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A new chaotic time series hybrid prediction method of wind power based on EEMD-SE and full-parameters continued fraction

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ABSTRACT

The wind power time series always exhibits nonlinear and non-stationary features, which make it very difficult to predict accurately. In this paper, a new chaotic time series prediction model of wind power based on ensemble empirical mode decomposition-sample entropy (EEMD-SE) and full-parameters continued fraction is proposed. In this proposed method, EEMD-SE technique is used to decompose original wind power series into a number of subsequences with obvious complexity differences. The forecasting model of each subsequence is created by full-parameters continued fraction. On the basis of the inverse difference quotient continued fraction, the full-parameters continued fraction model is proposed. The parameters of model are optimized by the primal dual state transition algorithm (PDSTA). The effectiveness of the proposed approach is demonstrated with practical hourly data of wind power generation in Xinjiang. A comprehensive error analysis is carried out to compare the performance with other approaches. The forecasting results show that forecast improvement is observed based on EEMD-SE and full-parameters continued fraction model.

1. Introduction

The report published by World Wind Energy Association shows that the total wind capacity of the world has reached more than 430 GW at the end of 2015, the global growth rate of 17.2% [1,2]. The total installed capacity of the report in Fig. 1. It can be seen that wind power has been becoming one of the most rapidly growing renewable energy over the last decades. The intermittent and randomness features of wind power will cause great impact on stability of power systems operations, which will bring great challenges in power systems. Accurately forecasting wind power is one of the effective strategies to cope with the unstability of wind farm output.

Due to the weather system exhibits a chaotic nature, many studies suggest that wind power time series has obvious chaotic characteristics [3–6]. Regular and random chaotic time series is difficult to achieve accurate and reliable wind power forecasting. To date, on the methods, there are mainly two groups of wind power forecasting methods: one group is physical methods and another is statistical methods [7–10]. The physical methods consider numerical weather prediction (NWP) data and onsite conditions at the location of the wind farm to predict wind power data. The statistical methods use historical data (NWP data or history wind power data) to map the relationship between these historical data and wind power data. Physical methods have advantages in long-term prediction while statistical methods do well in short-term prediction. The statistical methods can also divided into direct methods and indirect methods [10]. The indirect methods employ indirect data as wind speed time series-based or weather-based to gain wind power series. While the direct methods use history wind power series directly to predict wind power. From another angle, the statistical methods can also be divided into two subclasses: one is the NWP based statistical models and another is time series based models [8,11–14]. Many researches show that the time series based methods are suitable for short term (typically minutes to hours) forecasting since they can capture the hidden stochastic characteristics of wind power series [3,8].

Individual model cannot represent the majority of the traits in the complex characteristics of the original wind power series. To make use of the two types of approaches, a number of hybrid models that combined statistical and physical methods are studied in literature. Various attempts have been made to use hybrid methods for wind forecasting. Carpinone et al. [15] proposed a new

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Symbols and notation

EEMD

$x(t)$	the original wind power series
$n(t)$	the white noise series
$x_{new}(t)$	the waiting for decompose sequence
f_{im}	the k-th intrinsic mode functions

SE

N	the total number of data points
$x_m(i)$	the vectors of data
$d[x_m(i), x_m(j)]$	the distance value
r	the tolerance for accepting matrices
$B^m(i)$	the ratio value
$B_i^m(r)$	the average value
$SE(m, r)$	the sample entropy

Full-parameters continued fraction

$f(x)$	the continuous function
γ	the positive value
$F(x)$	the rational fraction function
$x(i)$	the node of $f(x)$
$f(x_i)$	the function value of $x(i)$
$g(x)$	the full-parameters continued fraction
$[a_0, \cdots, a_{n-1}]$	the parameters of $g(x)$
$[b_0, \cdots, b_n]$	the parameters of $g(x)$

PDSTA

x_k	the state of PDSTA
A_k, B_k	the state transition matrixes
u_k	the function about the state x_k
$f(x_k)$	the objective function
α	the rotation factor
β	the translation factor
γ	the expansion factor
δ	the axesion factor
R_r	the random matrix
$\|x_k\|_2$	the vector with 2-norm
R_t	the random variable
R_e, R_a	the random diagonal matrix

Errors

nRMSE	the normalized root mean square error
nMAE	the normalized mean absolute error
y_i	the actual value
$\hat{y}_i$	the prediction value

List of abbreviations (Here, all terms mentioned in this paper and their definitions are listed in alphabetical order)

EEMD	ensemble empirical mode decomposition
SE	sample entropy
PDSTA	primal dual state transition algorithm
NWP	numerical weather prediction
ARIMA	Autoregressive Integrated Moving Average
ELM	extreme learning machine
SVM	support vector machine
LSSVM	least square SVM
LS-SVM	least-squares support vector machine
ANN	artificial neural network
WT	wavelet transform
FA	fuzzy ARTMAP
FF	firefly optimization algorithm
nMAE	normalized absolute average error
MAPE	mean absolute percentage error
nRMSE	normalized root mean square error
EMD	empirical mode decomposition
PSR	phase space reconstruction
EP-P	error post-processing
CSA	clonal selection algorithm
PSO	particle swarm optimization
GA	genetic algorithm
SSO	simplified swarm optimization
GSA	gravitational search algorithm
IMF	intrinsic mode signals
HEA	hybrid evolutionary-adaptive
MLE	machine learning ensembles
RBF	radial basis function

method based on discrete time Markov chain model which can directly obtain wind power distributions on a very short term horizon. And the method analyzed first and second Order Markov Chain Model. Wang et al. [16] proposed a robust combination approach for short-term wind speed forecasting, which combines independent forecasts generated by various forecasting engines Autoregressive Integrated Moving Average (ARIMA), Extreme Learning Machine (ELM), Support Vector Machine (SVM) and Least Square SVM (LSSVM). Giorgi et al. [17] carried out a comparative study on wind power prediction models based on Least-Squares Support Vector Machine (LS-SVM) and Artificial Neural Network (ANN). The results showed that the hybrid methods mostly outperform other methods. In order to solve the prediction limits using of the existing tools for decision-making under uncertain conditions in wind power forecasting. Haque et al. [18] presented a novel hybrid intelligent algorithm for deterministic wind power forecasting that utilized a combination of wavelet transform (WT) and fuzzy ARTMAP (FA) network, which is optimized by using Firefly (FF) optimization algorithm. The mean normalized absolute average error (nMAE) of this method for 1 h, 3 h, 6 h and 12 h ahead forecasting were all lower than compared methods. Osório et al. [19] combined mutual information, wavelet transform, evolutionary particle swarm optimization, and the adaptive neuro-fuzzy inference system to build a new hybrid evolutionary-adaptive methodology for wind power forecasting. The average mean absolute percentage error (MAPE) value of hybrid evolutionary-adaptive methodology was only 3.75% for an average error variance of 0.0013 and a normalized root mean square error (nRMSE) of 2.66%. Peng et al. [20] investigated two forecasting methods based on artificial neural network (ANN) and hybrid strategy. The individual ANN prediction method has lower accuracy than hybrid strategy. But the hybrid strategy operated costly and slowly compared with the individual ANN.

With the improvement in wind power forecasting approaches, wind power forecasting have higher accuracy. But the normalized mean squared error still range from 8% to 22% [21,22]. The above mentioned models all focused on building models. These wind power models make use of wind power time series to obtain the forecast values. The analyzing of time series can be highly helpful with the help of predictability analysis. In order to improve the

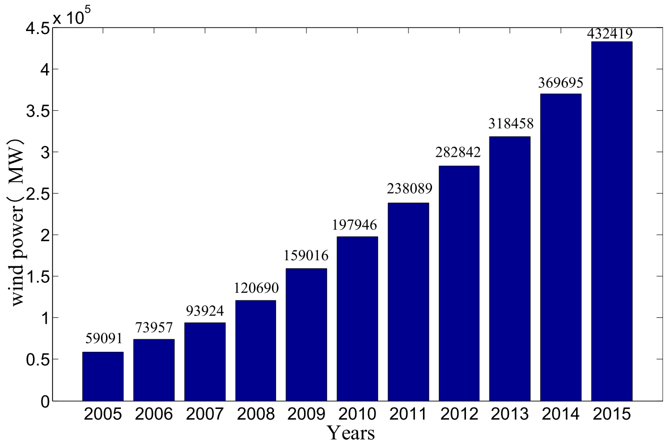


Fig. 1. The total wind capacity of the world.

prediction accuracy, some research works combine forecasting models with data pre-processing techniques, error post-processing techniques and parameter selection and optimization techniques [2].

