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Short-term prediction of wind power using EMD and chaotic theory

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ABSTRACT

Due to the strong non-linear, complexity and non-stationary characteristics of wind farm power, a hybrid prediction model with empirical mode decomposition (EMD), chaotic theory, and grey theory is constructed. The EMD is used to decompose the wind farm power into several intrinsic mode function (IMF) components and one residual component. The grey forecasting model is used to predict the residual component. For the IMF components, identify their characteristics, if it is chaotic time series use largest Lyapunov exponent prediction method to predict. If not, use grey forecasting model to predict. Prediction results of residual component and all IMF components are aggregated to produce the ultimate predicted result for wind farm power. The ultimate predicted result shows that the proposed method has good prediction accuracy, can be used for short-term prediction of wind farm power.

1. Introduction

With the large-scale wind power parallel in the power grid, wind power's intermittent and uncertainty increases the instability of its interconnected power grid. Wind turbine as a complex, non-linear and uncertain systems, its safe and reliable operation will have a direct impact on the stability of interconnected power grid, the load distribution and a reasonable quality of power supply. Timely and accurate prediction of wind power generation, have a significant role for improving overall power system scheduling reasonableness, safety and economy [1–7].

When wind turbine is running, due to the effects of wind speed, wind direction, pressure, temperature, etc., meteorological data, and wind fields, topography, vegetation, surrounded by obstacles, as well as the wheel hub height, power curve, mechanical drive, control strategy and many other factors of the wind turbine itself, the actual wind power output variation is very complicated and difficult to establish its mathematical model [1–7].

For obtaining timely the actual output power of wind farm, scheduling reasonable dispatching plan of the power grid, it is very important to accurately predict its output power. In this paper, a wind farm power hybrid prediction model is developed based on empirical mode decomposition, chaotic theory, and grey theory. Using empirical mode decomposition method to subdivide the non-stationary wind farm power time series in low and high frequencies parts, and then analyze the decomposed powers' characteristics, using largest Lyapunov exponent prediction method or grey prediction to predict each scale, respectively. The selection of prediction method is depending on the dynamic behavior on each scale. Reconstruct these predicted results to obtain the ultimate prediction result.

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2. Empirical mode decomposition

Empirical mode decomposition (EMD) is a nonlinear signal processing method developed by Huang et al [8–10]. It can decompose a signal into a sum of functions, intrinsic mode functions (IMFs). These IMFs must satisfy two conditions: ① the number of extrema and the number of zero-crossings either are equal or differ at the most by one; ② the mean value of the envelope defined by the local maxima and the local minima is zero at all points.

The detailed decomposition process for a time series $x(t)$ is summarized as follows:

(1) Identify all the local maxima and local minima of $x(t)$, obtain the lower envelope $x_l(t)$ and the upper envelope $x_u(t)$by interpolate the local minima and the local maxima, calculate the mean $m_1 = (x_l(t) + x_u(t))/2$.
(2) Extract the details, $h_1 = x(t) - m_1$, check the properties of h_1, if h_1 satisfies conditions ① and ② above, then $c_1 = h_1$, an IMF is derived; if h_1 is not an IMF, replace $x(t)$ with h_1, repeat step (1) $\sim$ (2) until it satisfies the stop conditions ① and ② above.
(3) Regard $r = x(t) - h_1$ as a new $x(t)$, the steps are applied repeatedly to the residue in order to obtain the second, the third and nth IMF until a predetermined threshold is achieved, or until the residue becomes a monotonic function.

$x(t)$ can be represented as the sum of IMFs with the residue:

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

where n is the number of IMFs, c_i $(i = 1, 2, \ldots, n)$ are the IMFs, which are nearly orthogonal to each other, and r is the final residue, which is the main trend of x(t).

3. Prediction model of wind farm power

For the sake of improving the operating economy and reliability of power systems, accurate forecast of wind farms power is essential. Due to wind farm power is highly nonlinear and non-stationary, it is very difficult to predict accurately. In order to improve prediction accuracy, a hybrid forecasting model based on empirical mode decomposition, chaotic time series and grey theory is presented. The empirical mode decomposition method is used to decompose the wind farm power to several detail parts associated with high frequencies (IMF) and an approximate part associated with low frequencies (r). 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.

For the IMF components, identify their characteristics, if it is chaos time series then use largest Lyapunov exponent prediction method [11,12] to predict. If not, use GM(1, 1) model to predict. For the r, the GM(1, 1) model [13–15] is used to predict. Finally, the short term wind farm power is forecasted by summing the predicted approximate part and the high frequencies parts.

3.1. Chaotic prediction of wind farm power

3.1.1. Identification of chaos

In order to predict the time series using chaotic theory, an important step is determining the presence of chaotic behavior. A method for reconstructing a phase-space from a single time series has been presented by Takens [16]. 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

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

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. The time delay τ is computed based on mutual information method [17], and the embedding dimension m is determined based on the Cao method [18].

