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A hybrid model of EMD and multiple-kernel RVR algorithm for wind speed prediction

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ABSTRACT

In this paper, the hybrid model of empirical mode decomposition and multiple-kernel relevance vector regression algorithm (EMD-MkRVR) is presented for wind speed prediction. The multiple-kernel relevance vector regression (MkRVR) model includes radial basis function (RBF) kernel and polynomial kernel whose proportions are determined by a controlled parameter. Grid method is used to select the kernel parameters and controlled parameter in this study. In addition, wind speed can be regarded as a signal and decomposed into several intrinsic mode functions (IMFs) with different frequency range by empirical mode decomposition (EMD), the prediction models of these decomposed signals can be established by MkRVR with their respective appropriate embedding dimension. The experimental results show that the EMD-MkRVR model has a better prediction ability for wind speed than the RBF kernel RVR (RBFRVR) model and the polynomial kernel RVR (PolyRVR) model.

Introduction

Wind energy is a sustainable source for generating electricity, and is regarded as one of the most important green energies [1–3]. The forecasting effect of wind energy is directly dependent on the prediction accuracy of wind speed because of the important impact of wind speed on wind power generation [4,5]. Recently, some intelligent prediction methods have been presented for wind speed prediction, such as support vector regression algorithm [6]. Support vector regression (SVR) algorithm has the better generalization performance than artificial neural networks, particularly under the condition of small training samples [7]. Relevance vector regression (RVR) algorithm is an intelligent learning technique based on sparse Bayesian framework [8], as the number of relevance vectors in RVR is much smaller than that of support vectors in SVR, which makes RVR have a sparser representation compared with SVR. In addition, there is no need to set the penalty parameter in RVR, which makes RVR more convenient to use than SVR. Thus, RVR has a better application prospect in wind speed prediction.

In this study, the hybrid model of empirical mode decomposition and multiple-kernel relevance vector regression algorithm (EMD-MkRVR) is presented for wind speed prediction. The multiple-kernel relevance vector regression (MkRVR) model includes radial basis function (RBF) kernel and polynomial kernel whose proportions are determined by a controlled parameter. As the selection of the parameters of the kernel functions and the controlled parameter has a certain influence on the prediction results of the MkRVR model, grid method is used to select its kernel parameters and controlled parameter. In addition, wind speed can be regarded as a signal and decomposed into several IMFs with different frequency range by empirical mode decomposition (EMD), the prediction models of these decomposed signals can be established by MkRVR with their respective appropriate embedding dimension. Thus, the corresponding MkRVR models of these decomposed signals have appropriate embedding dimensions, kernel parameters and controlled parameters. In order to show the superiority of the proposed EMD-MkRVR method, the RBF kernel RVR (RBFRVR) models with several different embedding dimensions and RBF kernel parameters, and the polynomial kernel RVR (PolyRVR) models with several different embedding dimensions and polynomial kernel parameters are used to compare with the proposed EMD-MkRVR method. The experimental results show that the EMD-MkRVR model has a better prediction ability for wind speed than the RBFRVR model and the PolyRVR model.

Multiple-kernel relevance vector regression model

Let $T = \{\mathbf{x}_l, t_l\}_{l=1}^{N}$ be a set of the training data, where $\mathbf{x}_l$ denotes the input vector and t_l denotes the corresponding output target, the target t_l includes the additive noise, that is,

