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An improved Grey-based Approach for Short-Term Wind Power Prediction

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Abstract

With the expansion of wind farm installations in most countries all over the world, the power generation has already significantly influenced on the stability and security of the power grid after grid-connection. Wind power forecasting is an effective method for guarantees stability of the power output from wind farm. This paper proposed an improved GM(1,1) based prediction method, and focuses on the wind power online prediction using the relationship between the wind speed and the wind power generation. The simulation results have verified that the developed approach, with GM rolling mechanism, data preprocessing and background value optimizing has better prediction precision over the traditional GM rolling model and data series smoothing model. Finally, utilized a case study at Azuoqi wind farm located in Inner Mongolia province of China, which obviously realized wind power generation prediction for optimizing the wind power control in the wind farm in real time.

Keywords: *Grey theory, GM(1,1), prediction, wind power*

1. Introduction

Nowadays, wind power generation is undergoing the fastest rate of growth of any form of electricity generation in the world. The power generation from the wind farms has significant influenced on the stability and security of the power grid after grid-connection. For a certain type of wind turbine, max output power is fixed under certain wind speed. In other words, wind power can indirectly predicted by forecasting wind speed at the hub height of each wind turbine, through the manufacture's power curve [1-4]. The physical approach invested for wind speed forecasting, which uses topographical information of the site to describe the wind flow in detail applying fluid dynamics equations [5]. Wind speed prediction is an effective method for power control.

In recent decades, several time-series-based models have been studied for wind speed forecasting, such as autoregressive (AR), moving average (MA) algorithm. Artificial intelligence and hybrid models, including adaptive network based Fuzzy interference system (ANFIS) and radial basis function (RBF), are also involved for hourly wind speed forecasting [6-9]. These models require large set of historical data for their parameters estimation, strong machine learning ability or complicated computing process, which limited application in real wind farm.

Grey system theory is suited to predict with poor data [10]. More and more scholars has tried to take GM(1,1) model into the study of prediction when lacking of large number of historical data for learning and computing power is limited [11, 12]. While the traditional GM(1,1) model is appropriate for steady development tendency of prediction background, lots of transformation methods proposed and most of them cannot work well when the discrete series change rapidly. Wind speed in wind power plant always changes sharply, so, it is necessary to find a more efficient method for wind speed forecasting.

In this paper, an improved GM(1,1) model proposed for predicting wind power continuously. First, rolling mechanism introduced for forecasting wind speed continuously, and only four historical values needed in one prediction cycle. Second, we preprocess data series with smoothing method and optimize background value of traditional algorithm, which improved prediction accuracy in the very great degree. Finally, the proposed approach is illustrated by implementing it in the wind speed and active power prediction of a middle-size wind power plant.

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2. Research Method

The common processes of traditional GM(1,1) algorithm for wind speed forecasting listed as below [10].

2.1. Accumulated Generating Operation (AGO)

Serve the sample data of wind speed, collected from wind turbine, as the input data set $V^{(0)} = \left\{V^{(0)}(1), V^{(0)}(2), ..., V^{(0)}(n)\right\}$ for the GM(1,1) modeling, and at least four data included in the data set. Then, a new accumulated row matrix $V^{(1)}$ generated by the first-order Accumulated Generating Operation (1-AGO).

$$V^{(1)} = \left\{V^{(1)}(1), V^{(1)}(2), ..., V^{(1)}(n)\right\} \tag{1}$$

$$\begin{cases} V^{(1)}(1) = V^{(0)}(1) \\ V^{(1)}(i) = \sum_{k=1}^{i} V^{(0)}(k) \end{cases} \quad \forall\, i = 1, 2, ..., n \tag{2}$$

2.2. Grey Differential Equation and Parameters Identification

The definition of GM(1,1) Model is formulated as:

$$V^{(0)} + az^{(1)}(i) = b \tag{3}$$

Where $z^{(1)}$, the background value, can be expressed as follow,

$$z^{(1)}(i) = \frac{1}{2}\left[V^{(1)}(i) + V^{(1)}(i-1)\right] \qquad \forall\, i = 2, ..., n \tag{4}$$

