WIND SPEED PREDICTION BASED ON EMPIRICAL MODE DECOMPOSITION AND IMPROVED LS-SVM

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Abstract

Wind speed forecasting plays an important role in sizing the capacity of the energy storage system and guaranteeing the security and stability of power system. In order to forecast wind speeds more accurately, a hybrid forecasting method based on empirical mode decomposition (EMD) and an improved least square support vector machine mode (LSSVM) has been proposed in this paper. Employing the EMD technique to decompose the measured wind speeds into many intrinsic mode function (IMF) components and a residue, which represent the original signal in both high-frequency and low-frequency signals. Meanwhile each IMF is analyzed and predicted using LS-SVM (high-frequency signals) and Persistence Approach (low-frequency signals), so does the residue. The sum of the predictive value for each decomposed component is the forecasted data. The proposed method was applied to the modeling and forecasting of a set of data from a given wind farm in Jiangsu Province, China. The results demonstrate the validity and practicability of the novel method. The forecasted results were compared to the measured values as well as those predicted with other traditional methods. The results indicate that the forecasting precision can be improved with the developed model.

1 Introduction

For the sake of protecting the environment, wind is supposed to be one of the best substitutes for coal or other primary energy. With the growth of wind power in power system, many more new challenges are brought to traditional power system, the reliability and stability, for example, have been challenged due to the randomness and intermittency of the wind. The large-scale integration of wind power in the grid may surely cause problems, including power quality, stability, allocation of the power storage system and power dispatching[1]-[2]. Sizing of the storage system is also limited by the output of the wind turbine and reliable operation of the power system. Accurate and reliable forecasting of the wind speeds and wind production is a key part to solve problems above. Besides, in order to use the wind in an affordable way, wind power forecasting is essential.

At present the main methods for wind power forecasting focus on persistence approach, which assumes that the forecasting value of the wind speeds is the last measured one[3], Time-series Analysis[4], Kalman Filters[5], Artificial Neural Networks[6], Fuzzy Logic[7], etc. Reference [8] presented a novel method for wind speed forecasting based on relating the predictive value to their corresponding historical value in previous years within the same period. Reference [9] proposed a new model based on local and spatial relations of the wind speed so as to improve the efficiency of short and long range forecasting ranging from minutes to several hours ahead. Methods that use the relationships of wind speeds among several sites have been proposed.

Due to the wind speed is sensitive to temperature, terrain, pressure and other factors, the data of the wind speeds are nonlinear and fluctuating. However, preprocessing the wind speed data and studying the internal characteristic information may improve the forecasting precision. Considering the efficiency of the prediction of short-term wind speeds and enhancing the forecast precision, a hybrid forecasting method based on Empirical Mode Decomposition (EMD) and improved least square support vector machine mode is presented in this paper. Empirical Mode Decomposition (EMD) technique has been verified to be more practical than other signal processing methods in many areas[10]. The hybrid forecasting method employs EMD to decompose the original wind speed data into a residue and many intrinsic mode function (IMF) components, which can be divided into high-frequency signals and low-frequency signals. Afterwards, the high-frequency parts are forecasted using LS-SVM, while the low-frequency parts are predicted using traditional Persistence Approach. The final results can be obtained from both the prediction of high and low frequency components. The proposed method (Empirical Mode Decomposition-Improved LS-SVM) was applied to the modeling and forecasting of a set of wind speed data from a given wind farm in Jiangsu Province, China. The results demonstrate the validity and practicability of the novel method.

2 Empirical Mode Decomposition

The theory of intrinsic mode function (IMF) has been pioneered by Norden E. Huang et al when they did research on nonlinear problems and Hilbert Transform. At the same time, they proposed a method for signal decomposition, namely Empirical Mode Decomposition (EMD). It not only makes the signal decomposition unique but also has good local characteristics both in time domain and frequency domain.

The nature of the EMD technique is to identify the intrinsic oscillatory modes by their characteristics time scales in the data empirically, and then decompose the data [11]. The data are then categorized into many IMF components, which are those functions that satisfy two constraints: (1) in the whole data set, the number of extremes and that of zero crossing must either equal or differ at most by one; and (2) at any point, the mean value of the envelope defined by the local maxima and that defined by the local minima is zero.