In order to determine chaotic behavior's presence of wind farm power, the Wolf method [11] is used to compute the largest Lyapunov exponent, which measures the divergence of nearby trajectories. If it is positive then the wind farm power time series is chaotic and unstable.

3.1.2. Prediction

If the chaotic characteristics of wind farm power can be determined, it can be predicted using chaotic method and the prediction results are valid for short term prediction. In this paper, the largest Lyapunov exponent prediction method [11,12] is used to forecast the wind farm power. This prediction method takes full account of the inherent characteristics of the time series, so the predicted result has higher reliability.

3.2. GM(1, 1) model

Grey forecasting model (GM(1, 1) model) was introduced by Deng, which has been widely applied in many fields [13–15]. The detailed introduction about GM(1, 1) model is presented in [13–15].

3.3. Evaluation criteria

To measure the forecasting performance, mean relative error (*MAPE*), normalized mean absolute error (*NMAE*), and normalized root mean square error (*NRMSE*) [4], are used for evaluation of different prediction methods, respectively. They can be defined by

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|p(i)-r(i)|}{r(i)} \times 100\% \tag{3}$$

$$NMAE = \frac{1}{P_{inst}N}\sum_{i=1}^{N}|p(i)-r(i)| \times 100\% \tag{4}$$

$$NRMSE = \frac{1}{P_{inst}}\sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}[p(i)-r(i)]^2} \times 100\% \tag{5}$$

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.

4. Application and analysis

The hybrid forecasting model described in the previous section is applied to Dongtai wind farm power prediction. The Dongtai wind farm situates in the east of China. The output power of a wind turbine is selected to verify the proposed model. The power data is 10 min a sampling point, choose 710 points to analysis.

The actual wind turbine output power time series have certain random volatility, it is necessary to be de-noised. Wavelet method is used to eliminate its noise. The de-noised wind turbine output power curve is shown in Fig. 1. As can be seen from Fig. 1, the de-noised power curve can better show the wind turbine actual output power trends. Fig. 1 also demonstrates that the complexity of actual power time series due to the fact that wind turbine is complex and it is affected by many cross-impact loads. It is difficult to analyze accurately its characteristics only from the graph, in order to research it, need to be decomposed.

Decompose the power time series of Fig. 1, using empirical mode decomposition method, the decomposition results are illustrated in Fig. 2. The IMF components, $c_1 \sim c_5$ are decomposed results whose frequency bands ranging from high to low, respectively; r is the residual component which maintains the original shape of the curve of whole power time series. It is obvious that the signal on the different levels demonstrates a quite different behavior. For the approximation level r, GM(1, 1) model fit is applied to predict the signal. The detail levels $c_1 \sim c_5$ 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.

Phase-space reconstruct $c_1 \sim c_5$, using mutual information computes the time delay τ of $c_1 \sim c_5$; applying Cao-algorithm calculate the embedding dimension m of $c_1 \sim c_5$, respectively. According to the calculated time delay τ and

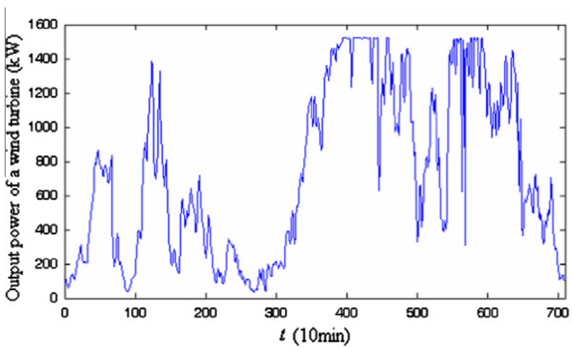

Fig. 1. The actual output power of wind turbine.

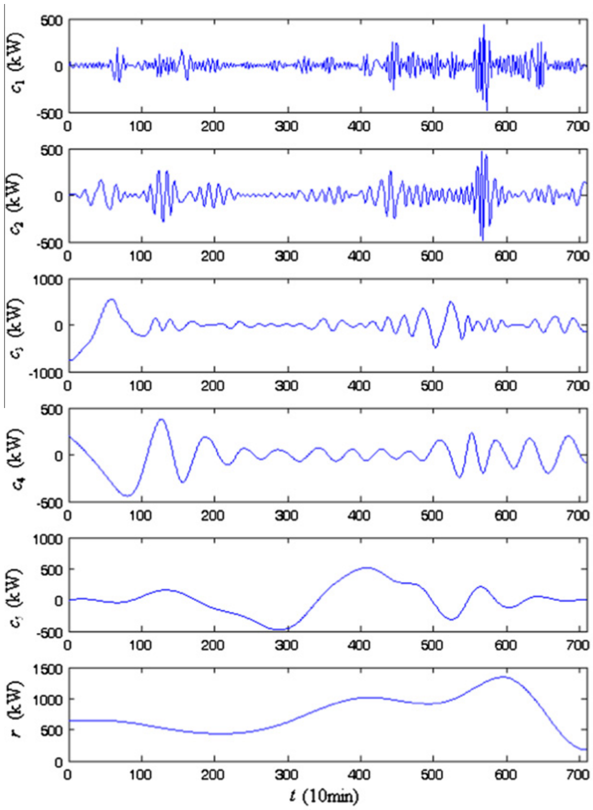

Fig. 2. The decomposed results of wind turbine power using empirical mode decomposition method.

