VOLATILITY AND DEVIATION OF DISTRIBUTED SOLAR

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ABSTRACT

Solar photovoltaic (PV) power production can be volatile, which introduces a number of problems to managing the electric grid. To effectively manage the increasing levels of solar penetration, the variability of distributed solar power production needs to be understood. PV ramp rates (i.e. changes in power production) have been studied previously in virtual simulations, laboratories, and limited field studies, but no large scale studies have been conducted in the field. This paper presents a large scale field study of solar power production variability around Los Angeles and Newark for 2012 using 5-minute interval power data from PV systems monitored in the field.

Two new metrics, Solar Volatility and Solar Deviation, are introduced to quantify the variability of PV output compared with expected output. These metrics are applied to the time series power data from over 1000 systems each around Los Angeles and Newark. The study concludes that aggregated system Solar Volatility decreases most with increasing number of systems, and is less sensitive to the geographic dispersion of systems. Solar Deviation decreases slightly with increased number of systems and geographic dispersion, but is less sensitive to these factors than Solar Volatility.

1 INTRODUCTION

In recent years, there has been significant growth in the installed capacity of solar photovoltaic (PV) systems throughout the world. While it is currently a small part of the overall power generation mix, there are areas of high penetration in which solar PV output supplies a significant amount of power.

PV power output can be variable, meaning that the power changes given the amount of sunlight striking the panels; as clouds move and block the sun, power output reacts accordingly. Because the electric grid needs to maintain power output to meet demand at any instant, this variable output impacts the stability of the grid, particularly in areas of high penetration.

Understanding and quantifying volatility is important to maintaining grid stability. Grid operators typically maintain a mix of reserve generation resources, such as regulating, following, contingency and ramping reserves (Ela, 2011). These reserves are dispatched based on time-frame, capacity, and cost. In the case of solar PV output falling, these reserves are activated to make up the difference and maintain constant power output for the system. By improving the information available to quantify the change in PV output, the proper reserves can be on hand to ensure a stable grid and optimum cost efficiency.

There have been a few previous studies regarding quantifying variability for distributed PV. These past studies have investigated the correlation of rates of changes between systems, using irradiance as a proxy for power output. In addition, these studies have investigated the variability of PV output compared with no PV output.

Perez et al investigated the variability of irradiance at small time scales using a virtual network of satellite-modeled irradiance and cloud-motion analysis. The study concluded that fluctuations become uncorrelated as time-period and distance increase. For example, 20-second fluctuations are uncorrelated at 500 meters, 1-minute fluctuations are uncorrelated at 1 km, and so forth in a linear relationship (Perez, 2011).

In another paper, Hoff and Perez investigated the variability of dispersed PV compared with centralized PV. This analysis used a virtual network of modeled irradiance data as a proxy for PV power output. The main result of this analysis was that optimally dispersed PV will most significantly reduce variability (Hoff, 2010).

This study differs from past research in order to better quantify variability. Rather than using virtual models or irradiance as a proxy, this investigation uses measured PV power data from over 2,000 distributed PV systems in the field. At 5-minute intervals, the time period for analysis is relatively short. Different geographies are studied in order to validate repeatability of results independent of local climate conditions. Lastly, rather than comparing against no output to determine variability, this paper quantifies variability by comparing output against expected output on a typical day.

2 SOLAR VOLATILITY

Volatility is a way to quantify variability in everything from stock market prices to rainfall to solar PV power outputs. The lower bound for volatility metrics has typically been zero, meaning no variation. Volatility is often reduced when considered in aggregate, as distinct sources of volatility are often imperfectly correlated.

The application of volatility reduction for solar PV is illustrated in Fig. 1. As a cloud moves across an individual PV system, it blocks some of the sun's rays and lowers power output. Individual solar PV systems – collections of strings of solar panels that span a small geographic region – are volatile because they are subject to point changes in cloud formations. Spreading the panels across a wider geographic region to form a distributed PV system, as shown at the bottom of Fig. 1, diversifies away much of this regional volatility.

