

Final Technical Report (FTR)

**Project Title:** Low-Cost Solar Variability Sensors for Ubiquitous Deployment

**Project Period:** 10/1/14 – 11/30/15

**Submission Date:** 12/23/15

**Recipient:** Sandia National Laboratories

**Address:** 1515 Eubank Blvd, SE  
Albuquerque, NM 87123

**Website:** [www.sandia.gov](http://www.sandia.gov)

**Award Number:** 29096

**Project Team:** Sandia National Laboratories

**Principal Investigator:** Matthew Lave, Senior Member of Technical Staff  
Phone: (925) 294-4676  
Email: [mlave@sandia.gov](mailto:mlave@sandia.gov)

**Business Contact:** Shannon Boynton, Project Management  
Phone: (505) 284-2303  
Email: [sboynto@sandia.gov](mailto:sboynto@sandia.gov)

**Technology Manager:** Rebecca Hott

**Project Officer:** Christine Bing



U.S. DEPARTMENT OF  
**ENERGY**



**Sandia  
National  
Laboratories**

## Executive Summary:

In this project, an integrated solution to measuring and collecting solar variability data called the solar variability datalogger (SVD) was developed, tested, and the value of its data to distribution grid integration studies was demonstrated. This work addressed the problem that high-frequency solar variability is rarely measured – due to the high cost and complex installation of existing solar irradiance measuring pyranometers – but is critical to the accurate determination of the impact of photovoltaics to electric grid operation. For example, up to a 300% difference in distribution grid voltage regulator tap change operations (a measure of the impact of PV) [1] has been observed due solely to different solar variability profiles.

The work was accomplished through four subtasks: (1) the testing of a preliminary “alpha” device, (2) testing and deployment of a refined “beta” device, (3) collection of data in a central database for easy comparison between locations, and (4) demonstration of the value of the solar variability measurements to distribution grid simulations.

Development and testing of the “alpha” device provided proof-of-concept that a low-cost sensor could measure solar variability with similar accuracy as a high-cost pyranometer. The “alpha” device measured solar variability to within a 2% error of a co-located pyranometer.

The beta device was truly a “solar variability datalogger” (SVD), as it incorporated on-board power, data storage, and wired and wireless (Wi-Fi and cellular modem) communications in addition to measurements of solar variability. Variability measurement accuracy was improved to within 0.7% of a pyranometer. The SVD is low cost: estimated to be \$200-\$300 in mass production.

This SVD was tested at four different locations through both wired and wireless data retrieval. Data retrieval success rates were above 90% for wireless communications and 100% for wired communications. Data is stored for 140 days, and wired communications can always be used to retrieve historical data.

Finally, the value of SVD data to distribution grid studies was demonstrated through a graphical user interface (GUI) tool. This tool allows a user to import data recorded from a SVD to run a distribution grid integration study and, e.g., determine the number of voltage regulator tap change operations.

## Contents

Executive Summary: .....	2
Contents.....	3
1. Background .....	4
Motivation .....	4
Previous Works.....	5
2. Project Objectives .....	7
3. Project Results and Discussion .....	9
Subtask 1.1: Requirements and Build of First Prototype .....	9
Evaluate Sensors .....	9
Alpha Prototype.....	11
Subtask 1.2: Second Prototype Based on Refined Requirements.....	14
Beta Prototype .....	14
Subtask 1.3: Data Collection and Quantify Differences by Location .....	20
Data Download.....	20
Comparison of Different Locations .....	22
Subtask 1.4: Value of Data to Distribution Grid Simulations .....	24
Final Deliverable: Submit a journal article and give a conference presentation to document and publicize the impact of this work. ....	26
4. Significant Accomplishments and Conclusion .....	27
Significant Accomplishments .....	27
Problems Encountered and Lessons Learned .....	27
5. Inventions, Patents, Publications, and Other Results.....	28
6. Path Forward.....	28
Funding Statement.....	28
References.....	29

## 1. Background

### Motivation

High-frequency solar irradiance is rarely measured, and, hence, local solar variability is rarely known. But, knowledge of local solar variability is essential to distribution grid integration studies which determine the impact of solar photovoltaics (PV) to electric grids [1]. Without such knowledge, the impact of PV may be overestimated leading to unnecessary limits on PV installations, or may be underestimated leading to an unforeseen increase in grid operation costs.

At the distribution level, solar variability causes voltage fluctuations which can cause flicker, increase voltage regulator tap change operations (leading to increased maintenance costs and potentially early failure), or cause the voltage to exceed allowable limits. Partly due to these concerns, the Hawaiian Electric Company (HECO) has limited residential PV installations on many distribution feeders [2]. However, without an understanding of the local solar variability, this limit can be considered arbitrary and may be unduly limiting PV installations.

At transmission levels, solar variability can cause an imbalance in load and generation leading to frequency fluctuations. Because of such concerns, the Puerto Rico Electric Power Authority (PREPA) instituted strict limits on solar plant ramp rates which require solar plants larger than 5MW to limit changes in their output to a rate of less than 10% of capacity per minute [3]. Since the solar variability in Puerto Rico is not well understood, this requirement has led to significant uncertainty among solar plant developers who do not know how much storage will be required to comply. This uncertainty makes it more difficult for projects to obtain funding, and therefore reduces the number of solar installations.

High-frequency solar irradiance data is scarce because most currently used solar irradiance sensors are expensive pyranometers (Table I) with high accuracy (relevant to annual energy estimates) that require additional components for power, data storage, and networking. In this project, we have developed a solar variability datalogger that uses a low-cost PV cell to measure irradiance, and has integrated power, data storage, and communications, resulting in simple installation and no required maintenance. The low cost and ease of installation and operation of the solar variability datalogger will enable ubiquitous deployment and hence a greater understanding of local solar variability. This will, in turn, reduce developer and utility uncertainty about the impact of solar photovoltaic installations and encourage greater penetrations of solar energy, where appropriate.

**Table I: Costs of currently used solar irradiance sensors.**

Pyranometer Name	Pyranometer Class	Pyranometer Cost	Data Logger Name	Datalogger Cost	Pyranometer + Datalogger Cost
Apogee SP-110	Second Class <sup>1</sup>	\$195 <sup>2</sup>	CR200X	\$650 <sup>3</sup>	\$845
			LI-1500G	\$1750 <sup>4</sup>	\$1945
Licor LI-200SL	First Class	\$295 <sup>4</sup>	CR200X	\$650 <sup>3</sup>	\$945
			LI-1500G	\$1750 <sup>4</sup>	\$2045
Eppley PSP	Secondary Standard	\$1975 <sup>5</sup>	CR200X	\$650 <sup>3</sup>	\$2625
			LI-1500G	\$1750 <sup>4</sup>	\$3725

### Previous Works

A handful of previous projects have attempted to design low cost solar irradiance sensors. Mancilla-David, et al. [4] developed a low-cost, neural network-based irradiance sensor to be used for evaluating the performance of PV power plants and for improving maximum power point tracking. The low-cost sensor was only validated against an instrument meant for indoor laser power measurements and not a pyranometer, but the measurements appeared plausible. The cost of the sensor was approximately \$40-50. Cruz-Colon, et al. [5] monitored the open circuit voltage and short circuit current of a small solar cell to calculate the effective irradiance. This setup resulted in errors between 0-1% compared to a pyranometer for one instantaneous measurement. The Navy Research Lab [6] developed a small, low powered spectral radiometer with integrated data storage and significant battery life for monitoring the performance of backpack-integrated photovoltaics. The authors mention the system could be produced for less than \$20.

These works suggest that designing a low-cost variability sensor should be technically feasible. However, they all focused on energy monitoring of PV system performance and not on solar variability analysis. There have been some efforts to monitor solar

---

<sup>1</sup> The Apogee SP-110 is not rated on the ISO 9060 standard, but is expected to be similar to a “second class” instrument.

<sup>2</sup> Apogee Instruments: <http://www.apogeeinstruments.com/pyranometer-sp-110/>, accessed 8/28/2014

<sup>3</sup> Campbell Scientific 2010 price list, accessed at [http://tge2008-2.wikispaces.com/file/view/March\\_2010-macs-Price.pdf](http://tge2008-2.wikispaces.com/file/view/March_2010-macs-Price.pdf) on 8/28/2014.

