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Wind farm power prediction based on wavelet decomposition and chaotic time series

Xueli An *, Dongxiang Jiang, Chao Liu, Minghao Zhao

State Key Laboratory of Control and Simulation of Power System and Generation Equipments (Dept. of Thermal Engineering, Tsinghua University), Haidian District, Beijing 100084, China

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ABSTRACT

In this paper, a prediction model is proposed for wind farm power forecasting by combining the wavelet transform, chaotic time series and GM (1, 1) method. The wavelet transform is used to decompose wind farm power into several detail parts associated with high frequencies and an approximate part associated with low frequencies. The characteristic of each high frequencies signal is identified, if it is chaotic time series then use weighted one-rank local-region method to predict it. If not, use GM (1, 1) model to predict it. And the GM (1, 1) model is also used to predict the approximate part of the low frequencies. In the end, the final forecasted result for wind farm power is obtained by summing the predicted results of all extracted high frequencies and the approximate part. According to the predicted results, the proposed method can improve the prediction accuracy of the wind farm power.

1. Introduction

The intermittence and uncertainty of wind power increases the instability of its interconnected power grid, with the large-scale wind power parallel in the power grid. It also has significant influence on the load distribution and the reasonable quality of power supply. In order to improve overall power system scheduling reasonableness, safety and economy, it is very important to predict wind farm power timely and accurately (Damousis, Alexiadis, & Theocharis, 2004; Kusiak, Zheng, & Song, 2009; Landberg, 1999; Louka, Galanis, & Siebert, 2008; Mabel & Fernandez, 2008; Pinson & Kariniotakis, 2004; Ramirez-Rosado, Fernandez-Jimenez, & Monteiro, 2009).

The actual wind power output variation is very complicated and difficult to establish its mathematical model, due to the power generation is known to be highly influenced by wind speed, wind direction, pressure, temperature, etc. meteorological data, and wind fields, topography, vegetation, surrounded by obstacles. Furthermore, it also is affected by the wheel hub height, power curve, mechanical drive, control strategy, and many other factors of the wind turbine itself (Damousis et al., 2004; Kusiak et al., 2009; Landberg, 1999; Louka et al., 2008; Mabel & Fernandez, 2008; Pinson & Kariniotakis, 2004; Ramirez-Rosado et al., 2009).

In this paper, a wind farm power prediction model is constructed based on wavelet transform, chaotic theory, and GM (1, 1) model. The wavelet transform is used to decompose the non-stationary wind farm power time series into several detail parts associated with high frequencies and an approximate part associated with low frequencies. After identifying their characteristics, the weighted one-rank local-region method or GM (1, 1) model is employed to make a short-term prediction for each part, respectively. Finally, the ultimate prediction result for the whole wind farm power is obtained by summing all predicted results. And the proposed method is applied to Dongtai wind farm which situates in the east of China, the predicted results is encouraging.

2. Wavelet transform

The wavelet transform is a mathematical tool for nonlinear and non-stationary signal analysis (Magosso, Ursino, & Zaniboni, 2009; Shahriar, Ilona, & Dominik, 2005; Yao, Song, & Zhan, 2000; Zhang, Coggins, & Jabri, 2001). It allows the decomposition of a signal into contributions from both the space and scale domains through a dilation and translation processes.

For a given square integrable signal $x(t)$, its continuous wavelet transform is defined as

$$\mathrm{CWT}(a,b) = a^{-\frac{1}{2}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right) dt, \tag{1}$$

where $\psi(t)$ is the mother wavelet, the a, b are scale parameter and location parameter, respectively.

By discretizing the parameters a and b, with $a = 2^j$, $b = k2^j$, j, $k \in Z$, the discrete wavelet transform of signal $x(t)$ can be obtained

* Corresponding author.
E-mail address: anxl614@163.com (X. An).

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$$\mathrm{DTW}(a,b)=\frac{1}{\sqrt{2^j}}\int_{-\infty}^{+\infty}x(t)\psi\left(\frac{t-2^jk}{2^j}\right)dt. \tag{2}$$

The discrete wavelet transform can decompose signal $x(t)$ into a hierarchical structure of details (high frequency) and approximations (low frequency) at limited levels as follows:

$$x(t)=D_1+D_2+\cdots+D_N+A_N, \tag{3}$$

where $D_1, D_2, \ldots, D_N$ represent the detail coefficients and A_N represents the approximation of the Nth level.