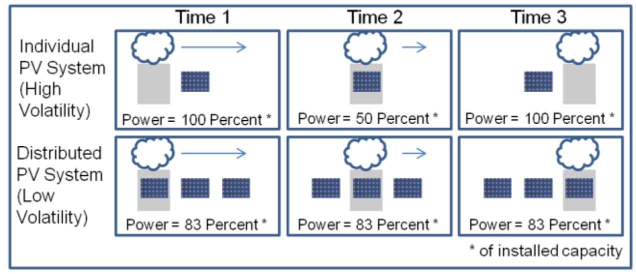

Fig. 1: Comparison of volatility for an individual PV system and a distributed PV system.

Fig. 2 illustrates the reduction in volatility using measured power data from PV systems. As the figure shows, the output from an individual PV system can be highly volatile, while the aggregate of many PV systems (bottom red line) is closer to expectations (bottom black line).

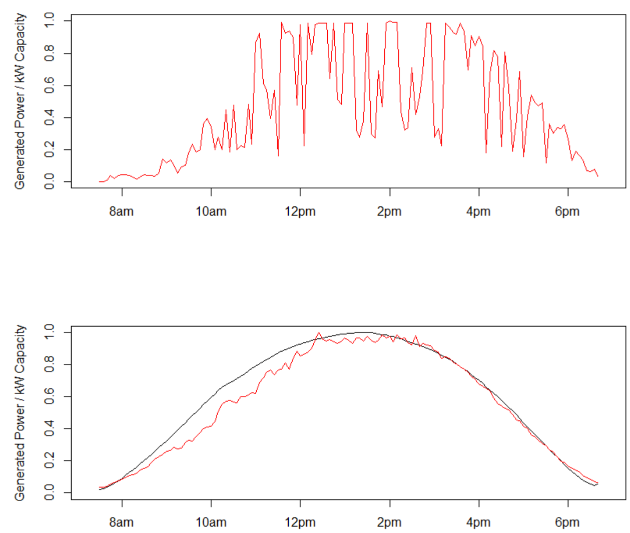

Fig. 2: One PV system (top) and a distributed PV system with 100 individual systems (bottom) for March 18th, 2012.

2.1 Past work

Hoff and Perez previously quantified volatility by using the equation below to compute a standard deviation of the changes in generated power values, or ramp rates, between neighboring time points (Hoff, 2010):

(1) $$V = \frac{1}{C_{Fleet}} SD\left\{ \sum_{n=1}^{N} [\Delta P_n] \right\}$$

While this standard volatility metric is useful in understanding ramp rates, it has some shortcomings. First, this metric can mistakenly identify expected PV output as volatile. As seen in Fig. 3, solar PV output naturally ramps up and down over the course of a day. Equation 1 would quantify this example day as volatile, even though the power output is changing as expected (see TABLE 1).

Second, Equation 1 often fails to identify days with volatile production. Because of the nature of the changes in the example day shown in Fig. 4, this would be classified as a low volatility day, even though the power output is different from the expected production curve (see Table 1).

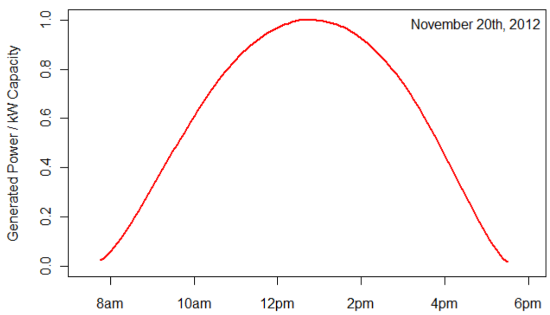

Fig. 3: Power output from aggregated PV systems on a clear day.

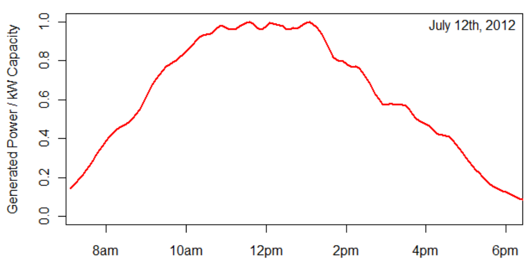

Fig. 4: Power output from aggregated PV systems on a cloudy day.