<sup>4</sup> Price Quote from LI-COR Biosciences.

<sup>5</sup> 1997 prices listed in Master’s Thesis “An Improved Multipyranometer Array for the Measurement of Direct and Diffuse Solar Radiation” accessed at [http://esl.tamu.edu/docs/publications/thesis\\_dissertations/ESL-TH-97-12-02.pdf](http://esl.tamu.edu/docs/publications/thesis_dissertations/ESL-TH-97-12-02.pdf) on 8/28/2014.

variability with conventional pyranometers, mostly on distribution scales. The Hawaii Electric Company (HECO) [7], the Sacramento Municipal Utility District (SMUD) [8], and the Electric Power Research Institute (EPRI) [9], among others, have installed a handful of irradiance sensors in utility service territories to monitor the solar variability. While this demonstrates the utility interest in solar variability, the geographic coverage of deployed sensors is limited to a few select areas and the data is often not publically available. We feel there is a gap in the monitoring of solar variability that creates the need for a low-cost solar variability sensor.

Relatively little work quantifying solar variability differences by location has been published, likely due to the lack of available data. Woyte, et al. [10] used up to 1-second irradiance measurements in Germany and Belgium and Perez, et al. [11] used the 20-second measured irradiance data from the ARM network in northern Oklahoma and southern Kansas, but neither paper focused on comparing the variability between the different locations. In recent work at Sandia, Lave, et al. [1] quantified and compared the variability at 10 different locations throughout the United States, showing that up to a 300% difference in voltage regulator tap change operations (an impact of PV to electric grids) could occur between different solar variability samples.

By creating a low-cost, easy to deploy solar variability sensor, we aim to dramatically increase the number of locations with solar variability measurements to enable further studies of the location-dependent impact of solar power variability.

## 2. Project Objectives

The high cost and complicated setup of existing pyranometers has been a barrier to large-scale deployment, and so solar variability is not well-resolved geographically. We address this barrier through development of the solar variability datalogger.

The project addressed three key topics of interest to the Systems Integration program: (1) Grid Performance and Reliability, (2) Dispatchability, and (3) Communications. Traditional generation sources (e.g., coal, nuclear, natural gas) are utility-owned and the output is well-monitored and well-controlled. As independently-owned solar power penetration increases to levels greater than 100% of peak load, it will be critical for utilities to understand the local solar variability to monitor and maintain control over the electric grid. This project will benefit solar developers and utilities by allowing power production estimates at short timescales to be more accurate and more representative of ramp rate characteristics. This will be especially critical in areas with ramp rate restrictions (e.g., Puerto Rico), where developers will need to know the typical variability before commissioning their solar generation system to know how to size supplemental storage and set controls. To enable ubiquitous variability sensor deployment, it will be essential for the sensors to communicate with a central data server that will collect and process the data to make it useful to grid operations and system design.

The project objectives were accomplished through 4 major subtasks:

**Subtask 1.1:** Develop requirements for variability sensor performance, hire contractor to design a first prototype, install and operate first prototype on Sandia campus.

Milestone 1.1: First sensor prototype delivered that is able to match ramp rate cumulative distributions when compared to a pyranometer.

**Subtask 1.2:** Update sensor requirements based on operating experience from first prototype, hire contractor or develop in house a second prototype based on refined requirements, install and operate second variability sensor at three or more different locations.

Milestone 1.2: Second sensor prototype deployed at 3 or more different locations that has enhanced ability to match ramp rate cumulative distributions.

**Subtask 1.3:** Establish data collection and storage methods and quantify the variability differences by location in the collected data.

Milestone 1.3: Reliable communications from variability sensor.

**Subtask 1.4:** Demonstrate the value of the collected data to distribution grid simulations by showing how the measured variability can be incorporated into Quasi Static Time Series Analysis (QSTS) OpenDSS of distribution feeders.

**Final Deliverable:** Submit a journal article and give a conference presentation to document and publicize the impact of this work.

### 3. Project Results and Discussion

#### Subtask 1.1: Requirements and Build of First Prototype

	Metric Definition	Success Values	Measured Value	Assessment Tool	Goal Met	Data
Milestone 1.1	First sensor prototype delivered that meets Sandia's requirements and is able to match ramp rate cumulative distributions when compared to a pyranometer. Sandia and the contractor will negotiate the ownership of the intellectual property developed in the variability sensor prototype.	<10% difference in variability	2%-	variability score from cumulate distribution ( $VS_{cdf}$ )	Yes	See Figure 5-

#### Evaluate Sensors

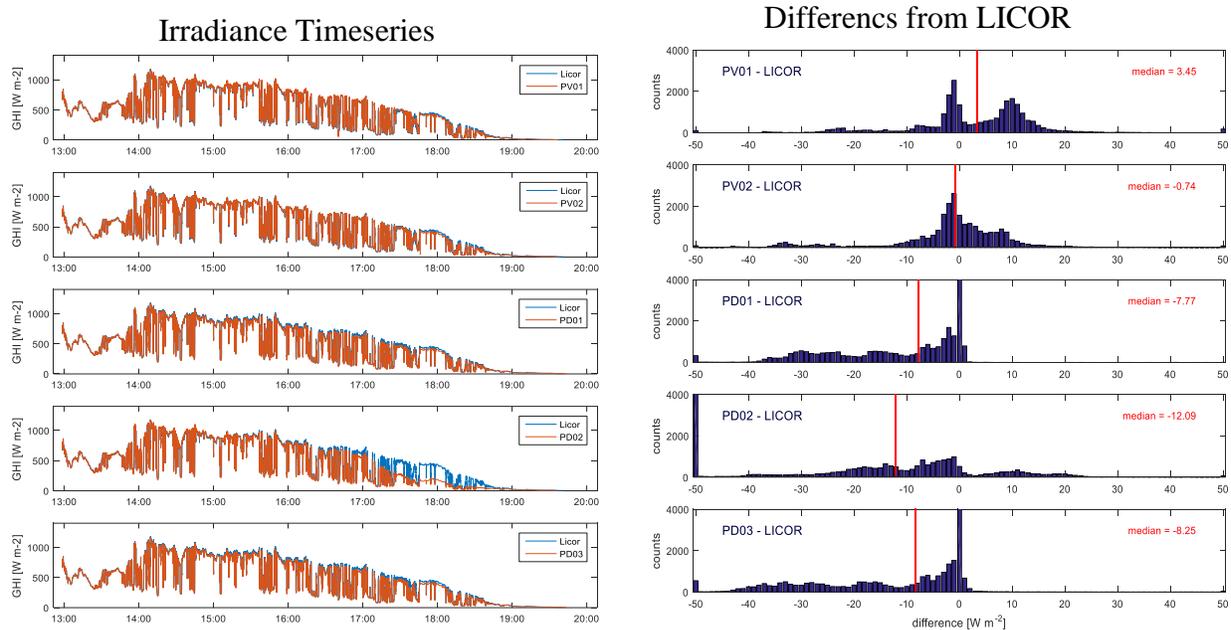
Prior to creation of a first prototype, five test sensors were created to test photodiodes versus PV cells and different diffusers and mounting setups. Test sensor details and images are shown in the table in Figure 1. To evaluate the test sensors, each of the five test sensors plus a LICOR LI-200SL were deployed in Austin, TX, as shown in the images in Figure 1. Austin was used as the test location for convenience since the sensors were assembled there.

