Solar Energy 174 (2018) 606–616

Contents lists available at ScienceDirect

Solar Energy

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

Quantifiers for the solar irradiance variability: A new perspective

Robert Blaga, Marius Paulescu*

Faculty of Physics, West University of Timisoara, V Parvan 4, 300223 Timisoara, Romania

ARTICLE INFO

Keywords:
Solar radiative regime
Clearness index
Sunshine number
Variability criteria

ABSTRACT

This paper focuses on variability in solar irradiance time series. Six quantifiers for the solar irradiance variability, very different in their nature, are analyzed. One of them, based on the cumulative distribution function of the increments of clearness index time series, is developed in this study. The new quantifier is obtained by integrating the complementary cumulative distribution function over all values of the increments. The same level of variability is expressed by different quantifiers of different magnitudes. In order to surpass this obstacle a normalizing procedure is applied. This is a key task in comparing the output of different quantifiers toward a unique standard in the evaluation of the solar irradiance variability. As application, a new multi-parameter ranking procedure for classifying the days according to the solar irradiance variability is introduced.

1. Introduction

The large-scale penetration of photovoltaic (PV) plants into an electric grid is firmly limited by the uncontrollable variability of solar irradiance at the ground level. This variability may cause erratic variations in the output power of a PV plant at different time scales, which are further propagated on the grid as flickers of voltage and frequency. On the other hand, the fatigue of the PV modules materials may also be accelerated by the solar irradiance fluctuations, which induces alternating thermal regimes (Tomson 2010). All the above motivate the importance of understanding the solar irradiance variability at different temporal scales. A recent study by Perez et al. (2016) concludes that considering the fundamentals of spatial and temporal scales in developing mitigating solutions for the variability of solar resources represents a prerequisite in order to maximize effectiveness and minimize costs of PV plants integration in an electrical grid.

Compact cloud fields lead to a low frequency variation of solar irradiance causing a significant steep increase/decrease in the PV output power. The transition occurs between two states, each of them being stable for a quite long period of time. Scattered clouds may cause high frequency variation in solar irradiance inducing a massive fluctuation in the output power of a PV plant. For fast moving clouds, changes in solar irradiance measured by a pyranometer can exceed more than half of its peak in seconds. The time taken for a moving cloud to shade an entire PV system depends on various factors, including the PV system size and cloud speed. Mills et al. (2011) showed that a 75% solar irradiance ramp in 10-seconds measured by a pyranometer was associated with 20% variation in output power in the same 10-second in a 13.2-MW PV plant in Nevada. A severe event that changed the output of a pyranometer by 80% in 60 s led to a 50% change of the output power in the same time. Therefore, understanding the variability of solar irradiance at various time scales is a key issue for an efficient performance of a solar plant.

Generally, the actual level of solar irradiance at the Earth's surface results from the synergistic action of two factors: a deterministic one associated with the Earth's movement and a stochastic one associated with moving clouds. A huge effort has been invested over time for accurately quantifying the stochastic component of solar irradiance. This component is isolated by means of the instantaneous clearness index, defined as the ratio of solar irradiance measured at the ground level to that at the top of the atmosphere (see Section 2.1 for a detailed definition). Woyte et al. (2007) argue that an analysis of the clearness index variability must focus on the amplitude, persistence and frequency of the fluctuations. Since the time series of the clearness index exhibit no periodicity, this information cannot be retrieved by means of Fourier analysis. Instead, a localized spectral analysis based on wavelet transformation allows the decomposition of the clearness index into orthonormal components, each of them representing a specific scale of persistence. Peled and Appelbaum (2013) quantified the solar irradiance fluctuations using a combination of a statistical approach and wavelet analysis. These authors reported a tool for converting the decomposed components of the clearness index into useful forecasts for the operator of the electric grid with high density of embedded PV generation. The stochastic component of solar irradiance can also be isolated by means of the clear-sky index, defined as the ratio of the solar irradiances measured at the ground level to that estimated under clear-sky

* Corresponding author.
E-mail address: marius.paulescu@e-uvt.ro (M. Paulescu).

https://doi.org/10.1016/j.solener.2018.09.034
Received 19 June 2018; Received in revised form 29 August 2018; Accepted 13 September 2018

conditions. Based on the clear-sky index Perez et al. (2011) presented an empirical model for quantifying the short-term variability using satellite-derived hourly solar irradiance data. Their model introduces the standard deviation of the global irradiance clear-sky index and the mean change in clear-sky index between two consecutive intervals as quantifiers for intra-hour variability of the solar resource.

There are different ways for classifying days from a meteorological perspective. Common examples are: the daily average temperature labels a day as "cold" or "warm", the daily precipitation level labels a day as "wet" or "dry", the combination of the ambient temperature and relative humidity labels a day as "comfortable" or "uncomfortable". Many quantifiers have likewise been defined for classifying different intervals of time (mainly at daily or hourly scales) according to the variability/stability in the solar irradiance time series. A procedure for accurate classification turns out to be a useful tool for many applications: generation of a solar irradiance series like the typical meteorological year (Cebecauer and Suri 2015), forecasting solar energy (Paulescu et al. 2014) or the synthetic generation of high temporal resolution solar radiation data (Polo et al. 2011). In particular, the decomposition of solar irradiance into its direct and diffuse components is strongly dependent on the type of the solar radiative regime (Paulescu and Blaga 2016, 2018).

