Solar Energy 144 (2017) 1–9

Contents lists available at ScienceDirect

Solar Energy

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

Strong short-term non-linearity of solar irradiance fluctuations

Ata Madanchi[a], M. Absalan[a], G. Lohmann[b], M. Anvari[c], M. Reza Rahimi Tabar[a,c,*]

[a] Department of Physics, Sharif University of Technology, Tehran 11155-9161, Iran
[b] Energy Meteorology Group, Institute of Physics, Carl von Ossietzky University, 26111 Oldenburg, Germany
[c] Institute of Physics and ForWind, Carl von Ossietzky University, 26111 Oldenburg, Germany

ARTICLE INFO

Article history:
Received 24 November 2016
Received in revised form 31 December 2016
Accepted 4 January 2017

Keywords:
Solar energy
Intermittency
Short-time scale nonlinearity

ABSTRACT

We investigate short-term non-linearity of solar irradiance fluctuations using the multifractal detrended fluctuation analysis (MFDFA). The MFDFA shows that time series of solar irradiance have a long range correlation function with a multifractal behavior. We apply this method to solar irradiance time series from several regions around the world with resolutions of seconds and minutes. The obtained generalized Hurst and Renyi exponents $h(q)$ and $\tau(q)$ suggest the non-linear and non-stationary essence of measured irradiance time series. Also, we analyze shuffled, random phase, and rank-wised surrogated data to reveal the nature of the multifractality and conclude that linear and non-linear correlations are the dominant contributions to observed multifractal and non-linear behavior of solar irradiance.

1. Introduction

The share of renewable wind and solar photovoltaic (PV) power in electricity production has constantly increased and is expected to grow further. For example, the European Union plans to generate 20% of its required electrical energy from renewables by 2020, and 60% by 2050 Schavan (2010). Recent studies on wind and solar power systems have shown that they feature strong fluctuations on different time scales, with the complexity of weather causing short-time non-Gaussian statistics in the power output of these renewable sources, see Anvari et al. (2016). These fluctuations have been characterized by Kolmogorov-like power spectra as well as q-exponential probability density functions, Anvari et al. (2016) and Rahimi Tabar et al. (2014). They complicate electrical grid operation and may endanger grid stability, Milan et al. (2013). Understanding their stochastic properties is therefore necessary for designing future power grids. It will also help to control and reduce dynamic power grid instabilities caused by renewable power production, Anvari et al. (2016) and Woyte et al. (2007).

In complex time series, two-point long-range correlations are usually characterized by scaling laws, where the scaling exponents classify the underling processes. According to the Wiener-Khinchin theorem, the two-point correlation function $\langle x(t+\tau)\cdot x(t)\rangle$ is directly related to the power spectrum by a Fourier transform. The correlation function is the linear regression in the $(x(t+\tau), x(t))$ plane, and it is therefore known as a linear quantity in the characterization of a given time series. There is a possibility that two completely different time series share a similar two-point correlation structure, but with different higher order stochastic properties. Therefore we need to analyze higher order (non-linear) statistical properties to fully characterize a given complex time series.

Let $\{x(t)\}$ be a given time series and consider its increment over a certain time scale τ, which is defined as $\Delta x(\tau) = x(t+\tau) - x(t)$. We denote $S(q,\tau)$ as the qth order absolute moment of $x(t)$:

$$S(q,\tau) = \langle |\Delta x(\tau)|^q \rangle. \tag{1}$$

The process is called scale invariant if the scaling behavior of the absolute moment $S(q,\tau)$ (i.e. structure function) has a power law behavior in a certain range of τ, Friedrich et al. (2011). Let us call ξ_q the exponent of the power law, i.e

$$S(q,\tau) \simeq C_q \tau^{\xi_q} \tag{2}$$

where C_q is a prefactor. $S(q,\tau)$ is called *monofractal* (or linear) if ξ_q is a linear function of q, and *multifractal* (non-linear) if ξ_q is non-linear with respect to q. Multifractality has been introduced in the context of fully developed turbulence in order to describe the spatial fluctuations of the fluid velocity at very high Reynolds number, Peng et al. (1994). Note that this formalism may not give correct results for non-stationary time series that are affected by trends or cannot be normalized.

The simplest type of multifractal analysis (to assess linearity and non-linearity of a time series) is based on the partition

* Corresponding author at: Institute of Physics and ForWind, Carl von Ossietzky University, 26111 Oldenburg, Germany.
E-mail address: mohammed.r.rahimi.tabar@uni-oldenburg.de (M. Reza Rahimi Tabar).

http://dx.doi.org/10.1016/j.solener.2017.01.008
0038-092X/

function multifractal formalism, Feder (1988), Barabasi and Vicsek (1991), Peitgen et al. (1992), and Bacry et al. (2001). An improved multifractal formalism called the wavelet transform modulus maxima (WTMM) method, Muzy et al. (1991) involves tracing the maxima lines in the continuous wavelet transform over all scales. The multifractal detrended fluctuation analysis (MF-DFA) is a third method based on the identification of scaling of the qth order moments depending on the signal length. Often experimental data are affected by non-stationarities (e.g. trends), which have to be well distinguished from the intrinsic fluctuations of the system in order to find the correct scaling behavior of the fluctuations, Feder (1988), Barabasi and Vicsek (1991), Peitgen et al. (1992), Bacry et al. (2001), and Muzy et al. (1991). Fractal and multifractal analyses are widely used in social and natural sciences, Mandelbrot (1983), for instance to characterize weather conditions, Koscielny-Bunde et al. (1998), Ivanova and Ausloos (1999), and Talkner and Weber (2000), cloud shapes, Ivanova et al. (2000), geophysics, Malamud and Turcotte (1999), DNA sequences, Peng et al. (1994), Ossadnik et al. (1994), and Buldyrev et al. (1998), neuron spikes, Blesic et al. (1999) and Bahar et al. (2001), medical, physiological, and astrophysical time series, Kantelhardt (2011), as well as economic time series, Mantegna and Stanley (2000) and Liu et al. (1999).