3. Chaotic property identification of wind farm power

3.1. Reconstruction of the phase-space

Wind farm power is affected by many factors, is a complex and nonlinear time series. In order to predict the time series using chaotic theory, an important step is determining the presence of chaotic property. A method for reconstructing a phase-space from a single time series has been presented by Takens (1981). When wind turbine is running, if the dynamics of a power time series $\{x(i)\}$, $(i=1,2,\ldots,n)$, are embedded in the m-dimensional phase-space ($m \geqslant 2d+1$, where d is the correlation dimension), then the phase-space can be defined by

$$Y(i)=[x(i),x(i+\tau),x(i+2\tau),\ldots,x(i+(m-1)\tau)], \tag{4}$$

where τ is the time delay; $i=1, 2, \ldots, N$, $N=n-(m-1)\tau$, is the number of elements of the wind farm power time series.

In this paper, the time delay τ and the embedding dimension m are calculated by the mutual information method (Fraser & Swinney, 1986) and the Cao's method (Cao, 1997), respectively.

3.2. Largest Lyapunov exponent

The Lyapunov exponent is an important parameter for depicting the characteristic of nonlinear time series. In order to determine chaotic behavior's presence of wind farm power, the Wolf method (Wolf, Swift, & Swinney, 1985) is used to compute the largest Lyapunov exponent, which measures the divergence of nearby trajectories. The Lyapunov exponent is the most basic and useful dynamical parameter for deterministic chaotic system. If it is positive then the wind farm power time series is chaotic and unstable. The magnitude of the Lyapunov exponent is a measure of the sensitivity to initial conditions.

4. Chaotic prediction of wind farm power

If the chaotic property of wind farm power can be determined, it can be predicted using chaotic method and the prediction results are valid for small prediction steps. In this paper, the weighted one-rank local-region method (Lv, Lu, & Chen, 2002) is used to predict the wind farm power. The detail process to formulate the weighted one-rank local-region method is described as follows:

- Step 1. Find nearest neighbor points.

In phase-space, assuming that Y_{ki} is the adjacent point of the center point Y_k, where $i=1, 2, \ldots, q$; d_i is the distance between Y_{ki} and Y_k; d_m is the minimum value among d_i ($i=1, 2, \ldots, q$), the weight of Y_{ki} is described below:

$$P_i=\frac{\mathrm{e}^{-l(d_i-d_m)}}{\sum_{i=1}^{q}\mathrm{e}^{-l(d_i-d_m)}}, \tag{5}$$

where l is constant coefficient, $l=1$ generally.

- Step 2. Weighted one-rank local linear is used to fit the neighborhood:

$$Y_{ki+1}=ae+bY_{ki}, \tag{6}$$

where $e=\begin{bmatrix}1\\1\\\vdots\\1\end{bmatrix}_m$, $i=1, 2, \ldots, q$; a, b are fitting parameters. When embedding dimension $m=1$, has

$$\begin{bmatrix}x_{k1+1}\\x_{k2+1}\\\vdots\\x_{kq+1}\end{bmatrix}=\begin{bmatrix}a+bx_{k1}\\a+bx_{k2}\\\vdots\\a+bx_{kq}\end{bmatrix}. \tag{7}$$

