Simulation of PV Variability as a Function of PV Generation and Plant Size

Preprint

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National Renewable Energy Laboratory

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Simulation of PV Variability as a Function of PV Generation and Plant Size

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***Abstract*—The deployment of photovoltaic (PV) systems continues to show significant expansion; however, this growth has brought added attention to issues around the variability of the solar resource. Both spatial and temporal variability exist. Temporal scales can range from the sub-second to multiyear, whereas spatial scales can range from a few meters to tens of kilometers. There are multiple methods described in the literature to quantify PV variability at various spatial and temporal scales. This study focuses on short-term temporal variability and uses similar approaches with the addition of PV plant size a parameter to quantify variability. The method employed here incorporates the normalization of clear- and cloudy-sky conditions and PV plant size to quantify nominal variability metrics. The distribution and fluctuations of these metrics provide relevant information that is useful for system operations. The National Solar Radiation Database (NSRDB) is used to simulate PV variability as a function of PV generation and plant size. Hypothetical but realistic system information at 33 locations is used to model PV generation by feeding NSRDB solar irradiance data to the National Renewable Energy Laboratory's System Advisor Model (SAM). Over the selected region, it is found that the aggregated ramp rates for the 1-minute data are associated with standard deviations ranging from 0.002–0.055 on a daily basis; however, hourly intervals induce higher aggregated ramp rates than the other timescales. Even though minute-to-minute variations are significant for the 1-minute timescale, the standard deviation aggregated into a daily metric is smaller because of the cancellation of values.**

***Keywords*—photovoltaic systems, NSRDB, irradiance, solar energy, SAM**

I. Introduction

The fraction of electricity generated from solar photovoltaic (PV) systems integrated into the grid is rapidly increasing [1]; however, the performance of these systems is susceptible to short- and long-term solar energy variability. The latter is typically associated with interannual and seasonal temporal scales [1]. The focus of this paper is on the short-term timescale, e.g., ramp rates or rapid change events. These events, which are typically associated with varying cloudiness, cause significant uncertainty in the dispatchability of power sources available for balancing generation and load [2]. The temporal scales of these events vary from the sub-second to hours [3]. This study analyzes ramping rates using various timescales from 1 minute to 1 hour by incorporating information on the capacity factor and plant rating of each plant. The impacts of the solar resource's variable nature on the performance of PV systems are analyzed here using appropriate statistical metrics. This approach is meant to provide valuable information toward a better understanding of power systems and grid operations.

II. Method

For this study, 33 locations have been selected within a ≈1800-km^2 area in a region of highly diverse topographic and climatic conditions. The system sizes are for residential and utility-scale PV systems ranging from 0.07 MW to 82 MW, respectively. One year (2019) of 5-minute irradiance data are obtained from the National Solar Radiation Database (NSRDB) [4]; however, for this study, a high-temporal-resolution data set is required to investigate minute-by-minute ramp rates. Therefore, a downscaling model is first applied to convert the 5-minute NSRDB data set into a new data set at 1-minute temporal resolution [5]. The 1-minute solar resource data in addition to some meteorological parameters are used as input to the System Advisor Model (SAM) [6] to predict the corresponding PV electric generation. From the model output, the calculated capacity factor (i.e., the ratio of predicted instantaneous power for a particular plant to its rated AC power) is used to analyze the short-term output variability, ranging from 1 minute to 1 hour.

To understand the aggregated impact of ramp rates from all sites at the specified timescale, the plant rating is incorporated in the estimation method. The method implements a nominal dimensionless metric, as described in the following steps.

Step 1: *Normalized plant rating*

A weighting factor for each PV site (*i*) is applied to incorporate its rating into the metric as:

$$nRating_i = \frac{Rating_i}{\sum_{i=1}^{n} Rating_i} \quad (1)$$

where *n* is the number of sites.

Step 2: *Normalized instantaneous capacity factor*

$$ncf_{i,t} = \frac{all\text{−}sky\ cf_{i,t}}{clear\text{−}sky\ cf_{i,t}} \quad (2)$$

where $all - sky\ cf_{i,t}$ and $clear - sky\ cf_{i,t}$ are the capacity factors for the all- and clear-sky conditions for plant (*i*) at each time step (*t*), respectively. This provides nominal dimensionless indices where the $ncf_{i,t}$ values are within the interval [0,1], with small values representing overcast conditions and thick clouds and 1 representing completely clear skies.