And the first-order whitened differential equation expressed as:

$$\frac{dV^{(1)}}{di} + \alpha V^{(1)} = b \tag{5}$$

2.3. Parameters Identification of the GM(1,1) Model

The parameters a and b can be calculated with the least square method as follow:

$$\begin{bmatrix} a & b \end{bmatrix}^T = (B^T B)^{-1} B^T Y \tag{6}$$

Where the matrixes B and Y can be expressed by:

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ ... & ... \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{7}$$

$$Y = \begin{bmatrix} V^{(0)}(2) \\ V^{(0)}(3) \\ ... \\ V^{(0)}(n) \end{bmatrix} \tag{8}$$

2.4. Calculate Prediction Value

Finally, the predicted time-series data $\hat{V}^{(1)}$ can be obtained by method of inverse accumulated generating operation (IAGO):

$$\begin{cases} \hat{V}^{(0)}(1) = \hat{V}^{(1)}(1) \\ \hat{V}^{(0)}(i+1) = (1-e^{a})\left[V^{(0)}(1) - \frac{b}{a}\right]e^{(-ai)} \end{cases} \quad (9)$$
$$\forall\, i = 1, 2, \ldots, n$$

2.5. Prediction Precision

The precision of prediction can be tested by the size of residuals and relative errors. Relative error $\phi(i)$ can be calculated as is shown in Equation (10):

$$\phi(i) = \frac{\left|V^{(0)}(i) - \hat{V}^{(0)}(i)\right|}{V^{(0)}(i)} \qquad \forall\, i = 1, 2, \ldots, m \quad (10)$$

Where m is the number of predicted values. And average error $\phi(avg)$ is expressed as:

$$\phi(avg) = \frac{1}{m}\sum_{i=1}^{m}\phi(i) \qquad \forall\, i = 1, 2, \ldots, m$$

3. Improved GM(1,1) Algorithm

3.1. Rolling Modeling and Wind Speed Prediction

The traditional GM(1,1) model can only be used for predicting limited number of data series, and rolling modeling mechanism is involved for predicting the continuous wind speed data series [10]. The method of rolling modeling is refreshing the real wind speed data series $V^{(0)}$, which has four data in this work, by removing the oldest value and inserting into the latest one. When the prediction finished with data series begin with $V^{(0)}(i)$, and $V^{(0)}$ will changed as follow by rolling.

$$V^{(0)} = \left\{V^{(0)}(i+1), V^{(0)}(i+2), \ldots, V^{(0)}(i+n)\right\} \quad (12)$$

Above operations repeated as long as newer wind speed value existed.

3.2. Optimizing the Background Value

From the prediction process of GM(1,1), we can see that prediction precision depends on parameters a and b, i.e. precision is closely related to original data series $V^{(0)}$ and background value $z^{(1)}(i)$.

In traditional GM(1,1) algorithm, Equation (4) is chosen to describe the background value based the assumption that there is no mutations appeared in a very short time interval. However, being a short period of time, Δt is only a relative conception. In this period of time, the change of wind speed may include mutations, as is shown in Figure 1.

A integral equation can be obtained from traditional GM(1,1) model in Equation (3) at region $[i-1, i]$.

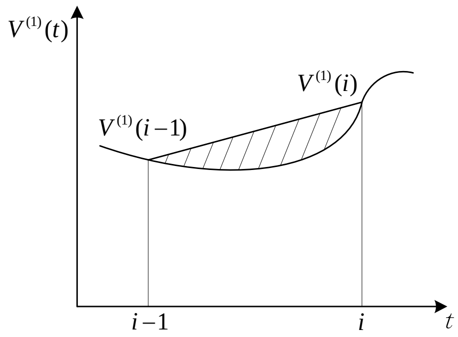

Figure 1. Error of Background Value

$$\int_{i-1}^{i}\frac{dV^{(1)}}{dt}dt + a\int_{i-1}^{i}V^{(1)}dt = b$$ i.e.

$$V^{(0)}(i) + a\int_{i-1}^{i}V^{(1)}dt = b \tag{13}$$

Comparing Equation (13) with GM(1,1) model in Equation (3), it is easy to find out that error comes from replacement $\int_{i-1}^{i}V^{(1)}dt$ by $z^{(1)}$.

