DETERMINING STORAGE RESERVES FOR REGULATING SOLAR VARIABILITY

Benjamin L. Norris[1] and Thomas E. Hoff[1]

[1]Clean Power Research, Napa, California, USA

As an initial experiment to validate a model of solar PV fleet variability, an inexpensive network of irradiance sensors was developed and fielded in a geographical region equivalent in size to a 400 MW solar power plant. The measurements were shown to correctly predict the reduction in variability due to spatial diversification. The model was also used in a sample calculation of fleet variability for the CPUC Long Term Procurement Plan. This work lays the foundations for future studies to quantify the required storage regulation reserves in ISO planning and operation.

Keywords: PV variability, storage, regulation, reserves

INTRODUCTION

One of the foremost technical challenges of accepting high levels of solar photovoltaic (PV) energy onto the state power grids is the high speed variability of PV caused by cloud transients. Depending upon the magnitude and speed of these power output changes, significant levels of regulation reserves would potentially be needed, and may even make high penetration targets impractical.

The issue is particularly pressing in light of aggressive state renewable energy targets. For example, to meet California's RPS goal of 33% renewables by 2020, industry experts anticipate that the resource mix will include about 5,000 MW of PV in only 10 years. The extent to which these resources will require regulation, however, is at present unknown, and the energy storage industry and grid operators alike will benefit from models and tools that address the issue.

A method of quantifying PV variability by using satellite-derived solar data has been proposed [1] that would allow grid operators to both forecast PV fleet output and to quantify fleet variability, given the design attributes and locations of individual PV systems. It uses advanced algorithms for tracking cloud patterns, calculating PV plant correlation coefficients, and quantifying diversification effects in a manner that could be used at the control area level.

Once proven, this method could be used for a number of purposes, such as evaluating the mitigating impact of multiple plan aggregation, determining required quantities of stored energy, scheduling reserve resources, and optimizing the location of PV. However, it has yet to be adequately validated through the use of empirical measurements in the field.

This paper describes the initial validation of the model, performed using a network of high-speed solar irradiance data loggers in and around Napa, California.

CALCULATING STORAGE RESERVES

A sample calculation of required reserves is presented in Table 1 for the California ISO control area using the CPUC Long Term Procurement Planning/Renewables Integration assumptions. This calculation illustrates the procedure for calculating required regulation reserves for 471 PV plants having a combined capacity of 5,434 MW.

Fleet variability is calculated for November 10, 2010 at 12:00 noon. This time was taken as one of the worst-case variability days of the year (data collection described later) in which the standard deviation of clearness index for a single point measurement was 0.17.

Table 1. LPPP Fleet Variability for November 10, 2010 at 12:00

Time Interval	1	minute
Clear Sky Irradiance	580	Watts/sq. meter
Std. Dev. Of Change in Clearness Index at 1 Location	0.17	
Plant Density	25	Watts/sq. meter

(1)	(2)	(3)	(4)	(5) = [(3) x (4)]^2	(6) = (1) x (5)
Number of Plants	**Plant Capacity (MW)**	**Plant Output (MW)**	**Std. Dev. of Change in Clearness Index**	**Variance Per Plant**	**Variance All Plants**
450	5	3	0.10	0.1	36
2	10	6	0.08	0.2	0
3	52	30	0.05	2.3	7
1	62	36	0.05	2.8	3
5	63	37	0.05	2.9	15
2	100	58	0.04	5.2	10
2	131	76	0.04	7.2	14
1	156	90	0.03	8.9	9
2	250	145	0.03	15.5	31
3	500	290	0.02	34.0	102
Total	**5,434**	**3,151**			**227**

(7) = SQRT(Total Variance All Plants)	**Standard Deviation (MW) =**	15
(8) = Total Plant Capacity / (7)	**Standard Deviation (% of Capacity) =**	0.28%

Using scaling methods developed separately that represent the inter-point diversification as a function of distance (see description of Napa network described later), this value was applied to plants of different sizes. The calculation assumes that, while each plant exhibits that same point variability, 1-minute changes in power output at each plant is uncorrelated with the others. That is, each plant is spaced sufficiently far from the others to assume uncorrelated power fluctuations.

By summing the variance for all plants and taking the standard deviation, the results show that the total variability of the 5,434 MW fleet is only 15 MW.

