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Executive Summary:

PV performance models are used to quantify the value of PV plants in a given location. They combine the performance characteristics of the system, the measured or predicted irradiance and weather at a site, and the system configuration and design into a prediction of the amount of energy that will be produced by a PV system. These predictions must be as accurate as possible in order for finance charges to be minimized. Higher accuracy equals lower project risk. The Increasing Prediction Accuracy project at Sandia focuses on quantifying and reducing uncertainties in PV system performance models. This is accomplished by:

(1) Systematically analyzing uncertainty in models used to predict PV energy production using research-quality data in various climates. These analyses will inform efforts to improve various models and can identify which models, if improved, offer the greatest potential improvements in prediction accuracy.

(2) Leading an international collaborative (PVPMC) to improve the practice of PV modeling through information sharing and research collaboration, to document existing and emerging modeling algorithms, and to make available open-source code for PV performance modeling.

(3) Making targeted improvements to models and to methods for technology characterization that can improve the accuracy of output predictions for concentrating photovoltaic (CPV) technologies and systems.

(4) Developing new data acquisition and analysis methods that can extract more information from PV monitoring systems and data streams.

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Task 1: End-to-End PV Performance Model Uncertainty Assessment

Background: As the photovoltaic (PV) industry continues to mature and incentives are reduced, investment in PV increasingly depends on the confidence that can be placed in predictions of the energy yield. Predicting energy yield requires use of a sequence of models, e.g., to translate measured irradiance to the system's plane-of-array, to estimate cell temperature, and to predict DC power for given conditions. Uncertainty in these models and their inputs arises from a variety of sources, including measurement errors, inexact model specification, and from the necessarily finite data used to calibrate models. In aggregate, these uncertainties contribute to uncertainty in predicted energy yield. Therefore, to understand what confidence can be placed in energy yield predictions, to identify how to improve model accuracy and to reduce prediction uncertainty, we must quantify the uncertainty introduced by each model and the effect of each model's uncertainty on energy yield predictions.

Previous analyses (e.g., Whitfield and Osterwald, 2001; Dominé et al., 2012; Dunn et al., 2012) generally examine the uncertainty in measured performance arising from the measurement processes themselves. For example, a detailed investigation of module performance uncertainties under natural sunlight including correction for irradiance and temperature was given by Whitfield et al (2001). The methodology was based on the analytical propagation of respective uncertainties using the Guide to the Expression of Uncertainty in Measurement (GUM) (ANSI, 1997). This methodology was used and expanded for long-term outdoor IV measurements for data of Northern latitude (Dominé et al., 2012). Dirnberger and Kraling (2013) provide a detailed analysis of uncertainty deriving from indoor measurements to determine module rating at standard test conditions (STC). Müller et al. (2015) compared measured and predicted performance of operating PV power plants over several years to quantify the uncertainty in predicted annual yield; they identified the solar resource and power reduction due to module degradation and/or soiling as the primary causes of differences between predicted and measured output.

Many of these analyses are dependent on the assumptions inherent in the GUM, neglect correlations among uncertain quantities (e.g., Thevenard and Pelland, 2013), or have focused on individual model steps (e.g., Hansen et al., 2011). Ours is the first analysis of which we are aware that examines the models themselves, quantifies uncertainty empirically using time series of measured quantities thus preserving correlations among measured quantities, and propagates this uncertainty through the sequence of modeling steps.

Task Objectives: PV performance modeling is comprised of a series of modeling steps as described in Figure 1. Uncertainties in PV performance predictions can be divided into two main categories: (1) uncertainties in the future solar resource and weather conditions, and (2) uncertainties related to models and data including: mathematical simplifications (derates) made in lieu of physically based submodels; variations between available modeling algorithms; inaccurate characterization data for system components; and simply leaving out whole steps in the modeling process (Figure 1). In a recent unpublished study by a large US module manufacturer and integrator, it was found that there is a 4% spread in the annual energy predictions made by a set of independent

engineers who were contracted to make predictions for the same project using the same solar resource and weather data. This discrepancy represents a significant opportunity for improvement in the industry.