$$t_l = y(\mathbf{x}_l, \mathbf{w}) + \varepsilon_l \tag{1}$$

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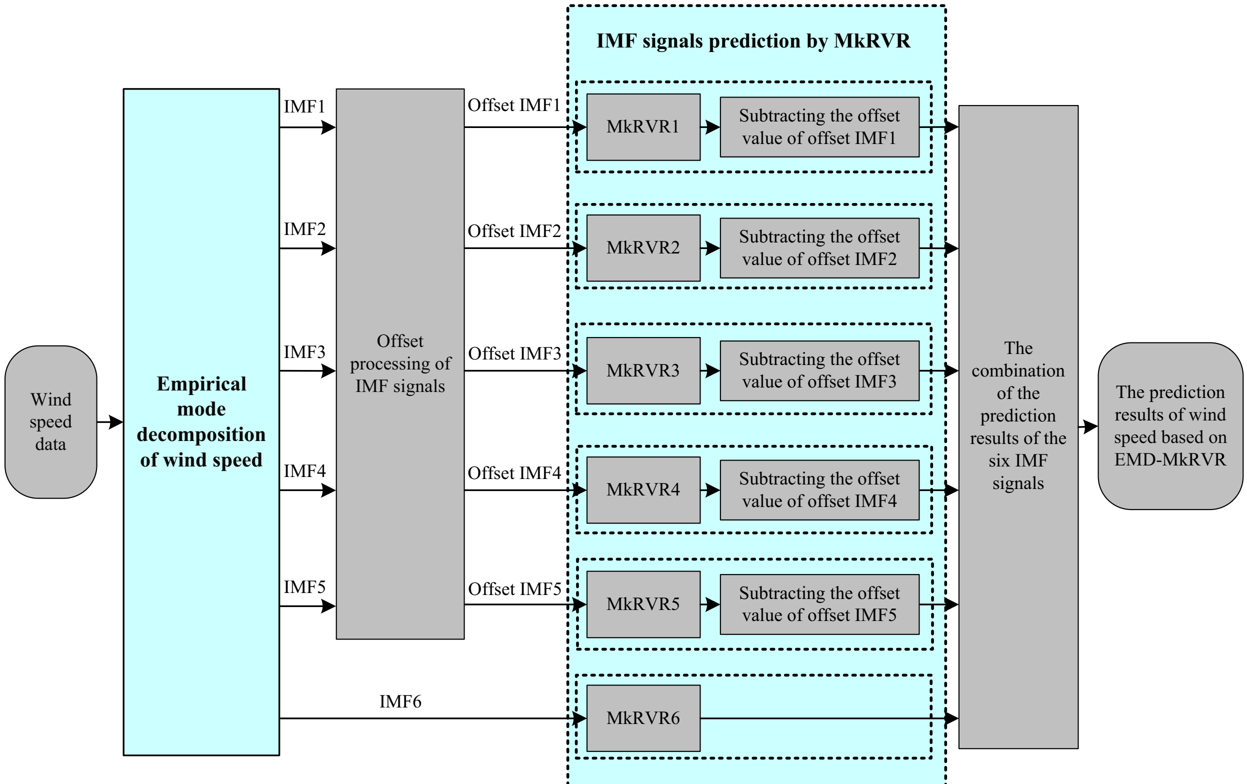

Fig. 1. Wind speed prediction process based on EMD and multiple-kernel RVR model.

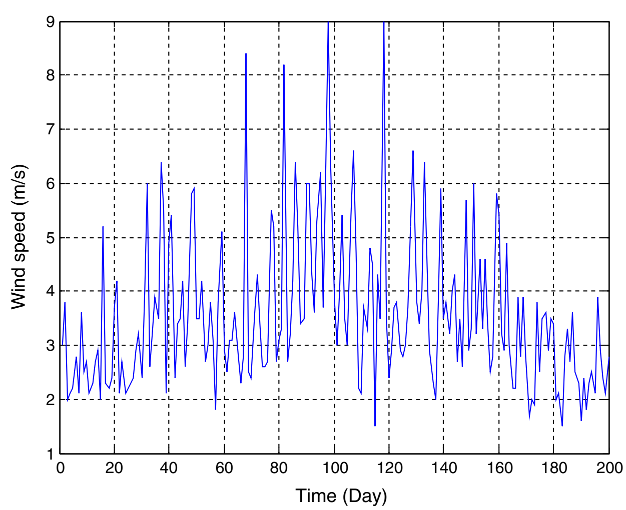

Fig. 2. Wind speed data of the first 200 days of Hohehot in 2013.

where ε_l is assumed to be mean-zero Gaussian noise with variance σ^2.