Serial Number	Sensor type	Diffuser Material	Distance, PD -> Diffuser	Glass Window Mounting
PV01	PV cell (KXOB22-12X1L)	N/A	N/A	Inside
PV02	PV cell (KXOB22-12X1L)	N/A	N/A	Outside
PD01	Photodiode (Thorlabs FDS100)	Teflon	4.13mm	N/A
PD02	Photodiode (Thorlabs FDS100)	FEP	4.13mm	N/A
PD03	Photodiode (Thorlabs FDS100)	Teflon	1.40mm	N/A



**Figure 1: [Left] Table showing details of test sensors. [Right] Reference LI-COR pyranometer (center) with test sensors (from left to right): PV01, PV02, PD01, PD02, PD03.**

Figure 2 shows timeseries and histograms of differences in measured irradiance between the test devices and the LICOR over 7 hours on a highly variable day (13:00 – 20:00 on April 6, 2015 in Austin, TX). Positive values in the histogram indicate that the test device measured more irradiance than the LICOR, and negative values indicate that the test devices measured less irradiance. Both the PV01 and PV02 devices have distributions that are centered close to zero. The PV01 device has a bimodal distribution with a peak around  $0 \text{ Wm}^{-2}$  caused by measurements within 1-hour of solar noon and another peak around  $10 \text{ Wm}^{-2}$  caused by measurements later in the day. The PV02 device does not show this behavior and has a single peak around  $0 \text{ Wm}^{-2}$ . The PD01 and PD03 devices have almost exclusively negative errors, perhaps explained by different diffuser materials between the PD01 and PD03 devices and the LICOR. The PD02 device shows significant differences (i.e., there is a large peak at the negative boundary of the histogram), which were caused by the diffuser casing shading the photodiode at low sun angles: the clear FEP diffuser material was not strong enough to eliminate this shading.



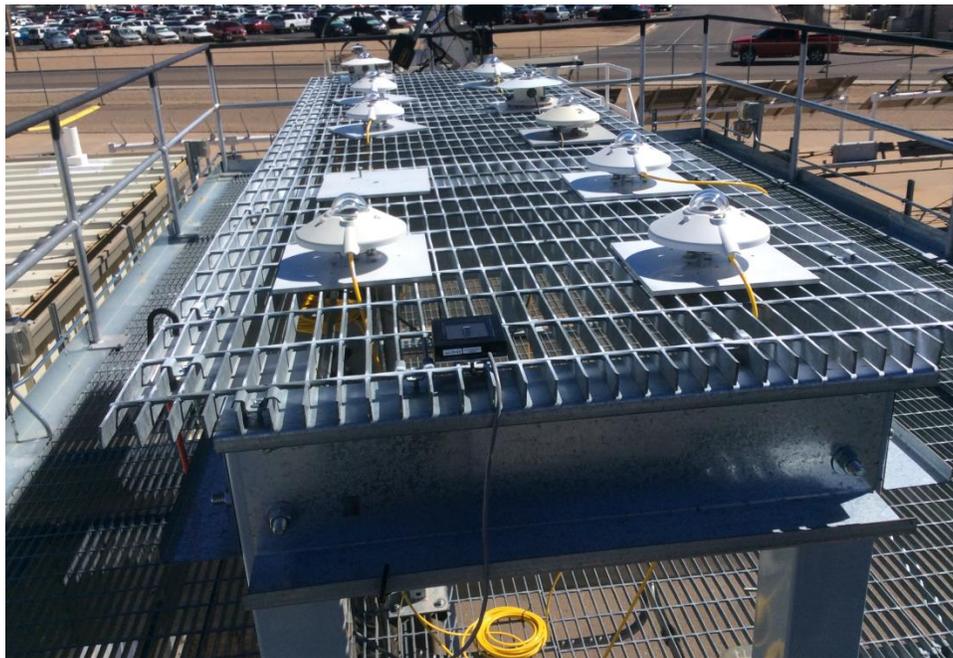
**Figure 2: [Left] Irradiance timeseries for reference LICOR (blue) and test sensors (red lines). [Right] Histogram of differences, test sensor irradiance minus LICOR irradiance.**

Based on the irradiance comparisons, the PV02 device showed the most promise and was selected as the main device for further testing. Additional benefits to the PV02 design include the outside glass window to prevent water pooling on the sensor and the potential to charge the device based on power generated from the PV cell.

## Alpha Prototype

An “alpha” solar variability sensor was built and deployed based on test device PV02. The alpha device does not have wireless communication or battery power (these will be incorporated later into the beta device), but allows for validation of irradiance and variability measurements and initial operating experience with the device and the data.

Testing of the alpha device was conducted at Sandia’s Photovoltaic Systems Evaluation Laboratory (PSEL) in Albuquerque, NM. Figure 3 shows the alpha prototype installed on a test rack at PSEL. PSEL has a Kipp & Zonen CMP 11 secondary standard pyranometer which is used for validation. Since the CMP 11 is a thermopile with a slower response time than the PV cell, and since data is only collected once every 3 seconds from the CMP 11, all comparisons (irradiance and variability) are done at 30-second timescales. This is still short enough to be relevant to distribution grid applications [12].

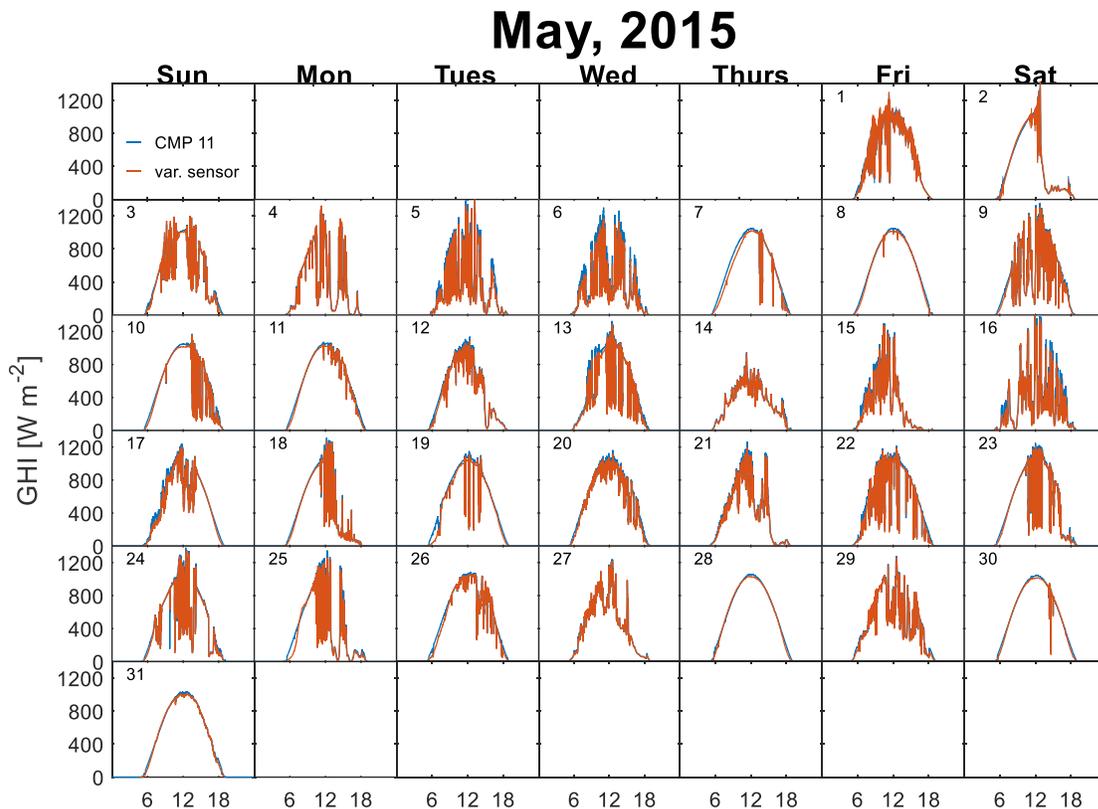


**Figure 3: Alpha prototype variability sensor deployed on a test rack at PSEL. The other devices on the rack are PSPs being calibrated.**

The alpha prototype was installed for the entire month of May 2015. Figure 4 shows a calendar plot of the irradiance on each day in May as measured by the CMP 11 and by the alpha variability sensor. Visual inspection of the calendar plot shows good agreement between the variability sensor and the CMP 11. A possible exception is May 6<sup>th</sup>, which is discussed in detail later.

