California Solar Initiative

RD&D: Research, Development, Demonstration and Deployment Program

GO solar CALIFORNIA

Final Project Report:

Integrating PV into Utility Planning and Operation Tools

Grantee:

Clean Power Research

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http://www.calsolarresearch.ca.gov/Funded-Projects/

Preface

The goal of the California Solar Initiative (CSI) Research, Development, Demonstration, and Deployment (RD&D) Program is to foster a sustainable and self-supporting customer-sited solar market. To achieve this, the California Legislature authorized the California Public Utilities Commission (CPUC) to allocate **$50 million** of the CSI budget to an RD&D program. Strategically, the RD&D program seeks to leverage cost-sharing funds from other state, federal and private research entities, and targets activities across these four stages:

- Grid integration, storage, and metering: 50-65%
- Production technologies: 10-25%
- Business development and deployment: 10-20%
- Integration of energy efficiency, demand response, and storage with photovoltaics (PV)

There are seven key principles that guide the CSI RD&D Program:

1. **Improve the economics of solar technologies** by reducing technology costs and increasing system performance;
2. **Focus on issues that directly benefit California**, and that may not be funded by others;
3. **Fill knowledge gaps** to enable successful, wide-scale deployment of solar distributed generation technologies;
4. **Overcome significant barriers** to technology adoption;
5. **Take advantage of California's wealth of data** from past, current, and future installations to fulfill the above;
6. **Provide bridge funding** to help promising solar technologies transition from a pre-commercial state to full commercial viability; and
7. **Support efforts to address the integration of distributed solar power into the grid** in order to maximize its value to California ratepayers.

For more information about the CSI RD&D Program, please visit the program web site at www.calsolarresearch.ca.gov.

Acknowledgements

This project was a success as a result of the contributions of people at a variety of organizations. The California Public Utilities Commission (CPUC), Sacramento Municipal Utility District (SMUD), and Pacific Gas and Electric Company (PG&E) provided support. Smita Gupta (Itron) managed the grant in such a way so as to result in a usable set of products, and Ann Peterson (Itron) provided support. Jim Blatchford (California ISO) and Obadiah Barthomy (SMUD) provided valuable direction and support from the independent system operator and municipal utility perspectives. Mike Taylor (SEPA) was effective at disseminating information. Dr. Richard Perez and his team (SUNY) made valuable SolarAnywhere advancements, including the production of High Resolution (1 km, 1 minute) data. Dr. Jan Kleissl and his team (UC San Diego) assessed the performance of SolarAnywhere. Thanks to all of these individuals and organizations, as well as many others, for their support and assistance.

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Abstract

The California Solar Initiative (CSI) has a goal of installing 3,000 MW of new solar electricity by 2016. CSI has identified that one potential barrier to accomplishing this goal is planning and modeling for high-penetration PV grid integration issues. A team led by Clean Power Research (CPR) received approval from the California Public Utilities (CPUC) for a grant titled, "Integrating PV into Utility Planning and Operation Tools." CPR led the team in the development, validation, and integration of PV fleet simulation tools that enable utilities and ISOs to cost-effectively integrate distributed PV resources into their planning, scheduling and operating strategies.

This project builds upon Clean Power Research's CSI Grant Solicitation #1 award, which was awarded in 2010 and titled, "Advanced Modeling and Verification for High Penetration PV." Two key accomplishments under that award were: production of a publicly-available enhanced resolution solar resource database for every location in California (SolarAnywhere® Enhanced Resolution, 1-km, 30-minute resolution, available at www.SolarAnywhere.com); and development of an advanced methodology to simulate PV fleet power production for any PV fleet configuration (SolarAnywhere FleetView).

This current project accomplishes the following grid-integration tasks:

1. Extend the SolarAnywhere Enhanced Resolution solar resource database, create high resolution (1-km, 1-minute resolution) solar resource data, and benchmark data accuracy.
2. Validate previously developed PV fleet simulation methodologies using measured ground data from fleets of PV systems connected to California's grid.
3. Integrate PV fleet simulation methodologies into utility software tools for use in activities ranging from distribution planning to balancing area operations using CAISO as a test case.

The tools and data streams developed as part of this work will be made available using CPR's existing software services (e.g., www.SolarAnywhere.com) to California utilities, ISOs and others to help cost-effectively and reliably integrate distributed PV into the grid.

Executive Summary

Introduction

The California Solar Initiative (CSI) has a goal of installing 3,000 MW of new solar electricity by 2016. CSI has identified that one potential barrier to accomplishing this goal is planning and modeling for high-penetration PV grid integration issues. A team led by Clean Power Research (CPR) received funding from the California Public Utilities Commission (CPUC) titled, "Integrating PV into Utility Planning and Operation Tools." The team included the California Independent System Operator (CAISO), Sacramento Municipal Utility District (SMUD), Pacific Gas and Electric Company (PG&E), State University of New York (SUNY), Solar Electric Power Association (SEPA), UC San Diego (UCSD), and Electric Power Research Institute (EPRI). CPR led the team in the development, validation, and integration of PV fleet simulation tools that enable utilities and ISOs to cost-effectively integrate distributed PV resources into their planning, scheduling and operating strategies.

Project Objectives

This project builds upon CPR's CSI Grant Solicitation #1 award, which was granted in 2010 and titled, "Advanced Modeling and Verification for High Penetration PV." Two key accomplishments under that award were: production of a publicly-available enhanced resolution solar resource database for every location in California (SolarAnywhere® Enhanced Resolution, 1-km, 30-minute resolution, available at www.SolarAnywhere.com); and development of an advanced methodology to simulate PV fleet power production for any PV fleet configuration (SolarAnywhere FleetView).

This current project accomplishes the following grid-integration tasks:[1]

1. Extend the SolarAnywhere Enhanced Resolution solar resource database, create high resolution (1-km, 1-minute resolution) solar resource data, and benchmark data accuracy.
2. Validate previously developed PV fleet simulation methodologies using measured ground data from fleets of PV systems connected to California's grid.
3. Integrate PV fleet simulation methodologies into utility software tools for use in activities ranging from distribution planning to balancing area operation using CAISO as a test case.

Results

Task 1: SolarAnywhere Data

The first task was to extend the SolarAnywhere Enhanced Resolution solar resource database (1-km, 30-minute resolution), to create high resolution (1-km, 1-minute resolution) data, and to benchmark data accuracy.

[1] The Grant Agreement lists four tasks with Task 1 being "Project Management." This report does not include the Project Management task. As such, all tasks are shifted back by one for this report. For example, Task 2 in the Grant Agreement corresponds to Task 1 in this report.

CPR continued to update the SolarAnywhere Enhanced Resolution data throughout the project. The data is publicly available at www.solaranywhere.com.

The updated SolarAnywhere Enhanced Resolution data was then used as an input to create the SolarAnywhere High Resolution (1-km, 1-minute) solar resource data. This was accomplished by applying the Cloud Motion Vector (CMV) approach developed by Dr. Richard Perez. The CMV approach projects cloud movement by comparing two consecutive enhanced resolution images. The result produces high temporal resolution (1-minute) data that is then used to create the SolarAnywhere High Resolution solar resource data.

It was challenging to produce such state-of-the-art data. It was even more challenging to produce the data at a speed fast enough to make it available for PV fleet forecasting for several hundred thousand individual PV systems every 30 minutes. CPR had to move its code base from running on servers in a local datacenter to a “massively parallel” architecture using Internet “cloud” computing. CPR performed this transition over a multi-month period that included designing, porting, testing, and running the system. The cloud computing approach allows CPR to flexibly and efficiently add additional compute power as the number of PV systems grows or as simulation time horizons are adjusted. By the end of the process, CPR was able to produce solar forecasts that could be used to forecast production for 170,000 PV systems (current number of systems as of the writing of this report) every 30 minutes. The system has been operating well for almost one year.

The accuracy of the SolarAnywhere data was validated in conjunction with a CEC project, titled, “Demonstration and Validation of PV Output Variability Modeling,” Project number CEC 500-10-059 (see Appendix 1). Results indicated that the SolarAnywhere High Resolution data is more accurate than SolarAnywhere Enhanced Resolution data which, in turn, is more accurate than SolarAnywhere Standard Resolution data.

Task 2: Validate PV Fleet Simulation

The second task was to validate PV fleet simulation methodologies using measured ground data from fleets of PV systems connected to California’s grid. This task was accomplished using measured PV production data for fleets of systems from two separate sources. CAISO provided data for large PV plants connected to its system. SMUD provided data for small distributed PV systems connected to its system.

CAISO provided measured fifteen-minute production data for 46 metered PV plants from March 10, 2013 to April 19, 2013. Results suggest that the relative mean absolute error (rMAE) ranged from 3 to 7 percent depending upon the level of model tuning and data filtering. SMUD provided measured hourly production data for 2,206 distributed PV systems from April 16, 2012 to October 10, 2012. SMUD also provided specifications for all of the PV systems. Model tuning was not applied to this data set. Results indicate an accuracy of 6 percent rMAE. The overall conclusion was that SolarAnywhere’s PV fleet simulation capabilities result in fairly accurate results.

Task 3: Integrate PV Fleet Simulation into Utility Software Tools

The third task was to integrate PV fleet simulation methodologies into utility software tools using the results from Tasks 1 and 2.

A fleet of PV systems can be defined very broadly. At one extreme, a fleet can refer to single PV system on the roof of one person's house. At the other extreme, a fleet can refer to all PV systems located within a balancing area across a state or even all PV systems in the U.S. or the world. User-defined collections of systems ("virtual" fleets) based on location, system attributes or other criteria are useful for planning and modeling purposes.

PV fleet simulations can be based on historical, real-time, or forecasted solar resource data. Historical data is useful for system planning. Real-time data is useful for assessing PV fleet operation. Forecasted data is useful for determining how to operate the rest of the utility system.

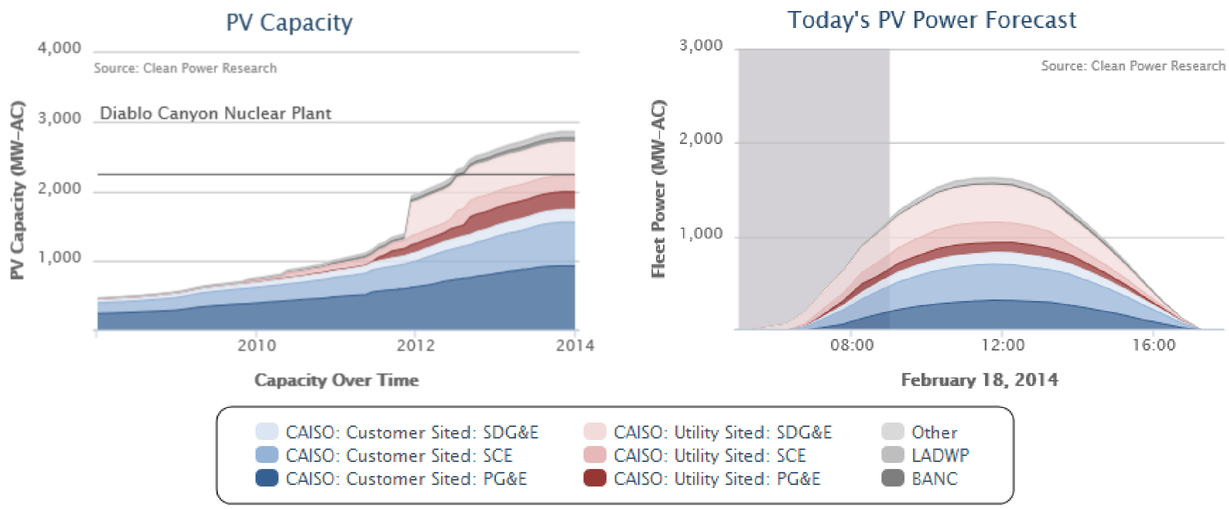
This broad definition of a PV fleet makes the simulation capabilities useful across a wide spectrum of utility applications. These applications range from planning and smart grid operation in the distribution system, utility load scheduling in the utility system, and balancing area planning and operation functions covering multiple utilities.

CAISO is responsible to maintain reliability and accessibility for California's utility grid. As such, they are concerned with the effect of power production from customer-owned PV systems on the balancing area. CAISO clearly understood the performance of the large PV systems through detailed production monitoring. They had no visibility, however, into the performance of the behind-the-meter PV systems. This was a concern to them. They needed to forecast behind-the-meter PV fleet performance.

It was initially planned to demonstrated limited PV fleet simulations across the variety of possible applications. Instead, it was determined that the greatest market need was the most complex application originally anticipated: behind-the-meter PV fleet forecasting for an entire balancing area. Furthermore, it was clear that what was needed was a full-scale application, not a limited scope test. As a result, CPR designed, tested, and implemented a PV fleet forecasting system that included all distributed PV systems in the state of California.

The three critical elements in performing a PV fleet simulation include: high resolution solar resource data, PV system specifications, and a simulation model to convert this information into production. The solar resource data was developed in Task 1. Detailed specifications for all PV systems in California were collected as part of a partner CEC project. The fleet simulation model was validated in Task 2. The result is that CPR began generating high resolution forecasts every 30 minutes for the entire state based on detailed PV system specifications for all behind-the-meter and metered PV systems. At the time of this report, there were 170,000 PV systems. The result is the capability of forecasting PV fleet output for the entire state of California as illustrated in the following figure.

Figure 1. California solar resource portfolio (Feb. 18, 2014).



Key Findings

This project built on the results produced under CSI RD&D Program Solicitation #1 for the CPR proposal entitled "Advanced Modeling and Verification for High Penetration PV." Key conclusions from this work are:

- High resolution solar resource data can be accurately produced.
- This solar resource data can be combined with PV system specifications to accurately simulate PV fleet production.
- The simulation process can be performed quickly enough to support even the challenging application of forecasting production for hundreds of thousands of systems while meeting forecasting time horizon requirements using the appropriate computing resources and underlying system architecture.

Benefits to California Ratepayers

This project has provided a number of benefits to the state of California.

Solar Resource Data

The first task was to extend SolarAnywhere. SolarAnywhere Enhanced Resolution provides 1 km spatial resolution with half-hour temporal resolution irradiance data. It is beneficial in that it is comprehensive for all of California and is freely available at www.SolarAnywhere.com. California project developers are also leveraging the increased Enhanced Resolution data accuracy to obtain lower financing rates because of reduced project risk; this lowers the cost of solar and increases the penetration of PV in the state. SolarAnywhere High Resolution extends the Enhanced Resolution to one-minute temporal resolution. The High Resolution data is used in PV penetration and variability studies.

PV Fleet Simulation Validation

The second task was to validate PV fleet simulation methodologies using measured ground data from fleets of PV systems connected to California's grid. It is critical to the utilities and balancing area authorities responsible to run the grid that they validate models using real-world data. The validation provides public benefits because grid operators need to gain confidence in the models intended to inform grid operation prior to their use.

PV Fleet Simulation Integration into Utility Software Tools

The third task was to integrate PV fleet simulation methodologies into utility software tools. CAISO has the responsibility of maintaining reliability and accessibility for California's utility grid. As such, they are concerned with the effect of power production from customer-owned PV systems on the balancing area. Prior to this contract, CAISO did not have visibility into the performance of behind-the-meter PV systems. CPR has been providing behind-the-meter PV fleet forecasts every 30 minutes to CAISO for one year. This is beneficial to California in that CAISO has visibility into behind-the-meter PV performance when none existed prior to this grant. It has the additional benefit of being a valuable case study for California's IOUs as they consider using the same approach for their needs.

1. Introduction

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CPR assembled a team that included the California Independent System Operator (CAISO), Sacramento Municipal Utility District (SMUD), Pacific Gas and Electric Company (PG&E), State University of New York (SUNY), Solar Electric Power Association (SEPA), UC San Diego (UCSD), and Electric Power Research Institute (EPRI). CPR led the team in the development, validation, and integration of PV fleet simulation tools that enable utilities and ISOs to cost-effectively integrate distributed PV resources into their planning, scheduling and operating strategies.

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This current project will accomplish the following grid-integration tasks:

1. Extend the SolarAnywhere Enhanced Resolution solar resource database to create high resolution (1-km, 1-minute resolution) data and benchmark data accuracy.
2. Validate previously developed PV fleet simulation methodologies using measured ground data from fleets of PV systems connected to California's grid.
3. Integrate PV fleet simulation methodologies into utility software tools for use in activities ranging from distribution planning to balancing area operation using CAISO as a test case.

The tools and data streams developed as part of this work will be made available to California utilities, ISOs and others to help cost-effectively and reliably integrate distributed PV into the grid.

2. Task 1: SolarAnywhere Data

The first task was to extend the SolarAnywhere Enhanced Resolution solar resource database, to create high resolution (1-km, 1-minute resolution) data, and to benchmark data accuracy.

2.1. Introduction

SolarAnywhere is a subscription-based, online satellite-based irradiance dataset (www.SolarAnywhere.com) currently available from Mexico to Canada. Prior to CPR's CSI Phase 1 grant, it contained hourly irradiance data at a 10-km by 10-km spatial resolution and 1-hour temporal resolution dating back from 1998. The functionality of SolarAnywhere was extended in three ways under CPR's CSI Phase 1 grant: (1) finer spatial resolution (1-km by 1-km grid); (2) finer temporal resolution (30-minute interval); and (3) freely available to users throughout California for the term of the project. The resulting product was referred to as SolarAnywhere Enhanced Resolution.

The objective of this task was to continue to provide SolarAnywhere Enhanced Resolution data for the duration of this contract, to extend the data to include SolarAnywhere High Resolution data (1-km by 1-km grid, 1-minute interval), and to benchmark data accuracy.

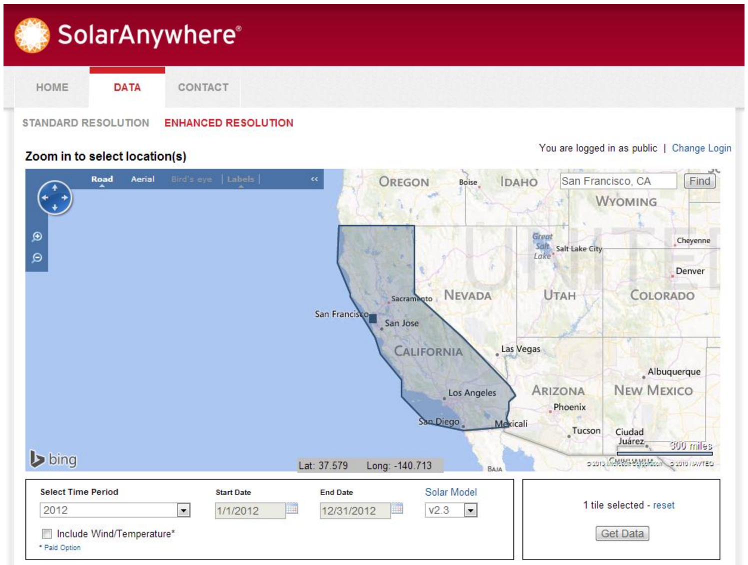
2.2. SolarAnywhere Enhanced Resolution

Production of the SolarAnywhere Enhanced Resolution data (1-km spatial resolution, 30-minute temporal resolution) began under CPR's CSI Phase 1 contract. Production was continued in order to keep it up-to-date and accessible.

The data has been used in multiple ways:

- The data is publicly available through the www.solaranywhere.com website (see Figure 2).
- High Resolution data uses Enhanced Resolution data as a core input.
- The data was used in some of the other tasks for this current project as they relate to tools and reports.
- Others have used the data for CPUC studies. For example, CPUC's subcontractor E3 used the data to perform a detailed net metering analysis for the California IOUs. CPR provided E3 with half-hour solar irradiance data for every PV system in the state of California for their analysis.

Figure 2. SolarAnywhere public data access.



Several activities were associated with continued production of the data. First, there was the daily activity of ensuring that the system operated correctly; operational issues were addressed immediately when they occurred. Second, there was the monthly activity of ensuring that end-of-month processing operated correctly. Third, there was the activity of speeding up data processing. In particular, end-of-month processing required a two-day process at the beginning of this project. This caused significant server performance problems and made it slow for any users to access the data. End-of-month server performance issues were eliminated as part of this project.

2.3. SolarAnywhere High Resolution

SolarAnywhere Enhanced Resolution data has a 1-km spatial resolution and 30-minute temporal resolution. Utility applications, however, require higher temporal resolution data. This project launched the first application of SolarAnywhere High Resolution data. This data set has 1-km spatial resolution and 1-minute temporal resolution. This data needed to be available on demand to generate the PV time series data for use in the validation and PV fleet forecasting described in the subsequent sections.

Two issues were addressed as part of this subtask. The first issue was to produce the high resolution data. The second issue was to produce the data at a speed fast enough to make it available for PV fleet forecasting for several hundred thousand individual PV systems every 30 minutes.

The first issue was to produce the data. The data is created using the enhanced resolution data as input and then applying a specially-designed Cloud Motion Vector (CMV) approach. Two consecutive enhanced resolution images are compared and the CMV approach is used to project the movement of the clouds based on a comparison of the two images. This produces a series of new enhanced resolution images. The 1-minute temporal resolution data was obtained from these images. This approach has been under development by Dr. Richard Perez for several years. It was further refined as part of this project.

The second issue was to produce the data quickly. While it was challenging to produce the 1-km, 1-minute data for the entire state of California, it was an even greater challenge to produce the data fast enough to work for forecasting behind-the-meter PV production for the entire state. In particular, new data needed to be produced for every location in California every half hour in order to update the forecast. This was an issue that had not been addressed in any previous projects.

The challenge of rapidly producing such a large volume of data required CPR to reevaluate how the solar resource data was produced. CPR ultimately decided to move its entire code base from running on servers in a local datacenter to a massively parallel architecture using Internet "cloud" computing. This enabled CPR to match the need for computing resources to the available supply without continually purchasing (and thus maintaining) new servers.

CPR performed this transition over a multi-month period. This included designing, porting, testing, and running the system. By the end of the process, CPR was able to produce solar forecasts that could be used to simulate the 10-day forecast of the output from 170,000 PV systems with 30-minute observations in less than 30 minutes. The system has been operating well for almost a year.

2.4. SolarAnywhere Validation

The final subtask was to validate the accuracy of the SolarAnywhere data. This subtask was performed in conjunction with a CEC project, titled, "Demonstration and Validation of PV Output Variability Modeling," Project number CEC 500-10-059. This CEC report is attached as Appendix 1.

2.4.1. Definitions

It is important to clearly define what is meant by accuracy before discussing solar resource data accuracy. Accuracy validation often means different things to different people. As such, it is useful to begin with a definition of how accuracy quantification can be performed.

Three fundamental questions need to be answered to provide a clear definition of how accuracy quantification is performed.

1. What is the data source?
2. What are the time attributes?

2.4.2. Data Source

The first step is to identify the data that is being evaluated. Options include irradiance data or simulated PV power production using irradiance data and other parameters. In addition, the analysis can be performed for individual locations or fleets (i.e., multiple locations). In this section, the focus is on irradiance.

2.4.3. Time Attributes

The second step is to specify the required time attributes. These include:

- **Time period**: total amount of data included in the analysis. This can range from a few minutes to many years.
- **Time interval**: how the data in the time period is binned. This can range from a few seconds to annually. For example, if the time period is one year and the time interval is one hour, the time period would be binned into 8,760 time increments.
- **Time perspective**: when the predicted observation is reported. This can range from historical (backward looking) to forecasted a few hours ahead to forecasted multiple days ahead (forward looking).

2.4.4. Evaluation Metric

The third step is to select the evaluation metric. Error quantification metrics used in assessing absolute irradiance model accuracy such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) have been precisely defined. Their relative counterpart (results expressed in percent), however, can be subject to interpretation and may cover a wide range of values for a given set of data depending on reporting practice.

MAE relative to available energy (rMAE) is a good method to measure relative dispersion error. This is the method used in the present analysis. The MAE relative to the average energy available is calculated by summing the absolute error for each time interval over the time period, and then dividing by the total available energy.

$$Relative\ Mean\ Abosolute\ Error = \frac{\sum_{t=1}^{N} \left| I_t^{test} - I_t^{ref} \right|}{\sum_{t=1}^{N} I_t^{ref}} \qquad (1)$$

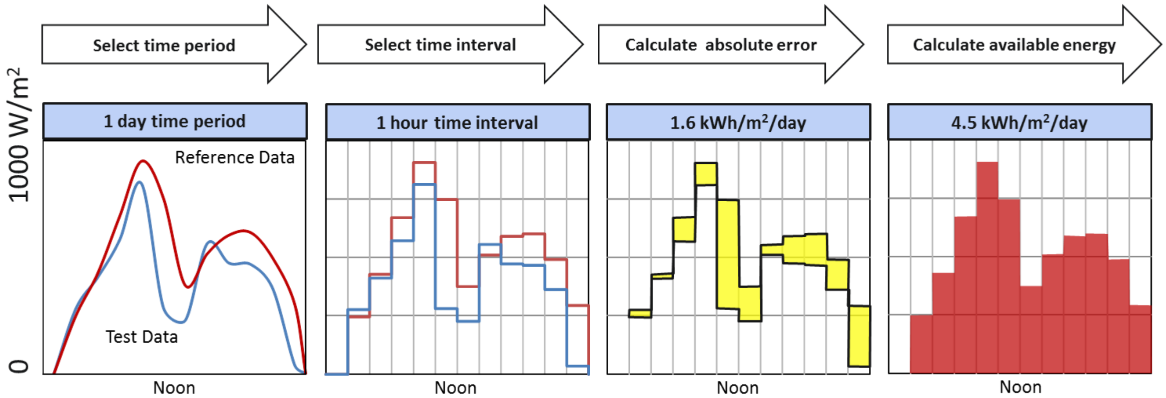
where I_t^{test} is the test irradiance at time t, I_t^{ref} is the reference irradiance at time t, and N is the number of time intervals.

It is useful to provide a hypothetical example of how to calculate the rMAE. A short time period (one day) is selected in order to graphically illustrate the calculations; the actual calculations in this paper use a one year time period.

As presented in Figure 3, the process is follows:

- Select time period: 1 day.
- Select time interval: 1 hour.
- Calculate absolute error for each hour and sum the result as described in the top part of Equation (1): 1.6 kWh/m^2/day.
- Calculate available energy for each hour from reference data and sum the result as described in the bottom part of Equation (1): 4.5 kWh/m^2/day.
- Calculate Relative Mean Absolute Error: 36% (i.e., 1.6/4.5).

Figure 3. Mean absolute error relative to available energy calculation example.



It is important to note that a more often reported measurement of error is MAE relative to generating capacity. In the above example, however, it is unclear over what time period the generating capacity should be selected. Should it be capacity during daylight hours or capacity over the entire day, including night time hours? MAE relative to daytime capacity is about 13.3% (i.e., 1.6/12) while Mean Absolute Error relative to full day capacity is about 6.6% (i.e., 1.6/24).

It is due to this sort of ambiguity, as well as the fact that MAE relative to energy is a much more stringent metric (e.g., in this example, MAE relative to energy is 6 times higher than MAE relative to daily generation capacity), that the MAE relative to energy (rMAE) is selected as the evaluation metric.

2.4.5. Locations Selected for Validation

This metric can be used to quantify irradiance data accuracy for a one-year time period (2011) with time intervals ranging from one-minute to one-year using a historical time perspective. The analysis was performed for both individual locations and the ensemble of those locations.

Ten of the 46 metered locations were randomly selected for validation purposes. In order to perform the detailed analysis, each location had to have two global horizontal insolation (GHI) monitoring devices available on site and have one year’s (2011) worth of data available. There were six locations that passed this initial screening.

A total of six test locations were analyzed where PV systems are located within the CAISO control area. The locations are identified as locations A through F. Each location is equipped with two redundant global horizontal irradiance (GHI) sensors. One of the sensors was used as a reference and compared to four test configurations: the second ground sensor, and three satellite-derived sources (SolarAnywhere Standard, Enhanced, and High Resolution data sets).

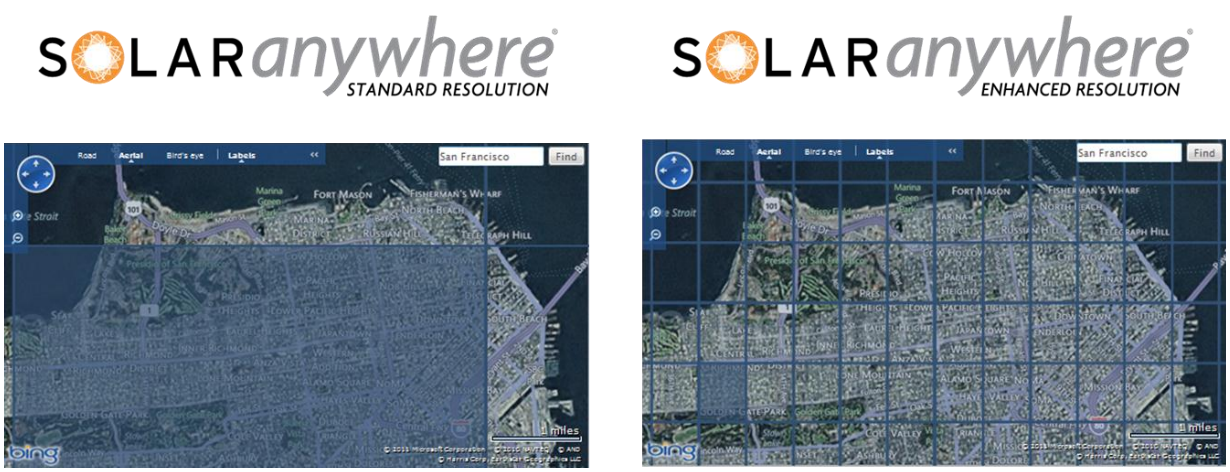
The validation approach involved the following steps:

- Obtain time-series GHI data for 2011 for six locations:
    - 4-second data averaged into 1-minute time intervals from two separate sensors at each location.
    - Satellite based data at the following SolarAnywhere resolutions:
        - 1 minute, 1 km grid (High Resolution).
        - ½ hour, 1 km grid (Enhanced Resolution).
        - 1 hour, 10 km grid (Standard Resolution)
- Time-synchronize data sets by converting ground sensor data from Pacific Daylight Time to Pacific Standard Time.
- Evaluate all observations for data quality; exclude data where any one of the data sources has data quality issues.
- Calculate rMAE using the ground sensor that minimizes SolarAnywhere error as a reference.
- Calculate rMAE using the other ground sensor as a reference.
- Repeat the analysis for fleets of locations.

2.4.6. Obtain Time Series Data

CPR extended SolarAnywhere Standard Resolution (10 km spatial/1 hour temporal resolution) to SolarAnywhere Enhanced Resolution (1 km spatial/ 30 minute temporal resolution) under a previous contract.[2] Figure 4 illustrates the increase in resolution for San Francisco, CA.

Figure 4. SolarAnywhere Standard and Enhanced Resolution



(San Francisco, CA)

A critical part of project was to extend SolarAnywhere Enhanced Resolution to SolarAnywhere High Resolution (1 km spatial/ 1 minute temporal resolution). The data was generated for all selected locations. Figure 5 presents a sample of the data for one day (July 4, 2011) at one location (CAISO Site A).