The relevance vector regression model [9] which consists of a linear combination of the weighted kernel functions 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 the kernel function, $\mathbf{w} = [w_1, w_2, \ldots, w_N]$ is the weight vector, and w_0 is the bias.

In order to improve the generalization ability of RVR, a multiple-kernel relevance vector regression model is constructed by the local kernel function and global kernel function. The RBF kernel (K_{RBF}) is a typical local kernel, in this study, the Gaussian kernel is used as the RBF kernel, which can be defined as follows:

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

where γ denotes the kernel parameter of the RBF kernel.

And the polynomial kernel (K_{Poly}) is a typical global kernel, which can be defined as follows:

$$K_{Poly}(\mathbf{x}_i, \mathbf{x}_j) = \left(\mathbf{x}_i \cdot \mathbf{x}_j^T + 1\right)^d \tag{4}$$

where d denotes the kernel parameter of the polynomial kernel.

The proportions of K_{RBF} and K_{Poly} are determined by the controlled parameter u. Thus, the multiple-kernel function can be expressed as follows:

$$K_{mix(RBF,Poly)}(\mathbf{x}_i, \mathbf{x}_j) = uK_{RBF}(\mathbf{x}_i, \mathbf{x}_j) + (1-u)K_{Poly}(\mathbf{x}_i, \mathbf{x}_j) \tag{5}$$

where $u(0 \leqslant u \leqslant 1)$ denotes the controlled parameter.

Grid method is used to select the kernel parameters γ, d and controlled parameter u of the MkRVR model. Mean validation error of all training samples can be used to evaluate the performance of the MkRVR models with the different values of the kernel parameters γ, d and controlled parameter u. Mean validation error can be defined as follows:

$$\tilde{e} = \frac{1}{H}\sum_{q=1}^{H}\left|\frac{y_q - \hat{y}_q}{y_q}\right| \tag{6}$$

where y_q is the actual value, $\hat{y}_q$ is the validation value, and H is the number of the training samples.

