A Novel Wind Speed Forecasting Method Based on Ensemble Empirical Mode Decomposition and GA-BP Neural Network

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***Abstract*—Wind energy is one of the most important renewable energy resources. Wind speed forecasting is a critical tool for wind energy conversion system implementation. However, the uncertainty and intermittency of wind speed always affect the prediction accuracy. This paper proposes a novel wind speed forecasting method based on ensemble empirical mode decomposition (EEMD) and GA-BP neural network. The wind speed data are decomposed into certain signals with different frequencies by EEMD. Each signal is taken as input data to establish GA-BP neural network forecasting model. Final forecasted wind speed data are then obtained by adding up the predicted data of each signal. A case study of a wind farm in Inner Mongolia, China shows that this method is more accurate than traditional GA-BP forecasting approach. The study also shows that method with EEMD is more accurate than that with empirical mode decomposition (EMD).**

***Index Terms*— EMD, EEMD, Genetic Algorithm, GA-BP Neural Network, Wind Speed Forecasting**

I. INTRODUCTION

Wind energy, being economically competitive and environmentally friendly has become the fastest growing renewable energy resource of electricity generation. Accurate wind speed information is of great importance for wind energy conversion system.

However, the biggest challenge in forecasting wind speed is its intermittency and uncertainty. A lot of wind speed forecasting methods over different time-scales have been proposed recently. For example, several physical models based on sophisticated weather data have been developed [1], [2]. These complex physical models always rely on numeric weather prediction (NWP) system and the data they need are not easy to get. Several statistical forecasting models known as autoregressive moving average (ARMA) models are proposed in [3] and the results indicate that the ability of ARMA forecast models would differ when applied to different time periods. A novel forecasting method for one hour ahead wind speed forecasting based on the grey model GM (1, 1) is presented in [4]. However, this model may be only suitable for a certain site with a specific wind characteristic, but will not be suitable for other areas. Some new methods based on artificial intelligence techniques have been developed [5], [6] and one of them is the GA-BP neural network. GA-BP neural network is a kind of BP neural network optimized by genetic algorithm. It can simulate any nonlinear function and has a wide range of applications. Three different neural network including BP, adaptive linear element and RBF for 1-hour ahead wind speed forecasting are compared by G. Li and J. Shi [7].The mean absolute percentage error of these methods is about 20% and root mean square error is about 1.50. Hybrid method like the combination of fuzzy logic and artificial neural network is established in [8] and the result is more accurate than single method.

Empirical mode decomposition (EMD) has been applied extensively to analyze nonlinear stochastic signal. Compared with wavelet transformation and Fourier transformation, it has many advantages such as good multi-resolution and wide applicability. However, the most significant drawback of EMD is mode mixing. To overcome this problem, a new noise-assisted data analysis method called ensemble empirical mode decomposition (EEMD) is proposed. The superiority of EEMD has been tested in many fields [9]-[12].

In this paper, a hybrid wind speed forecasting method based on EEMD and GA-BP neural network is established to further improve the forecasting accuracy. The principles of EMD and EEMD are described in section II. Section III illustrates the GA-BP neural network. Detailed process about setting the model in a case study from a wind farm in Inner Mongolia, China as well as the result analysis and discussion are shown in section IV.

II. PRINCIPLES OF EMPIRICAL MODE DECOMPOSITION AND ENSEMBLE EMPIRICAL MODE DECOMPOSITION

A. Empirical Mode Decomposition

Hilbert-Huang transform is an adaptive and efficient method to analyze nonlinear and non-stationary signals and its key part is EMD [13]. A series of intrinsic mode functions (IMFs) are extracted from the original signal by sifting stage by stage. An IMF is a function that satisfies the following two conditions: (1) in the whole data set, the number of extreme values and the number of zero crossings must either equal or

This work was supported in part by National Basic Research Program of China (2009CB219708), National Natural Science Foundation of China (NSFC 50837001, 51077098) and National High Technology Research and Development Program 863 of China (2011AA05A106).

978-1-4799-1303-9/13/$31.00 ©2013 IEEE

differ at most by one; and (2) at any point the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero.