- The data pre-processing techniques through analyzing and processing data to make original time series becoming multiple sequences or matrix, which have more obvious characteristics. So to some extent, the pre-processing techniques can improve the forecasting accuracy. Giorgi et al. [23] used wavelet decomposition to pre-processing wind power data, then build hybrid prediction model based on least-squares support vector machine (LS-SVM) and artificial neural network. But wavelet decomposition lacks the ability of self-adaptive data processing and requires the specification of wavelet basis and parameters beforehand. The empirical mode decomposition (EMD) were carried out to pre-processing data in Refs. [24–27]. These decomposition methods decompose wind time series into low and high frequency components which describe the approximate and detail levels, respectively. But the EMD is sensitive to noise and sampling and lacks a basis in mathematical theory. The phase space reconstruction is also one data pre-processing techniques, which is used to reconstruct the chaotic wind power series in Refs. [3,28,29]. The phase space reconstruction (PSR) can embed a single system variable to a new matrix time series. But the PSR results depend entirely on the delay time and embedding dimension.
- The error post-processing (EP-P) techniques use the estimated error, which is obtained from a forecasting model, to correct final forecasting results [30,31].
- Parameter selection and optimization techniques can improve prediction accuracy and reduce the prediction time through the training model. Clonal selection algorithm (CSA) [32], particle swarm optimization (PSO) [19], genetic algorithm (GA) [33], simplified swarm optimization (SSO) [34], gravitational search algorithm (GSA) [35], etc. are prevailing methods to select and optimize the parameters of the wind power forecasting models.

To a certain extent, in the above mentioned models, various measures improved the prediction accuracy. However, due to the stochastic and variable nature of the wind, the accuracy of such forecasts cannot be guaranteed and tended to be fairly low. Wind power prediction is the core of wind power forecasting system. Considering the different requirements of the forecasting time scale and the concrete application, the forecasting strategy and model can be used to obtain the power forecast data, and the predicted data results can be displayed and analyzed in an intuitive way. The Grid Dispatching Mechanism can plan and issue the wind power generation planning according to the power forecasting result. Accurate power prediction results can provide a more accurate power generation plan for the grid dispatching agencies, which can make the wind farms more accurate and rapid implement power generation scheduling plans and instructions and more timely adjust the active output. Hence, efficient wind power forecasting approaches are still required for practical applications.

In this paper, a new chaotic time series prediction model of wind power based on ensemble empirical mode decomposition-sample entropy (EEMD-SE) and full-parameters continued fraction is proposed. Firstly, ensemble empirical mode decomposition is used to decompose the chaotic wind power time series into a series of intrinsic mode signals with different characteristics scales. Secondly, sample entropy is used to analyze intrinsic mode signals (IMF). According to the entropy value of intrinsic mode signals, the new subsequences are created by combination stacking. Thirdly, the forecasting model of each subsequence is created with full-parameters continued fraction. The full-parameters continued fraction model is put forward on the basis of the inverse difference quotient continued fraction. The primal dual state transition algorithm (PDSTA) is used to optimize the parameters of the model. Lastly, the wind power forecasting results are the combination of all subsequences forecasting results. The proposed method has been thoroughly tested and benchmarked on real wind power data from Xinjiang,China.

The main contributions of the proposed method are presented as follows:

1) The ensemble empirical mode decomposition-sample entropy is used to analyze the chaotic wind power series, by which the chaotic wind power time series can translate into some new relatively stable subsequences. The ensemble empirical mode decomposition can decompose the chaotic wind power time series into a series of intrinsic mode signals with different characteristics scales, which can improve the accuracy of the forecasting. But it can increase the forecasting time. Sample entropy is used to create new subsequences by combination stacking, which can reduce the forecasting time. These findings suggest that the forecasting results will be more accurate.
2) The full-parameters continued fraction model is proposed on the basis of the inverse difference quotient continued fraction. It not only has the advantages in function and sequence prediction of inverse difference quotient continued fraction, but also solve the problems as large amount of calculation and the defects of low efficiency. It is not only easy to implement and has self-adaptive in terms of parameters, but also can avoid the choice of model structure. On the other hand, according to different actual needs, the orders of forecasting models can choose flexible.
3) PDSTA is used to train the parameters of the model. which avoids the choice of parameters. The state transition algorithm has fewer parameters and a simple algorithm structure, which is easily understood. PDSTA has better convergence and higher quality solution with lower iterations than most swarm intelligence algorithms. PDSTA can improve the forecasting accuracy and avoid the time consuming process of model optimization.

The structure of the paper is organized as follows: The methodology and models for wind power forecasting are described in

Section 2. Section 3 introduces detailed criteria for model evaluation. One case study based on EEMD-SE and full-parameters continued fraction model, including data description, models building and optimization, forecasting performance evaluations are all described in Section 4. The Conclusions is given in Section 5.

2. Proposed methodology

The relative methods including the ensemble empirical mode decomposition, sample entropy, the full-parameters continued fraction model and primal dual state transition algorithm are all described in this section. The prediction process is shown in Fig. 2.

2.1. The ensemble empirical mode decomposition(EEMD)

The EEMD method has been widely used to non-stationary and nonlinear signal analysis [36,37]. The wind power time series always exhibits nonlinear and non-stationary features, which make it very difficult to predict accurately. In order to solving the non-stationary problems of chaotic wind power time series, the ensemble empirical mode decomposition is used to decompose the chaotic wind power time series into some new relatively stable subsequences.

The principle of the EEMD is simple: the added white noise will populate the whole time–frequency space uniformly with the constituting components of different scales. No missing scales are present, and mode mixing is effectively eliminated by the EEMD process since white noise is added throughout the entire signal decomposition process [38].

Decomposition steps of EEMD are shown as follows:

Step 1: Add a white noise series, which has relatively smaller root mean square, to the original wind power series:

$$x_{new}(t) = x(t) + n(t) \tag{1}$$

where $x(t)$ is the original wind power series. $n(t)$ is white noise series. And $x_{new}(t)$ is a waiting for decompose sequence, which mixed with noise signal.

Step 2: Decompose the new wind power series with added white noise $x_{new}(t)$ into k-th intrinsic mode functions: $f_{im}, i = 1, 2, \cdots, k$.

Step 3: Add different white noise series each time, repeat step 1 and step 2 again and again. Get n groups of different component intrinsic mode functions, $m = 1, 2, \cdots, n$.

Step 4: Obtain the (ensemble) means of corresponding intrinsic mode functions of the decompositions as the final results: $f_i = \sum_{m=1}^{n} f_{im}/n$.

The essence of the decomposition using the EEMD is that the added white noise series cancel each other in the final mean of the corresponding intrinsic mode functions. The mean intrinsic mode functions stay within the natural dyadic filter windows and thus significantly reduce the chance of mode mixing and preserve the dyadic property [39].

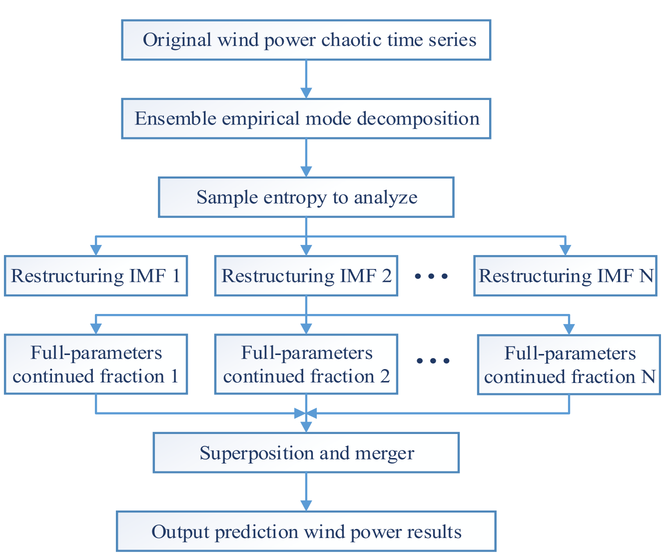


Fig. 2. The prediction process of the new method.