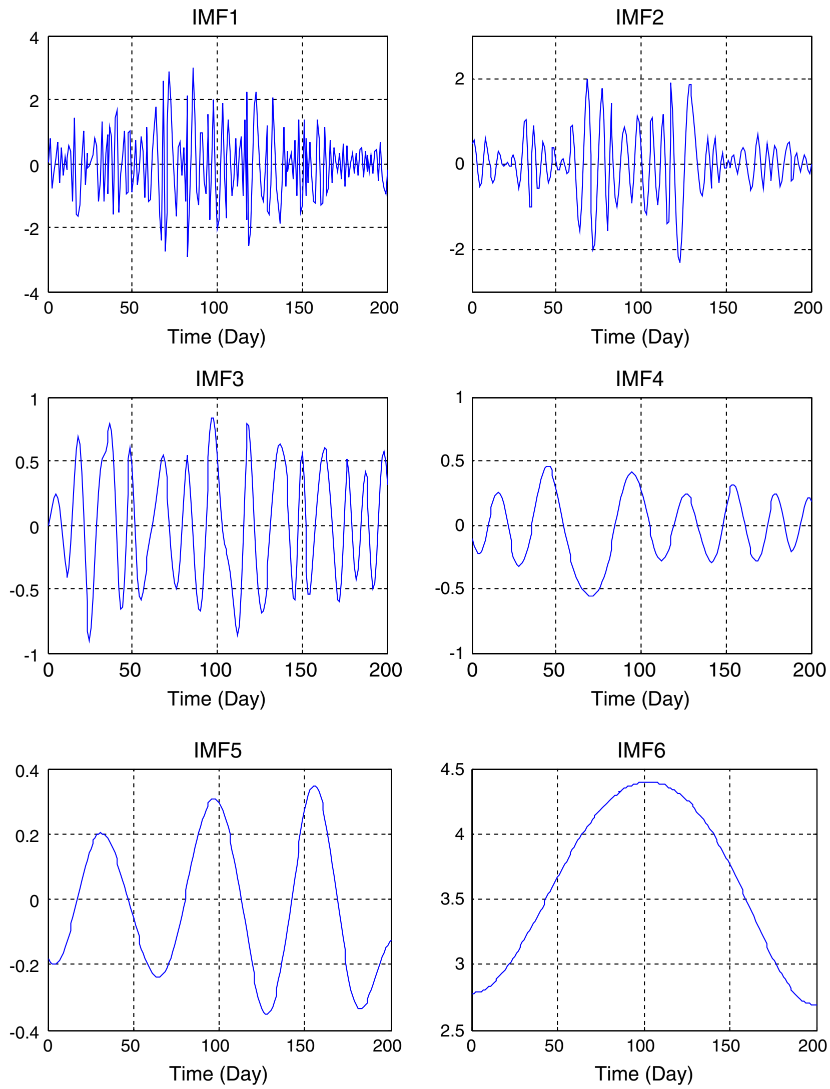

Fig. 3. The six decomposed signals of wind speed.

Wind speed prediction based on EMD and multiple-kernel RVR algorithm

Fig. 1 shows the wind speed prediction process based on EMD and multiple-kernel RVR model, which includes empirical mode decomposition of wind speed, offset processing of IMF signals, IMF signals prediction by MkRVR, and the combination of the prediction results of the six IMF signals.

Empirical mode decomposition of wind speed

Empirical mode decomposition (EMD) is a self-adaptive signal processing method, by EMD, the signal can be decomposed into several simple intrinsic mode functions (IMFs) which correspond to the signal's different frequency band ranging from high to low, and each IMF represents a kind of natural oscillatory mode embedded in the signal [10,11]. In this study, wind speed can be regarded as a signal and decomposed into six IMFs with different frequency range, which can be shown in Figs. 2 and 3. As shown in Fig. 3, the six decomposed signals can be denoted as IMF1, IMF2, IMF3, IMF4, IMF5 and IMF6 respectively, IMF6 is a lowest frequency signal, which reflects the variation trend of wind speed, and IMF1 is a highest frequency signal, which includes the detailed information of wind speed. As the six decomposed signals have different characteristics, six different prediction models should be respectively established to fit and predict them.

Predicting the empirical mode decomposed signals by multiple-kernel RVR model

As shown in Fig. 3, there are lots of data less than zero in IMF1–IMF5, thus, IMF1–IMF5 must be offset to ensure all data in them more than zero. Define 1 as an offset unit in this study, it is obvious that IMF1, IMF2 need three offset units and IMF3–IMF5 need one offset unit. That is, the offset values of IMF1, IMF2 are set to 3, and the offset values of IMF3–IMF5 are set to 1. The IMFs after offset processing are defined as offset IMF signals. Fig. 4 shows the IMF6 and offset IMF1–IMF5.

Each empirical mode decomposed signal (or offset signal) data is normalized to the range [0, 1] in order to improve the generalization ability of the prediction models. Assume the data set of a normalized empirical mode decomposed signal (or offset signal) are $a_1, a_2, \ldots a_m, \ldots, a_n, \ldots, a_{n+k}$, among which $a_1, a_2, \ldots, a_m, \ldots, a_n$ are used to establish the training samples, and $a_{n+1}, \ldots, a_{n+k}$ are used to test the prediction model. The training samples can be established as follows:

