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A hybrid forecasting approach applied to wind speed time series

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ABSTRACT

In this paper, a hybrid forecasting approach, which combines the Ensemble Empirical Mode Decomposition (EEMD) and the Support Vector Machine (SVM), is proposed to improve the quality of wind speed forecasting. The essence of the methodology incorporates three phases. First, the original data of wind speed are decomposed into a number of independent Intrinsic Mode Functions (IMFs) and one residual series by EEMD using the principle of decomposition. In order to forecast these IMFs, excepting the highest frequency acquired by EEMD, the respective estimates are yielded using the SVM algorithm. Finally, these respective estimates are combined into the final wind speed forecasts using the principle of ensemble. The proposed hybrid method is examined by forecasting the mean monthly wind speed of three wind farms located in northwest China. The obtained results confirm an observable improvement for the forecasting validity of the proposed hybrid approach. This tool shows great promise for the forecasting of intricate time series which are intrinsically highly volatile and irregular.

1. Introduction

With the rapid development of society, economy and industry, the demand for electricity, as a fundamental and indispensable power, is growing dramatically. However, natural resources, especially fossil fuels, are being extensively exploited. This encourages the exploration of renewable, clean and free energy sources [1]. Wind power is a required energy source. Wind energy projects have environmental, economical, and social benefits, and have been successfully introduced in many countries. To a large extent, wind energy is one of the predominant alternative sources of energy, e.g. wind energy represents about 10% of energy consumption in Europe, even over 15% in countries such as Spain and Germany [2]. Similarly, in China, the burgeoning wind energy industry is substantially supported by government. The installed wind power capacity was 44733.29 MW in 2010, with an average annual growth rate of 73.3%, ranking first in the world [3]. In 2011, the installed wind power capacity was 62364.2 MW, with an average annual growth rate of 39.4% [4].

It is well-known that one of the most significant factors of wind power generation is wind speed. Unfortunately, wind speed, viewed as one of most difficult meteorological parameters, is not an easy factor to forecast. A series of meteorological factors such as pressure and temperature differences, the rotation of the earth and local characteristics of the surface influence wind speed; additionally, the complex interactions between these meteorological factors made wind speed even more difficult to forecast [5]. However, in a liberalized electricity market, the excellent performance of wind speed forecasting will help boost competitiveness of wind energy compared to other forms of energy. Considering the operation of electric utilities which integrate wind energy, it is becoming increasingly important and pertinent to forecast wind speed. For example, a 10% deviation of the expected wind speed results approximately in a 30% deviation in the expected wind power generation [6].

In recent years, wind speed forecasting has attracted many researchers to do an array of studies in this field, which can be divided into short-term forecasting and long-term forecasting according to the time scales of wind speed data and the purpose of the forecast. While accurate short-term forecasts of wind speed minimize scheduling errors which has made a great impact on grid reliability and market based ancillary service costs [7], long-term forecasts provide important references for site location, planning of windmills and the selection of an optimal size of the wind machine for a particular site [8]. According to the data used by models, these models can be classified by two catalogs. One catalog belongs to meteorological methods. These models, developed by meteorologists for large scale area weather prediction, using physical data such as temperature, pressure and topographical information, are used to forecast the future wind speed [9–11]. These meteorological models do not give accurate results. Other kinds of models are employed to forecast wind speed using past wind data which may

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be analyzed with different statistical methods, including time series models such as the Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA) models [12,13] and artificial intelligence techniques including Support Vector Machines (SVM) [8] and Artificial Neural Networks (ANNs). ANNs are some of the most widely used models in the last decade for wind speed forecasting and other disciplines where time series are used. They include but are not limited to training algorithms including the Back-Propagation (BP) algorithm and the Levenberg Marquardt (LM) algorithm [4], the control algorithm based on the ANN model using the back-propagation method [14], a new strategy based on Fuzzy Logic and Artificial Neural Networks [15] and various other forms of neural networks such as Multi-layer Feed-forward Neural Networks [1,14,16–19] and Recurrent Neural Networks [20–22].

Relatively, these models using past wind data can provide moderately good results for wind speed. However, most of them are subject to shortcomings, mainly in two aspects. First, traditional time series techniques can obtain good prediction achievements under the assumption of conditions that time series present linearity and stationarity. Unfortunately, in reality, wind speed series can rarely adhere to this due to their intrinsic complexity and volatility. Secondly, despite showing superiority over traditional statistical techniques, artificial intelligence models possess their own defects and drawbacks, e.g. ANN models sometimes fall into dilemma of local minima as well as over-fitting, and also are sensitive to parameter selection. In view of the limitations of traditional techniques and artificial intelligence techniques, a novel approach is required in order to remedy the shortcomings of those models. Considering the distinction of the mean monthly wind speed data—non-constant mean and variance, high volatility and irregularity—the thought of taking a deep insight into the original data and taking advantage of artificial intelligence techniques should be adopted besides improving the models themselves.

Removing noisy data, an important part of data cleaning is significant and meaningful prior to the operation of forecasting wind speed. The methods such as Wavelet Decomposition [23] and Empirical Mode Decomposition (EMD) [19] can be applied to eliminate noisy data. However, the wavelet de-noising technology is sensitive to the selection of threshold and empirical mode decomposition suffers from an intrinsic drawback—the frequent appearance of mode mixing. Fortunately, there exists an improved method named Ensemble Empirical Mode Decomposition (EEMD) which makes up for the deficiency of EMD. The EEMD is different from other traditional decomposition methodologies such as the Fourier decomposition and wavelet decomposition. It is an empirical, intuitive, direct and self-adaptive data processing method created especially for non-linear and non-stationary signal sequences.

In an attempt to more precisely appraise the wind energy reserves in Zhangye, Jiuquan and Mazong Mountain, all located in northwest China, a hybrid approach is proposed in this paper for such tough forecasting tasks. This approach is developed through combining the EEMD, Partial Autocorrelation Function (PACF) and Support Vector Machine (SVM). The EEMD is firstly employed to disassemble the original wind speed time series into a number of independent Intrinsic Mode Functions (IMFs), thereby better understanding wind speed data structure. The PACF is used to determine the correlation between the data embedded IMF in the same frequency band and identify the lag orders, making preparation for prediction. The SVM algorithm which is a useful methodology and also a new kind of intelligent machine is applied to forecast future numerical values using the data of IMFs available in different frequencies. The simulation process and results show that this hybrid forecasting model is simple and quite efficient to forecast wind speed with the feature of high volatility and irregularity.

The rest of the paper is organized as follows. Section 2 describes acquired tools and the proposed hybrid approach in detail. Forecasting results and the effectiveness of the proposed methodology are discussed in Section 3. Finally, Section 4 concludes the paper.