This paper builds upon the standard volatility metric and develops two new metrics to more robustly quantify and differentiate the volatility in a distributed PV. The two new metrics measure the amount of power generated and the ramp rates relative to corresponding expected production.

This paper uses expected production, rather than no production, as a baseline because this scenario more accurately reflects a grid operations scenario. Utilities have forecasts of production and demand, which they use to plan their near-term generation mix. Active management is needed when PV output differs from the forecast expectations in order to balance production with demand.

2.2 Solar Volatility Metric

This paper defines "Solar Volatility" for a distributed solar PV system as the standard deviation of the (aggregated) differences between the observed ramp rates on a given day – the rates of change in power output – and the expected ramp rate curve for the month. The monthly expected ramp rate curve – $E(\Delta P_n)$ – is composed of the ramp rates at each five-minute interval for the average day in that month. The expected ramp rate curve can be interpreted as a typical day for each month.

$$VOL = \frac{1}{C_{Fleet}} SD\left\{ \sum_{n=1}^{N} [\Delta P_n - E(\Delta P_n)] \right\} \tag{2}$$

As Equation 2 shows, the solar volatility metric proposed here does not quantify the absolute volatility of ramp rates, but rather the relative volatility of ramp rates compared with expected ramp rates.

Applying Equation 2 to the example PV output curves shown in Fig. 3 and Fig. 4 results in more intuitive quantifications of each. Fig. 3 is appropriately classified as a low volatility day, while Fig. 4 has higher volatility (see Table 1).

2.3 Solar Deviation Metric

This paper defines "Solar Deviation" for a distributed solar PV system as the standard deviation of the (aggregated) differences between the observed amounts of power generated by the system at five minute intervals throughout a given day and the expected amounts of power generated by the system. As with the Solar Volatility metric, the expected curve is constructed using an aggregate of the days in the month of analysis, and can be considered a typical day for each month.

$$DEV = \frac{1}{C_{Fleet}} SD\left\{ \sum_{n=1}^{N} [P_n - E(P_n)] \right\} \tag{3}$$

Solar Deviation is not necessarily correlated with Solar Volatility, and there are many days throughout the year for which Solar Volatility and Solar Deviation differ significantly. There are two scenarios which cause this differentiation.

The first is when the amount of cloud cover gradually changes throughout the day, leading to a relatively high Solar Deviation and a low Solar Volatility, illustrated in Fig. 5. The gradual difference between measured and expected ramp rates causes low Solar Volatility, while the measured curve is clearly lower than the expected curve, causing higher Solar Deviation.

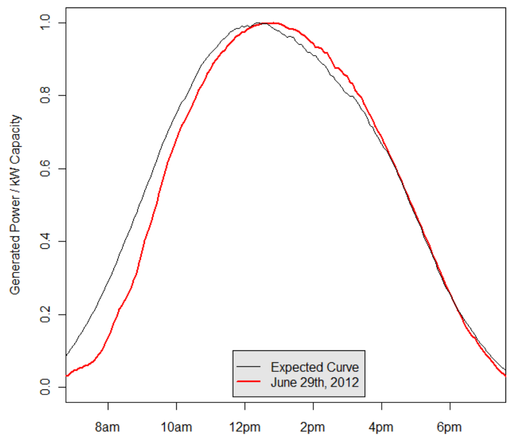

Fig. 5: Example day with low Solar Volatility and high Solar Deviation.

The second cause of difference between Solar Volatility and Solar Deviation is consistent, minor fluctuations of power output that closely follows the expected curve. Days that fall into this category have a low Solar Deviation and a relatively higher Solar Volatility, as shown in Fig. 6. In this example minor oscillations caused a difference in ramp rates, leading to moderate Solar Volatility, but only slight deviations from the expected normalized power curve, causing low Solar Deviation.