Figure 5 shows the ramp rate distributions calculated from the CMP 11 and alpha variability sensor over the month of May. Visually, the agreement is very good between the two sensors. To quantify the difference in ramp rate distribution, we computed the mean absolute difference (MAD) in ramp distributions. The MAD between the variability sensor and the CMP 11 was only 0.05%, indicating very close agreement. This means that over all ramp magnitudes, the variability sensor on average predicted a probability of occurrence only 0.05% different from the probability of occurrence measured by the CMP 11.

Also included in Figure 5 is the variability score from the ramp rate distributions, the  $VS_{RRdist}$ , which is described in [1]. The 30-second  $VS_{RRdist}$  was only 1 point different between the CMP 11 ( $VS_{RRdist} = 51$ ) and the variability sensor ( $VS_{RRdist} = 50$ ), which is very small compared to the range of values found at different locations (16 to 160) in [1]. This 2% difference in variability score shows successful completion of Milestone 1.1: first sensor prototype is able to match cumulative ramp rate distributions to within 10% of a pyranometer.



**Figure 4: Measured irradiance at PSEL in Albuquerque, NM in May 2015 for the CMP11 (blue) and alpha variability sensor (red).**

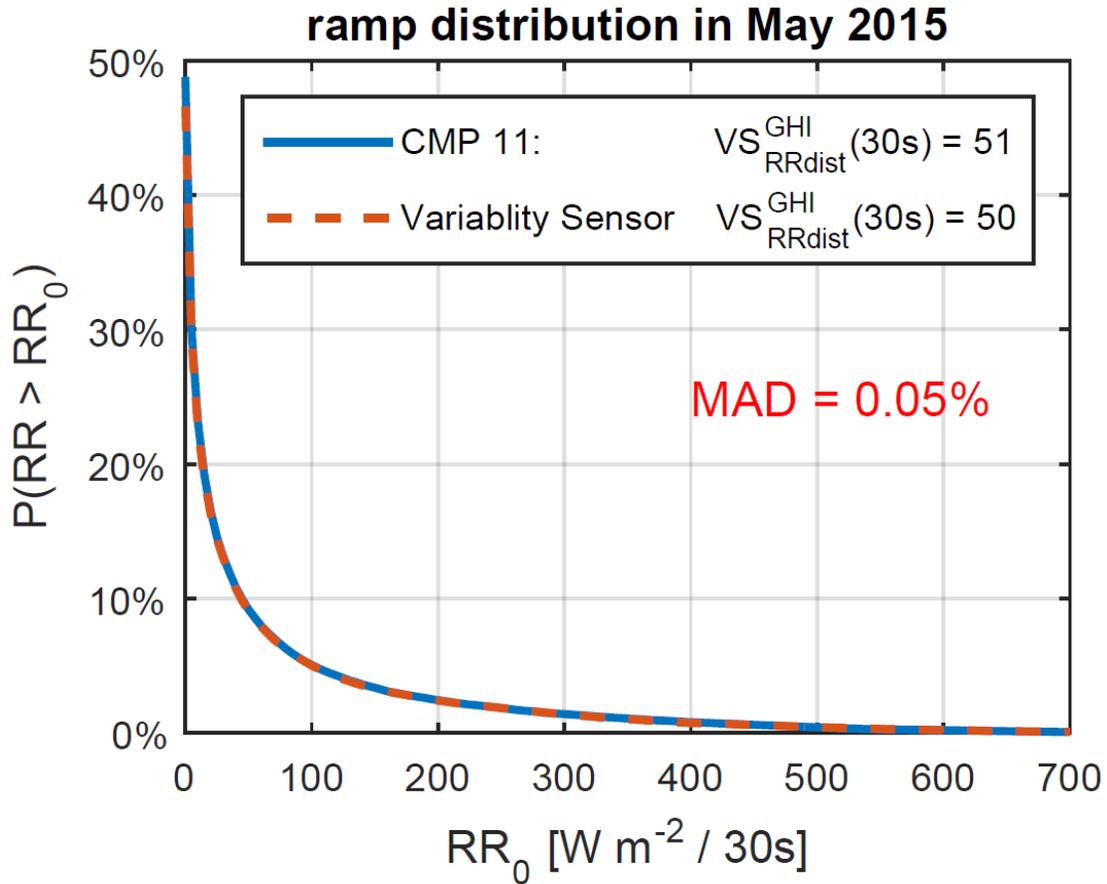


Figure 5: 30-second ramps in May 2015.

## Subtask 1.2: Second Prototype Based on Refined Requirements

	Metric Definition	Success Values	Measured Value	Assessment Tool	Goal Met	Data
Milestone 1.2	Second sensor prototype has enhanced ability to match ramp rate cumulative distributions when compared to a pyranometer. Sandia will deploy the second prototype at 3 or more different locations. Locations are expected to include, e.g., Regional Test Centers and the Sandia Livermore campus	<5% difference between 2 <sup>nd</sup> prototype variability sensor and pyranometer	0.71%; sensors deployed in Albuquerque, Livermore, Austin	variability score from cumulative distribution ( $VS_{cdf}$ )	Yes-	See Figure 10

### Beta Prototype

The “beta” solar variability sensor was built based on the alpha sensor design, but includes data storage, wireless communication, and battery power. Because of these integrated features, we refer to the beta device as a “solar variability datalogger” (SVD) instead of just a variability sensor, to emphasize its ability to be a complete solution to measuring solar variability. Figure 6 gives an overview of the SVD’s features.

Testing of the beta SVD was conducted at various locations, including at Sandia’s two campuses in Albuquerque, New Mexico and Livermore, California and in Austin, Texas. Figure 7 shows the beta SVD installed in Livermore, California. Also visible is the weather station including a precision spectral pyranometer (PSP) measuring global horizontal irradiance and that is used for direct comparisons with the SVD.

The hardware cost of the SVD was approximately \$280 per device. The cost of materials would be reduced if produced in large quantities. Hardware costs are expected to be reduced to approximately \$194 for 100 units or \$145 for 1000 units. Assembly costs would also be reduced in mass production, as significant automation could be achieved. Thus, it is expected that the final cost per device in mass production would be between \$200 and \$300. This compares very favorably to the costs shown in Table II. Plus, the SVD has power and Wi-Fi built in, which the devices in Table II do not.