2. Methodology

Owing to the inherent characteristics of nonlinearity, non-stationarity, high fluctuation and irregularity of wind speed series and the intermittent and stochastic nature of the wind source, a strategy which contains the ideology of decomposition, de-noise, single forecast and ensemble is introduced. According to the strategy, the forecasting wind speed process can be divided into three primary stages that are decomposition, de-noise plus single forecast and ensemble, respectively. First, with the help of some popular decomposition methods, the original wind speed series can be divided into a number of components depicting relatively simple but meaningful local time scales. Then, a useful prediction method is employed to forecast all components respectively. Finally, these estimates are aggregated into the final estimate as the forecast result. This type of strategy can provide both thorough components of the original data and an excellent forecasting result.

In terms of this strategy, a hybrid method integrating EEMD, PACF and the SVM is proposed to enhance the quality of wind speed forecast of three wind farms located in northwest China. This paper will demonstrate the effectiveness of the hybrid model for forecasting wind speed. Before starting to use the hybrid method, it is necessary to describe the theory of the acquired tools in the proposed approach. First, the decomposition techniques of EMD and EEMD and the theory of PACF are briefly introduced, and the principle of SVM algorithm is presented. Then the EEMD, PACF and SVM are combined into the developed approach.

2.1. Empirical Mode Decomposition (EMD)

The EMD has been widely accepted as a method of dealing with non-linear and non-stationary data. The basic idea of EMD is to identify the intrinsic oscillatory modes and to decompose original time series data into a finite and small number of oscillatory modes based on the local characteristic time scale by itself [24]. The decomposition is based on the following assumptions: (1) the signal has at least two extrema – one maximum and one minimum; (2) the characteristic time scale is defined by the time lapse between the extrema; and (3) if the data are totally devoid of extrema but contain only inflection points, then they can be differentiated one or more times to reveal the extrema. Final results can be obtained by integration(s) of the components. In the EMD method, the Intrinsic Mode Functions (IMFs) concept is introduced as one of the key innovations; it satisfies the following two properties: (a) In the whole data series, the number of extrema and the number of zero crossing in a whole sampled data set must either equal or differ at most by one; (b) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. With the assumptions of decomposition and the above definition for the IMF, an original data series $X(t)(t = 1, 2\cdots T)$ can be decomposed in terms of the following sifting procedure. Fig. 1 demonstrates the detailed process of the EMD algorithm.

The above sifting procedure may be repeated many times. In the procedure, the IMF series must retain enough physical sense of amplitude and frequency modulations. To serve this purpose, the threshold value mentioned in step (2) for the sifting process to stop needs to be determined; a standard deviation S_d is defined to accomplish this. The S_d is computed from the two consecutive sifting results as

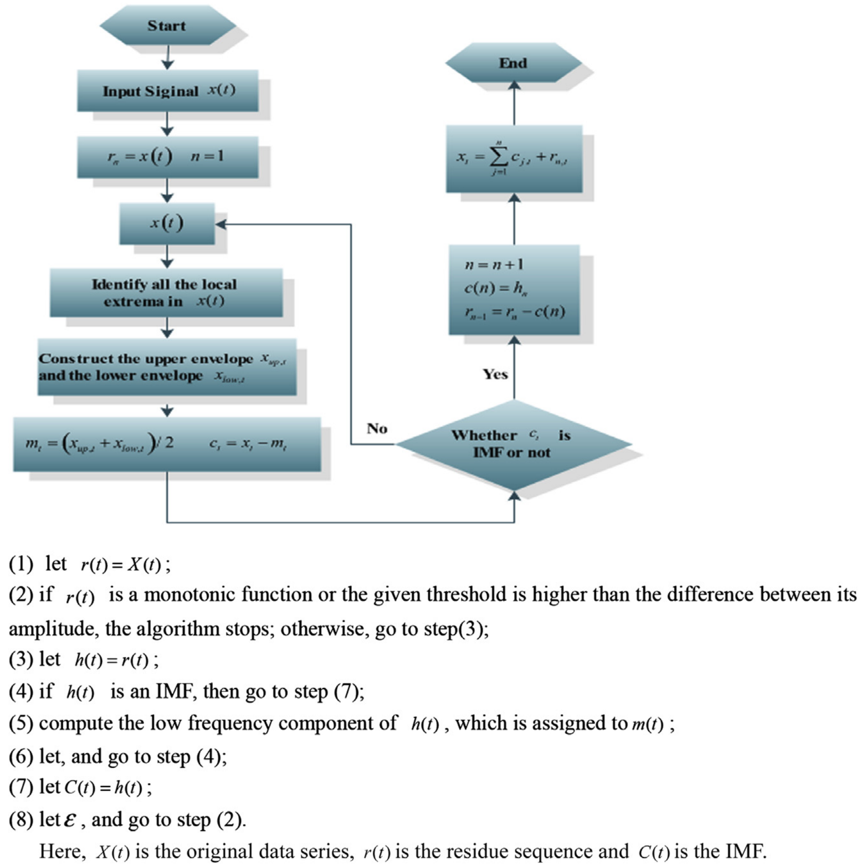


Fig. 1. The flowchart of EMD algorithm.

$$S_d = \sum_{t=0}^{T} \frac{\left|h_{1(k-1)}(t) - h_{1(k)}(t)\right|^2}{h_{1k}^2(t)} \tag{1}$$

After sifting processing, the original data series $X(t)$ can finally be expressed as a sum of IMFs and a residual:

$$X(t) = \sum_{i=1}^{n} C_i + r_n \tag{2}$$

where n denotes the number of IMFs, r_n is the final residual, and C_i denotes the IMF.

2.2. Ensemble EMD (EEMD)

The EEMD, proposed by Wu and Huang [25], is the inheritor of the EMD. Since EMD suffers from an intrinsic drawback – the frequent appearance of mode mixing defined as a single IMF including oscillations of dramatically disparate scales, or a component of a similar scale residing in different IMFs – the investigation promotes the advent of the EEMD method. EEMD defines the true IMF components as the mean of an ensemble of trials and each trial consists of the decomposition results of the signal plus a white noise of finite amplitude. The basic principle of EEMD is that the observed data are amalgamations of true time series and noise, while the ensemble means of data with different noise levels are closer to true time series. Therefore, an additional step adding white noise into the original data is adopted to help extract true signals in the data. The process of EEMD decomposition can be demonstrated by the following steps. Fig. 2 shows the detailed process of the EEMD algorithm.

The added white noise series can help extract the true IMFs, and can offset themselves via ensemble averaging after serving their purpose. Therefore, this can substantially reduce the chance of mode mixing and represent a significant improvement over the original EMD. The effect of the added white noise can be controlled according to the well-established statistical rule proved by Wu and Huang [25]:

$$\varepsilon_{\mathrm{ne}} = \frac{\varepsilon}{\sqrt{\mathrm{NE}}} \tag{3}$$

where NE is the number of ensemble members, ε is the amplitude of the added noise, and $\varepsilon_{\mathrm{ne}}$ is the final standard deviation of error, defined as the difference between the input signal and the corresponding IMFs.

2.3. Partial Autocorrelation Function (PACF)

The PACF plays a very important role in recognizing the non-stationarity of wind speed series and determining the lag orders.