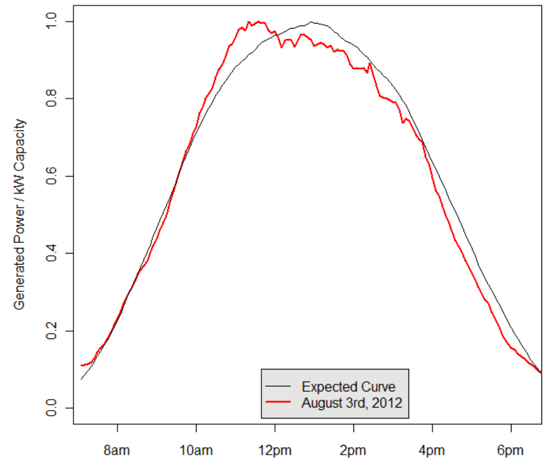

Fig. 6: Example day with low Solar Deviation and relatively higher Solar Volatility.

2.4 Comparison of Metrics

The three metrics described in this section all quantify volatility in different ways. The calculations for Fig. 3, Fig. 4, Fig. 5, and Fig. 6 are shown in the table below.

TABLE 1: Comparison of metrics. The lowest values and highest values are given to put the other values within context. Note that values are scaled to 10^{-2}.

Example	Hoff-Perez Volatility ($\times 10^{-2}$)	Solar Volatility ($\times 10^{-2}$)	Solar Deviation ($\times 10^{-2}$)
Observed Min 2012	1.15	0.21	1.43
Observed Max 2012	2.94	2.72	23.02
Fig. 3	1.79	0.42	5.18
Fig. 4	1.16	1.03	16.70
Fig. 5	1.45	0.70	11.91
Fig. 6	1.91	1.53	4.44

3 FLEET ANALYSIS

In a grid operations scenario, utilities are most interested in power output of PV systems in areas of high penetration. To address this scenario, power output was collected every five minutes for an entire year (January 2012 - December 2012) from 1,644 individual solar PV systems within a 100 km radius of Los Angeles, California, as well as from 1,140 individual systems within a 100 km radius of Newark, New Jersey. Los Angeles and Newark were chosen to represent two different regions of the country with dissimilar climates and weather patterns, as well as high densities of distributed PV installations. A map of systems around Los Angeles is shown in Fig. 7, and a map of systems around Newark is shown in Fig. 8.

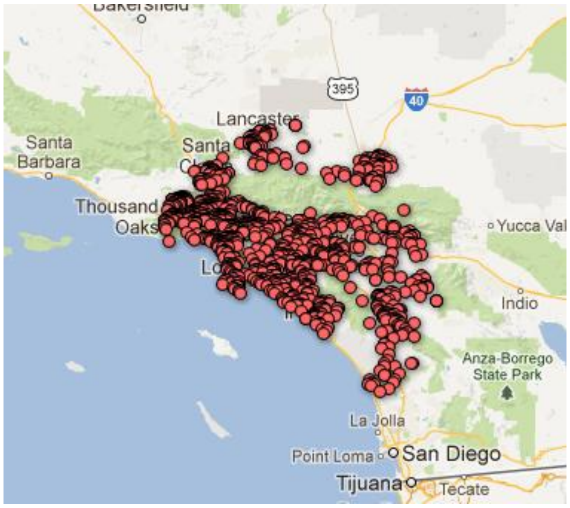

Fig. 7: PV systems within 100 km of Los Angeles, CA.

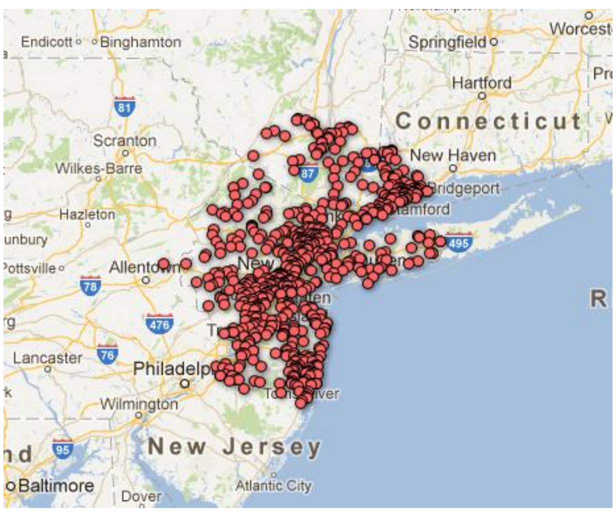

Fig. 8: PV systems within 100 km of Newark, NJ.