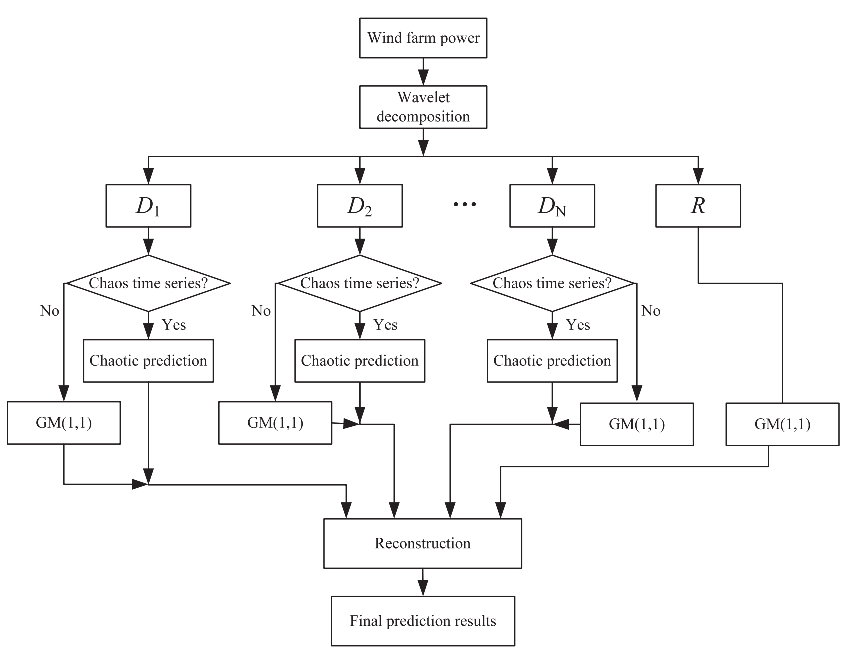

Fig. 1. Schematic diagram of wind farm power prediction based on wavelet decomposition, chaotic time series and GM (1, 1) model.

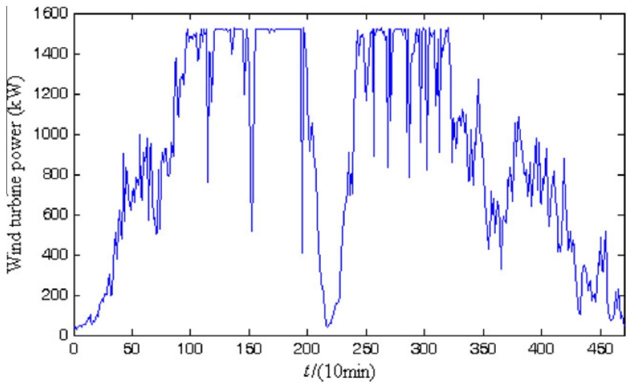

Fig. 2. The original data of wind turbine power.

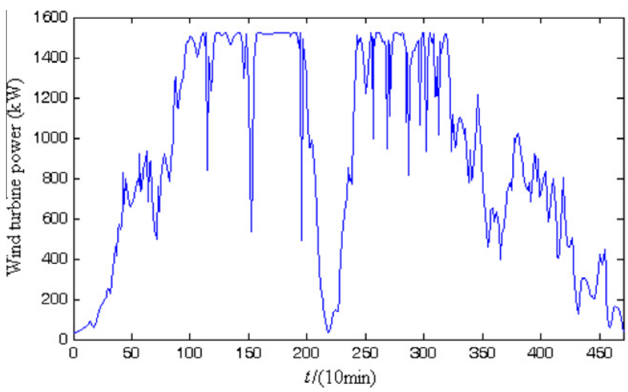

Fig. 3. The de-noised data of wind turbine power.

Using the weighted least squares, we obtain:

$$\sum_{i=1}^{q} P_i (x_{ki+1} - a - bx_{ki})^2 = \min. \tag{8}$$

The partial derivatives of Eq. (8) with respect to a, b, are calculated, respectively, as follows:

$$\sum_{i=1}^{q} P_i (x_{ki+1} - a - bx_{ki}) = 0, \tag{9}$$

$$\sum_{i=1}^{q} P_i (x_{ki+1} - a - bx_{ki}) x_{ki} = 0, \tag{10}$$

Eqs. (9) and (10) are used to calculate a, b:

$$a = \frac{\sum_{i=1}^{q} P_i x_{ki+1} \sum_{i=1}^{q} P_i x_{ki}^2 - \sum_{i=1}^{q} P_i x_{ki} \sum_{i=1}^{q} P_i x_{ki} x_{ki+1}}{\sum_{i=1}^{q} P_i x_{ki}^2 - \left(\sum_{i=1}^{q} P_i x_{ki}\right)^2}, \tag{11}$$

$$b = \frac{\sum_{i=1}^{q} P_i x_{ki} x_{ki+1} - \sum_{i=1}^{q} P_i x_{ki} \sum_{i=1}^{q} P_i x_{ki+1}}{\sum_{i=1}^{q} P_i x_{ki}^2 - \left(\sum_{i=1}^{q} P_i x_{ki}\right)^2}. \tag{12}$$

- Step 3. Prediction.