To analyze the contribution of each modeling step's uncertainty to uncertainty in overall system performance, it is necessary to systematically go through each step and compare appropriate measurements to model predictions to quantify the uncertainty at each step. Sandia started this process in FY13 as the Integrated Framework for Analysis of Technical Risk project. This project developed and demonstrated a methodology for assessing and quantifying uncertainties at key steps in the PV performance modeling chain.
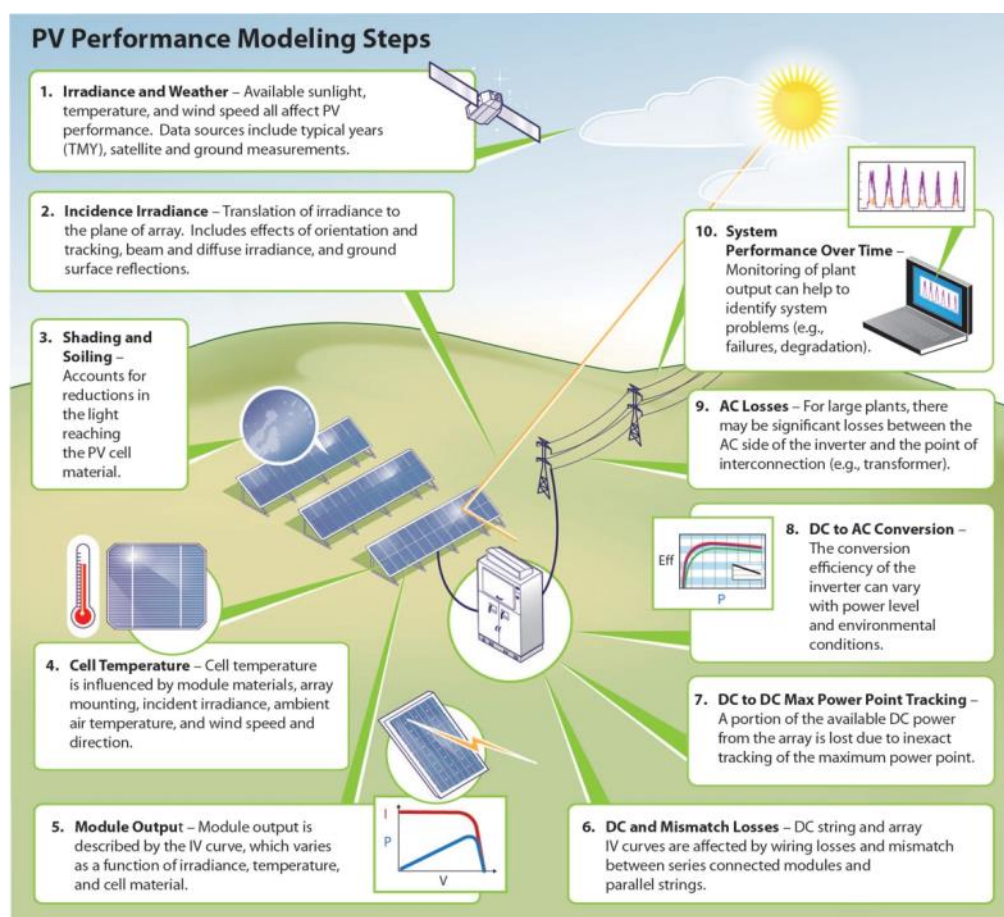

Figure 1: Standard PV Performance Modeling Steps

Task Results and Discussion: Uncertainties in PV performance modeling are detailed in SAND2015-6700, "Photovoltaic System Modeling: Uncertainty and Sensitivity Analysis." Here, an uncertainty and sensitivity analysis was completed that focused specifically on the models used to predict AC energy from photovoltaic systems. We considered a single system comprising 2493 First Solar modules connected to a 250

kW DC to AC inverter, located at Albuquerque, NM. We quantified uncertainty in the following modeling steps:

− Translation from measured GHI, DNI and DHI to POA irradiance;
− Estimation of effective irradiance (i.e., irradiance converted to electrical current);
− Prediction of cell temperature from measured air temperature and wind speed;
− Production of DC voltage and current from the module;
− Estimation of array DC power loss due to module mismatch and to maximum power point tracking inaccuracy;
− Estimation of DC-to-AC conversion efficiency.

Our analysis involved several significant limitations:

1. We do not consider uncertainty in the measurements that underlie the models nor the effect of measurement uncertainty on energy predictions. These effects are discussed in prior work (Whitfield and Osterwald, 2001; Dominé et al., 2012; and Dienberger and Kraling, 2013). If these effects were considered jointly with uncertainty in predictive models we believe that uncertainty in irradiance measurements in particular would be as influential (if not more so) than uncertainty in the models.

2. Our analysis implicitly assumes that each model is well fit to appropriate data. A model with parameters that are poorly matched to performance data will exhibit bias that is not represented in our work.

3. A number of features and processes important to accurate energy predictions are not considered in our work. For example, we assume uniform rather than spatially varying irradiance and temperature conditions across the PV array, and we do not consider soiling, degradation or damage to PV array components. We cannot conclude whether models of these processes are influential, or not, on uncertainty in energy prediction.

Due to the complexity and correlations among each model's parameters, we adopt an approach where we characterize the uncertainty in a model's output by quantifying the distribution of each model's residual, i.e., the difference between the model's prediction and the true value, rather than the traditional approach of quantifying uncertainty in each model's input parameters.

We found that, given the uncertainties we considered, the overall uncertainty in predicted PV system output, i.e., daily energy, to be relatively small, on the order of 1%. We considered four alternative models for the POA irradiance modeling step; and found that variance in predicted PV system output is not greatly dependent on the choice of one of these models. However, we found that all POA irradiance models exhibited a systematic bias of upwards of 4% that depends on location, and that this bias translates proportionally to predicted energy. Thus, choice of a POA irradiance model implies a bias to some degree in the predicted output, but not a greater (or smaller) variance in the predictions.

We performed a sensitivity analysis to relate uncertainty in the PV system output to uncertainty arising from each model. We found that uncertainty in the models for POA

irradiance and effective irradiance to be the dominant contributors to uncertainty in predicted daily energy. Our analysis indicates that efforts to reduce the uncertainty in PV system output predictions may yield the greatest improvements by focusing on the POA and effective irradiance models.

The effects of uncertainty in transposition models are detailed in (Hansen et al., 2014) and (Lave et al., 2015) which resulted from work done by Sandia in the Solar Resource research project. Within this project we examined the impact of albedo on transposition model performance as reported in SAND 2015-8803, "Albedo and Diffuse POA Measurements to Evaluate Transposition Model Uncertainty." We used albedo and diffuse plane of array (DPOA) measurements in addition to more standard global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DNI), and plane of array irradiance (POA) measurements to determine the impact of albedo on transposition model performance.

Albedo measurements allowed for analysis of daily albedo and albedo trends. Albedo values at the test site in Albuquerque, NM were typically between 0.2 and 0.25, slightly larger than the common 0.2 assumption. Daily average albedo values did not appear to show seasonal trends, though they did appear to be related to relative humidity. Larger relative humidity values led to smaller daily albedo values.

