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Short Term Wind Speed Forecasting Using Wavelet Transform and Grey Model Improved by Particle Swarm Optimization

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***Abstract*—Nowadays wind energy is one of the most important source of renewable energy worldwide. Wind power generation is an important form of wind energy utilization. The energy problem has become increasingly prominent, which requires to speeding up the development of wind energy industry. However, the existing wind speed forecasting using grey model is inaccurate. Direct prediction of original wind speed sequence produces large error because of the randomness of wind power. To solve the above problems, a novel method for short term wind speed forecasting based on grey model is proposed in this paper. In order to reduce the error of short term wind speed forecasting, one of the most successful approaches is particle swarm optimization algorithm, which chooses the parameters of grey model to avoid the man-made blindness and enhances the efficiency and capability of forecasting. In the present paper, the wavelet decomposition and reconstruction are used to separate the high frequency signal and the low frequency signal. To verify its efficiency, this proposed method is applied to a wind farm's wind speed forecasting in China. The result confirms that the performance of the method proposed in this paper is much more favorable in comparison with the original methods studied.**

Keywords—wind speed forecasting; wind power generation; grey model; particle swarm optimization algorithm; wavelet decomposition

I. INTRODUCTION

Wind energy is the most important source of renewable energy worldwide. It is very fast rate of growth implies for the electrical systems to be able to absorb large amounts of wind power and deliver it to the market. Wind speed has a close relationship with the efficiency of wind power generation. Therefore, reliable wind speed prediction systems are required for time scales. The simplest method is the continuous prediction method [1], which makes the closest point of the wind speed the forecast of the next point. Although the method is simple and easy to operate, the prediction effect is not stable. Other methods are time series method [2], fuzzy logic, *ANN* (Artificial Neural network) [3-5] and so on.

Often, both physical and statistical models are utilized together, where NWF results are usually regarded as input variables, together with historical data, to train the system on the local conditions according to statistical theories [6]. Ref [7] presents a robust two-step methodology for accurate wind speed forecasting based on Bayesian combination algorithm, and three neural network models. Ref [8] develops an improved grey forecasting model, which combines residual modification with genetic programming sign estimation. Ref [9] is based on *RVM* (relevance vector machine) the theory of phase space reconstruction.

GM (Grey Model) which can be used for short term wind speed forecasting is another method [10]. The results of forecasting obtained by this method are not accurate enough. Other methods should be integrated into improve the performance of *GM*. In this regard, Ref [11] proposes a new method of wind speed forecasting based on grey model, which is about the method of grey recursion. The basis of this dynamic change is time. Each moment has its own current parameters a, u. In Ref [12], based on the grey forecast *GM* (l, l) model and the stochastic processes Markov model, the deviation results of grey *GM* (l, l) model were used as the deviation transfer probability matrix of Markov model forecast. In Ref. [13], the Taylor approximation in the cubic spline function is applied to calculate the parameters of *GM* (T-3sp*GM*).

In this study, *PSO* (particle swarm optimization) is used to improve the grey model, and the wavelet decomposition and reconstruction are used upon the wind speed data. Then the high and the low frequency signal are forecast by *GMIPSO* (Grey Model improved by *PSO* Algorithm) respectively. Finally, the forecasting results of the original time series are the superposition of the respective forecasting results. To verify its efficiency, the proposed method is used for a wind farm's wind speed forecasting in China.

II. METHOD USED

In this paper, *WGMIPSO* (the combination of wavelet transformation and *GMIPSO*) is used to improve short term wind speed forecasting. This method consists of four stages including inputting data preprocessing, wavelet decomposition and reconstruction of data, training, testing and stacking data. At the first stage, historical wind speed data is pretreated to be input data. At the second stage, input data is manipulated with

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wavelet decomposition and reconstruction. At the third stage, the *PSO* method is used to determine the parameters of the *GM*. At the fourth stage, the high frequency component and the low frequency component of the next day is forecast. And the data of each component is added up to predictions. Fig.1 represents the flowchart of the proposed method.

