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Nowcasting solar irradiance using the sunshine number

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ABSTRACT

This paper focuses on short-term forecasting of solar irradiance. An innovative two-state model is proposed: if the sun is shining, the solar irradiance is estimated with an empirical model fitted on historical data; if the sun is covered, the clear sky solar irradiance is adjusted according to the cloud transmittance. The distinction between these two states is made by the sunshine number, a binary indicator of whether the Sun is covered by clouds or not, previously introduced by Badescu (2002). Sunshine number is the sole quantity effectively forecasted in the model. The general structure of the model and its advantages are discussed. Its performance on real data is demonstrated, and comparison of the model results against classical ARIMA approach applied to clearness index time series, as main competitor, is made. We conclude with an outlook to future developments oriented to improve the model accuracy.

1. Introduction

Renewable energy experiences an impressive boost in the energy market. While in some applications the primary resource can be used right away as in solar-thermal [1,2] or geothermal [3] systems, the main interest is for converting it into electricity, which is the most flexible form of energy. The European photovoltaic (PV) cumulative installed capacity has progressed rapidly over the past decade from less than 1 GW in 2003 to over 30 GW in 2010 and 70 GW in 2012. Regarding the energy mix, at the end of 2012 PV covers 2.6% of the electricity demand and 5.2% of the peak electricity demand in Europe [4].

The solar energy at ground level exhibits a continuous variation in time and space. This variation has a deterministic component, generated by the movements of rotation and revolution of the Earth, and a random one, generated by weather. Solar energy variations at ground level have a great influence on the output power of a photovoltaic (PV) plant, which can fluctuate significantly in short intervals due to the random component. This behavior is vastly different from the one of the traditional power plants (hydro, fossil, nuclear) which have an output power that can be better controlled. Thus, large-scale PV integration into the existing power grid has become a challenge for scientists and engineers today. One way of solving this problem is forecasting the output power of PV plants. A good forecast will enable grid operators to plan the other capabilities (mainly gas power plants) to compensate for the PV plants power variations. Currently, there are several ongoing research projects in Europe, testing different procedures to accurately forecast the PV output power. For example, COST Action ES1002 "Weather Intelligence for Renewable Energies" has the main objective to improve the forecast of the output power of solar and wind power plants [5].

The quality of forecasting the output power of the PV plants follows closely the solar irradiance forecasting accuracy. Some authors go even further and equalize the problem of forecasting the PV plant output power with the solar irradiance forecasting problem [6]. Forecasting the solar irradiance is currently done using statistical methods, the ARIMA model (e.g. see [7]) being the most popular. As in some other fields (e.g. [8]), there are also many attempts to develop models using artificial intelligence methods based on artificial neural networks [9,10], clustering procedures [11,12] or fuzzy logic theory [13].

The performance of a PV plant is intimately related to the incidence of beam radiation on the modules' surface. The relative position of sun and clouds is decisive for the amount of direct solar irradiance at ground level. A solution to describe the relative position of sun and clouds is proposed in [14] and updated in [15]. The model considers the solar irradiance as a stochastic process and uses a procedure that divides a time interval in sunny or cloudy, using a Markov process with two states. Another solution is proposed in [16], where the relative position of the sun and clouds is quantified by introducing a sunshine indicator. This is the sunshine number, SSN on short. SSN is a binary quantity, indicating

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whether the sun shines or not at a given time. Thus, SSN is a straightforward indicator of the presence of direct radiation at ground level. Results reported in Ref. [16] showed that using two parameters related to the state of the sky (cloud amount and SSN) strongly increases the accuracy of the estimation of solar irradiance. Ref. [17] describes the SSN's statistical properties. In [18] a new parameter related to SSN, sunshine stability number (SSSN), is defined in order to quantify the stability of the radiative regime. Elementary statistical and sequential properties of both SSN and SSSN are presented in [19]. Forecasting SSN on short-time interval was addressed in two recent works using logistic modeling [20] and autoregressive integrated moving average (ARIMA) models [21]. While these papers [17–21] generically deal with the estimation and the forecasting of the state of the sky, the present paper deals with the forecasting of solar irradiance.

Therefore, results reported in [17–21] establish the premises of the present work. Here, we go a step further and develop a model for forecasting the global solar irradiance including SSN. Basically, the proposed model consists of two states: (1) if the sun is shining, the solar irradiance is computed using an empirical model based on long-term data measured in-situ; (2) if the sun is covered by clouds, the clear sky solar irradiance is adjusted by a correction factor depending on the cloud transparency. The correction factor is being evaluated based on measurements performed during a short period of time prior to the moment of generating the forecast. SSN is the quantity that makes the distinction between the two states, SSN being the quantity actually forecasted by the model.