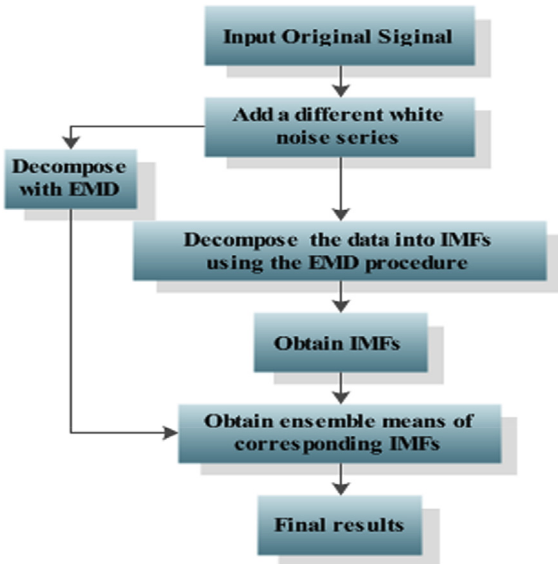
First we determine the ACVF $\gamma(\cdot)$ of the causal ARMA (p, q) process defined by

$$\varphi(B)X_t = \theta(B)Z_t, \quad \{Z_t\} \sim WN\left(0, \sigma^2\right) \tag{4}$$

where $\varphi(z) = 1 - \varphi_1 z - \cdots - \varphi_p z^p$ and $\theta(z) = 1 + \theta_1 z + \cdots + \theta_q z^q$.The causality assumption implies that

$$X_t = \sum_{j=0}^{\infty} \psi_j Z_{t-j}, \tag{5}$$

where



(1) Add a white noise series to the original data;
(2) Decompose the data with added white noise into IMFs using the EMD procedure;
(3) Repeat Steps 1 and 2 iteratively, but use different white noise series each time;
(4) Obtain the ensemble means of corresponding IMFs as the final results.

Fig. 2. The flowchart of EEMD algorithm.

$\sum_{j=1}^{\infty}\psi_j z_j = \theta(z)/\varphi(z), \ |z| \le 1$

Based on above, we can obtain

$$\gamma(h) = E(X_{t+h}X) = \sigma^2 \sum_{j=0}^{\infty} \psi_j \psi_{j+|h|}. \tag{6}$$

The PACF of an ARMA process $\{X_t\}$ is the function $\alpha(\cdot)$ defined by the equations

$\alpha(0) = 1$

and

$$\alpha(h) = \varphi_{hh}, \quad h \ge 1, \tag{7}$$

where φ_{hh} is the last component of

$$\varphi_h = \Gamma_h^{-1} \Upsilon_h, \tag{8}$$

$\Gamma_h = [\gamma(i-j)]_{i,j=1}^{h}$, and $\Upsilon_h = [\gamma(1), \gamma(2), \ldots, \gamma(h)]'$

2.4. Support Vector Machine (SVM)

The SVM, proposed by Vapnik and his co-workers, is based on a statistical learning theory called the VC (Vapnik–Chervonenkis) dimension theory and the structural risk minimization (structural risk minimization, SRM) principle. On the basis of limited sample information, the SVM pursues the best compromise between the model's complexity and the learning ability. In order to obtain the best generalization ability, the basic principle of SVM for regression is to map the data into a high dimensional feature space via nonlinear mapping and to perform a linear regression in this feature space [26,27]. The regression formula can be expressed as

$$f(x) = \sum_{i=1}^{D} w_i \varphi_i(x) + b \tag{9}$$

where $\{\varphi_i(x)\}_{i=1}^{D}$ are named features, b is the bias term and $\{w_i\}_{i=1}^{D}$ are weight vectors estimated from the data. Using the SVM method, thus mapping the input data points to a high-dimensional feature space, a nonlinear regression in the low dimensional input space is transformed into a linear regression in a high dimensional (feature) space. Based on the structural risk minimization (SRM) principle, the coefficients $\{w_i\}_{i=1}^{D}$ can be obtained from the data by optimizing the following quadratic programming problem

$$\begin{aligned} &\min_{w.b.\zeta} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right) \\ &s.t.\ |y_i - < w \cdot \Phi(x) > -b| \le \varepsilon + \xi_i, \\ &\xi_i \ge 0, \xi_i^* \ge 0, i = 1, 2, \cdots n \end{aligned} \tag{10}$$

where ξ_i is a slack variable and $C > 0$ is a constant which determines penalties. By solving the optimization problem, the estimation function can be obtained as follows

$$f\left(x, \alpha, \alpha^*\right) = \sum_{i=1}^{N}\left(\alpha_i - \alpha_i^*\right) k(x_i, x) + b \tag{11}$$

With $\sum_{i=1}^{N}(\alpha_i^* - \alpha_i) = 0, \quad 0 \le \alpha_i, \alpha_i^* \le C$ and the kernel function $k(x_i, x)$ represents the inner product in the D-dimensional feature space. SVM is characterized by the use of a technique known as "kernel trick" to apply linear classification techniques to nonlinear classification problems.

$$k(x, y) = \sum_{j=1}^{D} \varphi_j(x) \varphi_j(y) \tag{12}$$

It is not necessary to compute the features φ_j; rather, what is needed is the kernel function that is very simple and has a known analytical form. The only necessary condition is that the kernel function has to meet Mercer's condition. The typical kernel functions include polynomial kernel function, Gaussian kernel function and sigmoid kernel function.

2.5. The hybrid EEMD–SVM model

The SVM is a useful methodology and has been used extensively for classification, regression and pattern recognition and successfully applied to time-series prediction with satisfactory prediction results in various fields [28–33]. Single SVM shows many unique advantages in addressing small samples and nonlinear or high dimension pattern recognition problems, but it still has difficulties in extracting favorable forecasting results for wind speed series. Furthermore, the characteristics of nonlinearity and nonstationarity of original wind speed series make the morphogenetic movements of wind extraordinarily changeable, which intensifies the difficulty of recognizing and forecasting wind speed. Hence, there are some limitations of its independent application. Owing to the drawback that the single model cannot completely catch the characteristics of the data in a real problem, a hybrid methodology with the functions of decomposition, de-noise and forecasting modeling capabilities is proposed. The hybrid approach consists of EEMD and SVM. The EEMD, as an efficient decomposition method, divides the original data of wind speed into a quantity of independent IMFs. The SVM is selected as the forecasting tool in the developed model as the SVM can be applied to tackle non-linear problems besides linear matters, whereas traditional time series techniques such as AR, ARMA models can only address linear problems under the assumption of conditions that time series present the characteristics of linearity and stationarity. In addition, the SVM has good generalization ability and outreach capacity besides avoiding effects and drawbacks of artificial intelligence algorithm such as trapping in local optimum and over-fitting. Fig. 3 shows the overall framework of the presented hybrid method.