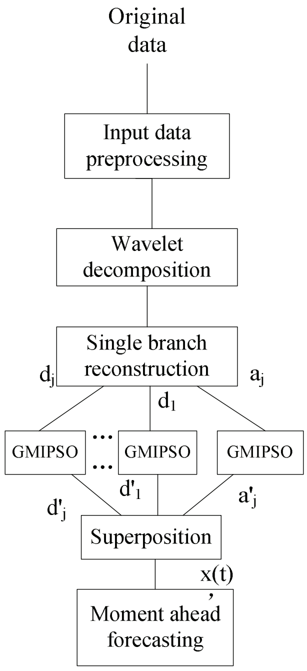


Fig.1 The general structure of the proposed method

A. Stage one: preprocessing input data

In this model, two consecutive numbers can be very different. This difference leads to the error of the wind speed forecast. In order to solve this problem, the wind speed at the moment ($m+1$ th input variable) and in the previous time (m th input variable) should be approximate. It is based on the following equation:

$$X_s(m+1) = X_s(m) + (X_s(m+1) - \frac{X_s(m)}{3}) \tag{1}$$

B. Stage two: wavelet decomposition and reconstruction of the data

The mean value of nonstationary series forecasting is trend. Therefore, the accuracy of the method is not only affected by the choice of the model, but also affected by the signal processing. The high frequency signal is a fluctuation, reflecting the details of the original signal, while the low frequency signal is a trend term, reflecting the general trend of the original signal. The high frequency signal and the low frequency signal are separated as the input for predicting. It ensures that the over-fitting of high frequency signal is reduced. The accuracy of the prediction also can be improved.

Each input sequence of the system is modeled by *GM* is $X_s = \{x_1, x_2, x_3 \ldots\}$. They are non-stationary short term wind speed series. After wavelet decomposition of the series, the time series of each layer is reconstructed.

Original series are as follows:

$$X_s = G_1 + G_2 + G_3 + X_3 \tag{2}$$

Where G_1, G_2, G_3 are the high frequency signal which are restructured from the first lay to the third lay. X_3 is the low frequency signal restructured in the third lay.

The elements of original series are as follows:

$$X_{s,i} = G_{1,i} + G_{2,i} + G_{3,i} + X_{3,i} \tag{3}$$

C. Stage three: training GM by PSO

1) *Grey model*

The grey system theory modeling is to find the mathematical relationship between the elements. In the grey model, the relationship between the unknown data and the output variables of the system can be considered as a differential equation model [14]. It should be noted that *GM* (1, 1) is used in the first-order grey model with 1 input variable for the short term wind speed forecasting problem. This paper takes reconstructed components as input one by one. Let be the input $X^{(0)}$.

a) Accumulated generating operation (AGO)

The *AGO* of each input sequence of the system modeled and each element of $X^{(1)}$ is as follows by *GM* is as follows, where $X^{(1)}$ is the *AGO* of $X^{(0)}$:

$$X^{(0)}(1) = X^{(1)}(1) \tag{4}$$

$$X^{(1)}(k) = \sum_{m=1}^{k} X^{(0)}(m), k = 2,3,...N \tag{5}$$

It should be noted that the superscript 1 denotes the *AGO* of the original sequences, and $N = 5$.

b) Calculation of the system background value

At this stage, the system background value is as follows:

$$z^{(1)}(k) = gX^{(1)}(k) + (1-g)X^{(1)}(k-1), k = 2,3...N \tag{6}$$

where g is the generating coefficient, and it is a positive value smaller than 1. It can be determined via *PSO*.

c) The determination of grey system equation

The equation is established as follows between the values of known system and unknown:

$$X^{(0)}(k)+az^{(1)}(k)=bX^{(1)}(k) \tag{7}$$

where a is development coefficient, b is the grey input coefficients obtained by the least squares method. To determine these coefficients, the matrix B and Y_N are defined as follows:

$$B=\begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(N) & 1 \end{bmatrix} \tag{8}$$

$$Y_N=\begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ \vdots \\ X^{(0)}(N) \end{bmatrix} \tag{9}$$

The values of coefficient a, b are determined by the following formula：

$$\begin{bmatrix} a \\ b \end{bmatrix}=(B^T B)^{-1} * B^T * Y_N \tag{10}$$

d) Determination of the differential equation

Having determined the coefficient a, b, the grey system differential equation is determined as follows:

$$\frac{dX^{(1)}}{dt}+aX^{(1)}=b \tag{11}$$

The solution of the above differential equation is as follows:

$$\hat{X}^{(1)}(k+1)=\{X^{(0)}(1)-b/a\}\times e^{-\hat{a}k}+b/a, k\geq 1 \tag{12}$$

where $\hat{X}^{(1)}(k)$ is the prediction of each component *AGO*.