DPOA measurements allowed for comparison of calculated DPOA values (from POA and DNI) to measured DPOA values. A within-day difference was observed, and it is thus suspected that the POA instrument is not at due south azimuth. This shows the value to having interrelated measurements: without the DPOA measurement, it would have been much more difficult to identify errors in the POA measurement. For example, without the DPOA measurements it would have been difficult or impossible to differentiate an azimuth offset from changes in atmospheric conditions (e.g., increased water vapor in the afternoons could lead to decreased POA irradiance similar to the decrease caused by an azimuth offset).

Figure 2. Instrument used to measure diffuse plan of array (DPOA) irradiance at Sandia National Laboratories.

When using measured albedo (averaging 0.214) versus fixed albedo of 0.2 in transposition models, little difference was seen – only about a 0.15% difference was seen in mean bias difference (MBD) and root mean squared difference (RMSD). Analysis at other fixed albedos showed that increasing albedo by 0.1 is found to increase total modeled insolation (and thus increase MBD) by approximately 1% for the irradiance time series and surface tilt studied. Thus, types of ground cover that are different from the gray gravel surrounding the albedometer in this study (e.g., persistent snow cover, black surfaces, etc.) could lead to significant (i.e., >1%) changes in MBD compared to the 0.2 albedo assumption.

Figure 3. Albedometer used to measure albedo at Sandia's PSEL/RTC facility.

While replacing measured albedo with fixed $albedo = 0.2$ was found to have a small impact for the location studied, measurement deviations had a larger impact. Up to 2% differences in MBD and RMSD were observed when switching between interrelated measurements. For example, when DNI and DHI were used as inputs to the transposition models, and the transposition model output was compared to the POA measurement, the largest magnitude MBDs resulted. When using GHI and DNI as inputs and comparing to POA calculated from DPOA and DNI measurements, the MBDs were about 2% more positive, resulting in the lowest magnitude MBDs.

Based on this analysis, it is recommended that, except in extreme cases of very high or very low albedo (e.g., due to persistent snow cover or black ground covering), plane of array irradiance modeling effort be directed towards quality controlling irradiance measurements and selecting a well-performing transposition model rather than collecting albedo measurements.

Finally, the latest results of an ongoing study evaluating uncertainties due to irradiance sensors are detailed in "Indoor and Outdoor Evaluation of Global Irradiance Sensors." (Driesse et al., 2015). Global irradiance sensors supply essential information in the business of planning and operating PV Systems. Errors and uncertainty in irradiance measurements propagate to uncertainty about performance and profitability. PV

Performance Labs initiated the PVSENSOR project in 2014 to more fully characterize commercial irradiance sensors, with the objective of reducing such uncertainties.

In the first phase of indoor testing we tested 21 pairs of instruments using multiple solar simulators (both pulsed & continuous, large area & small), environmental chambers, spectrally selective and neutral density filters, and corresponding reference instruments. The second phase has all sensors mounted outdoors on a two-axis tracker that is programmed to follow different trajectories while all sensor outputs are recorded. This paper provides selected results from both tests sets, highlighting differences between sensor categories.

It is readily apparent from the indoor and outdoor test results thus far that the conditions under which irradiance measurements are taken, such as instrument temperature or angle of incidence, influence measurement error in systematic ways. Some of these systematic errors are clearly linked to instrument category, but differences within each category are apparent as well. For the most part the physical appearance of the instruments gives few clues to nature or magnitude of these errors, so systematic testing is required to identify them.

Indoor and outdoor responsivity measurements show some variability that is more likely due to the particular operating conditions than to inaccurate manufacturer calibrations. However for the reference cells the conditions were tightly controlled and one manufacturer's calibrations are clearly out of spec.

The spectral response of the photovoltaic sensors is not inherently good or bad, but larger differences between sensors (or between a sensor and a PV system) will lead to larger mismatch between readings. This will be evaluated with measured outdoor spectra over the course of the extended monitoring period. Similarly, the response time of the thermal instruments is also not inherently good or bad. Faster response may however be useful when data are sampled and stored at high rates and also processed or evaluated at the same time resolution. This is more likely to happen in PV monitoring systems than other applications.

Indoor measurements show that temperature strongly affects the responsivity of many instruments. We will verify these effects in outdoor tests and evaluate their impact on long-term averages in the extended monitoring phase. Angular response also varied considerably between instrument models and instrument categories in both indoor and outdoor tests. There is still room to improve the absolute accuracy of these measurements through better diffuse irradiance measurements, but comparisons between different sensors in the same category should be valid despite this.

With phase one indoor testing complete and phase two outdoor testing well under way, the majority of the primary evidence has now been gathered. From this collection we are deriving individual characteristics and uncertainties associated with them. Phase three extended outdoor monitoring will provide corroborating evidence and opportunities to fine-tune the analysis.

Figure 4. PV Sensor irradiance test bed on the 2-axis tracker at Sandia.

Task 2: Leadership of the PV Performance Modeling Collaborative (PVPMC)

Background: Sandia National Laboratories initiated the PV Performance Modeling Collaborative (PVPMC) to create a forum for sharing methods, discussing needs, and documenting the body of knowledge required for PV performance modeling and to foster a culture of technical rigor and transparency within the PV performance modeling community. Task 2 maintains and improves the PVPMC through FY15. The PVPMC was started following the 1st PV Performance Modeling Workshop in 2010 where it was noted that much of the technical information about PV performance models was not readily available or collected in one place to be of general use the PV performance modeling community (Cameron et al., 2011). Initially started as a website (http://pvpmc.org), interest in the effort has grown over the subsequent years. The second workshop, held in May 2013 was organized as part of a PV Systems Symposium that included two additional events (PV O&M Workshop and the Inverter Reliability Workshop). The modeling workshop was the best attended of the three events with 150 participants and identified a number of key areas where significant uncertainties still exist. The 2013 Workshop was three times bigger than the 2010 Workshop and established this workshop/conference as a nexus of information sharing on modeling advancements and needs in the industry. In addition, in 2013 Sandia released a free Matlab library, PV_LIB, designed to facilitate research and education in PV system modeling.