The method reported here for forecasting the solar irradiance is new and original. As far as we know, there is no other paper reporting a forecasting model built by mixing estimation and forecasting in the manner presented here. The innovative elements are: using SSN to differentiate between the two states of the sky (one in which the sun is shining and the other in which the sun is covered by cloud) and the method employed for computing the cloud transmittance.

The paper is organized as follows. The sunshine number and the forecasting model are defined in the next section. Section 3 is dedicated to the description of relevant data. The accuracy of the proposed two-state model is discussed in Section 4. Section 5 contains the conclusion and an outlook for the future model expansion.

2. Theory

2.1. Definition of the sunshine number

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 Ref. [18]:

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

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. The average value of the sunshine stability number during the interval Δt (in this paper Δt equals the daylight length) is denoted $\bar{\zeta}$. Note that $\bar{\zeta}$ is not a Boolean variable. It ranges between 0 (when the instantaneous values of SSN are all 0 or 1, respectively, for all time moments t during Δt) and 1/2 (when the instantaneous values of SSN change every two consecutive moments during Δt). The radiative regime is *fully stable* in the first case and *fully unstable* in the last case.

2.2. Two-state model

The proposed model for nowcasting the global solar irradiance connects a physical model for estimating the clear sky solar irradiance to a statistical model for forecasting SSN. The equation of the model is:

$$\widehat{G}_t = \begin{cases} G_{0,t} & \text{if} \quad \widehat{\xi}_t = 1 \\ \bar{\tau} \cdot G_{0,t} & \text{if} \quad \widehat{\xi}_t = 0 \end{cases} \tag{3}$$

In Eq. (3) $\widehat{G}_t$ is the forecasted solar irradiance at time t, $G_{0,t}$ stands for the estimated solar irradiance under clear sky at time t, $\bar{\tau}$ is the correction applied to $G_{0,t}$ according to the cloud transmittance and $\widehat{\xi}_t$ is the forecasted SSN at time t. The forecasting is being made at time $t-1$. Eq. (3) is the key element in this study, and all its components are discussed next.

2.2.1. Forecasting SSN

The sole parameter that needs to be forecasted in Eq. (3) is SSN, all other quantities being estimated. In this study, ARIMA modeling was used to forecast SSN.

The general auto-regressive integrated moving average model ARIMA(p,d,q) allows to evaluate the variable z_t at the discrete time t as a function of its values at previous time moments. Its general form is provided by the classical Box-Jenkins theory [22]:

$$w_t = \phi_1 w_{t-1} + \ldots + \phi_p w_{t-p} + a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q} \tag{4}$$

where the new variable w_t is obtained by differencing d times the variable z_t:

$$w_t = \nabla^d z_t \tag{5}$$

Here ϕ_i $(i = 1,2,\ldots,p)$ are the autoregressive coefficients, θ_i $(i = 1,2,\ldots,q)$ are the moving-average coefficients and a_t is the white noise with zero mean and standard deviation σ_a. The coefficients ϕ_i and θ_i as well as the standard deviation, σ_a, are obtained in the following by using the maximum likelihood method [22].

2.2.2. Global solar irradiance estimation

If the sun is shining, the global solar irradiance $G_{0,t}$ from Eq. (3) is being estimated using a clear sky model. In this study, an empirical model fitted on data measured in Timisoara (see Section 3 for more information about location) [23] is used. The model equation is:

$$G_{0,t} = G_{ext}[1 - 0.4645 \cdot e^{-0.69\cos\theta_{z,t}}]e^{-\frac{0.05211}{\cos\theta_{z,t}}} \cdot \cos\theta_{z,t} \tag{6}$$

where G_{ext} denotes the extraterrestrial solar irradiance and $\theta_{z,t}$ is the zenithal angle at time t. Since $G_{0,t}$ depends only on geographical coordinates and temporal reference, the solar irradiance under clear sky ($\xi = 1$) can be estimated by Eq. (6) at any time t.

2.2.3. Cloud transmittance adjustment

Since Eq. (6) was fitted on data measured under clear sky conditions, it includes all the influences of the atmospheric constituents, except the clouds. The extinction of solar radiation due to the clouds is more significant than due to any other atmospheric constituent, but it is always difficult to be modeled because of the random distribution of clouds on the sky. Moreover, the transmittance of a layer of clouds is in a very complex relation with their type and depth.