By considering the estimation of the first element of the first *AGO* of a sequence is equal to the first element of the sequence, the following relation is determined:

$$\hat{X}^{(1)}(1)=X^{(0)}(1) \tag{13}$$

e) Inverse accumulated generating operation (IAGO)

Finally, to forecast the elements of original sequences, IAGO should be applied to the result. Then the prediction values are determined as follows:

$$\hat{X}^{(0)}(k)=\hat{X}^{(1)}(k)-\hat{X}^{(1)}(k-1), k\geq 2 \tag{14}$$

where $\hat{X}^{(0)}(k)$ is the estimated value of original sequence. It should be noted that the previous 5 wind speed figures act as inputs, when forecasting with *GM* (1, 1).

2) *Determining the g coefficient by PSO (training GM)*

The particle swarm is a population-based stochastic algorithm for optimization which is based on social–psychological principles. Unlike evolutionary algorithms, the particle swarm does not use selection; typically, all members survive from the beginning of a trial until the end. Their interactions result in iterative improvement of the quality of problem solutions over time [15].

A numerical vector of D dimensions, usually randomly initialized in a search space, is conceptualized as a point in a high-dimensional Cartesian coordinate system [13]. Each particle i has D-dimensional position vector $Xi=(Xi1,\ Xi2,\ldots,\ XiD)$ and velocity vector $Vi=(Vi1,\ Vi2,\ldots,\ ViD)$. When searching for the solution in search space, i will eventually become the best position in the search process, $Pi=(Pi1,\ Pi2,\ldots,\ PiD)$. In the iteration, the particle j will adjust its speed to its position according to its specific characteristics, the experience obtained from the other particles or their own, and the best position in the search process, $Pg=(Pg1,\ Pg2,\ldots,\ PgD)$. Where $c1$, $c2$ are acceleration factors, both of which are positive constants; $r1$, $r2$ are random numbers, evenly distributed from 0 to 1; d is the number of dimensions; ω is inertia weight factor.

PSO is used to determine the optimum value of generating coefficient. The optimum value is determined by solving the following optimization problem.

$$\mathit{Minimize}\ \sum_{i=1}^{10} MAPE_i\ ,\ \mathit{subject\ to}\quad 0\leq g\leq 1 \tag{15}$$

The process of securing the optimum value of generating coefficient in the grey model is as Fig.2.

A set of particles are randomly selected as the initial values to fit the particle swarm optimization algorithm model to search the objective space for new solutions. The position and the velocity of every particle at the iteration k in the search space are described by X_k^i and V_k^i .Each particle records its best local position P_{lbest}^l. Then, the velocity of particle i in the iteration $k+1$ is obtained from the following equation:

$$V_{k+1}^i=\omega\cdot V_k^i+c_1\cdot r_1(P_{lbest}^i-X_k^i)+c_2\cdot r_2(P_{global}^i-X_k^i) \tag{16}$$

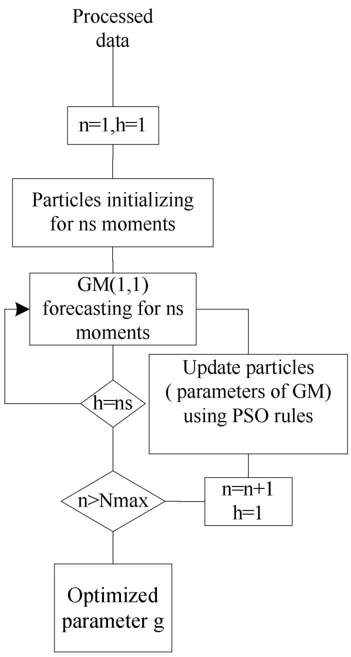


Fig.2 Determining the coefficient of *GM* using *PSO*

The equation is composed of three parts as follows.

(1) The initial value of the particle velocity. If large, it will help the global search； if small, it will help local search. It can make the global search and local search a relatively suitable state.

(2) The orientation of the particles themselves. The value changes with the changes of $c1$ and $r1$. It enhances the ability of global search according to the experience of the current search tendency.

(3) Cross learning between particle swarm. The value changes with the changes of $c1$ and $r1$. It implies that the information and experience in the particle swarm are cross shared, and transmit in multi direction.

The three parts of the above equations make the particle group constantly change their position and speed to reach an optimal value according to its orientation, namely its search experience.

ω is calculated by (17).