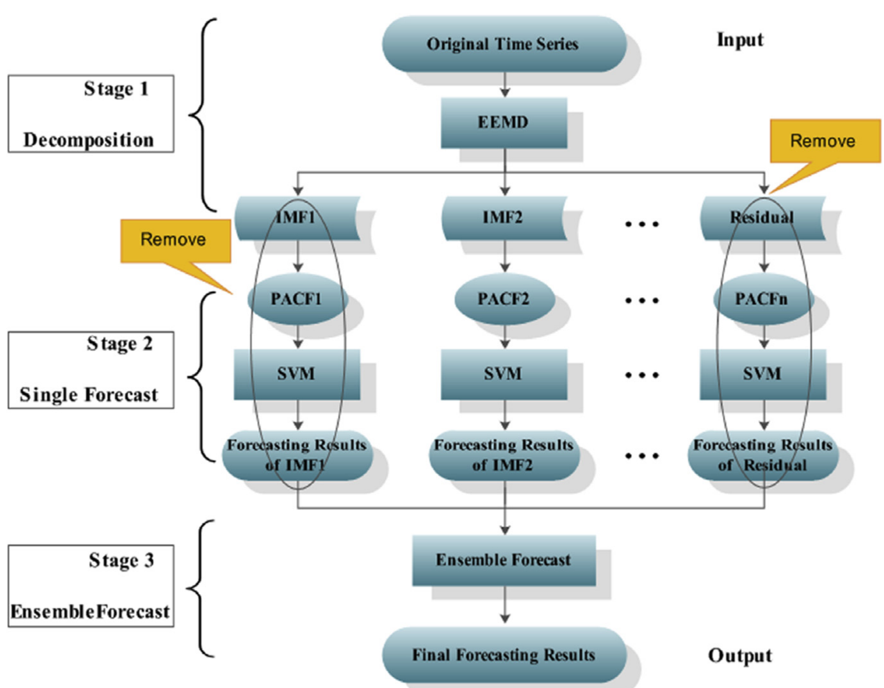
In Stage 2, the instantaneous frequency of each IMF is meaningful at any point and different IMFs possess different meanings, e.g. IMFn in the lowest frequency band represents the central tendency of data and IMF1 is the highest frequency band and it mainly contains a large quantity of noisy signals. Using the PACF can confirm that the correlation between the data in IMF1 is quite weak. As a result, the IMF1 can be regard as uncorrelated white noise series. Therefore, to exclude the interference factor and retain the core information of the original data, the series of IMF1 can be neglected. At the same time, the residual is ignored since there is no correlation between the data of the residual and it is so small that zero forecasting results are obtained in the modeling process. The strategy adopted has the effect of de-noising the original data and achieving forecasting accuracy. In Stage 2, before applying the SVM model for forecasting the mean monthly wind speed in terms of IMFs obtained by EEMD algorithm, it is necessary to overcome the limitation of ignoring the relationship between input(s) and output(s) of SVM model and identifying the correlation between input(s) and output(s). The PACF, a useful parameter identification method in the ARMA (p, q) model, is employed to address this matter. When the sample PACF values at lags greater than p are approximately independent N (0, 1/n) random variables, which means that roughly 95% of the sample PACF values beyond lag p should fall within the bounds $\pm 1.96/\sqrt{n}$, the lag order can be determined as p. After determining the relationship between input(s) and output(s), removal of dimension is essential to contribute to the accuracy of forecast. Thus, the inputs are normalized by the method of maximum and minimum normalization; after simulation, the corresponding estimate results are rescaled through the contrary process of the employed normalization method. This developed hybrid model can be applied to obtain multi-step ahead forecasts and the following simulation will manifest the availability.

3. Case study

3.1. Collection of data

The data of three farms in northwest China are collected to examine the hybrid model. In particular, first, the data of the wind farm in Zhangye are used to witness the whole process of the proposed method. In the same way, the corresponding forecasting results of Jiuquan and Mazong Mountain are shown and further confirm the validity of the method, accordingly.

The monthly behavior of the wind speed of Zhangye from January 2001 to December 2006 is illustrated in Fig. 4. It presents the high fluctuation and irregularity, periodicity and non-instability. In this paper, the 60 observations of mean monthly wind speed in former 5 years are used for ARIMA and SARIMA



Stage 1: EEMD is employed to decompose the original data into a number of independent intrinsic mode functions (IMFs) and one residual series.

Stage 2: IMF1 and the residual series are discarded to make preparations for the next stage and achieve forecast accuracy. Then, SVM is utilized to forecast the rest of the extracted IMFs independently. Thus, the corresponding estimates are achieved.

Stage 3: These forecasted results are aggregated into an ensemble result as a final forecast.

Fig. 3. The overall framework of the hybrid EEMD–SVM model.

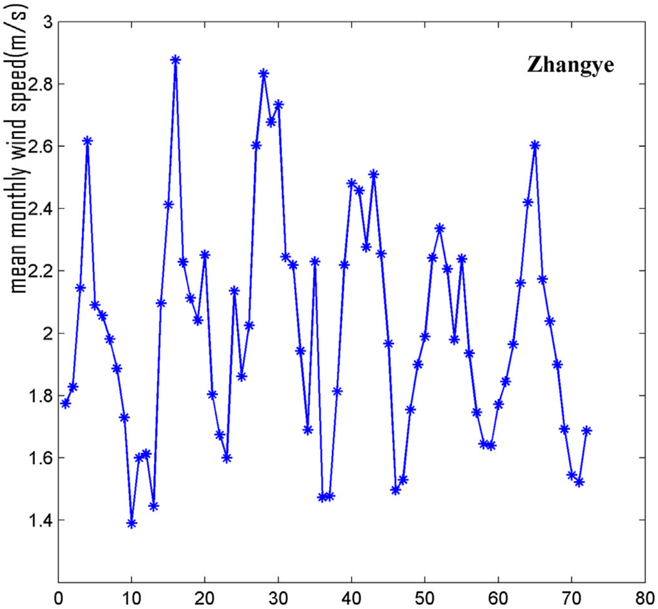


Fig. 4. Mean monthly wind speed from January 2001 to December 2006 for Zhangye.

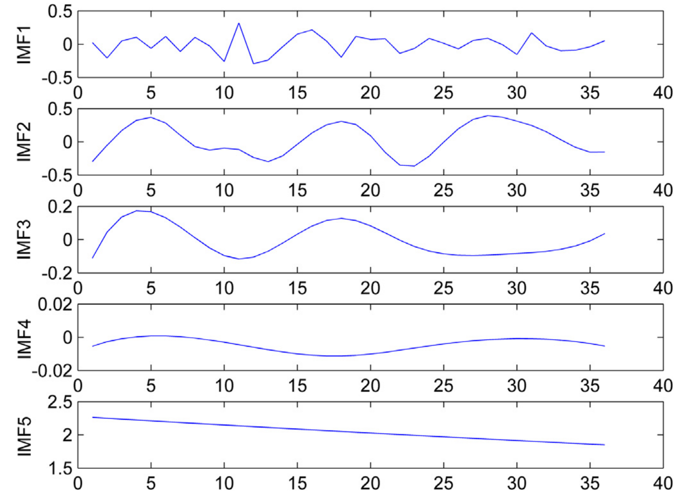


Fig. 5. The decomposition of the mean monthly wind speed from January 2003 to December 2005 for Zhangye by EEMD.

model training and the remaining 12 observations are used to test the effectiveness of the models. Since the SVM algorithm only requires a relatively small amount of data, the data from January 2003 to December 2005 are selected to train the model and the data of 2006 are used to test the effectiveness of the developed hybrid model.