2.2. Sample entropy (SE)

Approximate entropy as an important tool to quantify the complexity of time series, has been widely used in many research fields. However, approximate entropy value associates with the data length, and it also lacks relative consistency. Approximate entropy also has deviation caused by its own matching. Due to Sample entropy has better representation of the entropy in the analyzed signals, it was proposed to solve the problems in original approximate entropy [40]. This method's motivation is the classification of the complex system. The bigger sample entropy value is, the sequence has higher complexity and it has greater probability build a new pattern. Similarly, the smaller sample entropy value is, the sequences has lower complexity and the sequence has higher self similarity. The algorithm implementation process of SE is as follows:

Giving N total number of data points $x(1), x(2), \cdots, x(N)$, and the $N-m+1$ vectors $x_m(i)$ is formed as:

$$x_m(i) = [x(i), x(i+1), \cdots, x(i+m-1)] \tag{2}$$

where m is the length of sequences to be compared.

The distance between two such vectors $x_m(i)$ and $x_m(j)$ is defined as:

$$d[x_m(i), x_m(j)] = \max[x_m(i+k) - x_m(j+k)] \tag{3}$$

where $k = 0, 1, \cdots, m-1;\ i,j = 1, 2, \cdots, N-m;\ j \neq i$.

r is supposed as the tolerance for accepting matrices. $N(i)$ is the number of $d[x_m(i), x_m(j)] < r\ \ (i \leq N-m)$. Define the function:

$$B_i^m(r) = \frac{1}{N-m+1} B^m(i) \tag{4}$$

where $B^m(i) = \frac{N(i)}{N-m-1}$, $i = 1, 2, \cdots, N-m+1$.

When adding the dimension, the new function is defined as:

$$B_i^{m+1}(r) = \frac{1}{N-m+1} B^{m+1}(i) \tag{5}$$

where $B^{m+1}(i) = \frac{N(i)}{N-m}$, $i = 1, 2, \cdots, N-m+1$.

The sample entropy of the time series can be gotten as:

$$SE(m, r) = \lim_{N \to \infty} \left\{ -\ln\left[B^{m+1}(r)/B^m(r)\right] \right\} \tag{6}$$

When N is limited, sample entropy calculation formula is:

$$SE(m, r, N) = -\ln\left[B^{m+1}(r)/B^m(r)\right] \} \tag{7}$$

2.3. Full-parameters continued fraction

Definition 1: Supposed $f(x)$ is a continuous function and $x\in[a,b]$. For all positive value γ, there exists rational fraction function $F(x)=\frac{P(x)}{Q(x)}$ to let $[f(x)-F(x)]<\gamma$, $\forall x\in[a,b]$.

$x(i)$ $(i=0,1,\cdots,n)$ is the node of $f(x)$. $f(x_i)$ $(i=0,1,\cdots,n)$ is the function value of $x(i)$. According to definition 1, the continued fraction can be built as:

$$g(x)=b_0+\frac{x-x_0}{b_1+\frac{x-x_1}{b_2+\cdots+\frac{x-x_{n-1}}{b_n}}} \tag{8}$$

Here $g(x_i)=f(x_i)$ $i=0,1,\cdots,n$. To rewrite formula (8) and let: $g_0(x)=g(x)$, we get:

$$g_k(x)=b_k+\frac{x-x_k}{g_{k+1}(x)},\ k=0,1,\cdots,n-1 \tag{9}$$

From formulas (8) and (9), it has:

$$\begin{cases} g_0(x_i)=f(x_i), i=0,1,\cdots,n; \\ b_k=g_k(x_k), k=0,1,\cdots,n; \\ g_{k+1}(x_i)=\dfrac{x_i-x_k}{g_k(x_i)-b_k}, k=0,1,\cdots,n-1. \end{cases} \tag{10}$$

$g(x)$, which is determined by formula (8),(9) and (10), is the inverse difference quotient continued fraction.

In order to solve the complex calculation and low efficiency of the inverse difference quotient continued fraction, the full-parameters continued fraction model is proposed. It uses $[a_0,a_1,\cdots,a_{n-1}]$ to replace $x(i)$ $(i=0,1,\cdots,n)$, which can be defined as follows:

$$g(x)=b_0+\frac{x-a_0}{b_1+\frac{x-a_1}{b_2+\cdots+\frac{x-a_{n-1}}{b_n}}} \tag{11}$$

where $[a_0,a_1,\cdots,a_{n-1}]$ and $[b_0,b_1,\cdots,b_n]$ are parameters, which can be gotten by optimization methods.

2.4. Primal dual state transition algorithm (PDSTA)

The state transition algorithm was proposed by Zhou in 2011 [40]. A solution of specific optimization problem can be described as a state, and the optimization algorithm can be treated as state transition. Then the process of solving the optimization problem can be regarded as a state transition process.

The state transition algorithm has many advantages, such as less numbers of the parameters, simple algorithm structure, easy to understand et ac. The defining of state transition is shown as:

$$\begin{cases} x_{k+1}=A_kx_k+B_ku_k \\ y_k=f(x_{k+1}) \end{cases} \tag{12}$$

where $x_k\in R^n$ is a state and corresponds the optimization problem's solution. A_k, $B_k\in R^{n\times n}$ are state transition matrixes, which are also called the operators of optimization algorithm. $u_k\in R^n$ is the function about the state x_k. $f(x_k)$ is the objective function. This algorithm has four operators.

The details of the four operators are shown as follows:

Rotation Transformation (RT):

$$x_{k+1}=x_k+\alpha\frac{1}{n\|x_k\|_2}R_rx_k \tag{13}$$

Translational Operation (TT):

$$x_{k+1}=x_k+\beta R_t\frac{x_k-x_{k-1}}{\|x_k-x_{k-1}\|_2} \tag{14}$$

Expansion Transformation (ET):

$$x_{k+1}=x_k+\gamma R_ex_k \tag{15}$$

Axesion Transformation (AT):

$$x_{k+1}=x_k+\delta R_ax_k \tag{16}$$

where $x_k\in R^n$ is the state of STA, α is the rotation factor. β is the translation factor. γ is the expansion factor. And δ is the axesion factor. And they are all positive constants. $R_r\in R^{n\times n}$ is a random matrix, the elements of $R_r\in R^{n\times n}$ belongs to the range of [-1, 1]. $\|x_k\|_2$ is a vector with 2-norm. $R_t\in R$ is a random variable, the elements of $R_t\in R$ belongs to the range of [0,1]. $R_e\in R^{n\times n}$ is a random diagonal matrix, whose elements obeys the Gaussian distribution. $R_a\in R^{n\times n}$ is a random diagonal matrix, the elements of $R_a\in R^{n\times n}$ obeys the Gaussian distribution and only one random index has value.

In order to improve the performance of state transition algorithm, the primal dual state transition algorithm is proposed [41]. During the processing of search in the proposed PDSTA, primal dual is used to look for the best state in each iteration process. The method is elaborated by us by defining key terms and its execution was used in by the processes. The details can be seen in Ref. [41].

2.5. The method for wind power forecasting

A new chaotic time series prediction model of wind power based on EEMD-SE and full-parameters continued fraction is proposed. The principle of full-parameters continued fraction used in wind power forecasting is shown that there is a smooth function $g(x_i,\delta)$ letting:

$$\tilde{x}_{i+s}=g(x_i,\delta), i=1,2,\cdots,n-s. \tag{17}$$

where $\delta=[\delta_1,\delta_2,\cdots,\delta_{2r+1}]$ is the optimization parameters, which is optimized by PDSTA. x_i is the actual wind power. $\tilde{x}_{i+s}$ is the forecasting wind power. r is the order of the full-parameters fraction. s is the prediction step length.

The EEMD-SE and full-parameters fraction forecasting method used in wind power will now be described in successive steps. The details overall framework of the proposed model is shown in Fig. 3.