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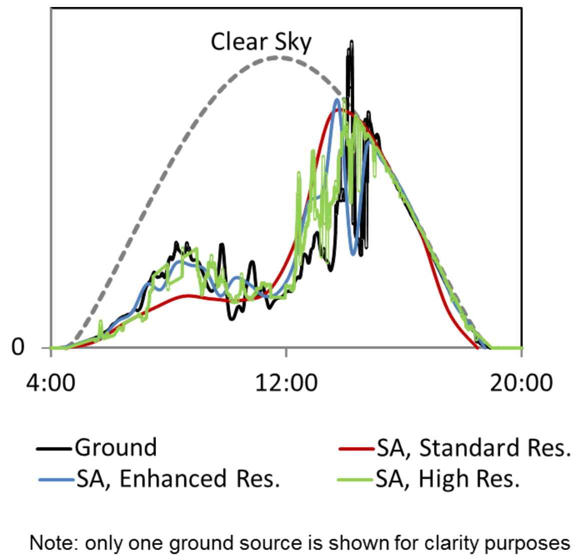
[2] California Solar Initiative Solicitation #1 Grant Agreement, "Advanced Modeling and Verification for High Penetration PV".

Figure 5. Time series data for all data sources on July 4, 2011 at CAISO Site A.



2.4.7. Evaluate All Observations for Data Quality

As mentioned above, one of the steps in the analysis was to evaluate all observations for data quality. When evaluating accuracy, it is often simply assumed that reference data is correct. This assumption is made due to the difficulty in determining whether or not the reference data is correct: to what can the reference data be compared?

A unique aspect of the data provided by the CAISO is that all the locations have two ground sensors. As a result, since either sensor could be the reference, the data quality of the ground sensors was assessed by comparing the two ground data sets.

This was the process used to assess data quality:

(1) Compare the two sets of ground sensor data to each other to determine when one value is substantially different than the other value.
(2) Compare the enhanced resolution satellite and ground sensor data to search for 0 values occurring at incorrect times (e.g., mid-day on otherwise clear day) to determine when the satellite data is invalid.
(3) Compare ground sensor data to the SolarAnywhere Enhanced Res. data to determine if both ground observations are the same but are obviously incorrect (e.g., the irradiance value remains at a constant level for many hours).

The complete data set was evaluated and then potential outliers were manually evaluated and screened for each of these steps. Figure 6 illustrates the screening result when comparing the two ground sensors at one location. All of the data points would lie on the 45 degree red line if they were identical. The blue symbols correspond to valid data and the black symbols correspond to invalid data. Figure 7 illustrates the issue for one of the invalid observations when one of the sensor's recorded values remained constant after solar noon. Figure 8 illustrates the case when both ground sensors produced a similar value but were obviously incorrect, reading a constant low value on an otherwise clear day as assessed from the satellite data. Figure 9 illustrates the case when there was a night-time calibration error across the year. Site E was missing more than a month of data during the first part of the year as well as a five percent difference between the two ground sensors.

Sites E and F were eliminated from the analysis as a result of the data filtering process. The remaining sites had about one percent of the ground data marked as invalid.

Figure 6. Half-hour energy production in 2011 from meter 2 vs. meter 1 (Site A).

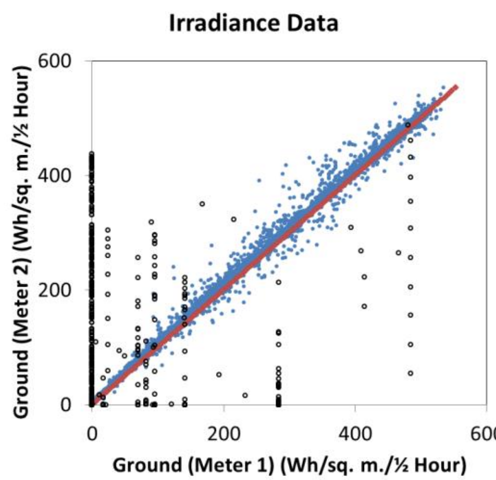
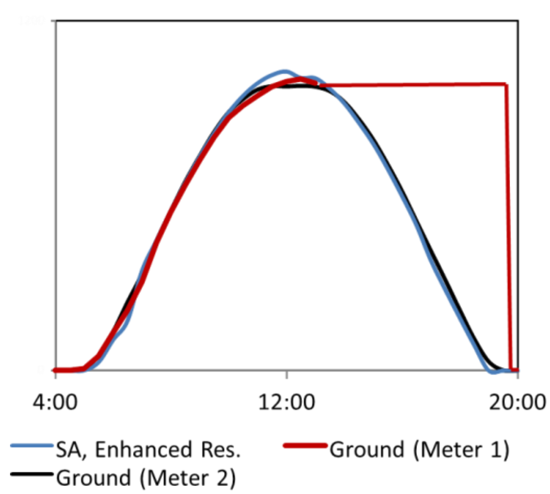
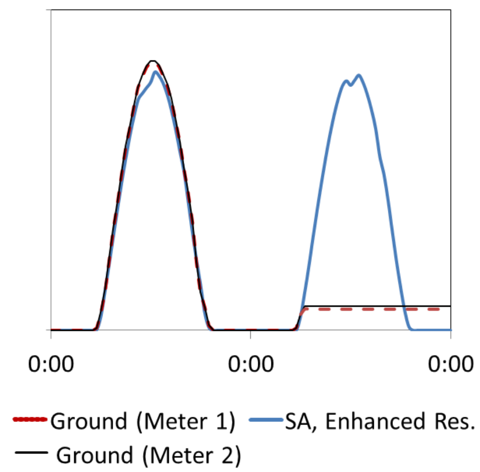


Figure 7. Example of when only one of the ground sensors has invalid data.



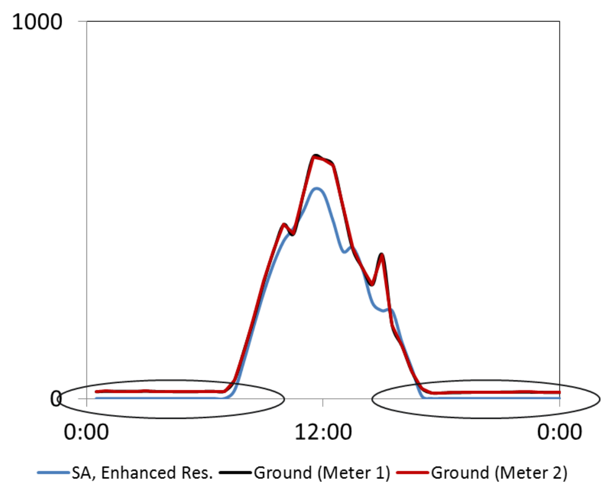
(Site A, June 22, 2011)

Figure 8. Example of when both ground sensors have invalid data.



(Site C, May 1-2, 2011)

Figure 9. Site F has a night-time calibration error across the year.



2.4.8. Results

rMAE was calculated for three scenarios:

- Each location individually.
- Average of individual locations.
- Fleet of locations.

Figure 10 presents the rMAE for each of the four locations using time intervals ranging from 1 minute to 1 year.

Figure 10. Relative MAE for each location individually.

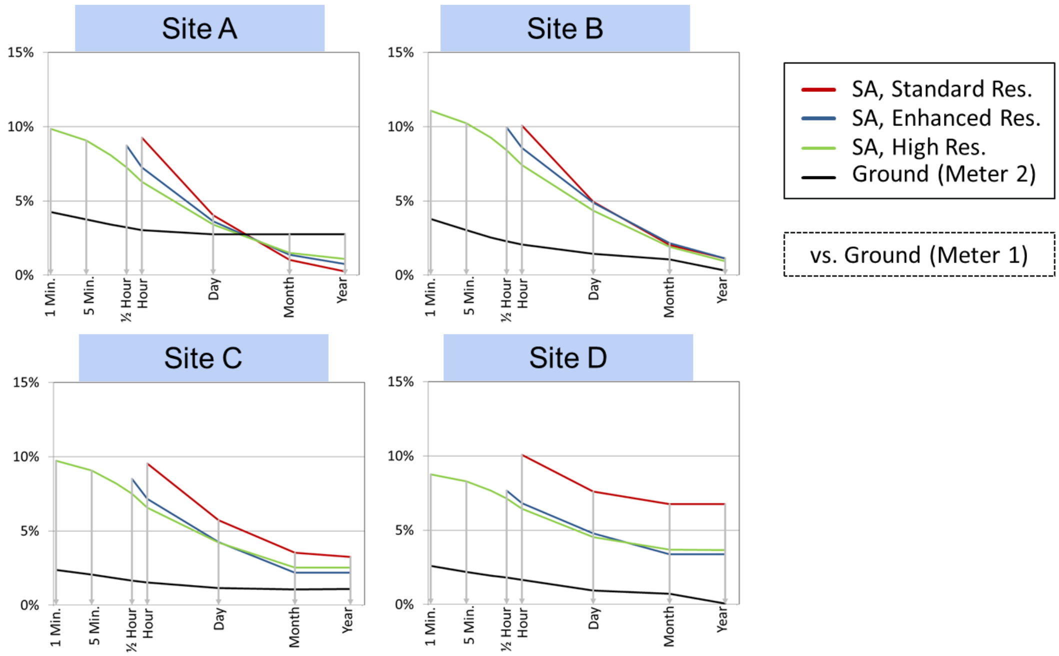
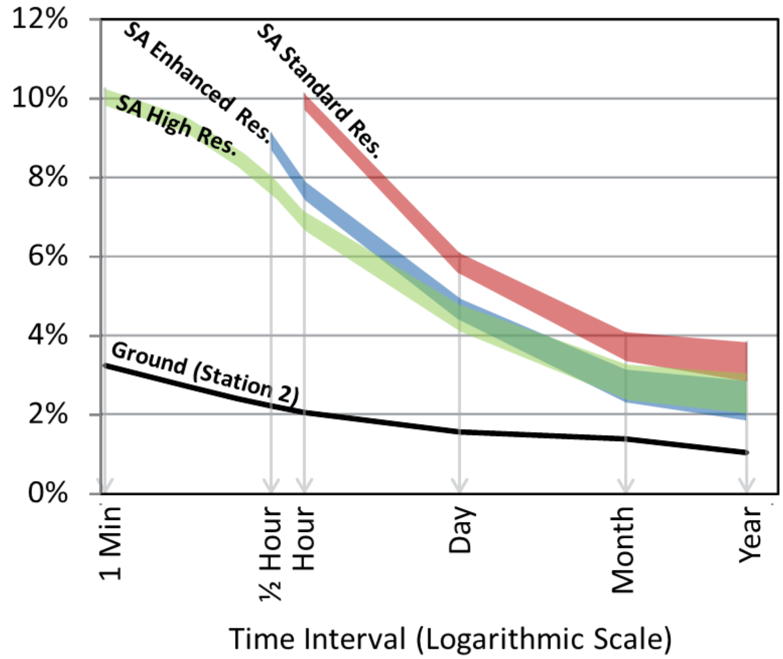


Figure 11 presents the average rMAE of four individual locations. The black line summarizes the error when two ground stations were used (one was the reference and the other was the test). The green, blue, and red regions summarize the error when SolarAnywhere High, Standard, and Enhanced Resolution were compared to the ground sensor. The green, blue, and red areas are regions rather than lines because they compare satellite data to ground data using the two different ground sensors: the top of the region is the comparison using the ground sensor that maximizes error; the bottom of the region is the comparison using the ground sensor that minimizes error.

There are several important things to notice in the figure. First, as expected, error decreases for all data sources as the time interval increases. Second, accuracy improves for each of the three satellite models as the spatial and temporal resolutions are increased. Third, error exists even between two ground sensors that are in almost the same location (i.e., ground sensors have 1 percent annual error). Fourth, SolarAnywhere High Resolution has only 10 percent error over a one minute time interval, 7 percent error over a one hour time interval, and 2 to 3 percent error on a one year time interval.

Figure 11. Average MAE of 4 individual locations.

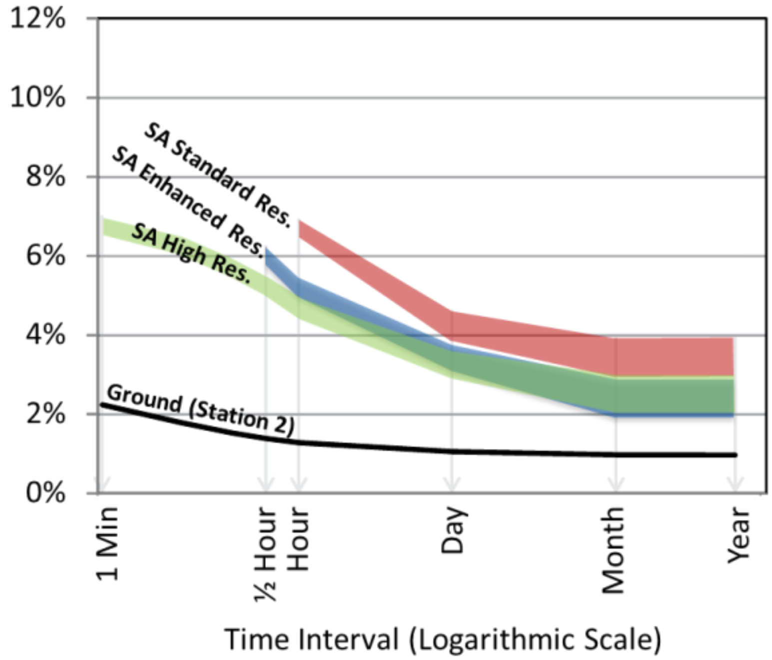


A consistent finding of many PV variability studies is that variability is reduced when PV systems are geographically dispersed. That is, variability is reduced as the number of systems increases across a sufficiently large geographic region.

So far, this section has focused on the error associated with individual locations. While individual locations are of interest in some cases, there are certainly many other cases in the utility industry when users are most interested in the error associated with a set of locations.

The rMAE analysis was repeated with the input data being the combined irradiance across four locations. The results are presented in Figure 12. A clear reduction in error due to combining locations can be seen by comparing Figure 12 to Figure 11. That is, the effect of geographic dispersion on reducing output variability reduction that has been observed by others is now also observed with regard to prediction accuracy: accuracy improves as a geographically diverse set of independent locations are combined.

Figure 12. MAE of 4 locations combined.



2.5. Conclusions

This task provided SolarAnywhere data and benchmarked data accuracy. The SolarAnywhere data included both Enhanced Resolution and High Resolution data. Enhanced Resolution is 1 km spatial resolution and half-hour temporal resolution while High Resolution is 1 km spatial resolution and 1 minute temporal resolution. Both versions were successfully developed and delivered over the term of the grant. Benchmarking results indicated that High Resolution data had about 7 percent rMAE on an hourly basis for a single location. Similar results were obtained for data provided for SMUD's extensive solar resource monitoring network.[3]

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[3] "Solar Monitoring, Forecasting, and Variability Assessment at SMUD." Presented at WREF 2012 (SOLAR 2012). Denver, CO, May 2012. Paper available at. http://www.cleanpower.com/wp-content/uploads/SMUD-Solar-Assessment_2012.pdf.

3. Task 2: Validate PV Fleet Simulation

3.1. Introduction

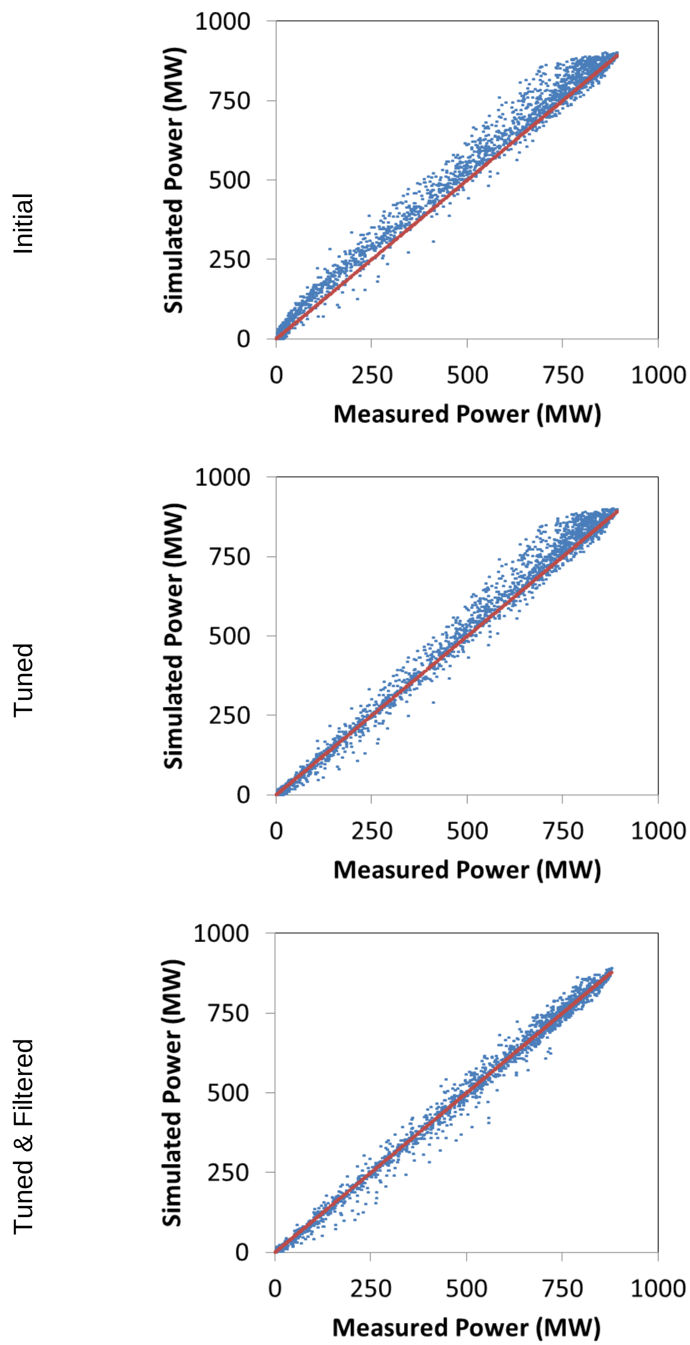
The second task was to validate PV fleet simulation methodologies using measured ground data from fleets of PV systems connected to California's grid. This task was accomplished using measured PV production data from two separate sources.

One set of data was provided by CAISO for large PV plants connected to its system. The other set of data was provided by SMUD for small distributed PV systems connected to its system. Analysis of the CAISO data was performed in conjunction with a CEC project, titled, "Demonstration and Validation of PV Output Variability Modeling," Project number CEC 500-10-059. This report is attached as Appendix 1. Analysis of the SMUD data was documented in a separate report. It is attached as Appendix 2. This section highlights results from those two reports. Additional details are presented in the appendices.

3.2. Results for Large PV Systems Connected to CAISO

CAISO provide fifteen-minute measured production data for 46 metered PV plants from March 10, 2013 to April 19, 2013. The measured data were used to infer system specifications including rating, azimuth angle, and tilt. These system specifications were then used to simulate production. Figure 13 presents simulated vs. measured 15-minute average PV fleet power for each interval. All of the blue markers would be on the red line if simulated and measured results matched perfectly. The top of the figure corresponds to the "Initial" case of PV fleet production without PV performance filtering for plant performance problems (it corresponds to Figure 20 in the CEC report). A consistent power-related bias can be observed. This bias can be reduced by applying an inverter model tuning curve. The "Tuned" case is presented in the center of Figure 13. Significant scatter, however, can still be observed. This can be reduced by filtering the data for PV performance using the filtering from the previous section. The "Tuned & Filtered" case is presented in the bottom of Figure 13. There is a good alignment between simulated and measured data after making the tuning and filtering adjustments. Results show that the Initial, Tuned, and Tuned & Filtered cases have 7.2, 5.2, and 3.1 percent rMAE, respectively.

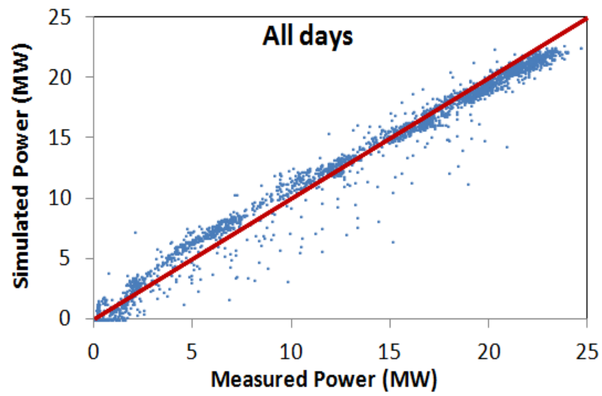
Figure 13. Simulated vs. measured average 15-minute power for CAISO metered PV fleet.



3.3. Results for Small Distributed PV Connected to SMUD

SMUD provided measured hourly production data for 2,206 distributed PV systems from April 16, 2012 to October 10, 2012. SMUD also provided specifications for all of the PV systems. PV production was then simulated using the system specification data combined with SolarAnywhere data. Figure 14 presents simulated versus measured hourly energy production for the fleet of 2,206 distributed PV systems from April 16, 2012 to October 10, 2012. Results indicate an accuracy of 6.2 percent Mean Absolute Error relative to energy (rMAE). These results demonstrate that accurate simulations of a large fleet of PV systems are obtainable. As was the case at CAISO, it is also likely that additional accuracy will be realized by improving the PV inverter model (e.g., see the CAISO results after tuning presented above). Note that this tuning is not applied for SMUD.

Figure 14. Simulated vs. measured hourly energy production for 2,206 distributed PV systems from April 16, 2012 to October 10, 2012.



3.4. Conclusions

Understanding the accuracy at which one can simulate fleet wide PV system energy production is a critical step towards facilitating increased PV penetration into California's electricity system. Factors such as irradiance, shading, soiling, and system configuration greatly influence the performance of an installed PV system. Proper characterization of these factors is important to the simulation of PV system energy.

Several conclusions can be drawn from these results. First, SolarAnywhere's PV fleet simulation capabilities result in fairly accurate results, especially for fleets of PV systems. Results for the large metered PV plants connected to CAISO suggest that total rMAE was 7 percent for 15-minute time interval data. This result can be reduced to about 3 percent by tuning the model and incorporating plant operating status in the simulation. Results for the small distributed systems at SMUD demonstrated an accuracy of 6 percent rMAE when all systems and all days were included. The error was reduced to 5 percent rMAE for a subset of well-behaved PV systems. Results further improved to 4 percent, when partly cloudy day conditions were removed

Second, there is room for improvement in the underlying PV simulation methodologies by further inspection of simulated and measured data at the hourly and sub-hourly levels. Additional work can be done to develop a more accurate inverter model and to understand better application of PV modeling derate factors. Better data tuning and measured data cleaning methods would help identify and rectify faulty PV system specifications and help improve simulations.

4. Task 3: Integrate PV Fleet Simulation Into Utility Software Tools

4.1. Introduction

Task 1 was to create a high resolution (1-km, 1-minute resolution) solar resource database. Task 2 was to validate PV fleet simulation methodologies. Task 3 was to use the results from Tasks 1 and 2 to integrate PV fleet simulation methodologies into utility software tools.

A fleet of PV systems can be defined very broadly. At one extreme, a fleet can refer to single PV system on the roof of one person's house. That is, it is a fleet of one. At the other extreme, a fleet can refer to all PV systems located within the balancing area of a major authority such as the California ISO (CAISO). A fleet could even be defined more broadly and refer to all PV systems in the U.S. or even the world. User-defined collections of systems ("virtual" fleets) based on location, system attributes or other criteria are useful for planning and modeling purposes.

The PV fleet simulation can be based on historical, real-time, or forecasted solar resource data. Historical data is useful for system planning. Real-time data is useful for assessing PV fleet operation. Forecasted data is useful for determining how to operate the rest of the utility system.

4.2. Original Plan

This broad definition of a PV fleet makes the simulation capabilities useful across a wide spectrum of utility applications. These applications range from planning and smart grid operation in the distribution system, utility load scheduling in the utility system, and balancing area planning and operation functions covering multiple utilities.

The original project plan was to demonstrate PV fleet simulation capabilities across the range of applications. The approach was to have short-duration, limited scope demonstrations of how fleet simulation could be used. The simplest planned application was to simulate the historical production of a small PV fleet on a single distribution feeder. The most complex planned application was to forecast the output of all PV systems in California and supply this information to the CAISO.

4.3. Revised Plan

Simulating the historical PV fleet production for CAISO was one of the first applications that CPR began to work on. CAISO has the responsibility of maintaining reliability and accessibility for California's utility grid. As such, they are concerned with the effect of power production from customer-owned PV systems on the balancing area.

CPR's interaction with CAISO revealed that, while CAISO clearly understood the performance of the approximately 50 large PV systems through detailed production monitoring, they had no visibility into the performance of the hundreds of thousands behind-the-meter PV systems. This was concerning to them. They needed to begin to develop a forecast for the fleet of behind-the-meter PV systems. That is, the greatest market need was the most complex application that CPR had originally anticipated. Furthermore, this was needed on a full-scale, not a limited scope.

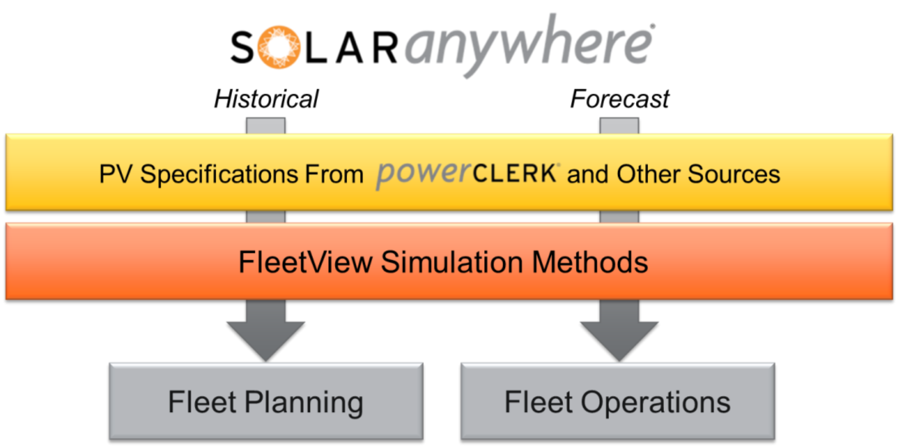
It became clear that even beginning to address CAISO's issue would require significant resources. It was determined that, rather than demonstrating PV fleet simulation for a wide range of applications with a limited scope, it would be more beneficial to begin the implementation of PV fleet forecasting for the most complex application: balancing area-wide, behind-the-meter PV fleet forecasting. PV fleet forecasting could then be applied to all other applications if it could be demonstrated for the CAISO balancing area.

CPR embarked on the task of designing, testing, implementing, and operating the PV fleet forecasting system for the entire state of California.

4.4. PV Fleet Simulation

Figure 15 illustrates that there are three critical elements in performing a PV fleet simulation: solar resource data (listed as SolarAnywhere in the figure), PV system specifications, and a simulation model to convert this information into production.

Figure 15. PV fleet simulation procedure.



4.5. Solar Resource Data

The first component required is the solar resource data. This data set was discussed above. Task 1 produced a SolarAnywhere High Resolution data for the entire state of California. This 1-minute data set is produced every half hour and covers the subsequent 60 minutes at which point the time interval shifts to 30 or 60 minutes, depending upon time frame. As discussed above, this step required significant effort to move CPR's processes to the Internet "cloud" in order to generate the data in an acceptable timeframe.

4.6. PV System Specifications

The second component required is the list of specifications for every PV system. At a minimum, this includes PV system rating, azimuth, tilt orientation, and fixed vs. tracking mode. This task was completed in conjunction with a CEC project. Together, these two projects obtained specifications for all PV systems in California that had received an incentive to get installed. Many of the PV systems for California are included in CPR's PowerClerk® database. As of the writing of this report, there are a total of more than 170,000 PV systems, with the number of systems continuing to grow each month.

4.7. PV Simulation Model

The third component required is a model that combines solar resource data with PV system specifications to simulate PV production. The simulation model needs to be capable of performing the simulation for each PV system individually and then combining the results for all systems into the PV fleet output. It needs to be able to perform the calculations rapidly, ideally in a parallel (concurrent) fashion.

4.8. Challenges

Three challenges were encountered in accomplishing this task. The first challenge was to obtain the data. This included both the solar resource data and PV system specification data for all systems in California. The second challenge was to perform the simulation quickly. The third challenge was to keep the data updated.

4.9. Obtain Data

The first challenge was to obtain the data. This included both the solar resource data and PV system specification data for all systems in California.

The production of the solar resource data was described above. The result was that data was available in a 1-km grid for the entire state of California.

The initial scope of the project was to simulate behind-the-meter PV production for a sample of PV systems in California. The scope was to simulate historical half-hour PV fleet output from 2008 to 2011.

It became clear early on in the project that CAISO needed visibility into all PV systems in California. Thus, the decision was made to provide comprehensive simulation for all behind-the-meter PV systems in California.

4.10. Behind-the-meter PV System Specifications

The task of collecting the specifications for all PV systems was performed in conjunction with a CEC-sponsored project. The details of the data collection are described in the Appendix. As described in the Appendix, covered programs included:

- Renewable Portfolio Standard systems
- Publicly owned utility Senate Bill-1 programs
- CEC's Emerging Renewables Program
- New Solar Homes Partnership
- Single Family Affordable Solar Homes
- Self-Generation Incentive Program
- California Solar Initiative

In addition to collecting data for all behind-the-meter systems, CPR needed to obtain specifications for PV systems connected to CAISO. CAISO provided high speed historical data for all of these systems. The specifications, however, were not available. CPR developed an approach to infer specifications from PV system performance data.[4]

4.11. Perform Simulation Quickly

The second challenge was to perform the simulation quickly. CPR originally planned to provide CAISO with simulated PV fleet production to use for planning purposes. As mentioned above, the decision was made to focus efforts on providing forecasts for all behind-the-meter PV system to CAISO. As a result, CPR needed to simulate production for hundreds of thousands of individual PV systems that could then be combined and delivered as fleets to CAISO. This needed to be done every half-hour.

CPR's forecasting system was not designed to accommodate high volume simulation requirements with short delivery schedules. As a result, this requirement presented CPR with a significant challenge. CPR's system was re-architected and redeployed to an Internet "cloud"-based platform. This allowed CPR to satisfy CAISO's technical requirements of high volume simulations delivered in short time-frames.