3.2. Evaluation criteria of forecast performance

To assess the forecast capacity of the EEMD–SVM model, two indices for error forecast serve as the criteria to evaluate the forecasting performance; they are mean absolute error (MAE) and mean absolute percent error (MAPE). The values of the indices are smaller and the forecast performance is better. The indices are defined as follows:

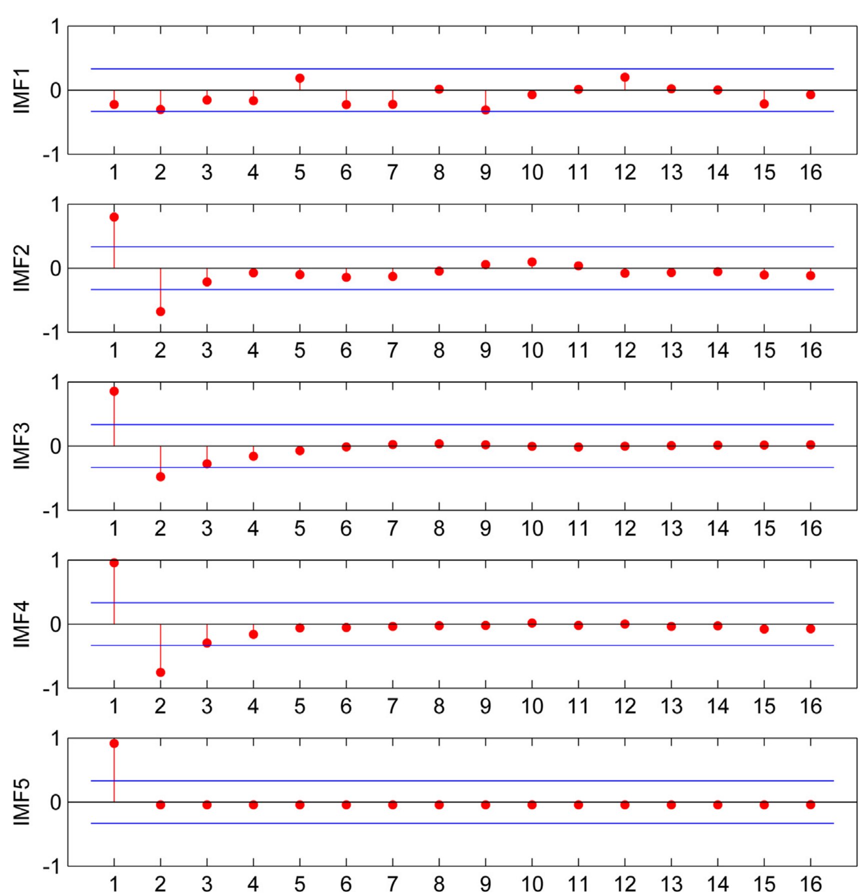


Fig. 6. The sample PACF of each IMF with the bounds $\pm 1.96/\sqrt{36}$ for Zhangye.

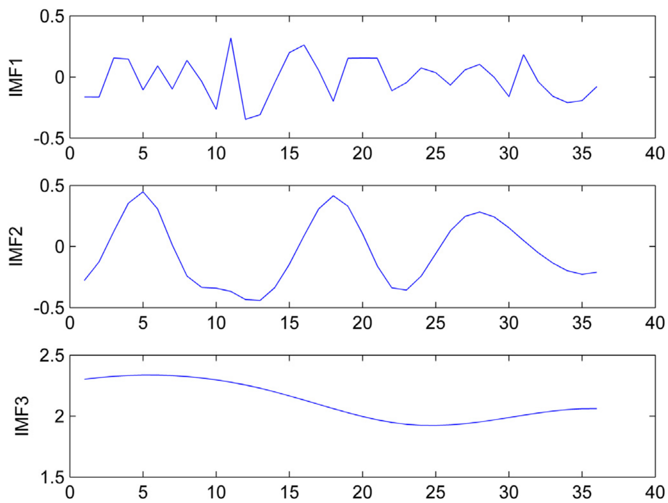


Fig. 7. The decomposition of the mean monthly wind speed from January 2003 to December 2005 for Zhangye by EMD.

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}\left|p_t^{\text{ture}} - p_t^{\text{forecast}}\right| \tag{13}$$

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\frac{\left|p_t^{\text{ture}} - p_t^{\text{forecast}}\right|}{p_t^{\text{ture}}} \times 100\% \tag{14}$$

where p^{ture} is the actual observation value for a time period t and p^{forecast} is the forecast value for the same period. The MAE reveals the average variance between the forecast value and the true value while the MAPE, as unit-free measure, has good sensitivity for small changes in data, does not display data asymmetry and has very low outlier protection.

3.3. Simulation

According to the proposed hybrid approach, in Stage 1, employing the EEMD technique, the original series of mean monthly wind speed data are decomposed into five independent IMFs (illustrated in Fig. 5) and one residual. In Stage 2, first, to improve the forecasting precision of the disorder wind speed series as a whole, there is the absolute need of the pretreatment of data. The relationship between the data of each IMF in the same frequency band should be identified prior to obtaining the forecasting results of IMFs. The PACF is employed as a detector to determine the correlations between them. It can be confirmed from Fig. 6 that the lag orders of the autoregressive process of each IMF are zero, two, two, three and one, respectively. After obtaining the correlations, the following strategy is adopted: on account of weak correlation between the data of IMF1, it is discarded to have the effect of denoising for the original wind speed series and the residual is also ignored because of its quite small value. Based on the correlation between the data of each IMF, the input and the output vectors of the proposed model can be generated. Then the respective SVM model is built and trained in terms of the input and the output vectors of the IMFs. After that, the established SVM model produces the twelve-step ahead forecasting results of each series of IMF. Particularly, to low frequency IMFs, the SVM is still employed to forecast the multiple-step ahead wind speed as traditional time series techniques such as ARMA, AR models need at least 50 sample data to ensure the effective fitting of the model [34]. By contrast, the SVM has no requirement for sample size. Furthermore, it cannot be guaranteed that the behavior of low frequency IMF shows as slow dynamics as the IMF5 in Fig. 5 for which some simpler models also suffice to provide accurate forecasts. In Stage 3, the final forecasting results can be obtained by accumulating the forecasting results of each IMF.