With the above definition for IMF, the signal can be decomposed in the following steps [13]:

a) For any signal $x(t)$, firstly, identify all the local maxima and minima. Connect all the maxima by a cubic spline curve to produce the upper envelop and connect all the minima by another cubic spline curve to produce the lower envelop. The mean value of the upper and lower envelop is defined as m and the difference between $x(t)$ and m is defined as h. That is:

$$h = x(t) - m \tag{1}$$

b) Take h as the new original signal $x(t)$ and repeat the operations in step (a) k times until h is an IMF. The termination criterion to judge whether h is an IMF or not is defined as follows:

$$D_k = \frac{\sum_{t=0}^{T} \left| h_{(k-1)}(t) - h_k(t) \right|^2}{\sum_{t=0}^{T} \left| h_{(k-1)}(t) \right|^2} \tag{2}$$

Here, if D_k is smaller than a predetermined value, h_k can be viewed as an IMF. Designate the first IMF as $c_1 = h_k$.

c) Once c_1 is determined, the residue r_1 can be obtained by separating c_1 from the rest of the data. That is:

$$r_1 = x(t) - c_1 \tag{3}$$

Then, take r_1 as the new original signal $x(t)$, repeat the operations in step (a) and step (b) until the second IMF c_2 is obtained. In order to get all the IMFs, above operations should be taken j times until r_j is smaller than a predetermined value or r_j becomes a monotone function. At last, a series of IMFs and a residue r can be obtained.

B. *Ensemble Empirical Mode Decomposition*

Mode mixing is the most significant drawback of EMD. Mode mixing implies either a single IMF consisting of signals of dramatically disparate scales or a signal of the same scale appearing in different IMF components, and usually causing intermittency of analyzing signal.

To solve the problem of mode mixing in EMD, a new noise-assisted data analysis method EEMD is proposed. In EEMD the true IMF components are defined as the mean of an ensemble of trails. Each trail consists of the decomposition results of the signal plus a white noise of finite amplitude [14]. EEMD method benefits from recent studies of white noise which showed that EMD method is an effective self-adaptive dyadic filter bank when applied to the white noise [15], [16]. The result demonstrates that noise can help data analysis in the EMD method. EEMD algorithm can be described as below:

a) Add a white noise series to the original signal.

b) Decompose the signal with added white noise into IMFs by EMD.

c) Repeat steps (a) and (b) for a certain number of times with different white noise each time and obtain corresponding IMF components of the decomposition. The repeat times is called the ensemble number and should be decided in advance. For example, if the ensemble number is 200, totally 200 different IMF1 will be obtained.

d) Calculate the mean of all the corresponding IMF components and take the mean as the final result for each IMF. Calculate the mean of all the residue components and take the mean as the final result for the residue.

In EMD, the combination of all IMFs and the residue r is the original data. However, in EEMD the combination is no longer the original data because of the added white noise. When EEMD is applied in forecasting area, one may argue that the forecasting result will become worse for that the original data which are to be forecasted have been changed. The truth is that better decomposed IMFs can be obtained by EEMD and the signals of IMFs become smooth which can help raise the accuracy of forecasting result a lot (details in section IV).

C. *Comparison between EMD and EEMD*

To better illustrate the superiority of EEMD to EMD, a simple example is shown below. In Fig. 1, signal y_1 denotes a sinusoid signal $y_1 = \sin(20\pi t)$, y_2 denotes an intermittent signal $y_2 = \begin{cases} 0.4\sin(100\pi t) & 0.05 \le t \le 0.15 \\ -0.2\sin(300\pi t) & 0.2 \le t \le 0.25 \\ 0 & others \end{cases}$ and y denotes $y = y_1 + y_2$. The signal y in Fig. 1 is decomposed respectively by EMD and EEMD. The first and the second IMF of EMD are shown in Fig. 2 and those of EEMD are shown in Fig. 3. In this example, the amplitude (standard deviation) of the noise added is 0.01 and the ensemble number is 100.