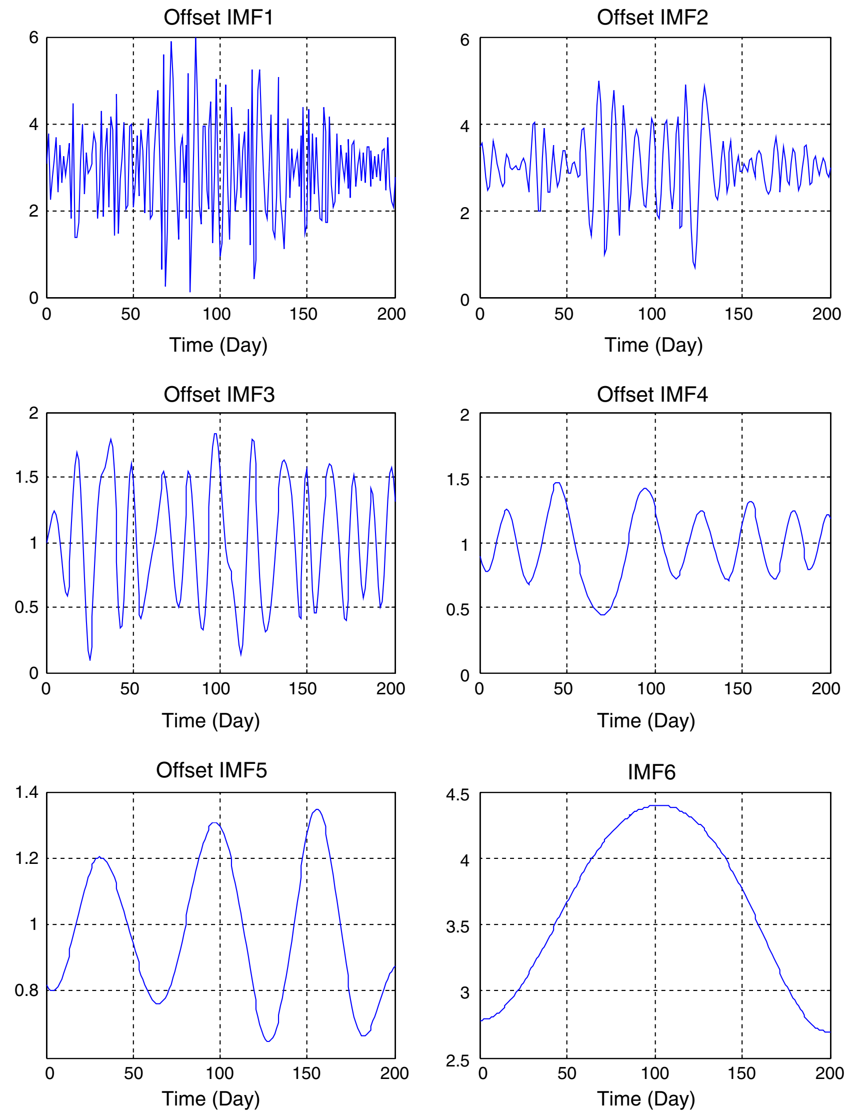

Fig. 4. The IMF6 and offset IMF1–IMF5.

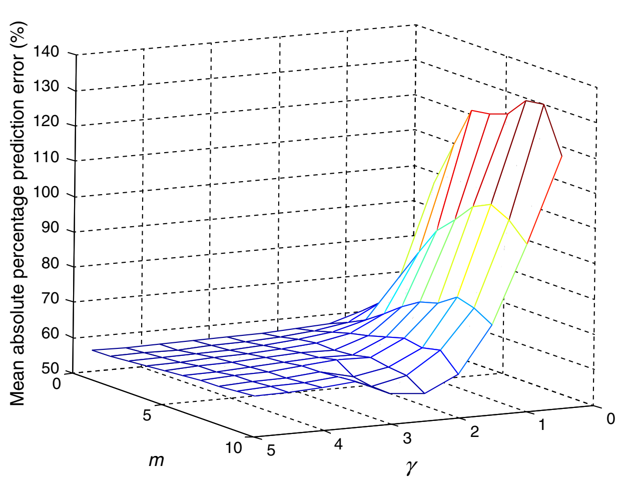

Fig. 5. Mean absolute percentage prediction errors for wind speed of one hundred RBFRVR models.

$$X = \begin{bmatrix} a_1 & a_2 & \cdots & a_m \\ a_2 & a_3 & \cdots & a_{m+1} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n-m} & a_{n-m+1} & \cdots & a_{n-1} \end{bmatrix}, \quad Y = \begin{bmatrix} a_{m+1} \\ a_{m+2} \\ \vdots \\ a_n \end{bmatrix} \tag{7}$$

where m denotes the embedding dimension, X denotes the set of input vectors, and Y denotes the set of corresponding outputs.