Step 3: *Combination of Step 1 and Step 2*

To understand the ramp rates at various timescales while considering multiple locations, a differencing technique is applied. Differencing between time steps for Step 2 and multiplying by the weighting factor for the corresponding plant from Step 1, $nRating_i$, provides us a normalized plant variability:

$$\Delta ncf_{i,t} = (ncf_{i,t} - ncf_{i,t-1})\ nRating_i. \quad (3)$$

Step 4: *Aggregation*

Once the results are obtained for all plants, they can be aggregated to provide a normalized aggregated variability for each time as follows:

$$\Delta ncf_i = \sum_{i=1}^{n} \Delta ncf_{i,t}. \quad (4)$$

Step 5: *Statistical metric*

The standard deviation for all 365 days of 2019 is finally calculated for both Step 3 and Step 4. That metric is used to evaluate the daily ramp rate variations for the individual locations and aggregated values, respectively. These calculations are only carried out during daytime by eliminating low-sun situations when the solar zenith angle is more than 80°.

III. Results

The procedure consists of two parts: (A) A baseline analysis checks the ramp rate effect for each individual site without incorporating that effect on the neighboring sites in the results (Fig. 1) ; and (B) The aggregated analysis is implemented by including the plant weighting factor of Step 3.

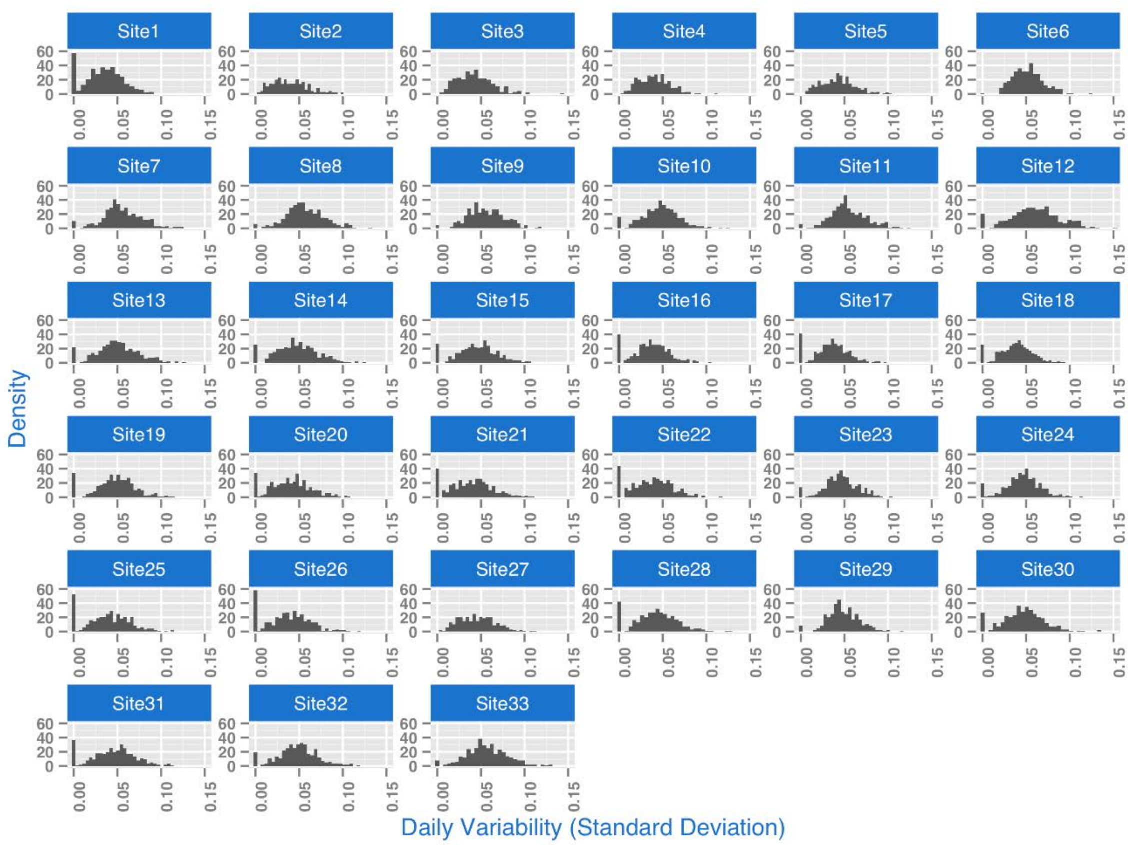

Fig. 1. Frequency distribution of daily variability (standard deviation) using the 1-minute timescale for each location. The first bin (at the origin of the X-axis) represents the frequency of clear days.