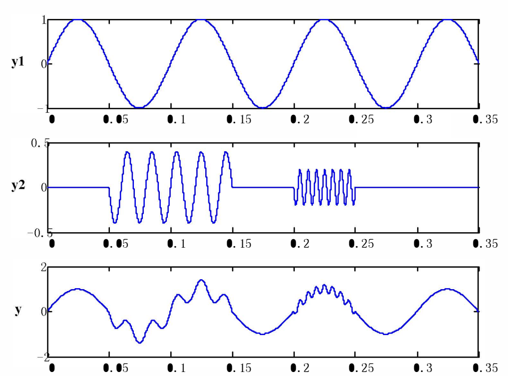

Figure 1. Synthesized signal y to be analyzed

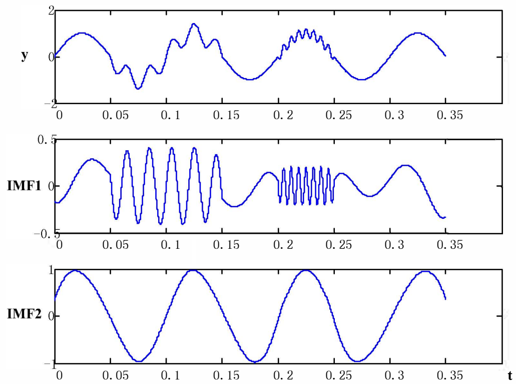

Figure 2. IMF1 and IMF2 obtained by EMD

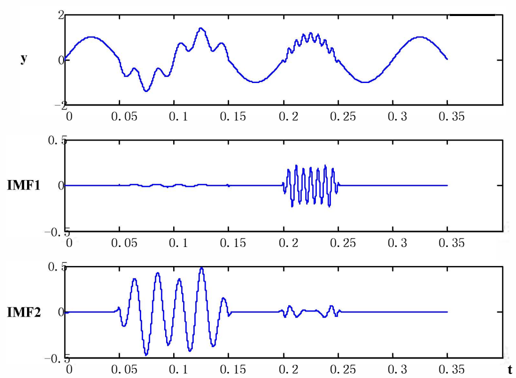

Figure 3. IMF1 and IMF2 obtained by EEMD

In Fig. 2, it is obvious that singnals with different frequencies exit in IMF1 and this mode mixing problem will affect further analysis. In Fig. 3, mode mixing problem is solved by EEMD and the two signals with different frequencies are separated clearly.

III. THE GA-BP NEURAL NETWORK

Genetic algorithm (GA) is a powerful stochastic algorithm based on natural selection mechanisms and Darwin's main principle: survival of the fittest. This algorithm has been quite successfully applied in optimization problems. The GA starts with an initial set of random solutions called population and each individual in the population is called a chromosome. The fitness of each chromosome is evaluated according to the objective function. After a series of operations including select, cross and mutation, chromosomes with low fitness are eliminated and a new population is obtained. Operations are repeated until the chromosome can satisfy certain criteria.

Artificial neural network (ANN) is an information processing approach based on the biological neural network. ANN which, in theory, can imitate any complex and non-linear relationship through non-linear units (neurons) has been widely used in the forecasting area. One of the most extensively used ANN model is BP neural network model based on the back propagation (BP) algorithm. BP neural network is composed of input layers, hidden layers, and output layers. The neural network is determined when all the weights between different layers are decided. Thus, the neural network should be trained to set all the weights before it can be used for forecasting. The initial weights are randomly set and during the forward direction of training process, output data can be obtained by some certain rules. Modify the weights according to the differences between output data and desired data and this process is called backward process. Repeat these forward and backward processes until the difference between output data and desired data can satisfy certain criteria. When applied to wind speed forecasting, the input data can be wind speed data in previous hours and the output data can be predicted wind speed data in present hour. The desired data for comparison is the real observed wind speed data. Detailed principles of BP neural network are described in [17].

Although BP neural network can surely obtain the final convergence of the network training course, its weakness is that the time of training is too long and it is easy to converge on local optimal value. To solve this problem, BP neural network has been improved by genetic algorithm technique (GA) [18] and it is called GA-BP neural network. The training starts with GA, which performs a global search on net weights range and finds out the best initial net weights for BP neural network. Then the BP neural network starts the training progress with the best initial net weights provided by GA and gets the optimum solution.

IV. WIND SPEED FORECASTING MODEL BASED ON EEMD AND GA-BP ALGORITHM

A. Detailed modeling process in a case study

Three steps are involved in this wind speed forecasting model. Firstly, original wind speed data are decomposed by EEMD; secondly, GA-BP neural network is used for the forecasting of each IMF and the residue *r*; and thirdly, combine the forecasting results of each IMF and the residue *r* and then the forecasting result for the original wind speed is obtained. The flow chart is shown in Fig. 4.