Since initiation of the PVPMC, no comparable effort has emerged. Perhaps the most similar effort is pveducation.org, an online textbook assembled by faculty at the University of Arizona. However, pveducation.org devotes more than 50% of content to device physics, and no code libraries are available with scope or content similar to PVLib. nanoHUB.org offers an online course which is also heavily targeted to device physics rather than systems (Lundstrom et al., 2011). PVPMC has been invited to provide tutorials at international conferences (40th IEEE PVSC in Denver, CO, in June 2014, and at the 6th World Conference on Photovoltaic Energy Conversion in Kyoto, Japan in November 2014). In addition, one international effort (IEA Task 13) has adapted its international outreach to conform to and leverage the PVPMC as a primary communication channel for PV system modeling.

Task Objectives: Prior to the organization of the PV Performance Modeling Collaborative (PVPMC), PV performance model developers and users did not have a forum for sharing methods, discussing needs, and documenting the body of knowledge required to technically understand PV performance models. This task is aimed at maintaining and improving communication of technical matters involved in PV system modeling, and to establish a culture of technical rigor and transparency within the PV performance modeling community. This is accomplished through five outreach activities: 1) organization and co-hosting of the annual PV Performance Modeling Workshop, 2) hosting and maintenance of the PVPMC website, 3) development and maintenance of the open source PV_LIB Toolbox, hosted at the PVPMC website, 4) teaching at least one tutorial on PV performance modeling, typically in conjunction with the annual IEEE-PVSC, and 5) authoring the first graduate textbook dedicated to PV performance modeling.

Task Results and Discussion: Three PV Performance Modeling Workshops were co-hosted by Sandia in 2013-2015. This workshop series is the only such event that brings together all key stakeholders in the area of PV performance modeling. The series has proven to be increasingly popular, growing by approximately 50 attendees each year. The 2015 PV Performance Modeling Workshop was held in Cologne, Germany on October 22-23, 2015. This workshop was hosted by TUV Rheinland, Sandia National Laboratories, and IEA PVPS Task 13. The workshop featured 35 presentations and, for the first time, a poster session with 13 posters. Major observations from the workshop include; satellite irradiance models are getting better, two new spectral models were introduced, new spectral irradiance datasets are being developed and field monitoring practices still vary and need more standardization.

Figure 5: 2015 PV Performance Modeling Workshop in Cologne, Germany

Year	Venue	Co-host	Attendance
2013	Santa Clara, CA	EPRI	100
2014	Santa Clara, CA	EPRI	150
2015	Cologne, Germany	TUV-Rheinland	215

Table 1: FY13-15 PV Performance Modeling Workshops

Additionally, three modeling tutorials were taught. The tutorial is comprised of 1.5 hours of lecture presented on models and algorithms walking forward from irradiance data and translation to conversion to AC power, followed by 2 hours of hands-on coached tutorials in the PV_LIB software, using either Matlab or Python. This tutorial has become a standard part of the tutorial sessions associated with IEEE-PVSC. The

tutorial is a more focused educational event than the Workshop and emphasizes hands-on instruction.

Year	Conference	Location	Attendance
2014	40th IEEE-PVSC	Denver, CO	30
2014	6th WCPEC	Kyoto, Japan	40
2015	41st IEEE-PVSC	New Orleans, LA	20

Table 2: FY14-15 PV Performance Modeling Tutorials

The PVPMC website, first launched in 2013, experienced a major update and moved to a more secure location behind Sandia's firewall in late 2014. The decision to perform these updates was made mid year to ensure that the ever increasing audience for this site (over 1,350 members) could safely interact with the content without incident well into the future. The initial website did not anticipate the level of traffic and was not optimized to handle true collaboration between members. The new site (www.pvpmc.sandia.gov) is designed to work more effectively for the increasing audience.

The PV_LIB Toolbox continues to be a popular offering of the PVPMC. In FY13 Sandia updated PV_LIB to version 1.1 to include many additional clear sky and incidence angle models from literature, capability for predicting PV output using single diode models, and a single axis tracker function. PV_LIB was updated to version 1.2 in FY14 to include several POA irradiance modeling functions, a new inverter model and to correct and improve various code elements. Over 800 users have downloaded this version. PV_LIB version 1.3 will be released early in FY16 and will provide a new effective irradiance model and to provide code to estimate parameters for single diode models (e.g., the CEC model and PVsyst) from measured IV curve data.

A Python version of PV_LIB was launched in June of 2014 (Andrews et al., 2014). The Python version enables users to make use of the algorithms without having to purchase any software (e.g., Matlab). The package is available on GitHub at: https://github.com/Sandia-Labs/PVLIB_Python. This package has quickly developed an active user community on the site with posted comments, issues, and new code additions. Significantly, PV_LIB is becoming an important avenue for model developers to publish and disseminate their models rapidly. Models can undergo testing and improvement by the PV modeling community as a whole.

In 2014, we launched an effort to write a new textbook on Photovoltaic Performance Modeling. We conducted a survey of recent textbooks in the subject area of PV performance and systems and identified only three relevant textbooks, none of which overlap much with our concept for a new textbook.