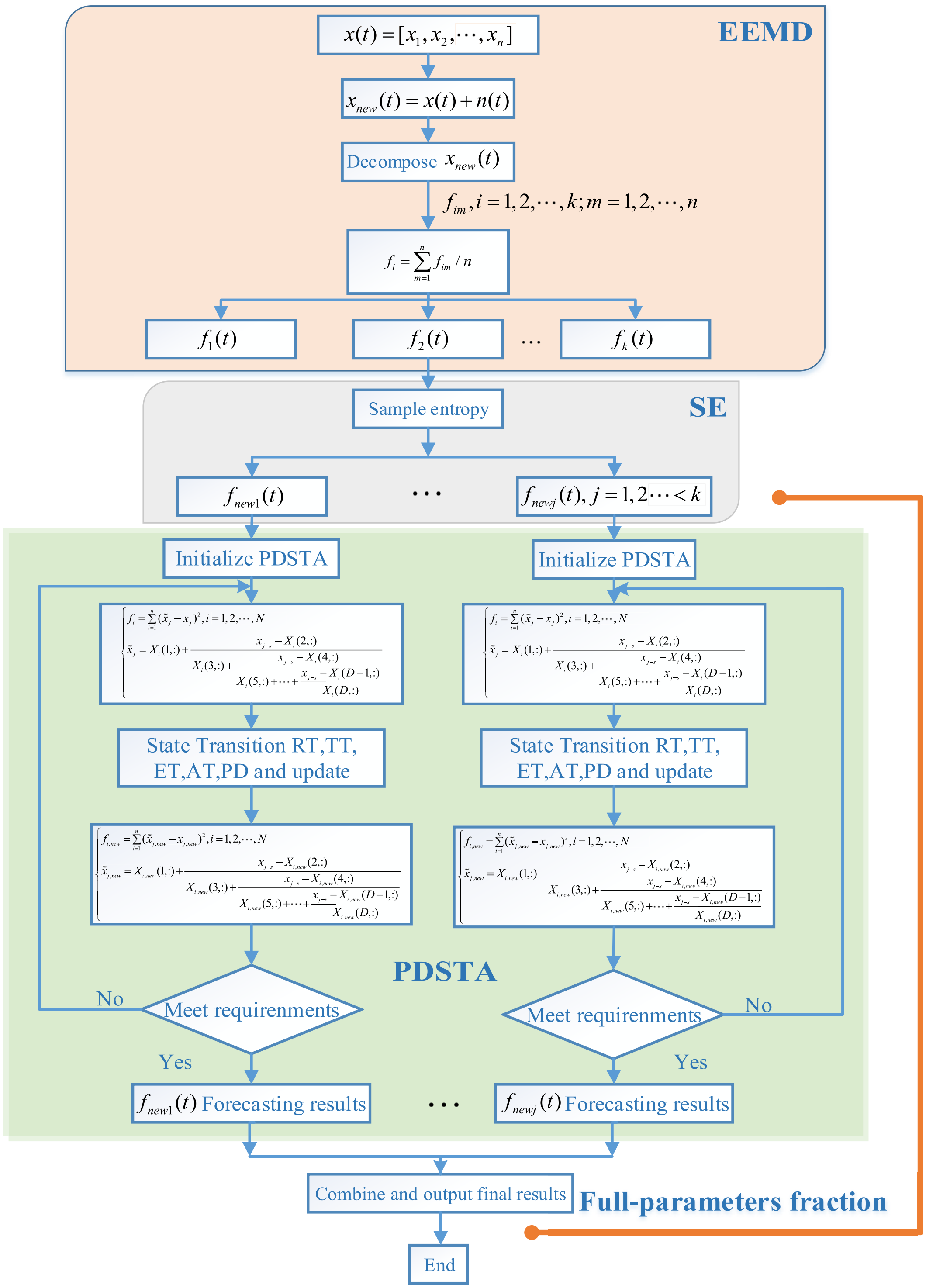
Decomposition steps of EEMD-SE and full-parameters fraction used in wind power forecasting are shown as follows:

Step 1: Use EEMD to decompose the chaotic wind power time series $x=[x_1,x_2,\cdots,x_n]$ into some new relatively stable subsequences $x_i=[x_{1i},x_{2i},\cdots,x_{ni}],(i=1,2,\cdots)$;

Step 2: Use Sample entropy to analyze intrinsic mode signals $x_i=[x_{1i},x_{2i},\cdots,x_{ni}],(i=1,2,\cdots)$ and create the new subsequences by combination stacking, get $x_{inew}=[x_{1j},x_{2j},\cdots,x_{nj}]+\cdots+[x_{1k},x_{2k},\cdots,x_{nk}],(j,k<i=1,2,\cdots)$;

Step 3: Build full-parameters fraction forecasting models to forecasting all the new subsequences $x_{inew}=[x_{1j},x_{2j},\cdots,x_{nj}]+\cdots+[x_{1k},x_{2k},\cdots,x_{nk}],(j,k<i=1,2,\cdots)$ respectively and use PDSTA to optimize the parameters. The forecasting steps are shown as follows:

1) Initialize. In this stage, the parameters of PDSTA are determined. The swarm population is N. Max. number of Iterations is T. The initialize state is $X=[X_1,X_2,\cdots,X_N]^T$. And $X_i=[\delta_{i1},\delta_{i2},\cdots,\delta_{iD}]^T$ is the parameters of the forecasting model to be optimized. D is the number of optimization parameters.



EEMD is ensemble empirical mode decomposition. SE is sample entropy. PDSTA is primal dual state transition algorithm

Fig. 3. The details overall framework of the proposed model.

2) Evaluate the fitness function. In this paper, the square of difference between actual values and prediction values is used to evaluate the fitness function f_i and the full-parameters fraction forecasting model is built, which are shown as:

$$\begin{cases} f_i = \sum_{i=1}^{n} (\tilde{x}_j - x_j)^2, i = 1, 2, \cdots, n \\ \tilde{x}_j = X_i(1,:) + \cfrac{x_{j-s} - X_i(2,:)}{X_i(3,:) + \cfrac{x_{j-s} - X_i(4,:)}{X_i(5,:) + \cdots + \cfrac{x_{j-s} - X_i(D-1,:)}{X_i(D,:)}}} \end{cases} \tag{18}$$

where x_j is the actual wind power value of subsequence wind power series. $\tilde{x}_j$ is the outputting forecasting wind power value. n is the number of samples. s is the forecasting step length. $j = s+1, s+2, \cdots, n$.

3) Update the states and Evaluate the fitness function.

$$\begin{cases} f_{i,new} = \sum_{i=1}^{n} (\tilde{x}_{j,new} - x_j)^2, i = 1, 2, \cdots, n \\ \tilde{x}_{j,new} = X_{i,new}(1,:) + \cfrac{x_{j-s} - X_{i,new}(2,:)}{X_{i,new}(3,:) + \cfrac{x_{j-s} - X_{i,new}(4,:)}{X_{i,new}(5,:) + \cdots + \cfrac{x_{j-s} - X_{i,new}(D-1,:)}{X_{i,new}(D,:)}}} \end{cases} \tag{19}$$

where $\tilde{x}_{j,new}$ is the outputting forecasting wind power value. n is the number of samples. s is the forecasting step length. $j = s+1, s+2, \cdots, n$.

4) Termination condition check. If the stopping criteria is satisfied, go to the next step 4. Otherwise, go back to Step 3.

Step 4: Output the forecasting wind power values of subsequences. The wind power forecasting errors with different criteria are computed to validate the methodology, and compare the results with other results of comparing methods. The state of PDSTA leading to the lowest objective function value, means the lowest value of f_i, is selected as the PDSTA solution.

Step 5: Combine all subsequences forecasting results and output the final forecasting results.

Step 6: End.

3. Performance criterion

To comprehensively assess the overall performance of the proposed method, the comparative criteria and data collection are employed, as follows.

3.1. Errors for deterministic performance

The normalized root mean square error (nRMSE), which is defined as:

$$\mathrm{n}RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2} \times 100\% \quad i = 1, 2, \cdots, n \tag{20}$$

The normalized mean absolute error (nMAE), which are defined as:

$$nMAE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad i = 1, 2, \cdots, n \tag{21}$$

where n is the number of time series. y_i is the actual value. $\hat{y}_i$ is the prediction value.

3.2. Data collection and problem description

The sampled data of wind power is simulated and analyzed to verify the performance of the proposed model.

The case use the data of a wind farm in Xinjiang, China. We collect data for the whole year of 2014. Considering factors such as seasons, the 5th, 15th, and 25th days of each month are chosen as samples. 10-min wind power output data sets' hourly averages are applied for the analysis. A total of 5184 samples are used to training and testing. 3456 data points of day 5 and 15 of every month are used for training models and the left 1728 data point of the day 25 of every month are used for model evaluation. The samples is shown in Fig. 4.

4. Results and discussions

The EEMD-SE and full-parameters continued fraction model are applied for the prediction of the wind power in Xinjiang, China.

