



Available online at www.sciencedirect.com

ScienceDirect



Solar Energy 112 (2015) 232-238

www.elsevier.com/locate/solener

Embedded nowcasting method using cloud speed persistence for a photovoltaic power plant

M. Lipperheide, J.L. Bosch, J. Kleissl*

Department of Mechanical and Aerospace Engineering, Center for Renewable Resources and Integration, University of California, San Diego, La Jolla, CA 92093-0411, United States

> Received 5 February 2014; received in revised form 7 November 2014; accepted 14 November 2014 Available online 18 December 2014

> > Communicated by: Associate Editor David Renne

Abstract

Accurate forecasting of the spatio-temporal variability of solar power is a critical enabler of economical grid-integration of large amounts of solar power. A new physically-based endogenous method to forecast power output and ramps a few minutes ahead is presented. This cloud speed persistence method consists of advecting the current distribution of power output across the plant using endogenous measurements of cloud motion vectors. The method was validated at a 48 MW photovoltaic power plant in south-western Nevada, USA. Excluding clear days and in terms of the percentage root mean squared error the new method outperformed persistence by 16.2% at 20 s, 10.6% at 60 s, and 4.0% at 120 s forecast horizon. Given plant dimensions (1807×539 m) and cloud motion vectors at the site, the method can be applied out to forecast horizons of 65 s, on average.

© 2014 Elsevier Ltd. All rights reserved.

Keywords: Solar forecasting; Photovoltaics; Cloud speed

1. Introduction

The large short-term power output variability of solar photovoltaic (PV) power plants caused by changing cloud cover is a major obstacle to high solar power penetration into the electrical grid. To maintain electric balancing in a grid with variable renewable energy generation such as PV, conventional rampable power plants or energy storage systems are needed (Hill et al., 2012). Forecasting improves design and operation of such ancillary services, especially under conditions of large ramp rates (Mammoli et al., 2013; Mills and Wiser, 2012).

For predicting solar irradiance one to several days ahead, numerical weather prediction models are advantageous since they take into account atmospheric phenomena as cloud formation, evaporation and atmospheric motion (see Coimbra et al. (2013) for a review). Since NWP lack granularity and computational efficiency, very short-term forecasts (covering a horizon of up to 30 min) are primarily obtained by calculating the motion of clouds with sky imagers or satellite data (Perez and Hoff, 2013; Marquez et al., 2013). Still, physically-based forecasting alone often presents worse aggregate errors than naive persistence forecasts. In specific for sky imagers, cloud detection in the solar region of the image is challenging (Chow et al., 2011; Yang et al., 2014; Urguhart et al., 2014). Therefore, simple persistence models or more advanced machine learning techniques are often used for nowcasting (Inman et al., 2013; Dong et al., 2013).

 ^{*} Corresponding author. Tel.: +1 (858)5348087; fax: +1 (858)5347599.
 E-mail addresses: mlipperheide@ucsd.edu (M. Lipperheide),
 jlbosch@ucsd.edu (J.L. Bosch), jkleissl@ucsd.edu (J. Kleissl).

However, information about the cloud speed, which is critical to describing the translation of sky conditions across the power plant is typically not used explicitly in these models (Lonij et al., 2013 is a notable exception). While cloud speed sensors (Fung et al., 2014) are not yet standard, Bosch and Kleissl (2013) showed that cloud motion can also be detected from spatio-temporal irradiance or power measurements across a PV plant. In specific, cloud motion vectors (cloud speed v and cloud direction α) were determined from the timing of cloud arrival at three different points. The main goal of this paper is to develop and apply a nowcasting method that explicitly takes advantage of the embedded cloud motion information. Similar methods are commonly applied in solar forecasts based on satellite imagery, but (i) satellite cloud motion vectors are determined from synoptic cloud fields while local clouds may deviate from that velocity and (ii) satellite imagery does not have the granularity to resolve withinplant differences in irradiance.