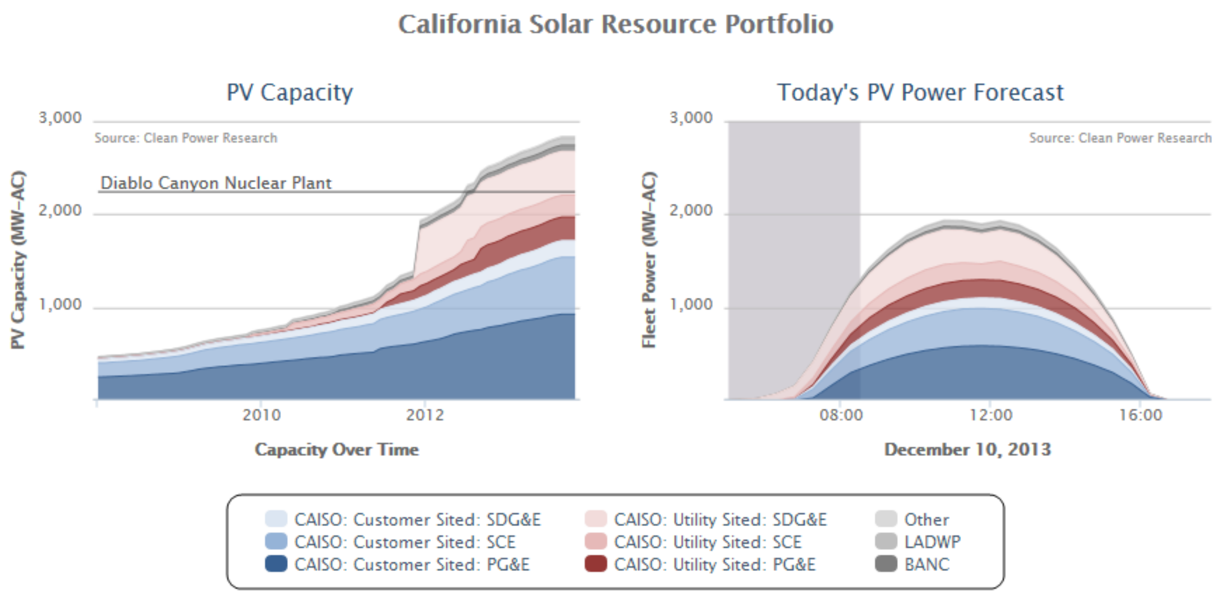
4.12. Keep Data Up-to-Date

The third challenge was to keep the data updated. The number of PV systems is growing rapidly in California. There were 70,000 PV systems in the state as of the end of 2011 (near the start of this project). There were more than 170,000 PV systems near the end of 2013 (as of the writing of this report). This means that the number of systems grew at a rate of faster than 50 percent per year. The number of systems has more than doubled in two years. There will be more than a million behind-the-meter PV systems before 2020 if the market continues to grow at this rate. The capacity of these systems and the associated PV fleet forecast is presented in Figure 7. The data is presented according to the five regions defined by CAISO with the blue regions corresponding to behind-the-meter data and the red to the directly connected systems.

To date, the maintenance of this information has been sustainable because most PV systems have received an incentive. More specifically, the PV system specification information has been collected in the process of receiving an incentive. This will change in places where incentives no longer drive the behind-the-meter market. This is one of the reasons CPR is extending PowerClerk to manage interconnection processes; in an incentive-less world, the system will provide a reliable, user- and utility-friendly online system to collect accurate, thorough system specification data in a format relevant not only to interconnection optimization but also for downstream purposes including planning and operations.

[4] Patent approved for "Computer-implemented system and method for inferring operational specifications of a photovoltaic power generation system."

Figure 16. California solar resource portfolio (Dec. 10, 2013).



4.13. PV Fleet Simulation Validation (CAISO Data)

PV fleet simulation results were validated using two sets of measured PV production data. The first set of data was provided by CAISO. The second set of data was provided by SMUD. Consider, first, results based on data provided by CAISO.

The CAISO measures power production every four seconds for 46 PV plants. A 15-minute time interval is critical to the CAISO's forecasting efforts above. Thus, the four-second measured PV power production was averaged to 15-minute data. CPR interacted with CAISO to determine data availability, resolve time synchronization issues, and take steps necessary to ensure data integrity.

4.13.1. Sources of Error

Inaccuracies degrade the ability of the simulation to reflect measured performance. These inaccuracies can be grouped into three categories.

1. Solar resource.
2. PV modeling.
3. PV plant performance issues.

Solar resource inaccuracies include errors in historical or forecasted solar resource data. PV modeling inaccuracies refer to limitations in the PV fleet modeling algorithms. PV plant performance issues reflect errors that occur because the plant is not operating as expected.

The effects of solar resource and PV modeling inaccuracies are fairly obvious. Inaccurate solar resource data (historical or forecasted) and/or PV fleet modeling algorithms clearly limit the simulation's ability to reflect measured performance.

PV plant performance issues are more subtle. Differences between simulated and measured PV production can still occur even if the simulation method perfectly predicts measured PV fleet power production for a fleet that is operating perfectly. Differences can occur if the actual PV fleet does not operate as expected due to system performance issues. That is, inaccuracies can occur that are unrelated to the fundamental simulation methodology. They are related to lack of incorporation of poor performance into the simulation.

4.13.2. PV Plant Performance Issues

The first step of the evaluation, therefore, is to determine how to address PV performance issues. One option is to incorporate plant status into the simulation methodology. The simulation, for example, would reflect a capacity reduction if a plant was only operating at 50 percent capacity. This option requires obtaining PV plant status information. This information, unfortunately, was unavailable for the CAISO fleet of PV systems.

An alternative approach is to identify days when the individual plants had sub-par performance. These days and plants are then eliminated from the fleet simulation. This is the approach that was taken for this project.

Fifteen-minute measured and simulated data were obtained for 46 CAISO metered PV plants from March 10, 2013 to April 19, 2013. The time series data were compared for each of the plants individually. The data was visually examined to assess days when the PV plant was either not operating or was clearly underperforming. Figure 17 and Figure 18 present the results of the analysis for two of the 46 plants. The red and blue lines correspond to simulated and measured data. The shaded areas represent days with plant performance issues. The dashed line corresponds to the daily rMAE. Figure 17 corresponds to a plant that operated well during the whole time period. Figure 18 corresponds to a plant that had significant operational issues.

Figure 17. Example of PV Plant that operated as expected.

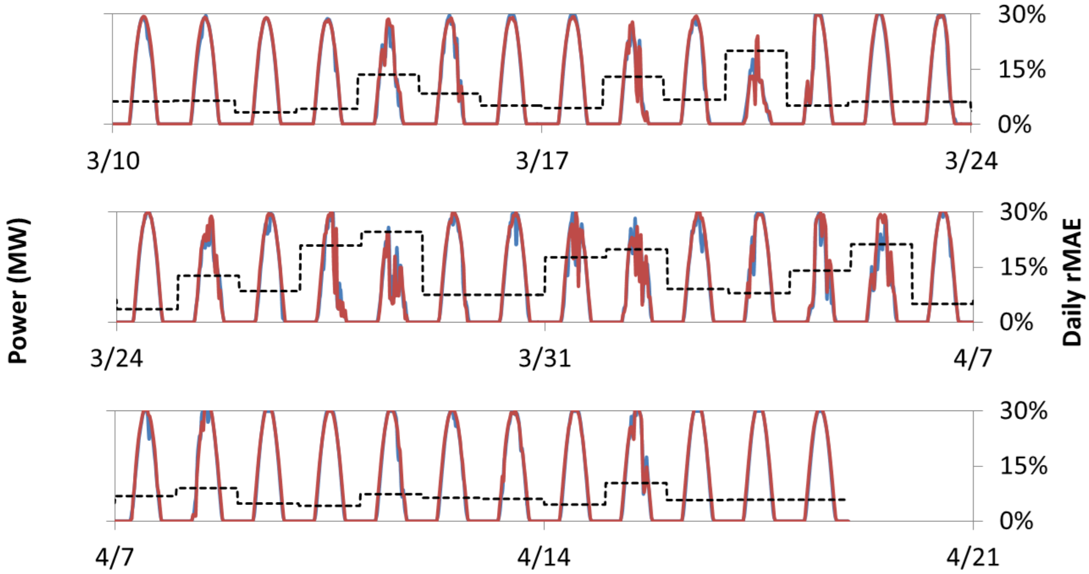
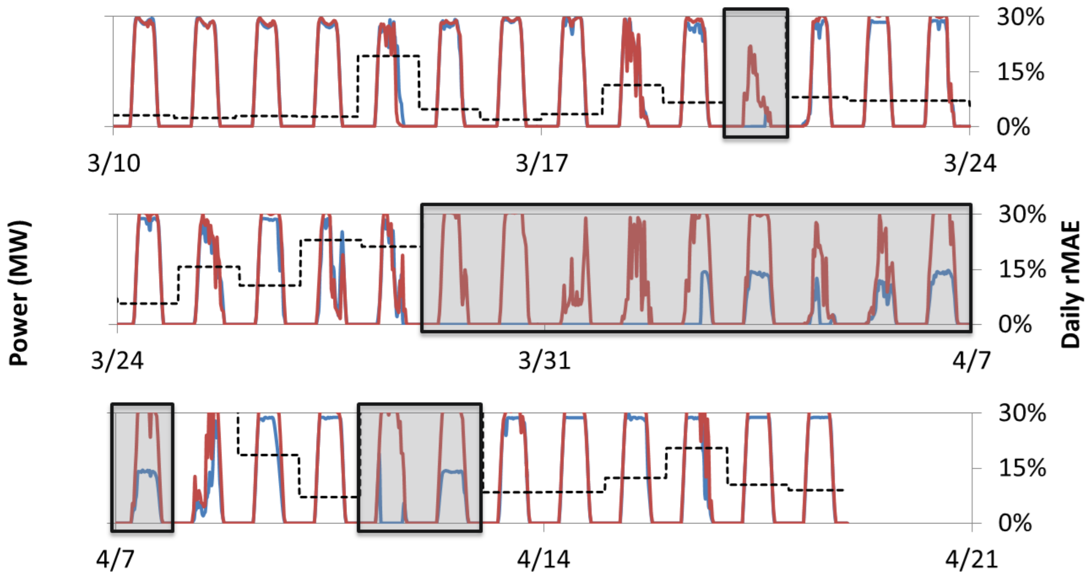
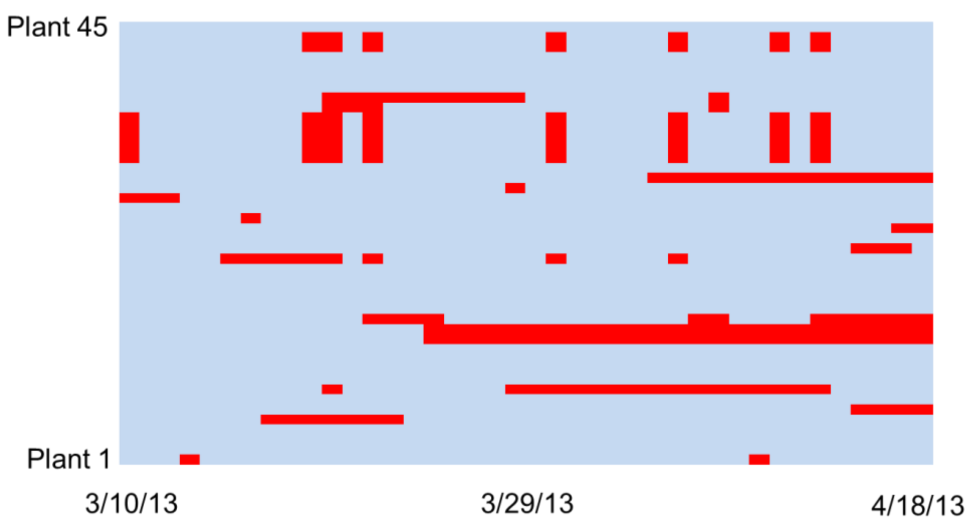


Figure 18. Example of PV Plant with possible performance issues.



This process was repeated for all of the plants. Figure 19 summarizes plant performance for all 46 plants. The y-axis corresponds to the plant number and the x-axis corresponds to the date. Blue corresponds to normal operation and red corresponds to performance issues. The figure suggests that the PV fleet experienced a significant number of performance issues over the six-week analysis period.

Figure 19. Summary of performance issues for all metered plants.



4.13.3. PV Fleet Simulations: Time Series Data

Simulations were performed using FleetView with and without plant filtering results from the previous section. Figure 20 presents PV fleet output without filtering. Figure 21 presents PV fleet output with filtering. A comparison of the two figures illustrates the improvement in accuracy by taking PV plant performance issues into consideration.

Figure 20. PV fleet production before PV performance filtering.

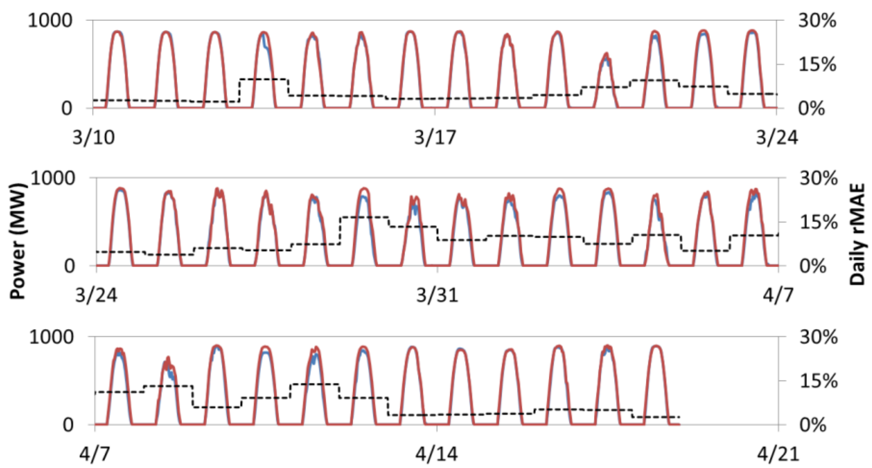
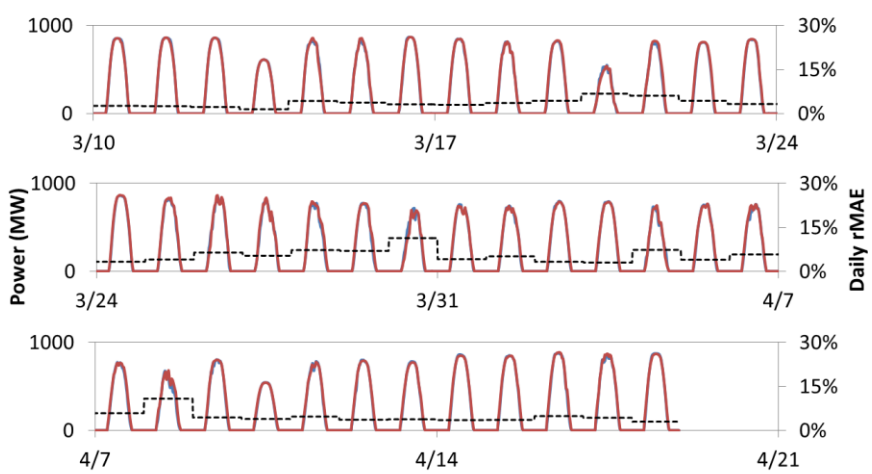


Figure 21. PV fleet production after PV performance filtering.



4.13.4. PV Fleet Simulations: Simulated vs. Measured Data

An alternative way to present the data in Figure 20 is to plot simulated vs. measured average power for each 15-minute interval. Figure 22 presents the data in this manner. All of the blue markers would be on the red line if simulated and measured results matched perfectly. The top of the figure corresponds to the “Initial” case of PV fleet output without PV performance filtering (it corresponds to Figure 20). A consistent power-related bias can be observed.

This bias can be reduced by applying the tuning curve presented in Figure 23. The “Tuned” case is presented in the center of Figure 22. Significant scatter, however, can still be observed. This can be reduced by filtering the data for PV performance using the filtering from the previous section.

The “Tuned & Filtered” case is presented in the bottom of Figure 22. There is a good alignment between simulated and measured data after making the tuning and filtering adjustments.

Figure 22. Simulated vs. measured average 15-Minute power for CAISO metered PV fleet.

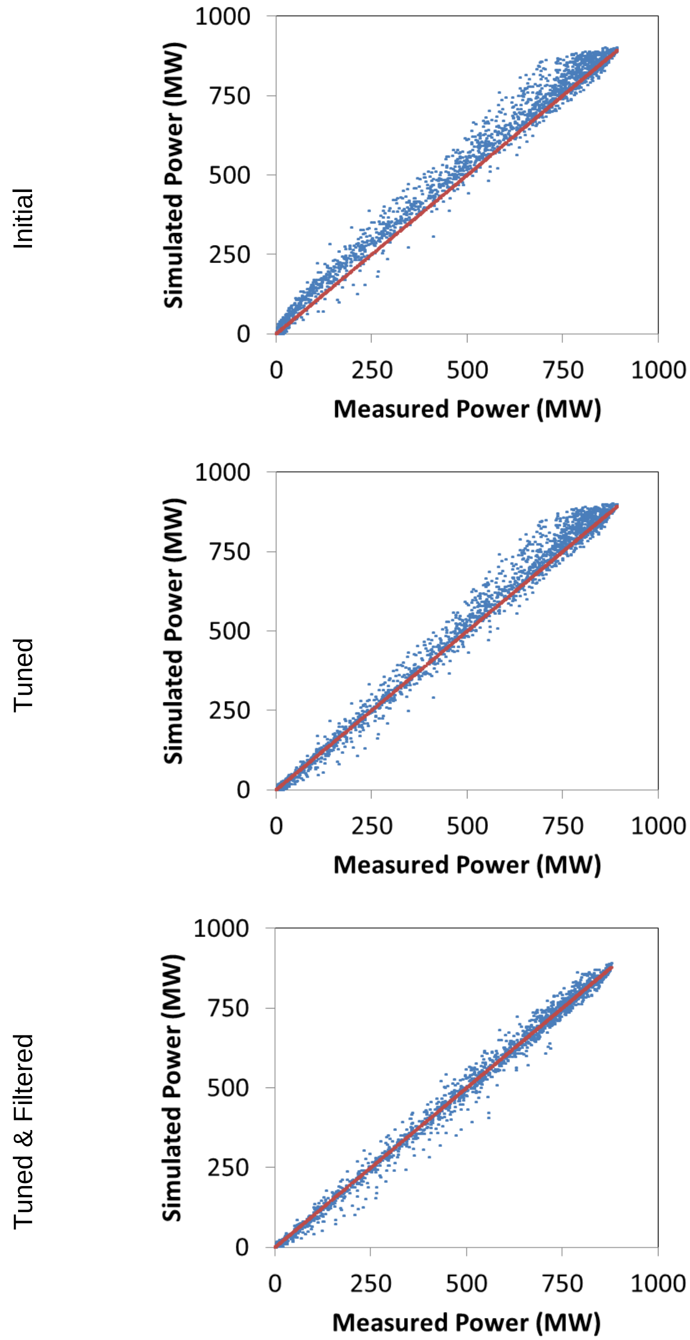
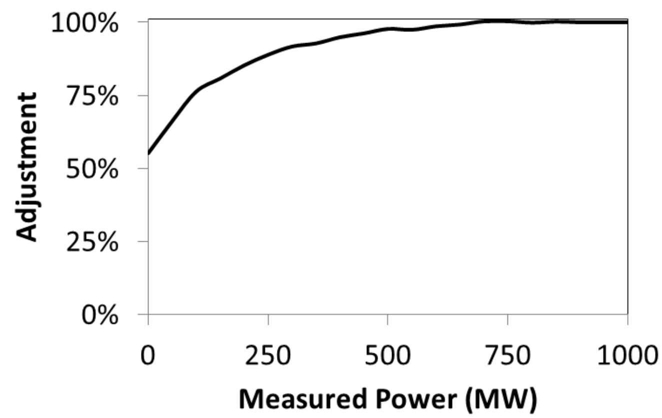


Figure 23. Power-based simulation tuning.



4.13.5. Relative Mean Absolute Error

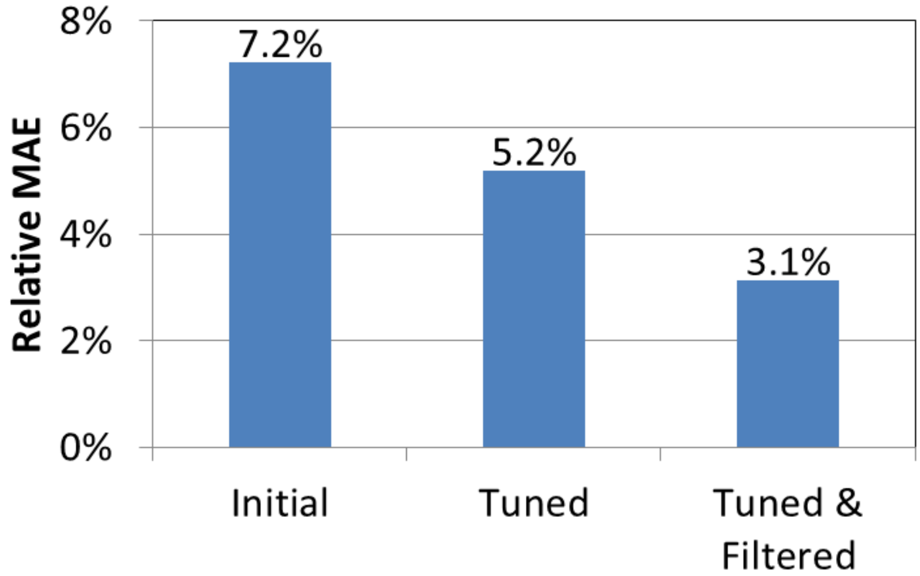
The final step of the analysis is to calculate the rMAE. The time series data were evaluated over the approximately six-week time period for the 15-minute time interval data. Figure 24 presents results for three cases: Initial, Tuned, and Tuned & Filtered. These cases correspond to the results presented in Figure 22. Results show that the Initial, Tuned and, Tuned & Filtered cases have 7.2, 5.2, and 3.1 percent rMAE.

Several observations can be made based on these results. First, overall, FleetView PV power modeling is pretty accurate. There is, however, room for improvement. In particular, improving the inverter power curve model for individual PV systems will substantially improve simulation results (i.e., the improvement identified by applying the tuning).

Second, there is a substantially negative effect due to poorly performing plants even after the PV fleet model has been tuned. Accurately representing plant status reduces error by more than 40 percent.

Third, three percent rMAE can be achieved for 15-minute time interval data using a well-tuned model that accounts for poor PV plant performance. This requires that: (1) accurate location-specific solar resource data is supplied; (2) correct PV specifications are used; (3) the inverter power curve is properly represented (i.e., the simulation is tuned); and (4) actual PV plant status is incorporated into the simulation.

Figure 24. Total rMAE.



It is useful investigate the error on a daily basis in addition to an analysis over the entire time period. Figure 25 and Figure 26 present the daily rMAE for the 15-minute time interval before and after tuning the model. The blue and red colors correspond to simulation error and PV plant performance error respectively. PV plant performance error is estimated by subtracting simulation error with and without filtering. The figure shows that rMAE varies from day to day. While absolute error increases on some of days, rMAE tends to be higher on low energy days. This is because the rMAE calculation is defined as absolute error divided by measured energy.

Figure 25. Daily relative MAE using 15-minute time interval before tuning.

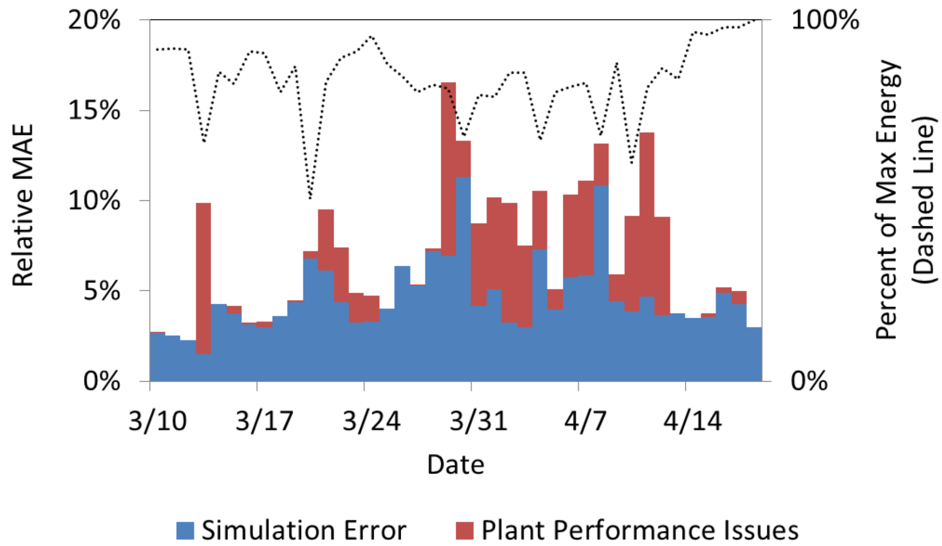
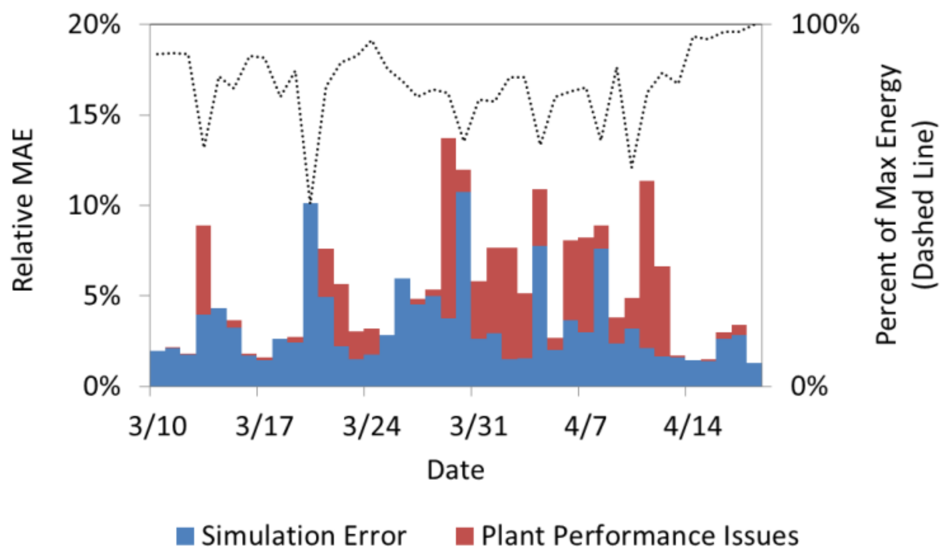


Figure 26. Daily relative MAE using 15-minute time interval after tuning.



4.13.6. Sample Days After Tuning and Filtering

It is useful to compare simulated and measured data for a range of days after tuning and filtering. Figure 27, Figure 28, and Figure 29 present measured and simulated PV fleet production. Figure 27 corresponds to a clear day. Figure 28 corresponds to a day with PV performance issues. Figure 29 corresponds to a day with variable weather and PV performance issues.

Several observations can be made. First, tuning the simulation model increases accuracy for all days. Second, modeling on a clear day is very good with a rMAE of less than 2 percent. Third, filtering for PV plant performance issues can be very important; rMAE was reduced from 20 percent to 4 percent on one particular day. Fourth, simulated data tracks measured data fairly well even for the worst performing day.

Figure 27. PV fleet production on clear day.

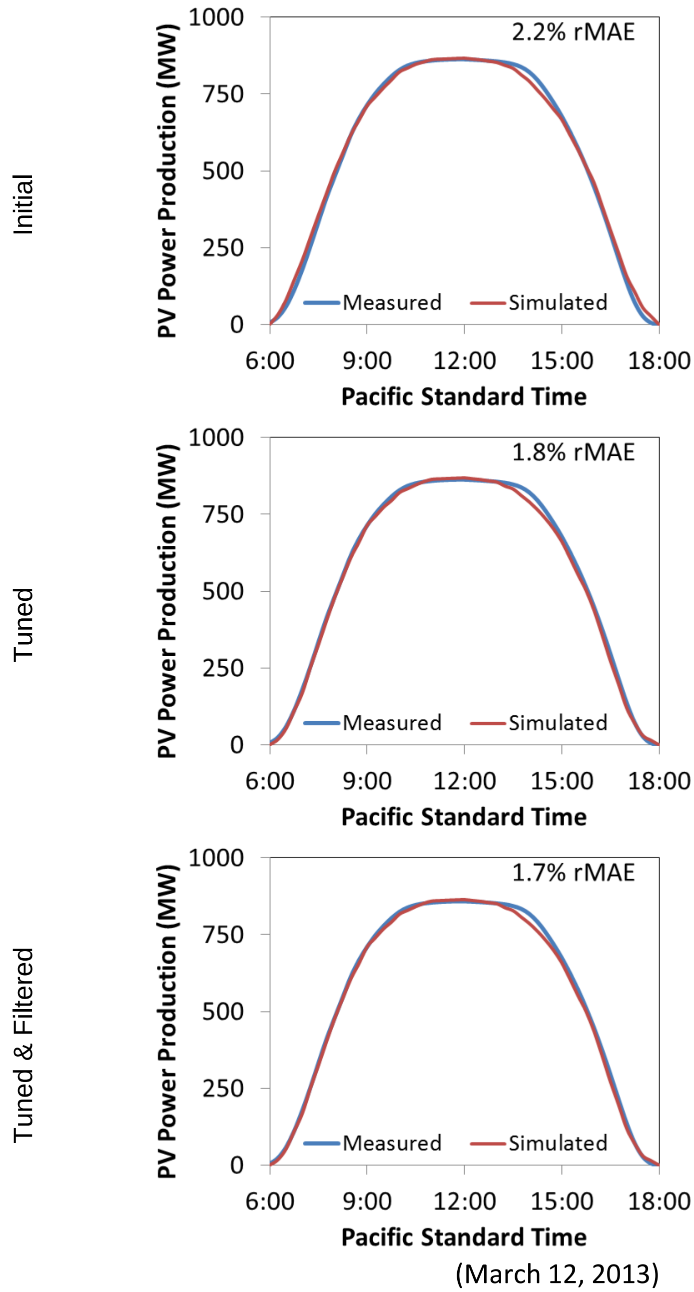


Figure 28. PV fleet production on clear day with production issues.