3 Improved predictive method

At present, there are still many drawbacks when use the main methods to forecast the wind speeds. Time-series method cannot guarantee the precision of the predictive results when the wind speed fluctuates fiercely. Kalman Filters method takes the wind speeds as state variables, this method builds the state space model and forecasts the wind speeds. However, it is hard to estimate the statistical properties of noise which is an essential element in this method. The algorithm used in Artificial Neural Networks is easy to fall into local minimum. Fuzzy Logic method is always used in conjunction with other methods. Compared with the above methods, Persistence Approach is easy to understand and implement. It turns out to be precise in short-term wind speed forecasting. However, as the traditional Persistence Approach requires, the original signal is supposed to have a greater similarity between two sampling points, which is unrealistic in high-frequency parts of wind speeds. The proposed method, Improved LS-SVM can solve this problem. The Improved LS-SVM is composed with traditional Persistence Approach and LS-SVM.

3.1. Traditional Persistence Approach

The original wind speed is separated into several parts. Due to the speed of the low-frequency parts changes softly and the measured wind speed is similar to that of sampling points nearby, Persistence Approach can guarantee the accuracy of prediction. It considers that the latest measured value is the predictive value of the next sampling point[12]:

$$v'_{t+k} = v_t (k = 1,2,3...) \tag{1}$$

v'_{t+k} is the predictive value at the time $t+k$; v_t is the measured value at the time t.

3.2. Least Square Support Vector Machine

Support Vector Machines (SVM) is a powerful methodology for solving problems in nonlinear classification, function estimation and density estimation which has also led to many other recent developments in kernel. SVMs have been in traduced within the context of statistical learning theory and structural risk minimization. In the methods one solves convex optimization problems, typically quadratic programs. Least Squares Support Vector Machines (LS-SVM) [13] are reformulations to standard SVMs which lead to solving linear KKT systems. LS-SVMs are closely related to regularization networks and Gaussian processes but additionally emphasize and exploit primal-dual interpretations. Links between kernel versions of classical pattern recognition algorithms such as kernel Fisher discriminate analysis and extensions to unsupervised learning, recurrent networks and control are available.

LS-SVM selects the square loss function, to replace the ε insensitive loss function which the support vector uses, so that the equality constraints can be used to replace the inequality constraints in the vector's optimization. It makes the optimization in least squares support vector equal to the solution of linear equations. The algorithm is as follows:
Given a set of training data

$$\{(x_1, y_1), (x_2, y_2), ..., (x_i, y_i)\} \subset R^n \times R^l$$

Where, $x_i \in R^n$ denotes input data, $y_i \in R^l$ is the targets and l is the total number of training samples. The optimization of least squares support vector can be described as:

$$\min_{\omega,b,e} J(\omega, \xi) = 1/2\omega^T \omega + 1/2\gamma \sum_i^l \xi_i^2$$

$$\text{St.} \quad y_i \omega^T \varphi(x_i) + b + \xi_i \quad i = 1, ..., l, \tag{2}$$

Here, γ is regularization parameter, b is deviation of constant value. The Lagrange function can be expressed as

$$L(\omega, b, \xi, a) = 1/2\omega^T \omega + 1/2\gamma \sum_i^l \xi_i^2 - \sum_i^l a_i [\omega^T \varphi(x_i) + b + \xi_i - y_i] \tag{3}$$

Here, $a_i (i = 1, 2, ..., l)$ is Lagrange multiplier. According to the Karush-Kuhn-Tucker (KKT), a linear equation can be got in consideration of eliminating ξ_i and ω for $i = 1, 2, ..., l$:

$$\begin{bmatrix} 0 & e_l^T \\ e_l & Q + I/\gamma \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{4}$$

Here, $y = [y_1, y_2, ..., y_l]^T$, $e_l = [1, 1, ..., 1]^T$, $a = [a_1, a_2, ..., a_l]^T$ $Q_{ij} = \phi(x_i) \bullet \phi(x_j) = K(x_i, x_j), i, j = 1, 2, ..., l.$ Then, the following regression LS-SVM model can be got

$$y(x) = \sum_{i=1}^l a_i K(x, x_i) + b \tag{5}$$

4 Predictive model based on EMD

As shown in Fig.1, a novel model of wind speed forecasting was developed. The EMD unit was used to decompose the original wind speed data into a residue and some IMF components; C_i is the obtained IMF and r_n is the residue; LS-SVM is the least square support vector machine modeling unit; PA is the persistence approach modeling unit.
For a given wind speed data X(t) ,the process of decomposition as follows[14]:

(1) Identify all extremes of X(t), all the extremes can be connected by a cubic spline line.

