Short-term wind power forecasting based on HHT

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Keywords: Wind power, Hilbert-Huang transform, combination forecasting, EMD

Abstract. Wind power has important effects on the stability and economic operation of power grid with its strong randomness and volatility, which become the important restriction factor of wind power generation. In order to have a good prediction effect on the volatility and uncertainty signal, the article proposes a combination forecasting model based on Hilbert-Huang transform, The power sequence data is decomposed into a number of intrinsic mode function components by the empirical mode decomposition (EMD) method, then different sequence can be forecasting by appropriate models and obtain the final prediction value by adding up the prediction results of each component. The model uses the actual data of wind farm in china to test. The simulation results indicate that the short-term wind power forecasting model established in the paper has higher prediction accuracy.

Introduction

With the constant development of wind power today,wind power is more and more important in the power grid,wind power generation is always weather dependent and has the trend of being integrated to power systems as the form of large-scale wind farms, which influences on power systems.Prediction of the output power in a wind farm is needed as to use wind power rationally and to increase the economical efficiency of the power system.Due to the intermittency of wind energy and the non-linearity of power system, there exist many uncertain variables which should be considered in the wind power prediction.

Short-term power forecasting method commonly include the time series method, neural network, support vector machine (SVM), wavelet transformation , Kalman filters and so on[1-2]. But a single forecasting model can't fully reflect the changing law of wind power. The combination forecast with a variety of models can complement each other's advantages. Empirical mode decomposition (EMD) is such a signal processing method, non-stationary signal can be decomposed into several intrinsic mode functions step by step according to different scales of fluctuations and trends, the decomposed signal has better regularity and stability, reducing the interference or coupling of feature information between the signals[3].Different sequence can be forecasting by appropriate models.

Hilbert-Huang Transform theory introduction

Hilbert Huang transform (HHT) is a new signal processing proposed by Norden E. Huang et in the late 1990s [4], mainly contains the empirical mode decomposition (EMD) and Hilbert spectrum analysis. The algorithm uses Empirical mode decomposition (EMD) decomposed the original sequence into a number of different frequency IMF (intrinsic mode function), then we can get instantaneous frequency of each IMF component by Hilbert transform. This method is similar to wavelet decomposition, but it do not have to preset base function, showed a good time-frequency concentration. Hilbert-Huang transform has been widely used in various fields, and have achieved good results in electric power system, it has been applied in many fields such as low frequency oscillation in power system, synchronous motor, load forecasting, harmonic analysis and so on[5-6].

EMD.First of all, use EMD decomposed the power data into a set of intrinsic mode function (IMF) and residual component. The EMD decomposition steps are as follows:

Find out all of the maximum and minimum points of $x(t)$,using cubic spline interpolation function to connect all the extreme value point, it will form upper and lower envelopes, and their mean value of

upper and lower envelopes recorded as $m_1(t)$. $h_1(t)=x(t)-m_1(t)$,If $h_1(t)$ meet the conditions of IMF, It is the first component of IMF as $\mathrm{Im}\, f_1(t)$,otherwise, repeat the previous steps n times until $\mathrm{Im}\, f_1(t)=h_{1n}(t)$, set $r_1(t)=x(t)-\mathrm{Im}\, f_1(t)$ as a new signal to repeat the previous steps and we can get $\mathrm{Im}\, f_2(t)$,then , get the rest component of IMF in turn, When residual term less than the preset value or as a monotone function, the decomposition is completed. The original signal is expressed as the sum of each IMF component and residual component. set $\mathrm{Im}\, f_i(t)=c_i(t)$,then,

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

The signal is decomposed into different IMF component frequency and residual component r, the component of IMF row in front mainly contain the high frequency signal of random element. the component of IMF in the back mainly include low frequency information with obvious periodic, the remaining component is low frequency information with obvious trend.