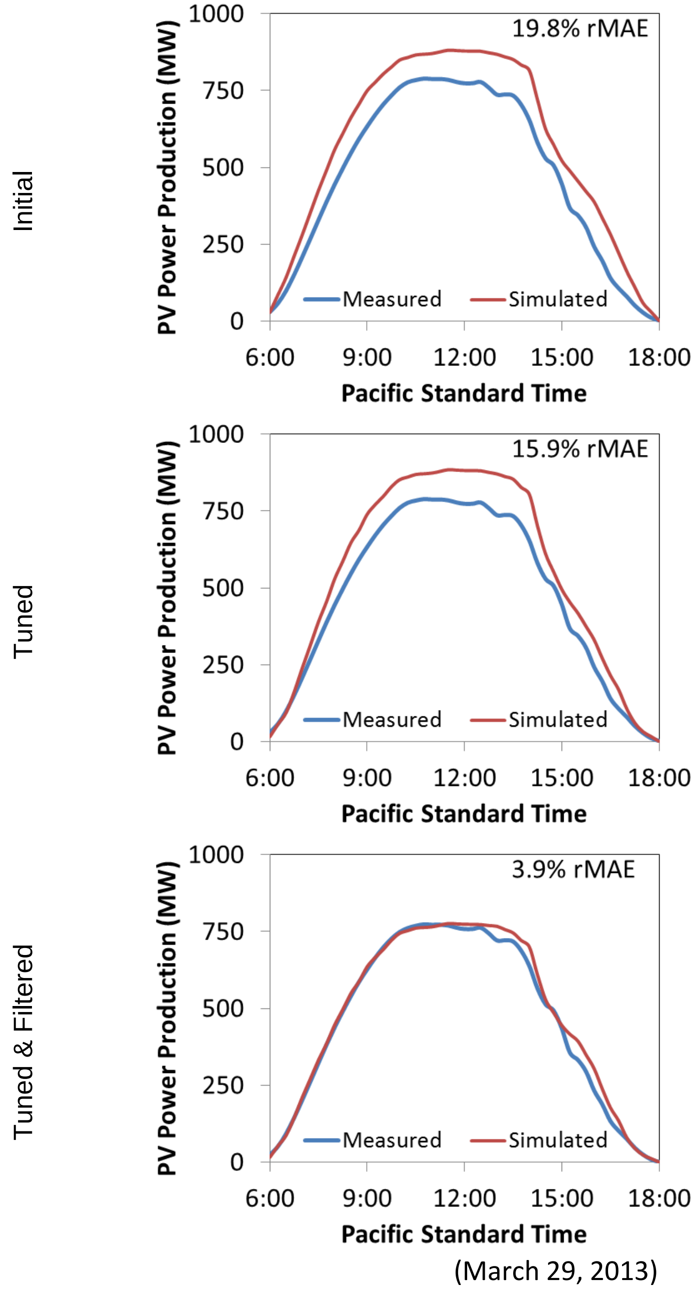
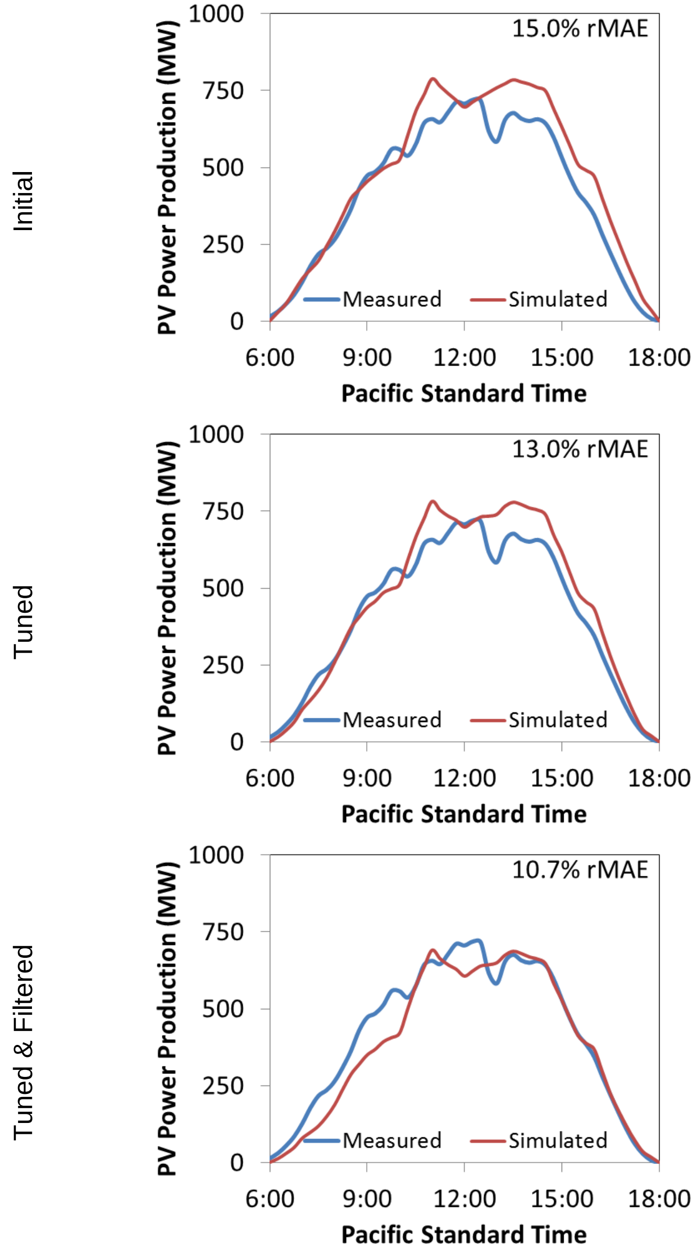


Figure 29. PV fleet production on variable weather day with production issues.



4.14. PV Fleet Simulation Validation (SMUD Data)

Consider, next, results based on data provided by SMUD.

4.14.1. Data Set Correlation

SMUD provided historical PV data for 2,550 distinct PV systems. The data contained a timestamp, measured energy production, duration of the measurement (time increments from 5 minutes up to hourly), and the system's Distributed Generation number (DG number).

PowerClerk® is used as the primary record for all PV systems in SMUD's service territory. PowerClerk contains detailed system specifications, including inverter type and quantity, PV module type and quantity, array tilt, azimuth orientation, and shading. PowerClerk identifies each system by its DG number.

The measured production data set and system specifications data set were linked using the DG number. The systems were assumed to be the same if the DG numbers matched. Random spot checks confirmed that this was a valid assumption.

Matches were obtained for 2,338 of the 2,550 PV systems (i.e., 92 percent of the systems). No DG number match could be found in PowerClerk for 212 of the systems.

4.14.2. PV Production Simulation

Hourly energy was estimated by performing hourly simulations for each system using FleetView by combining system specifications with the SolarAnywhere Enhanced Resolution (1km) hourly data that corresponded to the system's latitude/longitude. (Note: performing the simulation using two half-hour observations rather than one hourly observation would probably improve accuracy).

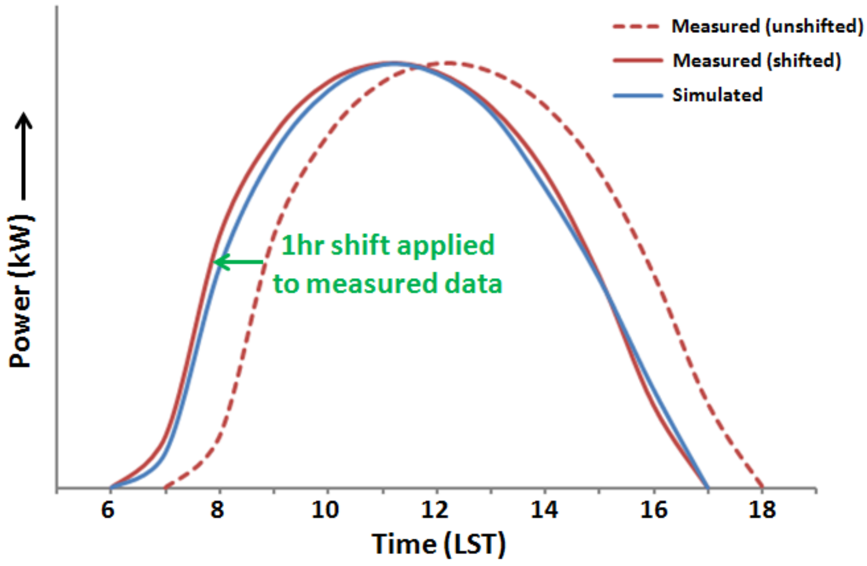
Measured data that contained sub-hourly time intervals were converted to hourly time intervals.

Simulated and measured data were time-correlated (i.e., matched up by date and time). Records were discarded where either the simulated or measured data was missing.

4.14.3. Data Quality Issues

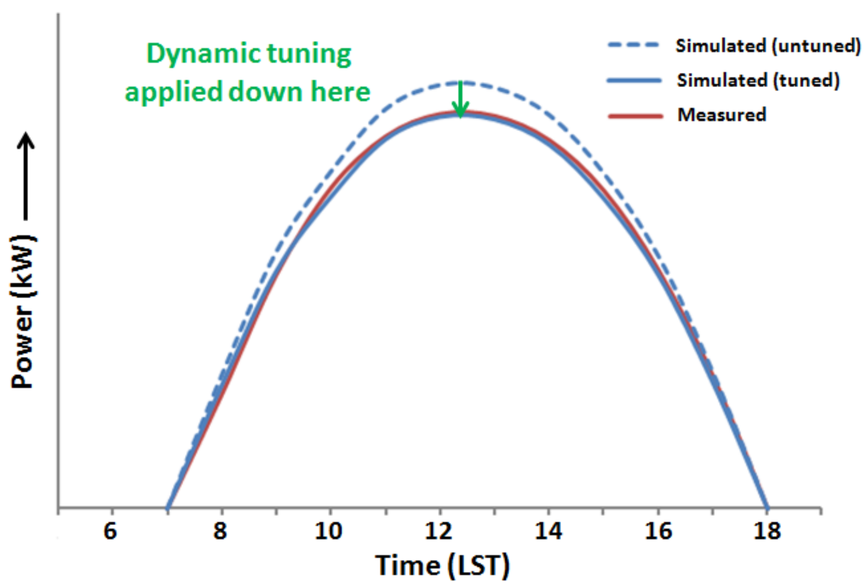
It was determined that some of the measured data did not properly time-correlate with the simulated data. This was corrected by shifting the measured data backward or forward up to 60 minutes in 15 minute intervals (-60,-45,-30, -15, 0, +15, +30, +45,+60). The rMAE was calculated for each time shift. The time shift that resulted in the lowest rMAE was assumed to be the most correct for the measured data. Figure 30 illustrates this measured data time shift procedure for one day for one system.

Figure 30: Illustration of CPR's measured data time shift correction process.



Site-specific tuning was applied to PV simulation results using CPR's dynamic tuning process once the simulated and measured data were time-correlated over the period of examination. A scale factor was selected that minimized certain error characteristics. Figure 31 illustrates the results of the dynamic tuning process for one day for one system.

Figure 31: Illustration of CPR's dynamic tuning methodology.



4.14.4. Results (Fleet of Systems)

Validation results were generated for both individual systems and fleets of systems. This section presents results based on the fleet of systems. Appendix B presents additional details.

CPR completed successful simulations of 2,338 SMUD PV systems of which 132 systems were excluded due to various missing or erroneous measured data issues. Results from the 2,206 remaining PV system simulations are presented here.

The time shift correction (illustrated in Figure 30) was applied to the measured data and the dynamic tuning analysis procedures (illustrated in Figure 31) was applied to simulated results for each PV system. Figure 32 presents the distribution of time shift analysis results for all measured PV systems. The majority of systems required little or no time correction.

Figure 32: Distribution of time shift corrections applied to all PV systems (2206).

The dynamic tuning methodology was applied to each PV system simulation. The distribution of results is presented in Figure 33. While the peak in scaling factors applied is centered about zero, there is strong asymmetry present towards the downscaling side of the distribution. This unevenness in the distribution is likely due to influences which tend to lead to PV system underperformance. These effects can include system soiling, module mismatch and degradation, and enhanced rooftop-related temperature losses. Figure 33 suggests that, in practice, it is more common for a PV system to underperform than to over perform.

Figure 33: Distribution of dynamic scaling factors applied to all locations (2206) derived from the six months of simulated vs. measured production data.

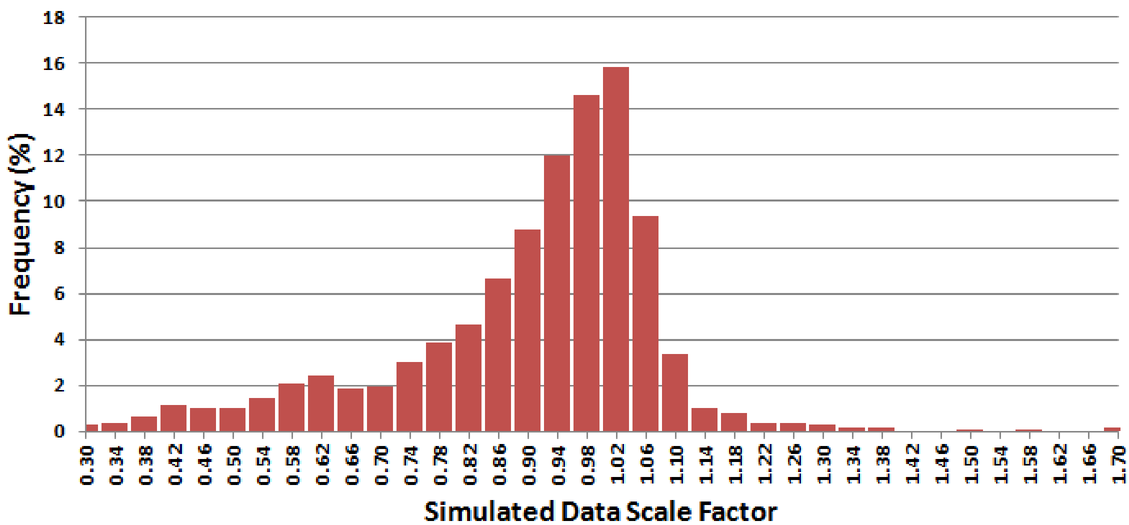


Figure 34 presents 5 days of the aggregate fleet hourly simulation and measured production data for all 2,206 PV systems. Overall, the fleet PV simulations line up with production better than at the individual level due to system wide smoothing effects. As noted before, simulations for clear days tend to line up better with measured data than those for cloudy days. The daily rMAE statistics in Figure 35 confirm that there is lower error on sunny days. There is also less error observed on cloudy days due to aggregating of fleet production.

Figure 36 presents the hourly-averaged MBE. It suggests that at a fleet-level the simulations tend to slightly over predict energy during the morning and late afternoon timeframes while under predicting energy during the peak sunshine part of the day. It is likely that this can be corrected through improvements to the inverter power curve modeling.

Figure 37 illustrates the cloudy vs. clear day simulation aspects of the fleet simulations by breaking down the hourly simulated vs. measured statistics in: (a) all conditions; (b) clear day conditions; and (c) cloudy day conditions. The systematic morning/later afternoon over prediction and midday under prediction tendencies are well illustrated here.

Figure 34: Simulated (red line) and measured (blue line) production for all 2,206 systems.

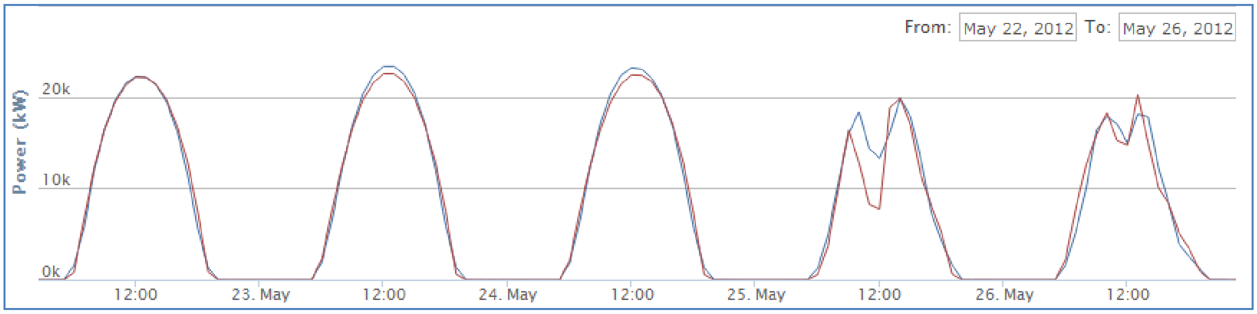


Figure 35: Aggregate daily MAE for all 2,206 systems from 4/16/2013 to 10/10/2013.

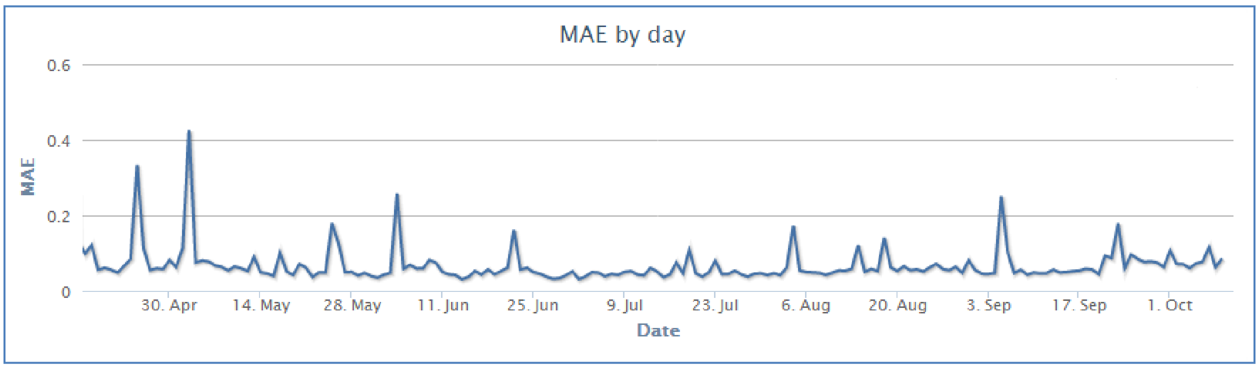


Figure 36: Hourly MBE for all 2,206 systems.

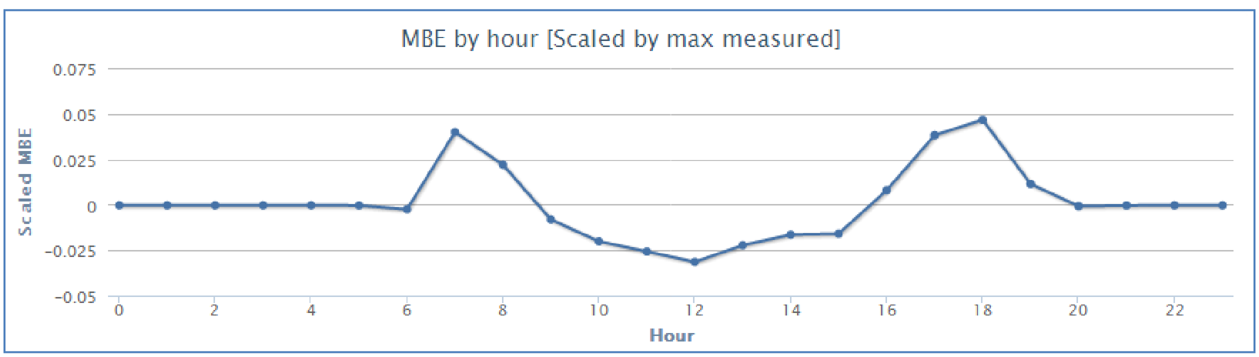


Figure 37: Scatter plot of simulated vs. measured hourly energy production for all 2,206 systems from 4/16/2012 - 10/10/2012 for all day conditions (a), clear days (b) and cloudy days (c).

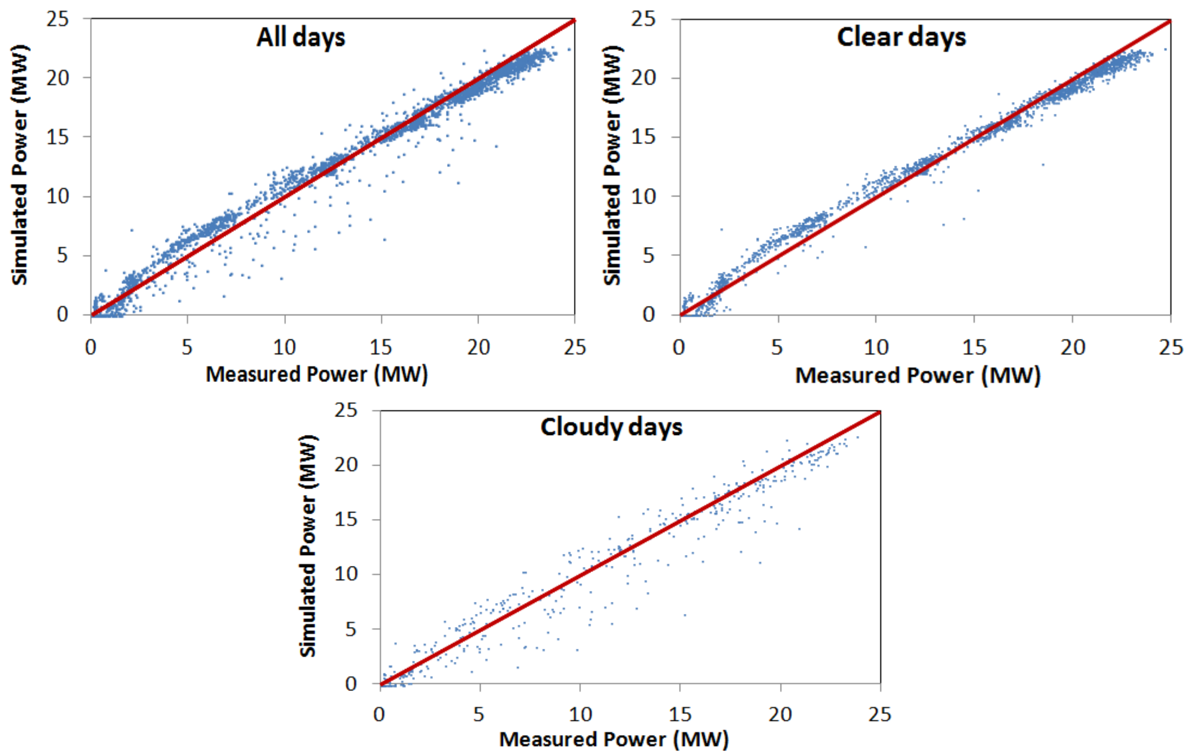


Table 1 presents error statistics for the fleet of 2,206 systems over a six-month period from 4/16/2012 to 10/10/2012. Overall rMAE is 6.2 percent during this observational period under all conditions. This error drops to 5.4 percent when only clear days are included due to the exclusion of higher error prone cloudy days which exhibit 11.1 percent error on their own.

Table 1: rMAE for all 2,206 systems.

	Clear Days	Cloudy Days	All Days
rMAE	**5.4%**	**11.1%**	**6.2%**
Ave Daily Energy	**185.8 MWh**	**143.9 MWh**	**178.2 MWh**
Number of Days	**145 days**	**32 days**	**177 days**

4.14.5. Fleet of Well-Behaved PV Systems

Further full fleet PV system simulation results are presented now. PV systems were removed with reported six-month MAE statistics higher than 10 percent to filter out some of the noise present in the fleet simulation process. This reduced the simulation pool to 1,102 systems.

Figure 38 presents examples of the trimmed down aggregate fleet hourly simulation and measured production data. Good partly cloudy day alignment can be seen with mostly cloudy days still presenting challenges. The daily rMAE statistics in Figure 39 confirm the presence of lower error on sunny days with less error also observed on cloudy days due to the aggregation of fleet PV production. The highest noted daily rMAE error day (May 3) is presented in Figure 38. Heavy overcast cloud conditions dominated the SMUD-footprint region on May 3 which resulted in lower energy simulations due to the under prediction of surface irradiance.

The improvement in fleet error statistics is further illustrated in the hourly-averaged MBE presented in Figure 40. There is less morning and afternoon error while the previously noted midday under prediction error almost disappears. Figure 41 further illustrates the cloudy vs. clear day simulation aspects of the fleet simulations by breaking down the hourly simulated vs. measured statistics during: (a) all conditions; (b) clear day conditions; and (c) cloudy day conditions.

Figure 38: Simulated (red line) and measured (blue line) production for 1,102 well-behaved systems over a four day period in May.

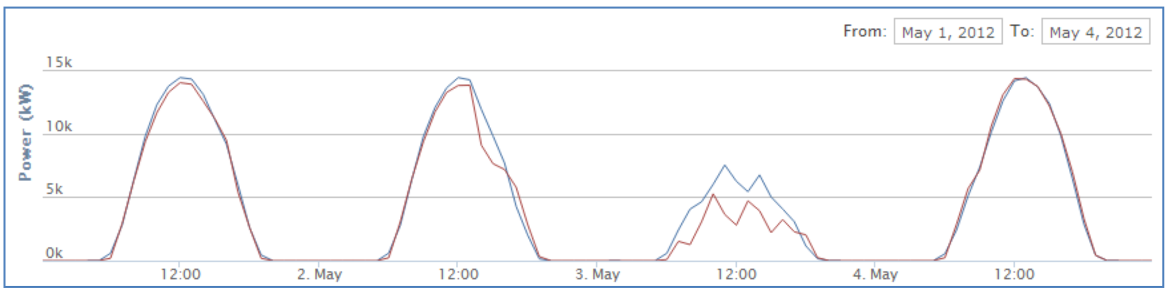


Figure 39: Aggregate daily MAE for 1,102 well behaved systems from 4/16/2012 to 10/10/2012.

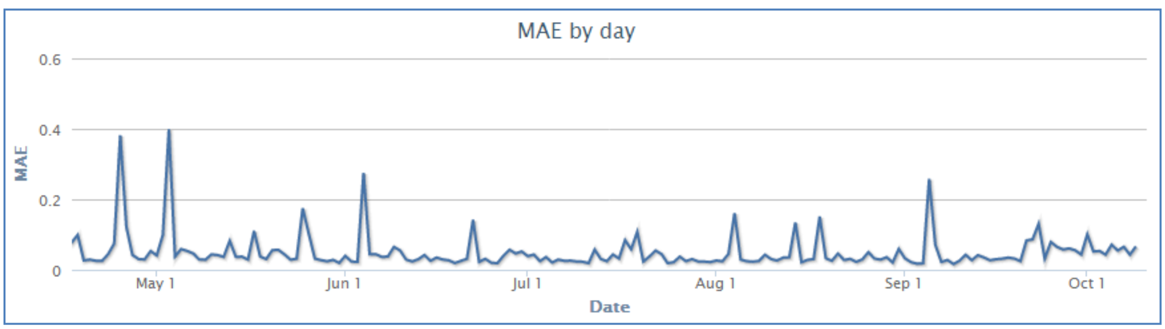


Figure 40: Hourly MBE for 1,102 well behaved systems.

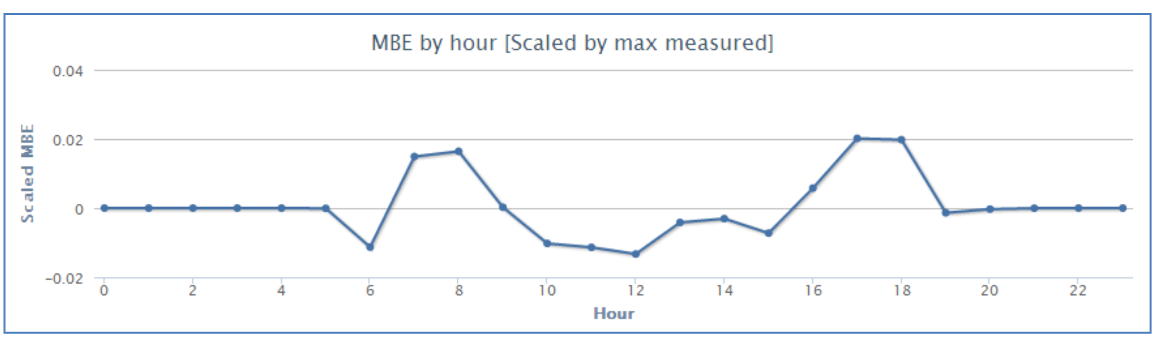


Figure 41: Scatter plot of simulated vs. measured hourly energy production for 1,102 well-behaved sites from 4/16/2012 to 10/10/2012 for all day conditions (a), clear days (b) and cloudy days (c).

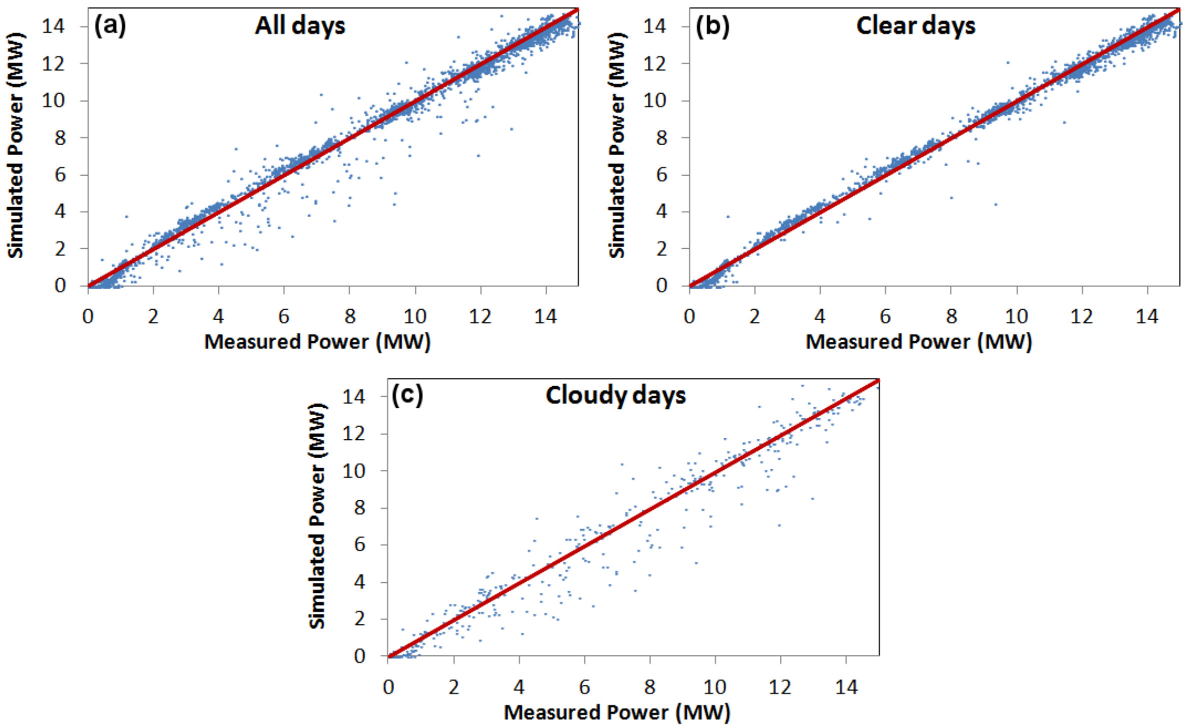


Table 2 presents error statistics for the fleet of 1,102 well-behaved systems over a six-month period from 4/16/2012 to 10/10/2012. Overall rMAE is 4.5 percent during this observational period under all conditions. This error drops down to 3.5 percent when only clear days are included due to the exclusion of higher error prone cloudy days which exhibit 10.0 percent error on their own.

Table 2: rMAE for 1,102 well-behaved systems.

	Clear Days	Cloudy Days	All Days
rMAE	3.5%	10.0%	4.5%
Ave Daily Energy	112.8 MWh	88.3 MWh	108.4 MWh
Number of Days	145 days	32 days	177 days

5. Technology Transfer

A substantial amount of work was performed under the grant agreement. In order to make the results as useful as possible, the results were extensively documented. The documentation includes six patent applications, a peer reviewed journal article, seven conference papers, and a state-of-the art solar resource database for all of California.

5.1.1. Pending Patents

The six patent applications include computer-implemented methods for:

- Tuning photovoltaic power generation plant forecasting.
- Bounding accuracy on a forecast of photovoltaic fleet power generation.
- Inferring operational specifications of a photovoltaic power generation system.
- Correlating satellite imagery for use in photovoltaic fleet output estimation.
- Estimating photovoltaic energy generation for use in photovoltaic fleet operation.
- Bounding accuracy on correlated overhead sky clearness for use in photovoltaic fleet output estimation.

5.1.2. Journal Article

The journal article includes:

- "Using Satellite Insolation Data to Calculate PV Power Output Variability." Paper published in Photovoltaics International, Second Quarter, May 2013, pages 94-99.

