Using satellite insolation data to calculate PV power output variability

Thomas E. Hoff, Clean Power Research, Napa, California, & **Richard Perez**, Atmospheric Sciences Research Center (ASRC), University at Albany, New York, USA

ABSTRACT

As the PV capacity of utility systems increases, utility planners and operators are becoming more and more concerned about the potential impacts of power supply variability caused by transient clouds. Utilities and control system operators need to adapt their planning, scheduling and operating strategies to accommodate this variability while at the same time maintaining existing standards of reliability. Effective management of these systems, however, requires a clear understanding of PV output variability and the methods to quantify it. The present objective is to develop analytical methods and tools to quantify PV fleet output variability. This paper presents a method using location-specific inputs for estimating correlation coefficients, and discusses the key findings that resulted from applying the method to three separate geographical regions in the USA. The approach has potential financial benefits for systems that are concerned about PV power output variability, ranging from individual distribution feeders to state-wide balancing regions.

Why measure PV output variability?

Whether forecasting loads and scheduling capacity several hours ahead or planning for reserve resources years into the future, utilities need to be able to quantify the expected output variability of their distributed solar resources – whether they consist of thousands or hundreds of thousands of PV systems spread across large geographical territories. The inability to adequately quantify PV output variability can have real operational and financial impacts. For example, a utility may underestimate reserve requirements, which would result in a failure to meet reliability standards and an unstable power system. On the other hand, overestimating reserve requirements may result in an unnecessary expenditure of capital and higher operating costs.

Variability over time intervals ranging from a few seconds to a few minutes is of primary interest, since control area reserves are dispatched over such time intervals. For example, regulation reserves might be dispatched at an ISO through a broadcast signal every five seconds. Knowledge about PV fleet variability in five-second intervals could be used to determine the resources necessary for providing frequency regulation service in response to power fluctuations.

> "The inability to adequately quantify PV output variability can have real operational and financial impacts."

The ability to analyze PV output variability has led to findings that relative output variability across a fleet of PV resources decreases as geographic dispersion increases. This implies that, in the same way that smoothing occurs when electric loads from multiple customers are combined, smoothing also occurs when the output from multiple PV systems is combined, so long as the systems are located sufficiently far apart.

How is PV fleet variability defined?

Variability of a PV fleet is defined as a measure of the magnitude of changes in its aggregate power output corresponding to the defined time interval and taken over a representative study period. Note that it is the *change* in output rather than the output itself that is desired. Also note that, for each time interval, the change in output may vary in both magnitude and sign (positive and negative). The statistical metric that is employed to quantify variability is the standard deviation of the change in fleet power output.

It is helpful to graphically illustrate what is meant by output variability. The example shown in Fig. 1 shows data gathered on November 7, 2010 from a network of 25 weather-monitoring stations in a 400m ×

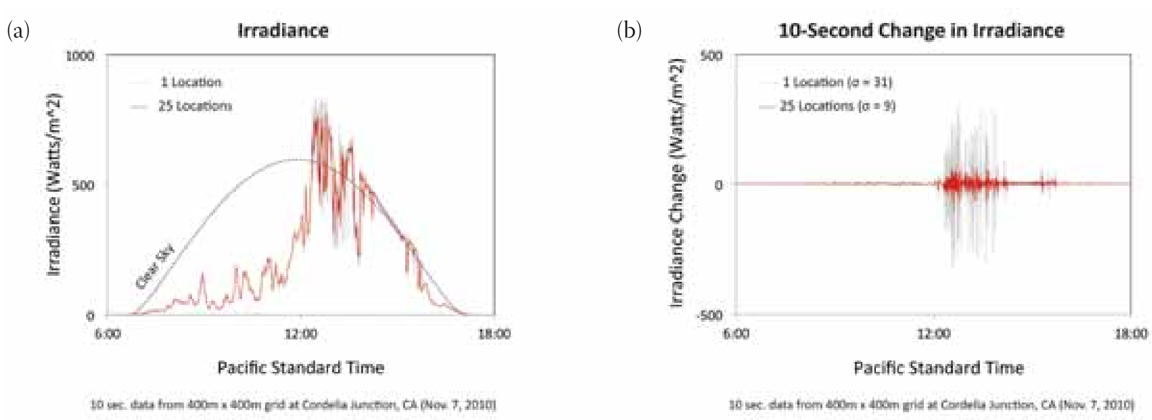

Figure 1. Data from a 400m × 400m grid at Cordelia Junction in California (November 7, 2010): (a) irradiance; (b) 10-second change in irradiance. A network of 25 locations reduces the 10-second variability by more than 70%.