Substituting Eqs. (11) and (12) into Eq. (7), the one-step prediction valve Y_{ki+1} of Y_{ki} can be obtained. The predicted point Y_{ki+1} is then set as the new starting vector and repeat the process.

5. Wind farm power prediction based on wavelet decomposition, chaotic time series and GM (1, 1) model

This section provides a schematic overview of a forecasting procedure based on wavelet decomposition, chaotic time series and GM (1, 1) model. Due to wind farm power is highly nonlinear and non-stationary, it is very difficult to predict accurately. In order to improve prediction accuracy, the wavelet decomposition method is used to decompose the wind farm power to several detail parts associated with high frequencies and an approximate part associated with low frequencies. The basic idea is to consider the wind farm power which can be decomposed by empirical mode decomposition method in different scales. The scales contain contributions of the power of different frequencies. The GM (1, 1) model (Diyar & Mehmet, 2007; Kayacan, Ulutas, & Kaynak, 2010; Thananchai, 2008) is used to predict the approximate part of the low frequencies. For the decomposed data of high frequencies, identify their characteristics, if it is chaos time series then use weighted one-rank local-region method to predict. If not, use GM (1, 1) model to predict. Finally, the short term wind farm power is forecasted by summing the predicted approximate part and the high frequencies parts. The schematic diagram of the process is shown in Fig. 1.

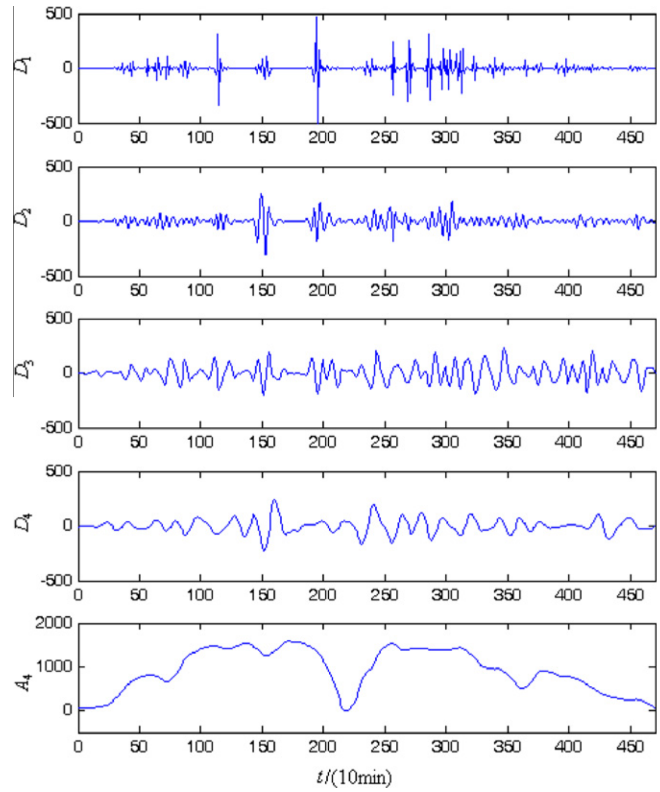

Fig. 4. Four level decomposition of the wind turbine power.

Table 1
Chaotic property identification of four level decomposition of the wind turbine power.