embedding dimension m, using Wolf method to calculate the largest Lyapunov exponent of $c_1 \sim c_5$, the calculation results as shown in Table 1. It can be seen from the table that the largest Lyapunov exponents of c_1, c_2, c_3, c_4, are positive, indicating they have chaotic characteristics, and they can be predicted using largest Lyapunov exponent prediction method. But the largest Lyapunov exponent of c_5, is negative, indicating it isn't chaotic time series, so using GM(1, 1) method to predict.

For the IMF components, c_1, c_2, c_3, c_4, the time delay τ and embedding dimension m, as shown in Table 1, are used to reconstruct phase space, and the largest Lyapunov exponent prediction method is chosen to predict the power, respectively. Using the former 610 points data to reconstruct phase-space to train model, the latter $611 \sim 710$ points are test data to measure the accuracy, the results as shown in Fig. 3(a) $\sim$ (d). Applying GM(1, 1) model to predict $611 \sim 710$ points data of c_5 and r, the results show in Fig. 4(a) $\sim$ (b).

Prediction results of residual component and all intrinsic mode function components are aggregated to produce the ultimate predicted result for wind farm power. The predicted result is presented in Fig. 5. The whole power time series are calculated with $\tau = 3$, $m = 10$, $\lambda = 0.0576$, so the largest Lyapunov exponent prediction method can direct predict the power based on the whole data. The forecasting result using direct prediction method (largest Lyapunov exponent prediction method) is presented in Fig. 5. It is clear that the predicted result using hybrid prediction model have better match the actual power than predicted result using direct prediction method which using undecomposed data. Table 2 gives the performance comparison of hybrid prediction model and direct prediction method. It is clear that the predicted result using hybrid prediction model (empirical mode decomposition method, largest Lyapunov exponent prediction method, and grey theory) has better precision than the predicted result using direct prediction method.

Table 1
The chaotic identification parameters of $c_1 \sim c_5$.

Decomposed power	Time delay (τ)	Embedding dimension (m)	Largest Lyapunov exponent (λ)
c_1	1	10	0.0551
c_2	3	7	0.0811
c_3	6	5	0.0009
c_4	11	5	0.0137
c_5	6	4	−6.3405