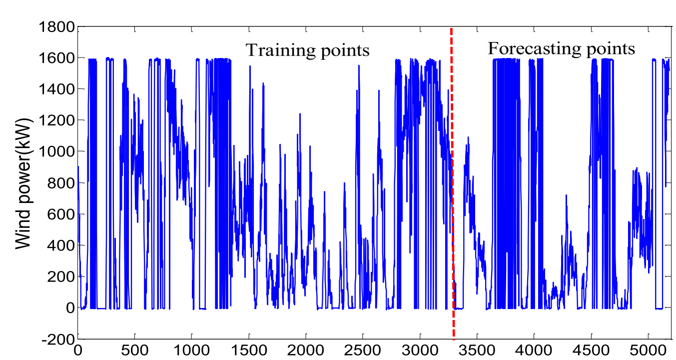


Fig. 4. The data points from Xinjiang, China.

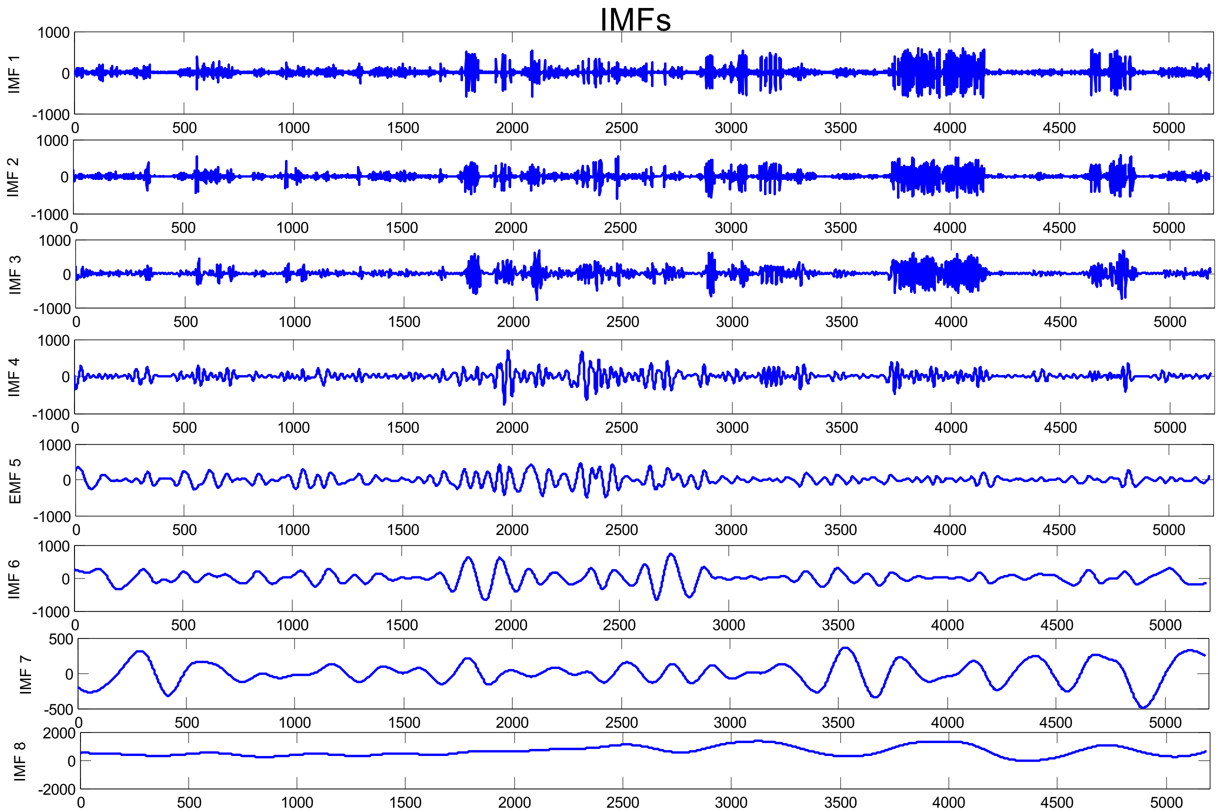


Fig. 5. Decomposition by EEMD of wind power series in Xinjiang, China.

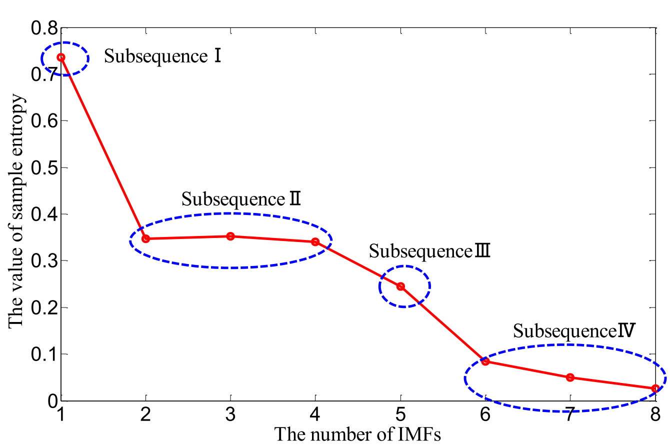


Fig. 6. The sample entropy values of IMFs.

decomposition is used to decompose the chaos wind power time series into a series of intrinsic mode signals with different characteristics scales. Then, the sample entropy is used to analyze intrinsic mode signals.

There are two important parameters to set of EEMD, i.e., the number of the ensemble and the amplitude of the added white noise. We use the statistical rule to control the effect of noise, which was established by Wu [42]. Decomposition results are shown in Fig. 5. There are eight independent IMF compositions.

Due to the nonstationarity of the wind power, it can be seen from Fig. 5 that there are a lot of IMF component after decomposition. If the full-parameters continued fraction model is used to build for each component respectively, the computing scale will be increased a lot. In order to forecast the wind power effectively, sample entropy theory is used to evaluate complexity of each IMF signal. The sample entropy values of all IMFs are shown as Fig. 6 and also in Table 1. Fig. 6 showed that sample entropy value of each IMF are reduced as the IMF component frequency reduced from high frequency to low frequency, which verified the validity of the sample entropy. The bigger sample entropy value is, the sequence has higher complexity. In order to reduce the computing scale of the models, the IMFs having the adjacent entropy values were merged superposition to a new series. The new subsequences

Table 1
The results of SE.

Original sequence	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF6	IMF 7	IMF8
SE Values	0.7351	0.3473	0.3516	0.3406	0.2450	0.0839	0.0499	0.0263
New sequence	IMFI	IMFII			IMFIII	IMFIV		

4.1. The results of EEMD-SE

The ensemble empirical mode decomposition-sample entropy is used to analyze the chaotic wind power series, by which the chaotic wind power time series can translate into some new relatively stable subsequences. The ensemble empirical mode