Island(ed) grids and areas that experience power quality issues due to high solar penetration would benefit from very short term forecasts like the one proposed here. For example, the Puerto Rico Electric Power Authority (PREPA) proposed penalizing ramps (both up and down) that exceed 10% of capacity per minute (PREPA). Oneminute ahead generation forecast in conjunction with feed-forward control of energy storage and inverters can avoid violations. While these restrictions and issues are at present mostly limited to island(ed) grids, once the solar penetration increases similar solutions will be needed in microgrids (military, mining) and grids with weak regional interconnections as encountered in many developing countries and remote areas.

2. Data

Solar power output data of 96 inverters from the Sempra US Gas and Power 48 MW_{AC} Copper Mountain Solar 1 PV Plant at Henderson, NV, was acquired with a sampling rate of 1 s. The PV plant (35.78° North; 115.00° West) covers a surface of 1.89 km² with thin-film Cd–Te panels (First Solar, 2011). To represent a typical power plant with regular gridded inverter spacings, only a rectangular part of the plant with 70 inverters is considered, spreading 1807 m in the east–west and 539 m in the north–south direction (Fig. 1). Other specifications cannot be provided due to non-disclosure agreements.

372 days of data are available (July 6 2011 to July 11 2012), but after discarding completely clear days by visual inspection only 171 days remain for further analysis. On these days the mean time elapsed between two cloud motion data points is 32 s. Forecasts are performed only when cloud motion vectors were available (see Bosch and Kleissl (2013) for specific information) and while global horizontal irradiance was greater than 20 W m⁻² as measured by one of the co-located reference cells. On the 171

non-clear days, these restrictions resulted in 66% forecast data coverage during daytime. Periods without data are primarily due to extended clear periods where obviously no cloud motion vectors can be detected. On the 171 non-clear days, cloud motion vectors were interpolated to 1 s resolution to yield 4,265,097 forecasts issue times.

Cloud velocity vectors are derived as in Bosch and Kleissl (2013) using two triplets of reference cells to measure the time delay between the cloud arrival at different sensors. Most clouds in the area result from monsoonal outflow (summer) or frontal passages (winter). Since day-time cloud heights average about 3000 m (from METAR stations in Las Vegas, NV) the cloud speeds are representative of mid-tropospheric wind speeds averaging 21.6 m s⁻¹. Assuming cloud direction was known, clouds speeds were validated against separate ground data using the cross-correlation method (Bosch and Kleissl, 2013) and the mean difference was found to be 21%.

3. Methods

3.1. Persistence and ramp persistence

Standard and ramp persistence methods are used as benchmarks to evaluate the new forecasting method. Generally, persistence is based on the assumption of no change in sky condition or constant clear sky index, see Eq. (1); changes in power output due to the change in solar position are accounted for by the use of the Ineichen clear sky model (Ineichen and Perez, 2002), modified by Perez et al. (2002) and extended to tilted surfaces as in Page (2003). The clear sky model is used to calculate the change of the plane of array irradiance (POA_{CS}) over the forecast horizon. Assuming a constant PV efficiency throughout the forecast horizon, forecast power output is adjusted by the relative change in POA_{CS}

$$P_{\text{Persistence}}(t + \Delta t) = P(t) \frac{\text{POA}_{\text{CS}}(t + \Delta t)}{\text{POA}_{\text{CS}}(t)}.$$
(1)

Ramp persistence projects the *change* in power output over the last second to persist for the forecast period, see Eq. (2). Clear sky corrections are not applied for ramp persistence since clear sky irradiance changes are approximately linear over these short forecast horizons.

$$P_{\text{Ramp}}(t + \Delta t) = P(t) + \Delta t [P(t) - P(t - 1s)].$$
(2)

The minimum and maximum power outputs are constrained between zero and the AC rating of the inverters (35 MW_{AC}), respectively. Other seemingly more realistic constraints that use minimum and maximum clear sky index were evaluated, but yielded worse results presumably because periods of cloud cover are often followed by cloud enhancement. Clear sky corrections are not applied for ramp persistence since clear sky irradiance changes are approximately linear over these short forecast horizons. Download English Version:

https://daneshyari.com/en/article/1549764

Download Persian Version:

https://daneshyari.com/article/1549764

Daneshyari.com