The Solar Volatility and Solar Deviation metrics introduced in sections 2.2 and 2.3 were systematically applied in order to quantify the impact of varying the following parameters of a distributed PV system:

- the number of individual PV systems that compose the distributed system
- the geographic radius across which these systems are spread out
- the geography where the data was collected

The effects of each parameter were determined by holding the other parameters constant. For example, the effect of number of systems was determined by holding distance between systems constant, and vice versa.

3.1 Solar Volatility

3.1.1 Number of Systems

Fig. 9 shows the effect of number of systems on volatility for a given power aggregate. Each gray dot represents one day of quantified Solar Volatility of aggregated systems within 100 km of Los Angeles. The downward shift of the dots (from left to right) is indicative of the general decrease in solar volatility as the number of systems that compose the aggregated PV systems increases. The colored lines underscore this point by showing the drop in the median volatility (50th percentile) as well as a drop in the maximum volatility (100th percentile). It is worth noting that the decrease in Solar Volatility is most evident in the upper quartile –the 92 out of 366 – most volatile days of 2012, shown between the green and blue lines. This range narrows considerably as the number of individual systems is increased. In fact, the Solar Volatilities for all 366 days for the 80-system distributed solar PV scenario fall below the 50th percentile for the 2-system distributed solar PV scenario.

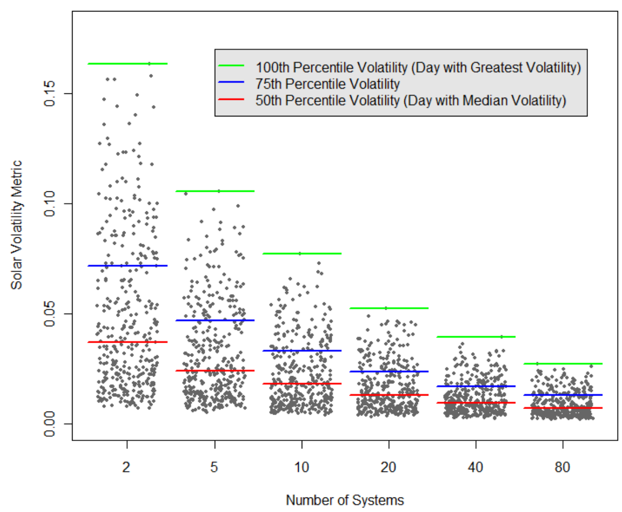

Fig. 9: 366 days of fleet Solar Volatility for distributed systems as a function of the number of systems; Los Angeles.

We can interpret the magnitude of Solar Volatility (VOL) for a given day by using the fact that it was computed as the standard deviation of a normally distributed set of power differences throughout the day: there is a roughly 95 percent chance that the change in power generated by the distributed PV system at the next data reading (five minutes later, for example) will result in a deviation of less than ±[2*VOL] percent from the expected ramp rate.

This has important implications for utilities. By understanding the difference from expected ramp rate, grid operators can maintain cost efficient reserves on hand to ensure grid reliability within the desired certainty levels.

3.1.2 Distance

The effect of distance was examined by keeping the number of systems analyzed constant and increasing the radial distance from the center of Los Angeles. As illustrated by Fig. 10, Solar Volatility shows a small decrease as distance increases. On this scale, Solar Volatility is less sensitive to distance than it is to number of systems.