In order to eliminate the error, $z^{(1)}$ can be calculated as follows,

$$z^{(1)}(i) = [1-\alpha(i)]V^{(1)}(i) - \alpha(i)V^{(1)}(i-1) \tag{14}$$

Where α determined by method of 'average system slope' [13] with the following rules:

1) $$\alpha(i) = \begin{cases} 0 & k_i \le i-2 \\ k_i & i-2 < k_i < i-1 \\ 1 & k_i \ge i-1 \end{cases}$$

$$\forall i = 2,3,\ldots,n-1$$

2) $\alpha(n)=1$

And the relative positions k_i determined by the following formula:

$$k_i = \frac{\ln\left(V^{(0)}(i) - V^{(0)}(1)\right)}{\ln\left(\sigma_{avg}\right)} \tag{15}$$

Where the average slope coefficient σ_{avg} calculated as follow:

$$\sigma_{avg} = \sqrt[(n-1)]{\frac{V^{(0)}(n)}{V^{(0)}(1)}} \tag{16}$$

3.3. Smoothing the Original Data Series

Equation (14) developed with the assumption that original data series is based on the homogeneous exponential law, and smoothness characteristic of original data series is the main factor that influences the prediction precision. Thus, it is necessary to preprocess the original data, to make it more smoothness and close to the characteristic of exponential law.

Function $\frac{1}{a-e^{-bx}}$ was utilized to improve the smoothness of original series, thus prediction accuracy improved [12]. But lots of nonsense predictive values appear when we use this function for predicting wind speed continually. So, the sum of mean value and max differ value served as reduction buffer operator d_{reduc} to eliminate the abnormal prediction results.

For keeping consistency of the equations as before, the original wind speed series expressed as $X^{(0)}$, instead of $V^{(0)}$. Before operation (1-AGO) in (1), series $V^{(0)}$ established from $X^{(0)}$ by the formula:

$$V^{(0)}(i) = \frac{1}{a - e^{-bX^{(0)}(i)}} + d_{reduc} \tag{17}$$

Where d_{reduc} can be calculated as:

$$d_{reduc} = \frac{1}{n}\sum_{i=1}^{n} V^{(0)}(i) + \max\left\{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[V^{(0)}(i) - V^{(0)}(j)\right]\right\} \tag{18}$$

Accordingly, the final prediction data will expressed as:

$$\hat{X}^{(0)}(i+1) = b\ln\frac{\hat{V}^{(0)}(i+1)}{a\hat{V}^{(0)}(i+1) - 1} - d_{reduc} \tag{19}$$

Once collected the current wind speed value, wind speed of next time interval can be predicted with the improved algorithm. Figure 2 shows the prediction process based on the improved GM(1,1) rolling model for wind speed prediction.