• Photovoltaics: Fundamentals, Technology, and Practice by Konrad Mertins (2014) (Wiley). This book translated from German is mostly conceptual in nature, with little emphasis on quantitative aspects of performance prediction.

- Photovoltaics System Design and Practice by Heinrich Häberlin (2012) (Wiley). This translated book from German is a bit more detailed but lacks practical quantitative problems and examples. The poor translation makes it quite difficult understand as an English speaker.

- Solar Engineering of Thermal Processes by Duffie and Beckman (2006) (Wiley). This great book is in its third edition and is a valuable resource. Unfortunately, photovoltaics and systems are not the focus of the book and are only covered in a single chapter; solar radiation material is covered in the beginning of the book. This book does not go into the detail that is necessary for adequately training future solar PV engineers and scientists. However, the rigor and depth of the book provide a good model to follow.

Given that Wiley Publishers appear to be the only publisher in this area, we submitted a proposal to Wiley. The proposal was accepted and the first draft of the book is due to the publisher in December 2015. Four chapters were complete as of October 2015.

Task 3: CPV Performance Model

Background: High concentrating photovoltaic (CPV) modules behave differently than standard flat plate modules. DC current can show a distinct dependence on spectral content due to the use of multi-junction cells, CPV modules can operate at very high (and difficult to measure) cell temperatures because of their use of concentrating optics, and CPV modules only use the direct beam component of the irradiance. Analysis by Hansen and Riley (2013) of the performance of a high-x CPV module from Semprius indicated that the general structure of the Sandia Array Performance Model (SAPM) could serve as the basis for an accurate predictive model. However, improvements were needed to account for the influence of spectral content on system current and to refine the cell temperature models.

For low-X CPV systems, the general structure of the SAPM also appeared promising based on FY12 analyses. However, the anisotropic features that are characteristic of the design of this type of module complicate modeling plane-of-array (POA) irradiance. Low-x CPV modules exhibit distinct light acceptance angles in the transverse direction and some degree of reflectance loss along the longitudinal axis. No industry accepted method is currently available to accurately characterize these performance features.

Task Objectives: The objectives of this Task are to extend, document, validate and promulgate methods for accurately modeling performance of concentrating photovoltaic (CPV) systems for both high- and low-concentration designs. For high-concentration CPV, we will develop methods to account for the effects of spectral content on cell current and will refine cell temperature models. For low-concentration CPV, we will promulgate a recommended industry best practice for characterizing light-acceptance and reflectance properties of these modules.

Task Results and Discussion: In FY13, Hansen and Riley demonstrated the ability to modify the SAPM to more accurately predict the performance of an individual Semprius HCPV module (Hansen and Riley, 2013). We believe that the SAPM equation forms are adequate to address the differences between flat-plate PV and HCPV, particularly the differences that arise due to increased spectral sensitivity of HCPV cells. Further work in FY14 confirmed this assertion.

At the end of FY13, Sandia and Semprius collaborated to install a Semprius product on a test tracker at Sandia with the goal of providing system data for refinement of the Sandia PV Array Performance Model (SAPM) for CPV systems. We initially published a paper at the CPV-10 conference that described the ability of the standard SAPM to predict the power of the Semprius system (King et al., 2014). However, the initial data acquisition system installed by Semprius consisted of only measurements from the PV inverter and we were unsuccessful at validating model performance with this data. To address this limitation, a more advanced data acquisition system was installed in mid-2014. The system continued to be plagued by operational problems throughout FY14 and well into FY15. We experienced continued tracker failure during this period resulting in long periods of lost data. As a result, we were ultimately unsuccessful at validating the predictive capability of the modified SAPM against system data.

A more successful activity involved methods to characterize the optical response of CPV modules. This activity was enabled by the development and implementation of advanced tracker controls and pointing algorithms. During FY14, we pursued a method to accurately characterize the isotropy (or anisotropy) of the electro-optical response of CPV modules (both high and low concentration) to solar angle of incidence (AOI). Initial work in this field required Sandia to develop a novel description for incident angle that includes both the solar incident angle and the direction that the incident angle takes relative to a CPV module's face. We then described an algorithm to calculate the appropriate tracker pointing angles necessary to achieve a desired incident angle for an arbitrary sun position. The back-calculation of tracker pointing angles is a much more difficult problem than one might expect, which may explain why we could find no prior publications on the subject. This work is detailed in SAND2014-3242, "Sun-Relative Pointing for Dual-Axis Solar Trackers Employing Azimuth and Elevation Rotations," and two follow-on publications.

Task 4: Novel PV Monitoring Methods and Strategies

Background: Current PV system monitoring practices are focused on data collection rather than system health assessment and intelligence. The current trend within industry is to push into more extensive data gathering, both in terms of greater time resolution and increased sensor count. This trend leads to higher initial costs, increased system complexity and greater potential for sensor failure. Further, there are several technical limitations to the current PV monitoring practice.

The first relates to the methods used to reduce the size - or decimate - sensor data. Traditionally, monitoring systems recorded data relatively infrequently (e.g., 15 min) as instantaneous values. More recently, typical monitoring systems measure at higher frequency (e.g. 1 minute or even 1 second) but the trend is still to down sample to reduce the computational overhead associated with very large data files. The most common method of down sampling the data is block averaging over a coarser time frame, still typically 15 minutes. There are more sophisticated methods than block averaging for decimating data that will reduce the data rate while still allowing increased data resolution. One example is data stream thresholding, in which only values that have changed by a certain amount are saved with a timestamp. Fields that have benefitted from these methods include telecommunications and SCADA systems.