This type of calculation could be used to determine reserve requirements dynamically for any time, and would apply to both fossil and storage resources. The sample calculation only addresses power requirements and not the temporal storage requirements. The storage capacity necessary to counteract this fleet variability, and an assessment of worst case variability, is left for future analysis.

The more pressing need in this line of inquiry is the validation of the proposed variability model. For this it is necessary to have actual field measurements of dispersed PV systems.

HIGH SPEED SOLAR MEASUREMENTS

The basic approach to validating a PV fleet variability model is straightforward: collect production data from a large set of PV systems, sum the measurements to obtain the total fleet output, and calculate the variability of the aggregate.

In practice, however, several difficulties arise with this approach. While metered production data for many large PV systems is readily available from utility billing systems or performance monitoring systems, the collected data is generally of insufficient time resolution. The variability of primary interest is in the 10-second to 1-minute time frame, whereas revenue metering is (at best) in intervals of 15 minutes and performance monitoring generally at 30 to 60 minute intervals.

In cases where high speed data could be made available from PV systems, for example through a utility's Energy Management System, this data is very costly to acquire, often thousands of dollars per system, making large scale experiments with many PV systems cost prohibitive. Also, PV systems are not located at regular spatial intervals, complicating the design of the experiment.

An alternative to high speed, centralized PV system monitoring was developed to overcome these issues and provides a means for collecting the required variability data. Small scale, isolated solar measurement stations were used to mimic the behavior of larger PV systems and avoid the costs and complexities of central monitoring.

This approach provides sufficient accuracy and temporal resolution to determine changes in PV system output. They may be located, spaced, and oriented according to the desired test regimen, rather than being dependent upon the location and orientation of installed PV systems. They may be re-used and installed at other utilities faced with different meteorological conditions, penetration levels, or stability issues. Most importantly, the systems may be built and installed at a small fraction of the cost of high speed PV system monitoring.

Solar Logger Design

Each PV variability monitor ("solar logger") consists of a single sensor and an independent, time-synchronized data logger (Figure 1). The sensor is made from a 15 V amorphous silicon PV module with leads connected to a resistor to complete the circuit. The voltage across the resistor is sampled, averaged, and stored in a single-channel USB data logger. The data is intended to represent PV system output (and changes in PV output), so it is not necessary to measure or correct for ambient temperature. Calibrated measurements of irradiance that require more costly instrumentation is not necessary.

Fig. 1. Solar logger unit.

Solar Logger Validation

To test the solar logger as a reliable source for PV variability measurements, its output was compared against two other data sources: a 1.7 kWDC residential grid-connected PV system and a commercial pyranometer. The three sources were installed side-by-side on a day of high cloud transients.

To carry out this test, the solar logger was detached from its support stake and fastened in a temporary arrangement alongside a pyranometer / amplifier / data acquisition circuit. These two systems were then time synchronized using the same computer clock prior to the test, and were configured to average over 10 second intervals. AC power measurements from the PV system were collected in 1-second intervals using a commercial home energy monitoring system. The clock on this device could not be accurately synchronized to the other two, so an approximation was made using visual cues, and then the final time synchronization for the test was done during post-processing. Data collected from the three systems is shown in Figure 3. Data from each system was normalized to its respective reference measurement (selected arbitrarily at 2:20 PM) to produce the relative scale shown in the plot. As can be seen, the three systems appear to track very closely except for some bias in the early morning and late afternoon hours.