5.1.3. Conference Presentations

The conference presentations include:

- "Behind-the-Meter PV Fleet Forecasting." Presentation and paper presented at ASES Solar World 2013. Baltimore, MD, April 2013.
- "Behind-the-Meter PV Fleet Forecasting: Results for 130,000 PV Systems in California" Presentation at SEPA Utility Solar Conference. Portland, Ore., April 2013. Presentation available at: http://www.cleanpower.com/wp-content/uploads/SPI-USC-2013-04-03.pdf
- "Integrating PV Into Utility Planning and Operation Tools." Presentation at DOE/CPUC High Penetration Solar Forum. San Diego, CA, Feb., 2013. Presentation available at: http://www.cleanpower.com/wp-content/uploads/SolarForum2013.pdf
- "Forecasting Output for 130,000 PV Systems in California." Presentation at Utility Wind Integration Group (UVIG) Workshop on Variable Generation Forecasting Applications to Power System Planning and Operations. Salt Lake City, UT, Feb., 2013. Presentation available at: http://www.cleanpower.com/wp-content/uploads/Forecasting-Output-for-130000-PV-Systems-in-California.pdf.
- "Behind-the-Meter PV Fleet Forecasting." Presentation at Utility Wind Integration Group (UVIG) Fall Technical Workshop. Omaha, NE, Oct., 2012.

- "Accuracy of Solar Modeling & Forecasting." Presentation at Solar Power International. Orlando, FL, Sep. 2012.
- "Solar Monitoring, Forecasting, and Variability Assessment at SMUD." Presented at WREF 2012 (SOLAR 2012). Denver, CO, May 2012. Paper available at. http://www.cleanpower.com/wp-content/uploads/SMUD-Solar-Assessment_2012.pdf.

5.1.4. Solar Data

The solar data was made publicly available:

- SolarAnywhere Enhanced Resolution (1 km x 1 km, half-hour) freely available to general public at www.solaranywhere.com.
- SolarAnywhere High Resolution (1 km x 1 km, one-minute) data used to forecast PV fleet production for CAISO.

6. Conclusions

6.1. Key Findings

The California Solar Initiative (CSI) has a goal of installing 3,000 MW of new solar electricity by 2016. CSI has identified that one potential barrier to accomplishing this goal is planning and modeling for high-penetration PV grid integration issues. A team led by Clean Power Research (CPR) received approval from the California Public Utilities (CPUC) for a grant titled, "Integrating PV into Utility Planning and Operation Tools."

The project accomplished the following grid-integration tasks:

1. Extend the SolarAnywhere Enhanced Resolution solar resource database, create high resolution (1 km, 1-minute resolution) solar resource data, and benchmark data accuracy.
2. Validate previously developed PV fleet simulation methodologies using measured ground data from fleets of PV systems connected to California's grid.
3. Integrate PV fleet simulation methodologies into utility software tools for use in activities ranging from distribution planning to balancing area operations using CAISO as a test case.

Key conclusions from this work are:

- High resolution solar resource data can be accurately produced.
- This solar resource data can be combined with PV system specifications to accurately simulate PV fleet production.
- The simulation process can be performed quickly enough to support even the challenging application of forecasting production for hundreds of thousands of systems while meeting forecasting time horizon requirements using the appropriate computing resources and underlying system architecture.

6.2. Benefits to California Ratepayers

This project has provided a number of benefits to the state of California.

6.2.1. Solar Resource Data

The first task was to extend SolarAnywhere. SolarAnywhere Enhanced Resolution provides 1 km x 1 km spatial resolution with half-hour temporal resolution irradiance data. It is beneficial in that it is comprehensive for all of California and is freely available at www.SolarAnywhere.com. California's project developers are also leveraging the increased Enhanced Resolution data accuracy to obtain lower financing rates because of reduced project risk; this lowers the cost of solar and increases the penetration of PV in the state. SolarAnywhere High Resolution extends the Enhanced Resolution to one-minute temporal resolution. The High Resolution data is used in PV penetration and variability studies as well as in solar forecasting for the CAISIO as described below.

6.2.2. PV Fleet Simulation Validation

The second task was to validate PV fleet simulation methodologies using measured ground data from fleets of PV systems connected to California's grid. It is critical to the utilities and balancing area authorities responsible to run the grid that they validate models using real-world data. The validation provides public benefits because grid operators need to gain confidence in the models intended to inform grid operation prior to their use.

6.2.3. *PV Fleet Simulation Integration Into Utility Software Tools*

The third task was to integrate PV fleet simulation methodologies into utility software tools. CAISO has the responsibility of maintaining reliability and accessibility for California's utility grid. As such, they are concerned with the effect of power production from customer-owned PV systems on the balancing area. Prior to this contract, CAISO did not have visibility into the performance of behind-the-meter PV systems. CPR has been providing behind-the-meter PV fleet forecasts every 30 minutes to CAISO for almost one year. This is beneficial to California in that CAISO has visibility into behind-the-meter PV performance when none existed prior to this grant. It has the additional benefit of being a valuable case study for California's IOUs as they consider using the same approach for their needs.

6.3. Potential Next Steps

The next steps of this work could be as follows:

- Continue to improve high resolution solar resource forecasting accuracy.
- Implement a streamlined interconnection process to simultaneously collect PV system specifications in order to continue to be able to define the PV fleet.
- Transition PV fleet forecasting from R&D to an operational environment and integrate into utility tools.
- Design and implement probabilistic/ramp event PV fleet forecasting system.
- Continue to validate results.

The tools and data streams developed as part of this work will be made available to California utilities, ISOs and others to help cost-effectively and reliably integrate distributed PV into the grid.

APPENDIX 1

Demonstration and Validation of PV Output Variability Modeling Approach

July 2013

ABSTRACT

The California Energy Commission's (CEC) Public Interest Energy Research (PIER) program awarded Clean Power Research a contract to evaluate satellite-derived irradiance and simulated PV fleet performance accuracy for PV resource management in the CAISO control area. The goals of the Agreement are to validate existing research and tools, and to integrate the results into the CAISO's planning process.

Under this research, Clean Power Research® (CPR) has collected a database that includes all of the solar PV systems installed in California and developed a unique method to predict PV fleet power production. SolarAnywhere® FleetView™ uses inputs of satellite-derived solar resource data and the design attributes and locations of PV systems to predict PV fleet power production.

The database includes locations of all PV systems in California. PV fleet power production was simulated using FleetView. Measured PV power production was provided by the CAISO. The measured data was used to identify performance issues and to compare with simulated results.

The PV fleet power production variability modeling results suggest that 3 percent Relative Mean Absolute Error (rMAE) can be achieved for PV fleet simulation for 15-minute time interval data over a six-week period given that accurate location-specific solar resource data is supplied; correct PV specifications are used; the PV simulation model is properly tuned; and PV plant operating status is reflected in the simulation to account for poor performance. Results also suggest that total error was over 7 percent if the model was not tuned and PV plant operating status was not reflected in the simulation.

Keywords: California Energy Commission, California Independent System Operator, Clean Power Research, SolarAnywhere, FleetView, PV production, PV production, PV variability, renewable energy

Please use the following citation for this report:

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EXECUTIVE SUMMARY

Photovoltaic (PV) plant production variability is a critical challenge to increased PV penetration into California's electricity system. A number of studies have examined the issue of PV output variability (see [1] through [12]). A consistent finding of these studies is that variability is reduced when PV systems are geographically dispersed. That is, variability is reduced as the number of systems increases across a sufficiently large geographic region.

The California Energy Commission's (CEC) Public Interest Energy Research (PIER) program awarded Clean Power Research® (CPR) a contract to evaluate satellite-derived irradiance and simulated PV fleet performance accuracy for PV resource management in the CAISO control area. The goals of this research are to validate existing research and tools, and to integrate the results into the CAISO's planning process. The accuracy of the method needs to be demonstrated for PV sources within the CAISO control area, and data needs to be delivered in a manner compatible with the existing energy and reserve market mechanisms.

Under this research, CPR has collected and delivered to CEC a database that includes all of the solar PV systems installed in California and developed a unique method to predict PV fleet power production variability. The method uses inputs of satellite-derived solar resource data and the design attributes and locations of PV systems. It combines these inputs with advanced algorithms to track cloud patterns to predict output.

The database includes locations of all PV systems in California. PV fleet power production was simulated using FleetView. Measured PV power production was provided by the CAISO. The measured data was used to identify performance issues and to compare with simulated results.

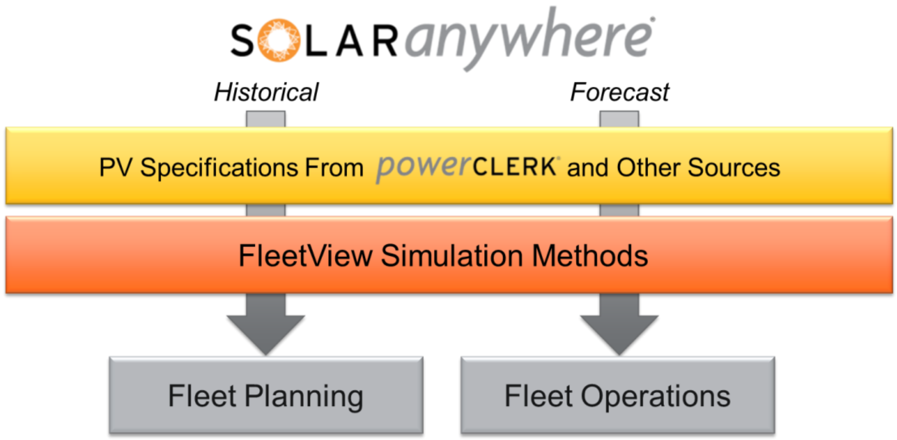
The PV fleet power production variability modeling results suggest that 3 percent Relative Mean Absolute Error (rMAE) can be achieved for PV fleet simulation for 15-minute time interval data over a six-week period given that accurate location-specific solar resource data is supplied; correct PV specifications are used; the PV simulation model is properly tuned; and PV plant operating status is reflected in the simulation to account for poor performance. Results also suggest that total error was over 7 percent if the model was not tuned and PV plant operating status was not reflected in the simulation.

The California Independent System Operator (CAISO) sees potential of using this approach in planning for system operations under alternative renewable energy scenarios. It also sees potential for using the approach for forecasting PV fleet production. Additional validation, however, is required before the method is usable by the CAISO to inform planning for future operational needs.

CHAPTER 1:
California PV System Database

PV fleet power prediction requires technical specifications for each PV system (see Figure 1). Thus, the first objective of this project is to develop a database of the PV systems in California.

Figure 1. Fleet simulation procedure.



Many of the PV systems for California are included in CPR's PowerClerk® database. Some systems, such as the large PPA projects and systems installed by utilities without PowerClerk, are not included. The PowerClerk data set must therefore be supplemented by other data sources to provide the basis for fleet simulation. This section summarizes the PV hardware database that describes the grid-connected PV fleet in California.

1.1 Existing System Data in Database

The first step was to document and characterize the set of existing PV system data already in the PowerClerk database. This was accomplished by analyzing the PowerClerk set of programs. Table 1 summarizes the results at the beginning of this project (2010). It illustrates that the CSI programs at the California IOUs are well-covered, as are LADWP, SMUD, and the City of Palo Alto (CPAU) and a portion of Anaheim Public Utilities (APU).

Table 1: Existing PV Systems in PowerClerk

Program ID	Agency	Program	State	Obsolete	Number of Completed Applications
25	APU	Solar Electric Program	CA	FALSE	239
20	BWP	Burbank Water and Power Solar Support Program	CA	FALSE	72
11	CCSE	Small Commercial (< 10 kW) and All Residential	CA	FALSE	7,128
12	CCSE	Large Commercial (>= 10 kW)	CA	FALSE	86
28	CCSE	Multifamily Affordable Solar Housing	CA	FALSE	28
33	CPAU	PV Partners	CA	FALSE	14
50	LADWP	Solar Incentive Program	CA	FALSE	14
51	LADWP	Solar Incentive Program - Legacy	CA	FALSE	4,088
7	PG&E	Small Commercial (< 10 kW) and All Residential	CA	FALSE	30,668
8	PG&E	Large Commercial (>= 10 kW)	CA	FALSE	537
26	PG&E	Multifamily Affordable Solar Housing	CA	FALSE	57
9	SCE	Small Commercial (< 10 kW) and All Residential	CA	FALSE	15,601
10	SCE	Large Commercial (>= 10 kW)	CA	FALSE	249
27	SCE	Multifamily Affordable Solar Housing	CA	FALSE	29
4	SMUD	Residential Retrofit PV Program	CA	FALSE	1,099
18	SMUD	Commercial PV Program	CA	FALSE	69
19	SMUD	Commercial New Construction PV Program (Obsolete)	CA	TRUE	
34	SMUD	SMUD PV-Commercial	CA	FALSE	3
35	SMUD	SMUD Contracted-Residential Retrofit	CA	FALSE	343
36	SMUD	SMUD Contracted-Commercial	CA	FALSE	32
37	SMUD	Conversions-From SMUD to Customer Owned	CA	FALSE	81
38	SMUD	Community Solar	CA	FALSE	16
39	SMUD	SolarSmart	CA	FALSE	0
40	SMUD	SMUD Financed Church Program	CA	FALSE	15
41	SMUD	SMUD Contracted-Residential New Construction	CA	FALSE	110
42	SMUD	Residential PV-New Construction (pre SolarSmart)	CA	FALSE	139
43	SMUD	Commercial Self Install-No Rebate	CA	FALSE	11
44	SMUD	Residential Self Install-No Rebate	CA	FALSE	44
45	SMUD	SMUD PV-Utility	CA	FALSE	24
					60,796

1.2 Categories of Systems

The second step was to characterize the "missing" systems that would be the focus of the data collection effort. The main categories include:

- Renewable Portfolio Standard systems (RPS).
- Publicly owned utility Senate Bill-1 programs (POU SB-1).
- CEC's Emerging Renewables Program (ERP).
- New Solar Homes Partnership (NSHP).
- Single Family Affordable Solar Homes (SASH).
- Self-Generation Incentive Program (SGIP).

1.3 Data Collection Plan

The following describes the plan to collect, qualify and enter the data necessary to supplement the existing database. Sunterra Solar Inc., of Novato, California was selected as the contractor to research these systems and contact utilities as necessary to obtain system location, hardware and orientation details required for modeling.

The subcontractor performed the following services:

- Review the materials provided by CPR:
  - Sample Data Format.
  - List of Major Solar Projects.
  - List of California LSEs.
  - PV System Specification Sources.
- Contact utilities, project owners, and others by email and telephone to obtain PV system specifications.
- Enter data into a CPR-provided web-based database interface.
- Attend up to 3 face-to-face meetings in CPR's Napa office.

1.4 All California PV Database

Table 2 summarizes the data that was collected as of March 2012, now constituting the "All California PV Database." 78,025 of these systems (773 MW) existed in PowerClerk, primarily from the CSI program. RPS systems are large, multi-MW systems used by the IOUs (or owned by the IOUs) to meet state RPS obligations. This includes the 290 MW Agua Caliente project.

Table 2: Summary of the All-California PV Database at Start of Project

	No. Systems	Capacity (MW)
PowerClerk (existing)	78,025*	773
RPS	37	644
POU (SB-1)	45	50
CEC ERP (Before 2005)	11,455	45
CEC ERP (2005 and later)	16,602	78
New Solar Homes Partnership (NSHP)	12,543	40
Single Family Affordable Solar Homes (SASH)	1,949	7
Self-Generation Incentive Program (SGIP)	917	144
Total	**121,573**	**1,781**

Data from publicly-owned utilities (POUs) was obtained from the SB-1 reporting requirements. ERP, NSHP, SASH, and SGIP represent various incentive programs available to California consumers over several years. System-level data from each of these programs was obtained and included in the database.

Table 3 summarizes the data collected for the publicly owned utilities (POUs) based on required reporting under SB-1. The fleets were analyzed to prevent duplication in cases where the utility had systems described in PowerClerk.

Table 3: Publicly-Owned Utility Capacity (POU SB-1)

POU	Capacity (MW)
Alameda Municipal Power	0.60
Anaheim Public Utilities	1.97
Azusa Light & Water	0.15
Banning Public Utilities	0.73
Biggs Municipal Utilities	0.01
Burbank Water & Power	2.01
Colton Electric Utility	1.03
Glendale Water & Power	1.32
Gridley, City of	0.01
Healdsburg, City of	0.27
Hercules Municipal Utility	0.02
Imperial Irrigation District	4.06
Lassen Municipal Utility District	0.10
Lodi Electric Utility	1.20
Lompoc, City of	0.44
Merced Irrigation District	0.04
Modesto Irrigation District	9.01
Moreno Valley Electrical Utility	0.08
Needles, City of	0.07
Palo Alto, City of	2.73
Pasadena, Water & Power Department	3.22
Pittsburg Power Company	0.09
Plumas-Sierra Rural Electric Cooperative	0.19
Rancho Cucamonga Municipal Utility	0.06
Redding Electric Utility	0.63
Riverside Public Utilities	3.26
Roseville Electric	2.11
Santa Clara, City of	0.03
Shasta Lake, City of	0.05
Silicon Valley Power	4.94
Trinity Public Utility District	0.07
Truckee Donner Public Utilities District	0.27
Turlock Irrigation District	6.39
Ukiah, City of	0.08

1.5 Metered PV Fleet

Renewable Portfolio Standard (RPS) systems include large systems that utilities built or contracted to satisfy obligations. These systems are directly metered by the CAISO. These systems are also referred to as the metered systems, or the CAISO metered fleet.

The CAISO metered fleet consists of 46 PV plants. Forty-four of the plants are located in California. Two of the plants are located in Arizona and tie electrically to the CAISO's control area. Figure 2 summarizes the PV plant capacity (MW-AC) of the metered systems. Table 4 provides a list of the plants. The blue bars correspond to the ratings of each individual plant. The plants are ordered according to decreasing capacity. The red line presents cumulative PV plant capacity vs. the number of plants.

Figure 2: PV Plant Capacity and Cumulative Fleet Capacity vs. Number Metered Plants (MW-AC)

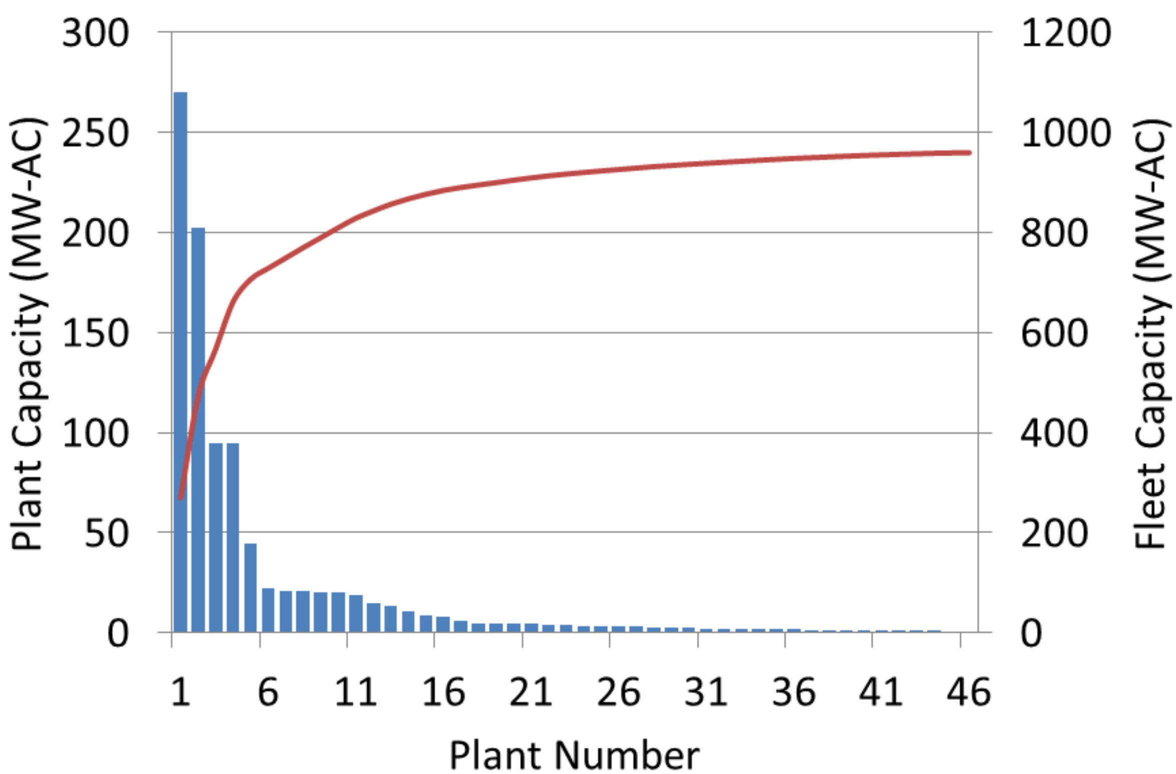


Table 4: List of Metered PV Plants

Plant Number	Capacity (MW-AC)
1	269.7
2	202.6
3	94.9
4	94.5
5	44.8
6	22.1
7	20.8
8	20.5
9	19.9
10	19.9
11	18.9
12	14.5
13	13.5
14	10.8
15	9.0
16	7.7
17	5.9
18	4.9
19	4.8
20	4.8
21	4.7
22	3.9
23	3.6

Plant Number	Capacity (MW-AC)
24	3.2
25	3.0
26	2.9
27	2.9
28	2.7
29	2.3
30	2.3
31	2.1
32	2.0
33	2.0
34	2.0
35	2.0
36	1.8
37	1.5
38	1.5
39	1.4
40	1.4
41	1.3
42	1.1
43	1.1
44	0.9
45	0.7
46	0.5

1.6 CAISO Control Area Groupings

CPR determined during the course of the project that it was insufficient to provide a single PV fleet prediction for the entire state of California. Rather, the CAISO required that PV fleet power predictions be grouped in specific ways. The CAISO specified that the data be grouped into five regions, as defined in Table 5.

In addition, the CAISO specified that PV systems need to be categorized as either metered systems or behind-the-meter systems for each region. Thus, ten PV fleet power predictions need to be provided to the CAISO.

Table 5: CAISO Regions

	Metered	Behind-the-Meter
PG&E Bay Area	✓	✓
PG&E Non-Bay Area	✓	✓
SCE Coastal	✓	✓
SCE Inland	✓	✓
SDG&E	✓	✓

After all of PV specifications were collected, each PV system was matched to one of the ten groups.

Figure 3 illustrates the mapping process for one PV system. Detailed PV specification data for a single system was mapped to the city of San Francisco. This, in turn, was mapped to the PG&E Bay Area CAISO region. Finally, it was a behind-the-meter PV system so it was mapped to the "PG&E Bay Area Behind-the-Meter" group.

This process was repeated for all metered and behind-the-meter PV systems. The resulting capacity as of January 1, 2013 for the state of California is presented in Figure 4. In addition, the PV systems that supplied power to other control areas were mapped to their respective control areas.

Figure 3: PV System Mapping Process

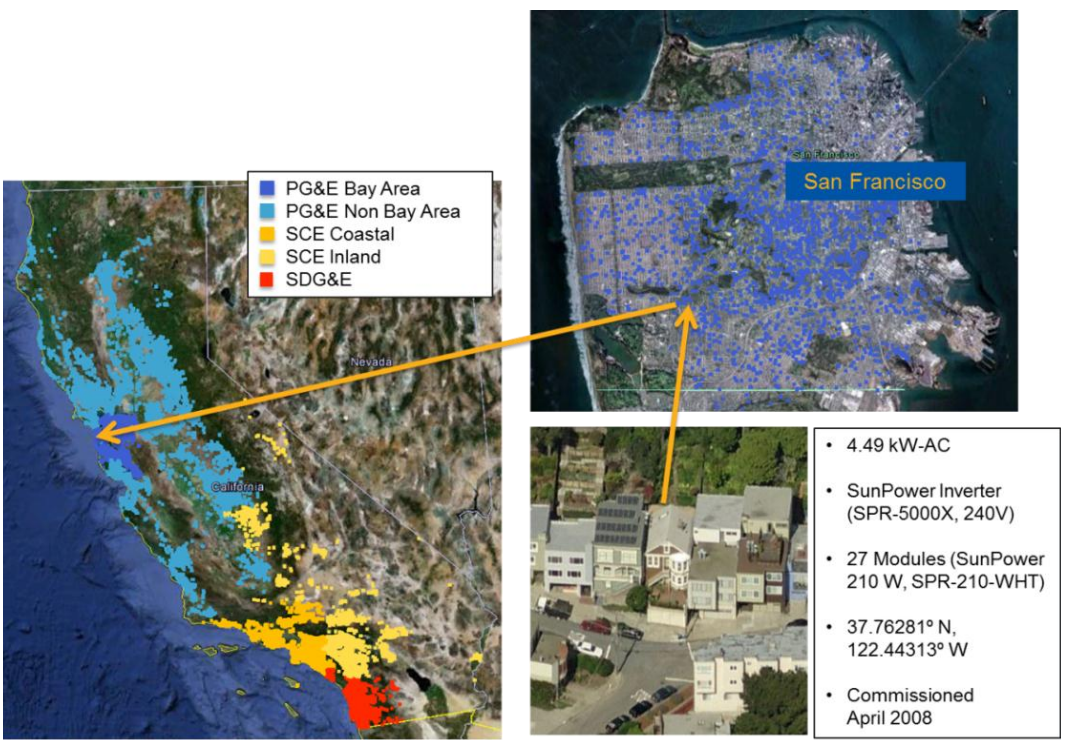
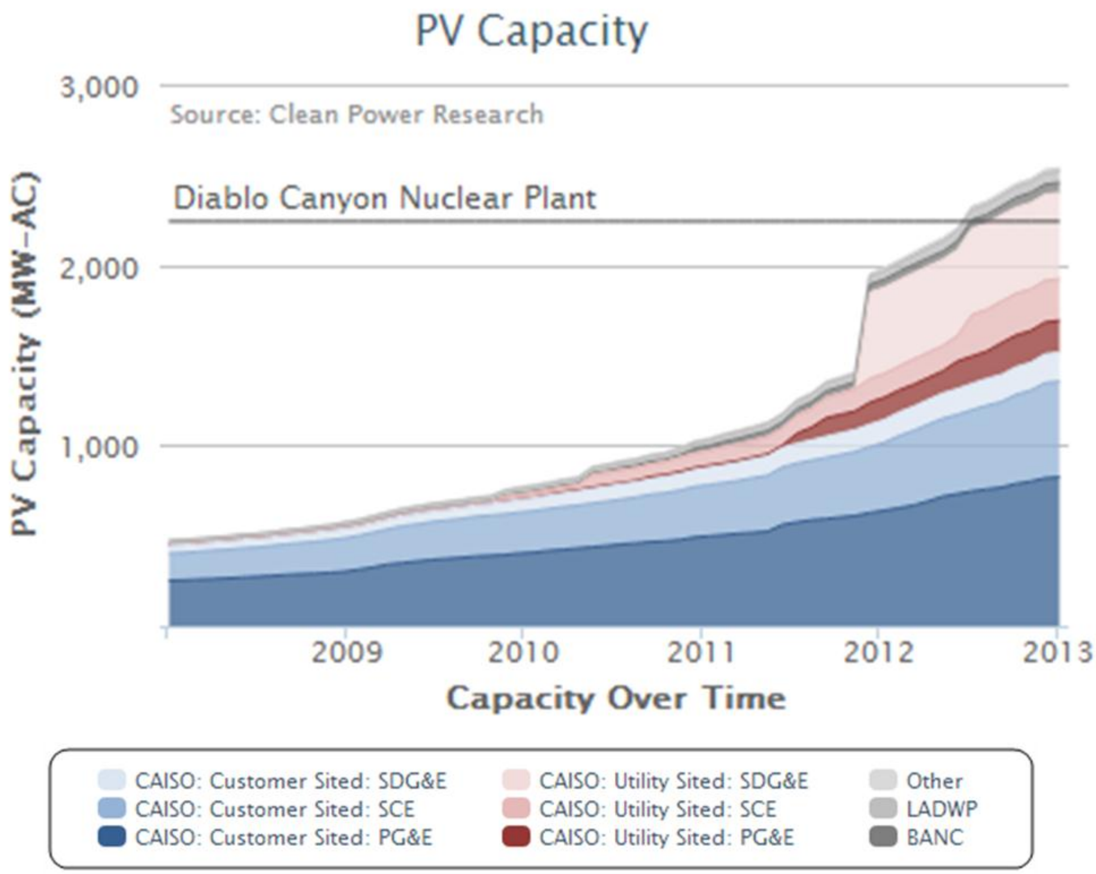


Figure 4: California PV Capacity



Chapter 2:
High Resolution Solar Resource Data

PV fleet power prediction requires solar resource data that corresponds to the location of each PV system (see Figure 1). The second task of this project was to assess high resolution solar data accuracy for a defined fleet of PV systems.

2.1 Definitions

It is important to clearly define what is meant by accuracy before discussing solar resource data accuracy. Accuracy validation often means different things to different people. As such, it is useful to begin with a definition of how accuracy quantification can be performed.

Three fundamental questions need to be answered to provide a clear definition of how accuracy quantification is performed.

1. What is the data source?
2. What are the time attributes?
3. What is the evaluation metric?

2.1.1 Data Source

The first step is to identify the data that is being evaluated. Options include irradiance data or simulated PV power production using irradiance data and other parameters. In addition, the analysis can be performed for individual locations or fleets (i.e., multiple locations). This chapter focuses on irradiance data. The analysis is performed for both individual locations and fleets. A subsequent chapter assesses accuracy for PV fleet production data.

2.1.2 Time Attributes

The second step is to specify the required time attributes. These include:

- **Time period**: total amount of data included in the analysis. This can range from a few minutes to many years. This chapter focuses on one year worth of data.
- **Time interval**: how the data in the time period is binned. This can range from a few seconds to annually. For example, if the time period is one year and the time interval is one hour, the time period would be binned into 8,760 time increments. This chapter examines one-minute to one-year time intervals.
- **Time perspective**: when the predicted observation is reported. This can range from historical (backward looking) to forecasted a few hours ahead to forecasted multiple days ahead (forward looking). This chapter focuses on historical data.

2.1.3 Evaluation Metric

The third step is to select the evaluation metric. Error quantification metrics used in assessing absolute irradiance model accuracy such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) have been precisely defined [17], [18]. Their relative counterpart (results expressed in percent), however, can be subject to interpretation and may cover a wide range of values for a given set of data depending on reporting practice.

Appendix A suggests that the MAE relative to available energy (rMAE) is a good method to measure relative dispersion error. This is the method used in the present analysis. The MAE relative to the average energy available is calculated by summing the absolute error for each time interval over the time period, and then dividing by the total available energy.

$$Relative\ Mean\ Abosolute\ Error = \frac{\sum_{t=1}^{N} \left| I_t^{test} - I_t^{ref} \right|}{\sum_{t=1}^{N} I_t^{ref}} \qquad (1)$$

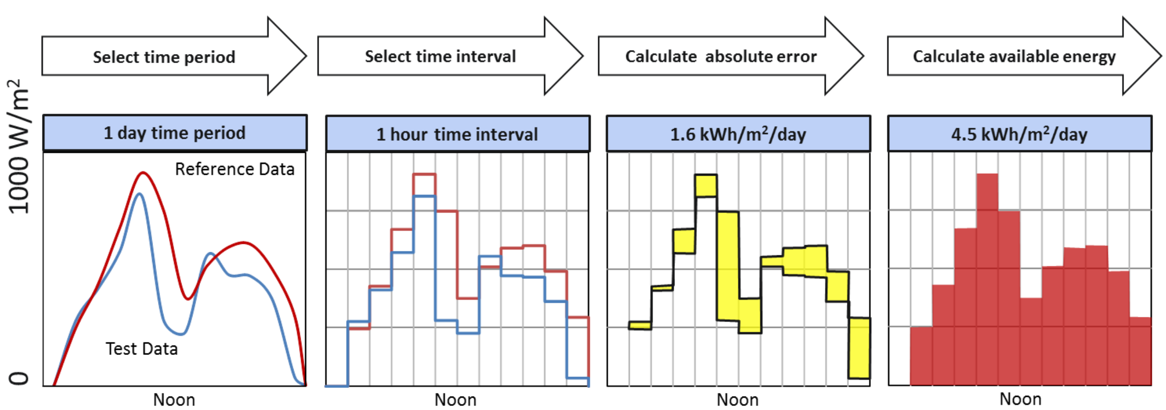
where I_t^{test} is the test irradiance at time t, I_t^{ref} is the reference irradiance at time t, and N is the number of time intervals.