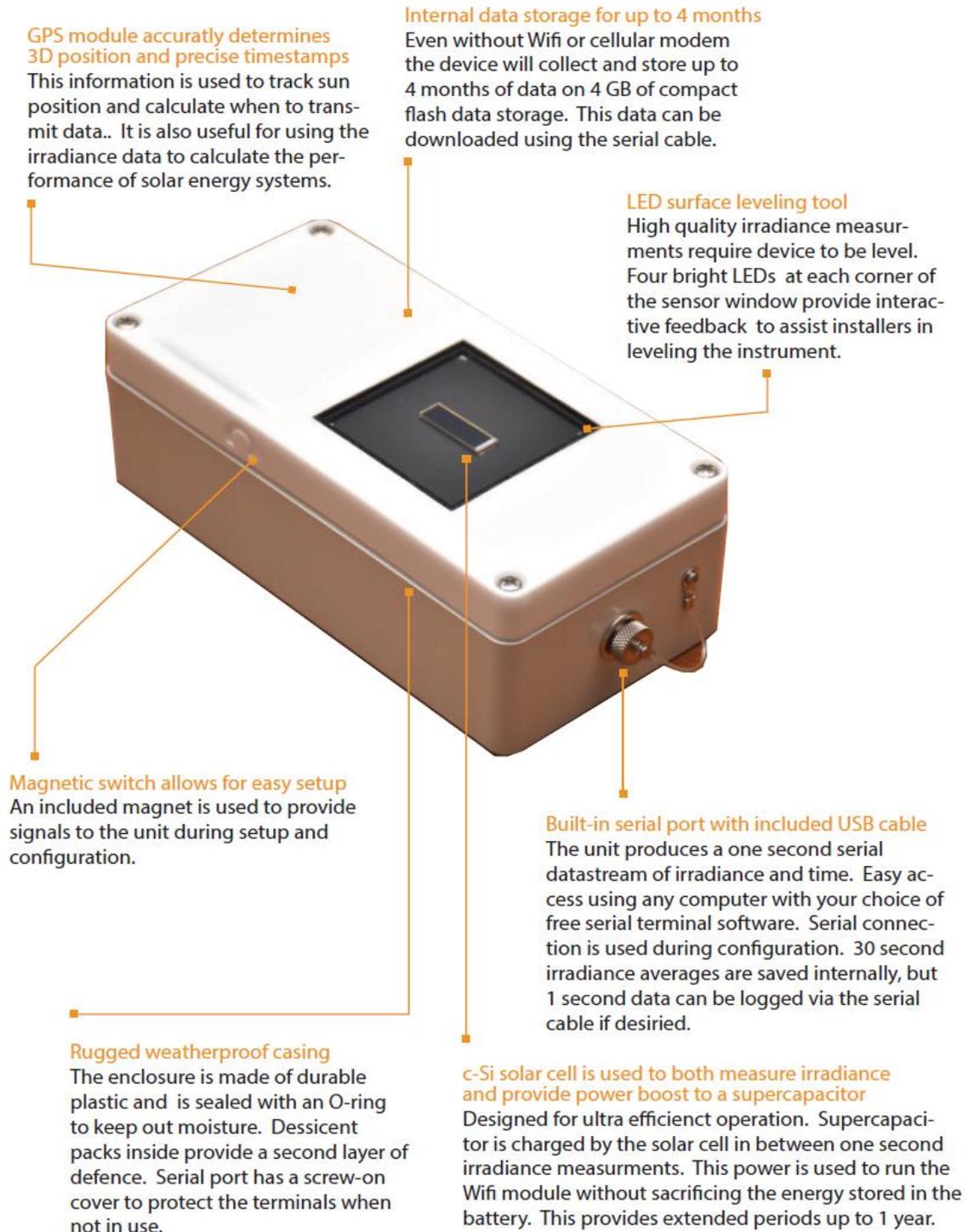


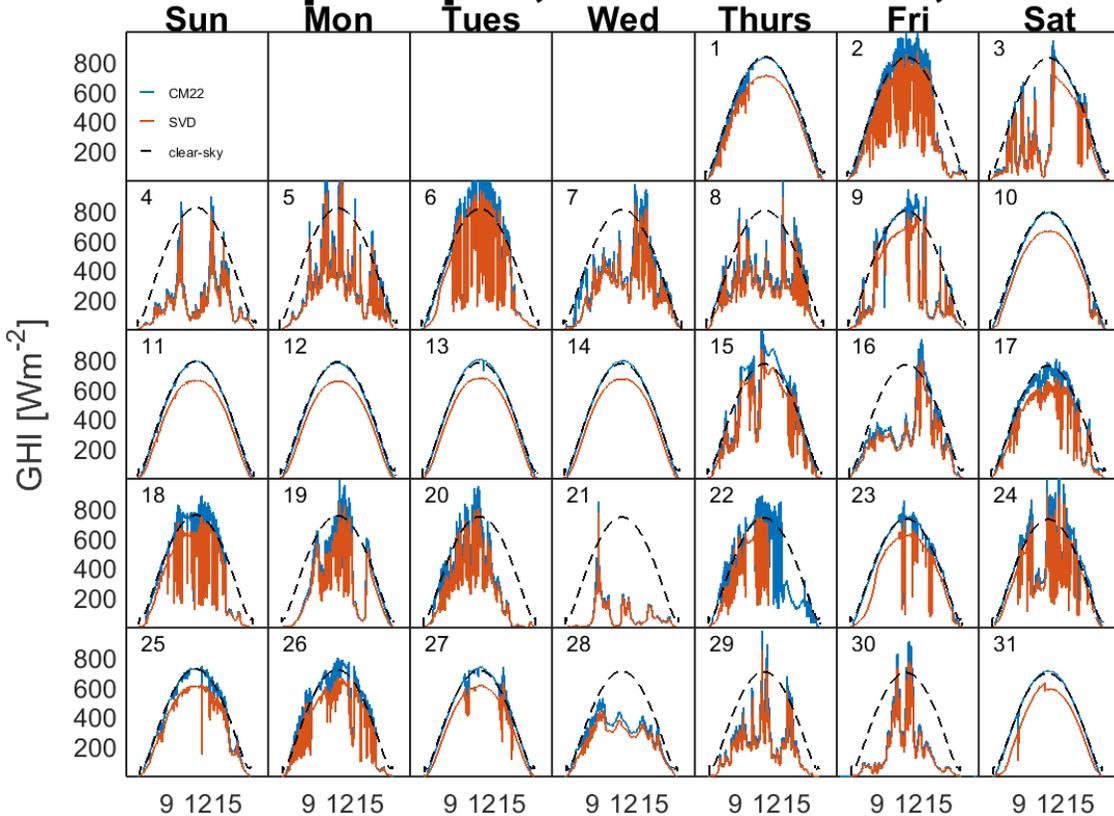
Figure 6: Solar variability datalogger features.



**Figure 7: Solar variability datalogger (circled) deployed with a weather station in Livermore, CA.**

At time of writing, the longest SVD deployment was in Albuquerque, NM, so that data is presented here for validation. Data from additional collection locations is shown under Subtask 1.3. SVD GHI measurements in Albuquerque were found to be low both when compared to a co-located CM22 and to a clear-sky model. This is seen in Figure 8, where on clear days (such as October 11-14), the SVD midday GHI measurements are up to 15% lower than the CM22 and clear-sky model. Visual inspection of the SVD device did not reveal any significant soiling, suggesting instead a calibration offset.

