Available online at www.sciencedirect.com

ScienceDirect

Solar Energy 101 (2014) 272–282

SOLAR ENERGY

www.elsevier.com/locate/solener

Generalized additive models for nowcasting cloud shading

Marek Brabec [a], Marius Paulescu [b,*], Viorel Badescu [c,d]

[a] Department of Nonlinear Modeling, Institute of Computer Science, Academy of Sciences of the Czech Republic, Pod Vodarenskou vezi 2, 182 07 Prague 8, Czech Republic

[b] Physics Department, West University of Timisoara, V. Parvan 4, 300223 Timisoara, Romania

[c] Candida Oancea Institute, Polytechnic University of Bucharest, Spl. Independentei 313, 060042 Bucharest, Romania

[d] Romanian Academy, Calea Victoriei 125, Bucharest, Romania

Received 29 October 2013; received in revised form 22 December 2013; accepted 3 January 2014
Available online 23 January 2014

Communicated by: Associate Editor Jan Kleissl

Abstract

The response time of a photovoltaic plant is very short and its output power follows the abrupt change in solar irradiance level due to alternate shadow by clouds. Presence of shading may be quantified by a binary variable: sunshine number (SSN). Various logistic Markovian models of SSN dynamics are introduced and discussed in this paper, going from simple to more complicated model structures. Radiometric data measured at 15 s lag during 2010 in Timisoara (Romania) are used to illustrate their real-world performance. The models are useful for short term forecasting related e.g. to photovoltaic conversion control, including more complicated events like ramp-like switches between overcast and clear regimes. Importantly, presented models are not black-box forecasting tools. They contain physically interpretable structure which is advantageous both in developing, checking and improvement of the model itself, but also as a tool for characterizing various systematic properties of cloud shading.

Keywords: Sunshine number; Nowcasting; Generalized additive model; Markov chain

1. Introduction

Nowadays, the *smart grid* concept is usual in the electricity grid management. Forecasting of grid load (e.g. Charlton and Singleton, 2013) and the power generated from renewable energy resources (wind (e.g. Sanchez, 2006) and solar (e.g. Pedro and Coimbra, 2012)) are important tasks to provide intelligence to the grid. Accurate forecasting will enable the computers to take control actions to balance the power grid.

This paper is focused on the second topic, dealing with forecasting the solar resource for the photovoltaic (PV) plant operation. This is motivated by the fact that the response time of a PV plant is almost instantaneous and, consequently, its output power can vary significantly in short time intervals. Thus, a PV plant is a hazard factor for network security and creates a challenge for network operators in their task to maintain stability and quality of the electricity for end users.

The performance of a PV plant depends essentially on the fact that direct solar radiation is incident or not on the array of modules. The rapid variation of solar irradiance causes the so called "solar ramp" problem which is one of the biggest obstacles in managing the power grid (Mills et al., 2011). This term refers to the grid management when solar irradiance changes rapidly causing a massive change in the output power. When the sun comes out of the clouds, direct solar radiation is incident on the area of PV modules causing a surge in the grid. The operator will have to reduce the power generated by other plants (or to disconnect the PV plant) to avoid grid instability.

* Corresponding author. Tel./fax: +40 256 592383.
E-mail address: marius@physics.uvt.ro (M. Paulescu).

0038-092X/$ - see front matter © 2014 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.solener.2014.01.005

When the sun is suddenly covered by clouds, the shortage of energy in the grid has to be compensated by increasing the power of the controllable power sources. Note that the short-term variability of solar radiation is relevant not only for PV plants but also for the production and operability of concentrating solar power plants.

An appropriate parameter describing the relative position of the sun and clouds has been introduced in Badescu (2002). It is the sunshine number (SSN), a Boolean quantity stating whether the sun is covered by clouds or not. Statistical properties of SSN are described in Badescu and Paulescu (2011a) while ARIMA modeling of SSN is studied in Paulescu et al. (2013). The subject of this paper is focused on the practice of SSN nowcasting on very short time intervals by using logistic modeling.

