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Suppressing power output fluctuations of photovoltaic power plants

M. Anvari[a,*], B. Werther[b], G. Lohmann[c], M. Wächter[a], J. Peinke[a], H.-P. Beck[b]

[a] Institute of Physics and ForWind, Carl von Ossietzky University of Oldenburg, Carl-von-Ossietzky-Straße 9-11, 26111 Oldenburg, Germany
[b] Institute of Electrical Power Engineering, Leibnizstraße 28, 38678 Clausthal-Zellerfeld, Germany
[c] Energy Meteorology Group, Institute of Physics, Carl von Ossietzky University of Oldenburg, 26111 Oldenburg, Germany

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ABSTRACT

The use of solar photovoltaic (PV) power has recently increased in electric distribution grids. However, the stochastic properties of solar energy, such as intermittency (i.e. the presence of a correlated high frequency of large fluctuations), can negatively affect power quality and cause grid instabilities, especially in microgrids. In this study, we differentiate the diffusive and jumpy characteristics of solar power and introduce a stochastic dynamical jump-diffusion equation to model non-gaussian PV power. Using the obtained dynamical equation, we generate new synthetic data sets with varying jump rates. Finally, we implement a straightforward filtering method, i.e. a combination of an inverter and a battery storage system to show the applicability of our proposed stochastic method.

1. Introduction

Recently, increasing numbers of wind and photovoltaic (PV) power systems have been deployed in order to reduce carbon dioxide emissions and avoid the use of nuclear power. By the end of 2014, for example, PV power had already reached a total installed capacity of over 178 GW worldwide, which is expected to increase to between 396 and 540 GW by 2019 (SPE, 2015). Similarly, wind power had reached a total installed capacity of over 369 GW worldwide by the end of 2014, and it is expected to increase to 712 GW by 2019 (GWEC, 2015). Though the general availability of wind and solar energy is high, they can strongly vary depending on geographic location, meteorological conditions, time of year, and time of day. Wind and PV power production exhibit intermittent characteristics (Chakraborty et al., 2008), which present a challenge for the reliable grid integration of increasing shares of wind and solar energy, especially in case of decentralized power generation on the distribution grid level (Beck and Hesse, 2007).

A microgrid is a type of distribution network that can help to integrate large numbers of decentralized power systems into existing distribution grids (Beck and Hesse, 2007). It is capable of operating either in grid-connected or grid-disconnected mode, and can actively contribute to maintaining voltage and frequency stability of both the microgrid itself and the higher-level power grid. With microgrids, it may be possible to reduce the need for transmission system lines and large power plants in the future design of distributed systems (Peças Lopes et al., 2007; Hadjsaid et al., 1999; Lee et al., 2009). However, avoiding disturbances of the higher-level grid when connected, and upholding microgrid stability when disconnected, both become more difficult when the shares of renewable energies increase.

In this paper, at first we focus on the variability of PV power, which could influence the stability of microgrids. This variability is characterized by pronounced fluctuations on many time scales, from seasonal variations of the order of months, to weather-induced variations ranging from days to hours, minutes, and even seconds (Anvari et al., 2016). Here It is worth noting that because of the spatio-temporal correlation in PV power, one expects a smoothing effect in the cumulative power of the total solar filed, as has been discussed in detail in Remund et al. (2015). However, as a microgrid typically covers a relatively small area, PV power fluctuations from different systems within the grid may be correlated, depending on the time scale of interest (the longer the time scale, the larger the correlation). For example, It has been shown in Lohmann et al. (2016) that 60-s increments of 1 s data begin to be uncorrelated for distances >1 km in Germany. Thus any PV systems that are closer than about 1 km (which is the typical size for microgrids) would ramp up or down in a correlated fashion, which amplifies the absolute magnitude of the ramps.

We use high resolution (i.e. 1 Hz) measured irradiance data in Hawaii (as an exemplary data) to study the stochastic behaviour of short-term PV fluctuations, and classify its states as cloudy, sunny and flickering. Our main aim is the construction of a simple dynamical equation (jump-diffusion stochastic equation) that governs the stochastic process of PV-fluctuations, so that the statistics of the modelled

* Corresponding author.
E-mail addresses: mehrnaz.anvari@uni-oldenburg.de (M. Anvari), benjamin.werther@tu-clausthal.de (B. Werther).

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time series are identical to those of the measured ones. The proposed method has potential for forecasting of the PV-fluctuations, and we will get back to this issue elsewhere. In the literature, there are some autoregressive methods that are proposed to forecast high resolution PV power (Monjoly et al., 2017; Clack, 2016). These methods are linear in their approach and can not produce intermittent and jumpy behaviour, as one observes in measured power or solar irradiance time series. Furthermore, these methods mostly use meteorological observations, such as wind speed, cloud height and atmospheric pressure (Lappalainen and Valkealahti, 2017) to model the dynamics of PV power. In contrast, in our modelling all functions and parameters of the dynamics are determined directly from measured data.

Various energy storage systems (ESS) and control strategies to suppress both the magnitude and frequency of short-term PV fluctuations in a distribution grid have recently been proposed in the literature. For instance, to mitigate small-scale fluctuations of a few seconds up to a few hours, flywheels, super- conducting coils, double layer capacitors and hybrid PV-storage are suggested as suitable ESS (Woyte et al., 2003; Bullich-Massagué et al., 2017). In addition different control strategies such as ramp control, moving average and step-rate control strategy have been discussed in Haaren et al. (2015), Alam et al. (2014), Salehi and Radibratovic (2014), Marcos et al. (2014), de la Parra et al. (2015), Beltran and Segundo (2011), and in each case an attempt is made to minimize the energy storage capacity required. In this work, we choose a storage converter, i.e. lead-acid battery, in combination with a PV inverter in order to show the applicability of our suggested stochastic method for suppressing the strong short-term fluctuations of PV power.