Generally, in order to make the prediction model have good prediction ability, the embedding dimension is set to bigger value for low frequency signal, and is set to smaller value for high frequency signal. Offset IMF1 is the highest frequency signal among IMF6 and offset IMF1–IMF5, whose embedding dimension is set to 4; and IMF6 is the lowest frequency signal among IMF6 and offset IMF1–IMF5, whose embedding dimension is set to 10. As offset IMF2–IMF3 have higher frequency than offset IMF4–IMF5, thus, the embedding dimensions of offset IMF2–IMF3 are set to 6; and the embedding dimensions of offset IMF4–IMF5 are set to 8.

In this study, grid method is used to select the kernel parameters γ, d and controlled parameter u of the MkRVR prediction

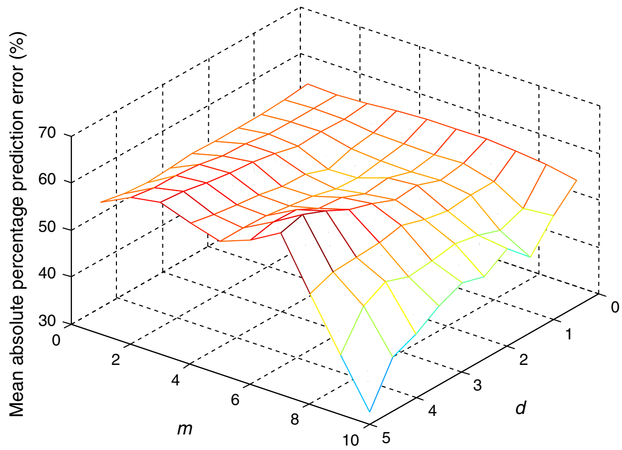

Fig. 6. Mean absolute percentage prediction errors for wind speed of one hundred PolyRVR models.

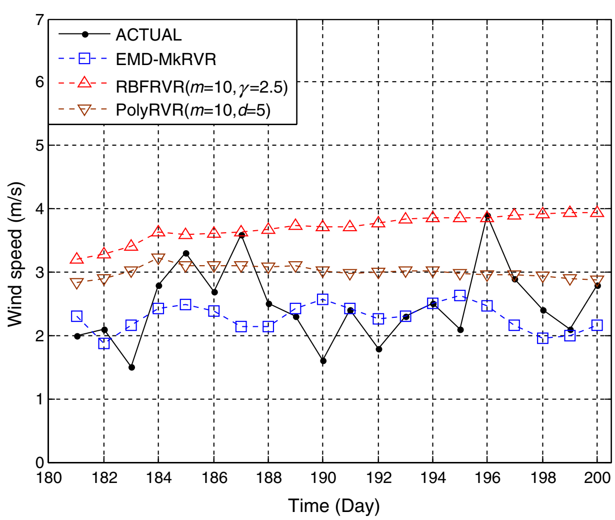

Fig. 7. The comparison of wind speed prediction results among EMD-MkRVR, RBFRVR ($m = 10$, $\gamma = 2.5$) and PolyRVR ($m = 10$, $d = 5$).

models of IMF6 and offset IMF1–IMF5 respectively, and the MkRVR prediction models of IMF6 and offset IMF1–IMF5 are established respectively. The prediction results of IMF1–IMF5 can be obtained by subtracting their offset values. Finally, the prediction results of wind speed can be obtained by the combination of the prediction results of the six IMF signals.

Experimental analysis for wind speed prediction based on EMD and multiple-kernel RVR algorithm

Hohehot is one of the most wind energy reserve areas in China, thus, daily mean wind speed data of Hohehot are used in the experiment. Daily mean wind speed data of the first 200 days of Hohehot in 2013 are used as the experimental data, among which daily mean wind speed data of the first 180 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.