(2) The upper and lower envelope can be obtained then, denoted by u(t) and v(t), and the mean of the upper and lower envelope is denoted by m(t);

$$m(t) = \frac{u(t) + v(t)}{2} \tag{6}$$

(3) Subtract from the signal to obtain h(t);

$$h(t) = X(t) - m(t) \tag{7}$$

(4) Whether h(t) satisfy the constraints? Yes: go to (5); No: h(t) is treated as the new data and put back to (1).

$$h_k(t) = h_{k-1}(t) - m_{k-1}(t) \tag{8}$$

(5) Let c=h(t), then the first IMF c(t) and the residual of the signal r(t) can be obtained.

$$r(t) = X(t) - c(t) \tag{9}$$

(6) After extracting an IMF, this same IMF is subtracted from the signal X(t). The residual is treated as the new data. Then do the steps (2)-(5). The cycle can stop by the predetermined criteria.

$$r_n(t) = r_{n-1}(t) - c_n(t) \tag{10}$$

(7) The last r(t) which cannot be extracted is the residue. It can be either a monotonic function or a single cycle. The original signal can be represented in the following equation

$$X(t) = \sum_{i=1}^{n} c_i(t) + r(t) \tag{11}$$

The above screening process may repeat many times. To make sure that the IMF components retain enough physical characteristics of amplitude and frequency, a criterion for the process to stop is needed. A standard deviation, SD, is chosen as a threshold value to satisfy this. The SD is computed from the two consecutive sifting results as:

$$\mathrm{SD} = \left\{ \sum_{t=0}^{T} \left[\frac{\left[h_{1(k-1)}(t) - h_{1k}(t) \right]^2}{h_{1(k-1)}^2(t)} \right] \right\}^{1/2} \tag{12}$$

A typical value of SD should be lower than 0.1.
Through the screening process, the data, $X(t)$, is finally decomposed into several IMFs and a residue r(t), i.e.

$$X(t) = \sum_{i=1}^{n} C_i + r_n \tag{13}$$

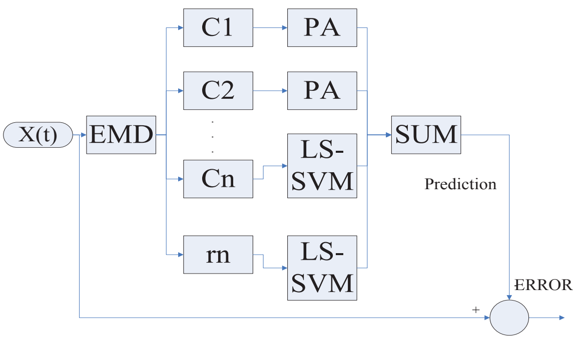

Fig.1. The proposed predictive model

5 Forecasting results and discussion

This paper takes a set of wind speed data, which is collected from a certain wind farm located at Jiangsu Province in China, as an example. The sampling interval is 10 minutes. The proposed model was built up on the basis of every 10 minutes mean wind speed samples, thus guaranteeing the precision of the prediction of wind speeds at future time-step.

In experiments, we regard the first two-day (288 points) values as sampling points, while the following one-day (144 points) values are used as checking data for validating the novel method we proposed. The original wind speed data were shown in Fig.2. According to the terminal constraints introduced in above equation (12), we obtained all of the IMFs and a residue shown in Fig.3.

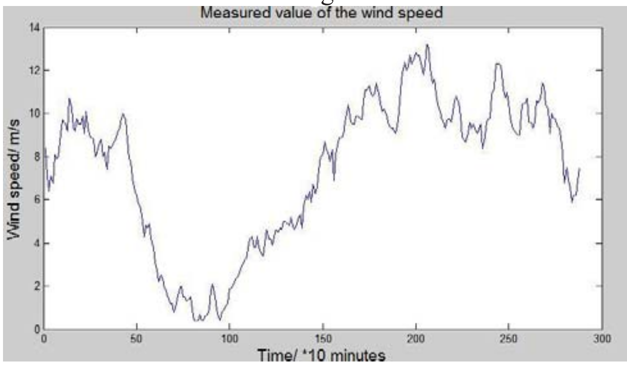

Fig.2. Original wind speeds

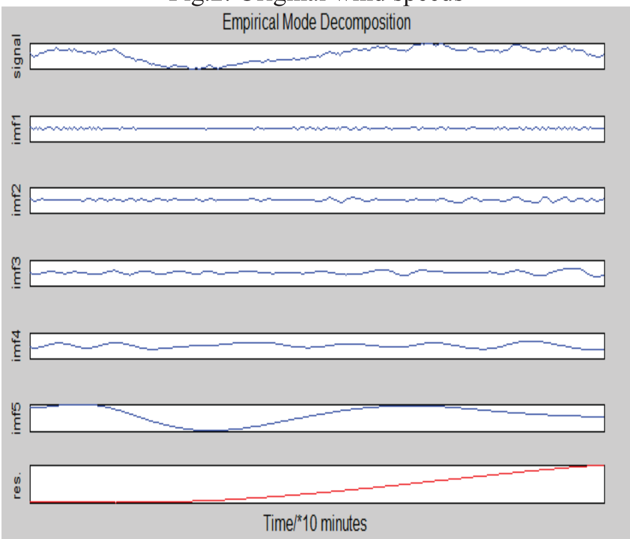

Fig.3. Results of EMD

Before forecasting each IMFs and residue, we should divide them into high and low frequency parts. Fig.4 demonstrates the frequency of the wind speeds of IMF3, while Fig.5 illustrates that of IMF4.