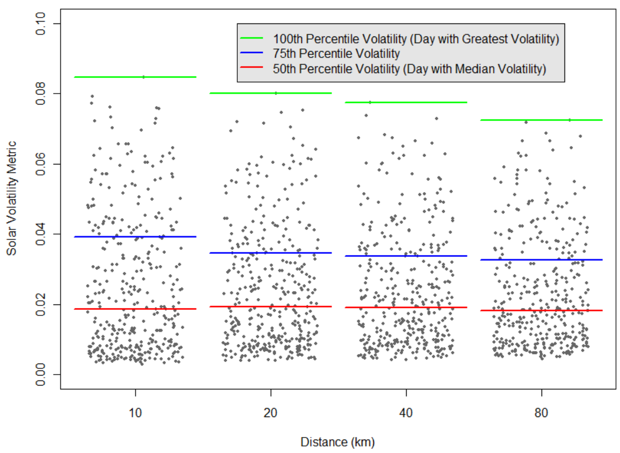

Fig. 10: 366 days of fleet Solar Volatility for 10 distributed systems as a function of distance; Los Angeles.

3.1.3 Geography

Furthermore, this reduction in volatility is not limited to the sunny confines of Los Angeles. Fig. 11 shows an analysis of Solar Volatility as a function of number of systems for Newark. Although the reader will notice the distribution of daily Solar Volatility is slightly greater (shifted upwards), the general shape of the reduction in volatility is nearly identical between the two cities. Fig. 12 illustrates that the Newark region shows a similar lack of decrease due to increasing distance as was found in LA.

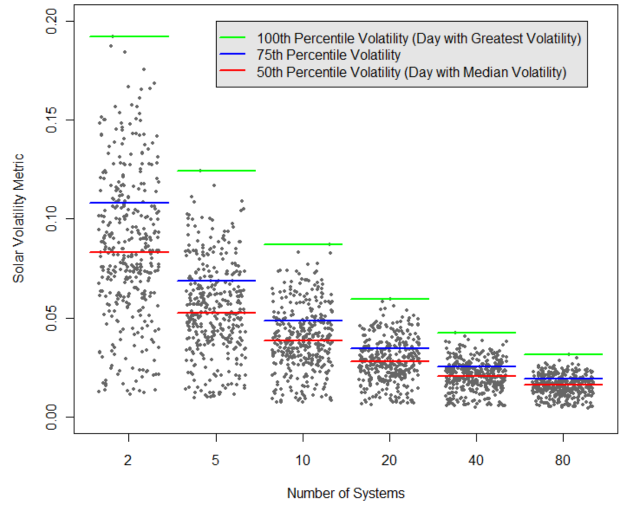

Fig. 11: 366 days of fleet Solar Volatility for distributed systems as a function of the number of systems; Newark.

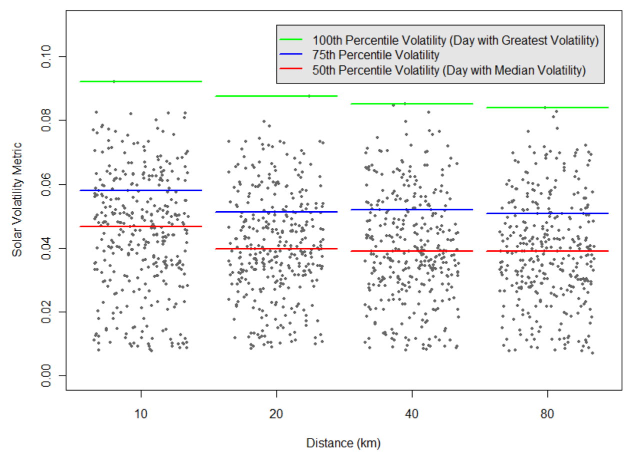

Fig. 12: 366 days of fleet Solar Volatility for 10 distributed systems as a function of distance; Newark.

3.2 Solar Deviation

3.2.1 Number of Systems

Fig. 13 shows the magnitude of Solar Deviation for all days in 2012 with respect to the number of individual PV systems in the distributed system, illustrating that Solar Deviation can only be reduced for about 75% of the days throughout the year. Additionally, the days with the greatest Solar Deviation do not see similar reductions by increasing the number of systems.