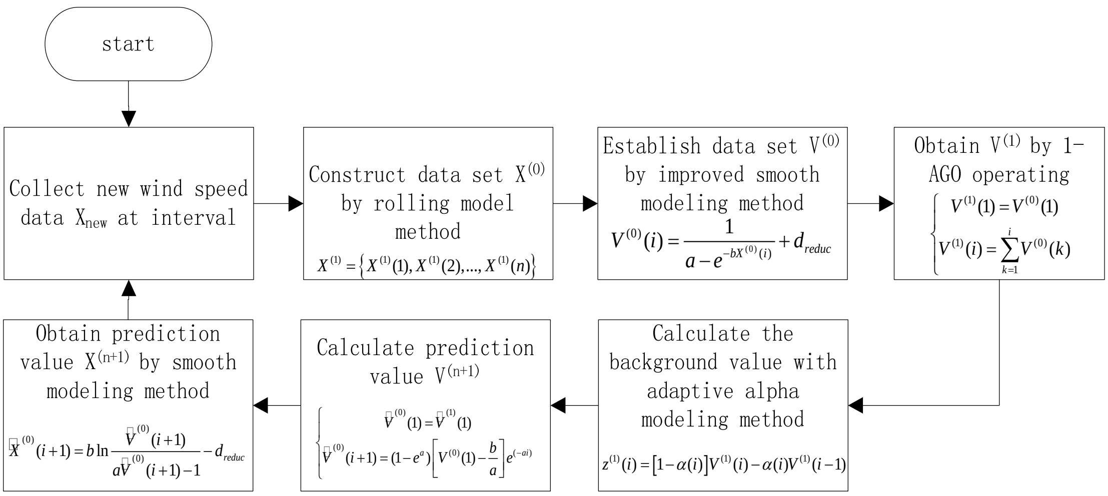

Figure 2. Flow Chart of Wind Speed Prediction with Improved GM(1,1) Algorithm

4. Results and Analysys

Sample data of wind speed and power collected from Azuoqi wind farm located in Inner Mongolia province of China. The rate power of wind turbine is 1.5MW, which is characterized by a cut in wind speed of 3m/s, rated wind speed of 11.7m/s and a cutting out wind speed of 25m/s.

Original wind speed data was sampled every 100 milliseconds from anemometers mounted on cabin of the wind turbine, and the mean value in 5 minutes calculated for active power prediction. In order to ensure the precision of prediction, 3 decimal digits retained in the mean value of 5 minutes. A whole day's sample data set of wind speed and power collected from one wind turbine, as presented in Figure 3.

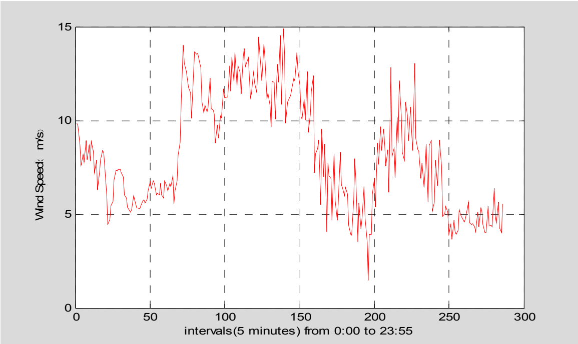

Figure 3. Sample Data Set of Wind Speed

From Figure 3, we can see that wind speed keeps stable relatively between point 41th and 60th, while continues change sharply between point 160th and 240th in the sample data set. So, we will verify the algorithm prediction precision not only with the wind speed data series of whole day and in the condition of stable and raped changing.

4.1. stable Wind Simulation

We selected real wind speed data set from 41th to 60th as S1 to verify the algorithms, and S2={5.32, 5.35, 5.28, 5.45, 5.74, 5.78, 5.59, 5.83, 6.25, 6.72, 6.37, 6.79, 6.65, 6.03, 6.12, 6.02, 6.63, 6.05, 5.86, 6.77}. Prediction results with different methods listed in Table 1.

