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A Poisson model for anisotropic solar ramp rate correlations

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Abstract

Spatial correlations between ramp rates are important determinants for output variability of solar power plants, since correlations determine the amount of geographic smoothing of solar irradiance across the plant footprint. Previous works have modeled correlations empirically as a decreasing function of the distance between sites, resulting in isotropic models. Field measurements show that correlations are anisotropic – correlations are different for along-wind site pairs than for cross-wind site pairs. Here, cloud fields are modeled using a spatial Poisson process. By advecting the cloud field using a constant cloud velocity, spatial correlations for ramp rates are obtained. Spatial correlations were shown to be a function of along-wind and cross-wind distance, ramp timescale, cloud speed, cloud cover fraction, and cloud radius. The resulting anisotropic correlation model explains the anisotropic effects well at timescales less than 60 s but performs worse than existing empirical isotropic models at longer time scales.

Keywords: Solar ramp rate; Spatial correlations; Variability; Geographic dispersion

1. Introduction

As opposed to traditional generation sources such as coal or nuclear power plants, power generated by solar photovoltaics (PV) can be variable due to the passing of clouds. As the penetration of solar PV on an electric grid increases, the ramp rates can become a concern for grid operators. When considering the aggregate of many PV systems spread over a geographic area, though, the relative variability is reduced as the PV systems' fluctuations are often not correlated (Perez et al., 2011; Lave et al., 2012a,b; Perpiñán et al., 2013).

This geographic smoothing effect is well documented. Sites a few meters to hundreds of kilometers apart were shown to have a smoothed aggregate output (Otani et al., 1997; Wiemken et al., 2001; Curtright and Apt, 2008; Lave et al., 2012a,b). The amount of smoothing generally increases as the distance between sites increases, but also depends on the timescale and local meteorological conditions.

To determine the amount of geographic smoothing, the correlations of ramp rates at different sites must be determined. Mills and Wiser (2010) proposed a correlation equation of the form:

$$\rho = \frac{1}{2}\left[e^{-\frac{C_1}{\bar{t}}d_{k,l}^{b_1}} + e^{-\frac{C_2}{\bar{t}}d_{k,l}^{b_2}}\right],$$

where C_1, C_2, b_1, and b_2 are empirical constants, $\bar{t}$ is the timescale, and $d_{k,l}$ is the distance between sites k and l, but this equation is difficult to apply as it requires a unique calibration at each location. Lave and Kleissl (2013) and Perez et al. (2011) proposed similar, but universal correlation models that depend on the distance, timescale, and cloud speed (CS):

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$$\rho = \exp\left(-\frac{d_{k,l}}{0.5CS\bar{t}}\right),$$

and

$$\rho = \exp\left(\frac{\ln(0.2)d_{k,l}}{1.5CS\bar{t}}\right),$$

respectively. All of these correlation models are isotropic; they depend on the distance, but not direction between sites.

Hinkelman (2013) showed that correlations are not isotropic, and instead can vary significantly in the along-wind and cross-wind directions. This anisotropic effect was strongest at short timescales, where negative correlations were observed in the along-wind direction but not in the cross-wind direction. In parallel with the present paper, Lonij et al. (2013) developed an empirical anisotropic model with exponential decreases in correlation as a function of spatial distance relative to the cloud position based on cloud advection (distance minus cloud speed multiplied by time elapsed), time elapsed, and averaging time.

While previous works (Mills and Wiser, 2010; Perez et al., 2011; Lave and Kleissl, 2013; Lonij et al., 2013) have developed models through empirical fits to measured correlations, in this paper, we present a mathematical model for spatio-temporal correlations between irradiance ramps. This is relevant to the modeling of ramp rates of utility-scale solar power plants from (point) solar irradiance data, as correlations can be used to upscale the irradiance to simulate PV plant power output (Lave et al., 2012a,b). Based on the ramp frequency and magnitudes of the simulated plant power, energy storage and/or solar forecasting systems can be designed to mitigate large ramps and comply with interconnection or power purchase agreements. Relative to their size, utility-scale solar power plants cause smaller ramps compared to rooftop systems, since it is more likely that during a cloud passage some modules are cloud-covered while others see clear sky. The amount of this reduction in variability changes with changing correlations between PV modules, and so depends on plant layout, the timescale of interest, and daily meteorological conditions. The correlation functions derived in this paper allow quantifying the reduction in variability based on cloud speed, along-wind and cross-wind plant dimensions, cloud cover fraction, cloud size, and timescale.

The mathematical model for correlations between sites presented here is called the Anisotropic Correlation Model (ACM). The ACM is distinct from previous models in that it was derived from direct physical modeling of the passing of clouds at a constant velocity. It is inherently anisotropic. In Section 2, the method for determining the correlation in *irradiance at two spatial locations* is described. This method is used in Section 3 to determine the correlation of irradiance *ramp rates* between two spatial locations. In Section 4, the sensitivity of the ACM to along-wind and cross-wind distances between sites as well as to the cloud propagation distance is investigated, and is compared to the measured correlations found in Hinkelman (2013). Section 4 also contains a comparison of ramp rates simulated using the ACM to measured ramp rates and ramp rates simulated with other correlation models. The conclusions and implications of the ACM are described in Section 5. The novelty in the present paper is that (i) an analytical expression for correlation functions is derived directly from a physical model, and (ii) despite the simplicity of the underlying model, these functions explain differences in along-wind and cross-wind correlation that were observed in experiments.

2. Correlation of irradiance at two spatial locations

In this section, we present a simple Poisson model for determining the covariance of global horizontal solar irradiance (GHI) incident at two spatial locations, e.g. two PV modules in a PV power plant. Clouds are depicted as opaque circles and the irradiance field is represented by binary states:

$$P_k(t) = \begin{cases} 1, & \text{if no cloud covers point } k \text{ at time } t \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

This binary model oversimplifies real GHI signals since cloud opacity varies and since power output is not reduced to zero even when a point is covered by a cloud (due to diffuse radiation). For correlation modeling of ramp rates the latter effect is not significant since correlations are independent of the signal mean. The impact of various model assumptions is discussed in Section 4.4.

Let $\{M_k : k = 1, \ldots, K\} \subset \mathbb{R}^2$ denote the 2D spatial sensor locations. The cloud centers are generated using a homogeneous spatial Poisson process in two dimensions, as shown in Fig. 1. The number of spatial locations in C_1 and C_2 are independent if C_1 and C_2 do not intersect. The center of the ith cloud is denoted $C_i \in \mathbb{R}^2$ and the C_i 's are assumed to be the realization of a 2D spatial Poisson

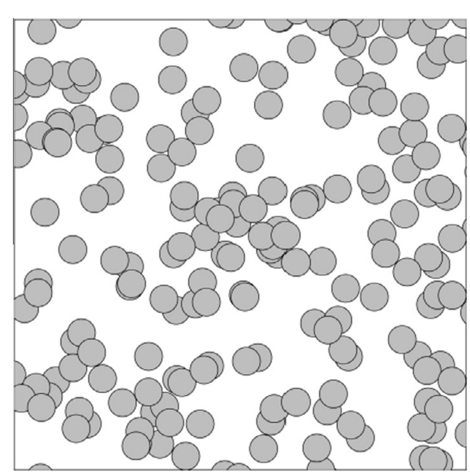

Fig. 1. An example of clouds generated according to a Poisson process, in this case with the probability of any area being covered by a cloud equal to ½: $p_{r,\lambda} = 0.5$.