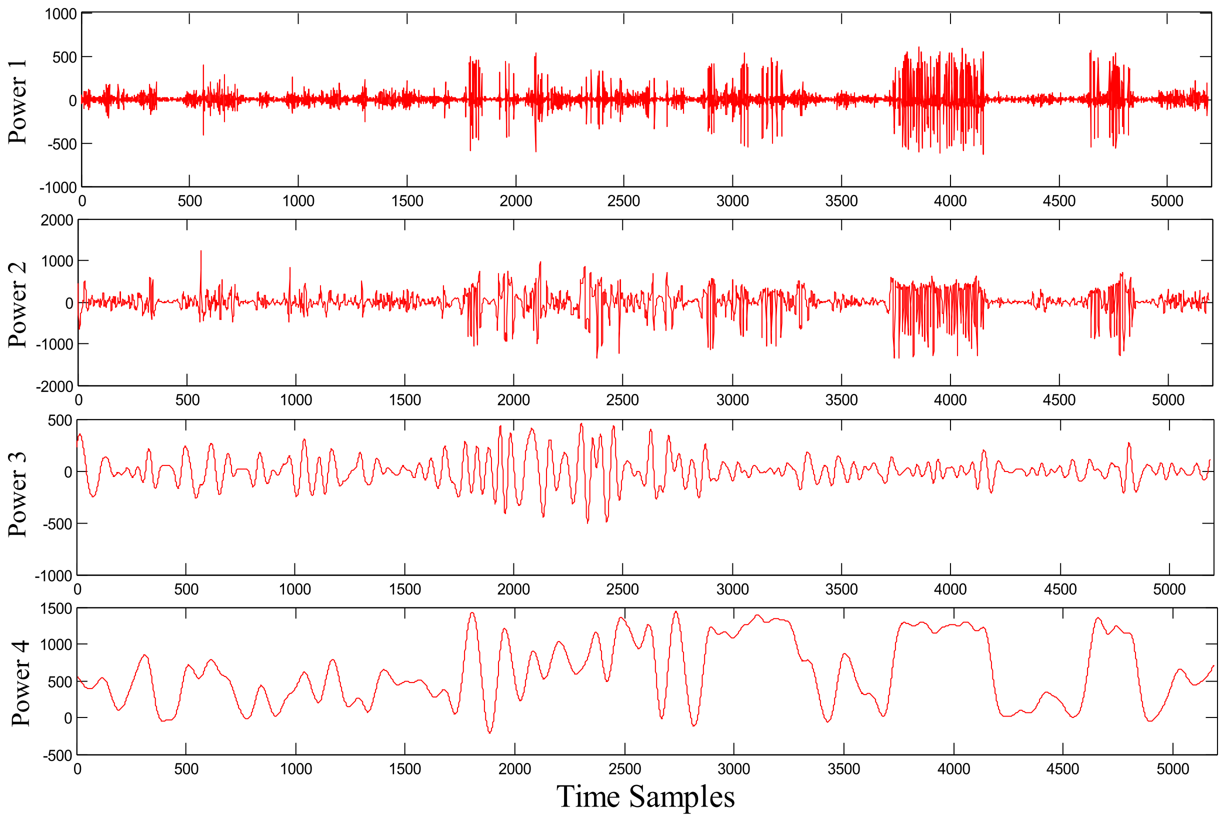


Fig. 7. Decomposition by EEMD-SE of wind power series in Xinjiang, China.

processed by SE is shown in Fig. 7.

Table 2
Parameters of PDATA.

Swarm size	80	Constant coefficient f_c	2
max. number of iterations	500	communication frequency CF	30
rotation factor α	1 to 1e-4	primal dual parameter ε	1e-5
other factors β γ δ	1		

4.2. *Parameters of full-parameters continued fraction models*

Two parameters for full-parameters continued fraction are parameter $[a_0, a_1, \cdots, a_{n-1}]$, $[b_0, b_1, \cdots, b_n]$ and the order of model. The parameter $[a_0, a_1, \cdots, a_{n-1}]$, $[b_0, b_1, \cdots, b_n]$ is determined by PDSTA. The setting parameters of PDSTA is given in Table 2.

So we only discuss the processing of the order. To illustrate the

Table 3
The values for different order models for various time horizons.

Forecasting lead hour	Order of model	Number of parameters	Performance criterion		
			Average modeling time(s)	nMAE	nRMSE
One hour	2-order	5	21.83	3.83	5.61
	3-order	7	21.94	**3.22**	**5.17**
	4-order	9	32.85	3.46	5.38
	5-order	11	44.01	3.42	5.41
Three hour	2-order	5	20.81	4.02	5.86
	3-order	7	22.16	**3.24**	**5.21**
	4-order	9	37.82	3.73	5.57
	5-order	11	46.03	3.38	5.35
Six hour	2-order	5	21.20	4.14	5.79
	3-order	7	24.01	**3.22**	**5.30**
	4-order	9	39.81	3.66	5.58
	5-order	11	45.23	3.40	5.39
Nine hour	2-order	5	22.02	4.38	5.91
	3-order	7	25.14	**3.42**	**5.67**
	4-order	9	39.90	3.99	5.88
	5-order	11	48.34	3.62	5.61
Twelve hour	2-order	5	21.97	4.53	6.02
	3-order	7	23.46	**3.51**	5.86
	4-order	9	41.86	4.02	5.93
	5-order	11	47.00	3.68	**5.76**

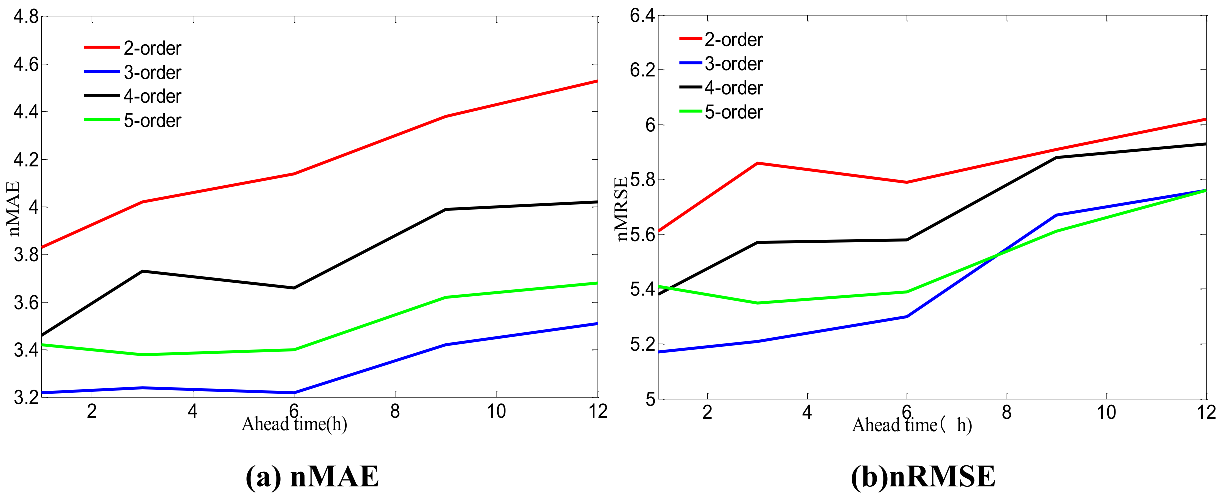


Fig. 8. The trend of the nMAE and nRMSE with varying orders.

parameterization of the order, the case of forward forecasting for IMFl is considered in this section.

A variety of different order models are chose to forecast the series of IMFl. It all knows that the model has higher order, the more complex structure is and the more modeling time spend. So the discussion of higher order full-parameters continued fraction has few significance. Considering the forecast time and model complexity, we choose 2-order, 3-order, 4-order and 5-order models for 1 h ahead, 3 h ahead, 9 h ahead and 12 h ahead time forecasting, and the errors are shown in Table 3. The trend of the nMAE and nRMSE with varying orders is shown in Fig. 8.

It can be seen from Fig. 8(a) that the nMAE of 3-order and 5-order models are all smaller than other two orders and also decrease slowly with the increasing of look-ahead time. However, 3-order model has the smallest values than other orders. Table 3 shows that the average modeling time of 3-order model is only longer 0.11s, 1.35s, 2.81s, 3.12s and 1.49s than 2-order model, which is much shorten than others. Fig. 8(b) and Table 3 illustrate that the nRMSE of 3-order model is mostly smaller in all four models. Only the value of 9 h ahead time is bigger than 5-order model. But the average modeling time of 3-order model is only 1.94s, which is shorter than 5-order model.

The performance evaluation using nMAE, nRMSE and average modeling time all show that 3-order model is better compared with other order models. So 3-order full-parameters continued fraction is chose to predict wind power in last section.

4.3. Results and discussion

This section analyzes the forecasting results of proposed method and compares with different forecasting methods described previously.

The numerical results with the proposed methods are provided in Fig. 9 for 3 h ahead, 6 h ahead, 9 h ahead and 12 h ahead, correspondingly. From this figure, we can see the forecasts follow the trend of the actual values closely in general for various time horizons. The distribution of nMAE for 3 h ahead is between 3.2% and 3.4%. The distribution of nMAE for 6 h ahead is between 3.2% and 3.52%. The distribution of nMAE for 9 h ahead is between 3.4% and 4.18%. The distribution of nMAE for 12 h ahead is between 3.7% and 4.28%. These results show that the errors of proposed method decrease slowly with the increasing of look-ahead time.