Secondly, Applying the Hilbert transform to each IMF component to get the instantaneous frequency of each component, the steps are as follows: Applying the Hilbert transform to each IMF to get $\hat{c}_i(t)$,

$$\hat{c}_i(t)=\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{c_i(t)}{t-t}dt \tag{2}$$

we can get complex sequence $z_i(t)$ by $c_i(t)$ and $\hat{c}_i(t)$.

$$z_i(t)=c_i(t)+j\hat{c}_i(t)=a_i(t)e^{j\Phi_i(t)} \tag{3}$$

Among them, the phase function and amplitude value function is:

$$\Phi_i(t)=\arctan\left(\frac{\hat{c}_i(t)}{c_i(t)}\right) \tag{4}$$

$$a_i(t)=\sqrt{c_i^2(t)+\hat{c}_i^2(t)} \tag{5}$$

Instantaneous frequency:

$$f_i(t)=\frac{1}{2\pi}w_i(t)=\frac{1}{2\pi}\frac{d\Phi_i(t)}{dt} \tag{6}$$

Establishment of Model

LS-SVM[7].LS-SVM is based on SVM (Support Vector Machine) and turn inequality constraints into equality constraints. it reduces the computational complexity of SVM and solve the slow computation speed problem of large sample calculation, which has its advantages in wind power prediction. LS-SVM model has a good effect in predicting high frequency, high volatility and strong randomness signal.

BP neural network . BP neural network with simple structure, the basic idea of BP neural network is the least square method. it has strong approximation capability, applicable to predict strong periodicity, weak randomness and relatively stable time series.

Time Series . First of all, use the time series to establish a model and estimate the parameters, then using the established model to calculate predicted value of the time series. Time series autoregressive model forecasting speed fast, lack of self-learning ability, applicable to predict simple change regularity , low frequency, strong trend time series.

The article prediction steps as follows:

(1) Wind power data should be decomposed into a series of intrinsic mode function components and remainder.
(2) To analyze the characteristics of each component serious .
(3) Different sequence should be forecasting by appropriate models.
(4) Using forecasting samples to predict the future wind power and obtain the final forecasting value by adding up the prediction results of each component.

This paper uses the mean absolute percentage error and absolute percentage error to assess prediction effect, formulas for calculation:

$$E_{\mathrm{MAPE}} = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{u_i - u_i^{'}}{u_i}\right| \times 100\% \tag{7}$$

$$E_{\mathrm{APE}} = \left|\frac{u_i - u_i^{'}}{u_i}\right| \times 100\% \tag{8}$$

Above formula: $u_i^{'}$ is predictor, u_i is true value

Analysis of simulation

The model uses the actual data of wind farm from April 1, 2015 to April 29 in china to test the wind power data of 24 hours on April 30. The original wind power data has been decomposed into the seven IMF components and a remainder which is shown in Fig.1. The spectrum of each IMF component which has been processed by the Hilbert transformation is shown in Figure 2. And the average instantaneous frequency of each component is shown in table 1.