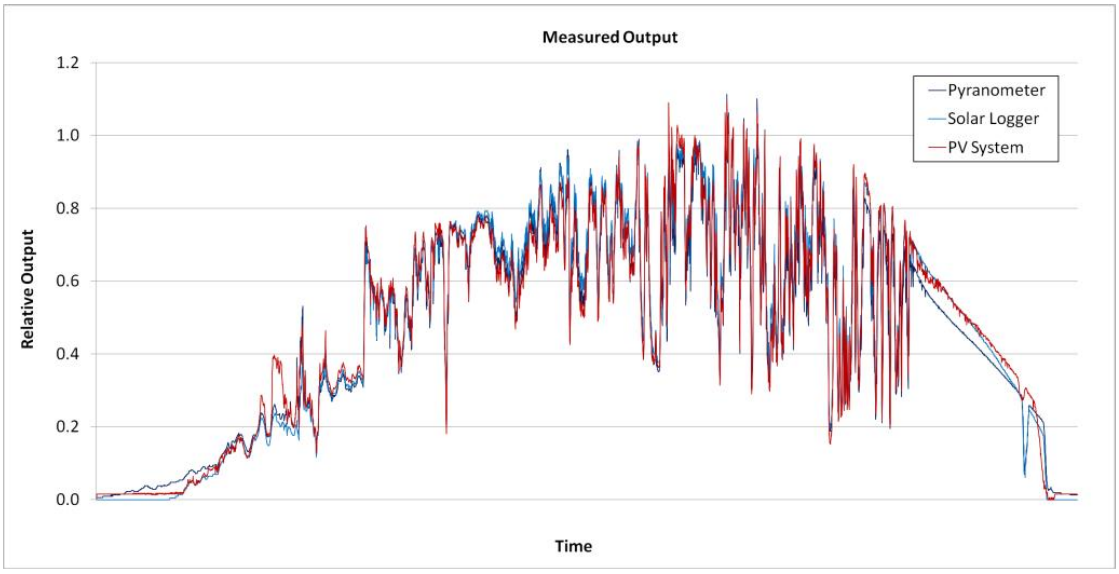

Figure 3. Comparison of three data sources on September 14, 2010 at Napa, California.

FLEET VARIABILITY FIELD TEST

The first field test included a network of 25 solar loggers spaced 100 m apart in a grid representing the geographical spread of a 4 MW plant. The second test redeployed these devices in a 4 km grid (see Figure 4) representing a 400 MW plant. The results were used to confirm the model accuracy and quantify the diversification.

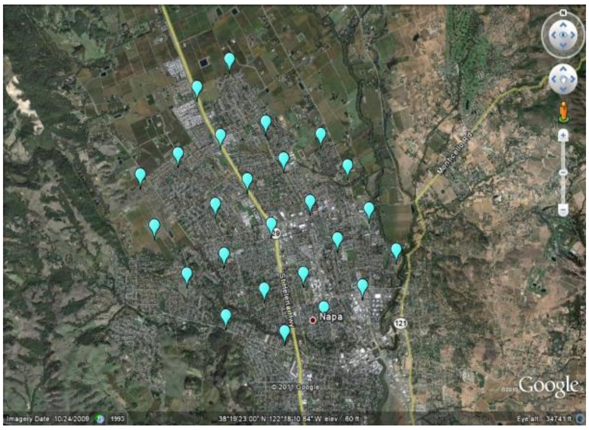

Fig. 4. Napa data network representing a virtual 400 MW PV power plant.

Results are shown for a single solar logger and for the aggregate fleet in Figure 5. Both irradiance and change in irradiance is shown. Clearly, the aggregate output is significantly less than the output of a single system. By comparing variance of individual point pairs, an empirical model can be developed to give variance as a function of distance, and this relationship was used in column 4 of Table 1. Thus, the aggregate results can be used to show both reduced variability of a single, large plant, or a the combined output of a fleet.

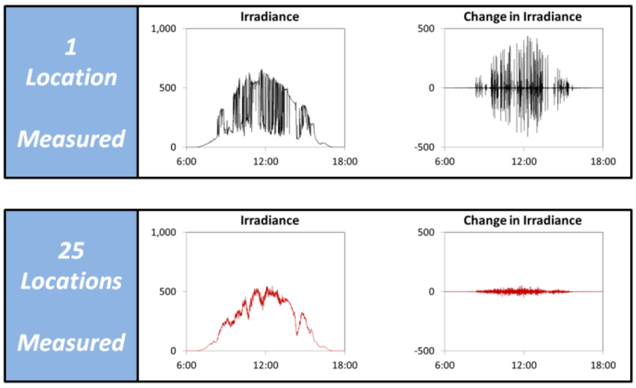

Fig. 5. Napa data network results for single system and fleet.

Fleet model results

An initial comparison of the fleet variability predictive model and the measured fleet power from the Napa network is shown in Figure 6. The predictions appear to fit very well. This validation is simplistic in that all PV systems (the solar loggers) are identical and are oriented horizontally.