It is useful to provide a hypothetical example of how to calculate the rMAE. A short time period (one day) is selected in order to graphically illustrate the calculations; the actual calculations in this paper use a one year time period.

As presented in Figure 5, the process is follows:

- Select time period: 1 day.
- Select time interval: 1 hour.
- Calculate absolute error for each hour and sum the result as described in the top part of Equation (1): 1.6 kWh/m²/day.
- Calculate available energy for each hour from reference data and sum the result as described in the bottom part of Equation (1): 4.5 kWh/m²/day.
- Calculate Relative Mean Absolute Error: 36% (i.e., 1.6/4.5).

Figure 5: Mean Absolute Error Relative to Available Energy Calculation Example



It is important to note that a more often reported measurement of error is MAE relative to generating capacity. In the above example, however, it is unclear over what time period the generating capacity should be selected. Should it be capacity during daylight hours or capacity over the entire day, including night time hours? MAE relative to daytime capacity is about 13.3% (i.e., 1.6/12) while Mean Absolute Error relative to full day capacity is about 6.6% (i.e., 1.6/24).

It is due to this sort of ambiguity, as well as the fact that MAE relative to energy is a much more stringent metric (e.g., in this example, MAE relative to energy is 6 times higher than MAE relative to daily generation capacity), that the MAE relative to energy (rMAE) is selected as the evaluation metric.

2.2 Approach

This metric can be used to quantify irradiance data accuracy for a one-year time period (2011) with time intervals ranging from one-minute to one-year using a historical time perspective. The analysis was performed for both individual locations and the ensemble of those locations.

2.3 Location Selection

2.3.1 Locations Selected for Validation

Ten of the 46 metered locations were randomly selected for validation purposes. In order to perform the detailed analysis, each location had to have two global horizontal insolation (GHI) monitoring devices available on site and have one year's (2011) worth of data available. There were six locations that passed this initial screening.

A total of six test locations were analyzed where PV systems are located within the CAISO control area. The locations are identified as locations A through F. Each location is equipped with two redundant global horizontal irradiance (GHI) sensors. One of the sensors was used as a reference and compared to four test configurations: the second ground sensor, and three satellite-derived sources (SolarAnywhere Standard, Enhanced, and High Resolution data sets).

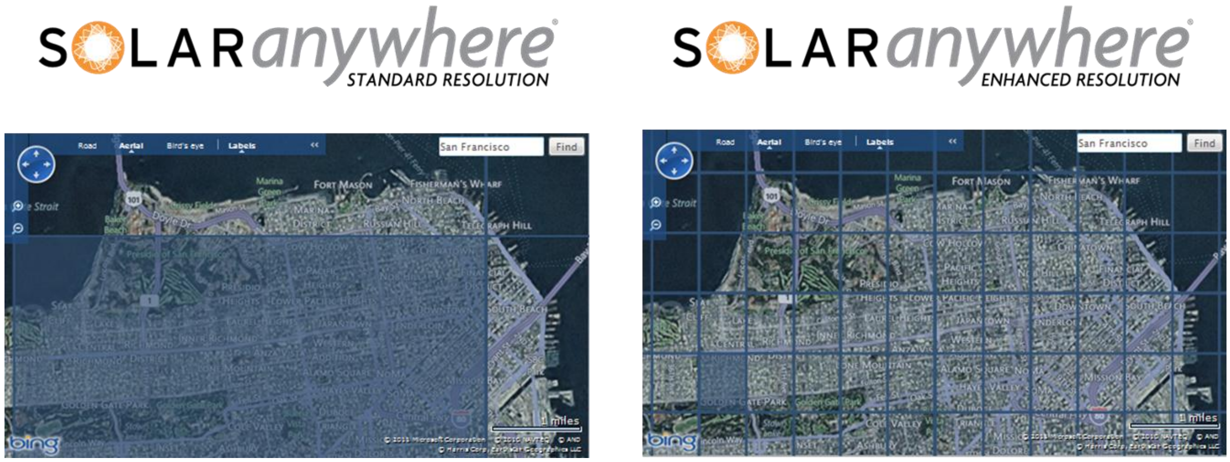
The validation approach involved the following steps:

- Obtain time-series GHI data for 2011 for six locations:
  - 4-second data averaged into 1-minute time intervals from two separate sensors at each location (sources: CAISO [20])
  - Satellite based data at the following resolutions (source: SolarAnywhere [14])
    - 1 minute, 1 km grid (High Resolution)
    - ½ hour, 1 km grid (Enhanced Resolution)
    - 1 hour, 10 km grid (Standard Resolution)
- Time-synchronize data sets by converting ground sensor data from Pacific Daylight Time to Pacific Standard Time.
- Evaluate all observations for data quality; exclude data where any one of the data sources has data quality issues.
- Calculate rMAE using the ground sensor that minimizes SolarAnywhere error as a reference.
- Calculate rMAE using the other ground sensor as a reference.
- Repeat the analysis for fleets of locations.

2.3.2 Obtain Time Series Data

CPR extended SolarAnywhere Standard Resolution (10 km spatial/1 hour temporal resolution) to SolarAnywhere Enhanced Resolution (1 km spatial/ 30 minute temporal resolution) under a previous contract.[1] Figure 6 illustrates the increase in resolution for San Francisco, CA.

Figure 6: SolarAnywhere Standard and Enhanced Resolution

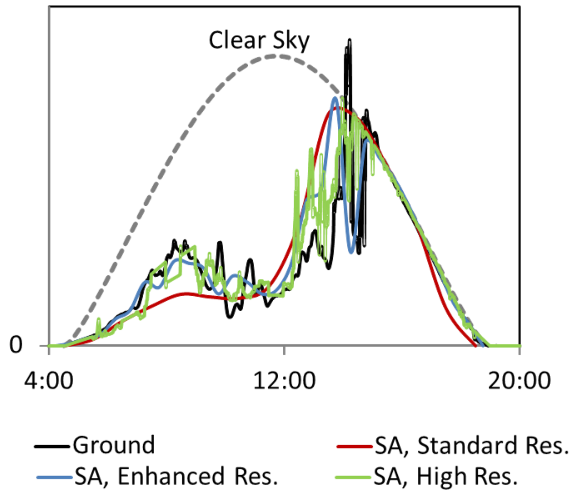


(San Francisco, CA)

A critical part of this CEC project was to extend SolarAnywhere Enhanced Resolution to SolarAnywhere High Resolution (1 km spatial/ 1 minute temporal resolution). The data was generated for all selected locations. Figure 7 presents a sample of the data for one day (July 4, 2011) at one location (CAISO Site A).

[1] California Solar Initiative Solicitation #1 Grant Agreement, "Advanced Modeling and Verification for High Penetration PV".

Figure 7: Time Series Data for All Data Sources on July 4, 2011 at CAISO Site A



Note: only one ground source is shown for clarity purposes

2.3.3 Evaluate All Observations for Data Quality

As mentioned above, one of the steps in the analysis was to evaluate all observations for data quality. When evaluating accuracy, it is often simply assumed that reference data is correct. This assumption is made due to the difficulty in determining whether or not the reference data is correct: to what can the reference data be compared?

A unique aspect of the data provided by the CAISO is that all the locations have two ground sensors. As a result, since either sensor could be the reference, the data quality of the ground sensors was assessed by comparing the two ground data sets.

This was the process used to assess data quality:

(1) Compare the two sets of ground sensor data to each other to determine when one value is substantially different than the other value.
(2) Compare the enhanced resolution satellite and ground sensor data to search for 0 values occurring at incorrect times (e.g., mid-day on otherwise clear day) to determine when the satellite data is invalid.
(3) Compare ground sensor data to the SolarAnywhere Enhanced Res. data to determine if both ground observations are the same but are obviously incorrect (e.g., the irradiance value remains at a constant level for many hours).

The complete data set was evaluated and then potential outliers were manually evaluated and screened for each of these steps. Figure 8 illustrates the screening result when comparing the two ground sensors at one location. All of the data points would lie on the 45 degree red line if they were identical. The blue symbols correspond to valid data and the black symbols correspond to invalid data. Figure 9 illustrates the issue for one of the invalid observations when one of the sensor's recorded values remained constant after solar noon. Figure 10 illustrates the case when both ground sensors produced a similar value but were obviously incorrect, reading a constant low value on an otherwise clear day as assessed from the satellite data. Figure 11 illustrates the case when there was a night-time calibration error across the year. Site E was missing more than a month of data during the first part of the year as well as a five percent difference between the two ground sensors.

Sites E and F were eliminated from the analysis as a result of the data filtering process. The remaining sites had about one percent of the ground data marked as invalid.

Figure 8: Half-Hour Energy Production in 2011 from Meter 2 vs. Meter 1 (Site A)

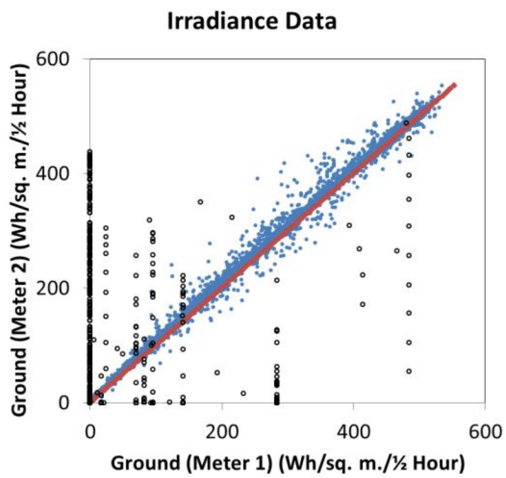
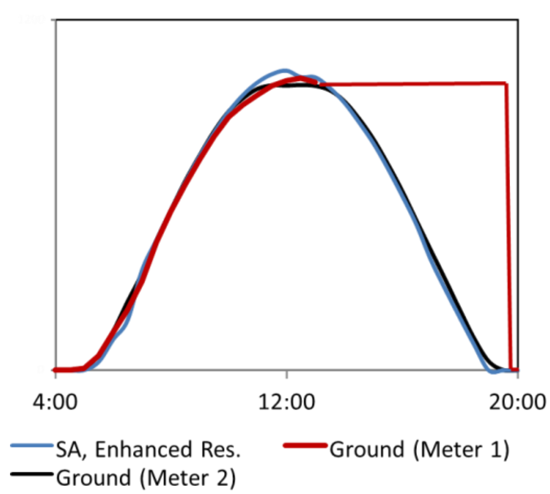
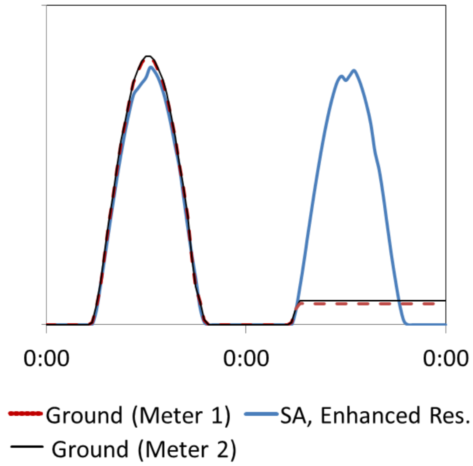


Figure 9: Example of When Only One of the Ground Sensors Has Invalid Data



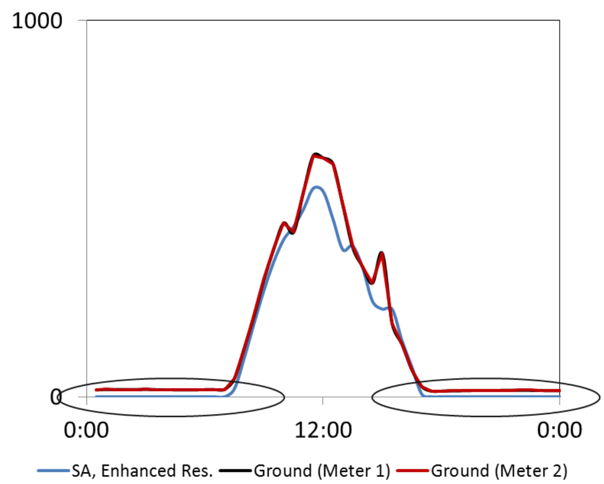
(Site A, June 22, 2011)

Figure 10: Example of When Both Ground Sensors Have Invalid Data



(Site C, May 1-2, 2011)

Figure 11: Site F Has a Night-Time Calibration Error across the Year



2.4 Results

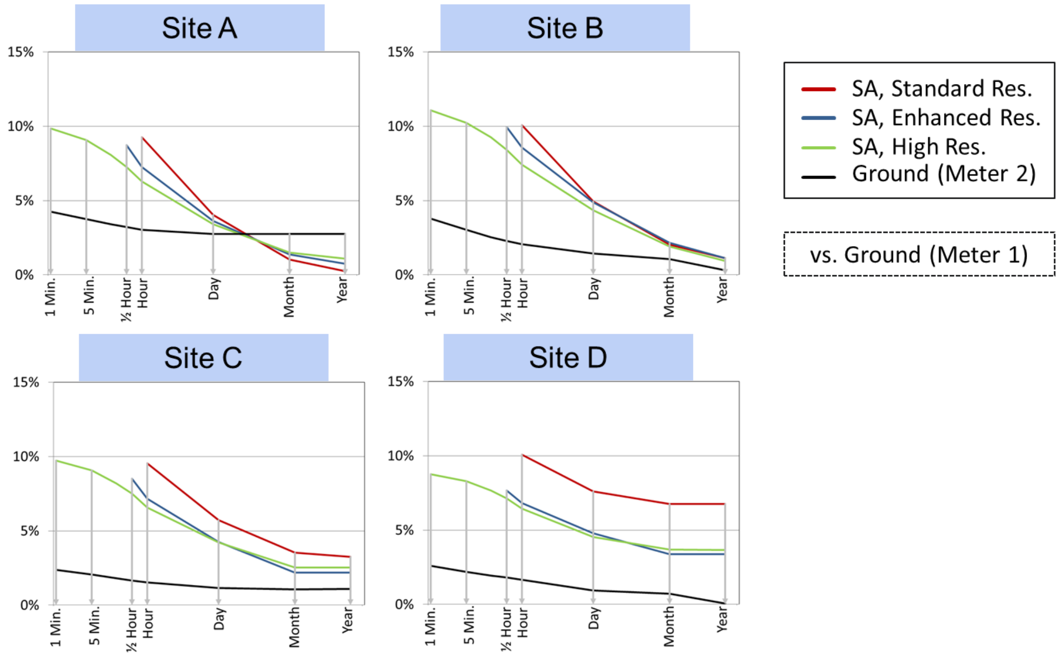
rMAE was calculated for three scenarios:

- Each location individually.
- Average of individual locations.
- Fleet of locations.

2.4.1 Each Individual Location

Figure 12 presents the rMAE for each of the four locations using time intervals ranging from 1 minute to 1 year.

Figure 12: Relative MAE for Each Location Individually

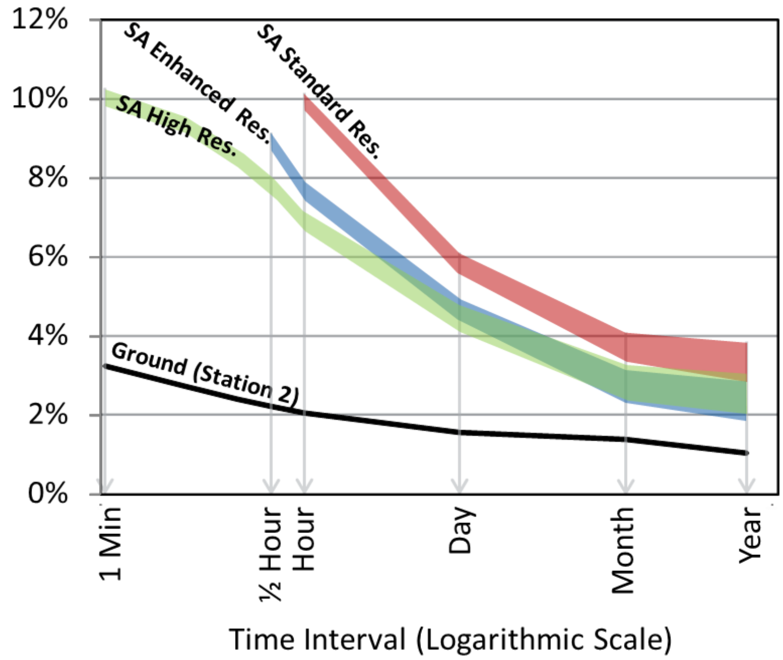


2.4.2 Average of Individual Locations

Figure 13 presents the average rMAE of four individual locations. The black line summarizes the error when two ground stations were used (one was the reference and the other was the test). The green, blue, and red regions summarize the error when SolarAnywhere High, Standard, and Enhanced Resolution were compared to the ground sensor. The green, blue, and red areas are regions rather than lines because they compare satellite data to ground data using the two different ground sensors: the top of the region is the comparison using the ground sensor that maximizes error; the bottom of the region is the comparison using the ground sensor that minimizes error.

There are several important things to notice in the figure. First, as expected, error decreases for all data sources as the time interval increases. Second, accuracy improves for each of the three satellite models as the spatial and temporal resolutions are increased. Third, error exists even between two ground sensors that are in almost the same location (i.e., ground sensors have 1 percent annual error). Fourth, SolarAnywhere High Resolution has only 10 percent error over a one minute time interval, 7 percent error over a one hour time interval, and 2 to 3 percent error on a one year time interval.

Figure 13: Average MAE of 4 Individual Locations



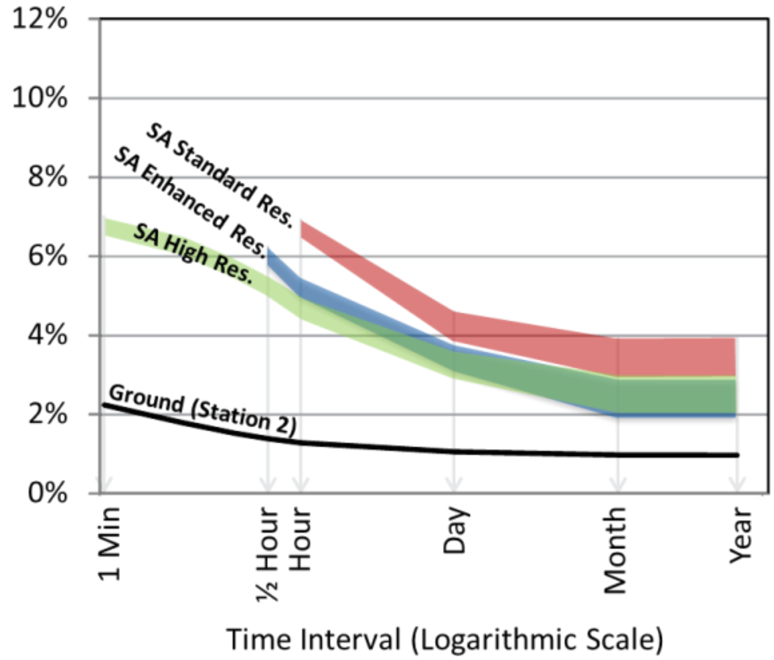
2.4.3 Fleet of Locations

As illustrated by the list of References, a number of studies have examined the issue of PV output variability. A consistent finding of these studies is that variability is reduced when PV systems are geographically dispersed. That is, variability is reduced as the number of systems increases across a sufficiently large geographic region.

So far, this report has focused on the error associated with individual locations. While individual locations are of interest in some cases, there are certainly many other cases in the utility industry when users are most interested in the error associated with a set of locations.

The rMAE analysis was repeated with the input data being the combined irradiance across four locations. The results are presented in Figure 14. A clear reduction in error due to combining locations can be seen by comparing Figure 14 to Figure 13. That is, the effect of geographic dispersion on reducing output variability reduction that has been observed by others is now also observed with regard to prediction accuracy: accuracy improves as a geographically diverse set of independent locations are combined.

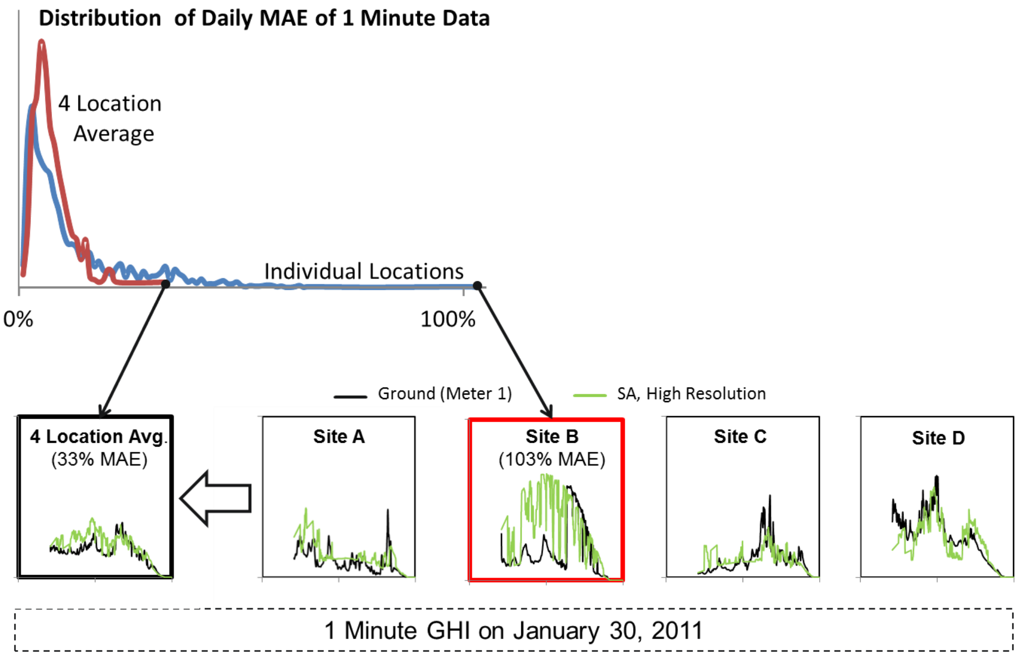
Figure 14: MAE of 4 Locations Combined



In order to demonstrate why this is occurring, a "worst day" analysis was performed. In particular, the "worst day of the year was selected (i.e., the day that had the highest MAE calculated using a one-day time period and one-minute time interval for any of the four locations). The results are illustrated in Figure 15. The top graph in the figure is a probability distribution of the daily MAE for all 4 sites and 365 days per year. As can be seen in the figure, the worst day of the year had 103 percent daily rMAE on a one minute basis.

The black line in the figure points to the graph of the one minute GHI for January 30, 2011, at Site B, the worst day and worst site of the year. SolarAnywhere High Resolution clearly over predicted irradiance on this day. The prediction at the other three sites, however, was good. As a result, the combined error for the day is 33 percent. As shown by the red line in the top distribution figure, this was still the day that had the highest daily error, but it is much lower than the one site by itself.

Figure 15: Worst Day, Worst Site Analysis.



Site B Had Highest Daily Error on Jan. 30, 2011.
The 4 Location Average Reduces Effect.

Furthermore, fleet error appears to be able to be approximated from average individual location error as follows.

$$\begin{aligned}&\mathit{Predicted\ Mean\ Abosolute\ Error}\\&= \frac{\mathrm{E}[\mathit{MAE\ for\ selected\ time\ interval}]}{\sqrt{N}} + |\mathrm{E}[\mathit{MBE}]|\left(1 - \frac{1}{\sqrt{N}}\right)\end{aligned} \tag{2}$$

where E[] is the expected value, MBE is the mean bias error, and N is the number of independent locations. This proposed relationship will have to be ascertained with a larger sample of data points, but it can be stated that the $\sqrt{N}$ dependence is an inference of the reasonable assumptions that errors at individual locations are not correlated. This follows along the Strong Law of Large Numbers that states that the average of a sequence of independent random variables having a common distribution will, with probability 1, converge to the mean of that distribution as the number of observations goes infinity [21].

2.5 Summary

Results suggest that, first, satellite-based irradiance has annual error comparable to ground sensors. Thus, satellite data may perform as well as ground data for plant siting at a fraction of the cost plus the benefit of long-term data streams. It should be noted that ground sensors, even well maintained, produce considerably more invalid data points than the satellite (a ratio of one hundred to one in the present study), and that the satellite data were key in detecting these erroneous data points (particularly when both redundant sensors were inaccurate at the same time).

Second, high resolution satellite-based irradiance has 10 percent one minute error for a single location, making it suited to provide the basis for data required to perform high penetration PV studies.

Third, accuracy improves predictably due to the benefit of geographic dispersion. That is, the effect of geographic dispersion on reducing output variability reduction that has been observed by others is now also observed with regard to prediction accuracy.

Chapter 3:
PV Fleet Simulation

3.1 Introduction

This chapter describes how to generate time series PV fleet production data for consumption by CAISO processes. This required the following:

- Interact with the CAISO to develop a data format specification for time series PV fleet data that will be compatible with their system expectations.
- Design, test, and implement a method to produce a set of synthetic PV fleet performance data.
- Create time series data streams, deliver to the CAISO for their use, and assist the CAISO in analyzing, using, and implementing this data as required.

3.2 Forecast Requirements

The first step of the process was to interact with the CAISO to develop data format specifications for time series PV fleet data that will be compatible with their system expectations. The CAISO and CPR met on several occasions to finalize this information. Table 6 and Table 7 present the CAISO's near-term and long-term requirements. The requirements are classified according to the Real-Time Power Dispatch (RTPD) market and the Day-Ahead market.

The requirements specified how often the forecasts needed to be updated, when the forecasts were due, forecast time interval, forecast time horizon, and whether or not the forecasts should include uncertainty bounds (i.e., confidence intervals). The goal under this project is to satisfy the CAISO's near-term requirements. Subsequent work will satisfy their long-term requirements.

Table 6: Near-Term CAISO Requirements

Market	Update Frequency	Forecast Due	Forecast Interval	Forecast Horizon	Include Uncertainty?
Real-Time Power Dispatch	30 min	Every 30 minutes	15 min	12 hours	No
Day-Ahead	Daily	7:45 am of day before	1 hour	6 days	No

Table 7: Long-Term CAISO Requirements

Market	Update Frequency	Forecast Due	Forecast Interval	Forecast Horizon	Include Uncertainty?
Real-Time Power Dispatch	15 min	Every 15 minutes	15 min	12 hours	Yes
Day-Ahead	Hourly	45 min past hour	1 hour	6 days	Yes

3.3 PV Fleet Simulation Method

The second step was to design, test, and implement a method to simulate PV fleet performance data per the CAISO's requirements listed in Table 6. Three components are required to simulate PV fleet power production (as illustrated in **Error! Reference source not found.**):

1. Solar resource data.
2. PV plant specification data.
3. PV fleet simulation model.

3.3.1 Solar Resource Data

The first component that is required to simulate PV fleet power production is the solar resource data. The SolarAnywhere Enhanced Resolution data is used for the simulation for all of the plants in California. This database consists of solar resource observations produced every 30 minutes based on satellite imagery for the state of California using a 1 km grid. Higher speed data observations are generated using these native images using a cloud motion vector interpolation approach. The cloud motion vector approach takes two consecutive images and infers cloud movement (i.e., speed and direction) based on a comparison of the two images.

The SolarAnywhere Standard Resolution data is used for the simulation for the plants in Arizona. This database consists of solar resource observations produced every 60 minutes based on satellite imagery using a 10 km grid.

Details of the solar resource data are described above.

3.3.2 PV Plant Specification Data

The second component that is required to simulate PV fleet power production is a set of PV system specifications. PV systems in California can broadly be categorized as being either metered or behind-the-meter. The key is which systems should be included.

Validating simulated vs. measured data requires that measured data is available. As a result, the metered systems provide the basis for validation efforts. An earlier chapter described how the CAISO metered fleet consists of 46 PV plants. It also presented the capacity (MW-AC) of each system. The total capacity of this fleet is 959 MW-AC.

Details of this data collection effort are described above.

3.3.3 PV Fleet Simulation Model

The third component that is required to simulate PV fleet power production is a PV fleet simulation model. SolarAnywhere® FleetView™ is used for this task.

One approach to simulating PV fleet output is to calculate average irradiance across the fleet and average capacity of the fleet and then to perform a single simulation. This approach, however, fails to capture the weather variability associated with specific locations because it artificially smooths fleet output.

FleetView takes a much more detailed approach. Power production is simulated for every PV plant independently. The simulations from the individual plants are then summed to obtain fleet production. This approach captures site-specific resource variability.

3.3.4 Rapid Calculations

In addition to having three requirements to be able to produce the fleet predictions, the calculations need to be performed at a speed that satisfied the CAISO requirements. The SolarAnywhere FleetView software service was initially designed to provide forecast data across large geographic areas for a limited number of PV systems. The CAISO, however, required forecast data every 30 minutes for a large number of PV systems (currently at 130,000 systems). As a result, the method of producing and delivering the data needed to be modified to accommodate the CAISO's requirements.

Two broad categories of modifications were required. One category was to identify inefficiencies in existing solar resource forecast software code and to implement code changes to speed processing. Another category was to migrate SolarAnywhere software solution from a single server application to a multi-server, cloud-based application. This was required in order to make the forecasting process scalable according to the number of PV systems.

It initially required more than 30 minutes to produce forecasts. This was an issue because the CAISO needed a forecast every 30 minutes, but the forecast could not be completed in less than 30 minutes. The forecast production time has now been reduced to less than 30 minutes.

3.4 Time Series Data

The next step was to create time series data streams, deliver the data to the CAISO for their use, and assist the CAISO in analyzing, using, and implementing this data as required. CPR began producing forecasts and posting them to a secure FTP site in January, 2013. CPR went through several months of testing to ensure that the data was reliably delivered. The CAISO has initiated the process of downloading the data.

An Excel file is posted to the secure FTP site every half hour for the RTPD market. A file is posted every day for the Day-Ahead market. Each file contains three columns: Period Ending, Region, and Power (MW). Figure 16 presents the first several rows in an RTPD file that was produced on 5/9/2013 at 10:30.

