Physica A 392 (2013) 4106–4120

Contents lists available at SciVerse ScienceDirect

Physica A

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

Multifractal description of wind power fluctuations using arbitrary order Hilbert spectral analysis

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HIGHLIGHTS

- We decompose the aggregate power output into IMFs using Empirical Mode Decomposition.
- Arbitrary order Hilbert spectral analysis is applied on these data to estimate the scaling exponents.
- The aggregate power output from a wind farm possesses intermittent and multifractal properties.
- In order to check this result, numerical stochastic simulations are performed using a log-normal multifractal random walk.

ARTICLE INFO

Article history:
Received 19 November 2012
Received in revised form 26 March 2013
Available online 30 April 2013

Keywords:
Wind farm
Intermittency
Multifractal analysis
Empirical mode decomposition
Hilbert spectral analysis
Multifractal random walk

ABSTRACT

The objectives are to study and model the aggregate wind power fluctuations dynamics in the multifractal framework. We present here the analysis of aggregate power output sampled at 1 Hz during three years. We decompose the data into several Intrinsic Mode Functions (IMFs) using Empirical Mode Decomposition (EMD). We use a new approach, arbitrary order Hilbert spectral analysis, a combination of the EMD approach with Hilbert spectral analysis (or Hilbert–Huang Transform) and the classical structure-function analysis to extract the scaling exponents or multifractal spectrum $\zeta(q)$: this function provides a full characterization of a process at all intensities and all scales. The application of both methods, i.e. structure-function and arbitrary-order Hilbert spectral analyses, gives similar results indicating that the aggregate power output from a wind farm, possesses intermittent and multifractal properties. In order to check this result, we generate stochastic simulations of a Multifractal Random Walk (MRW) using a log-normal stochastic equation. We show that the simulation results are fully compatible with the experimental results.

1. Introduction

The installed capacity of wind power is increasing substantially in response to the worldwide interest in low-emission power sources and to a desire to decrease the dependence on petroleum. The extent of uncertainty and variability in wind generation makes this resource different from the traditional, dispatchable generation resources with the consequence that wind power generation cannot be readily integrated into standard system operating procedures. This is particularly the case of island networks as in the Guadeloupean archipelago (French West Indies), where the installed 25 MW wind power generation already represents 11% of the electrical consumption. Therefore, the wind energy has become a significant part of the local electricity networks. An objective of at least 50% of renewable energies in the final energy consumption, would be reached

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http://dx.doi.org/10.1016/j.physa.2013.04.038

in this territory. However, in a small electric system, voltage and frequency stability is critical for operators. Wind power fluctuations are a menace for the balance between load and generation. In order to anticipate the eventuality of power shortage, the first step towards the development of simulating or forecasting tools is to characterize the wind power dynamics.