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})}{k_{\max}} \times k \qquad (17)$$

where $k_{\max}$ is maximum number of iterations. At each iteration, each particle's new position is calculated by adding its previous position to its current speed:

$$X_{k+1}^{i} = X_{k}^{i} + V_{k+1}^{i} \qquad (18)$$

D. Stage four: testing and stacking data

The optimal value of g has been determined with grey model training optimized by *PSO*. At this stage, the required input is called the test set. The test procedure uses the decomposed and reconstructed data of the first few moments (stage 2) as well as the optimal values of the parameters (stage 3). Output is the forecast value of each component. The outputs should be stacked, returning the result of the *GMIPSO* model for short-term wind speed forecasting.

III. Evaluating Procedure

There have been many ways to evaluate the error of wind speed forecast. There are some methods such as: *APE* (Absolute Percentage Error), *MAPE* (Mean Absolute Percentage Error), *MAE* (Mean Absolute Error), *MPE* (Mean Absolute Error). The definitions of these methods are as follows:

$$APE_i = (\frac{|L_f - L_a|}{L_a}) \times 100 \qquad (19)$$

$$MAPE = (\frac{1}{n}) \sum_{i=1}^{n} APE_i \qquad (20)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |L_f - L_a| \qquad (21)$$

$$MPE = \frac{1}{n} \sum_{i=1}^{n} \frac{L_f - L_a}{L_a} \times 100 \qquad (22)$$

where L_f and L_a are the predicted value and the actual value of wind speed, respectively. i expresses the time, and n is the number of moment. These indexes are used to evaluate the performance of the method.

IV. Results and Discussions

A set of wind speed data from a wind farm, recorded from mid-April to July 2009 is selected. Arranged in chronological order, the data of first 1163 figures is training sample, and of the following 288 figures is testing sample. The data is shown in Fig.3. The result of wind speed forecasting with traditional grey model is as follows. The *MAE* is 0.4948, and the *MAPE* is 9.0012%. *MAE* and *MAPE* of the *GMIPSO* are 0.4836 and 8.8045% respectively. *MAE* and *MAPE* of the *WGMIPSO* are 0.1283 and 8.1678% respectively. All above are shown in Table I. Actual speed and forecast speed using the original *GM*, *GMIPSO*, *WGMIPSO* for the wind farm are presented in Fig.4 respectively.

As is shown in Table I, *MAE*, as well as *MAPE*, decreases gradually from *GM* to *GMIPSO*, and then *WGMIPSO*. It can be concluded that *PSO* can effectively improve the traditional grey model for short term wind speed forecasting. The high frequency signal and the low frequency signal are separated, and are input onto prediction model respectively. It ensures that the fitting degree of low frequency components is improved, and the over-fitting of the high frequency components is reduced. In short, the method can effectively improve the accuracy of prediction.

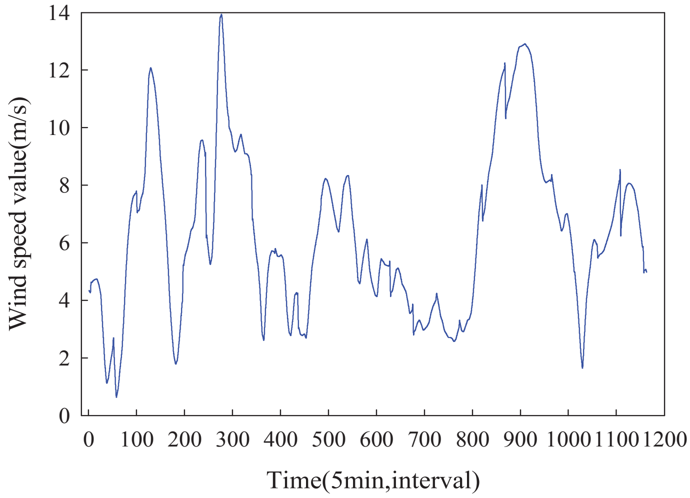
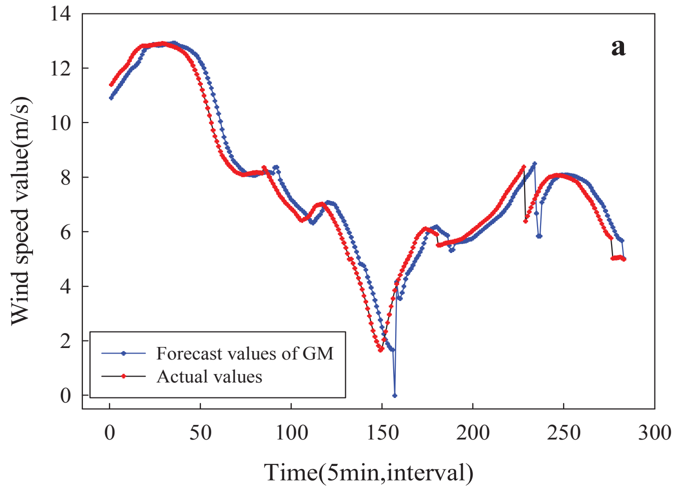


