Renewable Energy 94 (2016) 629–636

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and GA-BP neural network method

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ARTICLE INFO

Article history:
Received 31 August 2015
Received in revised form
9 March 2016
Accepted 27 March 2016

Keywords:
EMD
EEMD
GA
BP neural network
Wind speed forecasting

ABSTRACT

Wind speed is the major factor that affects the wind generation, and in turn the forecasting accuracy of wind speed is the key to wind power prediction. In this paper, a wind speed forecasting method based on improved empirical mode decomposition (EMD) and GA-BP neural network is proposed. EMD has been applied extensively for analyzing nonlinear stochastic signals. Ensemble empirical mode decomposition (EEMD) is an improved method of EMD, which can effectively handle the mode-mixing problem and decompose the original data into more stationary signals with different frequencies. Each signal is taken as an input data to the GA-BP neural network model. The final forecasted wind speed data is obtained by aggregating the predicted data of individual signals. Cases study of a wind farm in Inner Mongolia, China, shows that the proposed hybrid method is much more accurate than the traditional GA-BP forecasting approach and GA-BP with EMD and wavelet neural network method. By the sensitivity analysis of parameters, it can be seen that appropriate settings on parameters can improve the forecasting result. The simulation with MATLAB shows that the proposed method can improve the forecasting accuracy and computational efficiency, which make it suitable for on-line ultra-short term (10 min) and short term (1 h) wind speed forecasting.

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1. Introduction

Wind energy, being economically competitive and environmentally friendly, has become the fastest growing renewable energy resource for electricity generation. The wind speed forecast is of great importance for predicting the power output of wind energy systems.

However, the biggest challenge in forecasting wind speed is its intermittency and uncertainty. Many forecasting methods have been proposed recently to predict wind speeds over different time-scales. They include physical models, time series method, grey model method, artificial neural network, support vector machine (SVM) method, the wavelet transform method, empirical mode decomposition method, etc. Each method has its own advantages and limitations. For instance, the complex physical models always rely on the numeric weather prediction (NWP) system and the required input data are usually difficult to obtain [1,2]. Statistical forecasting models, such as autoregressive moving average (ARMA) models, were described in Ref. [3]. The parameters could be a function of time and the performance of ARMA forecast models would vary when applied to different time periods. A grey model GM (1, 1) based technique was presented in Ref. [4] for one hour ahead wind speed forecasting. However, this model may be suitable for certain sites with specific wind characteristics, but would not be generalizable to other locations. Artificial neural network was applied in wind speed forecasting in Refs. [5,6]. Three different neural networks including BP, adaptive linear element, and RBF for 1-h ahead wind speed forecasting were compared in Ref. [7]. These methods could approximate complex nonlinear functions, but with a complex network structure, the training time would be very long and more liable to fall into local minimum value. In order to improve the performance of artificial neural network, some researchers applied genetic algorithm to update its learning rule and the network weights, which improves the learning rate and the ability to approach to global optimality. On the other hand, the wavelet transform can provide the frequency of signals and the time associated with those frequencies, which makes it very convenient for the application in forecasting fields, but the forecasting accuracy depends on the choice of base functions [8,9].

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http://dx.doi.org/10.1016/j.renene.2016.03.103
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Based on SVM-enhanced Markov model, the short-term distributional forecasts and point forecasts were also derived in Ref. [10]. Hybrid methods, such as the combined fuzzy logic and artificial neural network approach, were established in Ref. [11], which may outperform individual methods.

Empirical mode decomposition (EMD) has been applied extensively for analyzing nonlinear stochastic signals. 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) was proposed. The superiority of EEMD has been tested in many fields [12–15].

This paper proposes a novel wind speed forecasting method based on a hybrid EEMD and GA-BP neural network method. The original wind speed data is decomposed into certain signals by EEMD. Then, each signal is taken as an input data to establish the GA-BP neural network forecasting model. The final wind speed forecast is obtained by aggregating the predicted data of individual signals. The applicability of the proposed hybrid method for different time-scale wind speed forecasting is also discussed.

The paper is organized as follows. Section 2 presents the principles of EMD and EEMD. Section 3 introduces the GA-BP neural network. The proposed hybrid model is described in Section 4. Case studies and conclusions are drawn in Section 5 and Section 6, respectively.

2. Principles of empirical mode decomposition and ensemble empirical mode decomposition

2.1. Empirical mode decomposition

Hilbert-Huang transform, developed by Huang et al., in 1998, is an adaptive and efficient method for analyzing nonlinear and non-stationary signals and its key part is EMD [16]. Since the wind speed is a kind of nonlinear and non-stationary signal, this method is efficient to analyze the wind speed signal. A series of intrinsic mode functions (IMFs) is extracted from the original signal by sifting stage by stage. An IMF is a function that satisfies the following two conditions: (1) in the entire data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one; and (2) at any point, the mean value of the envelopes defined by the local maxima and the local minima must be zero.

With the above definitions for IMF, a signal could be decomposed through the following steps [16]:

For wind speed signal $x(t)$, identifying all local maxima and minima. Connect all maxima by a cubic spline line to produce the upper envelop, and connect all minima by another cubic spline line to produce the lower envelop. The mean value of the upper and the lower envelops is defined as m, and the difference between $x(t)$ and m is defined as h.

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

Take h as the new original signal $x(t)$, and repeat Step (a) k times until h is an IMF. The criterion (2) is used to determine whether h is an IMF.

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

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

Once c_1 is determined, the residue r_1 can be obtained by separating c_1 from the rest of the data (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 IMFs, the above operations should be taken j times until r_j is smaller than the predetermined threshold or r_j becomes a monotone function. Finally, a series of IMFs and the residue r can be obtained.

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

2.2. Ensemble empirical mode decomposition

Mode mixing is the most significant drawback of EMD, which implies that a single IMF consists of signals with dramatically disparate scales or a signal of the same scale appears in different IMF components. This usually causes intermittency when using EMD to analyze signals.

To solve the mode mixing problem 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 [17]. EEMD benefits from recent studies on white noises, which showed that EMD is an effective self-adaptive dyadic filter bank when applied to white noises [18,19]. The results demonstrate that noise can help data analysis in the EMD method. The EEMD algorithm is described as follows:

1) Add a white noise series to the original wind speed signal.
2) Decompose the signal with added white noise into IMFs using EMD.
3) Repeat Steps (1) and (2) with different white noises and obtain the corresponding IMF components. The number of repeated procedures is called the ensemble number.
4) Take the mean of all IMF components and the mean of residue components as the final results.

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 added white noises. When applying EEMD, one may argue that the forecasting results will become worse because the original data have been changed. On the contrary, the truth is that as better decomposed IMFs can be obtained by EEMD and the signals of IMFs become smooth, the accuracy of forecasting results has been significantly enhanced. More detailed discussion on this is provided in Section 4.

2.3. Comparison between EMD and EEMD

To better illustrate the superiority of EEMD over 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 $y = y_1 + y_2$. signal y in Fig. 1 is decomposed by EMD and EEMD. The first and the second IMFs of EMD are shown in Fig. 2 and those of EEMD are shown in Fig. 3. In Fig. 2, it is obvious that signals with different frequencies exit in IMF1. However, in Fig. 3, it is observed that this mode mixing problem is solved by EEMD and the two signals with different frequencies have been successfully separated.

3. The GA-BP neural network

Genetic Algorithm (GA) is a powerful stochastic algorithm based

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