In order to reflect the model superiority, it is necessary to build other models to compare with the proposed model. Some other popular single forecasting approaches recommended by recent works on wind speed forecasting are selected as benchmarks. The benchmarks include time series techniques and artificial intelligence (AI) techniques. Amongst time series techniques, the autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) models are adopted. For AI tools, single SVM is employed for the purpose. Furthermore, a hybrid ensemble learning approach with the EMD selected as decomposition method is also utilized. The simulation of this method is in general similar to the proposed model. The results of EMD are shown in Fig. 7. We can discern that the subseries yielded by EMD are different from the ones acquired by

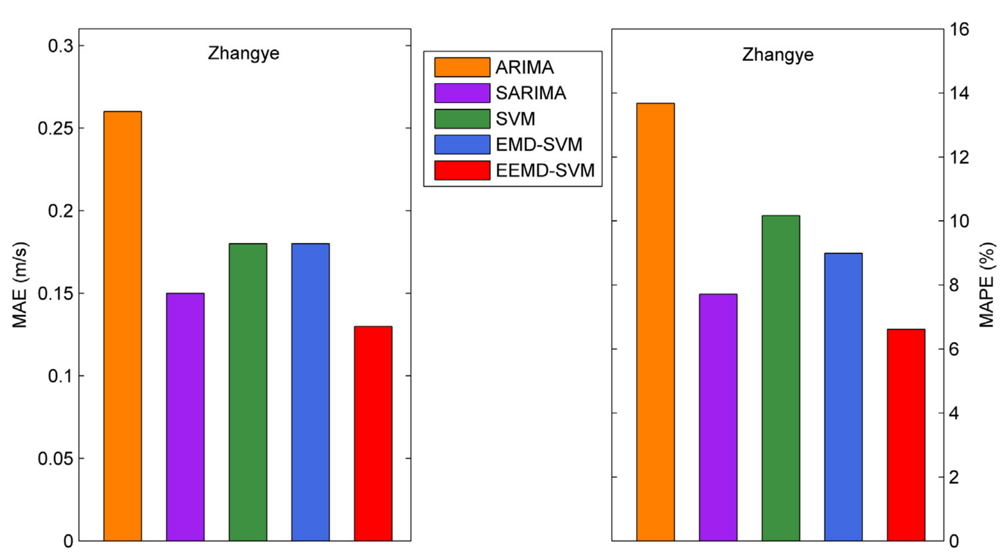


Fig. 8. MAPE and MAE comparisons among different forecasting models for Zhangye.

Table 1
Mean monthly wind speed forecasting results by different models.

Model errors	Forecasting models				
	ARIMA	SARIMA	SVM	EMD–SVM	EEMD–SVM
MAE (m/s)	0.26	0.15	0.18	0.18	0.12
MAPE (%)	13.68	7.71	10.17	8.99	5.81

EEMD in quantitative terms and the lowest frequency IMF yielded by EMD fluctuates a little more fiercely than the one acquired by EEMD.

After comparison among these models mentioned above, it can be found that both the two statistical errors (MAE and MAPE) of the proposed model are lower. This indicates that the combination of the EEMD method and the SVM algorithm is an available and effective approach. In order to give clear proof of the strong prediction capacity of the proposed hybrid model, the model comparisons are given in the next section. At the same time, the SVM algorithm is simple in model calculation and it only requires small data quantity. Thus the hybrid model in this paper is simple and quite efficient in actual applications.

3.4. Comparison and discussion

The comparisons of forecasting models for the mean monthly wind speed of Zhangye are made between the ARIMA(1,1,1) model, SARIMA(1,1,1)(1,1,1) model, the single SVM model, the hybrid EMD–SVM model and the hybrid EEMD–SVM model. The forecasting results of different models are revealed in Fig. 8 and the forecasting performances are shown in Table 1. Through model comparisons, the proposed hybrid EEMD–SVM model performs best. This phenomenon signifies that the hybrid design concept can combine different advantages from each individual model.

As seen from Table 1 and Fig. 8, it is clear that the hybrid EEMD–SVM model performs much better than ARIMA model and single SVM model, and outperforms the SARIMA model and the hybrid EMD–SVM model. More precisely, compared with ARIMA and SARIMA models, the proposed model leads to reductions of 57.53%, 24.64%, 42.87% and 35.37% in total MAPE, and reductions of 54.09%, 18.75%, 32.85% and 35.10% in total MAE, respectively.

More analyses are shown as follows. First, overall, compared with these hybrid models, single forecasting models do not achieve

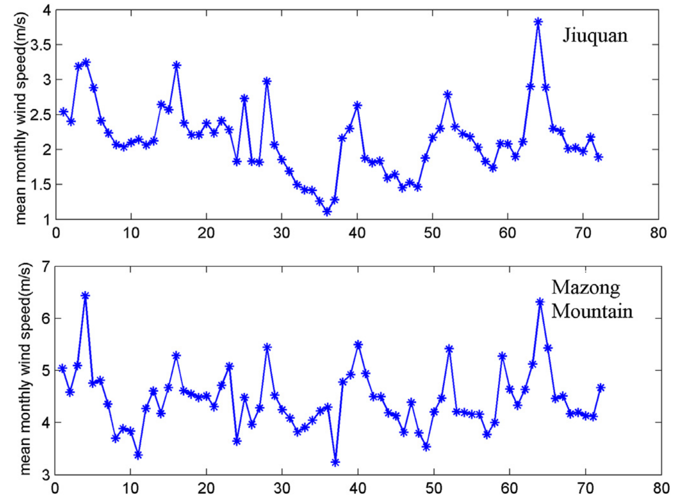


Fig. 9. Mean monthly wind speed from January 2001 to December 2006 for Jiuquan and Mazong Mountain.

good performance. Specifically, single ARIMA is the worst model in forecasting accuracy as this model is designed for capturing linear patterns hiding in the data. Then, comparison between the ARIMA model and SARIMA model indicates the periodicity of the wind speed time series, as the SARIMA model can effectively identify periodicity, thus obtain more precise prediction. Single SVM gets a moderate forecasting result. The possible reason is that wind data include interference factors although the SVM has unique advantages in addressing small sample size problems and nonlinear problems. Second, comparisons among single SVM, hybrid EMD–SVM and EEMD–SVM models reveal that the proposed decomposition methods are very effective in enhancing the forecasting accuracy as a preprocessor. The proposed hybrid model adequately makes use of the advantages of the decomposition methods and SVM algorithm and integrates them well. Third, in comparisons between EMD–SVM and EEMD–SVM, the decomposition method of EEMD is superior to EMD in terms of contribution to the forecasting accuracy. Fourth, the proposed EEMD–SVM method produces a slightly better result compared with the SARIMA model, but its operation is a little more complicated than SARIMA model because of multiple SVM regression. However, the hybrid method