The second opportunity is to use monitored sensor data to not only *measure* system performance (e.g., AC power, module temperature, etc.) but to also *detect* anomalous performance or component failures. Uncertainty in modeled system power output is typically much larger than sensor precision, limiting its use as a real-time analytical tool. However, comparative measurements between sensors on systems or subsystems may be able to identify performance outliers. A related known problem with monitoring systems is data dropouts and data noise. These effects can be minimized through the interaction of multiple sensors or through the use of Kalman filters, Bayesian networks, and other filters operating on physical or simulated sensor signals created by real-time PV system models.

Third, opportunities exist to develop and implement novel in-situ monitoring systems beyond the traditional passive measurement of voltage and current. Advancements in solid-state electronics have made it possible to design and build compact and affordable solutions for directly measuring string and module IV curves on operating systems.

Task Objectives: Current PV system monitoring practice is focused on data collection rather than system health assessment and intelligence. This practice pushes the industry into more extensive data gathering (greater time resolution and more sensors), which raises initial costs, adds system complexity and increases potential failures. The objective of this task is to perform a series of exploratory studies to determine if more advanced monitoring methods could increase the value of data from fewer sensors and thus save money.

Task Results and Discussion:

High Frequency Monitoring of PV Systems

A detailed assessment of high speed sampling and filtering is presented in SAND2014-19137, "Sampling and Filtering in Photovoltaic System Performance Monitoring." In this study we investigated how the interplay between complex signals and the way in which they are measured can lead to errors in the data delivered by PV monitoring systems.

To assess the signal complexity we acquired data of the most important signal types from a grid-connected PV system and associated weather instruments using a very high sampling rate (2,000 samples per second). In this high-resolution view of the signals we were able to observe various rapid fluctuations and we found explanations for the origins of many of them. The most prominent fluctuations were found to be caused by the active anti-islanding system, which caused periodic changes of AC current and power at intervals equal to 25 line cycles. The effect of this was also seen on the DC voltage and current signals.
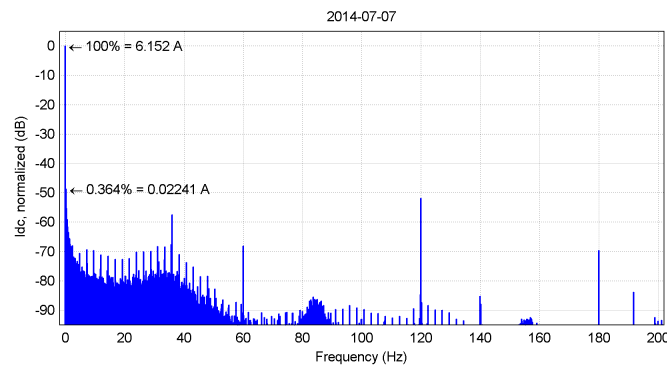

Figure 6. Frequency spectrum of DC current measurement showing effect of 60 Hz harmonics on the signal. Notice a peak at 35.9 Hz, which is caused by the inverters anti-islanding detection.

The signal characteristics we report were observed over relatively short time intervals on a single PV system, which means that they certainly cannot be considered as representative of all systems. But the fact that they were all found on the first system we examined, suggests that signals in other systems are likely also affected, although maybe not for the same reasons and not in the same proportions. Further evidence needs to be gathered from other operating PV systems before more general statements can be made.

To explore how measurement errors can arise in PV monitoring systems, we simulated their operation using a wide range of sampling intervals and archive intervals, and using several different filtering options. We saw how the anti-islanding system perturbations dominated the measurement errors in AC power over a specific range of sampling rates, and found that a simple two-pole low-pass filter preceding the analog-to-digital conversion could be tuned to reduce those measurement errors. Furthermore, we showed that the low-pass filter could be tuned to reduce the measurement error at any sampling rate. As PV monitoring systems often have sampling rates that are too low to capture rapid fluctuations in irradiance and power, the addition of a low-pass filter

presents itself as a possible solution to obtaining more accurate average values for many signals.

Because there is a strong link between various parameters of a monitoring system and the quality of the archived values, is very important to know what those parameters are. Documentation for PV monitoring systems should always include specifications of filtering methods, sampling rates, summary calculations, archive rates and time stamp conventions, and this metadata should always accompany the data files that are produced.

Module-Level Automatic IV Tracer Evaluation

The results of a development effort to produce and characterize in-situ module level IV tracers are described in "In-Situ Module-Level IV Tracers for Novel PV Monitoring." In this work, Sandia partnered with Stratasense LLC to investigate the benefits of automatic, module-level current-voltage (I-V) curve tracers for system monitoring. Module I-V curves offer significant detection advantages over other monitoring methods and the in-situ design adds ease to the implementation of the tracers into operational PV arrays.

The module level I-V tracers are designed to regularly perform in-situ I-V traces at the module-level for modules connected in series to an inverter. These traces are taken regardless of load type, allowing nearly uninterrupted power production. When multiple units are connected to modules in a string, each module is disconnected and swept individually, which allows the current and voltage to the inverter to remain within the maximum power-point tracking operating window. Each trace causes a module bypass lasting less than two seconds.

To test the capabilities of the IV tracers, we performed several tests using a 15-tracer testbed. These tests were designed to collect module-scale I-V curves and investigate the ability to identify specific problems within an array that might be "invisible" with only system-level monitoring. The tests consisted of applying partial shading to selected modules (using three different approaches) and adding series resistance to a module to simulate degradation. It was demonstrated that the in-situ IV tracers were capable of detecting each of these simulated faults.

Figure 7. Testing string-level automatic IV tracers at Sandia National Laboratories.