In this paper, we address the non-linear character of solar irradiance and clear-sky index time series (i.e. irradiance normalized to clear-sky conditions) by means of the multifractal detrended fluctuation analysis (MF-DFA) using data from several regions around the world with temporal resolutions of seconds and minutes. We obtain the generalized Hurst and Renyi exponents $h(q)$ and $\tau(q)$ and show that solar irradiance time series have strong non-linear and non-stationary properties.

The paper is organized as follows. Section 2 describes and introduces the solar irradiance datasets used throughout the analyses. In Section 3, we provide a brief review of detrended fluctuation analysis (DFA) and MF-DFA methods to study scaling and multifractality of time series. MF-DFA results based on random-phase (RP) and rank-wised (RW) surrogated data are also given in this section. In Section 4, we present our results of analyzing data to probe the multifractal behavior of solar irradiance and clear-sky index and compare it to the MF-DFA results for shuffled and surrogated data sets. Section 5 contains the conclusions.

2. Description of solar irradiance data sets

Our analyses are based on large solar irradiance data sets from several countries, as summarized in Table 1. The first data set has been recorded in Hawaii using 17 horizontally oriented LI-COR LI-200 pyranometers distributed across an area of about $750 \cdot 750\ \mathrm{m}^2$ and operating at 1 Hz between March 2010 and March 2011, Sengupta and Andreas (2010). We use both single-sensor data as well as the average of all sensors.

Also, we derive minute-averages of the single-sensor 1 Hz measurements, and use another three single-sensor data sets with the temporal resolution of minutes. Two of these data sets originate from the global Baseline Surface Radiation Network (BSRN) BSRN (2016). They were collected in northern Spain between July 2009 and February 2013, and in Algeria (Sahara) between March 2000 and December 2013. The third minute-averaged set was recorded on the roof of the University of Oldenburg, Germany, using small ($0.242 \times 0.556\ \mathrm{m}^2$) PV modules. It was presented in Beyer et al. (1994), and we use single-panel measurements.

Table 1
Data description.

Dataset	Data points	Measurement duration (days)	Frequency (Hz)
Solar irradiance, Hawaii	14×10^6	~365	1
Solar irradiance, Spain	1.3×10^6	~1331	1/60
Solar irradiance, Sahara (Algeria)	3.7×10^6	~3740	1/60
Solar irradiance, Germany	2.7×10^5	~430	1/60

Additionally, we use estimated clear-sky irradiance $I_{clearsky}$, i.e. global horizontal irradiance under a completely cloud-free atmosphere, to detrend the measured irradiance I by deriving the clear-sky index

$$k^* = \frac{I}{I_{clearsky}}. \tag{3}$$

There are different clear-sky models available, Ineichen (2006) and we use the one presented in Hammer et al. (1998) to estimate clear-sky irradiance for all the above-mentioned locations. To ensure conservative results, we only use k^* data associated with solar elevation angles greater than 10°. The clear-sky index values are positive and the maximum is around unity, except for short periods of over irradiance caused by cloud reflection, Yordanov et al. (2013).

As an example of the utilized data, Fig. 1(a) presents measured solar irradiance by a single sensor in Hawaii, where night times are removed. The corresponding clear-sky index time series is shown in panel (b), and the beginning and end of a single day are indicated by vertical lines.

3. Theory: methods of analysis

3.1. Description of methods

In this section, we review two standard methods, namely the analysis of the correlation function and the MF-DFA to investigate the fractal and multifractal properties of stochastic processes. Also, we provide details to surrogate a given time series by random-phase and rank-wised methods.

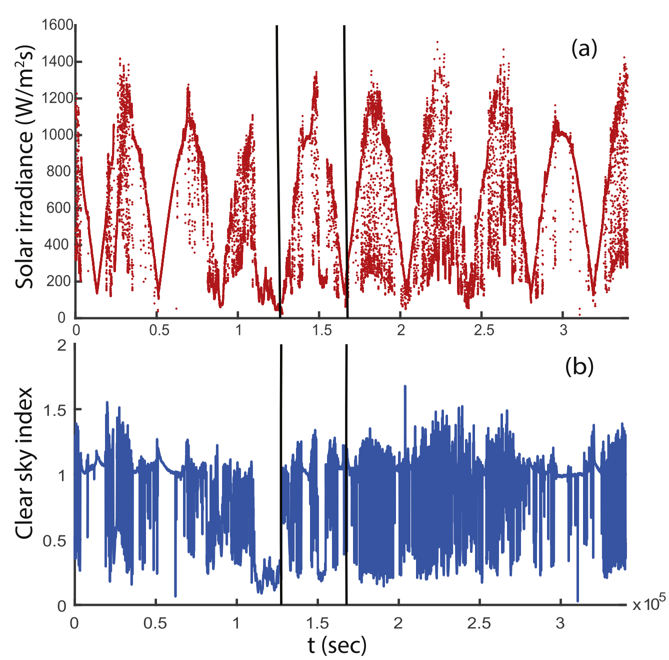

Fig. 1. (a) Measured solar irradiance of a single sensor for Hawaii and (b) its corresponding clear sky index time series. Night times have been removed.