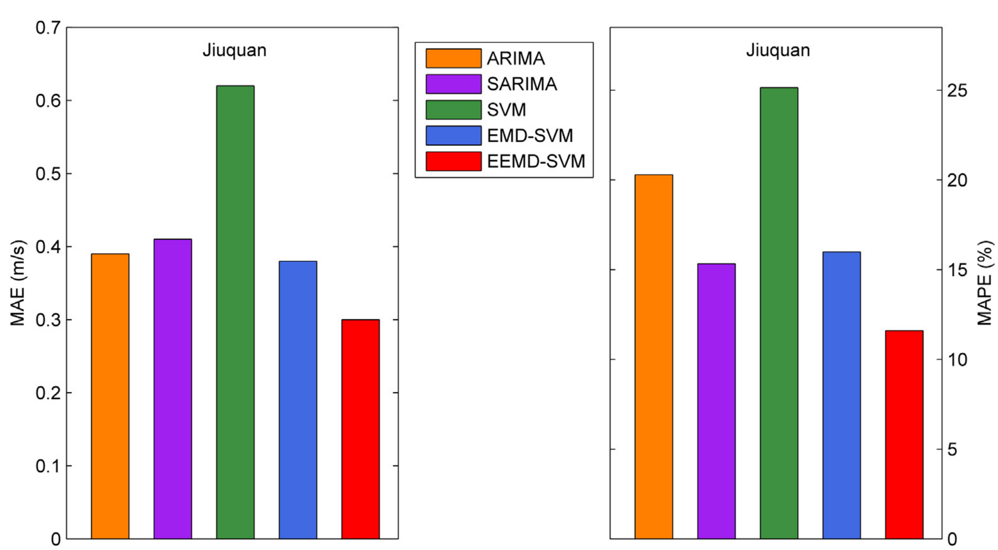


Fig. 10. MAPE and MAE comparisons among different forecasting models for Jiuquan.

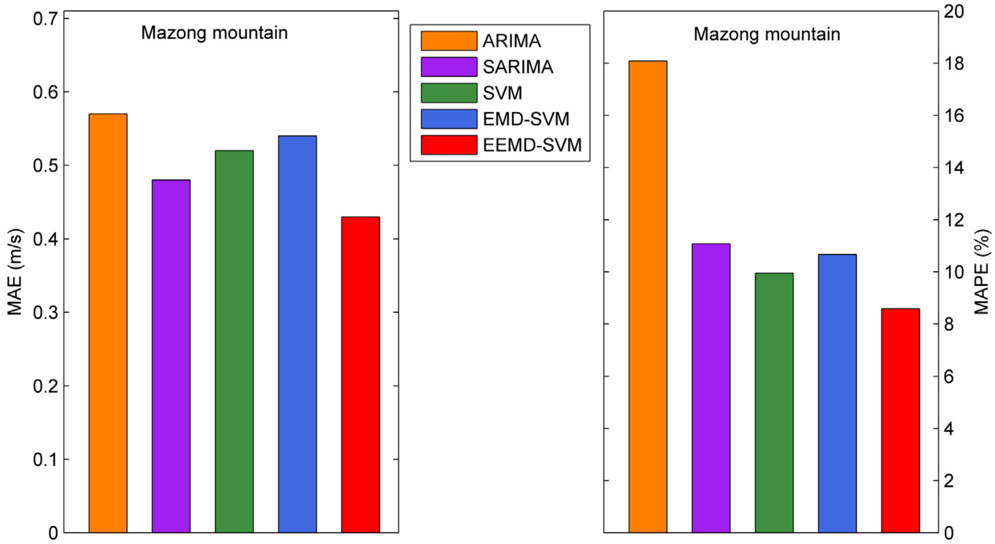


Fig. 11. MAPE and MAE comparisons among different forecasting models for Mazong Mountain.

still should be promoted as the time spent on computation is acceptable in practice thanks to the small sample size. Actually, it takes only a few minutes to fulfill the task. Finally, the two indices for forecasting error suggest the proposed model catches the properties of wind speed time series. Therefore, the model comparisons have shown a good forecasting performance of the developed hybrid EEMD–SVM model through the analyses of the prediction results.

When applied to the mean monthly wind speed forecasting of Jiuquan and Mazong Mountain, the developed hybrid EEMD–SVM model also performs well. Fig. 9 shows that the series of wind speed is obviously non-stationary and shows fluctuation of the wind speed. By means of different forecasting models, the forecasting results of those models are shown in Figs. 10, 11 and Table 2.

Similarly, we analyze the forecasting results of Jiuquan and Mazong Mountain in detail. When applied to prediction of wind speed in Jiuquan and Mazong Mountain, the proposed model shows its advantages in terms of contribution to the forecasting accuracy. More precisely, Compared with the ARIMA model, SARIMA model, the single SVM model and the hybrid EMD–SVM model (illustrated in Figs. 8 and 9 and Table 2), the proposed hybrid model boosts wind speed prediction level for Jiuquan, where the MAPE is reduced by 42.83%, 24.33%, 53.86% and 27.45%. It also improves the degree of wind speed prediction precision in Mazong Mountain; the MAPE deduced by the EEMD–SVM model is reduced by 52.49%, 22.47%, 13.67% and 19.49%. In addition, single ARIMA model gets better performance than single SVM model in the forecasting accuracy of the wind speed in Jiuquan wind farm, as the sample data of wind speed in this wind farm show more linearity than nonlinearity. These results demonstrate that EEMD, as an efficient decomposition method, is very effective in obtaining the accuracy of wind speed forecasting as a preprocessor.

Table 2
Forecasting results by different models for Jiuquan and Mazong Mountain.

Area	Model errors	Forecasting models				
		ARIMA	SARIMA	SVM	EMD–SVM	EEMD–SVM
Jiuquan	MAE(m/s)	0.39	0.41	0.62	0.38	0.30
	MAPE(%)	20.29	15.33	25.14	15.99	11.60
Mazong Mountain	MAE(m/s)	0.57	0.48	0.52	0.54	0.43
	MAPE(%)	18.08	11.08	9.95	10.67	8.59

Observing the charts and tables of three wind farms, we can discern that the range of wind speed in Mazong mountain wind farm is the largest while the data of wind speed in Jiuquan wind farm possess the worst feature of nonlinearity. These forecasting results reveal that selecting single SVM as a predictor is a right choice in terms of the characteristics of wind speed. Meanwhile, it should be pointed out that the greater and more irregular the wind speed is, the worse the resulting forecasting precision. In addition, volatility reflects the intrinsic complexity and uncertainty in wind energy, which is affected by factors such as average relative humidity, average temperature and mean pressure. In the present study only univariate time series are taken into account and analyzed, some other factors are excluded from the proposed hybrid approach. If these factors can be incorporated into it, then a better forecast performance may emerge. Furthermore, the present work focuses on the monthly wind speed series, achieving desired forecasting results. Whether the proposed method is suitable for shorter time scale prediction, i.e. daily, hourly and so forth can be the direction of the following work. It may be a difficult task as the characteristics of daily wind speed series are much more complicated and volatile than those of monthly wind speed series.

4. Conclusion

With the deterioration of the environment and depletion of conventional resources, renewable energy has attracted people's attention. As a kind of non-polluting renewable energy, wind power has been growing rapidly in many areas. In order to capture the intrinsic characteristic of wind speed time series and handle wind speed forecasting, many methods have been developed. Nonetheless, these models cannot always obtain a satisfactory forecasting accuracy when the wind speed shows the simultaneous nonlinearity and non-stationarity. In this paper, a hybrid approach integrating the EEMD algorithm, PACF with the SVM model is proposed to settle this troublesome problem. Forecasting results demonstrate that it is useful to forecast the mean monthly wind speed in Zhangye, Jiuquan and Mazong Mountains in northwest China. Compared with other single traditional methods (such as ARIMA, SARIMA) and hybrid methods (for instance EMD–SVM), this mixed approach is better and more efficient for forecasting wind speed in those areas.