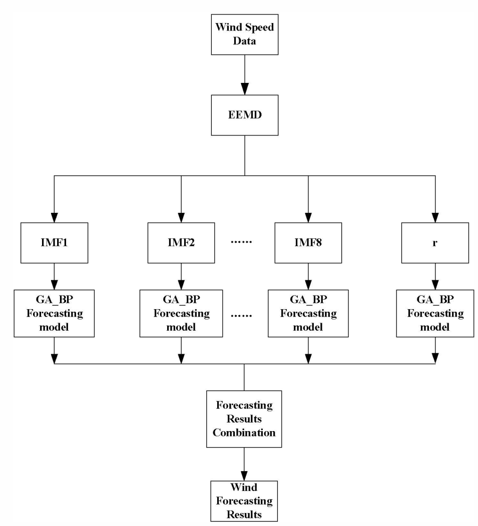

Figure 4. The flow chart of wind speed forecasting model based on EEMD and GA-BP algorithm

Wind speed data sampled every ten minutes from 6:00 January 4, 2011 to 6:00 January 9, 2011 in a wind farm of Inner Mongolia in China are taken as an example of analysis. In this example, the first six wind speed data are used to forecast the seventh data and this is a rolling forecasting process. That is to say, prediction is done using the previous one hour data for one step ahead, ten minutes.

The wind speed data are decomposed by EEMD into 8 different IMFs and a residue *r* as shown in Fig. 5. In this case study, the amplitude (standard deviation) of the noise added is 0.5 and the ensemble number is 200.

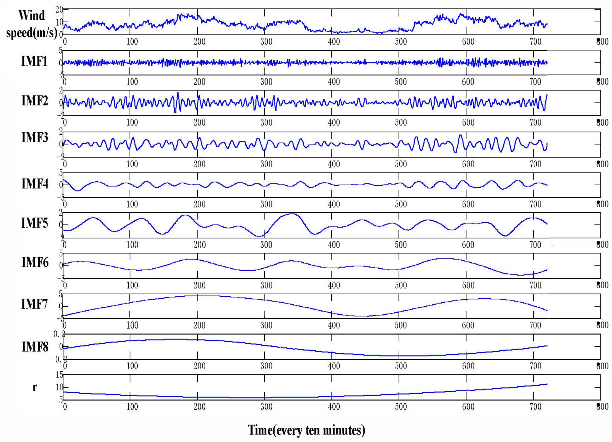

Figure 5. Decomposed result of wind speed data by EEMD

As shown in Fig. 5, different IMFs have different frequencies. The frequencies of IMF1 and IMF 2 are much higher and they mainly reflect the randomness information of the original wind speed signal. The periodic trends of IMF3 to IMF6 are obvious and they are called the periodic components of the original signal. The rest IMF7, IMF 8 and *r* are called the trend components.

After wind speed signal is decomposed by EEMD, the problem of forecasting wind speed is changed into the forecasting of each IMF and the residue *r*. GA-BP neural network is used for the forecasting of each IMF and the residue *r*. In each IMF and the residue *r* there are 721 data. The first 450 data are selected as training data for GA-BP neural network and the rest 271 data are selected as test data. As a result, in test process, 265 forecasted data are obtained for that the first six wind speed data are used to forecast the seventh data. In this rolling process, the second to seventh data are used to forecast the eighth data and so on. In this paper, the input number, hidden number and output number of GA-BP neural network are respectively 6, 10 and 1. The forecasting results of IMF4 to IMF8 and *r* by GA-BP neural network are nearly the some with the real data because the frequencies of them are low and the periodic trend is obvious. The forecasting result of IMF1 is the least accurate because the signal in IMF1 has strong random information.

B. Results analysis and discussion

Forecasting wind speed data are obtained by simply adding up forecasting results of each IMF and the residue *r*. Forecasting result of the method based on EEMD and GA-BP neural network is shown in Fig. 6. For comparison, forecasting results of the method based on traditional GA-BP neural network and the method based on EMD and GA-BP neural network are shown in Fig.7 and Fig. 8 respectively.