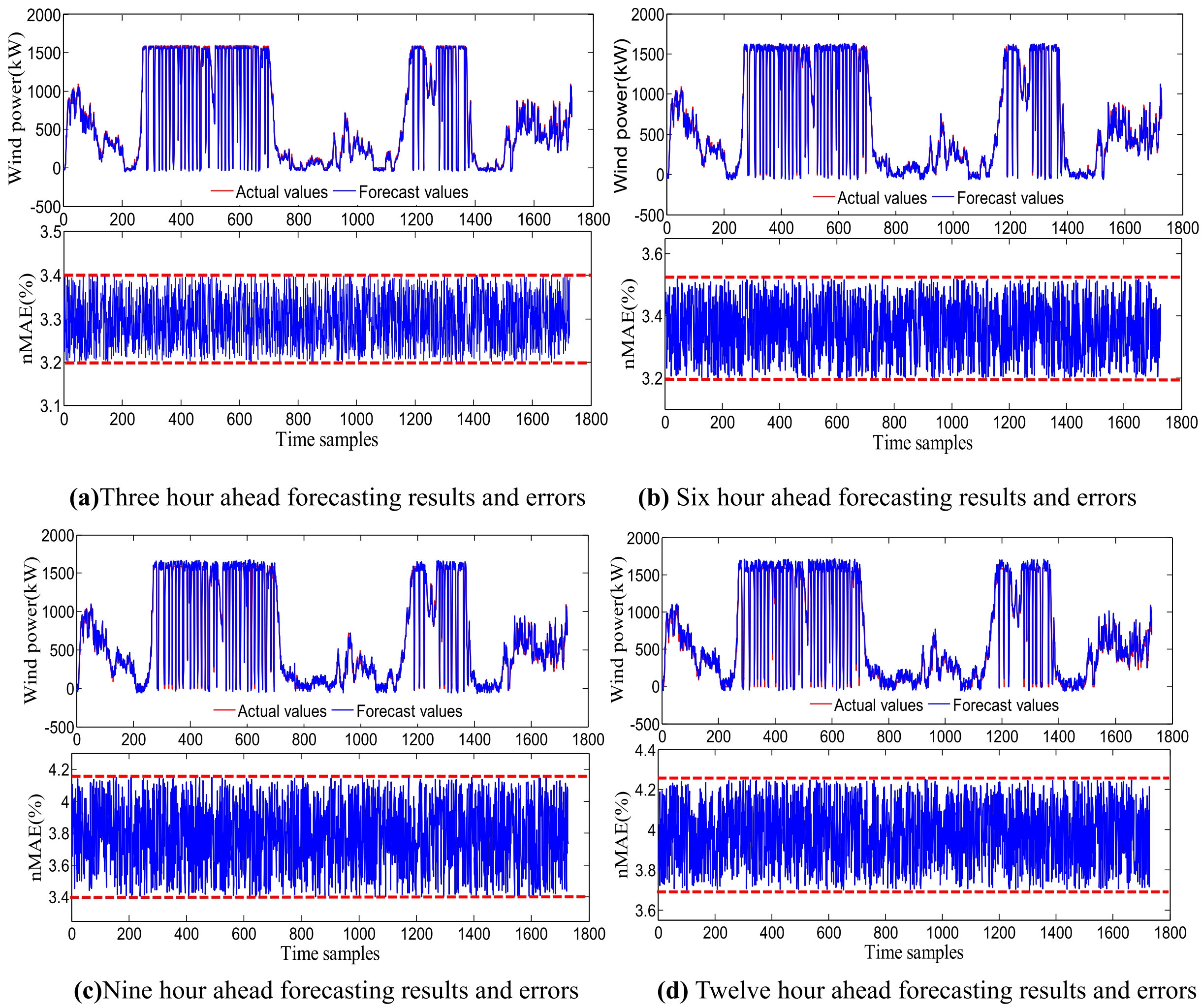
In order to further analyze the effectiveness of the proposed method in wind power forecasting, we analyze the forecasting results for different forecasting methods described previously. These methods include the hybrid evolutionary-adaptive (HEA) [19], MLE [43], Bidirectional method [8], SVM and RBF. The nMAE and nRMSE criteria defined in Section 3 are used to evaluate these methods. The nMAE and nRMSE are used for more accurate error analysis. The nMAE and nRMSE can describe the contribution of positive and negative errors to the lack of accuracy. The nMAE and nRMSE are shown in Table 4. In order to more clearly compare performances of these forecasting methods, the trends of nMAE and nRMSE with the increasing look-ahead time are shown in Fig. 10. Fig. 11 presents the average errors to evaluate the overall performance of the six methods.

It can be seen from Table 4 and Fig. 10 that, the nMAE and nRMSE of HEA, MLE, Bidirectional method, SVM and the proposed methods are all decrease slowly with the increasing of look-ahead time. The errors of the RBF model present a monotonically increasing trend. And the all nMAE and nRMSE values of the proposed method are the smallest in all six models. Compared with the other models, the proposed method consistently exhibits the best forecasting error for the vast majority of time-steps ahead. Large errors can significantly increase the value of nRMSE. The trend of nRMSE for proposed method in Fig. 10(b) shows that the growth of prediction error in entire process is smaller than others.

It can be observed from Table 4 and Fig. 11 that the average nMAE and nRMSE values of the proposed method leads to the lowest average errors for 12 look-ahead hours over the entire evaluation period. The proposed nMAE value is 3.54%, which is considerably below the 0.21%, 0.74%, 1.02%, 1.08%, 1.53% errors of the HEA, MLE, Bidirectional method, SVM and RBF respectively. The proposed nRMSE value is 5.47%, which is also considerably below the 0.46%, 1.04%, 1.63%, 1.84%, 6.1% errors of the HEA, MLE, Bidirectional method, SVM and RBF respectively.

The error results with the six methods are provided for 12 h ahead are shown in Fig. 12, correspondingly. It can be seen from Fig. 12 that the distribution of nMAE of the proposed method is between 3.7% and 4.21%. The distribution of nMAE of HEA, MLE, Bidirectional method, SVM and RBF are 4.1%–4.34%, 4.6%–4.8%, 5%–5.05%, 5.2–5.25% and 5.8%–5.95%, respectively. Compared with the other models, the proposed method consistently exhibits the best forecasting error for the vast majority of 12 h ahead, which shows the proposed method has higher accuracy for long-term horizon.

The modeling time for these six methods are shown in Table 5. The proposed method has a relatively fast prediction speed and the



(a) Three hour ahead forecasting results and errors **(b)** Six hour ahead forecasting results and errors

(c) Nine hour ahead forecasting results and errors **(d)** Twelve hour ahead forecasting results and errors

Fig. 9. Measured and predicted results of proposed method for various time horizons.

Table 4
Wind power forecasting error for different methods.

Forecasting lead hour	HEA		MLE		Bidirectional		SVM		RBF		Proposed	
	nMAE	nRMSE	nMAE	nRMSE	nMAE	nRMSE	nMAE	nRMSE	nMAE	nRMSE	nMAE	nRMSE
1	3.41	5.56	3.82	6.09	4.11	6.65	4.24	7.06	4.42	7.89	3.23	5.10
2	3.45	5.61	3.94	6.17	4.18	6.73	4.31	7.04	4.44	9.21	3.22	5.24
3	3.52	5.69	4.01	6.22	4.24	6.84	4.23	7.12	4.60	10.07	3.31	5.31
4	3.57	5.77	3.99	6.37	4.35	6.91	4.34	7.17	4.70	10.34	3.39	5.33
5	3.59	5.82	4.18	6.36	4.42	6.99	4.51	7.21	4.81	11.05	3.31	5.29
6	3.71	5.90	4.22	6.45	4.52	7.08	4.59	7.24	4.92	11.47	3.37	5.34
7	3.68	5.88	4.30	6.52	4.59	7.16	4.62	7.31	5.12	11.98	3.43	5.40
8	3.80	6.04	4.39	6.68	4.68	7.24	4.67	7.40	5.24	12.31	3.62	5.43
9	3.91	6.11	4.51	6.75	4.80	7.29	4.79	7.39	5.41	13.02	3.77	5.59
10	4.02	6.19	4.58	6.80	4.84	7.31	4.88	7.53	5.59	13.36	3.89	5.75
11	4.13	6.28	4.69	6.82	4.95	7.42	5.08	7.62	5.73	13.90	3.96	5.87
12	4.22	6.31	4.72	6.91	5.02	7.58	5.22	7.64	5.90	14.23	4.01	5.93
Average	3.75	5.93	4.28	6.51	4.56	7.10	4.62	7.31	5.07	11.57	3.54	5.47

average modeling time is less than 25s per iteration, on average. It can be observed from Table 5 that the average modeling time of proposed method is less 16.93s, 26.45s, 37.66s, 20.33s and 48.27s than HEA, MLE, Bidirectional method, SVM and RBF. The comparative analysis show that not only the training time of proposed method is almost negligible, but also the accuracy is higher and the uncertainty is lower.

