Applied Energy 159 (2015) 51–61

Contents lists available at ScienceDirect

Applied Energy

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

# Analysis of multi-scale chaotic characteristics of wind power based on Hilbert–Huang transform and Hurst analysis

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## HIGHLIGHTS

- A scale division method of wind power based on HHT and Hurst analysis is proposed.
- The time–frequency components of wind power show different fractal structures.
- These components are superposed and reconstructed into three scale subsequences.
- Each subsequence has a chaotic characteristic and shows its own properties.
- The EMD-LSSVM + ELM method improves the short-term wind power forecasting accuracy.

## ARTICLE INFO

*Article history:*
Received 6 April 2015
Received in revised form 22 August 2015
Accepted 24 August 2015

*Keywords:*
Wind power
Multi-scale
Hilbert–Huang transform
Hurst analysis
Chaos analysis
Short-term forecasting

## ABSTRACT

The causes of uncertainty in wind farm power generation are not yet fully understood. A method for the scale division of wind power based on the Hilbert–Huang transform (HHT) and Hurst analysis is proposed in this paper, which allows the various multi-scale chaotic characteristics of wind power to be investigated to reveal further information about the dynamic behavior of wind power. First, the time–frequency characteristics of wind power are analyzed using the HHT, and then Hurst analysis is applied to analyze the stochastic/persistent characteristics of the different time–frequency components. Second, based on their fractal structures, the components are superposed and reconstructed into three series, which are defined as the Micro-, Meso- and Macro-scale subsequences. Finally, indices related to the statistical and behavioral characteristics of the subsequences are calculated and used to analyze their nonlinear dynamic behavior. The data collected from a wind farm of Hebei Province, China, are selected for case studies. The simulation results reveal that (1) although the time–frequency components can be decomposed, the different fractal structures of the signal are also derived from the original series; (2) the three scale subsequences all present chaotic characteristics and each of them exhibits its own unique properties. The Micro-scale subsequence shows strong randomness and contributes the least to the overall fluctuations; the Macro-scale subsequence is the steadiest and exhibits the most significant tendency; the Meso-scale subsequence which possesses the greatest variance contribution rate and the maximum largest Lyapunov exponent, is the dominant factor driving the fluctuation and dynamic behavior of wind power; (3) the short-term predictions of these three subsequences based on extreme learning machine (ELM) and least-squares support vector machine (LSSVM) models have validated the above analysis results, which show that the number of steps of look-ahead predictability have pursued an ordinal trend in term of the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) and the prediction error contribution rate of the Meso-scale subsequence is the maximum. Furthermore, the short-term wind power forecasting of 6-step-ahead based on the multi-scale analysis is performed by EMD-LSSVM + ELM and the normalized Mean Absolute Error (nMAE) and normalized Root Mean Square Error (nRMSE) have been decreased by 49.45% and 44.30% compared with those of LSSVM, and 37.96% and 27.12% compared with those of EMD-LSSVM, respectively.



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http://dx.doi.org/10.1016/j.apenergy.2015.08.111
0306-2619/

## 1. Introduction

Throughout the world, the utilization of wind energy is becoming wide spread because of its advantages of reproducibility and environmental friendliness as well as the rapid development of wind power generation technology. With the increasing integration of wind power into the grid, however, the stochastic and intermittent nature of wind power generation [1] poses an increasing risk to the system reliability and power quality, and thus grid operation issues such as generation schedules and reserve allocation become topics of concern [2–6]. These difficulties hinder the further exploitation of wind energy.

In recent years, extensive efforts have been devoted to analyzing the probability distribution and fluctuation characteristics of wind power using statistical approaches based on real measured data regarding wind power or wind speed. The Weibull probability density function [7–9] has been widely used to model the wind speed distribution on various time scales, e.g., daily, monthly, seasonal or annually. The skewed generalized error and skewed *t* distributions proposed to model the wind speed in Turkey were proved to be quite flexible and to offer improvements over the Weibull distribution in the estimation of the wind speed distribution and the wind power density distribution [10]. Yu et al. [11] assessed seasonal and diurnal wind power patterns to characterize the multi-regional wind power fluctuations in China based on wind speed data from the NASA GEOS-5 DAS system. In [12], the *t* location-scale and Laplace distributions were used to describe the minute-scale wind power distribution and the average wind power variations, respectively. When describe the distribution of hourly wind power variations modeled as an exponential decay, the Laplace distribution was superior to a general extreme value and a normal distribution according to $\chi^2$ goodness-of-fit tests [13,14]. Moreover, in several recent studies, wind speed or wind power variability has been characterized based on power spectral density analysis in the frequency domain [15–18].