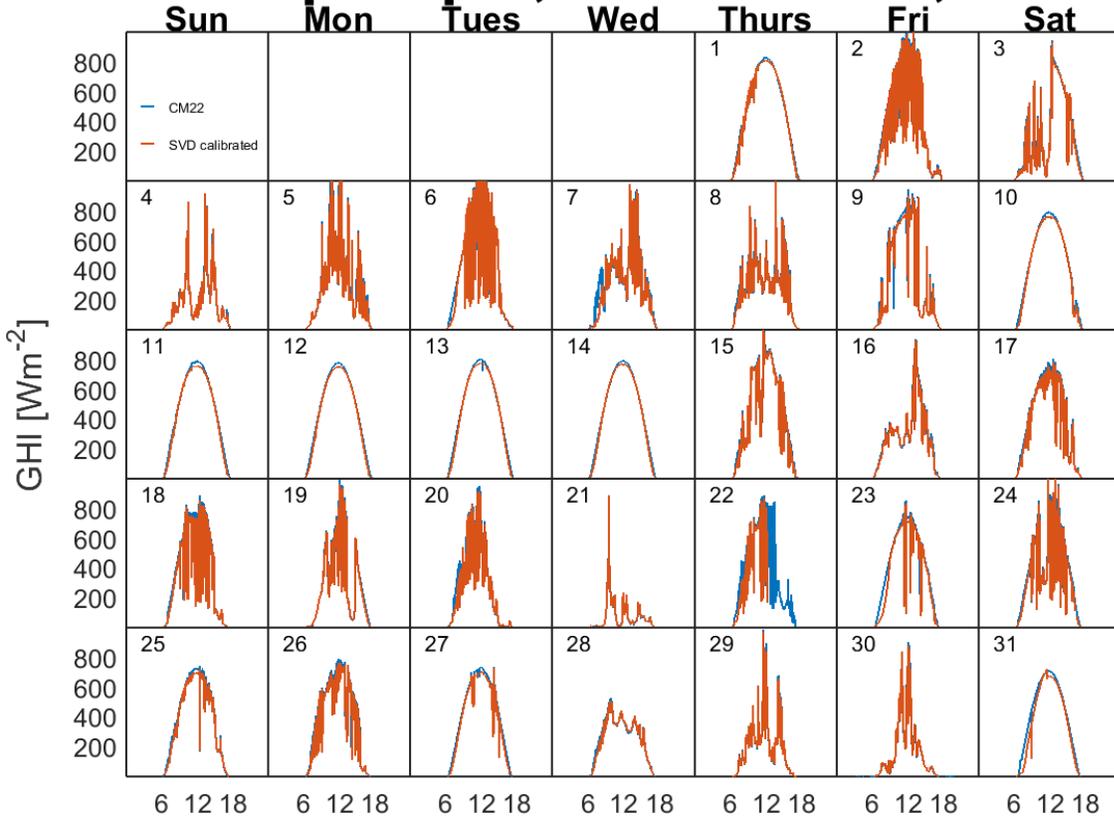
# Albuquerque, NM October, 2015



**Figure 8: SVD measured GHI (red) compared to a co-located CM22 pyranometer (blue) and a clear-sky model (black).**

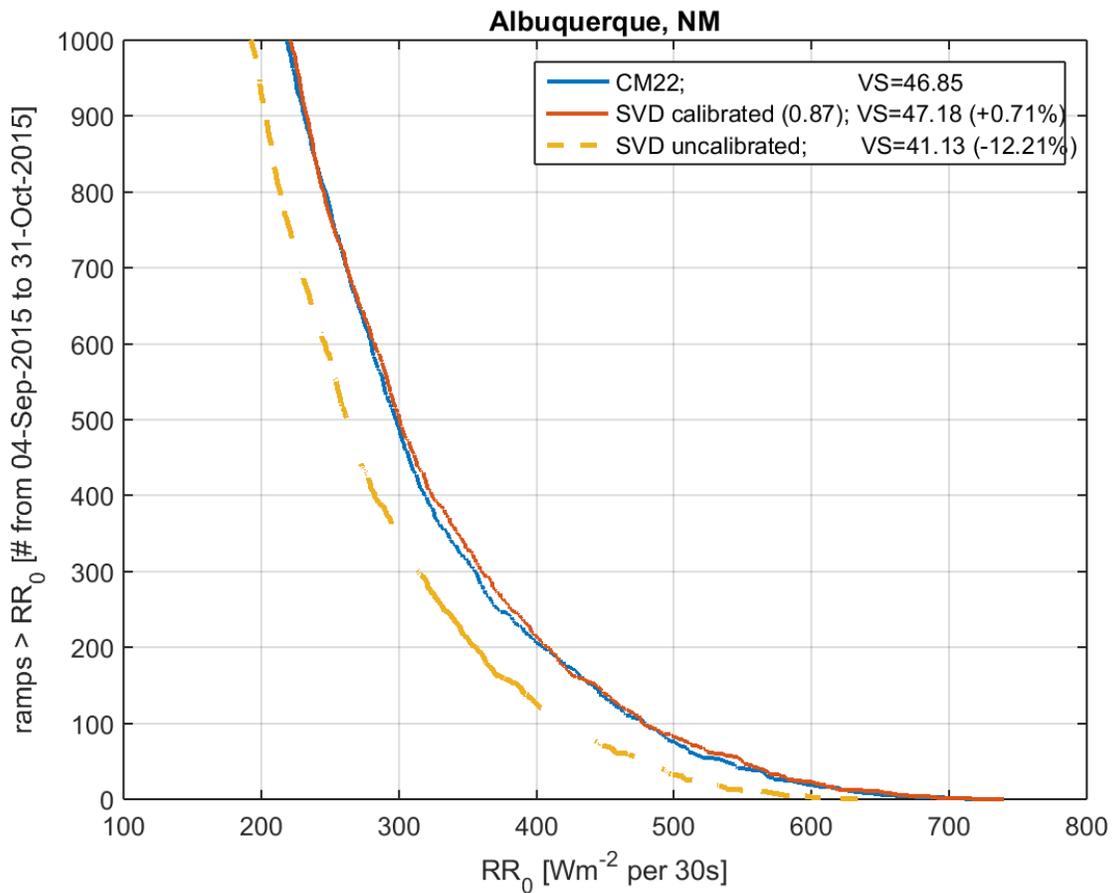
To calibrate the solar variability datalogger (SVD), the SVD data was corrected using a clear-sky model. This clear-sky calibration is described in Reno et al [13]. The calibration requires only a clear-sky model (e.g., Ineichen et al. [14]) so can be applied to any SVD, without need for any other co-located measurements. The calibration coefficient was found to be 0.8717 (i.e., the SVD data was 13% low from the clear-sky model). Figure 9 shows the match of the SVD GHI measurements to the CM22 when using this calibration. The calibrated data matches the CM22 much better than the uncalibrated data shown in Figure 8.

# Albuquerque, NM October, 2015



**Figure 9: Calibrated SVD GHI (red) compared to a co-located CM22 pyranometer (blue).**

The calibrated and uncalibrated SVD data was compared to the co-located CM22, just as was done for the alpha. This comparison is shown in Figure 10. It is clear from Figure 10 that the calibration is a significant improvement over the uncalibrated data: the error in matching the variability score is reduced from 12.21% to 0.71%. This 0.71% difference in variability score, plus the deployment of the variability sensor in Albuquerque, Livermore, and Austin, shows successful completion of Milestone 1.2: sensor prototype is deployed at 3 locations and is able to match cumulative ramp rate distributions to within 5% of a pyranometer.



**Figure 10: Distribution of 30-second ramp rates in Albuquerque, NM for CM22 (blue), calibrated SVD (red), and uncalibrated SVD (dashed yellow). Included in the legend are the calibration factor (0.87), variability scores (VS) for each measurement, and percent error from the CM22 variability score for the two SVD measurements.**

### Subtask 1.3: Data Collection and Quantify Differences by Location

	Metric Definition	Success Values	Measured Value	Assessment Tool	Goal Met	Data
Milestone 1.3	Reliable communications from variability sensor.	>90% successful data upload by day	93% to 100%	Daily download of data successful	Yes	See Table II.-

#### Data Download

There are three different ways to download data from the SVD: serial cable, Wi-Fi, and cellular modem. Installation locations and data download methods are described in Table II.

Download via serial cable is the simplest and most reliable way to download SVD data. A serial cable is connected to the SVD, with the other end connected via USB to a computer. A serial data logging program, such as PuTTY, is used to log the output from the SVD. Under normal operation, 1-second irradiance measurements are output in real time (i.e., every second). This allows for collection of 1-second data if a serial cable is continuously connected to the device, as is done at the Sandia Albuquerque location. If a cable is not continuously connected and instead there are periodic visits to the SVD to collect data (as is done in Livermore), a dump of all data stored on the device is activated by holding a magnet to the SVD while a serial cable is connected. This activates a special operation mode of the SVD where it prints all of its data to the serial log. The historical data stored on the device is at 30-second resolution to conserve data storage space, and covers up to 140 days in the past. Serial data connection has been 100% reliable: no data has been lost prior to retrieval.

The second data download option is through Wi-Fi. The SVD has a Wi-Fi chip on board. This chip can be set up to run on any Wi-Fi network within range. Setup requires only the SSID and password of the Wi-Fi network. When Wi-Fi is setup, at sunset the SVD connects to a web server. The SVD uploads its data (30-second resolution) from the current day to the web server. This data is then hosted on the web server for later retrieval and data analysis. Figure 11 shows an example of the data on the server that was uploaded by a SVD via Wi-Fi. Wi-Fi data upload has been tested at residences in Albuquerque, Austin, and Oakland, CA. Wi-Fi success rates are high, but not 100%. Wi-Fi upload protocols have been refined as we have gained operating experience: upload success rates have improved over time.

Finally, the SVD can also upload its data via cellular modem. The cellular modem is contained in a separate enclosure, with its own battery and solar panel since the modem requires significantly more power than the SVD. However, data upload with the cellular modem is otherwise identical to upload using Wi-Fi. The data is uploaded to the

same web server shown in Figure 11. Limited cellular modem upload success figures are available at the time of writing (testing for ~2 weeks), but initial results show 100% success rates. Since the cell modems are connected directly to the SVDs and there is one cell modem per SVD, cell modem upload does not suffer from some issues that may be affecting Wi-Fi transmission, such as network congestion or weak Wi-Fi signals.

We note that even if Wi-Fi or cellular modem is used as the main data download method, serial download can always be used as a backup to retrieve all historic data. This ensures that no data is lost.

