificial bee colony algorithm

The main steps for selecting the kernel parameter of RVM based on ABC algorithm can be described as follows:

Step 1: Randomly initialize a population of M positions in a certain range, the position of each food source can be generated by Eq. (4).
Step 2: Evaluate the fitness for each food source by Eq. (5). In Eq. (5), the objective function can be defined as follows:

$$\mathrm{Obj.Fun.}_i = \frac{1}{v} \sum_{q=1}^{v} \left| \frac{y_q - \hat{y}_{q,i}}{y_q} \right| \tag{8}$$

where y_q is the actual value, $\hat{y}_{q,i}$ is the validation value, and v is the number of the training samples in training sample sets.
Step 3: Generate a new food source $x_{i,j}^{\mathrm{new}}$ for each employed bee $x_{i,j}$ in the neighborhood of its present position by Eq. (6), here, $j = 1$. Evaluate the new food source $x_{i,j}^{\mathrm{new}}$ and compare with $x_{i,j}$. If the fitness of $x_{i,j}^{\mathrm{new}}$ is better than that of $x_{i,j}$, $x_{i,j}$ will be replaced by $x_{i,j}^{\mathrm{new}}$, and $x_{i,j}^{\mathrm{new}}$ becomes a new member of the population; otherwise, $x_{i,j}$ is retained.
Step 4: After all employed bees complete the search process, they share the information related to the nectar amounts and their position with the onlooker bees on the dance area, onlooker bees evaluate the nectar amounts taken from all employed bees and choose a food source with a probability p_i calculated by Eq. (7).
Step 5: Once the onlooker has selected its food source $x_{i,j}$, it will search for a new food source $x_{i,j}^{\mathrm{new}}$ in its neighborhood according to Eq. (6). Then, evaluate the fitness of new food source $x_{i,j}^{\mathrm{new}}$ and compare it with the fitness of $x_{i,j}$. If the fitness of $x_{i,j}^{\mathrm{new}}$ is better than that of $x_{i,j}$, then replace $x_{i,j}$ with $x_{i,j}^{\mathrm{new}}$; otherwise, $x_{i,j}$ is retained.
Step 6: If the abandoned food source exists, replace it with a new randomly produced solution $x_{i,j}$ for the scout by using Eq. (4).
Step 7: Memorize the position (solution) of the best food source found so far.
Step 8: Repeat the procedure from step 3 to step 7 until the maximum cycle number of the search process is reached.

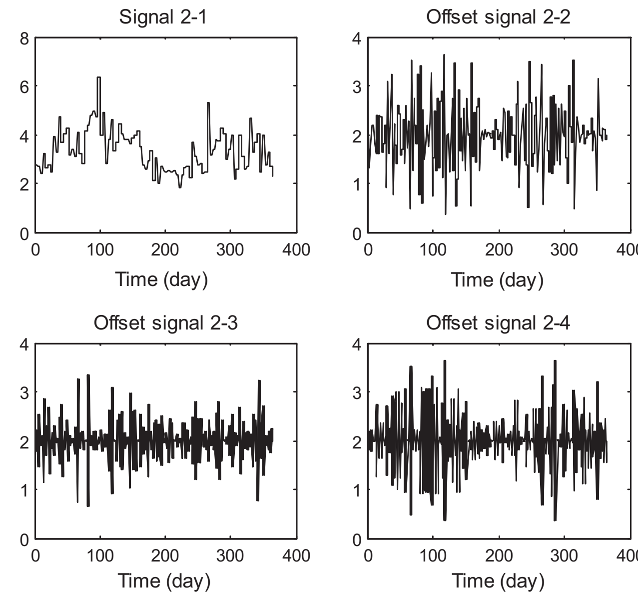

Fig. 2. The offset processing of wavelet decomposed signal 2-2, 2-3, 2-4.