Fig.3 Original wind speed data of the wind farm



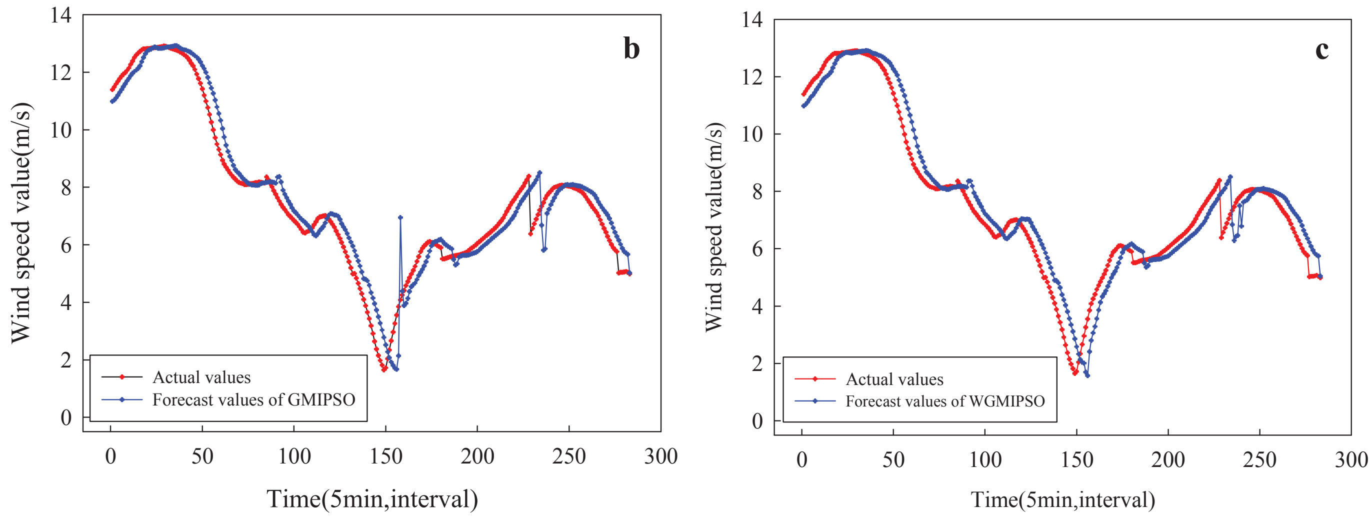


Fig.4 Actual speed (red-line) and forecast speed (blue-line) for the wind farm of *GM*, *GMIPSO*, *WGMIPSO*

TABLE I. COMPARING THE MAE, MAPE OF SHORT TERM WIND SPEED FORECASTING

	GM	*GMIPSO*	*WGMIPSO*
MAE	0.4948	0.4836	0.1283
MAPE	9.0012	8.8045	8.1678

It is noted that the *MAE* of *WGMIPSO* is very different from the other two methods. It is concluded that although the forecast accuracy of *WGMIPSO* is not obvious in most cases, the possibility of a large error in a certain point is smaller. That is, the stability of the forecast will be higher.

V. Conclusion

Combining the advantages of *WT* and *PSO*, short term wind speed forecasting based on grey model is the focus of this study. Once the history wind speed data collection is relatively completed, *WT* can be applied to decompose it to different frequencies and the grey forecast model can be established. The generating coefficient values and wind speed fitting values can be obtained, which are optimized by *PSO*.

As an exponent model, *GM* (l, l) model deviation is inherent itself and is inevitable. It will be more satisfaction that an approximate background value is chosen in grey model. And the high frequency signal and the low frequency signal are separated to input into prediction model respectively, so as to improve the fitting degree of low frequency components and reduce the over-fitting of the high frequency components.

The improved grey model was then applied to predict the wind speed of a wind farm. Finally, through this study, the improved grey model in this paper is an appropriate forecasting method to yield more accurate results than the original *GM* (l, l) model.

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