Maafi and Harrouni (2003) introduced fractal measures for daily solar irradiance variability, aiming to classify days into three groups: clear sky, partly-cloudy sky and overcast. Soubdhan et al (2009) classified the daily distribution of the clearness index in four classes using a mixture of Dirichlet distributions. The sequential analysis of the time series suggested that the solar radiative pattern is governed by a hidden Markov chain with four states. Tomson et al. (2008) used criteria based on the notion of global solar irradiance increment for characterizing a given interval of time as stable or unstable. An increment is defined as the difference between two subsequent measurements in a time series. The magnitude of large-scale fluctuations is assessed by measuring their positive and negative fronts (Tomson 2010). A positive/negative front is defined as an event with monotonous increase/decrease in the solar irradiance series with at least one increment greater than $50\ \mathrm{W\,m^{-2}\,s^{-1}}$. Thus, the solar irradiance series appears as a stochastic process including positive and negative fronts and small-scale fluctuations in between. Paulescu and Badescu (2011) introduced a binary parameter, the sunshine stability number, for assessing the variability a solar irradiance time series. Basically, the sunshine stability number counts how many times the Sun is covered (or uncovered) by clouds in a given time interval. Classifying the days from the view-point of the stability of their radiative regime is performed by using the daily average value of the sunshine stability number.

In recent years, special attention has been paid to characterizing the solar irradiance variability at small temporal scales. Lave et al. (2015) introduced a metric for quantifying high-frequency solar irradiance variability, called the variability score from the ramp rate distribution. The ramp rate in a solar irradiance time series is computed using a definition based on moving averages. Schroedter-Homscheidt et al. (2018) proposed an algorithm for classifying the hours within a day in respect to the variability of the 1-minute direct-normal solar irradiance. The algorithm is based on a combination of previously proposed quantifiers. Lohmann (2018) reviewed recently published studies on the quantification and small-scale averaging of solar irradiance variability in time and space. The author emphasized that even if there are many articles dealing with solar irradiance variability at small temporal scales, there is an acute need for more high-resolution measurements to robustly validate the existing models.

The above summary shows that different quantifiers highlight different facets of the variability in a solar irradiance series. Currently there is no general consensus on which a particular quantifier is the most suitable for classifying different intervals of time according to the solar irradiance variability. Because every quantifier is associated with a set of criteria for classifying a given period of time as stable or unstable, the border between stable and unstable is marked by uncertainty.

This paper focuses on the characterization of the stochastic nature of a solar irradiance series from various perspectives. Six different techniques for classifying days according to the solar irradiance variability pattern are analyzed. Among the novelties reported in this study we mention here the following: (1) A new quantifier is introduced, based on the cumulative distribution function of the increments of the clearness index. The new quantifier is obtained by integrating the complementary cumulative distribution function and integrating over all existing values of the increments. (2) A normalizing procedure of different quantifiers is proposed. Note that different quantifiers express the same level of variability at different scales (in a mathematical sense). Thus, the development of an accurate procedure for comparing different quantifiers is a key task toward a unique standard in the evaluation of the solar irradiance variability; (3) A new multi-parameter ranking procedure for classifying days according to the solar irradiance variability pattern is introduced.

The structure of the paper is as follows. In Section 2 the raw data used in this study are presented and the post-processed quantities (clearness index and sunshine number) are defined in detail. In Section 3, six quantifiers for the solar irradiance variability pattern (stability index, standard deviation of increments, number of fronts, integrated cumulative distribution function, sunshine stability number and fractal dimension) are defined and assessed. In Section 4 the quantifiers are standardized and a multi-parameter ranking procedure for classifying the solar irradiance variability based on the aggregated behavior of the six quantifiers is presented. The ability of the various quantifiers to capture different types of variability is analyzed. The main conclusions of this study and an outlook on the standardization of the definition of stable and unstable solar irradiance pattern are given in Section 5.

2. Data

Global G and diffuse G_d solar irradiances recorded at the Solar Platform of the West University of Timisoara (Solar Platform 2017) are used in this study. The town of Timisoara (latitude 45°46′N, longitude 21°25′E, altitude 85 m asl) has a warm temperate climate, fully humid, with warm summer, typical for the Pannonian Basin (Köppen climate classification *Cfb*, based on the Kottek et al. (2006) digital world map on climate classification). Measurements on the Solar Platform are performed all day long at equal time intervals of *PleaseCheck*. DeltaOHM LP PYRA 02 first class pyranometers which fully comply with ISO 9060 standards and meet the requirements defined by the World Meteorological Organization are employed. The sensors are connected to a data acquisition system based on a National Instruments PXI Platform.

2.1. Clearness index

The instantaneous clearness index is defined as follows (Liu and Jordan, 1960):

$$k_t = \frac{G}{G_{ext}}, \tag{1}$$

where G and G_{ext} are the horizontal solar irradiance measured at ground level and estimated at extraterrestrial level, respectively. G_{ext} can be written as function of the solar elevation angle h: $G_{ext} = G_{SC}\,\varepsilon \sin h$, were $G_{SC} = 1366.1\ \mathrm{W\,m^{-2}}$ (Gueymard 2004) is the solar constant and ε is the eccentricity correction factor that can be calculated with Spencer's equation (Spencer 1971).

2.2. Sunshine number

For an observer placed on the Earth's surface, the sunshine number $SSN(t)$ is defined as a time dependent random binary variable, as