Predicting the wavelet decomposed signals by ABCRVM

As shown in Fig. 1, there are lots of data less than zero in wavelet decomposed signal 2-2, 2-3, 2-4. In order to predict for them conveniently, wavelet decomposed signal 2-2, 2-3, 2-4 must be offset to ensure all data in them more than zero. Thus, we set offset value to 2 for wavelet decomposed signal 2-2, 2-3, 2-4 in this study, the signals after offset processing are defined as offset signals. Fig. 2 shows the wavelet decomposed offset signal 2-2, 2-3, 2-4.

Each wavelet decomposed signal (or offset signal) should be normalized to the range [0,1] in order to improve the generalization ability of the prediction model. Assume the data set of a normalized wavelet decomposed signal (or offset signal) can be given as follows: $a_1, a_2, \cdots a_m, \cdots, a_n, \cdots, a_{n+k}$, among which $a_1, a_2, \cdots, a_m, \cdots, a_n$ are used to establish the training sample sets, and $a_{n+1}, \cdots, a_{n+k}$ are used to test the prediction model. The training sample sets can be described by the following formula:

$$\mathbf{X} = \begin{bmatrix} a_1 & a_2 & \cdots & a_m \\ a_2 & a_3 & \cdots & a_{m+1} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n-m} & a_{n-m+1} & \cdots & a_{n-1} \end{bmatrix}, \mathbf{Y} = \begin{bmatrix} a_{m+1} \\ a_{m+2} \\ \vdots \\ a_n \end{bmatrix} \tag{9}$$

where m denotes the embedding dimension, $\mathbf{X}$ denotes the set of input vectors, and $\mathbf{Y}$ denotes the set of corresponding outputs.

Generally, in order to make the prediction model have good prediction ability, the embedding dimension m is set to bigger value for low frequency signal, and is set to smaller value for high frequency signal. As wavelet decomposed signal 2-1 is a low frequency signal, we set the embedding dimension to 9 to create its prediction model, and other wavelet decomposed signals have higher frequency than wavelet decomposed signal 2-1, we set the embedding dimension to 6, 4, 4 to create the prediction models of wavelet decomposed offset signal 2-2, 2-3, 2-4 respectively.

Then, we use artificial bee colony algorithm to obtain the kernel parameters of the RVM prediction models of wavelet decomposed signal 2-1, offset signal 2-2, 2-3, 2-4 respectively, and establish the RVM prediction models of wavelet decomposed signal 2-1, offset signal 2-2, 2-3, 2-4 respectively. The prediction results of wavelet decomposed signal 2-2, 2-3, 2-4 can be obtained by subtracting the offset values of the prediction results of wavelet decomposed offset signal 2-2, 2-3, 2-4 respectively. Finally, the wind speed prediction results can be obtained by the combination of the prediction results of the four wavelet decomposed signals.

Experimental analysis

Hohehot is one of the most wind energy reserve areas in China, thus, daily mean wind speed data of Hohehot are used in the experiments. In experiment 1, daily mean wind speed data of 365 days of Hohehot in 2013 are used as the experimental data, among which daily mean wind speed data of the first 345 days are used to train the proposed prediction model, and daily mean wind speed data of the remaining 20 days are used to test the proposed prediction model. In experiment 2, daily mean wind speed data of the first 345 days of Hohehot in 2013 are used as the experimental data, among which daily mean wind speed data of the first 325 days are used to train the proposed prediction model, and daily mean wind speed data of the remaining 20 days are used to test the proposed prediction model. In experiment 3, daily mean wind speed data of the first 325 days of Hohehot in 2013 are used as the experimental data, among which daily mean wind speed data of the first 305 days are used to train the proposed prediction model, and wind speed data of the remaining 20 days are used to test the proposed prediction model.