A. Baseline Analysis

A baseline analysis is carried out to extract the effects of ramp rates on each system under study in a location-specific way. Most importantly, this kind of analysis provides interesting insight for PV plants that are off grid because the effect of ramp rates is then independent from what occurs at nearby sites. Each system under scrutiny is affected by varying atmospheric conditions coupled with terrain specificities, such as from coastal locations to higher elevation grounds, and even valleys in some cases. (The elevation of the pool of 33 sites varies from ~100 m to ~1000 m; however, there are nearby locations that reach up to 2,500 m.) The baseline analysis undertaken here excludes steps 1 and 4 from Section 2. Fig. 1 shows that the daily standard deviation of the ramp rates for the 1-minute timescales is highly location specific. Some sites experience none to a few clear days, as indicated by the low frequency of cases in the lowest, or 0-bin, of daily variability on the X-axis.

For example, Site6 does not experience any completely clear days because of its cloud-dominated climate. Moreover, that site is more susceptible to broken clouds, such as cumulus clouds, which frequently cause higher ramp rates. Conversely, because the dimensionless variability statistic metric (standard deviation) is never close to zero at that site, we can infer that this location is also not affected by overcast cloud conditions.

Additionally, the analysis also attempts to depict the individual correlations among the PV plants. To do this, a correlation matrix is computed and shown in Fig. 2.

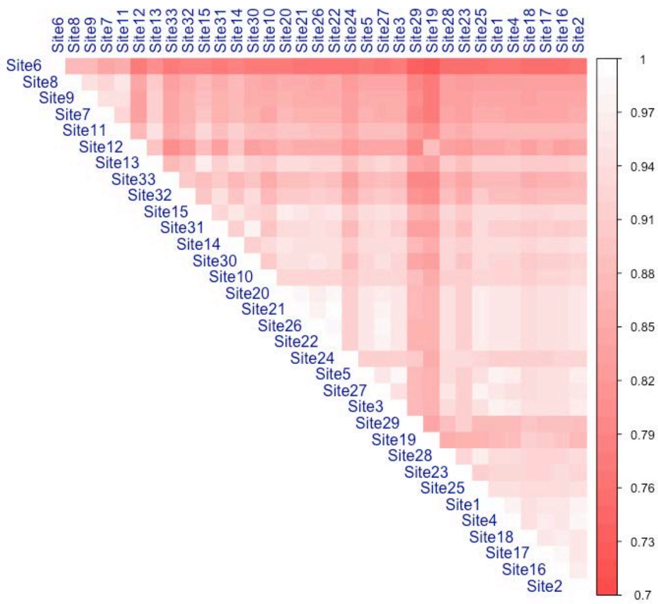

Fig. 2. Correlation matrix for all locations.

The results of the correlation matrix are consistent with those in Fig. 1, where, for example, Site6 is relatively poorly corelated with other sites. When evaluating the regional impact of ramp rates, an important aspect is the variation of correlation with distance. Previous studies (e.g., [3, 7]) described that the spatial correlation among sites varies inversely with distance. The present results indicate that this is not always true. For example, Site6 is relatively far (55 km) from Site33, but the correlation between them is higher than for some of the sites closest to Site6 that are within 15 km. Therefore, even though distance is a critical factor, it is not the sole criterion determining correlation. Other factors, such as microclimate or topography and relative geographic direction between plants, apparently contribute to reduce the correlation.

B. Aggregated Short-Term Variability Analysis

Steps 1 to 5 (described in Section 2) are critical to understanding the effect of ramp rates on power system operations. As mentioned, the goal of this approach is to incorporate the same variation of plant capacity factor that is defined as a function of the weighting factor from Step 1 to quantify an aggregate metric. In the present case, PV plants with larger system sizes are expected to show relatively higher output variability, which is then reflected in the actual impact of variability and ramps on system operation.

Fig. 3 provides the aggregated result of the variability analysis for the 1-minute timescale. This time series of the aggregated ramp rates shows that, on a daily basis, the nominal standard deviation can vary between 0.002 and 0.055 over the selected region.