Figure 16: Sample RTPD PV Fleet Forecast File

	A	B	C
1	**Period Ending**	**Region**	**Power (MW)**
2	5/9/2013 10:45	Non-Metered: PG&E Bay Area	147.3
3	5/9/2013 11:00	Non-Metered: PG&E Bay Area	151.7
4	5/9/2013 11:15	Non-Metered: PG&E Bay Area	156.0
5	5/9/2013 11:30	Non-Metered: PG&E Bay Area	159.3
6	5/9/2013 11:45	Non-Metered: PG&E Bay Area	162.6
7	5/9/2013 12:00	Non-Metered: PG&E Bay Area	163.1
8	5/9/2013 12:15	Non-Metered: PG&E Bay Area	163.5
9	5/9/2013 12:30	Non-Metered: PG&E Bay Area	164.0
10	5/9/2013 12:45	Non-Metered: PG&E Bay Area	164.5
11	5/9/2013 13:00	Non-Metered: PG&E Bay Area	167.0
12	5/9/2013 13:15	Non-Metered: PG&E Bay Area	169.6
13	5/9/2013 13:30	Non-Metered: PG&E Bay Area	191.7

3.5 Summary

This chapter described how CPR is providing time series PV fleet production data for the CAISO. This included interacting with the CAISO to determine forecast data requirements, modifying the PV fleet power production simulation method in SolarAnywhere FleetView to accommodate these requirements, and creating the time series data. The next chapter validates simulated PV fleet power production in comparison to measured data provided by the CAISO.

Chapter 4:
PV Fleet Simulation Validation

4.1 Introduction

This chapter describes the validation of simulated PV fleet production using measured data provided by the CAISO. This required the following:

- Work with the CAISO to determine data availability, resolve time synchronization issues, and take steps necessary to ensure data integrity.
- Obtain data and upload to the contractor's data servers.
- Perform analysis using methods previously used for similar United States data sources.

4.2 Approach

Validation requires simulated and measured data. The previous chapter discussed how the data was simulated using FleetView. The measured data was provided by the CAISO. The CAISO measures power production every four seconds for 46 PV plants. A 15-minute time interval is critical to the CAISO's forecasting efforts above. Thus, the four-second measured PV power production was averaged to 15-minute data.

4.3 Results

4.3.1 Sources of Error

Inaccuracies degrade the ability of the simulation to reflect measured performance. These inaccuracies can be grouped into three categories.

1. Solar resource.
2. PV modeling.
3. PV plant performance issues.

Solar resource inaccuracies include errors in historical or forecasted solar resource data. PV modeling inaccuracies refer to limitations in the PV fleet modeling algorithms. PV plant performance issues reflect errors that occur because the plant is not operating as expected.

The effects of solar resource and PV modeling inaccuracies are fairly obvious. Inaccurate solar resource data (historical or forecasted) and/or PV fleet modeling algorithms clearly limit the simulation's ability to reflect measured performance.

PV plant performance issues are more subtle. Differences between simulated and measured PV production can still occur even if the simulation method perfectly predicts measured PV fleet power production for a fleet that is operating perfectly. Differences can occur if the actual PV fleet does not operate as expected due to system performance issues. That is, inaccuracies can occur that are unrelated to the fundamental simulation methodology. They are related to lack of incorporation of poor performance into the simulation.

4.3.2 PV Plant Performance Issues

The first step of the evaluation, therefore, is to determine how to address PV performance issues. One option is to incorporate plant status into the simulation methodology. The simulation, for example, would reflect a capacity reduction if a plant was only operating at 50 percent capacity. This option requires obtaining PV plant status information. This information, unfortunately, was unavailable for the CAISO fleet of PV systems.

An alternative approach is to identify days when the individual plants had sub-par performance. These days and plants are then eliminated from the fleet simulation. This is the approach that was taken for this project.

Fifteen-minute measured and simulated data were obtained for 46 CAISO metered PV plants from March 10, 2013 to April 19, 2013. The time series data were compared for each of the plants individually. The data was visually examined to assess days when the PV plant was either not operating or was clearly underperforming. Figure 17 and Figure 18 present the results of the analysis for two of the 46 plants. The red and blue lines correspond to simulated and measured data. The shaded areas represent days with plant performance issues. The dashed line corresponds to the daily rMAE. Figure 17 corresponds to a plant that operated well during the whole time period. Figure 18 corresponds to a plant that had significant operational issues.

Figure 17: Example of PV Plant that Operated as Expected

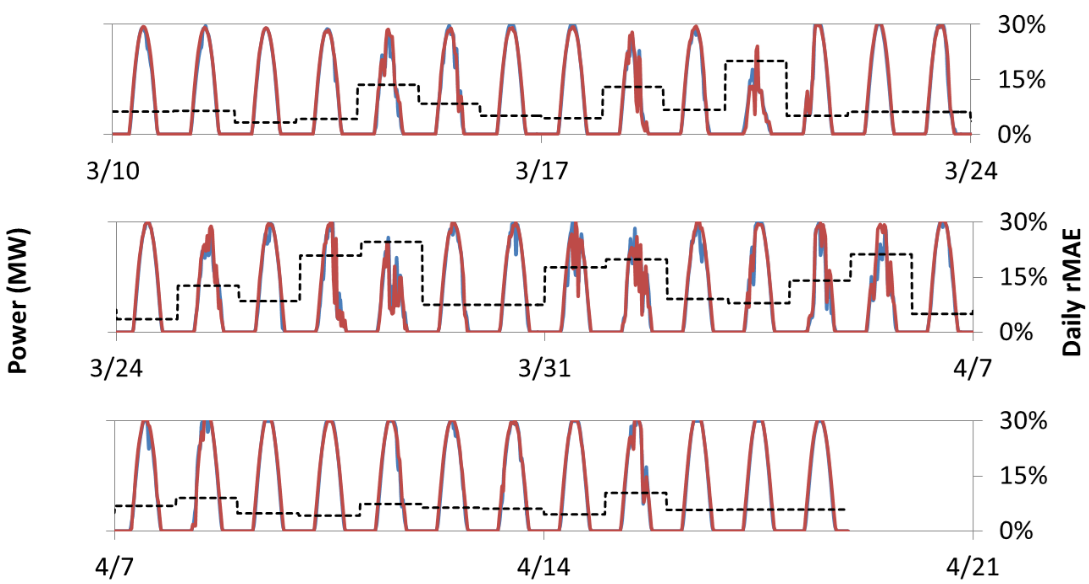
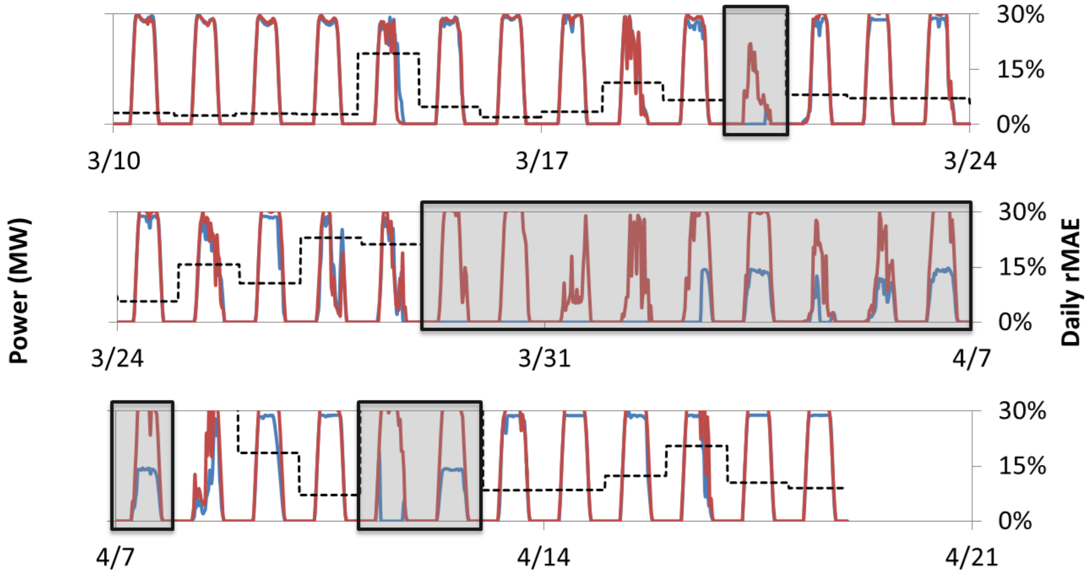
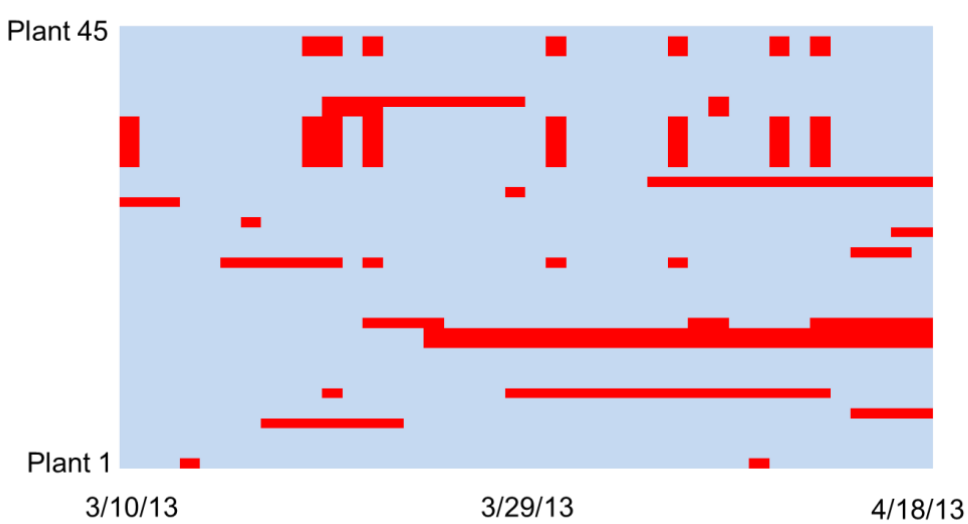


Figure 18: Example of PV Plant with Possible Performance Issues



This process was repeated for all of the plants. Figure 19 summarizes plant performance for all 46 plants. The y-axis corresponds to the plant number and the x-axis corresponds to the date. Blue corresponds to normal operation and red corresponds to performance issues. The figure suggests that the PV fleet experienced a significant number of performance issues over the six-week analysis period.

Figure 19: Summary of Performance Issues for All Metered Plants



4.3.3 PV Fleet Simulations

4.3.3.1 Time Series Data

Simulations were performed using FleetView with and without plant filtering results from the previous section. Figure 20 presents PV fleet output without filtering. Figure 21 presents PV fleet output with filtering. A comparison of the two figures illustrates the improvement in accuracy by taking PV plant performance issues into consideration.

Figure 20: PV Fleet Production before PV Performance Filtering

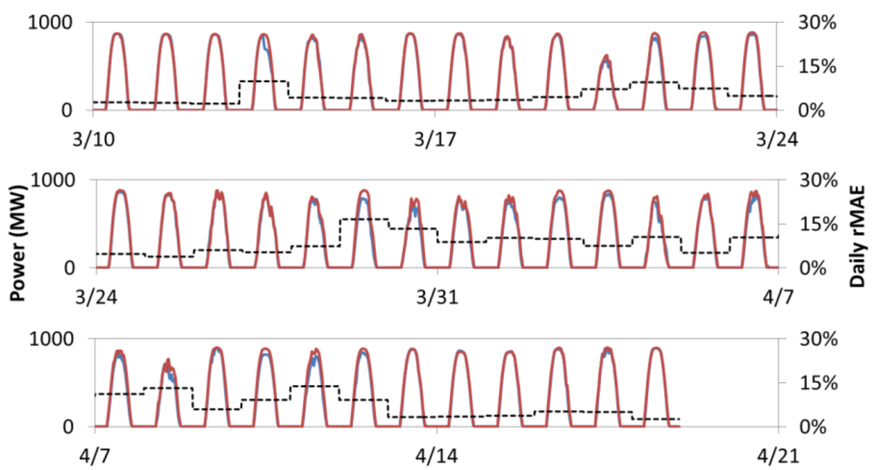
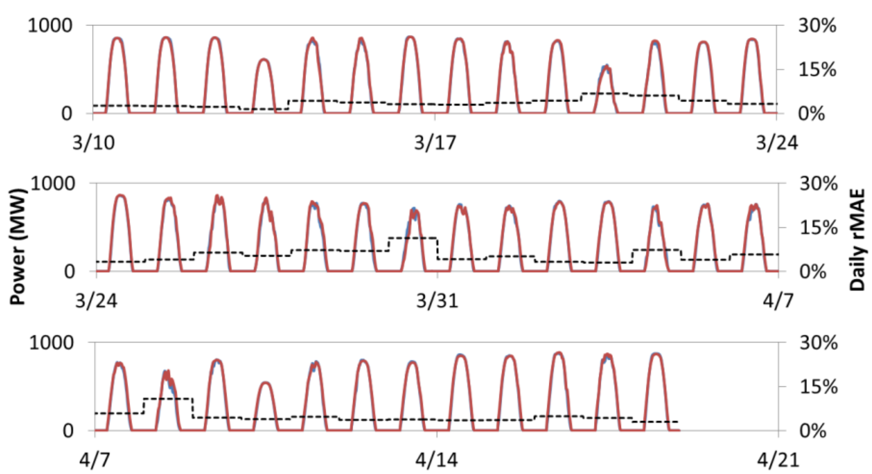


Figure 21: PV Fleet Production after PV Performance Filtering



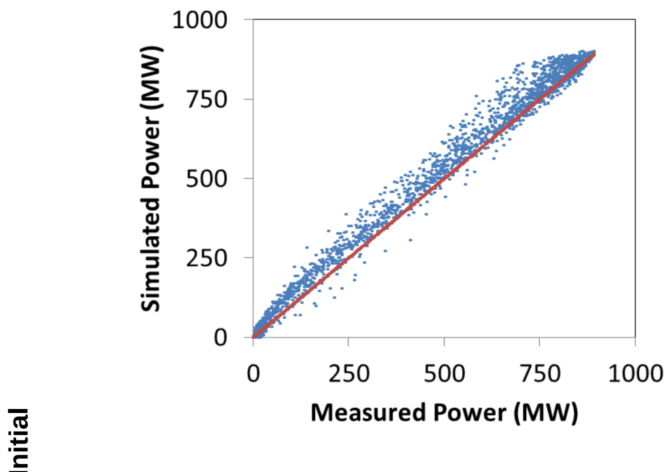
4.3.3.2 Simulated vs. Measured Data

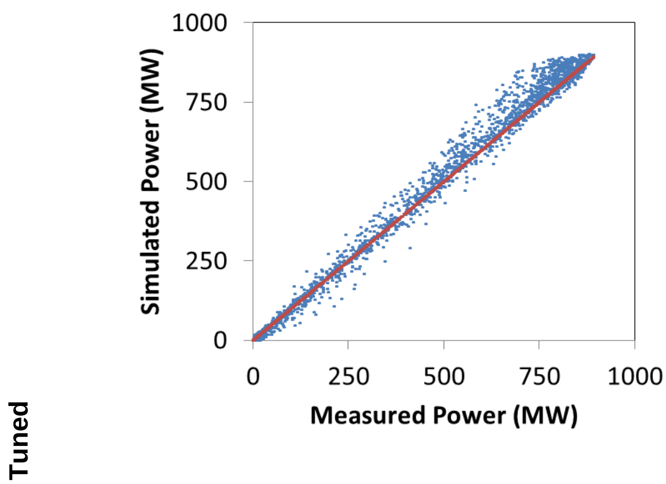
An alternative way to present the data in Figure 20 is to plot simulated vs. measured average power for each 15-minute interval. Figure 22 presents the data in this manner. All of the blue markers would be on the red line if simulated and measured results matched perfectly. The top of the figure corresponds to the "Initial" case of PV fleet output without PV performance filtering (it corresponds to Figure 20). A consistent power-related bias can be observed.

This bias can be reduced by applying the tuning curve presented in Figure 23. The "Tuned" case is presented in the center of Figure 22. Significant scatter, however, can still be observed. This can be reduced by filtering the data for PV performance using the filtering from the previous section.

The "Tuned & Filtered" case is presented in the bottom of Figure 22. There is a good alignment between simulated and measured data after making the tuning and filtering adjustments.

Figure 22: Simulated vs. Measured Average 15-Minute Power for CAISO Metered PV Fleet





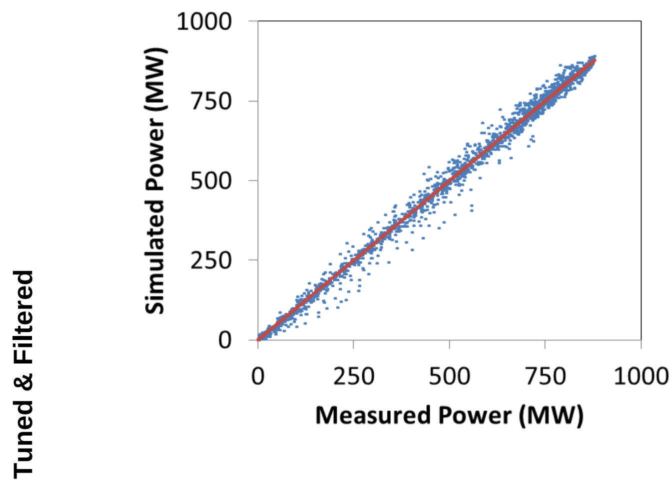
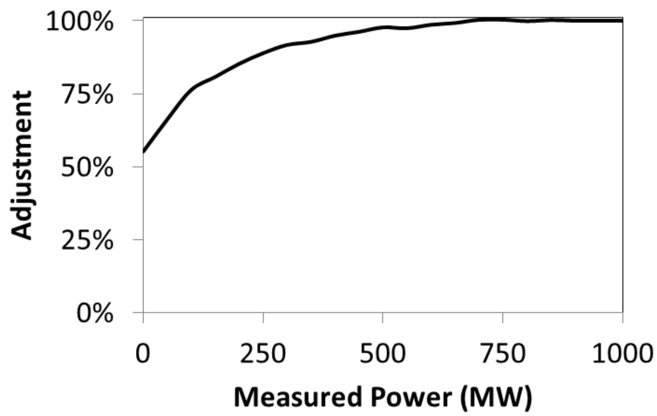


Figure 23: Power-Based Simulation Tuning



4.3.4 Relative Mean Absolute Error

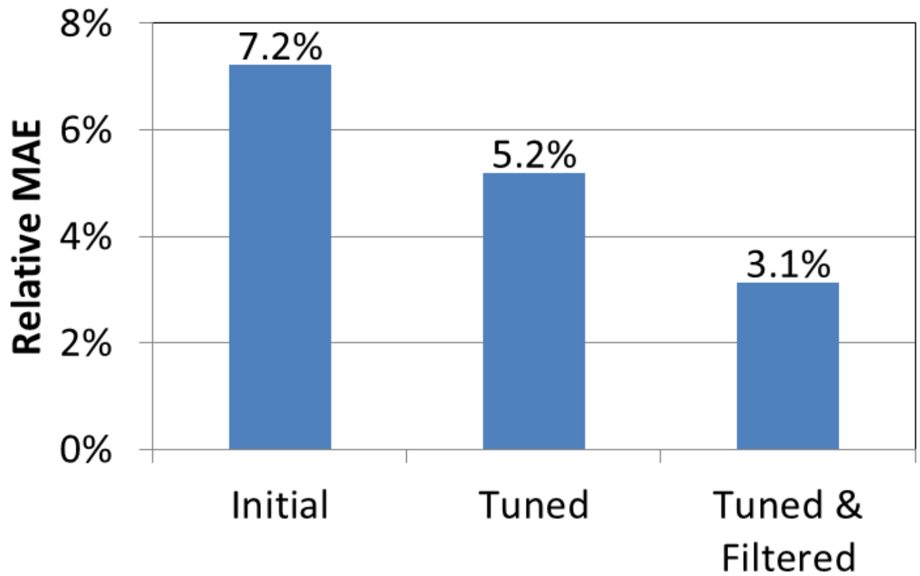
The final step of the analysis is to calculate the rMAE. The time series data were evaluated over the approximately six-week time period for the 15-minute time interval data. Figure 24 presents results for three cases: Initial, Tuned, and Tuned & Filtered. These cases correspond to the results presented in Figure 22. Results show that the Initial, Tuned and, Tuned & Filtered cases have 7.2, 5.2, and 3.1 percent rMAE.

Several observations can be made based on these results. First, overall, FleetView PV power modeling is pretty accurate. There is, however, room for improvement. In particular, improving the inverter power curve model for individual PV systems will substantially improve simulation results (i.e., the improvement identified by applying the tuning).

Second, there is a substantially negative effect due to poorly performing plants even after the PV fleet model has been tuned. Accurately representing plant status reduces error by more than 40 percent.

Third, three percent rMAE can be achieved for 15-minute time interval data using a well-tuned model that accounts for poor PV plant performance. This requires that: (1) accurate location-specific solar resource data is supplied; (2) correct PV specifications are used; (3) the inverter power curve is properly represented (i.e., the simulation is tuned); and (4) actual PV plant status is incorporated into the simulation.

Figure 24: Total rMAE



It is useful investigate the error on a daily basis in addition to an analysis over the entire time period. Figure 25 and Figure 26 presents the daily rMAE for the 15-minute time interval before and after tuning the model. The blue and red colors correspond to simulation error and PV plant performance error respectively. PV plant performance error is estimated by subtracting simulation error with and without filtering. The figure shows that rMAE varies from day to day. While absolute error increases on some of days, rMAE tends to be higher on low energy days. This is because the rMAE calculation is defined as absolute error divided by measured energy.

Figure 25: Daily Relative MAE Using 15-Minute Time Interval before Tuning

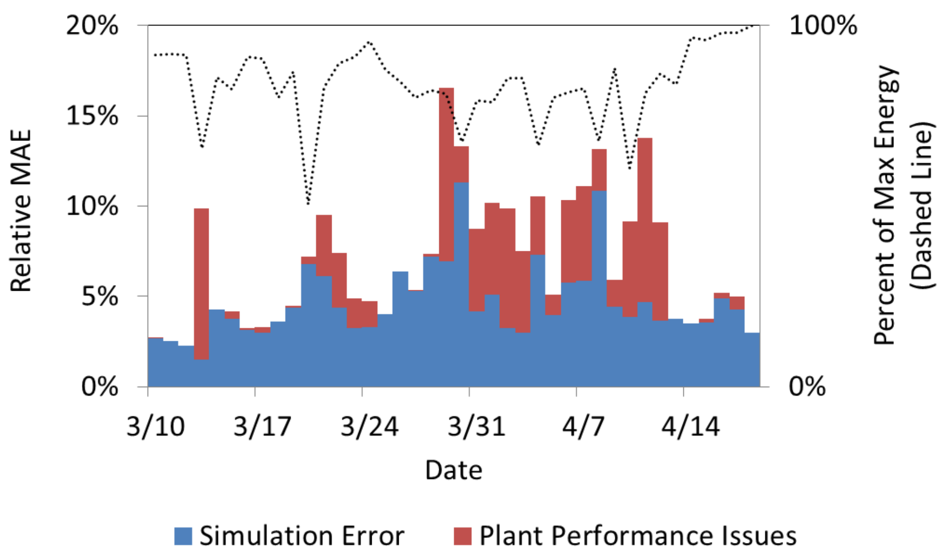
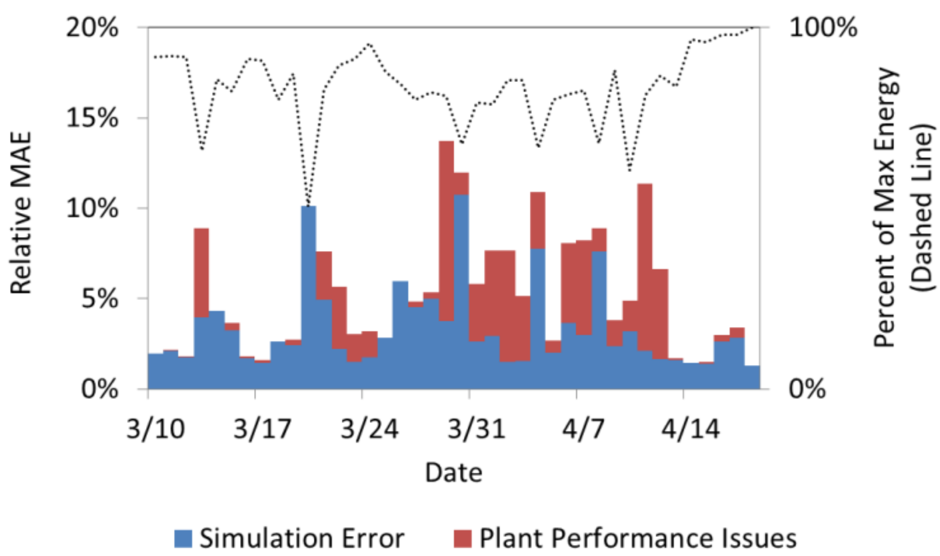


Figure 26: Daily Relative MAE Using 15-Minute Time Interval after Tuning

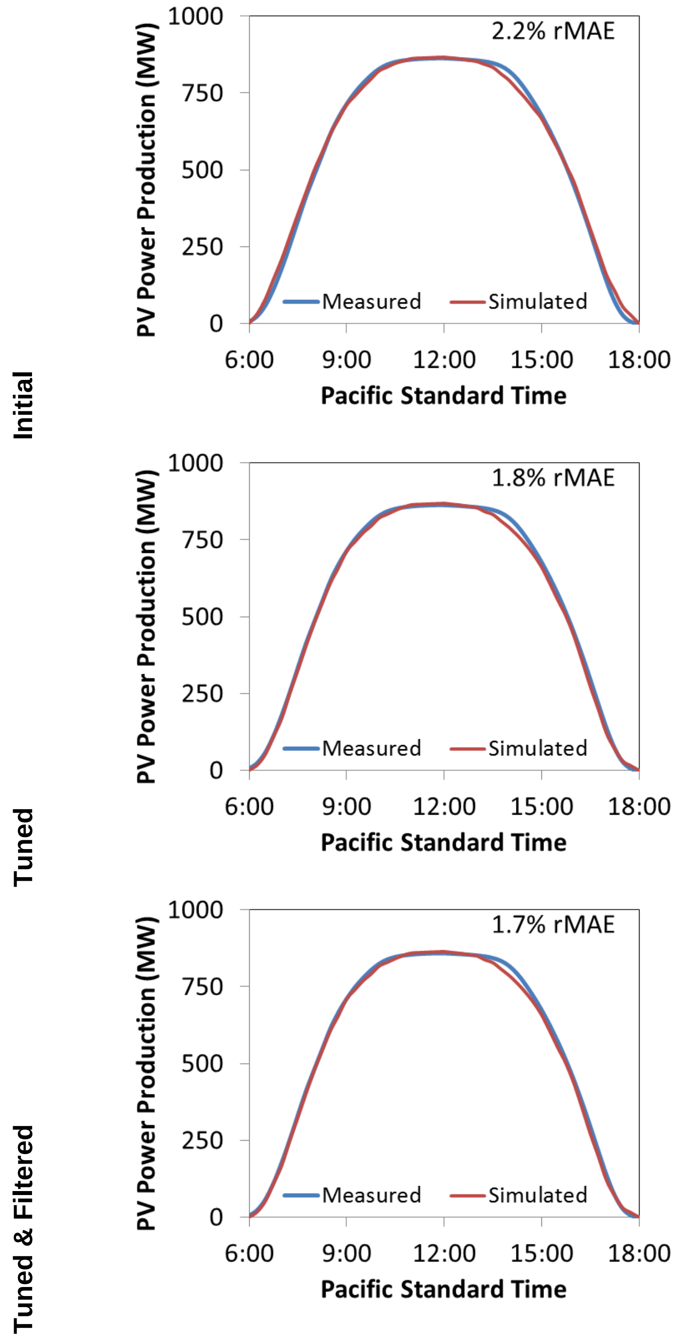


4.3.5 Sample Days After Tuning and Filtering

It is useful to compare simulated and measured data for a range of days after tuning and filtering. Figure 27, Figure 28, and Figure 29 present measured and simulated PV fleet production. Figure 27 corresponds to a clear day. Figure 28 corresponds to a day with PV performance issues. Figure 29 corresponds to a day with variable weather and PV performance issues.

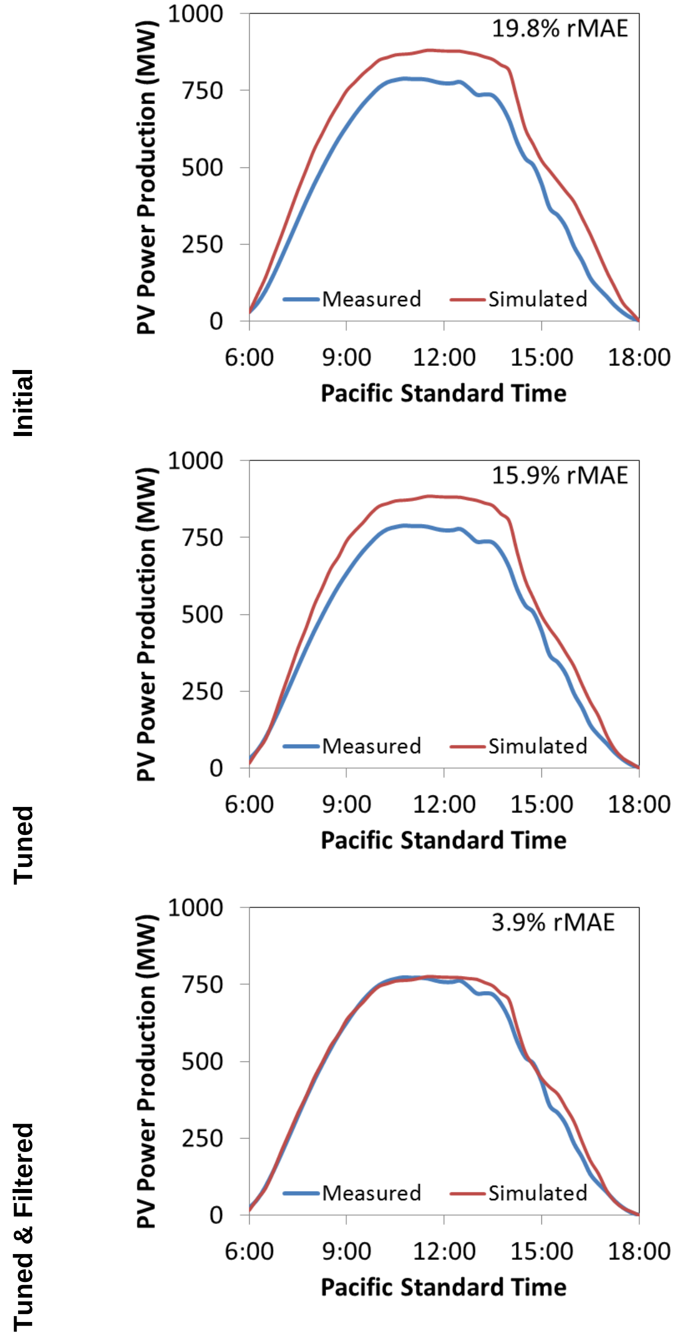
Several observations can be made. First, tuning the simulation model increases accuracy for all days. Second, modeling on a clear day is very good with a rMAE of less than 2 percent. Third, filtering for PV plant performance issues can be very important; rMAE was reduced from 20 percent to 4 percent on one particular day. Fourth, simulated data tracks measured data fairly well even for the worst performing day.