Grid method is used to select the kernel parameters γ, d and controlled parameter u. Here, the value ranges of the RBF kernel parameter γ and the polynomial kernel parameter d are [0.5,5], the interval between the adjacent values of the RBF kernel parameter γ is 0.5, and the interval between the adjacent values of the polynomial kernel parameter d is 0.5; and the value range of the controlled parameter u is [0,1], the interval between the adjacent values of the controlled parameter u is 0.1.

Table 1
The comparison of mean absolute percentage prediction errors for wind speed among EMD-MkRVR, RBFRVR ($m = 10$, $\gamma = 2.5$) and PolyRVR ($m = 10$, $d = 5$).

Prediction model	Mean absolute percentage prediction error (%)
EMD-MkRVR	19.97
RBFRVR ($m = 10$, $\gamma = 2.5$)	57.71
PolyRVR ($m = 10$, $d = 5$)	32.53

In order to show the superiority of the proposed EMD-MkRVR method, the RBFRVR models with several different embedding dimensions and RBF kernel parameters, and the PolyRVR models with several different embedding dimensions and polynomial kernel parameters are used to compare with the proposed EMD-MkRVR method. In the RBFRVR models and the PolyRVR models, the value ranges of the RBF kernel parameter γ and the polynomial kernel parameter d are [0.5,5], the interval between the adjacent values of the RBF kernel parameter γ is 0.5, and the interval between the adjacent values of the polynomial kernel parameter d is 0.5. The value ranges of the embedding dimensions of the RBFRVR models and the PolyRVR models are [1,10], the interval between the adjacent values of the embedding dimensions of the RBFRVR models is 1, and the interval between the adjacent values of the embedding dimensions of the PolyRVR models is 1. Thus, one hundred RBFRVR models with different embedding dimensions and RBF kernel parameters, and one hundred PolyRVR models with different embedding dimensions and polynomial kernel parameters are employed. Mean absolute percentage prediction errors for wind speed of one hundred RBFRVR models are shown in Fig. 5, and mean absolute percentage prediction errors for wind speed of one hundred PolyRVR models are shown in Fig. 6. By the comparison of mean absolute percentage prediction errors for wind speed of one hundred RBFRVR models, the RBFRVR model whose embedding dimension is 10 and parameter's value of the RBF kernel is 2.5 has the smallest mean absolute percentage prediction error among one hundred RBFRVR models; and by the comparison of mean absolute percentage prediction errors for wind speed of one hundred PolyRVR models, the PolyRVR model whose embedding dimension is 10 and parameter's value of the polynomial kernel is 5 has the smallest mean absolute percentage prediction error among one hundred PolyRVR models. Thus, the comparison of wind speed prediction results among EMD-MkRVR, RBFRVR ($m = 10$, $\gamma = 2.5$) and PolyRVR ($m = 10$, $d = 5$) is performed and given in Fig. 7.

Table 1 gives the comparison of mean absolute percentage prediction errors for wind speed among EMD-MkRVR, RBFRVR ($m = 10$, $\gamma = 2.5$) and PolyRVR ($m = 10$, $d = 5$). Thus, it can be deduced that the wind speed prediction ability of EMD-MkRVR is better than those of one hundred RBFRVR models and one hundred PolyRVR models. The experimental results show that the EMD-MkRVR model has a better prediction ability for wind speed than the RBFRVR model and the PolyRVR model.

Conclusion

In this paper, the hybrid model of empirical mode decomposition and multiple-kernel relevance vector regression algorithm is presented for wind speed prediction. Here, wind speed can be regarded as a signal and decomposed into six IMFs with different frequency range, the prediction models of the six decomposed signals can be established by MkRVR with their respective appropriate embedding dimension, and grid method is used to select the appropriate kernel parameters and controlled parameters of their MkRVR models. Thus, the corresponding MkRVR models of these decomposed signals have appropriate embedding dimensions, kernel parameters and controlled parameters. The experimental results indicate that the EMD-MkRVR model has a better prediction ability for wind speed than the RBFRVR model and the PolyRVR model.

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