This matches intuition – while it is possible to smooth the rate of change in output (Solar Volatility) by spreading the impact of weather changes across more point sources, it is more difficult to compensate for days in which there is less sunlight than expected in a given region (Solar Deviation).

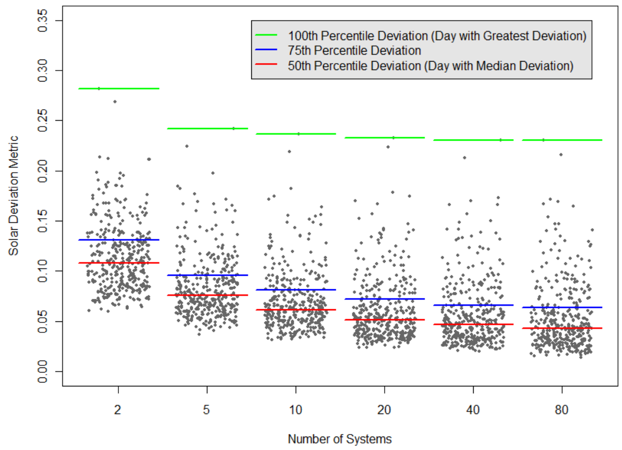

Fig. 13: 366 days of fleet Solar Deviation for distributed systems as a function of the number of systems; Los Angeles.

3.2.2 Distance

Fig. 14 shows that an increase in radial distance for the distributed system results in slight Solar Deviation reductions for 75% of the days throughout the year and has a negligible effect on the 25% of days throughout the year with the greatest Solar Deviation.

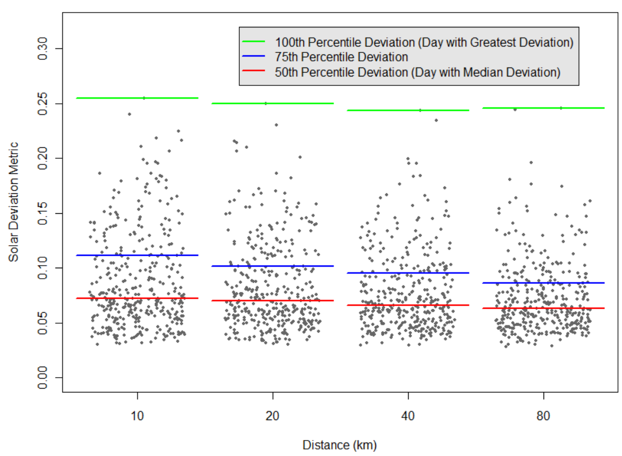

Fig. 14: 366 days of fleet Solar Deviation for 10 distributed systems as a function of distance; Los Angeles.

3.2.3 Geography

The general trends seen with Solar Deviation in Los Angeles are also applicable to the geography of Newark. Fig. 15 shows a small decrease in Solar Deviation as number systems increase, with slightly higher magnitudes than those experienced in Los Angeles. Shown in Fig. 16, deviation slightly decreases for 75% of the systems in Newark, but less so than for the same analysis in Los Angeles.

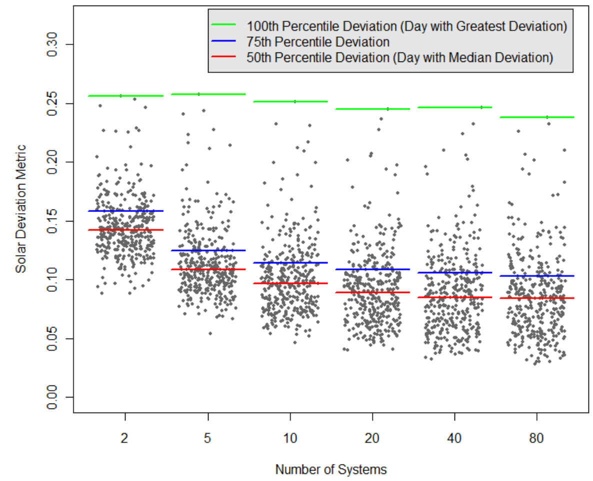

Fig. 15: 366 days of fleet Solar Deviation for distributed systems as a function of the number of systems; Newark.