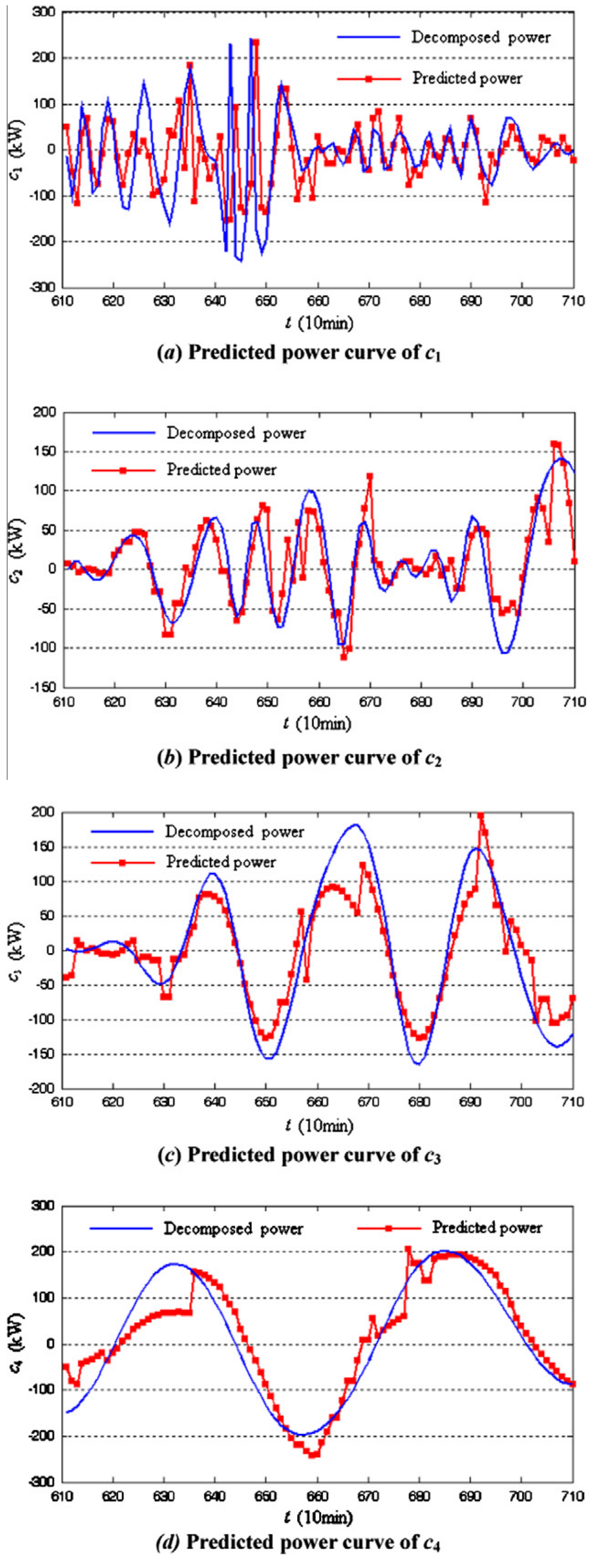

Fig. 3. The predicted power curves of $c_1 \sim c_4$ using largest Lyapunov exponent prediction method.

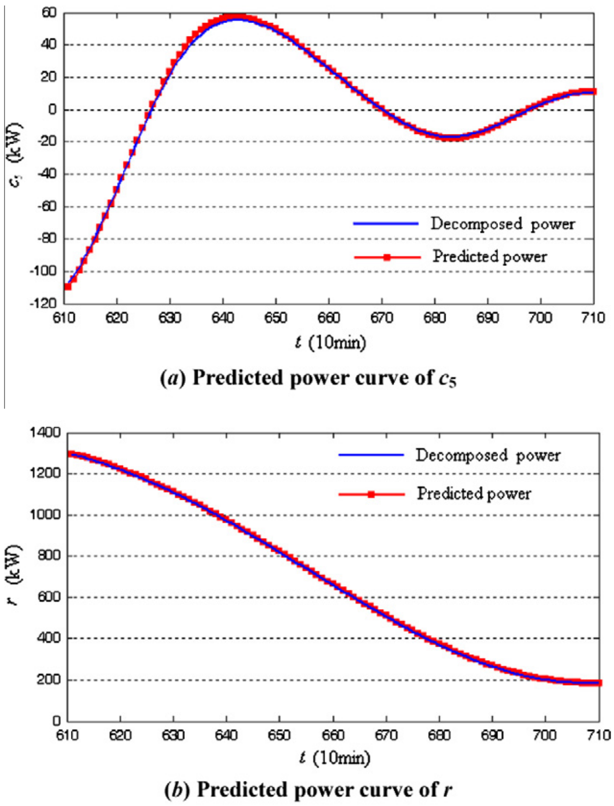

Fig. 4. The predicted power curves of c_5 and r using GM(1,1) model.

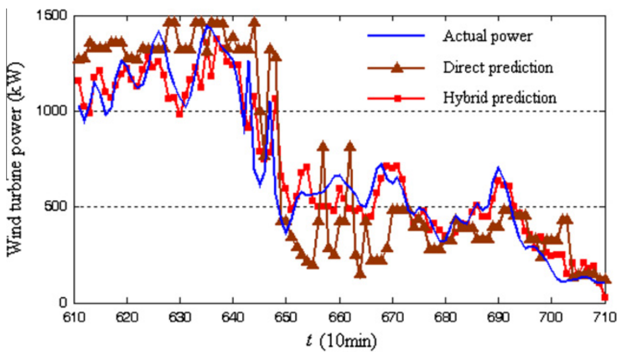

Fig. 5. The actual and predicted power by hybrid prediction model and direct prediction method.

Table 2
The performance of two prediction methods.

Prediction method	*MAPE* (%)	*NMAE* (%)	*NRMSE* (%)
Hybrid prediction model	18.33	5.71	7.80
Direct prediction method	34.03	11.76	15.31

5. Conclusion

It is difficult to find an appropriate model to predict wind farm power due to the fact that the power is highly complex and non-linear. In this paper, a hybrid prediction model using empirical mode decomposition, largest Lyapunov exponent prediction method, and grey theory is constructed. The empirical mode decomposition method is used to decompose the wind farm power into several intrinsic mode function components and one residual component. This can reduce the non-stationary of the power time series and enhance the prediction accuracy. The residual component is predicted using GM(1, 1) model. The chaotic characteristic of each IMF component is identified. According to the characteristics of IMF components, select largest Lyapunov exponent prediction method or GM(1, 1) model to predict. The final predicted result for wind farm power is produced by aggregating all the predicted results. Compared with direct prediction method for using directly the power data, this result of proposed method shows better prediction accuracy.

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