String-Level Automatic IV Tracer Development

A parallel effort to develop string-level IV tracers was conducted in partnership with Pordis, LLC and Delacor LLC. Sandia provided a list of requirements to Pordis/Delacor and they built several prototype devices that have been tested at Sandia. The devices are in the form of a 8-string combiner box that can be controlled to automatically switch out one string at a time and perform an IV curve while the inverter still operates on the remaining connected strings. The control software allows the user to trigger IV sweeps according to user-defined conditions, such as irradiance level and or timing and frequency. For example, the unit can be programmed to perform an IV curve three times per day, 1 hour apart when and if the irradiance is above 900 W/m^2. The user has full control of the unit. A final prototype was delivered to Sandia and we are testing it on one of the RTC systems in NM. Several US companies (e.g. Sun Edison) have expressed interest to test units.

Figure 8. Model of the Multi-string IV tracer built by Pordis LLC and Delacor LLC. The bottom board handles the string switching while the top board holds the IV sweep circuit.

Accomplishments:

Peer-Reviewed Journal Articles:

D. Riley, C.W. Hansen, "Sun-Relative Pointing For Dual-Axis Solar Trackers Employing Azimuth and Elevation Rotations," *ASME Journal of Solar Energy Engineering,* vol. 137, 2015

J. S. Stein and B. H. King, "Modeling for PV plant optimization," in Photovoltaics International magazine, Solar Media Ltd. 19th, pp. 101-109, 2013

Conference Publications:

R. Andrews, J. Stein, C. Hansen, D. Riley, "Introduction to the Open Source PV_LIB for Python Photovoltaic System Modeling Package," 40th IEEE Photovoltaic Specialists Conference, Denver CO, 2014

A. Driesse, J. S. Stein, D. Riley, C. Carmignani, "Monitoring Current, Voltage and Power in Photovoltaic Systems," 42nd IEEE Photovoltaic Specialists Conference, New Orleans, LA, 2015

A. Driesse, W. Zaaiman, D. Riley, N. Taylor and J. S. Stein, "Indoor and Outdoor Evaluation of Global Irradiance Sensors," 31st European Photovoltaic Solar Energy Conference, Hamburg, Germany, 2015

M. G. Farr and J. S. Stein, "Spatial Variations in Temperature across a Photovoltaic Array," 40th IEEE Photovoltaic Specialists Conference, Denver CO, 2014

B. R. Fisher, K. Ghosal, D. Riley, C. Hansen, B. King, S. Burroughs, "CPV Field Performance Modeling using Semprius' System Performance Model (SPM)," 40th IEEE Photovoltaic Specialists Conference, Denver, CO, 2014

C. W. Hansen and A. Pohl, "Which Models Matter: Uncertainty and Sensitivity Analysis for Photovoltaic Power Systems," 40th IEEE Photovoltaic Specialists Conference, Denver CO, 2014

C. Hansen, M. Farr, L. Pratt, "Correcting Bias in Measured Module Temperature Coefficients," 40th IEEE Photovoltaic Specialists Conference, Denver CO, 2014

W. F. Holmgren (Department of Atmospheric Sciences, University of Arizona), R. W. Andrews (Heliolytics), A. T. Lorenzo (College of Optical Sciences, University of Arizona), J.S. Stein, "PVLIB Python 2015," 42nd IEEE Photovoltaic Specialists Conference, New Orleans, LA, 2015

B. H. King, J. E. Granata and A. J. Luketa-Hanlin, "Systems Long Term Exposure Program: Analysis of the First Year of Data," 39th IEEE Photovoltaic Specialists Conference, Tampa, FL, 2013

B. H. King, D. Riley, C. Hansen, M. Erdman, J. Gabriel and K. Ghosal, "HCPV Characterization: Analysis of Fielded System Data," CPV-10, Albuquerque, NM, 2014

J.E. Quiroz, J.S. Stein, C.K. Carmignani, and Kellen Gillispie (Stratasense LLC), "In-Situ Module-Level I-V Tracers for Novel PV Monitoring," 42nd IEEE Photovoltaic Specialists Conference, New Orleans, LA, 2015

D. Riley, "Mapping HCPV Module or System Response to Solar Incident Angle," International Conference on Concentrating Photovoltaics, April 2015

J. Sutterlueti (Gantner Instruments Environment Solutions GmbH), S. Ransome (Steve Ransome Consulting), J. Stein, J. Scholz (Gantner Instruments Environment Solutions GmbH), "Improved PV Performance Modelling by Combining the PV_LIB Toolbox with the Loss Factors Model (LFM)," 42nd IEEE Photovoltaic Specialists Conference, New Orleans, LA, 2015

J. S. Stein, J. Sutterlueti, S. Ransome, C. W. Hansen and B. H. King, "Outdoor PV Performance Evaluation of Three Different Models: Single-diode, SAPM and Loss Factor Model," 28th EU Photovoltaic Solar Energy Conference, Paris, France, 2013

J. S. Stein, S. McCaslin, C. W. Hansen, W. E. Boyson and C. Robinson, D., "Measuring PV System Series Resistance Without Full IV Curves." 40th IEEE Photovoltaic Specialists Conference, Denver CO, 2014

Sandia Technical Publications:

C. W. Hansen and D. Riley, "Technical Memo: Performance Model for Semprius Module," SAND2013-9078P, Sandia National Labs, Albuquerque, NM, 2013

C. W. Hansen, A. Pohl, and D. Jordan, "Uncertainty and Sensitivity Analysis for Photovoltaic System Modeling," SAND2013-10358, Sandia National Labs, Albuquerque, NM, 2013

