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Characterizing local high-frequency solar variability and its impact to distribution studies ☆

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Abstract

Accurately representing the local solar variability at timescales relevant to distribution grid operations (30-s and shorter) is essential to modeling the impact of solar photovoltaics (PV) on distribution feeders. Due to a lack of available high-frequency solar data, some distribution grid studies have used synthetically-created PV variability or measured PV variability from a different location than their study location. In this work, we show the importance of using accurate solar PV variability inputs in distribution studies. Using high-frequency solar irradiance data from 10 locations in the United States, we compare the ramp rate distributions at the different locations, use a quantitative metric to describe the solar variability at each location, and run distribution simulations using representative 1-week samples from each location to demonstrate the impact of locational solar variability on the number of voltage regulator tap change operations. Results show more than a factor of 3 difference in the number of tap change operations between different PV power variability samples based on irradiance from the different locations. Errors in simulated number of tap changes of up to −70% were found when using low-frequency (e.g., 15-min) solar variability.
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Keywords: Solar variability; Distribution grid integration; Voltage regulator; Tap changes

1. Introduction

Understanding the impact of interconnecting solar photovoltaics (PV) on a distribution electric grid is crucial to efficient operation of the electric grid. Underestimating the effects of PV can lead to grid damage and blackouts, while overestimating the PV impact will unduly limit the installations of this renewable energy resource. The main concern about PV interconnection is that PV is a variable generation resource; its output is not constant and depends on the amount of incident solar radiation. This variability can lead to voltage fluctuations which cause increased use of regulation equipment (e.g., on-load tap changers) and therefore increased grid maintenance costs (Ari and Baghzouz, 2011).

To understand the impact of PV, it is necessary to understand the local high-frequency solar variability. High-frequency (30-s resolution or better) solar variability data is critical since tap changers typically have time constants shorter than 1-min, some as short as 30-s. High-frequency solar variability has been quantified at a

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few specific locations previously: Woyte et al. (2007) used up to 1-s irradiance measurements in Germany and Belgium; Perez et al. (2012) used the 20-s measured irradiance data from the ARM network in northern Oklahoma and southern Kansas; Lave et al. (2012) used 1-s irradiance measurements from a network in San Diego; and Hinkelman (2013) used 1-s measured irradiance data from Oahu, Hawaii.

Understanding the solar variability at a few select locations, though, may not be helpful to an operator whose distribution grid is not located near one of these known locations. To create more high-frequency data, some studies have taken widely available low-frequency data and downscaled it to represent high-frequency data. Wegener et al. (2012), Hansen et al. (2011), Hummon et al. (2012), and Hummon et al. (2013) have all presented methods for producing high-frequency data from low-frequency measurements. However, it is not clear that these downscaling methods will be accurate for distribution-scale applications, as they were not intended for (Hansen et al., 2011; Hummon et al., 2012) or were not well-validated at (Wegener et al., 2012 and Hummon et al., 2013) 30-s and shorter timescales.

The lack of representative, high-frequency solar variability samples has led some distribution simulations to use synthetically-created solar variability profiles or measured solar variability from a different location than the location of the distribution feeder under study. Godfrey et al. (2010) assumed a synthetic PV power ramp of 10% per second as representative of cloud transients, but did not provide a physical justification for this ramp rate. While that study focused on communications to dispatch distributed storage units, they do mention that such a profile would lead to a shortened life for the tap changer and possible voltage quality issues on the feeder. Quiroz and Reno (2012) used irradiance data from southern Colorado for study of a feeder in central Utah. The irradiance was scaled to account for the different intensity of clear-sky irradiance between the two locations, and shifted to represent the accurate sunrise and sunset times in Utah. In both studies, since measured data was not available at the feeder being studied, there was no way to know if the variability profiles used were representative of the actual variability.

The focus of this work is to show the importance of using representative solar variability inputs when running distribution grid simulations. In a related study, Bank and Mather (2013) differentiated between clear and cloudy days, and overall found that tap change operations were higher on the clear days due to the larger magnitude of PV power.

We explore the impact of different solar variability profiles collected at different locations on tap change operations. The 10 locations across the United States with measured high-frequency irradiance that were used for this study are described in Section 2. Section 3 discusses the ramp rate definition we used and shows the ramp rate distributions for each of the locations. In Section 4, we propose a variability metric that is useful for quantifying high-frequency variability and use it compare both the annual and daily variability between the different locations. Section 5 presents results of distribution feeder simulations to determine the number of tap change operations caused by sample PV profiles for each of the 10 locations. Finally, in Section 6, we present the conclusions describing the importance of using representative solar inputs.

2. High-frequency data

We assembled a database of high-frequency (time resolution of 30-s or better) global horizontal irradiance (GHI) measurements from 10 different locations in the United States. We chose to use GHI data to allow for direct comparisons between the different locations. Plane of array (POA) irradiance measurements with varying tilts would make comparisons between sites impractical.

The site locations are shown on a map in Fig. 1, and details about the date ranges of available data and time resolution of the data are listed in Table 1. Albuquerque (PSEL) was collected at Sandia National Laboratories while Albuquerque (Mesa) was collected approximately 10 km southwest. These two sites will allow for validation of methods, as similar results should be obtained for each site due to their close proximity.

As close to one year of data as possible was used to capture seasonal trends. The Albuquerque Mesa and Lanai sites only had 11 months of data, but are still expected to

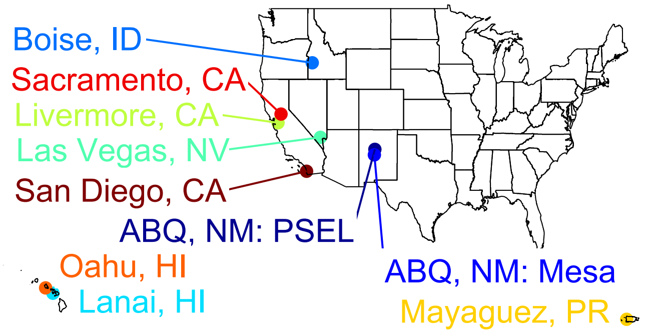

Fig. 1. Map of high-frequency data.

Table 1
Data description.

Location	Data Used	Time Res. (s)
Albuquerque, NM (PSEL)	2/2013–12/2013	3
Albuquerque, NM (Mesa)	2/2013–12/2013	1
Boise, ID	5/2013–4/2014	10
Lanai, HI	2/2010–12/2010	1
Las Vegas, NV	1/2010–12/2010	1
Livermore, CA	12/2013–11/2014	2
Mayaguez, PR	9/2012–8/2013	1
Oahu, HI	3/2010–2/2011	1
Sacramento, CA	1/2012–12/2012	30
San Diego, CA	1/2011–12/2011	1