Table 1. Prediction Result when Wind Speed Change Gently

Time point	real wind speed (m/s)	predicted wind speed(m/s) and MRE		
		Traditional GM(1,1)	Smooth GM(1,1)	Improved GM(1,1)
45th	5.74	5.46(4.85%)	5.45(4.98%)	5.45(5.07%)
46th	5.78	5.97(3.24%)	5.95(2.86%)	5.81(0.59%)
47th	5.59	5.99(7.19%)	6.01(7.50%)	5.87(5.07%)
48th	5.83	5.56(4.70%)	5.55(4.87%)	5.56(4.69%)
49th	6.25	5.78(7.45%)	5.78(7.60%)	5.81(7.07%)
50th	6.72	6.58(2.07%)	6.54(2.71%)	6.35(5.47%)
51th	6.37	7.21(13.16%)	7.17(12.63%)	6.89(8.18%)
52th	6.79	6.57(3.31%)	6.58(3.14%)	6.45(5.00%)
53th	6.65	6.70(0.73%)	6.68(0.38%)	6.76(1.67%)
54th	6.03	6.88(14.16%)	6.92(14.68%)	6.67(10.63%)
55th	6.12	5.77(5.66%)	5.69(6.98%)	5.90(3.55%)
56th	6.02	5.74(4.57%)	5.81(3.53%)	5.98(0.62%)
57th	6.63	6.05(8.80%)	6.05(8.81%)	6.03(9.09%)
58th	6.05	6.79(12.29%)	6.69(10.55%)	6.65(9.84%)
59th	5.86	6.26(6.87%)	6.25(6.59%)	6.09(3.99%)
60th	6.77	5.44(19.64%)	5.49(18.96%)	5.69(15.89%)
MRE	-	7.42%	7.30%	6.03%

From the value of mean relative error (MRE), we can see that improved GM(1,1) has better predicted result and the precision of prediction improved 18.7%, 17.4%, 0.5% comparing with traditional, smooth, and adaptive alpha-based GM(1,1) algorisms respectively.

4.2. Rapid Changing Wind Simulation

The wind speed data set from 206th to 225th in rapid changing wind speed section are selected as S2, and S2={9.54,8.57,7.58,8.45,6.18,12.83,8.11,8.52,6.93,10.16,8.31,12.14,10.23,8.32,7.86,10.99,10.3,8.92,10.74,9.44}. Prediction result of using the above mentioned methods based on rolling modeling technique to predict wind speed values listed in Table 2.

Table 2. Prediction Result when Wind Speed Change Rapidly

Time point	real wind speed (m/s)	predicted wind speed(m/s) and MRE		
		Traditional GM(1,1)	Smooth GM(1,1)	Improved GM(1,1)
210th	6.18	8.08(30.67%)	8.06(30.4)	8.34(35.00%)
211th	12.83	6.19(51.76%)	5.64(56.07%)	5.98(53.41%)
212th	8.11	15.32(88.94%)	8.25(1.76%)	10.75(32.50%)
213th	8.52	10.75(26.12%)	13.48(58.19%)	8.15(4.40%)
214th	6.93	5.94(14.22%)	7.42(7.00%)	8.23(18.75%)
215th	10.16	6.79(33.20%)	6.40(37.00%)	6.74(33.69%)
216th	8.81	10.49(19.04%)	8.65(1.79%)	9.64(9.40%)
217th	12.14	10.50(13.49%)	12.22(0.68%)	10.23(15.69%)
218th	10.23	12.68(23.91%)	10.78(5.36%)	11.79(15.21%)
219th	8.32	11.77(41.46%)	13.02(56.46%)	11.63(39.84%)
220th	7.86	6.95(11.52%)	7.17(8.83%)	7.64(2.78%)
221th	10.99	6.63(39.71%)	6.98(36.53%)	7.44(32.30%)
222th	10.3	12.26(19.00%)	10.08(2.16%)	10.57(2.65%)
223th	8.92	12.23(37.09%)	13.99(56.85%)	11.60(30.08%)
224th	10.74	8.19(23.78%)	8.06(24.91%)	8.61(19.80%)
225th	9.44	10.46(10.80%)	10.06(6.61%)	9.92(5.07%)
MRE	-	30.30%	24.41%	21.91%

When wind speed changes rapidly, the precision of prediction based on improved GM(1,1) increased 27.7% and 10.2%, comparing with that of traditional GM(1,1) algorithm and smooth GM(1,1) algorithm respectively.

4.3. Whole day wind speed simulation

In order to evaluate the actual result of these prediction methods, all data set of 13th May 2013 used for forecasting. The mean absolute error (MAR) and MRE listed in Table 3.