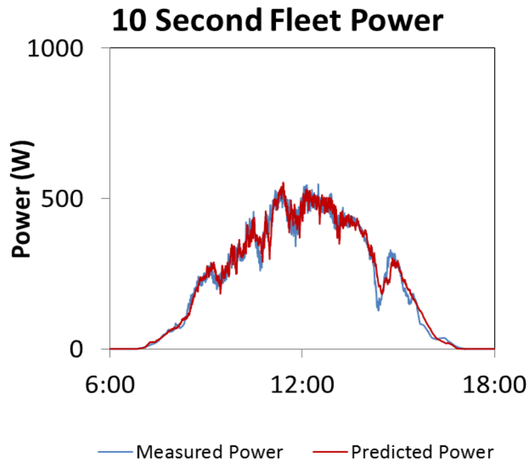

Fig. 6. Comparison of predicted and measured fleet power.

CONCLUSIONS

The above analysis shows that the inexpensive solar logger may be used to assess solar irradiance variability for easily controlled experiments at utilities. Due to the high-speed data required, instrumentation of actual PV systems is very expensive, so the solar logger offers a much more affordable alternative for a temporary test setup.

The variability of a combined fleet is shown through direct measurements to be significantly less than the variability of a single point, and the proposed fleet variability model was able to predict very well the output of this simplified fleet.

With initial confirmation of the fleet variability model, it is possible that the model could be used in actual PV fleets, such as those defined by an ISO or RTO territory. In this case, the same model can be used with satellite-based resource data for operational purposes. The resulting tool could be used to plan and schedule regulation reserves— including storage resources— in anticipation of seasonal and daily periods of high variability. Accuracy in quantification of needed regulation would avoid the two extremes of grid instability on the one hand and over-commitment of resources on the other.

This ongoing work has direct implications for the energy storage community as it relates to the market needs for regulation in each of the continent's eight NERC regions.

RECOMMENDATIONS

Additional study is required to further validate the variability model. First, satellite data and empirical PV models should be used against actual PV systems in the field. This first step is scheduled for an upcoming study with the California ISO.

The second research need would be to use the above methods and actual fleet attributes to calculate actual storage reserves in both MW and MWh. This would require an assessment of historical data, for example using the available 10 years of satellite-based solar resource to determining worst-case variability. It would also involve development of a storage system model to calculate required energy storage to meet this worst-case variability.

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REFERENCES

[1] Patents pending: "Computer-Implemented System and Method for Estimating Power Data for a Photovoltaic Power Generation Fleet"; "Computer-Implemented System and Method for Determining Point-to-Point Correlation of Sky Clearness for Photovoltaic Power Generation Fleet Output Estimation"; "Computer-Implemented System and Method for Efficiently Performing Area-to-Point Conversion of Satellite Imagery for Photovoltaic Power Generation Fleet Output Estimation".

ABOUT THE AUTHORS

Benjamin L. Norris has managed technical and economic assessments of grid-connected renewable and storage technologies in the electric power industry for 26 years. His experience covers photovoltaics, solar thermal electric, flywheels, advanced batteries, and fuel cells. He has developed methods for dynamically managing transmission line thermal ratings and for effectively using infrared imaging in T&D maintenance. Mr. Norris currently manages the Consulting Group at Clean Power Research in Napa, California. Clients include research organizations, financial institutions, utilities, and manufacturers in the US and abroad. He studied Mechanical Engineering at Stanford University and was on the Board of Directors for the Electricity Storage Association for 8 years.

Thomas E. Hoff is the Founder of Clean Power Research and President of its Research and Consulting Group. Tom assists Clean Power Research in pursuing its mission of Powering Intelligent Energy Decisions by taking an analytical approach to solving problems. The most relevant mathematical models that result from this process are integrated into commercial grade online software services and delivered to customers by Clean Power Research's Software Services Group. These software services include PowerClerk, SolarAnywhere, Clean Power Estimator, PVCheck, and QuickQuotes.

Dr. Hoff has published extensively for over 25 years. Research areas include: the value of photovoltaics, the value of distributed generation, risk management and renewables, and most recently, methods to characterize PV output variability. He began his career at Pacific Gas and Electric Company. He holds a Ph.D. from Stanford University's School of Engineering.