From the case study of wind farms in Xinjiang, China, we can see that the proposed method has certain advantages compared with HEA, MLE, Bidirectional method, SVM and RBF for one-day ahead wind power forecasting. Introducing EEMD-SE data pre-processing techniques into the model improves forecast accuracy and prediction speed. Furthermore, full-parameters continued fraction has the advantages in function and sequence prediction of inverse

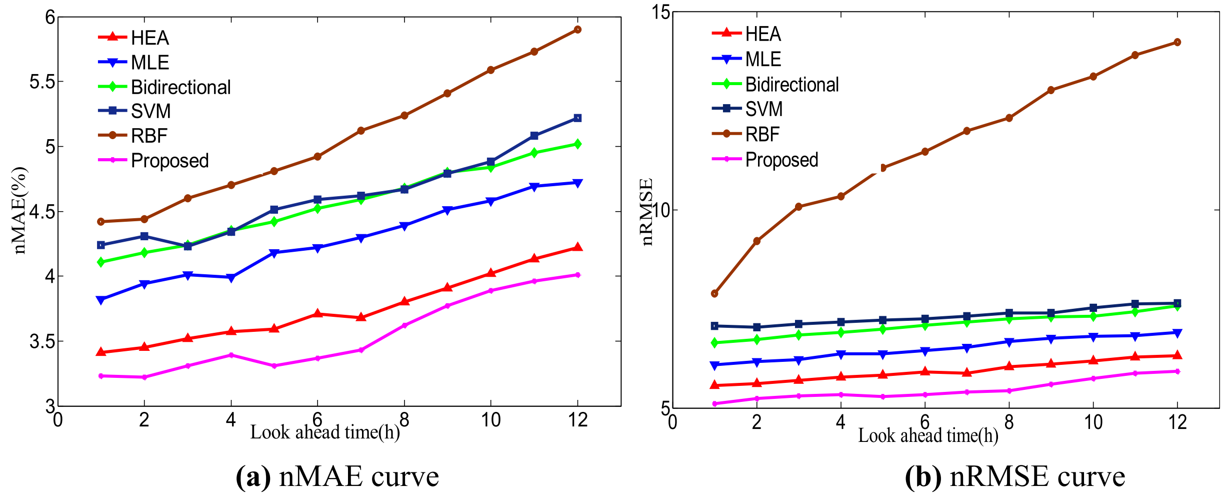


Fig. 10. Trend of nMAE and nRMSE with look ahead time for six different models.

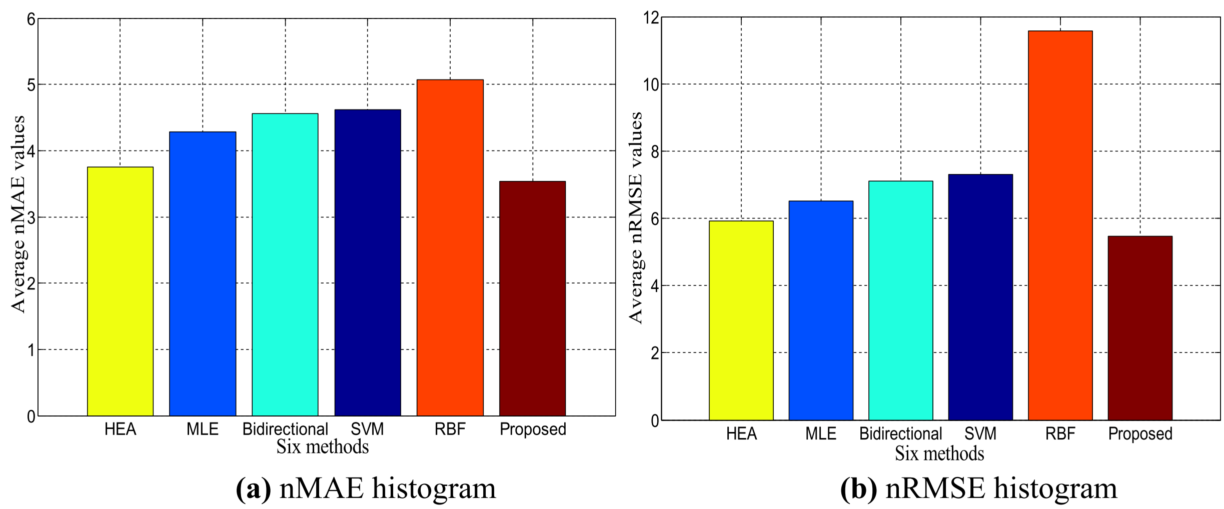


Fig. 11. Average errors for the six methods.

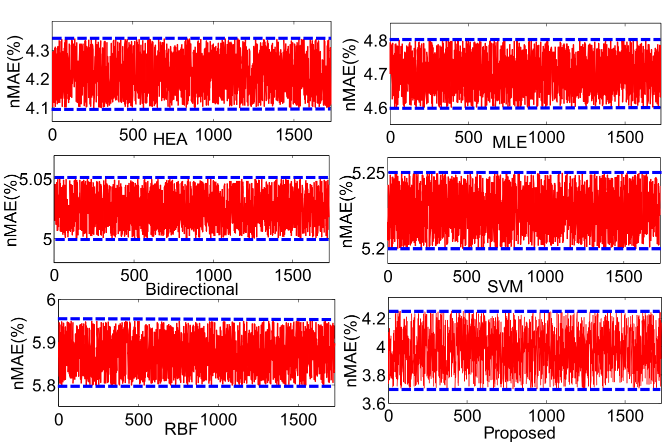


Fig. 12. Twelve-hour-ahead forecasting errors of the 12 test days for six methods.

difference quotient continued fraction, but also solve the problems as large amount of calculation and the defects of low efficiency. PDSTA is used to train the parameters of the model, which has better convergence and higher quality solution with lower iterations than most swarm intelligence algorithms and allows improving the forecasting accuracy and avoiding the time consuming process of model optimization.

Table 5
The modeling time for these six methods.

Methods	HEA	MLE	Bidirectional	SVM	RBF	Proposed
The longest time	43.32s	50.11s	64.82s	45.28s	79.15s	23.04s
The shortest time	35.01s	47.16s	56.47s	39.98s	67.34s	20.02s
Average time	38s	48.42s	59.63s	42.30s	70.24s	21.97s

In summary, the EEMD-SE and full-parameters continued fraction model are beneficial to performance improvement. This modeling process provides reliable wind power forecasts, which is of great significance for wind power integrated grid operations. In addition, the proposed model is simple and flexible. On the one hand, full-parameters continued fraction has simple structure, which is proposed on the basis of the inverse difference quotient continued fraction. The parameters of forecasting model are all optimized by PDSTA, which avoids the choice of parameters. On the other hand, according to different actual needs, the orders of forecasting models can choose flexible.

From above results and discussion, the proposed forecasting method has higher accuracy than several current prominent research findings. The proposed forecasting model can be used as the core forecasting strategy of wind power forecasting system, which can let wind power forecasting system getting more accurate power prediction results. According to the prediction results, the generation schedule can plan reasonably to lower the spinning reservation and improve power grid economy. On the basis of the reasonable generation schedule, operation mode and countermeasures can be arranged properly to improve power grid security and reliability. The wind power can be dispatched efficiently and managed scientifically to improve the power grid accommodation ability. It can also instruct the planned maintenance of wind farm to improve operation economy.

5. Conclusion

In this paper, a new forecasting method based on EEMD-SE and full-parameters continued fraction is proposed. And the parameters of full-parameters continued fraction is optimized using PDSTA. EEMD is an effective method to decompose the chaos wind power time series into a series of intrinsic mode signals with different characteristics scales. And sample entropy can useful to analyze intrinsic mode signals and reduce the computing scale of the models. By this way, the new series is not only clearly describe the sequence features, but also can reduce the computing scale. The forecasting model of each subsequence is created with three-order full-parameters continued fraction, which is verified more useful than other orders. The full-parameters continued fraction model is proposed on the basis of the inverse difference quotient continued fraction. It not only has the advantages in function and sequence prediction of inverse difference quotient continued fraction, but also solve the problems as large amount of calculation and the defects of low efficiency. So the full-parameters continued fraction can ensure the forecasting speed and accuracy. In addition, the parameters optimization problem of model is transformed into the function optimization problem on the multidimensional space. The parameters of forecasting model are all optimized by PDSTA, which avoids the choice of parameters. This guarantees the accuracy of the full-parameters continued fraction. For a fair and clear comparative study, identical test cases (forecasting for horizons from 1 h to 12 h in Xinjiang, China) used by other method are considered.

The comparison results verified that the effectiveness of the proposed method in wind power forecasting. The proposed method not only has higher accuracy but also use less modeling time, which is more practical.

Acknowledgments

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