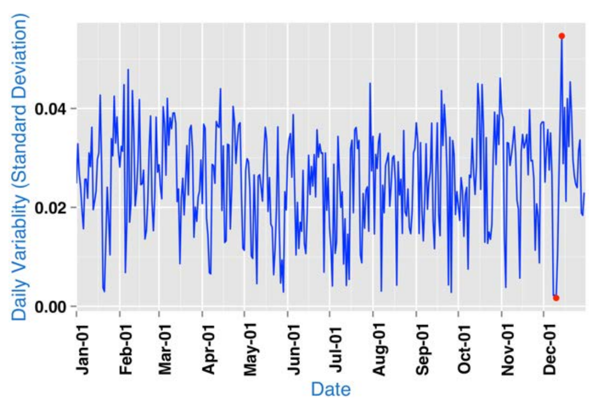

Fig. 3. Nominal daily variability aggregated from the 1-minute data. The red points show the maximum and minimum variability, which coincidentally both occur during December 2019.

The capacity factors for the maximum and minimum variability days (December 14 and 10, 2019, respectively, as highlighted in Fig. 3) are shown in Fig. 4. All PV plants demonstrated high variability on Dec. 14 (Fig. 4 top) and, vice versa, very low variability on Dec. 10 (Fig. 4 bottom).

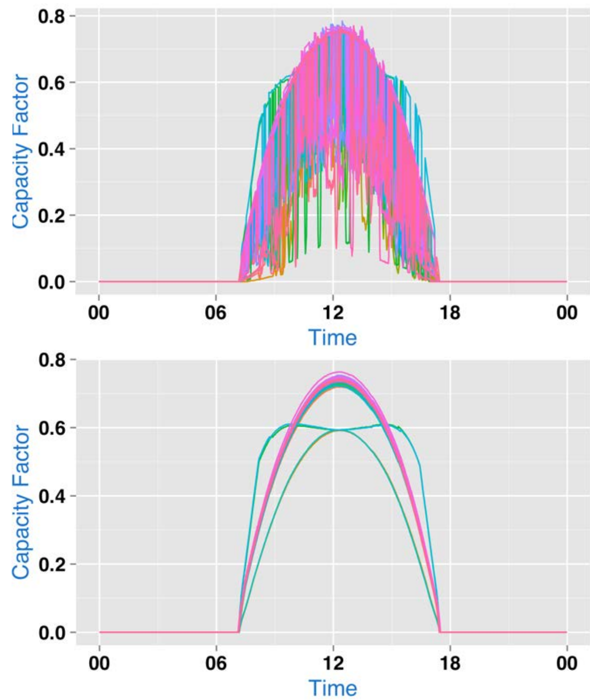

Fig. 4. High (top plot) and low (bottom plot) output variability for various PV systems having differing geometries (fixed tilt or 1-axis tracking) during Dec. 14 and Dec. 10, 2019, respectively.

A more general, albeit similar, analysis can be undertaken using various other time resolutions, namely, with 5-, 15-, 30-, and 60-minute timescales. These results are shown in Fig. 5 in the form of frequency distributions. These results demonstrate that, on a daily basis, hourly intervals induce higher aggregated ramp rates than the other timescales. Even though minute-to-minute variations are significant at the 1-minute timescale, the standard deviation aggregated into a daily metric is smaller because of the cancellation of variability. This finding is consistent with those from a previous study [8].

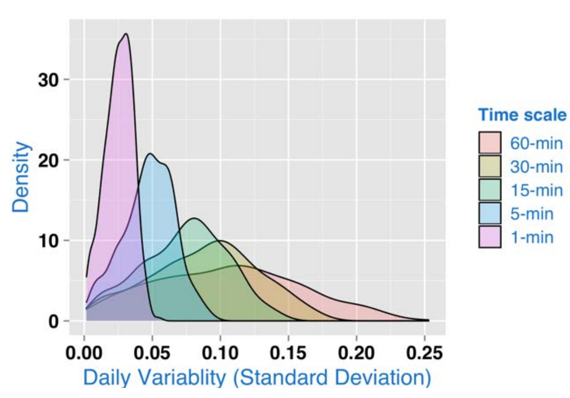

Fig. 5. Differences among various timescales on aggregated daily variability.

IV. Conclusion

Intra-minute fluctuation and ramps in solar generation from PV cause challenges for system operations. These events are caused by the nature of variability in cloud cover, which can prompt rapid fluctuations in the incident solar irradiance that is available for conversion. These events need to be understood clearly to mitigate their effects on system operations, both for individual systems and fleets of systems at the regional scale. Using solar resource data from 33 sites within a relatively small—but highly inhomogeneous—region, this study provided a method to quantify these effects using a new statistical metric. One important finding was that the correlation between the output of different systems was not solely conditioned by their distance, contrary to what the current literature suggests. This approach will help system and grid operators to understand the actual impacts of ramp rates on PV systems operation and the electric grid as a function of distance, topography, relative direction between plants, and microclimatic features.

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