Decomposed power	τ	m	λ
D_1	7	7	0.3257
D_2	2	5	0.1959
D_3	4	6	0.2425
D_4	3	6	0.0631

The absolute error *AE*, relative error *RE*, mean relative error *MAPE*, normalized mean absolute error *NMAE*, and normalized root mean square error *NRMSE* (Louka, Galanis & Siebert, 2008), are used to measure prediction accuracy of different prediction methods. Their definitions are expressed as

$$AE(i) = p(i) - r(i), \tag{13}$$

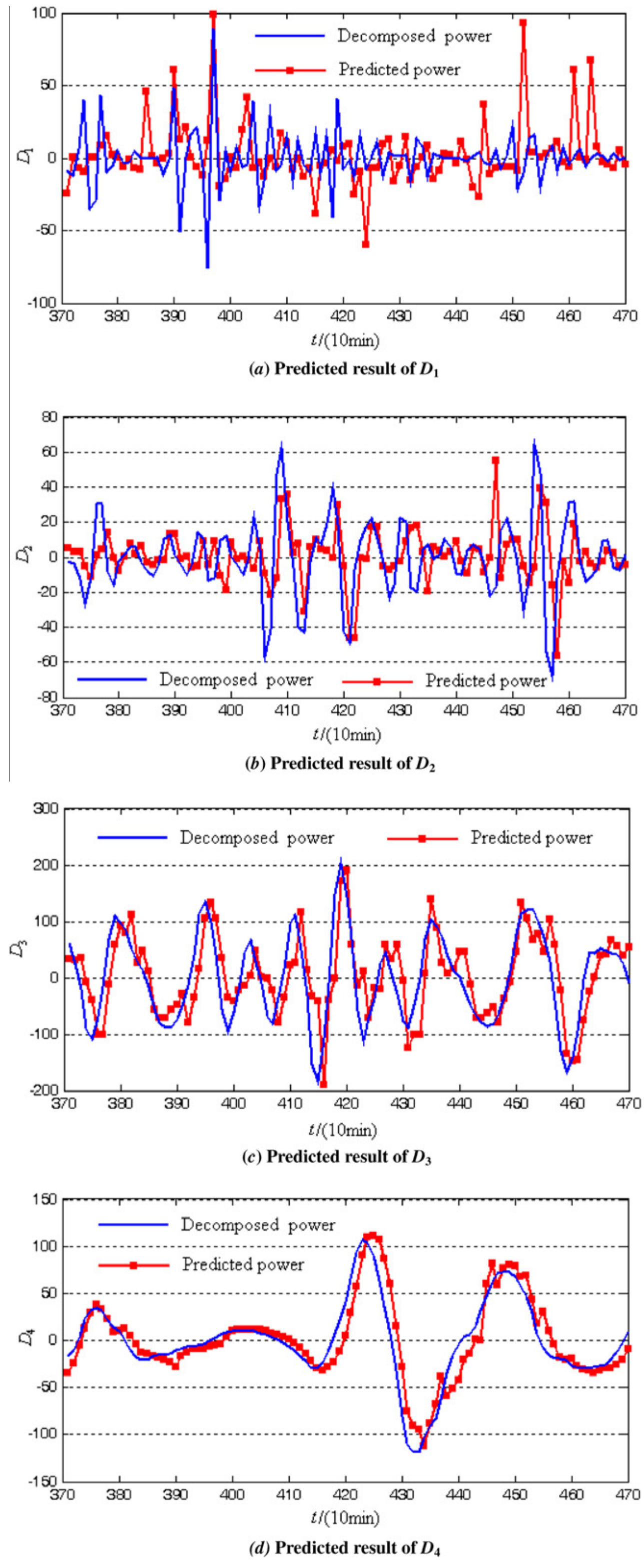

Fig. 5. The predicted results of wind turbine power using weighted one-rank local-region method.

$$RE(i) = \frac{p(i) - r(i)}{r(i)} \times 100\%, \tag{14}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|p(i) - r(i)|}{r(i)} \times 100\%, \tag{15}$$

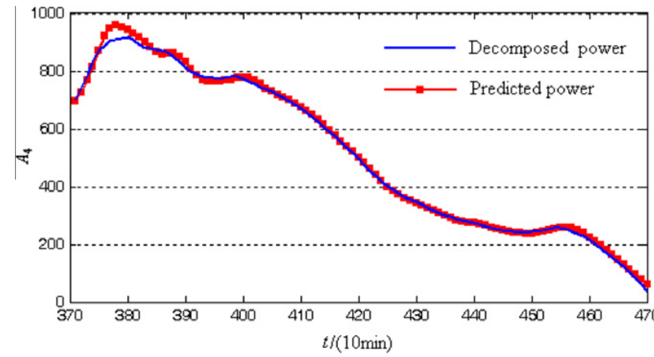

Fig. 6. The predicted results of wind turbine power using GM (1, 1) model.