In order to show the superiority of the proposed WABCRVM method, the RVM models with several different embedding dimensions and Gaussian RBF kernel parameters are used to compare with the proposed WABCRVM method. Firstly, the RVM models with embedding dimension 4 including RVM4-1 (embedding dimension is 4, parameter's value of Gaussian RBF kernel is 1), RVM4-2 (embedding dimension is 4, parameter's value of Gaussian RBF kernel is 2), RVM4-3 (embedding dimension is 4, parameter's value of Gaussian RBF kernel is 3) are used to compare with the proposed WABCRVM method. Secondly, the RVM models with embedding dimension 6 including RVM6-1 (embedding dimension is 6, parameter's value of Gaussian RBF kernel is 1), RVM6-2 (embedding dimension is 6, parameter's value of Gaussian RBF kernel is 2), RVM6-3 (embedding dimension is 6, parameter's value of Gaussian RBF kernel is 3) are used to compare with the proposed WABCRVM method. Thirdly, the RVM models with embedding dimension 9 including RVM9-1 (embedding dimension is 9, parameter's value of Gaussian RBF kernel is 1), RVM9-2 (embedding dimension is 9, parameter's value of Gaussian RBF kernel is 2), RVM9-3 (embedding dimension is 9, parameter's value of Gaussian RBF kernel is 3) are used to compare with the proposed WABCRVM method.

In the experiment 1, the comparison of wind speed prediction results among WABCRVM, RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3 is given in Fig. 3; in the experiment 2, the comparison of wind speed prediction results among WABCRVM, RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3 is given

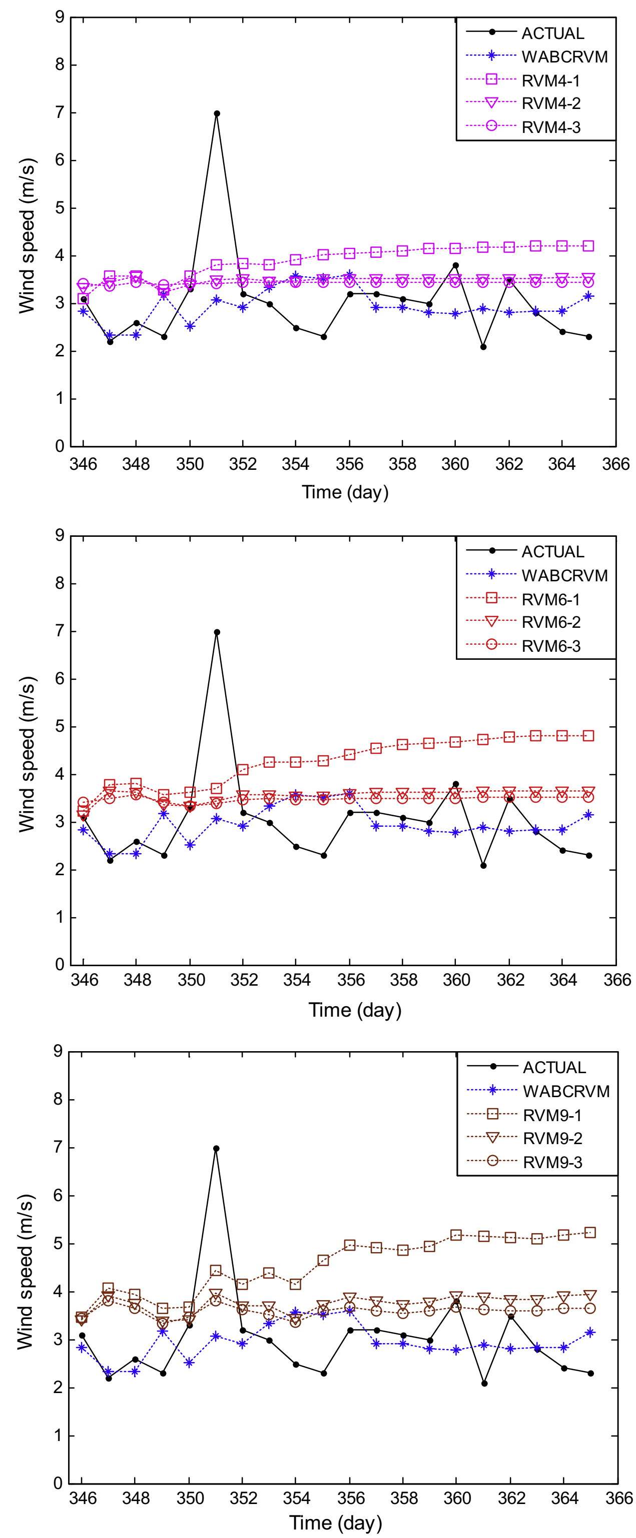

Fig. 3. The comparison of wind speed prediction results among WABCRVM, RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3 in Experiment 1.

