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Solar variability zones: Satellite-derived zones that represent high-frequency ground variability

Matthew Lave [a,*], Robert J. Broderick [b], Matthew J. Reno [b]

[a] Sandia National Laboratories, 7011 East Avenue, Livermore, CA 94550, United States[1]

[b] Sandia National Laboratories, 1515 Eubank SE, Albuquerque, NM 87123, United States[1]

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ABSTRACT

To determine the impact of solar variability to electric grid operations, appropriate samples of solar variability must be used, but determining appropriate variability samples is difficult for locations without ground measurements. In this work, we evaluate and model the relationship between high-frequency and low-frequency solar variability. The developed model is then used to define solar variability zones – zones of similar high-frequency solar variability – using low-frequency satellite data. A map of the United States is presented indicating areas of high, moderate, and low solar variability. To demonstrate the value of the variability zones, quasi-static time series (QSTS) simulations are used to determine the impact of variability samples from each zone on distribution grid voltage regulator tap change operations (a measure of the impact of solar variability to electric grid operations). Strong correlation is found between satellite-derived variability zone and QSTS simulated tap changes based on ground samples of solar variability, showing that solar variability zones can be useful to approximate the impacts of high-frequency solar variability. The relationship between high-frequency and low-frequency variability is found to apply to timescales as short as 10-s.

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1. Introduction

The variable power output of solar photovoltaics (PV) can lead to increased distribution grid operation impacts (Palmintier et al., 2016). For example, PV variability may lead to additional voltage regulator tap change operations, necessitating more maintenance and earlier replacement of these mechanical devices. Previous work (Lave et al., 2015) has shown that the number of voltage regulator tap changes can vary by as much as 300% when using solar variability samples from different locations. However, there are a limited number of locations with high-frequency irradiance measurements. In this work, we define solar variability zones of similar sub-minute solar variability and then use them to determine representative proxies for distribution grid integration studies.

Solar variability at distribution timescales (30-s and shorter) has been quantified at specific locations previously. Woyte et al. (2007) used up to 1-s irradiance measurements in Germany and Belgium to quantify the variability at various timescales using a wavelet transform. Perez et al. (2012) used the 20-s measured irradiance data from 17 sensors in the ARM network located in northern Oklahoma and southern Kansas to show the difference between high-frequency (20-s) and low-frequency (15-min) variability, and to determine station-pair correlations. Hinkelman (2013) used 1-s measured irradiance data from a network of 17 pyranometers in Oahu, Hawaii to determine the solar ramp rates, with a special focus on the correlation of ramp rates between different pyranometers. Lave et al. (2015) compared both the variability score and the impact to voltage regulator operations of 30-s or better irradiance samples from ten locations across the United States. Gagn et al. (2016) characterized sub-second solar variability at two locations in Eastern Canada.

Understanding the solar variability at a few select locations, though, is not helpful to understanding the impact of PV at distribution grids that are not located near one of these known locations. To synthesize high-frequency data, some studies have taken widely available low-frequency data and downscaled it to represent high-frequency data. Wegener et al. (2012) downscaled 15-min PV system data from California to 1-s data using wavelet-based hidden Markov models. Hansen et al. (2011) created a library of measured 1-min irradiance data from the Las Vegas, Nevada region, and used this data to downscale 1-h satellite irradi-

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* Corresponding author.
E-mail address: mlave@sandia.gov (M. Lave).

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ance from nearby areas. The satellite values were used to pick which 1-min segments to sample from the library. In this way, all downscaled data was actual measured data (from a nearby location), but rearranged to match the satellite data at the location of interest. Hummon et al. (2012) found links between 1-min measured irradiance data at 7 locations in California, Nevada, and Arizona and the 1-h satellite irradiance data around those locations, and used these links to determine classes of variability. Downscaling of 1-h satellite data to 1-min was achieved by synthesizing data that fit into the class defined by the local satellite data. This method was later extended to downscale from 1-h satellite data to 4-s data using a similar method (Hummon et al., 2013). Watanabe et al. (2016) characterized variability in surface solar irradiance using cloud properties derived from satellite observations. Huang and Davy (2016) attempted to derive sub-hourly solar variability from hourly solar forecasts.

However, it is not clear that these downscaling methods will be accurate for distribution-scale applications. Wegener et al. (2012) was compared to measured high-frequency data, but had significant errors in matching the cumulative distributions of short-timescale ramp rates (Fig. 4 in Wegener et al. (2012)). The other methods either were meant for transmission-scale applications and so did not downscale to shorter than 1-min (Hansen et al., 2011; Hummon et al., 2012; Watanabe et al., 2016; Huang and Davy, 2016), or have not been validated against measured data (Hummon et al., 2013).