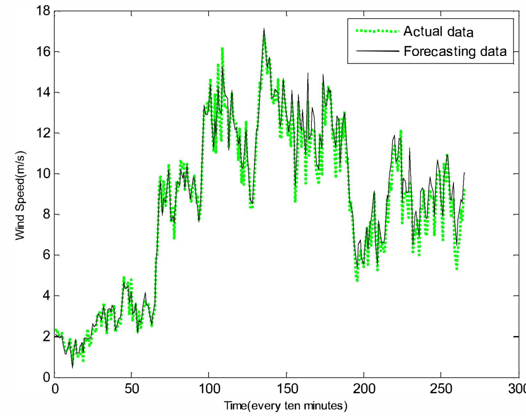

Figure 6. The result of wind speed forecasting based on EEMD and GA-BP neural network

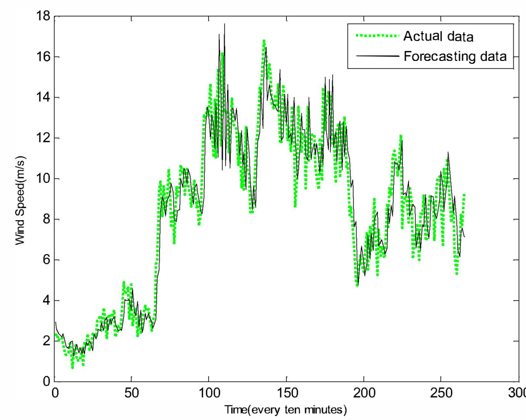

Figure 7. The result of wind speed forecasting based directly on traditional GA-BP neural network

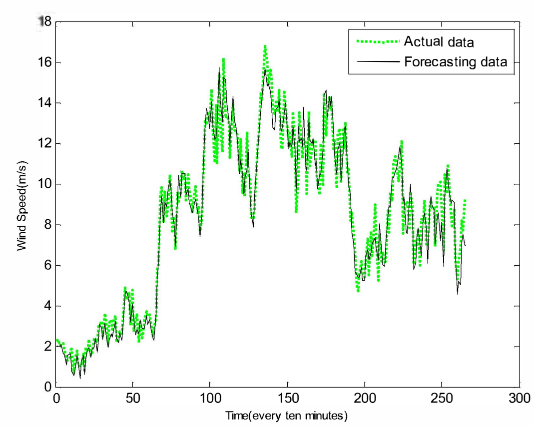

Figure 8. The result of wind speed forecasting based on EMD and GA-BP neural network

Root mean square error (RMSE) and mean absolute percentage error (MAPE) are taken as metrics to assess the performance of different methods.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - f_t)^2} \quad (4)$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - f_t}{y_t}\right| \quad (5)$$

Where y_t and f_t denote the real observed values and the forecast values respectively. T is the number of data used for performance evaluation and comparison. Results are shown in Table I.

TABLE I. RESULTS ANALYSIS OF DIFFERENT METHODS

Methods	MAPE	RMSE
Traditional GA-BP	16.87%	1.56
EMD and GA-BP	9.21%	0.79
EEMD and GA-BP	6.82%	0.59

From the results in Table I, a conclusion can be safely drawn that forecasting results obtained by EEMD and GA-BP neural network are much more accurate than those obtained by traditional GA-BP direct forecasting method. That is because after EEMD, the original unsteady and nonlinear data are changed into certain components which have fixed frequency and periodicity. When forecasted by GA-BP neural network, results of these certain components are much more accurate than the forecasting results of the original data. In addition, another conclusion is that the method based on EEMD and GA-BP is more accurate than the method based on EMD and GA-BP. Compared with Fig. 8, forecasting data in Fig. 6 follow the variation trend of the real signal tighter. Although improved by EMD, EEMD has not been applied in forecasting area because in this method a series of white noises are added into original data which may influence the forecasting accuracy at first glance. However, the decomposition results of EEMD are more stable and smooth although the original data have been changed (about 2%). And when predicted by GA-BP neural network the results of each IMF are more accurate because GA-BP neural network performs well on stable and smooth data.

V. CONCLUSION

This paper presents a novel wind speed forecasting method based on EEMD and GA-BP neural network. Through EEMD, wind speed data are decomposed into different IMFs and a residue r. GA-BP neural network is applied on the forecasting of each IMF and the residue r. Final result is obtained by simply adding the forecasting results of each IMF and r up. In the case study, MAPE and RMSE of this method are respectively 6.82% and 0.59 which are much smaller than those of traditional GA-BP forecasting method and the method based on EMD and GA-BP neural network. It proves that the proposed method can be employed to forecast wind speed precisely.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support from National Basic Research Program of China (2009CB219708), National Natural Science Foundation of China (NSFC 50837001, 51077098) and National High Technology Research and Development Program 863 of China (2011AA05A106).

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