in Fig. 4; and in the experiment 3, the comparison of wind speed prediction results among WABCRVM, RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3 is given in Fig. 5. As shown in Figs. 3–5, the prediction results of the proposed WABCRVM method are more stable than those of RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3. Then, the superiority of the proposed WABCRVM method can be shown through quantification analysis. Table 1 gives the comparison of mean absolute percentage prediction errors for wind speed among WABCRVM, RVM4-1, RVM4-2,

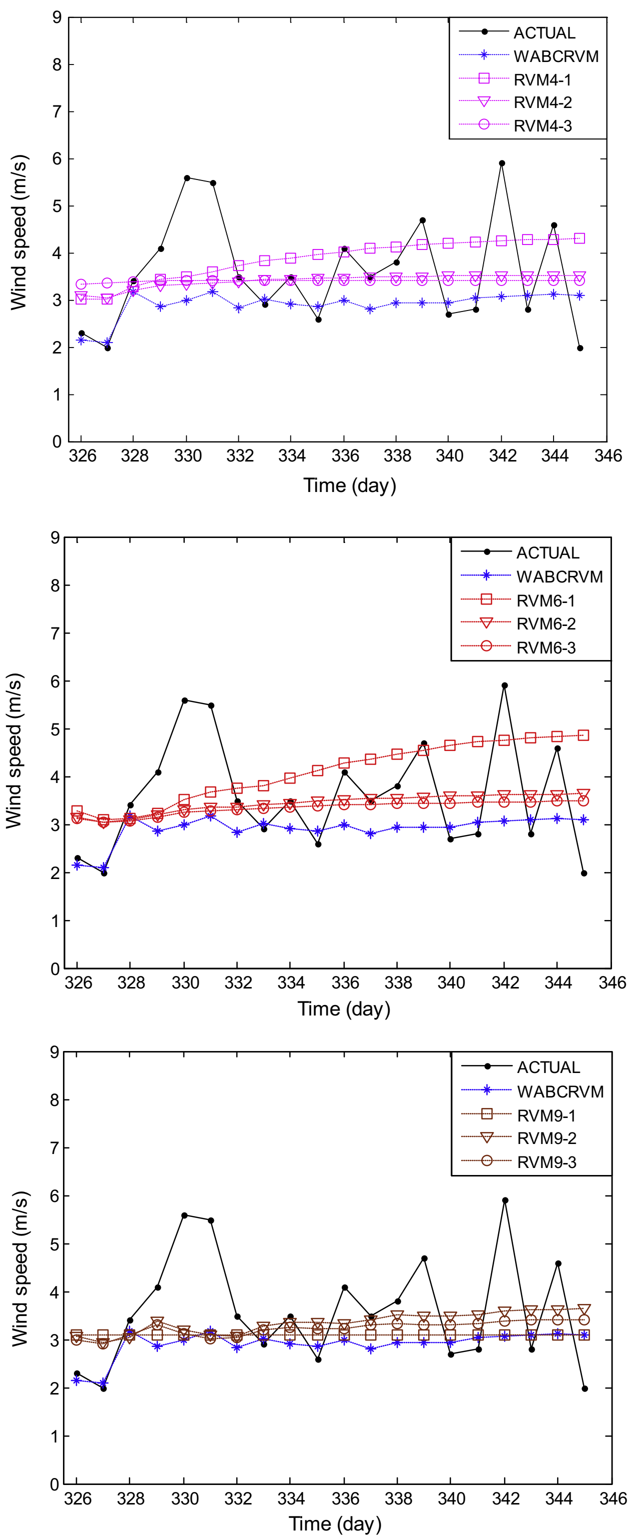

Fig. 4. The comparison of wind speed prediction results among WABCRVM, RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3 in Experiment 2.