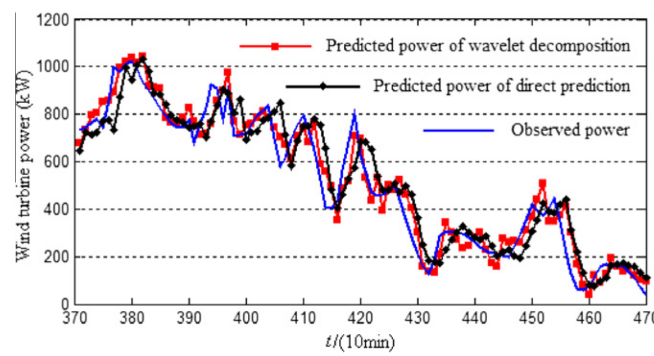

Fig. 7. The final predicted results of wind turbine power.

$$NMAE = \frac{1}{P_{inst}N} \sum_{i=1}^{N} |p(i) - r(i)| \times 100\%, \tag{16}$$

$$NRMSE = \frac{1}{P_{inst}} \sqrt{\frac{1}{N} \sum_{i=1}^{N} [p(i) - r(i)]^2} \times 100\%, \tag{17}$$

where $r(i)$ is the real wind farm power, $p(i)$ is the predicted power, N is the test samples number for prediction model, P_{inst} is the installed capacity for which the forecasts are computed.

6. Case study

To demonstrate the effectiveness and reliability of the proposed method, we use the actual power generation data for a wind turbine of Dongtai wind farm which situates in the east of China as an illustrating example. In this paper, though the data is generated with a wind turbine, the proposed method applies to large numbers of data. The detailed analysis steps as follows:

- Step 1: Pre-processing of original data.

The actual wind turbine output power time series from the wind farm is depicted in Fig. 2, have certain random volatility, it is necessary to be de-noised. Wavelet transform method is used to eliminate noise interference. The power data is 10 min a sampling point, choose 470 points to analysis. As can be seen from Fig. 3, de-noised wind turbine power curve eliminate the random volatility, can better show the wind turbine actual output power trends. Fig. 3 clearly indicates the intermittent and complex nature of wind turbine output power, it is essential for prediction to decompose it.

Table 2
The prediction results of wind turbine power.

No.	Real power $r(i)$ (kW)	Wavelet-based method			Direct prediction method		
		Predicted power $p(i)$ (kW)	Absolute error $AE(i)$ (kW)	Relative error $RE(i)$ (%)	Predicted power $p(i)$ (kW)	Absolute error $AE(i)$ (kW)	Relative error $RE(i)$ (%)
441	242	302.88	−60.88	−25.16	272.73	−30.73	−12.70
442	222	227.43	−5.43	−2.45	285.93	−63.93	−28.80
443	214	173.08	40.92	19.12	245.01	−31.01	−14.49
444	215	159.34	55.66	25.89	204.7	10.3	4.79
445	205	274.34	−69.34	−33.82	219.64	−14.64	−7.14
446	200	262.58	−62.58	−31.29	230.52	−30.52	−15.26
447	239	267.43	−28.43	−11.90	202.07	36.93	15.45
448	289	260.77	28.23	9.77	193.46	95.54	33.06
449	351	309.53	41.47	11.81	246.88	104.12	29.66
450	420	366.02	53.98	12.85	304.81	115.19	27.43
451	393	441.94	−48.94	−12.45	353.13	39.87	10.15
452	374	506.07	−132.07	−35.31	426.39	−52.39	−14.01
453	406	346.06	59.94	14.76	386.7	19.3	4.75
454	444	345.14	98.86	22.27	383.61	60.39	13.60
455	346	372.58	−26.58	−7.68	422.12	−76.12	−22.00
456	212	407.74	−195.74	−92.33	441.67	−229.67	−108.33
457	128	302.34	−174.34	−136.20	309.41	−181.41	−141.73
458	65	166.45	−101.45	−156.08	217.31	−152.31	−234.32
459	57	79.95	−22.95	−40.26	133.34	−76.34	−133.93
460	74	36.40	37.60	50.81	78.194	−4.194	−5.67
461	112	119.51	−7.51	−6.71	72.878	39.122	34.93
462	158	88.96	69.04	43.70	92.865	65.135	41.22
463	165	126.04	38.96	23.61	110.73	54.27	32.89
464	158	193.57	−35.57	−22.51	160.59	−2.59	−1.64
465	159	155.77	3.23	2.03	165.2	−6.2	−3.90
466	156	135.87	20.13	12.90	170.79	−14.79	−9.48
467	134	150.47	−16.47	−12.29	159.79	−25.79	−19.25
468	109	123.49	−14.49	−13.29	154.68	−45.68	−41.91
469	72	99.33	−27.33	−37.96	133.57	−61.57	−85.51
470	37	95.68	−58.68	−158.59	111.36	−74.36	−200.97