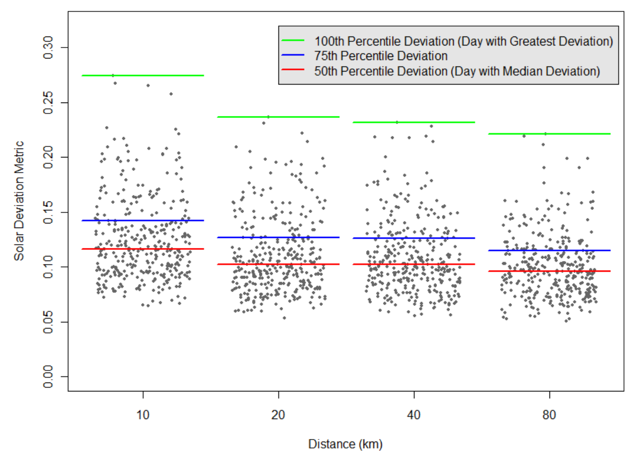

Fig. 16: 366 days of fleet Solar Deviation for 10 distributed systems as a function of distance; Newark.

4 CONCLUSION

The metrics introduced in this paper provide useful new tools in quantifying the variability of distributed PV. Solar Volatility calculates the difference between the actual and expected ramp rates, while Solar Deviation measures the difference between the actual and expected power output. Both metrics make comparisons against expectations because this reflects the forecasts that utilities use for grid operation planning.

Solar Volatility decreases significantly as the number of systems aggregated increases. However, Solar Volatility does not decrease as much with increases in geographic dispersion. Limited evidence shows that the general trends are independent of geography, although local conditions do affect magnitude of the trends.

Solar Deviation can be slightly decreased by adding more systems or increasing geographic dispersion. The trends of changes to Solar Deviation with respect to number of systems and geographic dispersion appear to be independent of geography, although further investigation is needed to obtain a statistically significant sample size.

4.1 Recommendations

By quantifying volatility with the methodology introduced in section 2.2, grid planners will know with certainty how much PV output could vary compared to expectations. This knowledge should be used to determine the amount and type of reserves in order to maximize cost efficiency and grid stability.

When planning for added distributed solar capacity, utilities should take into account the number of systems in a specific region. Many small distributed systems, rather than a few larger PV systems, will reduce volatility to ensure that power output is more predictable. The findings presented here show that geographic dispersion beyond 10 km has little effect on reducing volatility, and should not be a major factor when adding distributed PV to the grid at distances greater than 10 km. It remains to be investigated the effect of geographic dispersions at less than 10 km.

Solar Deviation should be used to measure the reserve margin needed. Utilities should note that Solar Deviation will not be significantly reduced in a distributed scenario, and should be prepared to handle the worst case scenario with the appropriate level of reserve capacity.

4.2 Future Work

This study took PV output for a typical day as expected output in order to facilitate analysis. However, this expectation can be improved upon by using forecasted PV output instead.

Power is an instantaneous quantity, and as such grid operators need to maintain grid stability at very short time intervals. Conducting a fleet analysis using more time granular data, such as 1-minute or 1-second, would provide more applicable validation for grid operators.

As mentioned in the recommendations section, further investigation of more dense, smaller regions of distributed PV is needed to test the conclusions regarding insensitivity of Solar Volatility and Solar Deviation to geographic dispersion.

Utilities are often most concerned about capacity limits around physical grid elements, such as distribution feeders or substations. This paper's analysis could be conducted using systems connected to these grid elements to better model volatility and deviation in a physical system. A region of sufficiently high PV penetration would need to be found in order to analyze the effect of increasing the number of systems with any statistical significance.

Investigations in more geographic regions would strengthen the empirical evidence to understand if these metrics were truly independent of geography. The general trend supports this claim, but further analysis is required.

5 REFERENCES

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