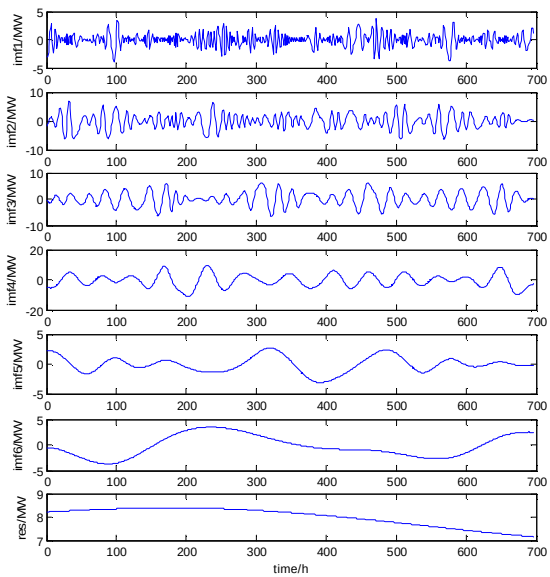

Fig. 1 The EMD results of wind power time series

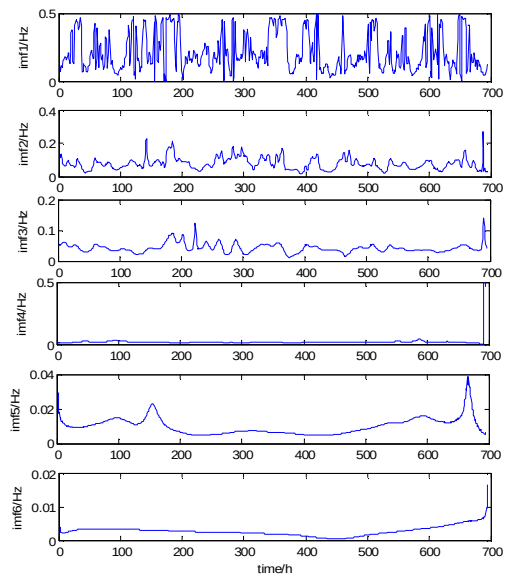

Fig.2 Spectrum of each IMF

Tab.1 The mean instantaneous frequency of each IMF

Component	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
The average instantaneous frequency	0.214	0.077	0.042	0.021	0.009	0.003

It can be seen from Tab.1 that all IMF components almost are 1/2 attenuation relationship, using respectively different predictive models for each component according to their different characteristics.

We will use the LS-SVM model for the IMF1 because it has the highest frequency which mainly contains the random component of wind power. Its volatility is very obvious which is affected by wind, the weather and so on. Because the average instantaneous frequency of IMF2 and IMF3 is higher and the volatility is large, so we will use a BP neural network model for them. As to the low frequency of IMF4-5, the periodicity is obvious, the remainder is main containing trend data, so we select a time series autoregressive model for IMF4-5and remainder.

In order to verify the accuracy of combination forecasting method based on HHT, we use the BP neural network model and the LS-SVM model at the same time to separately predict wind power. All the simulation results of the predict models are shown in Fig.3

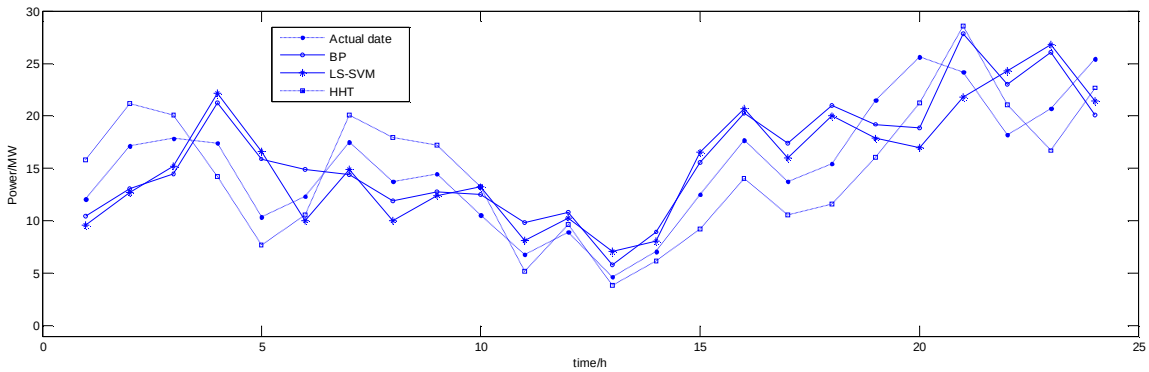

Fig.3 Comparison of each model forecasting result

Scientific error indicators have very important significance in assessing prediction effect. We use the mean absolute percentage error and the maximum absolute percentage error as the evaluation index which has been shown in Tab.2.

Tab.2 Comparison of the wind power results based on different models

Forecasting model	BP	LS-SVM	HHT
the mean absolute percentage error	23.85	24.55	19.87
The maximum absolute percentage error	44.92	49.73	37.67

it is observed from fig.3 and tab.2 that the combination forecast model raised in this paper has higher prediction accuracy than a single forecasting model.

Conclusions

This paper proposed a short-term wind power prediction model based on the HHT, the wind power time series is decomposed by the EMD into several IMF components, different forecast methods are established respectively according to their frequency of the spectrum of each component, using the combination model for the high frequency component; we can directly select a single model for the low frequency component. The prediction result of each component is superposed to get the final forecast value. At last, we use the real wind power data of wind farm in china to verify the combination prediction model proposed in the paper, the result shows that it has higher prediction accuracy.

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