Table 3
The error comparison of two prediction methods.

Prediction method	*MAPE* (%)	*NMAE* (%)	*NRMSE* (%)
Wavelet-based method	18.39	3.68	4.62
Direct prediction method	24.43	4.89	6.38

- Step 2: Decompose power using wavelet transform method.

Decompose the power time series of Fig. 3, using wavelet transform method, the decomposition results are illustrated in Fig. 4. D_1–D_4 are decomposed data of high-frequency parts; A_4 is the trend part (low-frequency) which maintains the original shape of the curve of power time series. It is obvious that the signal on the different levels demonstrates a quite different behavior. For the approximation level A_4, GM (1, 1) model fit is applied to predict the signal. The detail levels D_1–D_4 show higher frequencies. Therefore GM (1, 1) model might not be appropriate. Since the oscillations occur in the detail parts, the chaotic time series fit seems to be more appropriate for predicting those parts. But this should be identified.

- Step 3: Identify chaotic property of D_1–D_4, respectively.

The phase space of D_1–D_4 are reconstructed, the time delay τ and the embedding dimension m of D_1–D_4 are calculated, respectively, by the mutual information and Cao's methods. Subsequently, the largest Lyapunov exponents of D_1–D_4 are calculated by the Wolf algorithm, the calculation results are shown in Table 1. From Table 1, we can conclude that the time series of D_1–D_4 are chaotic, so they can be predicted using weighted one-rank local-region method.

- Step 4: Warm farm power prediction.

Using time delay τ and embedding dimension m, as shown in Table 1, to reconstruct phase space, adopting weighted one-rank local-region method to predict the power of D_1–D_4, respectively. Using the former 370 points data to reconstruct phase-space to train model, the latter 371–470 points are test data to measure the accuracy, the results are shown in Fig. 5(a)–(d). Applying GM(1, 1) model to predict 371–470 points data of A_4, the results show in Fig. 6. The final forecasting results of wind turbine power obtain reconstruct the seven predicted results, as shown in Fig. 7. In this paper, the whole power time series are calculated with $\tau = 4$, $m = 10$, maximum Lyapunov exponent $\lambda = 0.0551$, so it also be direct predicted from the whole data using weighted one-rank local-region method, as shown in Fig. 6. Table 2 gives the last 30 samples of wind turbine real power and predicted power of two prediction methods. Table 3 shows the comparison of prediction error based on wavelet transform and direct prediction. According to the results shown in Fig. 7 and Table 3, it can be seen that the proposed model has lower forecasting errors than direct prediction method. It is indicated that the proposed model can reduce prediction errors effectively.

7. Conclusion

In this paper, a prediction model is constructed by combining wavelet transform, chaotic theory, and GM (1, 1) model. We use wavelet transform to decompose the power into different scales, this can reduce the non-stationary of the power time series and enhance the prediction accuracy. By analyzing the characteristics of the decomposition of the wind farm power, the forecasting strategies of weighted one-rank local-region and GM (1, 1) are applied to predict each scale individually. In the end, summing all the predicted results obtain the ultimate forecasting result for the wind farm power. The proposed model is applied to predict the Dongtai wind farm power of China. The predicted result shows that the wavelet-based method is more accurate than the direct prediction method, which indicated that wavelet-based method can be applied as a promising and efficient methodology for wind farm power prediction.

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