There are several advantages of the proposed methodology. First, thanks to the nonlinearity and non-stationarity of wind speed, combining the EEMD algorithm and SVM model is a very wise practice for the mean monthly wind speed. Moreover, it has rarely been mentioned in previous literature. Thus, applying this hybrid method to forecast wind speed is very important for the future studies. Furthermore, from the simulation process and results, we can find this hybrid approach is useful in forecasting the mean monthly wind speed, and especially helpful for site selection, performance prediction and planning of windmills. Next, in terms of empirical results, it is a clear finding that the hybrid model, for the kind of wind speed series—mean monthly wind speed—can describe them comprehensively. The conventional single forecasting models cannot do this very well, because wind, with some complicated characteristics, is so complex that it is difficult to handle. However, a hybrid method can integrate the advantages of other single models which conduce to boosting the model prediction ability and enhancing forecasting efficiency. From this point of view, in terms of different criteria (MAE and MAPE), it is unsurprising that the hybrid approach performs better than the single ARIMA, SARIMA and SVM methods, and also superior to other hybrid models, for instance, EMD—SVM model. Both statistical errors are reduced effectively in this hybrid model for mean monthly wind speed in Zhangye, Jiuquan and Mazong Mountains. Finally, it is demonstrated from practice that this hybrid model is simple in computation and the SVM algorithm only requires small data quantity. Thus, the developed model not only can show a satisfactory forecasting accuracy, but also can easily be implemented in wind parks.

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References

[1] Mohandes MA, Rehman S, Halawani TO. A neural networks approach for wind speed prediction. Renew Energ 1998;13(3):345–54.
[2] Mabel MC, Fernández E. Analysis of wind power generation and prediction using ANN: a case study. Renew Energ. 2008;33:986–92.
[3] http://www.nea.gov.cn/2011-07/05/c_131086514.htm.
[4] http://www.cwea.org.cn/download/display_info.asp?id=44.
[5] Sfetsos A. A comparison of various forecasting techniques applied to mean hourly wind speed time series. Renew Energ 2000;21:23–35.
[6] Ackermann T, Soder L. Wind energy technology and current status: a review. Renew Sustain Energy Rev 2000;4:315–74.
[7] Kavasseri RG, Seetharaman K. Day-ahead wind speed forecasting using f-ARIMA models. Renew Energ 2009;34:1388–93.
[8] Mohandes M, Halawani T, Rehman S, Hussain AA. Support vector machines for wind speed prediction. Renew Energ 2004;29:939–47.
[9] Landberg L. Short-term prediction of the power production from wind farms. J Wind Eng Ind Aerod 1999;80:207–20.
[10] Alexiadis MC, Dokopoulos PS, Sahsamanoglou HS, Manousaridis IM. Short-term forecasting of wind speed and related electrical power. Sol Energy 1998;63(1):61–8.
[11] Negnevitsky M, Potter CW. Innovative short-term wind generation prediction techniques. IEEE Power Syst Conf Exposition 2006:60–5.
[12] Torres JL, García A, De Blas M, De Francisco A. Forecast of hourly average wind speed with ARMA models in Navarre (Spain). Sol Energy 2005;79:65–77.
[13] Khashei M, Bijari M, Raissi-Ardali GA. Improvement of auto-regressive integrated moving average models using fuzzy logic and artificial neural networks (ANNs). Neurocomputing 2009;72:956–67.
[14] Flores P, Tapia A, Tapia G. Application of a control algorithm for wind speed prediction and active power generation. Renew Energ 2005;30(4):523–36.
[15] Monfared M, Rastegar H, Kojabadi HM. A new strategy for wind speed forecasting using artificial intelligent methods. Renew Energ 2009;34:845–8.
[16] Abdel-Aal R, Elhadidy M, Shaahid S. Modeling and forecasting the mean hourly wind speed time series using GMDH-based abductive networks. Renew Energ 2009;34:1686–99.
[17] Bilgili M, Sahin B, Yasar A. Application of artificial neural networks for the wind speed prediction of target station using reference stations data. Renew Energ 2007;32:2350–60.
[18] Cadenas E, Rivera W. Short term wind speed forecasting in La Venta, Oaxaca, México, using artificial neural networks. Renew Energ 2009;34:274–8.
[19] Guo ZH, Zhao WG, Lu HY, Wang JZ. Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model. Renew Energ 2012;37:241–9.
[20] Barbounis T, Theocharis J. A locally recurrent fuzzy neural network with application to the wind speed prediction using spatial correlation. Neurocomputing 2007;70:1525–42.
[21] Barbounis T, Theocharis J. Locally recurrent neural networks for long-term wind speed and power prediction. Neurocomputing 2006;69:466–96.
[22] Barbounis T, Theocharis J. Locally recurrent neural networks for wind speed prediction using spatial correlation. Inform Sci 2007;177:5775–97.
[23] Haven E, Liu XQ, Shen L. De-noising option prices with the wavelet method. Eur J Oper Res 2012;222:104–12.
[24] Huang NE, Shen Z, Long SR. The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis. Proc Roy Soc A 1998:903–95.
[25] Wu Z, Huang NE. Ensemble empirical mode decomposition: a noise-assisted data analysis method, centre for ocean-land-atmosphere studies. Tech Rep 2004;193(51).
[26] Mukherjee S, Osuna E, Girosi F. Nonlinear prediction of chaotic time series using support vector machines. Neural networks for signal processing [1997] VII. In: Proceedings of the 1997 IEEE workshop 1997. p. 511–20.
[27] Müller K-R, Smola A, Rätsch G, Schölkopf B, Kohlmorgen J, Vapnik V. Predicting time series with support vector machines. Advances in kernel methods—support vector learning. Cambridge, MA: MIT Press; 1999. p. 243–54.
[28] Trafalis BT, Adrianto I, Richman MB. Active learning with support vector machines for tornado prediction. Lect Notes Comput Sci 2007;4487:1130–7.
[29] Hong W. Rainfall forecasting by technological machine learning models. Appl Math Comput 2008;200:41–57.
[30] Osowski S, Garanty K. Forecasting of the daily meteorological pollution using wavelets and support vector machine. Eng Appl Artif Intell 2007;20:745–55.
[31] Zhou J, Shi J. Performance evaluation of object localization based on active radio frequency identification technology. Comput Ind 2009;60:669–76.
[32] Widodo A, Kim EY, Son J-D, Yang B-S, Tan ACC, Gu D-S, et al. Fault diagnosis of low speed bearing based on relevance vector machine and support vector machine. Expert Syst Appl 2009;36:7252–61.
[33] Lin GF, Chen GR, Huang PY, Chou YC. Support vector machine-based models for hourly reservoir inflow forecasting during typhoon-warning periods. J Hydrol 2009;372:17–29.
[34] Chatfield C. The analysis of time series. 5th ed. New York; NY: Chapman & Hall; 1996.