The aggregate power output from a wind plant is often qualified to as being an intermittent resource with high variability at all spatial and temporal scales. A better understanding of wind power processes is of acute practical importance to manage the electrical network integrating this kind of energy. Traditionally in the wind energy community, the variability of wind power fluctuations is characterized using a second-order statistics, e.g., Fourier power spectral density or standard deviation [1–7]. These statistical estimators describe a medium level of fluctuations [8,9]. They are not sufficient for fully describing the fluctuations of a process at all intensities and all scales especially when taking into account extreme events [8,9]. Multifractal properties have been highlighted in several disciplinary fields, such as turbulence [10–14], finance [15–18], physiology [19], rainfall [20–22], geophysical fields [23–26], etc. We study here the aggregate wind power data in the multifractal framework in order to describe the fluctuations at all scales and at all intensities (low level, medium level and high level) [27,11,28]. Here, we consider the scaling exponent $\zeta(q)$ which characterizes the scaling behavior or measures the distance between a monofractal and multifractal process [11]. Indeed if $\zeta(q)$ is linear, the process is thus considered to be monofractal, and if $\zeta(q)$ is nonlinear, the process is then regarded as being multifractal. Furthermore, the concavity gives information on the intermittency degree: the more concave the curve is, the more intermittent the process [11,9,29]. Several methods exist for estimating the scaling exponent $\zeta(q)$, the most classical being structure-function analysis [30–32], wavelet-based methods (wavelet leader, wavelet transform modulus maxima) [33–36], detrended fluctuation analysis or multifractal detrended fluctuation analysis [37–40] (due to strong periodicity commonly present in empirical data a DFA version is also proposed to account for periodicity in data [41]) and a Hilbert-based methodology developed by Huang et al. [42], namely arbitrary-order Hilbert spectral analysis [43,44], which is an extension of the Hilbert–Huang Transform (HHT) [45,46]. The last method consists of two steps, i.e., Empirical Mode Decomposition (EMD) and Hilbert Spectral Analysis (HSA). The EMD is a self-adaptive method to decompose a given signal into a sum of Intrinsic Mode Function (IMF) without *a priori* basis [47,45,46,48]. The HSA is designed to extract the instantaneous amplitude and frequency information, in which the classical Hilbert transform is involved [49,45,46,42,44,50]. The Hilbert-based methodology has shown its efficiency for various types of nonstationary and nonlinear time series [51,45,46,52,42,23,53–55].

This paper is organized as follows. In Section 2, materials and methodology are described: we present the structure-function and arbitrary-order Hilbert spectral analysis methodologies in Section 2.2. Analysis results are given in Section 3 for Fourier spectrum and structure-function analysis and arbitrary-order Hilbert spectral analysis. We then use a log-normal stochastic model in Section 3.4 to mimic the aggregate power output $P(t)$. After a discussion section, we finally draw our main conclusions in Section 5.

2. Materials and methodology

2.1. Materials: experimental data

Wind speed fluctuations can lead to electrical power variations of the order of the nominal power output. For example, the variation of the output $P(t)$ is from 16 to 7935 kW, about 2.7 orders of magnitude for the present data set. Indeed, rapid changes in the local meteorological condition as observed in tropical climate, could provoke large variations of wind speed. Consequently, the electric grid security can be jeopardized due to these fluctuations.

In this study, we consider time series of aggregate power output measurements $P(t)$ from the wind energy production site of Petit-Canal in Guadeloupe, an island in the West Indies, located at $16°15'N$ latitude and $60°30'W$ longitude (see Fig. 1). This 10 MW production site is positioned at approximately 60 m (197 ft) above sea level, at the top of a sea cliff (see Fig. 2). The aggregate power output for the entire wind farm was recorded with a sampling rate $f_s = 1$ Hz during one year from January 2006 to January 2007, corresponding to 30, 168, 890 data points. An example of the aggregate power output time series is shown in Fig. 3a. It shows a strong intermittency, with fluctuations at all scales.

Furthermore, we plot in Fig. 3b the corresponding 2 days portion of the wind speed history measured with a cup anemometer mounted on a tall mast erected 20 m (66 ft) from the cliff edge in front of the wind farm, 38 m (125 ft) from the ground. We give here some basic parameters for the turbulent wind speed $u(t)$ during the period of measurements: the mean wind speed $\overline{U} = 8.20$ m/s, the standard deviation $\sigma_u = 3.32$ m/s (hence a very high turbulence intensity of 40%) and the Reynolds number $Re = 2.57 \times 10^{10}$. One can notice a possible cross-correlation between two time series displayed in Fig. 3. Several methods exist for quantifying power-law cross-correlations between different simultaneously non-stationary experimental time series [56–59]. The cross-correlation study between the wind speed and aggregate power output simultaneous data is investigated in Ref. [60].

2.2. Methodology

2.2.1. Structure-function analysis

Intermittency in turbulence has been a major subject of turbulent research for almost 50 years now, following Kolmogorov's 1962 seminal work [61]. Here we define intermittency as the property of having large fluctuations at all