Indeed, we will show how one can tune a control parameter, for different jump rate values (which we generate with the jump-diffusion equation) in order to mitigate the fluctuations. In fact, our introduced stochastic equation makes it possible to quantify the control parameter in this study. For this purpose, we install an active distribution grid in our laboratory, feed it with our modelled flickering-state time series, and show how to parametrize the control parameter with respect to stochastic properties to suppress short-term fluctuations.

The rest of the paper is organized as follows. In Section 2, we provide details on the irradiance data and its conversion to clear-sky index (which is irradiance normalized to cloud-free conditions), classify different fluctuation regimes, introduce the nonparametric estimation of Langevin and jump-diffusion equations, and determine all model parameters from the clear-sky index time series. Section 3 is devoted to the reconstruction of clear-sky index and solar power time series, so that we can generate many high resolution samples with similar statistical properties. In Section 4, we simulate an exemplary control system and compare the results of the simulation with those of the laboratory grid, using the previously generated PV power time series as input. The paper is summarized in Section 5.

2. Modelling stochastic power feed-in from photovoltaics

2.1. Global horizontal irradiance in Hawaii

In this paper, we use high resolution irradiance data measured in Hawaii. The United States' National Renewable Energy Laboratory (NREL) performed a one-year measurement campaign at Kalaeloa Airport (21.312°N, −158.084°W), Hawaii, USA, from March 2010 until March 2011 using 19 LI-COR LI-200 pyranometers to measure global irradiance on horizontal and inclined surfaces with a 1 Hz temporal resolution (Sengupta and Andreas, 2010). Two of the instruments were tilted with a 45 degree orientation, while the other 17 were horizontally mounted and scattered across an area of about $750 \times 750\,\text{m}^2$. From this publicly available data pool, the subset of global horizontal irradiance was selected, processed and checked to yield about 20 million synchronised values of 1 Hz temporal resolution measured by the aforementioned 17 pyranometers on 378 days.

Changes in horizontal solar irradiance are not only the result of stochastic fluctuations but are also governed by deterministic processes. Therefore a version of irradiance is needed that only exhibits stochastic changes. The dominating deterministic process influencing global irradiance is the apparent movement of the sun in the sky that accounts for both diurnal and annual variations of the available solar energy on the earth's surface (Lave et al., 2012). Thus, by calculating the clear-sky irradiance G_{clear} (i.e. irradiance on earth with cloud-free atmosphere) for a location, the instantaneous global irradiance G may be converted to clear-sky index $Z = G/G_{\text{clear}}$. Clear-sky irradiance G_{clear} depends on astronomical relationships and also needs to include parameters of atmospheric conditions, such as air composition and turbidity.

For this study, the clear-sky model of Fontoynont et al. (1998) is used to compute clear-sky irradiance time series for Hawaii. In order to ensure conservative results, only data associated with solar elevation angles $\alpha > 10°$ are processed in the clear-sky index calculation. Otherwise, the relatively low global irradiance values occurring after sunrise and before sunset, coupled with path prolongation and corresponding higher uncertainties in clear-sky calculations at these times, can result in unrealistic clear-sky index values (Woyte et al., 2007). In this way, we are able to derive the sets of purely stochastic time series of clear-sky index from the original irradiance measurements in Hawaii.

2.1.1. The classification of clear-sky index

Detailed study of the clear-sky index Z indicates that there are at least three different types of fluctuations, associated with cloudy, sunny and flickering states. For typical examples of time series linked to these conditions see Fig. 1. In the cloudy state $Z(t)$ fluctuates smoothly around its very low mean value ~ 0.06, whereas in the sunny state the mean is about ~ 0.98 and it fluctuates around the mean less smoothly. As shown in this figure, the data of the flickering state have an on-and-off behaviour, because clouds cover and uncover the sun within different time intervals.

In the flickering state, the waiting times between two strong jumps can be analyzed by considering the number of times that the clear-sky index crosses its mean ($\overline{Z} \sim 0.7$, see the broken line in Fig. 1) (Reza Rahimi et al., 2014). An average jump rate can then be evaluated as

$$\bar{\lambda} = \frac{1}{T-1}\sum_{t=1}^{T-1} I\{(Z(t-1)-0.7)(Z(t)-0.7) < 0\}, \tag{1}$$

where the indicator $I\{O\}$ is 1 if its argument is true, and 0 if it is false. This average jump rate accounts for all crossings of the specific level, here the

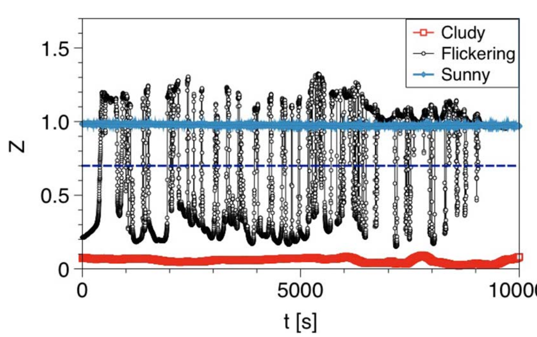

Fig. 1. Different stochastic behaviour of solar clear-sky index in cloudy (red), sunny (blue) and flickering (black) states. The broken line shows the mean value of Z for the flickering state given by $\overline{Z} \sim 0.7$. It is clear that in flickering state, there are times when the value of Z is bigger than 1. The reason for this is the phenomenon of cloud enhancement, which means that sunlight is being reflected by surrounding clouds (see Refs. Yordanov et al., 2013; Piacentini et al., 2011). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)