**Table II: Data collection locations and data download types and success rates.**

<b>Location</b>	<b>Data Download</b>	<b>Success Rate</b>
Albuquerque, NM (Sandia)	Serial, continuously connected	100%
Albuquerque, NM (House)	Wi-Fi	93%
Oakland, CA	Wi-Fi	96%
	Cell Modem	100%
Livermore, CA	Serial, periodic retrieval	91% <sup>6</sup>
	Cell Modem	100%
Austin, TX	Serial, Wi-Fi, Cell Modem	N/A (development) <sup>7</sup>

---

<sup>6</sup> An unintentional reset resulted in loss of Livermore data from 11/26-11/29.

<sup>7</sup> Statistics are not presented for Austin since installations were intentionally intermittent (i.e., installed, removed for modifications, reinstalled, etc.).



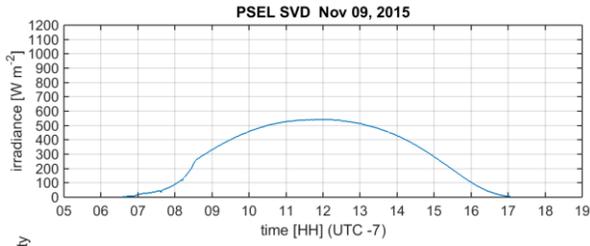
		<a href="#">30-Second Averages</a>
2015-10-25	23:50:21	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-10-27	23:48:27	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-10-28	15:55:27	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-10-28	23:47:23	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-10-29	05:53:56	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-10-29	06:02:11	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-03	09:49:06	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-03	09:50:13	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-03	23:42:24	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-04	23:41:37	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-05	23:40:52	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-06	23:40:08	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-09	23:38:04	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-10	23:37:25	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>
2015-11-11	23:36:48	<a href="#">Ramp Rate Bins</a> <a href="#">30-Second Averages</a>

**Figure 11: Example of data uploaded to the web server.**

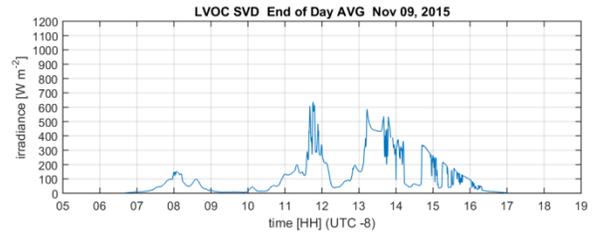
### Comparison of Different Locations

Figure 12 shows plots of SVD measured irradiance timeseries at four different locations on November 9<sup>th</sup>, 2015. The differences in variability at the different geographic locations can be easily seen. It was clear in Albuquerque, but cloudy in both Livermore and Austin. In Livermore, dark rain clouds led to very low irradiance in the morning, and then broken clouds led to high variability in the afternoon. In Austin, it was partly cloudy much of the day, with periods of high variability. Only a single day is shown in Figure 12, but seasonal and annual differences will similarly exist. These differences show the importance of using a SVD to measure local solar variability.

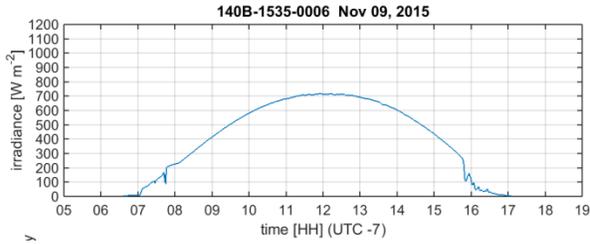
### Albuquerque (Sandia)



### Livermore (Sandia)



### Albuquerque (House)



### Austin

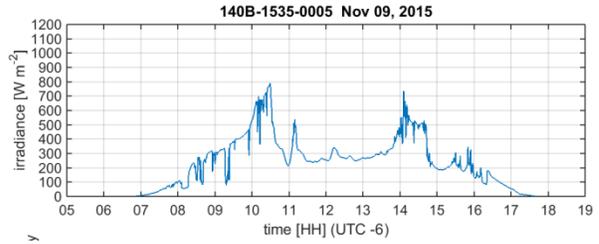


Figure 12: SVD data collected on November 9<sup>th</sup>, 2015 at four different locations.

## Subtask 1.4: Value of Data to Distribution Grid Simulations

To show the value of the SVD measured data and make it easier to be incorporated into distribution grid studies, we have developed a graphical user interface (GUI) using the GridPV toolbox in the MATLAB data analysis program [15]. The GUI allows the user to easily load in the variability sensor data and a distribution feeder (or use a default feeder) to run a distribution feeder simulation with PV. The PV power is determined based on variability sensor measured irradiance (from either the alpha prototype or the upcoming beta prototype) and a user input tilt and azimuth angle of the PV. The GUI then presents simulation results including power through each voltage regulator, the regulator tap position, the cumulative number of tap changes, and the minimum and maximum feeder voltage.

A screenshot of the GUI, including results, is shown for a clear day (May 8<sup>th</sup>) in Figure 13 and for a cloudy day (May 5<sup>th</sup>) in Figure 14. The same feeder load profile was used on both days to allow for direct comparison between the clear and cloudy PV inputs. On the clear day, the PV on the feeder causes a significant change in the power through the voltage regulator, but actually decreases the total number of tap changes due to the negative correlation of PV production and load in the morning (~07:00 through ~12:00). There were 19 tap changes in the base case without PV but only 16 tap changes with PV. On the cloudy day, however, the PV variability increases the number of tap change operations to 84, substantially more than the base case.

The significant difference in tap change operations on the clear versus cloudy day shows the importance of accurately representing the local solar variability when running distribution grid integration studies. Overestimating the PV variability would result in too many simulated tap change operations and likely lead to an undue limit of PV penetrations. Conversely, underestimating the PV variability could lead to unexpected issues and increased cost in operating the electric grid. By using a low-cost solar variability sensor, local understandings of the PV variability can be easily obtained and used to accurately determine the number of tap change operations and other impacts to the grid operation.

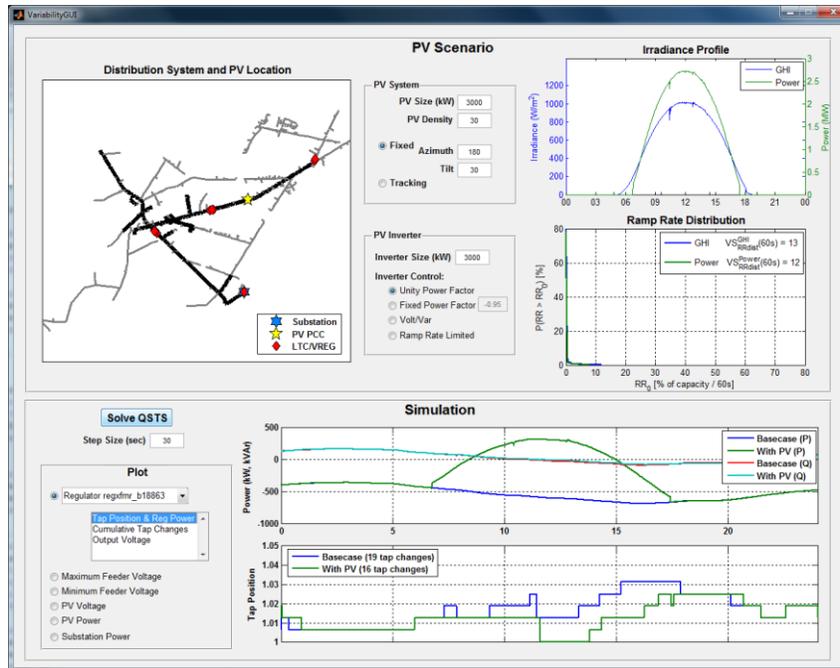


Figure 13: GUI for a clear day showing (top left) the study distribution feeder with substation, PV, and voltage regulators labeled, (top right) measured irradiance from variability sensor (blue) and simulated power (green), (middle right) ramp distributions for measured irradiance and simulated power, and (bottom) distribution grid simulation results of power through the voltage regulator and tap position.