Table 3. Statistic of whole Day Wind Speed Prediction

Prediction algorithm	MAE	MRE
traditional GM(1,1)	1.43	19.24%
smooth GM(1,1)	1.39	19.05%
improved GM(1,1)	1.18	16.01%

In Table 3, the smooth GM(1,1) modeling make out nonsense predict values in some points changing sharply, which result in the large error. The improved GM(1,1) model in this work using both data set smoothing and background value optimizing technologies has higher prediction precise comparing with the smooth GM(1,1) rolling model, with its MAE and MRE reduced by 15.1% and 15.96%, so the improved GM(1,1) rolling model have the best prediction precision among the three models.

4.4. Wind Power Prediction

Wind turbine has wind speed-power curve in theory, which can be used for calculating the active power by relationship between wind speed and wind power. So, the predictive wind power P_{pred} can be expressed as below,

$$P_{pred} = \begin{cases} 0 & v \notin [3, 25] \\ P_{rate} & v \in [17.5, 25] \\ P_{curve} & v \in [3, 17.5\} \end{cases} \tag{20}$$

Where P_{pred} is predicted wind power, P_{rate} the rate power of wind turbine, P_{curve} the queried wind power according to power-speed curve, v the predictive wind speed.

However, real situation of wind turbine, such as mechanical property and electrical character, is different from theory values which were calculated in the period of designing. Figure 4 shows the comparison of the theory curve and real wind speed-power points, real value close to theory value on the curve but not one and the same.

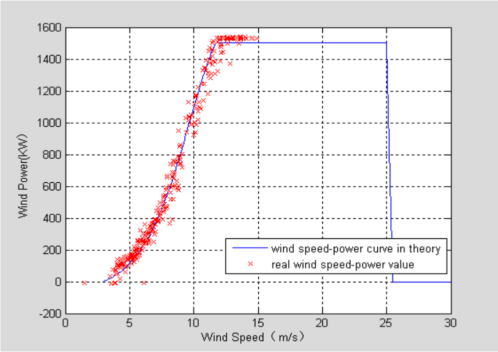

Figure 4. Power in Theory vs. Real Power

The curve expresses the relationship between wind speed and output power can be established by methods as below.

1) Serve the power value as reference value at every wind speed interval of 0.1m/s on theory curve.

2) Collect the wind speed and output power from wind turbine, and remove abnormal points.

3) Group the real power values on wind speed interval as before, and statistic offset from theory curve.

4) Revise reference values according offset value and frequency of occurrence.

The continuous predicted power calculated by the predicted wind speed data with the MAE value of 136.20 and MRE value of 23.72%. Comparison between predicted power and real power shown as Figure 5.

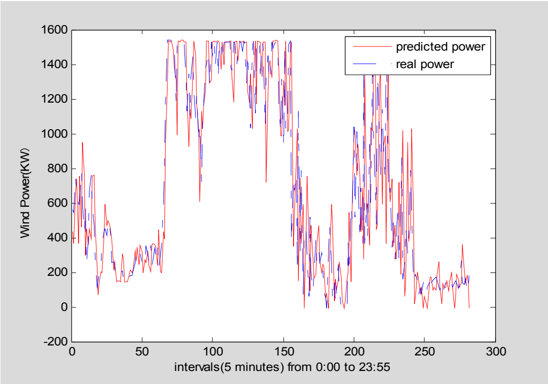

Figure 5. Wind speed-power curve in theory

5. Conclusion

The computing power and historical data are limited in most wind power plant, so a poor data required short-term wind power prediction algorithm is necessary for wind power prediction and control. An improved GM(1,1) rolling prediction model proposed in this paper with better performance in the very short-term prediction compared to other GM(1,1) based similar type methods with actual wind speed at a middle-sized wind farm. From the test results of real case, it can be seen that prediction precision of the improved algorithm are 18.7% and 27.7% higher than that of traditional algorithm under relatively gentle wind speed and rapid changing wind speed respectively. The wind power prediction result obtained based on the relationship between the wind speed and wind power with MRE value of 23.72%, which confirm that the improved GM(1,1) model is favorable for improving the accuracy of wind speed prediction and achieving wind power prediction.

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