In this work, we produce appropriate high-frequency solar inputs for distribution studies by using a combination of 1-h satellite-derived irradiance and ground-measured 30-s or better solar irradiance datasets. Our approach is different from other works as we do not attempt to downscale the 1-h satellite data but instead use it to define zones of similar variability. Using these variability zones, ground measurements at high-frequency collected anywhere within the zone are considered representative of the high-frequency variability of all locations within the zone. In this way, at locations across the United States, we will be able to produce a representative solar input that does not have any synthetic data, but still accounts for local high-frequency variability.

2. Data

Two data sets were used for this work: satellite-derived irradiance data for creation of the variability zones and ground measurements of irradiance for validation.

Satellite-derived irradiance was obtained from the National Solar Radiation Database (NSRDB) 1991–2010 update (Wilcox, 2012). Specifically, we used the gridded data which reports global horizontal irradiance across a 0.1 by 0.1 grid (roughly 10 km by 10 km) at 1-h intervals for years 1998 through 2009. The NSRDB grid covers the entire continental United States, plus Hawaii. It does not cover Puerto Rico. NSRDB coverage is shown in Fig. 1.

We used the nine ground measurements of global horizontal irradiance (GHI) described in Lave et al. (2015) which overlap the NSRDB: Albuquerque, NM (x2); Boise, ID; Lanai, HI; Las Vegas, NV; Livermore, CA; Oahu, HI; Sacramento, CA; and San Diego, CA. These locations are plotted in Fig. 1, and details of the time periods used and temporal resolution are listed in Table 1. All ground measurements were collected at 30-s or better resolution, and were available for at least 11 months, so should capture seasonal trends. Additional high-frequency irradiance measurements at various tilts (i.e., latitude tilt at various locations) were not considered in this analysis since the differing tilt angles would complicate variability comparisons between locations. Lower frequency (1-min or worse) data were also not considered in this study as our intent was to examine high-frequency data most relevant to distribution

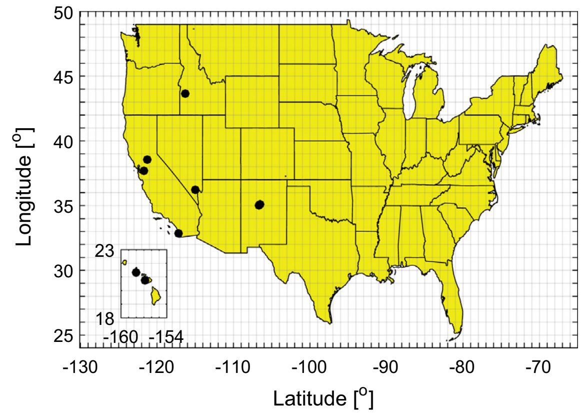

Fig. 1. NSRDB coverage area (yellow) and ground measurement locations (black dots). Gridlines are set at 1° longitude by 1° latitude, such that 100 satellite pixels would be contained in each displayed grid cell. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Ground-measured high-frequency data.

Location	Data Used	Time Res.
Albuquerque, NM (PSEL)	2/2013–12/2013	3 s
Albuquerque, NM (Mesa)	2/2013–12/2013	1 s
Boise, ID	5/2013–4/2014	10 s
Lanai, HI	2/2010–12/2010	1 s
Las Vegas, NV	1/2010–12/2010	1 s
Livermore, CA	12/2013–11/2014	2 s
Oahu, HI	3/2010–2/2011	1 s
Sacramento, CA	1/2012–12/2012	30 s
San Diego, CA	1/2011–12/2011	1 s

grid operations, such as voltage regulator tap changers which have time constants of less than 1-min. Previous work (Lave et al., 2016,) has shown the importance of high-frequency data to accurate distribution grid simulations, though the importance of high-frequency data also depends on the amount of variability (as seen in Fig. 13 in Lave et al. (2015)) – high-frequency data is most important in highly variable areas.

3. Ground data: high vs. low frequency variability

For variability zones derived from low-frequency satellite data to be valid at representing high-frequency solar variability, there must be a relationship between high and low frequency solar variability. To explore this relationship, the ground measurements were used. Since the ground measurements were recorded at various intervals ranging from 1-s resolution to 30-s resolution, they were all averaged to 30-s resolution for consistency. To simulate lower frequency data (e.g., 1-h resolution), additional temporal averaging was applied.

3.1. Variability score

The variability score from ramp rate distribution (VS_{RRdist}) is a simple-to-calculate metric to quantify solar variability. The variability score (Lave et al., 2015) is defined as:

$$VS_{RRdist}(\Delta t) = 100 \times \max_{0 \le RR_0 \le max(RR_{\Delta} t)} [RR_0 \times P(|RR_{\Delta t}| > RR_0)]. \quad (1)$$

where Δt is the timescale considered and $RR_{\Delta} t$ is each measured ramp in the timeseries considered (e.g., GHI timeseries). RR_0 and $P(|RR_{\Delta} t| > RR_0)$ are both expressed as percentages, the former as a