400m grid located at Cordelia Junction in California [1]. Fig. 1(a) shows measured 10-second irradiance data (PV power output is almost directly proportional to irradiance); Fig. 1(b) presents the change in irradiance using a 10-second time interval. The grey lines correspond to irradiance and variability for a single location, and the red lines correspond to average irradiance distributed across 25 locations. The results suggest that spreading capacity across 25 locations rather than concentrating it at a single location reduces variability by more than 70% in this particular instance.

PV variability measurement approaches

Numerous approaches exist for calculating the output variability of a fleet of PV systems. One of these might be referred to as a 'fleet computation' approach and is taken as follows:

1. Identify the PV systems that constitute the fleet to be studied.
2. Select the time interval and time period of interest (e.g. 1-minute changes evaluated over a 1-year period).
3. Obtain time-synchronized solar irradiance data for each location where a PV system is to be sited.
4. Simulate the output for each PV system using standard modelling tools.
5. Sum the outputs from the individual systems to obtain the combined fleet output.
6. Calculate the change in fleet output for each time interval.
7. Calculate the resulting statistical output variability from the stream of values.

A more viable approach is to streamline the calculations through the use of a general-purpose PV output variability methodology. The method needs to quantify short-term fleet power output variability using the observations that:

- sky clearness and sun position drive the changes in the short-term output for individual PV systems;
- physical parameters (i.e. dimensions, plant spacing, number of plants, etc.) determine overall fleet variability.

Hoff and Perez [2] have already developed a simplified model as a first step towards a general method to quantify the output variability resulting from an ensemble of equally-spaced, identical PV systems. Output variability was defined as the standard deviation of the change in output over some time interval (such as 1 minute) using data taken from some time period (such as 1 year). The simplified model covered the special case where the change in output between locations is uncorrelated (i.e. the impacts of clouds at one site are too distant to have predictable effects at another for the particular timescale considered), the fleet capacity is equally distributed, and the variance at each location is the same. Under these conditions, it was shown that fleet output variability equals the output variability at any one location divided by the square root of the number of locations. Other investigators, for example Mills and Wiser [3], have derived a similar result that relates variability to the square root of the number of systems when the locations are uncorrelated.

Development of analytical tools to quantify PV output variability

Utility planners clearly require a tool that can reliably quantify the maximum output variability of PV fleets using a manageable amount of data and analysis. The methods referred to above would potentially meet this requirement if the changes in output between locations were uncorrelated (i.e. correlation coefficient is zero). In actual fleets, however, PV systems will generally

Region	Southwest	Southern Great Plains	Hawaii
Location #1	Latitude: 32° to 42° Longitude: –125° to –109° Grid size: 2.0°	Latitude: 35° to 38° Longitude: –99° to –96° Grid size: 1.0°	Latitude: 19° to 20° Longitude: –156° to –155° Grid size: 0.5°
Location #2	0.1°, 0.3°, …, 1.9° from location #1	0.1°, 0.3°, …, 2.9° from location #1	0.1°, 0.2°, …, 1.0° from location #1
Time intervals	1, 2, 3 and 4 hours	1, 2, 3 and 4 hours	1, 2, 3 and 4 hours
Clear sky irradiance	10 irradiance bins in intervals of 0.1kW/m^2	10 irradiance bins in increments of 0.1kW/m^2	10 irradiance bins in increments of 0.1kW/m^2

Table 1. Summary of input data.

have some degree of correlation, so any planning tool will have to incorporate correlation effects into the calculation of actual fleet variability.