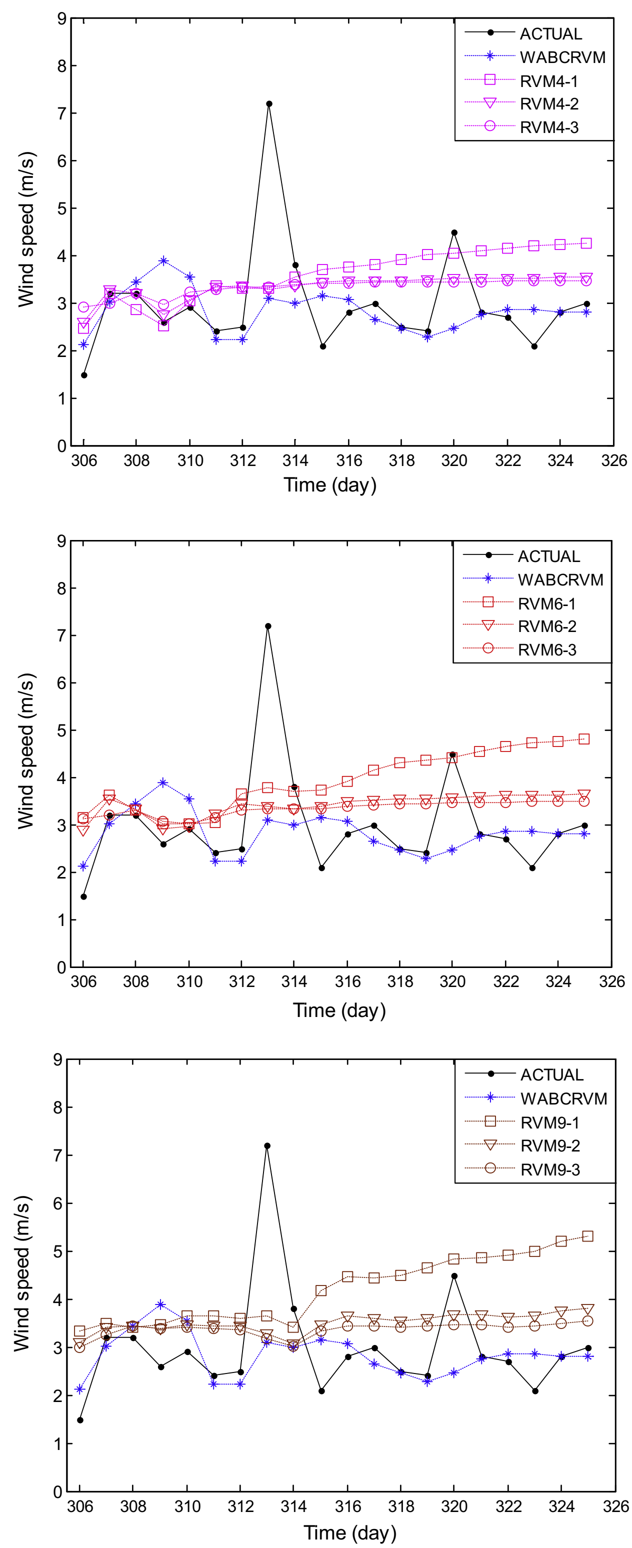

Fig. 5. The comparison of wind speed prediction results among WABCRVM, RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3 in Experiment 3.

Table 1
The comparison of mean absolute percentage prediction errors for wind speed among WABCRVM, RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3.