Clearly, the frequency of the first four components is high, while the frequency of the other components is low. We may

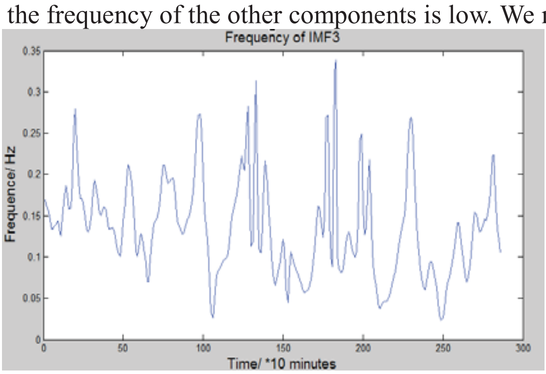

Fig.4. Frequency of IMF3

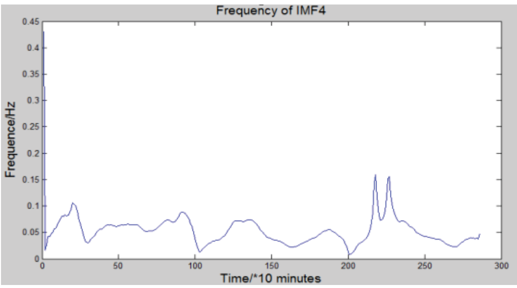

Fig.5. Frequency of IMF4

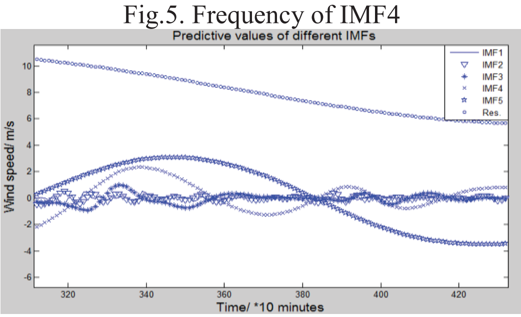

Fig.6. Predictive values of each IMF

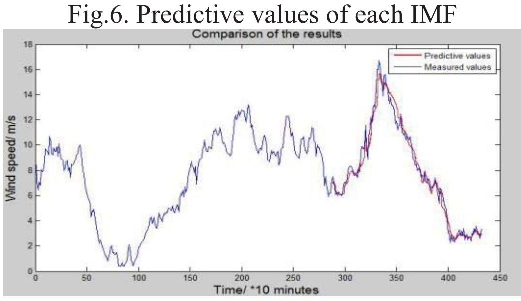

Fig.7. Comparison of the results

predict the wind speeds of each component respectively, shown in Fig.6. The forecasting results from each part are summarized as the future wind speed, which were compared to the measured values in Fig.7. The trends of the forecasting result can match that of the real one. However, the tracking of the extremes still needs to be improved. Table.1 listed the Relative Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) employing the traditional Persistence Approach, time-series analysis together with the proposed method. Compared with the other two traditional methods, the new method reduced almost a 13% and 4.8% MAPE respectively. Also the RMSE was greatly decreased.

Error	Persistence Approach	ARMA	Proposed Method
RMSE	1.5467	0.9472	0.3564
MAPE	20.37%	12.15%	7.32%

Table.1. Comparison of the forecasting error

6 Conclusions

In this paper, a novel approach for wind speed prediction is proposed. The problem of the proposed method is to preprocess the wind speed data and divide them into several stationary components that can be distinguished by their different frequencies. As a result, the coupling between all the characteristics information in data are weakened to some extent. Further, the corresponding predictive model is built. After each wind speed data are predicted, the results are summarized as the wind speed predictive results. Ten-minute ahead forecasting is used in this paper. The rigor of the arithmetic has been testified by example above. The interrelationship between the precision accuracy and the sampling period is analyzed in this paper. The proposed method is used to forecast a set of wind speed data collected from Jiangsu Province in China. The results indicate the effectiveness of the developed method in promoting the prediction precision.

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