The studies mentioned above, which have focused on statistical distribution characteristics and time and/or frequency analyses have made significant contributions to understanding the uncertainties of wind power. Quantitative analysis on the behavior characteristics of wind speed or wind power is more beneficial for capturing the inherent characteristics of wind power. The fractal dimension was used to quantitatively analyze the self-similarity of hourly and daily wind speeds [19,20]. And combined with the Hurst exponent which was commonly utilized to evaluate the long-term persistence of time series [21], the predictability indices of daily wind speed time series from Saudi Arabia were calculated [22]. In [23], the Lyapunov exponent was calculated to characterize the chaotic dynamic behavior of wind power. It should be noted that these studies were all performed on a single scale.

In essence, wind power exhibits extremely complex nonlinear dynamic characteristics, which are affected by many factors, such as wind direction, air temperature, air humidity, illumination and earth surface roughness. These complex behavior characteristics cannot be revealed through investigations at only a single scale. Various widely used multi-scale analysis methods can reveal the non-stationary or transitory characteristics of signals, such as abrupt changes and trends, and the physical phenomena underlying them [24]. Furthermore, many studies have shown that the accuracy of wind speed or wind power prediction can be enhanced by applying wavelet transforms (WTs) and empirical mode decomposition (EMD) [25–27]. However, traditional analyses of the characteristics of wind power on different scales based solely on time or frequency lack to mine the characteristics of the different scales that affect the overall wind power behavior. Moreover, to apply WTs, it is necessary to select the mother wavelet a priori and the resulting lack of self-adaptability of this method somewhat limits its ability to analyze nonlinear and non-stationary signals. By contrast, the HHT algorithm, which was first proposed by Huang et al. [28] and can be used to adaptively decompose and transform signals based on their intrinsic features, is more suitable for analyzing nonlinear and non-stationary time-varying signals.

Therefore, in this paper a method for the scale division of wind power based on the HHT and Hurst analysis is proposed, and the multi-scale chaotic characteristics of wind power are thus investigated. First, the HHT is adopted to analyze the time–frequency characteristics of wind power, and then Hurst analysis is applied to determine the fractal characteristics of the time–frequency components. The Hurst exponents and self-similar dimensions are calculated to quantitatively analyze the persistent/stochastic and fractal characteristics of these wind power components. Second, these time–frequency components which exhibit approximate random walk modes, dual fractal structures and strongly persistent tendency are superposed and reconstructed into three scale subsequences, defined as Micro-, Meso- and Macro-scale subsequences, respectively. And then indices related to the statistical and behavioral characteristics of these three subsequences are calculated to analyze their multi-scale nonlinear dynamic behaviors. After that, short-term predictions of these three subsequences are generated using the ELM and LSSVM methods to test the validity of the analysis results. Finally, a case study of short-term wind power forecasting for 6-step-ahead is performed to clarify the real implementation of the multi-scale analysis results of wind power.

This paper is structured as follows. The methods of data preprocessing and analysis, including the Hilbert–Huang transform and the end effect, the Hurst analysis and the chaos analysis, are described in Section 2. The simulation data and results as well as the analysis and verification of the proposed method are presented and a case study of short-term wind power forecasting is also performed based on the multi-scale analysis in Section 3. Finally, Section 4 summarizes and concludes the study.

## 2. Data preprocessing and analysis methods

### 2.1. Hilbert–Huang transform and end effect

The HHT is a multi-resolution analysis method and is widely applied in many research fields, such as earthquake studies [29], machinery fault diagnosis and detection [30] and ocean studies [31]. This paper makes full use of the advantages of this method to study the time–frequency characteristics of wind power. The method includes two steps: empirical mode decomposition (EMD) and the Hilbert transform. Using the EMD method, a signal can be decomposed into a finite set of intrinsic mode functions (IMFs). For any IMF, the following two conditions must be satisfied: (1) the numbers of maxima and zero-crossings in the entire dataset must be equal or differ by at most one and (2) the mean value of the envelope defined by the local minima and the envelope defined by the local maxima should be equal to zero at every point in a time series. Then a "sifting process" is designed to decompose a given signal into several IMF modes without any a priori basis assumption. The first extracted IMF corresponds to the highest frequency component of the signal, whereas the lower frequency components are represented by higher-order IMFs. The signal $x(t)$ can be exactly expressed as the following linear combination:

$$x(t) = \sum_{i=1}^{n} \mathrm{IMF}_i(t) + r(t) \quad (1)$$