ABSTRACT: As the cost of photovoltaic systems is driven lower and the “grid parity” milestone of energy cost appears closer, the grid-integration challenges posed by the variable output of those systems have received increasing attention. At the same time due to economies of scale and an operations mode that is familiar to electric utilities, large, “central-generation” PV systems are being constructed at an ever increasing pace. While the output variability of distributed PV systems is mitigated from geographical dispersion and low correlation over typical distances, the output of central-generation systems is much more sensitive to local weather variability. Still, the sheer size of a very large system already provides a smoothing effect to the total output as such a system can be described as an aggregation of smaller arrays connected to a single inverter each. In this work we demonstrate and characterize the smoothing effect of the spatial expanse for the continent’s largest contiguous PV system in Rovigo, Italy. We will explore the variability of power output across multiple time, spatial, and capacity domains. Keywords: Variability, Aggregation, Rovigo, Grid Integration

1 INTRODUCTION

The output variability of large “central generation” PV systems is of concern for the grid operator/planner as they have to plan for adequate reserve capacity. At high-voltage interconnections, voltage variation is not of concern because HV transmission systems are well equipped and strong enough to tolerate and compensate for the voltage fluctuations caused by the output variability of a large (70 MWp) PV site. Most important in those cases is the balancing over load-following time domains of 5-15 minutes [1].

This work will explore the output variability of Europe’s largest PV power plant over 8 months across a number of time scales with the goal of exploring the impacts of spatial dispersion and temporal averaging on a variety of variability metrics. Our observation is that increased spatial footprint is reducing output variability but the dependence over multiple time scales is more complex.

2 METHODOLOGY

2.1 System Characteristics

The system observed in this study is a 70 MWp fixed-tilt PV power plant covering 850,000 m² in Rovigo, Italy. At the time it was completed by SunEdison (December 2010) it was the largest contiguous PV plant in the European continent. There are 60 arrays that make up the full system, each between 1.1-1.3 MWp. The arrays, built with multicrystalline and monocrystalline Silicon PV modules, connect to inverter cabinets which represent 1 MWac-rated units.

2.2 Data Sources

In this study we observe the AC power readings from the revenue grade meters at each of the 60 inverter cabinets, and the irradiance measurements in the Plane-Of-the-Array (POA) from a Kipp & Zonen CMP-11 pyranometer at 1-minute resolution. All power measurements are collected and time-stamped at SunEdison’s SEEDS™ gateways whose clocks are synchronized over the NTP protocol. The data was collected over 9 months from the inception of the plant in December 2010 through the end of August 2011. We observe measurements only during the middle of the day between 10:00 and 14:00 local standard time, when power production, and therefore the impact of power drops and ramps, is highest.

2.3 Power deltas and aggregation

We observe the output from the pyranometer and meters over various time intervals aggregated across various ensembles comprising some subset of the 60 arrays. We then calculate power deltas between adjacent intervals, i.e. (mean power from 10:05-10:09) – (mean power from 10:00-10:04). The time intervals range from 1-60 minutes, with the load following range of 5-15 minutes being most relevant.

The ensembles separate into two groups, I and II. In Group I, we observe the effect of capacity density within a fixed radius. The first ensemble in this group is a set of 6 arrays with capacity totaling 8MWp located at points around the perimeter of the plant. In the second ensemble, we add a few more arrays from the center of the system, totaling 17 MWp. We do this again to build an ensemble of 35 MWp, and finally we create a 70 MWp ensemble containing all 60 arrays. In each case, the subset of arrays chosen is distributed over the full geographic footprint of the system.

In Group II, we fix the capacity of each ensemble at 6 MWp, but choose arrays separated by a variable radius (see Figure 1). The irradiance sensor represents a zero-radius measurement.

2.4 Variability Metrics

Figure 1: Map of Ensembles in Group II

2.4 Variability Metrics
The next step is to calculate the step changes between successive power output and irradiance measurements. To compare the variability of systems of different sizes, we need to normalize the power output. We chose the nameplate DC capacity— the sum of the nameplate rating of the PV modules— of each ensemble to normalize on. Though the maximum AC output is limited in these cases by the nameplate rating of the inverter, such a high output from the PV array so as to be clipped by the capacity of the inverter is very rarely the case. The DC capacity is indeed much more representative of the anticipated output of a given array. Variability metrics in this paper will generally be given in normalized terms as a fraction of nameplate capacity, unless otherwise noted.

Both power drops and power ramps can pose challenges to the grid operator. In this study, as shown in Table 1, we have observed the distribution of drops and ramps to be symmetrical around 0. We choose then to observe only the absolute value of any given step change. We will refer to a “delta” of power or irradiance as the absolute change from the previous measurement.

### Table 1: Distribution of Drops vs. Ramps

<table>
<thead>
<tr>
<th></th>
<th>Max</th>
<th>3σ</th>
<th>2σ</th>
<th>1σ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop</td>
<td>-52.7%</td>
<td>-36.6%</td>
<td>-16.9%</td>
<td>-2.1%</td>
</tr>
<tr>
<td>Ramp</td>
<td>53.9%</td>
<td>35.9%</td>
<td>17.6%</td>
<td>2.7%</td>
</tr>
</tbody>
</table>

Some of the variability metrics that we use have been defined and used in similar analyses in the literature [2], [3], [4]. The simplest of them is the standard deviation of the step changes.

However, the standard deviation of the step changes in power output does not convey all the information about a real PV system’s behavior. We have observed that the distribution of the step changes is not normal but exhibits a pronounced peak and long tails; i.e. the probability of a large step change is higher than what would have been calculated for a normal distribution with a given standard deviation.