> "Any planning tool will have to incorporate correlation effects into the calculation of actual fleet variability."

In this study a step has been taken towards a general method by analyzing the correlation coefficient of the change in clearness index between two locations as a function of distance, time interval and other parameters. The analysis used hourly global horizontal insolation data from SolarAnywhere to calculate the correlation coefficients for 70,000 station pair combinations across three separate geographical regions in the USA (Southwest, Southern Great Plains and Hawaii). The measured correlation coefficients taken from these combinations were then compared to a model that could prove useful when integrated into utility planning and operations tools.

For this method, PV fleet variability was defined as the standard deviation of its power output changes using a selected sampling time interval (such as 1 minute or 1 hour) and analysis period (such as one year), as expressed relative to the fleet capacity. To simplify the work, the variability was formulated in terms of the change in insolation rather than the change in PV power.

As stated earlier, sky clearness and sun position drive the changes in short-term output for individual PV systems. Mills and Wiser [3] and Perez et al. [4] subsequently isolated the random component of output change and examined changes attributable only to changes in global clear sky (or clearness) index. The global clearness index equals the measured global horizontal insolation divided by the clear sky insolation.

This paper continues in the direction of Mills and Wiser and Perez et al. and focuses on changes in the global clearness index. The analysis is performed as follows:

1. Select a geographical region for analysis.
2. Select a location for the first part of the pair.
3. Select a location for the second part of the pair.
4. Select a time interval for the analysis.
5. Select a clear sky irradiance level bin.
6. Obtain detailed insolation data.
7. Calculate the change in the clearness index.
8. Calculate the correlation coefficient.
9. Repeat the calculation for all sets of location pairs, time intervals and clear sky irradiance bins.

Case study results

This study was carried out to investigate the existence of patterns that help to better quantify correlation coefficients. A method was tested that produces the desired output parameter of the correlation coefficient of the change in the clearness index between two separate locations. The inputs to this method include the distance between the two locations, the time interval and the location-specific

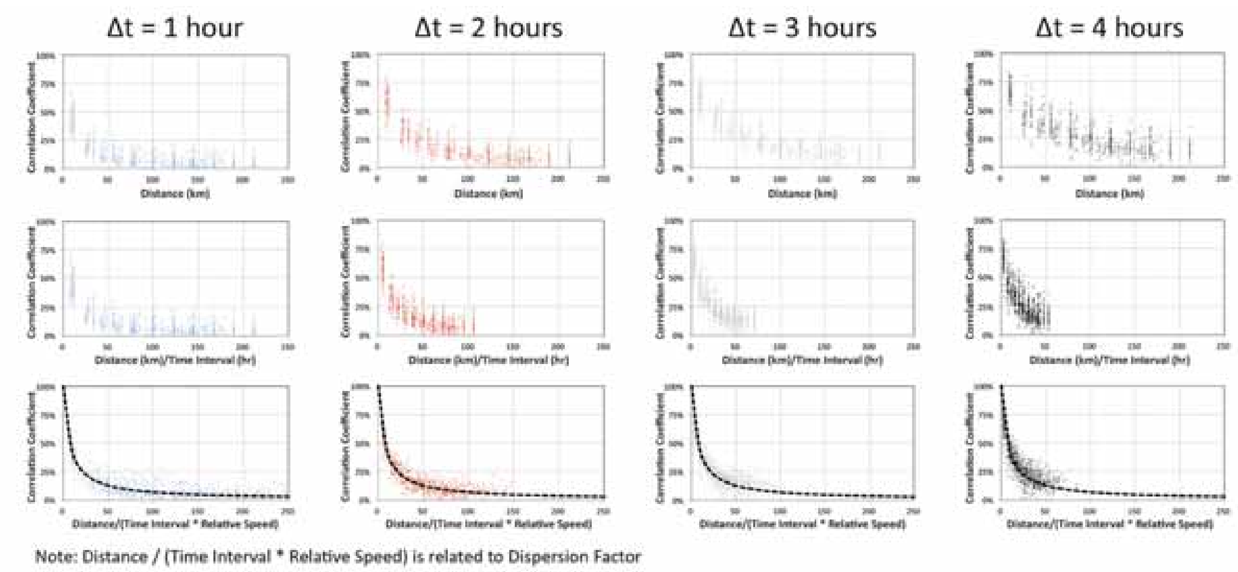

Figure 2. Correlation coefficients presented by time interval for the Southwest.