D. Riley and C.W. Hansen, "Sun-Relative Pointing for Dual-Axis Solar Trackers Employing Azimuth and Elevation Rotations," SAND2014-3242, Sandia National Labs, Albuquerque, NM, 2014

C. W. Hansen and C. M. Martin, "Photovoltaic System Modeling: Uncertainty and Sensitivity Analysis." SAND2015-6700, Sandia National Labs, Albuquerque, NM, 2015

M. S. Lave, "Albedo and Diffuse POA Measurements to Evaluate Transposition Model Uncertainty." SAND2015-8803, Sandia National Labs, Albuquerque, NM, 2015

Path Forward:

Several efforts in this research program were approved for carryover activities to extend into FY16. These include:

Task 1: PV Sensor project - The purpose of this effort is to obtain a more comprehensive understanding of the characteristics of commercial irradiance sensors used for PV system monitoring. Per the SOPO, we initiated an international collaboration with the European Joint Research Centre in Ispra, Italy, leveraging research funding from the European Union Sophia Project. The outdoor testing at Sandia will serve to both corroborate indoor measurements and evaluate additional characteristics. Sandia has already completed irradiance sensor indoor and characterizations. Per the SOPO, we are preparing to install the sensors on a fixed tilt array in FY15, and collect data for a minimum of 6 months, as required to meet the research goals. The original schedule slipped because of a delay in receiving these sensors from our European partners. We have worked hard to complete the characterization (the bulk of the work) in a shorter time. In FY16 we will maintain the sensor array for at least 6 months, collect the data, provide analysis support and return the sensors to Europe at the conclusion of the project.

Task 2: Performance Modeling Textbook – We are currently under contract to Wiley to write a textbook on PV Performance Modeling. There is very high interest in this topic from academia and practitioners, and no such textbook currently exists. Three major chapters have been drafted by the main authors (Joshua Stein and Cliff Hansen), but substantial work remains. The original schedule was delayed is due to multiple competing priorities. The publisher, Wiley, has agreed to reassess the schedule at the start of 2016. Both authors are committed to finishing the project.

In addition to carryover activities, the PV Performance Modeling Collaborative has grown into a very active group in the past three years and Sandia believes that it would be unfortunate and unwise to abandon our leadership role in this organization. Annual workshops on PV performance modeling are increasingly popular and influential with the events becoming the main venue for PV performance modelers to communicate and network. Many of the new features being added to the widely used models had their impetus at one of our PVPMC workshops. The most recent workshop held in Cologne, Germany was no exception. New ideas for including spectral mismatch corrections as a function of weather measurements were discussed and the major model developers committed to adding this capability to future releases. Sandia has committed to hold the next workshop in Santa Clara in early May 2016. DOE has agreed to offer some funding to support a limited effort going forward. Sandia plans to provide a new proposal to increase this base funding to fully take advantage of the momentum generated in this group so that technical results get transferred to the commercial models rapidly and developers and financers can benefit from the increases in accuracy as a result.

Finally, Sandia will continue to represent the US and the DOE as part of the IEA PVPS Task 13 working group on PV performance and reliability. This working group will remain active through the middle of 2017 and possibly beyond, if the work is extended.

Sandia's representative, Joshua Stein will continue to attend meetings and even is planning on hosting a meeting in New Mexico in September 2016. DOE has agreed to fund this continuation through the end of FY16.   Sandia will encourage DOE to continue this funding next year to make sure there is continuity till the end of the task.

References:

Andrews, R, et al., Introduction to the Open Source PV LIB for Python Photovoltaic System Modelling Package, Proc. of the 40th IEEE Photovoltaic Specialist Conference, Denver, CO, 2014.

ANSI, American National Standard for Expressing Uncertainty--U.S. Guide to the Expression of Uncertainty in Measurement, 1997, ANSI.

Dirnberger, D. and U. Kraling, Uncertainty in PV Module Measurement; Part I: Calibration of Crystalline and Thin-Film Modules. Photovoltaics, IEEE Journal of, 2013. 3(3): p. 1016-1026.

Dominé, D., et al. Uncertainties of PV Module – Long-term Outdoor Testing. in 25th PVSEC, 2012. Valencia, Spain.

Dunn, L., M. Gostein, and K. Emery. Comparison of Pyranometers vs. PV Reference Cells for Evaluation of PV Array Performance. in 38th IEEE Photovoltaic Specialists Conference, 2012. Austin, TX: IEEE.

Hansen, C., et al. Parameter Uncertainty in the Sandia Array Performance Model for Flat-Plate Crystalline Silicon Modules. in 37th IEEE Photovoltaics Specialists Conference, 2011. Seattle, WA.

Hansen, CW. Et al., Evaluation of Global Horizontal Irradiance to Plane of Array Irradiance Models at Locations across the United States, Proc. of the 40th IEEE Photovoltaic Specialist's Conference, Denver, CO, June 2014

Lave, M, et al., Evaluation of Global Horizontal Irradiance to Plane-of-Array Irradiance Models at Locations Across the United States, Journal of Photovoltaics **5**(2), 597-606, March 2015

Müller, B., et al., Yield predictions for photovoltaic power plants: empirical validation, recent advances and remaining uncertainties. Progress in Photovoltaics: Research and Applications, 2015

Thevenard, D. and S. Pelland, Estimating the uncertainty in long-term photovoltaic yield predictions. Solar Energy, 2013. 91(0): p. 432-445.

Whitfield, K. and C.R. Osterwald, Procedure for determining the uncertainty of photovoltaic module outdoor electrical performance. Progress in Photovoltaics: Research and Applications, 2001. 9(2): p. 87-102.