To better describe this effect we have employed a metric, defined in [3] as $\kappa_3$, which quantifies the ratio of the 99.7th percentile of the step changes to the standard deviation of the distribution. A high value of $\kappa_3$ points to a higher probability of extreme step changes.

Another simple and intuitive metric is the maximum delta observed across all step changes, which represents the worst case scenario from a grid management and balancing perspective.

The final metric explored is the probability of power deltas exceeding a certain magnitude. This third metric is essentially a slice of a Cumulative Distribution Function (CDF) plot. In such a chart we can identify the magnitude of power deltas vs. the likelihood of a drop that is larger or smaller than a certain magnitude. In this study we wish to observe how the choice of time interval impacts the likelihood of power deltas above a given magnitude, so we choose the cross-section of the 30% or 50% delta, and measure, at various time intervals, how likely is a power delta of this size or larger.

## 3 RESULTS

### 3.1 Standard Deviation

We observe first the standard deviation of Group I of ensembles. From Figure 2, we see that the density of power within a given radius is essentially invariant with aggregated capacity. This uniformity was seen across all variability metrics for the ensembles of Group I.

![Figure 2: Standard deviation of deltas among ensembles in Group I](image)

In Figure 3, we see significant separation among the ensembles in Group II. The benefit of the larger geographic radius is clear, with the wider ensembles being smoother in all cases.

![Figure 3: Standard deviation of deltas among ensembles in Group II](image)

### 3.2 Compare to normal distribution

We observe below the $\kappa_3$ of deltas across time intervals. In all of the power ensembles, there is a steep decline in the shorter intervals, as the distribution becomes more normal, and at around the 30-minute interval, the value of $\kappa_3$ begins to rise again. The irradiance measurements continue to drop in the longer time intervals.

![Figure 4: $\kappa_3$ of deltas](image)

### 3.3 Maximum Step Change

We observe only up through the 30-minute time interval. Beyond that, interval deltas are significantly influenced by the rising or setting sun. Since the capacity
of the ensembles is their nameplate capacity, i.e. the expected power output at Standard Test Conditions of 1000 W/m$^2$ and 25 °C, we define the “capacity” of the irradiance measurements as one sun, i.e. 1000 W/m$^2$.

![Graph](image)

**Figure 5**: Maximum delta observed across the full span of the study

3.4 Fraction of deltas above threshold

We measure the probability that a power delta of at least 50% of capacity occurs over a specified time interval. Note the break in the y-axis, where the values for the irradiance curve are 1-2 orders of magnitude higher than the rest of the curves.

![Graph](image)

**Figure 6**: Likelihood of power deltas greater than 50% of nameplate capacity.

4 DISCUSSION

We first observe the standard deviation, the most simple and intuitive of variability metrics, in the ensembles of Group I. We see increased capacity within a given radius makes no difference to the variability of the ensemble when normalized by nameplate size. This is a promising result as it shows that increased capacity within a fixed area is not of concern for greater variability.

In Group II, the standard deviation does show improved variability across a set of ensembles. As the radius of observation grows from a point source, in the case of the irradiance measurements, up to 600m, in the largest ensemble, the variability decreases monotonically.

The sharp increase in variability from 1 to 10 minutes is likely explained by the relationship between the speed of the clouds and the radius of the ensemble. The slower increase beyond that is likely an effect of the deterministic nature of the sun’s motion through the sky.

The $\kappa_3$ shows that as the time interval increases beyond 1-minute observations, the shape of the distribution of the deltas becomes more normal. This is expected, as there will be fewer very large deltas and fewer near-zero deltas in the longer time intervals, but a higher concentration of small to moderate deltas. Such a change in the distribution would drive the $\kappa_3$ down. The irradiance performs as expected, continuing to drop as the time interval grows to the longest interval of 60-minutes. The shape of the $\kappa_3$ of the power deltas though, where they begin to rise again after the 30-minute mark, is a subject for future work.

The plot of the maximum delta versus time interval shows an interesting effect, where the smallest radius ensembles – irradiance and the 100m – show their worst case deltas at the shortest intervals. The largest ensemble – the 600m radius – in fact has the smallest maximum delta in this time. This is again an observation of the smoothing effect over a plant of this size.

In Figure 6 we observe the probability that a certain power delta exceeds 50% of the nameplate capacity of the ensemble. In all cases, the likelihood of a power drop of 50% is at least an order of magnitude less likely to occur than such a drop in the irradiance. If irradiance variability in a region is known when constructing a plant, especially at small time scales, one can be reassured that the likelihood of such extreme drops in power will be significantly less.

The largest ensemble shows nearly zero probability of a 50% power drop, until around the 25-minute interval, where it begins to pick up. To fully understand this effect, some knowledge about the nature of cloud type and movement in the region would need to be known.

5 CONCLUSIONS

In analyzing the variability behavior of the AC output from one of the world’s largest PV power plants we have observed that the standard deviation of the power deltas is invariant with respect to the installed power density inside a fixed perimeter, i.e. the variability does not change with the plant capacity, as long as that capacity is distributed over a fixed area. However, as expected, it is reduced when the density of a fixed-capacity system increases, i.e. the variability decreases as a fixed-capacity system is allowed to cover a greater area.

The shape of the probability distribution of the power deltas does not seem to depend on the power density but shows a marked reduction from short time scales to time scales of approximately 20 minutes and then a moderate increase at longer time scales. The reason for the presence of a minimum in the spread of extreme events is a finding that requires further investigation. We believe that it may be related to the temporal dependence of other variability metrics, such as the fraction of deltas above a certain threshold and the standard deviation of the deltas, which in turn are likely related to the speed, type and size of the clouds prevalent in the region.
REFERENCES