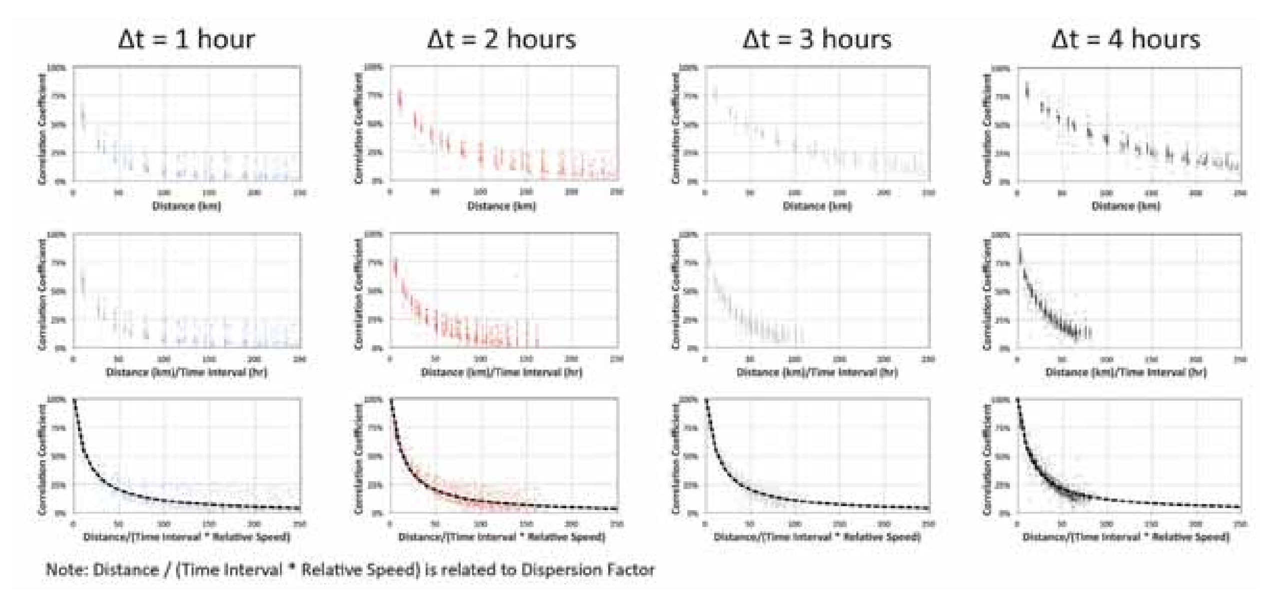

Figure 3. Correlation coefficients presented by time interval for the Great Plains.

parameters based on empirical weather data, particularly cloud speed.

Three separate geographical regions in the USA were selected for analysis: Southwest, Southern Great Plains and Hawaii (see Table 1). The first location was selected using a grid size of 2.0°, 1.0° and 0.5° for the Southwest, Southern Great Plains and Hawaii respectively. The second location was selected between 0.1° and 2.9° (about 10–300km) from the first location (other map coordinates were available but the selected points provided sufficient data for the analysis).

Hourly insolation data covering the period January 1, 1998 to September 30, 2010 for each of the two locations was obtained from SolarAnywhere [5]. The analysis was then performed as described above for time intervals of 1, 2, 3 and 4 hours and for 10 separate clear sky irradiance bins. This analysis resulted in more than 70,000 correlation coefficients.