	Experimental data	Training data	Testing data	Prediction model	Mean absolute percentage prediction error (%)
Experiment 1	Daily mean wind speed data of 365 days of Hohehot in 2013	Daily mean wind speed data of the first 345 days of Hohehot in 2013	Daily mean wind speed data of the remaining 20 days (the 346th ∼365th day of Hohehot in 2013)	WABCRVM	21.61
				RVM4-1 ($m = 4$, $\gamma = 1$)	41.53
				RVM4-2 ($m = 4$, $\gamma = 2$)	28.03
				RVM4-3 ($m = 4$, $\gamma = 3$)	26.49
				RVM6-1 ($m = 6$, $\gamma = 1$)	55.37
				RVM6-2 ($m = 6$, $\gamma = 2$)	30.86
				RVM6-3 ($m = 6$, $\gamma = 3$)	28.34
				RVM9-1 ($m = 9$, $\gamma = 1$)	63.98
				RVM9-2 ($m = 9$, $\gamma = 2$)	35.85
				RVM9-3 ($m = 9$, $\gamma = 3$)	30.98
Experiment 2	Daily mean wind speed data of the first 345 days of Hohehot in 2013	Daily mean wind speed data of the first 325 days of Hohehot in 2013	Daily mean wind speed data of the remaining 20 days (the 326th ∼345th day of Hohehot in 2013)	WABCRVM	22.93
				RVM4-1 ($m = 4$, $\gamma = 1$)	31.10
				RVM4-2 ($m = 4$, $\gamma = 2$)	25.85
				RVM4-3 ($m = 4$, $\gamma = 3$)	26.34
				RVM6-1 ($m = 6$, $\gamma = 1$)	36.77
				RVM6-2 ($m = 6$, $\gamma = 2$)	26.76
				RVM6-3 ($m = 6$, $\gamma = 3$)	26.47
				RVM9-1 ($m = 9$, $\gamma = 1$)	25.98
				RVM9-2 ($m = 9$, $\gamma = 2$)	26.69
				RVM9-3 ($m = 9$, $\gamma = 3$)	25.95
Experiment 3	Daily mean wind speed data of the first 325 days of Hohehot in 2013	Daily mean wind speed data of the first 305 days of Hohehot in 2013	Daily mean wind speed data of the remaining 20 days (the 306th ∼325th day of Hohehot in 2013)	WABCRVM	19.83
				RVM4-1 ($m = 4$, $\gamma = 1$)	38.91
				RVM4-2 ($m = 4$, $\gamma = 2$)	30.13
				RVM4-3 ($m = 4$, $\gamma = 3$)	30.82
				RVM6-1 ($m = 6$, $\gamma = 1$)	48.40
				RVM6-2 ($m = 6$, $\gamma = 2$)	32.72
				RVM6-3 ($m = 6$, $\gamma = 3$)	30.94
				RVM9-1 ($m = 9$, $\gamma = 1$)	59.61
				RVM9-2 ($m = 9$, $\gamma = 2$)	37.42
				RVM9-3 ($m = 9$, $\gamma = 3$)	33.00

RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3, which indicates that the wind speed prediction ability of WABCRVM is better than those of RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3. Therefore, we can conclude that it is feasible for the proposed combination scheme to improve the prediction ability of RVM for wind speed.

Conclusion

In this paper, the hybrid model of wavelet decomposition and artificial bee colony algorithm-based RVM is proposed for wind speed prediction. The prediction models of the four decomposed signals obtained by 2-layer wavelet decomposition for wind speed data can be established by RVM with their each appropriate embedding dimension, artificial bee colony algorithm is used to select the appropriate kernel parameters of their RVM models. Thus, each decomposed signal's RVM model of wind speed has appropriate embedding dimension and kernel parameter. The comparison of mean absolute percentage prediction errors for wind speed among WABCRVM, RVM4-1, RVM4-2, RVM4-3, RVM6-1, RVM6-2, RVM6-3, RVM9-1, RVM9-2 and RVM9-3 indicates that the wind speed prediction ability of WABCRVM is better than those of other nine RVMs. Therefore, we can conclude that it is feasible for the proposed combination scheme to improve the prediction ability of RVM for wind speed. In the future, it will be very significant to study kernel parameter optimization of RVM based on the improved artificial bee colony algorithms, such as chaotic artificial bee colony algorithm, and study their application effects in wind speed prediction.

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