The results presented here are more appropriate for small-size PV installations, where the binary description provided by the SSN quantity is entirely valid. Large PV-plants are covered by a single shadow (resulting from *Cumulus fractus*, *Cumulus mediocris* or *Cumulus humilis* clouds) only partly and/or are affected with several shadows simultaneously. In these cases general influence to the grid is smoothed. Also, there is empirical evidence showing that when PV plants are rather uniformly distributed over large surface areas, the time variability of the aggregate output power is somehow smoothed out. Mills et al. (2011) shows that changes in solar irradiance at a point due to a passing cloud can exceed 60% of the peak of solar irradiance in seconds. Since there are situations when the fluctuation on solar radiative regime is on a time scale of minute or less (Tomson, 2010), nowcasting of passing clouds on very short time horizon is necessary (Brabec et al., 2013). Thus, this study was conducted on 15-s basis. Such studies on very short time horizon are also performed for load forecasting (Taylor, 2008).

The structure of the paper is as follows. SSN is defined in Section 2. Section 3 is devoted to description of the relevant data. Generalized additive models for SSN nowcasting are discussed in Section 4. The main conclusions are collated in Section 5.

2. Definition of SSN and SSSN

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

$$\xi_t = \begin{cases} 0 & \text{if the sun is covered by clouds at time } t \\ 1 & \text{otherwise} \end{cases} \tag{1}$$

The average value of SSN $\bar{\xi}$ over a given period Δt equals the relative sunshine σ during Δt, i.e. $\sigma \equiv \bar{\xi}$.

In order to quantify the stability of the solar radiative regime, a parameter related to SSN, the sunshine stability number (SSSN), was defined in Paulescu and Badescu (2011):

$$\zeta_t \equiv \begin{cases} 1 & \text{if } \begin{cases} \xi_t < \xi_{t-1} & (\text{when } \xi_1 = 1) \text{ or} \\ \xi_t > \xi_{t-1} & (\text{when } \xi_1 = 0) \end{cases} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Depending on the initial value ξ_1, Eq. (2) quantifies just one of the two different phenomena: sun appearance or sun disappearance on/from the sky, respectively. Elementary statistical and sequential properties of both SSN and SSSN are studied in Badescu and Paulescu (2011b).

Note that other ways of defining the stability of the radiative regime may be imagined, such as that used by Tomson (2010) or simply by comparing two neighboring SSN values. These alternative definitions might be equally well useful, depending on the context. The definition Eq. (2) has the advantage that quantifies the stability of a given day, with respect to its initial state. This may be useful for operators of PV installations.

The average value of the SSSN during the interval Δt is denoted $\bar{\zeta}$. Note that $\bar{\zeta}$ is not a Boolean variable. Preliminary results concerning $\bar{\zeta}$ have been presented in Paulescu and Badescu (2011). However, one error exists in that paper. There it has been stated that $\bar{\zeta}$ ranges between 0 (when the instantaneous values of SSN are all 0 or 1, respectively, for all time moments t during Δt) and 1 (when the instantaneous values of SSN change every two consecutive moments during Δt). In fact, $\bar{\zeta}$ ranges between 0 and 1/2. The radiative regime is *fully stable* in the first case and *fully unstable* in the last case.

3. Data and method of comparison

Global and diffuse solar irradiance (G and G_d, respectively) recorded at the Solar Platform of the West University of Timisoara are used in this study (Solar Platform, 2013). The town of Timisoara (latitude 45°46′N, longitude 21°25′E and 85 m a.s.l.) has a warm temperate climate, fully humid, with warm summer, typical for the Pannonian Basin (Köppen climate classification *Cfb*). This is based on the Kottek et al. (2006) digital Köppen–Geiger world map on climate classification, build with data from the second half of the 20th century.

Measurements are performed all day long at equidistant time intervals of $\Delta\tau = 15$ s. 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 integrated into an acquisition data system based on the National Instruments PXI platform including a PXI-6259 data acquisition board.

Series of SSN values have been derived using the World Meteorological Organization sunshine criterion (WMO, 2008): the "sun is shining" at a time moment t if direct solar irradiance exceeds 120 W/m^2. Therefore:

$$\xi_t = \begin{cases} 1 & \text{if } (G_t - G_{d,t})/\sin(h_t) > 120\ \text{W/m}^2 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$