Fig. 2 presents a randomly selected set of correlation coefficients for the Southwest. The graphs in the columns summarize the results for each time interval of 1, 2, 3 and 4 hours. The graphs in the rows present the measured correlation coefficients versus several alternative candidate sets of variables. Specifically, the top row presents the

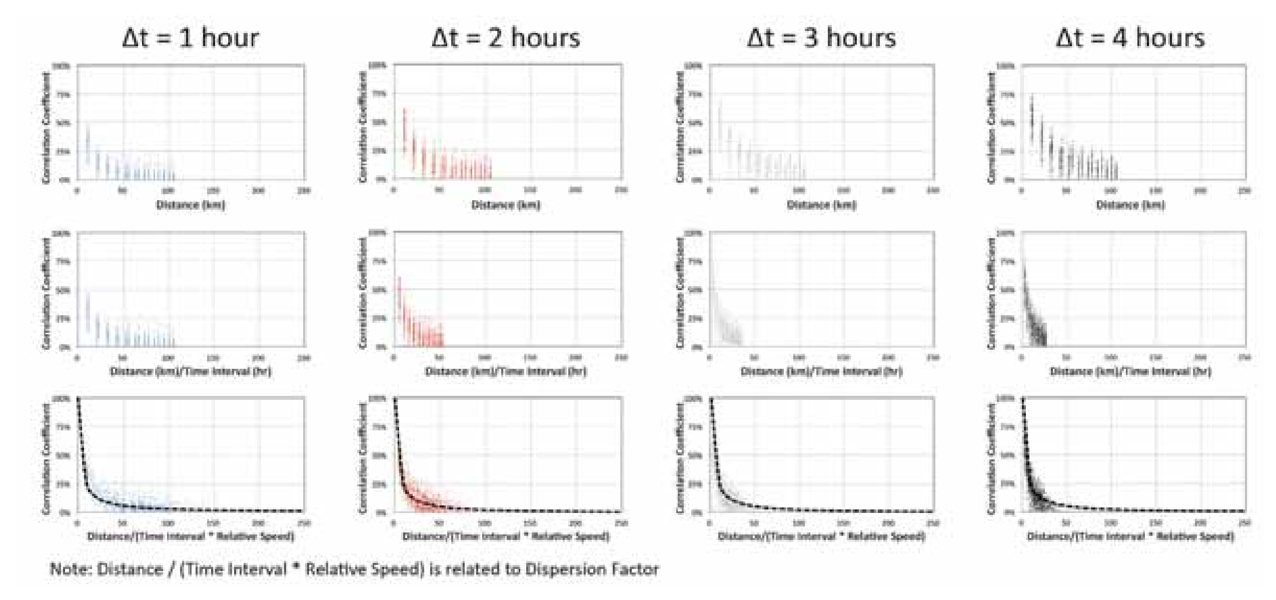

Figure 4. Correlation coefficients presented by time interval for Hawaii.

correlation coefficients versus the distance between the two locations, while the middle row presents the correlation coefficients versus the distance divided by time interval. The graphs shown in the bottom row are the correlation coefficients versus the distance divided by the product of time interval and relative speed (this term is related to the dispersion factor DF, introduced by Hoff and Perez [2]). The dashed line in the bottom graphs represents the results of a generalized method, proposed in this paper for use in future tools, that will be validated in the present analysis. Calculations using parameters obtained from SolarAnywhere were used to obtain these results.

Figs. 3 and 4 present the results relating to the Great Plains and Hawaii for comparison purposes. The patterns presented in the graphs are similar across all time intervals for the three geographical locations.

"Critical factors that affect output variability are the clearness of the sky, sun position and PV fleet orientation."

Key findings: correlation versus distance

Critical factors that affect output variability are the clearness of the sky, sun position and PV fleet orientation (i.e. dimensions, plant spacing, number of plants, etc.). To improve accuracy, a parameter called the dispersion factor (DF) was introduced. This factor incorporates the layout of a fleet of PV systems, the timescales of interest and the motion of cloud interferences over the PV fleet.

The results of the study demonstrated that relative output variability resulting from the deployment of multiple plants decreased quasi-exponentially as a function of the generating resource's DF. The results demonstrated that relative output variability

- decreases as the distance between sites increases;
- decreases more slowly as the time interval increases;
- decreases more slowly as the cloud transit speed increases.