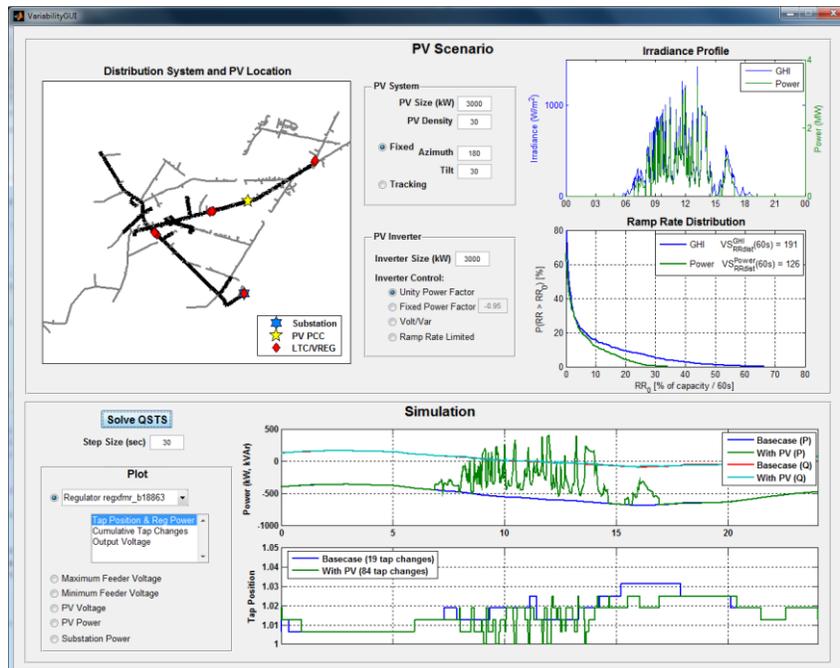


Figure 14: GUI for a cloudy day.

**Final Deliverable: Submit a journal article and give a conference presentation to document and publicize the impact of this work.**

The work was presented at the Photovoltaic Specialists Conference (PVSC) in New Orleans in June 2015 and at the UVIG Fall Meeting in San Diego in October 2015. A journal article documenting the work has been submitted to the ASME Journal of Solar Energy Engineering.

## 4. Significant Accomplishments and Conclusion

### Significant Accomplishments

- Successful proof-of-concept that low-cost irradiance sensors can achieve similar accuracy at measuring solar variability as expensive pyranometers.
- Developed solar variability datalogger (SVD) that is an integrated solution for measuring solar variability: integrated irradiance sensor, data logging, power, and communications.
- SVD cost will be in the \$200-300 range, many hundreds of dollars cheaper than other options to measure solar variability (\$850 to \$3725 or more).
- Communications, both wired (serial) and wireless (Wi-Fi or cell modem), integrated with SVD and shown to be highly reliable (>90%).
- Data from SVD integrated into quasi-static timeseries analysis, showing the impact on voltage regulator tap change operations using different samples of SVD collected data.

### Problems Encountered and Lessons Learned

- Supplemental hardware (sensor casing, power management, etc.) required more testing and development time than originally expected. For example, to obtain a fully weatherproof setup, a custom-designed sensor casing was required, adding cost and increasing production time of the SVD.
- Due to differences in PV cell (i.e., sensor) manufacturing, a clear-sky calibration was required for each device, as described under Subtask 1.2.
- Cellular modem protocols were poorly documented and the manufacturer did not respond well to requests for assistance (directed us to seller, who sent us back to manufacturer). Eventually, cellular modem upload using the same protocol as Wi-Fi upload was achieved, but this required more development time than expected.

## **5. Inventions, Patents, Publications, and Other Results**

A Sandia technical advance has been filed for the solar variability datalogger, and a provisional patent is being filed.

The work was presented at the Photovoltaic Specialists Conference (PVSC) in New Orleans in June 2015 and at the UVIG Fall Meeting in San Diego in October 2015.

A journal article has been submitted to the ASME Journal of Solar Energy Engineering.

## **6. Path Forward**

There has been significant interest in the solar variability datalogger (SVD) from both utilities and research institutions. Ideally, SVDs would be installed ubiquitously across the United States to gain a better understanding of solar variability. It would also be useful for a utility to install SVDs at high-density across their service territory or particular feeders of interest to monitor the change in solar variability at different locations.

Modifications to the SVD could further expand its use. For example, if data were transmitted in real time (instead of collected at sunset every day), SVD data could be integrated into real time monitoring and or used as data input for solar forecasting. The SVD could also be used as a low-cost monitor of PV module performance to alert PV plant owners of, e.g., underperforming modules.

We are currently seeking further funding for SVD related projects through a variety of funding opportunities.

## **Funding Statement**

Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

## References

- [1] M. Lave, M. J. Reno, and R. J. Broderick, "Characterizing local high-frequency solar variability and its impact to distribution studies," *Solar Energy*, vol. 118, pp. 327-337, 8// 2015.
- [2] C. Yost. (2014) The Interconnection Nightmare in Hawaii and Why It Matters to the US Residential PV Industry. *Renewable Energy World*. Available: <http://www.renewableenergyworld.com/rea/news/article/2014/02/the-interconnection-nightmare-in-hawaii-and-why-it-matters-to-the-u-s-residential-pv-industry>
- [3] PREPA. (2012, April 30, 2013). *Puerto Rico Electric Power Authority Minimum Technical Requirements for Photovoltaic Generation (PV) Projects*. Available: [http://www.fpsadvisorygroup.com/rso\\_request\\_for\\_qual/PREPA\\_Appendix E PV Minimum T echnical\\_Requirements.pdf](http://www.fpsadvisorygroup.com/rso_request_for_qual/PREPA_Appendix_E_PV_Minimum_Technical_Requirements.pdf)
- [4] F. Mancilla-David, F. Riganti-Fulginei, A. Laudani, and A. Salvini, "A Neural Network-Based Low-Cost Solar Irradiance Sensor," *Instrumentation and Measurement, IEEE Transactions on*, vol. 63, pp. 583-591, 2014.
- [5] J. Cruz-Colon, L. Martinez-Mitjans, and E. I. Ortiz-Rivera, "Design of a low cost irradiance meter using a photovoltaic panel," in *Photovoltaic Specialists Conference (PVSC), 2012 38th IEEE*, 2012, pp. 002911-002912.
- [6] D. Parry. (2013) NRL Develops Low Cost, High Efficiency Solar Sensor - See more at: <http://www.nrl.navy.mil/media/news-releases/2013/nrl-develops-low-cost-high-efficiency-solar-sensor#sthash.dUHRgJ0L.0KazffPQ.dpuf>. *NRL News*.
- [7] L. Dangelmaier, "HECO Companies Experience with Distributed PV 2012," Presented at PJM/EPRI/NREL Inverter-based Gen Interconnection Workshop, 2012.
- [8] "High Penetration Photovoltaic Initiative: Final Project Report," Sacramento Municipal Utility District.
- [9] EPRI. (7/2014). *Distributed PV Monitoring and Feeder Analysis*. Available: <http://dpv.epri.com/>
- [10] A. Woyte, V. Van Thong, R. Belmans, and J. Nijs, "Voltage fluctuations on distribution level introduced by photovoltaic systems," *Energy Conversion, IEEE Transactions on*, vol. 21, pp. 202-209, 2006.
- [11] R. Perez, S. Kivalov, J. Schlemmer, K. Hemker Jr, and T. E. Hoff, "Short-term irradiance variability: Preliminary estimation of station pair correlation as a function of distance," *Solar Energy*, vol. 86, pp. 2170-2176, 8// 2012.
- [12] M. Lave, J. Kleissl, and E. Arias-Castro, "High-frequency irradiance fluctuations and geographic smoothing," *Solar Energy*, vol. 86, pp. 2190-2199, 8// 2012.
- [13] M. J. Reno, C. W. Hansen, and J. S. Stein, "Global Horizontal Irradiance Clear Sky Models: Implementation and Analysis," Sandia National Laboratories SAND2012-2389, 2012.
- [14] P. Ineichen and R. Perez, "A new airmass independent formulation for the Linke turbidity coefficient," *Solar Energy*, vol. 73, pp. 151-157, 2002.
- [15] M. J. Reno and K. Coogan, "Grid Integrated Distributed PV (GridPV) Version 2," Sandia National Labs SAND2014-20141, 2014.