These findings are consistent with other studies. Mills and Wiser [3] analyzed measured 1-minute insolation data over an extended period of time for 23 time-synchronized sites in the Southern Great Plains network of the Atmospheric Radiation Measurement (ARM) Program. Their results demonstrated that the correlation of the change in the global clearness index decreases as the distance between sites increases, and decreases more slowly as the time interval increases.

In another example, Perez et. al. [6] analyzed the correlation between the variability observed at two neighbouring sites as a function of their distance and of the considered variability timescale. These authors used 20-second to 1-minute data to construct virtual networks at 24 US locations from the ARM Program [7] and the SURFRAD Network, together with cloud speed derived from SolarAnywhere, to calculate the station pair correlations for distances ranging from 10m to 100km and for variability timescales ranging from 20 seconds to 15 minutes. Their results also showed that the correlation of the change in global clearness index decreases as the distance between sites increases, and decreases more slowly as the time interval increases.

The consistent conclusions of all studies are that as the distance between sites increases, the correlation decreases, and as the time interval increases, the correlation decreases more slowly. This latest study presents the additional finding that the correlation decreases more slowly as the speed of the clouds increases.

Conclusions

The analysis yields several key findings. First, consistent with previous studies, the correlation coefficients decrease with increasing distance. Second, also consistent with previous studies, this decrease occurs more slowly with longer time intervals. An alternative way of viewing this result is that correlation coefficients decrease at a similar rate when plotted versus distance divided by time interval. Third, the scatter in the results is further decreased when a relative speed is introduced for the first location in the pair of locations. Finally, the generalized method (shown by the dashed black lines in the bottom row of graphs in Figs. 2–4) fits the empirical data quite well when calibrated using the location-specific derived input parameters.

"The scatter in the results is further decreased when a relative speed is introduced for the first location in the pair of locations."

These results are important because they enable the methods to be applied to fleet simulation to accurately determine PV fleet output without having to measure high-speed power or irradiance data at every location.

References

[1] Hoff, T.E. & Norris, B. 2010, "Mobile high-density irradiance sensor network: Cordelia Junction results".

[2] Hoff, T. E. & Perez, R. 2010, "Quantifying PV power output variability", *Solar Energy*, Vol. 84, pp. 1782–1793.

[3] Mills, A. & Wiser, R. 2010, "Implications of wide-area geographic diversity for short-term variability of solar power", Lawrence Berkeley Nat. Lab. Tech. Report LBNL-3884E.

[4] Perez, R. et al. 2011, "Parameterization of site-specific short-term irradiance variability", *Solar Energy*, Vol. 85, No. 7, pp. 1343–1353.

[5] Solar Anywhere 2011, Satellite-derived solar irradiance data [available online at: http://www.SolarAnywhere.com].

[6] Perez R. et al. 2012, "Short-term irradiance variability: Preliminary estimation of station pair correlation as a function of distance", *Solar Energy*, Vol. 86, No. 8, pp. 2170–2176.

[7] Stokes, G.M. & Schwartz, S.E. 1994, "The atmospheric radiation measurement (ARM) program: Programmatic background and design of the cloud and radiation test bed", *Bulletin Amer. Met. Soc.*, Vol. 75, pp. 1201–1221.

About the Authors

Tom Hoff is the founder of Clean Power Research, and the president of its research and consulting group. He assists Clean Power Research in pursuing its mission of powering intelligent energy decisions by taking an analytical approach to solving problems. A pioneer in the science of valuing distributed solar generation, Tom holds several patents in the area of PV fleet power estimation. He has published extensively for more than 25 years and holds a Ph.D. from Stanford University's School of Engineering.

Richard Perez is a research professor at the University at Albany's ASRC. He sits on the advisory board of the GW Solar Institute at George Washington University in Washington, D.C., and has served multiple terms on the board of the American Solar Energy Society (ASES). Richard has produced more than 200 journal articles, conference papers and technical reports, and holds two US patents on methods of load management using PV. He earned his doctorate in atmospheric sciences at the University at Albany.

Enquiries

Website: www.cleanpower.com