Figure 27: PV Fleet Production on Clear Day



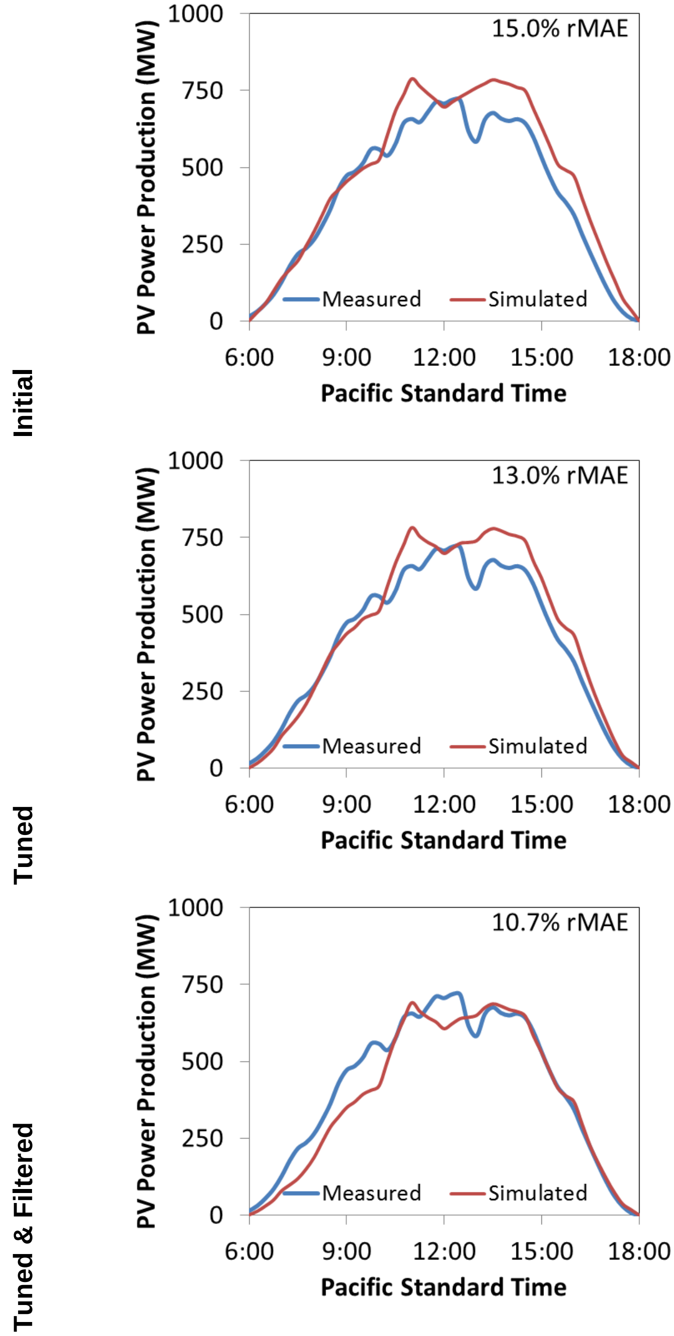
(March 12, 2013)

Figure 28: PV Fleet Production on Day with Production Issues



(March 29, 2013)

Figure 29: PV Fleet Production on Variable Weather Day with Production Issues



(March 29, 2013)

Chapter 5: Conclusions and Future Research

5.1 Conclusions

CPR has developed a unique method to predict PV fleet power production. The method uses inputs of satellite-derived solar resource data and the design attributes and locations of PV systems. It combines these inputs with advanced algorithms to track cloud patterns to predict output.

The objective of this project was to validate simulated PV fleet power production using measured PV fleet power production. This required:

- Obtaining PV system specifications for all PV systems in California.
- Obtaining solar resource data for the location of each PV system.
- Obtaining measured PV power production data for a subset of the fleet of systems.
- Screening the measured data for performance issues.
- Simulating PV fleet output using SolarAnywhere FleetView.
- Comparing measured and simulated results.

Results suggest that 3 percent Relative Mean Absolute Error (rMAE) can be achieved for 15-minute time interval data given that:

- Accurate location-specific solar resource data is supplied.
- Correct PV specifications are used.
- The PV simulation model is properly tuned.
- PV plant operating status is reflected in the simulation to account for poor performance.

Total error can be caused by solar resource inaccuracies, PV simulation model inaccuracies, and PV plant performance issues. Results also suggest that total error was over 7 percent if the model was not tuned and PV plant operating status was not reflected in the simulation.

This research also has the following benefits to CAISO:

- Prediction of behind-the-meter PV fleet performance for 1st time
- Fleet forecasts categorized by CAISO's five regions for both behind-the-meter and metered PV
- Gained confidence in CPR's PV fleet simulation accuracy
- Gained understanding into performance of metered PV plants
- Positioned to begin evaluation of integration of PV fleet forecasts into load forecasts
- PV fleet prediction tools available to support for PV fleet forecasting
- PV fleet prediction tools available to produce data required for high PV penetration grid planning

5.2 Future Research

There are several areas of future research.

- Improve inverter power curve modeling to reduce the need for tuning.
- Implement SolarAnywhere Enhanced Resolution data in Arizona to increase solar resource data resolution for all plants (i.e., Arizona plants, which represent almost half of the measured fleet capacity, currently use Standard Resolution data).
- Expand the analysis to incorporate solar resource forecast error.
- Incorporate PV plant performance status into the simulation to reduce total error.
- Continue validation efforts, especially during worst case conditions, to provide guidance as to how to use the data and to identify areas for improvement.
- Expand the analysis to probabilistic forecasting.
- Continue efforts to integrate results in to the CAISO processes.

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Appendix A:
Reporting of Relative Irradiance Prediction Dispersion Error

Introduction

Statistical methods for calculating and quantifying error have long been established across a wide range of sciences and industries. Whether quantifying the accuracy of an electrical meter, the tolerance of a precision part, or the expected range of forecasted temperatures, the methods for determining error are generally accepted. It is somewhat surprising, then, that these same methods have proved confusing and sometimes misleading when applied to commonly used diurnal quantities in the solar energy field.

Error calculations related to solar irradiance and PV power production, for example, are complicated by observations taken during nighttime and other low solar conditions. These conditions are often of little interest to the solar researcher, but they do cover the majority of time over a multi-day test period. Since these observations are subject to very low absolute error, their inclusion and weighting have a large impact on overall relative error.

As part of recent European and International Energy Agency (IEA) tasks [22], [23], a group of experts have developed recommendations for reporting irradiance model accuracy [24], [25]. Root Mean Square Error (RMSE), Mean Bias Error (MBE) and Kolmogorov Smirnoff Integral (KSI) are the three key recommended validation metrics. These respectively provide a measure of model's dispersion (RMSE), overall bias (MBE), and ability to reproduce observed frequency distributions (KSI).

In many contexts, however, relative error is more commonly desired than absolute error. While the IEA tasks developed recommendations for absolute errors, they have not developed recommendations on how to calculate error in percentage terms, aside from using the informally (but not universally) accepted approach of dividing RMSE by the day-time mean of the considered irradiance. This is unfortunate because users in the utility industry desire to understand error in relative terms rather than absolute terms.

A simplified reporting approach for the %KSI metric was proposed in a recent article [26]. The present note focuses on the relative dispersion error metrics (RMSE and MAE) with the objective of setting a standard for reporting these metrics in the industry and research community to facilitate comparison between forecast models.

Forecast model error also depends on meteorological conditions, forecast horizon, and averaging interval. There is not an attempt to create a metric that makes forecasts comparable across these dependencies. Rather, the focus is on which metric should be chosen to compare two forecasts at the same site, same forecast horizon, and same averaging interval. This discussion only focuses on methods concerned with expressing the relative error between two time series with a single statistic.

It should be remembered that methods that calculate relative or absolute error for each value in the time series may be more useful in practice, since they can uncover patterns that are obscured when the error for time series prediction is lumped into a single statistic.

Absolute errors

Root Mean Square Error (RMSE)

The RMSE is defined to be the square root of the sum of the squares of the difference between modeled and reference irradiances using some time interval (e.g., hourly) over some time period (e.g., one year) divided by the number of observations.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}\left(I_t^{test} - I_t^{ref}\right)^2}{N}} \qquad (3)$$

where I_t^{test} is the test irradiance at time t, I_t^{ref} is the reference irradiance at time t, and N is the number of observations.

One ambiguity with the RMSE calculation (as well as all other error calculations that involve any sort of averaging) is that a decision is required as to whether or not to include all values. The prevalent practice in the solar resource community has been to only include daytime values, sometimes filtered by solar zenith angle less than 80˚ to avoid shading and/or sensor cosine response issues under low sun angles.

Mean Absolute Error (MAE)

The MAE is defined to be the sum of the differences between modeled and reference irradiances using some time interval over some time period divided by the number of observations.

$$MAE = \frac{\sum_{t=1}^{N}\left|I_t^{test} - I_t^{ref}\right|}{N} \qquad (4)$$

Relative (Percent) Errors

Quantifying relative error requires that absolute error (i.e., RMSE or MAE) be divided by a normalizing number. To emphasize, the normalization is not carried out for each I_t^{test} and I_t^{ref} pair, but rather using a single number representative of typical irradiances during the entire time series. Three possible candidates to use in the denominator to calculate *Percent Error* are:

- Average irradiance (Avg.).
- Weighted average irradiance (Weighted Avg.).
- Maximum nominal irradiance (Capacity).

Average

Average irradiance equals the sum of the irradiance values divided by the number of observations.

$$Average = \frac{\sum_{t=1}^{N} I_t^{ref}}{N} \tag{5}$$

Weighted Average

Weighted Average irradiance may be used to assign more importance to high-level irradiance observations. It is defined to be the sum of the irradiance values weighted by a factor.

$$Weighted\ Average = \sum_{t=1}^{N} W_t I_t^{ref} \tag{6}$$

One meaningful way to weight the irradiance is by its magnitude. That is, let

$$W_t = \frac{I_t^{ref}}{\sum_{t=1}^{N} I_t^{ref}} \tag{7}$$

Substituting Equation (7) into Equation (6) results in a Weighted Average of

$$Weighted\ Average = \frac{\sum_{t=1}^{N} \left(I_t^{ref}\right)^2}{\sum_{t=1}^{N} I_t^{ref}} \tag{8}$$

Unlike for the simple average, the day-time weighted average equals the 24-hour weighted averages since the weight of night-time points is zero.

Capacity

A third option is the peak irradiance or Capacity (C). For global horizontal irradiance, for example, the Capacity would be 1,000 W/m^2.

The wind industry has adopted this approach of normalizing to installed generating capacity for the reporting of output prediction errors [27].

Percent Error Calculation Methods

With two measures of dispersion (RMSE and MAE) and three normalizing means, there are six possible methods to calculate *Percent Error*. These methods are summarized in Table 8.

Table 9 presents the mathematical definitions used to calculate *Percent Error* by combining Equations (3) through (8) (see appendix for the detailed derivations).

Table 8: Possible *Percent Error* Calculation Methods

	RMSE	MAE
Average	RMSE/Avg.	MAE/Avg.
Weighted Average	RMSE/Weighted Avg.	MAE/Weighted Avg.
Capacity	RMSE/Capacity	MAE/Capacity

Table 9: Mathematical Definitions of *Percent Error* Methods

Percent Error Method	Definition	
RMSE/Avg.	$\sqrt{N}\left(\frac{1}{\sum_{t=1}^{N} I_t^{ref}}\right)$	$\sqrt{\sum_{t=1}^{N}\left(I_t^{test}-I_t^{ref}\right)^2}$
RMSE/Weighted Avg.	$\left[\frac{1}{\sqrt{N}}\right]\left[\frac{\sum_{t=1}^{N} I_t^{ref}}{\sum_{t=1}^{N}\left(I_t^{ref}\right)^2}\right]$	$\sqrt{\sum_{t=1}^{N}\left(I_t^{test}-I_t^{ref}\right)^2}$
RMSE/Capacity	$\left(\frac{1}{\sqrt{N}}\right)\left(\frac{1}{C}\right)$	$\sqrt{\sum_{t=1}^{N}\left(I_t^{test}-I_t^{ref}\right)^2}$
MAE/Avg.	$\left(\frac{1}{\sum_{t=1}^{N} I_t^{ref}}\right)$	$\sum_{t=1}^{N}\left\|I_t^{test}-I_t^{ref}\right\|$
MAE/Weighted Avg.	$\left[\frac{1}{N}\right]\left[\frac{\sum_{t=1}^{N} I_t^{ref}}{\sum_{t=1}^{N}\left(I_t^{ref}\right)^2}\right]$	$\sum_{t=1}^{N}\left\|I_t^{test}-I_t^{ref}\right\|$
MAE/Capacity	$\left(\frac{1}{N}\right)\left(\frac{1}{C}\right)$	$\sum_{t=1}^{N}\left\|I_t^{test}-I_t^{ref}\right\|$

24 Hours vs. Daytime

The effect of including 24 hours in the analysis vs. only including daytime values can be analyzed using the equations presented in

Table 9. *Total Error* (i.e., $\sqrt{\sum_{t=1}^{N}\left(I_t^{test}-I_t^{ref}\right)^2}$ or $\sum_{t=1}^{N}\left|I_t^{test}-I_t^{ref}\right|$) remains unchanged by including night-time values. However, *Absolute Error* (RMSE or MAE) is affected by the distinction since the results are obtained by dividing *Total Error* by the number of considered points. *Percent Error* is further affected by the daytime vs. 24-hour distinction since the normalizing means are different.

Table 10 summarizes the impact of the distinction on the selected error reporting metrics. It shows that *Percent Error* calculated using RMSE/Avg. method increases from 24 hour to daytime, the MAE/Avg. is unchanged, and *Percent Error* calculated using the other four methods decreases.

In all of the changed scenarios, the change is a function of the fraction of daytime hours. For example, if there are 4,380 daytime hours in a 12-month test period, the fraction Daytime Hours is 0.5. If night time hours are considered, *Percent Error* calculated using RMSE/Avg. will increase by 41 percent ($\sqrt{\frac{1}{0.5}}$), *Percent Error* calculated using RMSE/Weighted Avg. will decrease by 29 percent ($\sqrt{0.5}$), and *Percent Error* calculated using MAE/Weighted Avg. or MAE/Capacity will decrease by 50 percent. The only method independent of nighttime hours is the MAE/Avg. method.

Table 10: Ratio of *Percent Error* Using All Hours to *Percent Error* Using Daytime Hours

Percent Error Method	Ratio of Daytime to 24h Percent Error			
	$\sqrt{\frac{N^{All\ Hours}}{N^{Daytime\ Hours}}}$	100% (No change)	$\sqrt{\frac{N^{Daytime\ Hours}}{N^{All\ Hours}}}$	$\frac{N^{Daytime\ Hours}}{N^{All\ Hours}}$
RMSE/Avg.	✓			
RMSE/Weighted Avg.			✓	
RMSE/Capacity			✓	
MAE/Avg.		✓		
MAE/Weighted Avg.				✓
MAE/ Capacity				✓

Application Example

An effective way to compare and contrast the six possible methods is to quantify results using an actual irradiance data set. Hourly satellite-derived global horizontal insolation (GHI) data was obtained for Hanford, CA, from January 1, 2010 to December 31, 2010. The reference data are from a high-quality ISIS ground site [28]. The modeled data are from a satellite-based irradiance service [14].

Figure 30 plots one year's worth of hourly modeled data vs. measured data. A perfect match would occur if all blue dots were on the red line. As can be seen from the figure, the selected modeled data are a good visual match to the reference data.

Figure 30: Irradiance Data for Hanford, CA, 2010

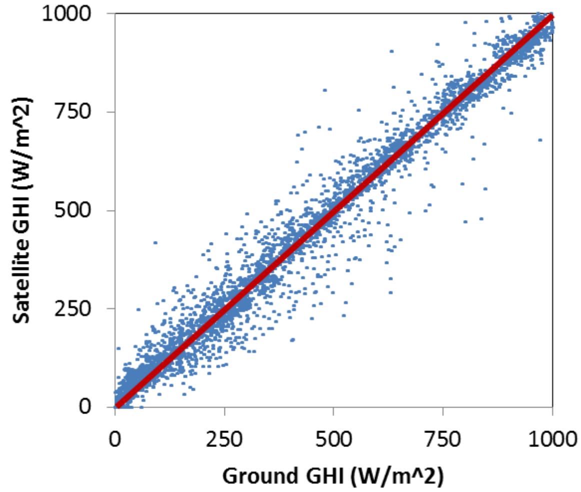
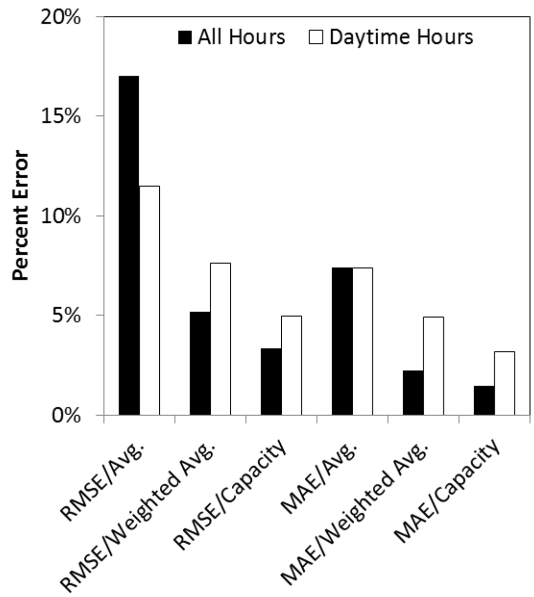


Figure 31 presents *Percent Error* for the six methods using the two scenarios of All Hours (24 hours per day) and Daytime Hours only. The "All Hours" scenarios are represented by the black bars. The "Daytime Hours" are represented by the white bars. Several observations can be made based on the figure:

- *Percent Error* ranges by a factor of more than 10 depending upon which method and scenario is selected
  - RMSE/Avg. method using nighttime values results in a 17.0 *Percent Error.*
  - MAE/Capacity method using nighttime values results in 1.5 *Percent Error*.
- The exclusion/inclusion of nighttime values changes results for five of the six definitions; *Percent Error* is lower for one case and higher for four cases.
- Only the MAE/Avg. *Percent Error* definition is independent of the inclusion of nighttime data.

Figure 31: Comparison of Error Results for Six Methods Using "All Hours" and "Daytime Hours" for Hanford, CA, 2010



Threshold Dependence

The *Irradiance Threshold* is the value below which data are excluded. Use of a threshold is relevant because while the current practice is to exclude night-time values, the industry lacks a precise definition of what is night-time. Is night-time when irradiance is 0 W/m^2, 0.1 W/m^2, 1 W/m^2?

The 24-hour and daytime scenarios are specific threshold points, occurring respectively when irradiance is larger than, or equal to a zero *Irradiance Threshold* for the former and above the zero *Irradiance Threshold* for the latter.

Figure 32 presents the percent of solar energy that occurs below a given *Irradiance Threshold*. It is interesting to note that much of the collectable energy resides above significant threshold levels. For example, the dashed line shows that GHI observations less than an *Irradiance Threshold* of 250 W/m^2 correspond to only 8 percent of the annual GHI at Hanford, CA in 2010.

Figure 32: Energy Distribution of Irradiance Data for Hanford, CA, 2010

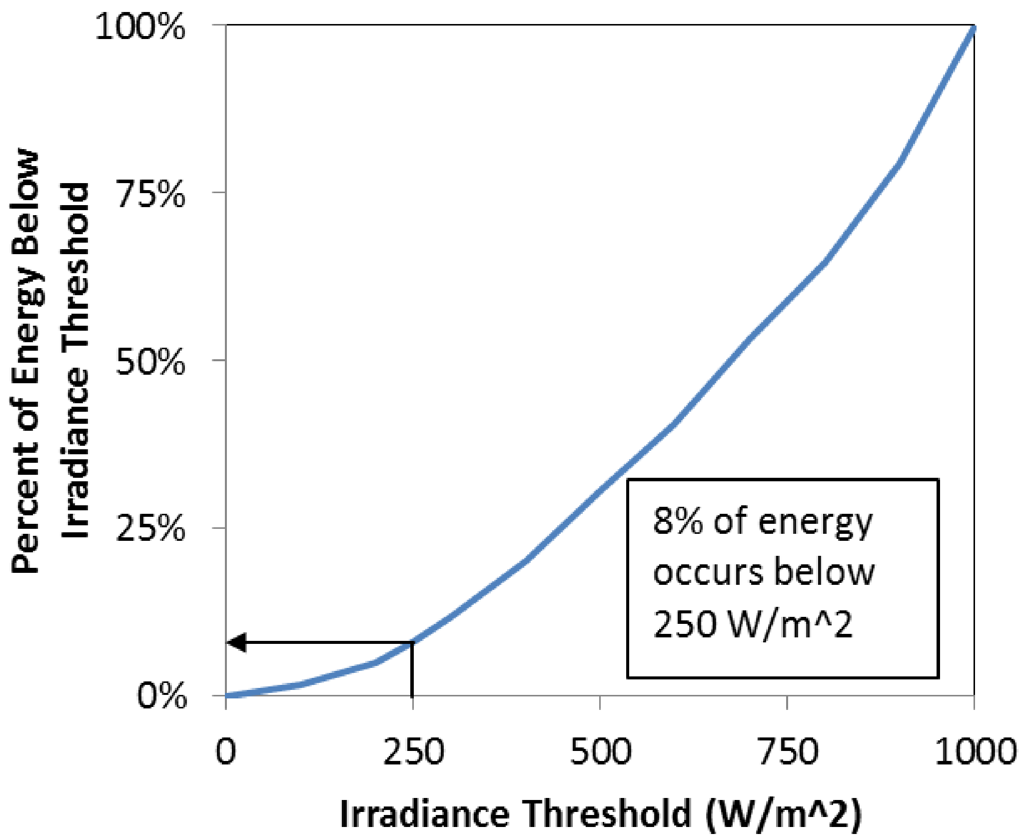
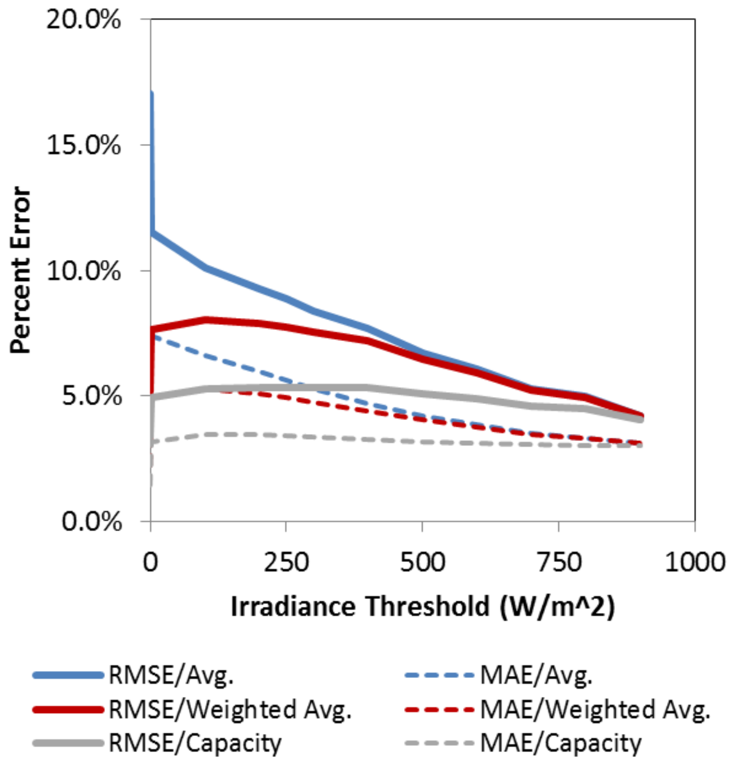


Figure 33 presents *Percent Error* as a function of *Irradiance Threshold* for all six methods. Several observations can be made based on the figure.

- All *Percent Error* definitions based on *RMSE* converge to the same result as the *Irradiance Threshold* increases.
- All *Percent Error* definitions based on *MAE* converge to the same result as the *Irradiance Threshold* increases.
- *RMSE/Weighted Avg.* results are similar to *MAE/Avg.* when "Daytime Hours" are included.

Figure 33: Comparison of Error Results for Hanford, CA, 2010



RMSE vs. MAE

Aside from the *Percent Error* reporting issue, it is worthwhile to explore the question whether the RMSE or the MAE is the most appropriate method to report dispersion error.

The main difference between the two is that the RMSE is driven by the square of the differences unlike the MAE. As a result, outliers are considerably more influential on the reported accuracy when using the RMSE metric. In the above example the addition of four far outliers to the data set (representing 0.1 percent of the data samples) increases the RMSE by a factor of 1.12, but only increases the MAE by a factor of 1.04.

Discussion

Table 4 summarizes the comparative observations made above using a subjective grading for the attributes of each relative dispersion error reporting method. The attributes we considered include:

- Whether the method is commonly accepted,
- Whether it is simple to understand
- Whether it depends on the 24-hr vs. daytime only distinction
- Whether it depends on the data selection threshold
- Whether it is affected by outliers

A grade of 0 to 2 is assigned to each method to represent its strength (2) or its weakness (0) with respect to a given attribute.

Table 11: Subjective Evaluation of Relative Error Reporting Method.

	Commonly accepted	Simple to understand	Depends on night time Values	Depends on selected threshold	Affected by outliers	Total
RMSE/Avg.	2	2	0	0	0	4
RMSE/Weighted Avg.	0	1	1	1	0	3
RMSE/Capacity	2	2	1	1	0	6
MAE/Avg.	1	2	2	1	1	7
MAE/Weighted Avg.	0	1	0	1	1	3
MAE/ Capacity	0	2	0	2	1	5

The MAE/Avg. provides the best practical measure of relative dispersion error based on the selected evaluation criteria and the subjective evaluations. The MAE/Avg. is attractive in that it is independent of the number of observations and is simple to understand. The RMSE/Capacity method is also desirable because it is commonly accepted (the wind power industry has already adopted this method) and is simple to understand.

The value of agreeing on a simple to calculate method has the benefit that multiple predictions and forecasts can be quickly evaluated and compared. Given that irradiance and PV power predictions and forecasts will be applied to a variety of applications (resource assessment, electrical grid operations and planning, etc.), it is not expected that the single statistic proposed here will necessarily be a complete measure of forecast quality. The authors, however feel that it is a good start towards promoting a standard metric in the industry.

Appendix B: Percent Error Calculations

This appendix derives the Percent Error calculations based on the definitions of RMSE, MAE, Avg., Weighted Avg., and Capacity.

RMSE/Avg.

$$RMSE/Avg. = \frac{\sqrt{\frac{\sum_{t=1}^{N}\left(I_t^{test} - I_t^{ref}\right)^2}{N}}}{\frac{\sum_{t=1}^{N} I_t^{ref}}{N}} = \frac{\sqrt{N}}{\sum_{t=1}^{N} I_t^{ref}} \sqrt{\sum_{t=1}^{N}\left(I_t^{test} - I_t^{ref}\right)^2} \tag{9}$$

RMSE/Weighted Avg.

$$RMSE/Weighted\ Avg. = \frac{\sqrt{\frac{\sum_{t=1}^{N}\left(I_t^{test} - I_t^{ref}\right)^2}{N}}}{\frac{\sum_{t=1}^{N}\left(I_t^{ref}\right)^2}{\sum_{t=1}^{N} I_t^{ref}}} = \left[\frac{\sum_{t=1}^{N} I_t^{ref}}{\sqrt{N}\sum_{t=1}^{N}\left(I_t^{ref}\right)^2}\right] \sqrt{\sum_{t=1}^{N}\left(I_t^{test} - I_t^{ref}\right)^2} \tag{10}$$

RMSE/Capacity

$$RMSE/Capacity = \frac{\sqrt{\frac{\sum_{t=1}^{N}\left(I_t^{test} - I_t^{ref}\right)^2}{N}}}{\mathrm{C}} = \left(\frac{1}{C\sqrt{N}}\right) \sqrt{\sum_{t=1}^{N}\left(I_t^{test} - I_t^{ref}\right)^2} \tag{11}$$

MAE/Avg.

$$MAE/Avg. = \frac{\frac{\sum_{t=1}^{N}\left|I_t^{test} - I_t^{ref}\right|}{N}}{\frac{\sum_{t=1}^{N} I_t^{ref}}{N}} = \left(\frac{1}{\sum_{t=1}^{N} I_t^{ref}}\right) \sum_{t=1}^{N}\left|I_t^{test} - I_t^{ref}\right| \tag{12}$$

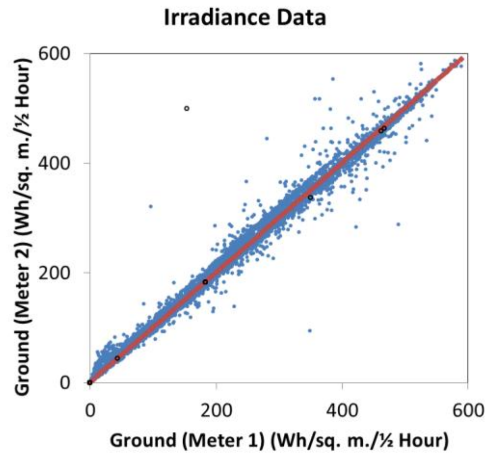
MAE/Weighted Avg.

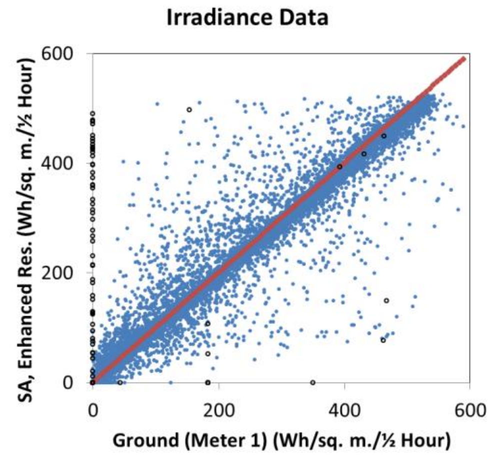
$$MAE/Weighted\ Avg. = \frac{\frac{\sum_{t=1}^{N} \left| I_t^{test} - I_t^{ref} \right|}{N}}{\frac{\sum_{t=1}^{N} \left(I_t^{ref} \right)^2}{\sum_{t=1}^{N} I_t^{ref}}} = \left[\frac{\sum_{t=1}^{N} I_t^{ref}}{N \sum_{t=1}^{N} \left(I_t^{ref} \right)^2} \right] \sum_{t=1}^{N} \left| I_t^{test} - I_t^{ref} \right| \qquad (13)$$

MAE/Capacity

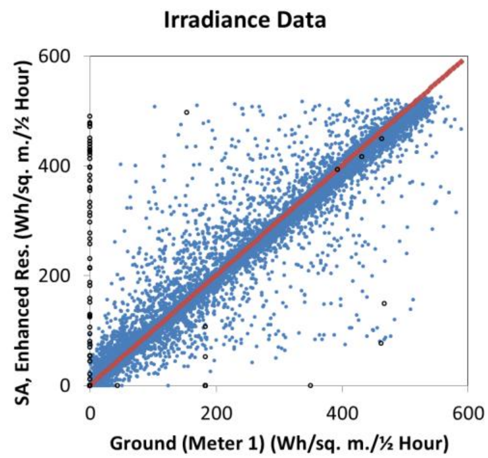
$$MAE/Capacity = \frac{\frac{\sum_{t=1}^{N} \left| I_t^{test} - I_t^{ref} \right|}{N}}{\mathrm{C}} = \left(\frac{1}{CN} \right) \sum_{t=1}^{N} \left| I_t^{test} - I_t^{ref} \right| \qquad (14)$$

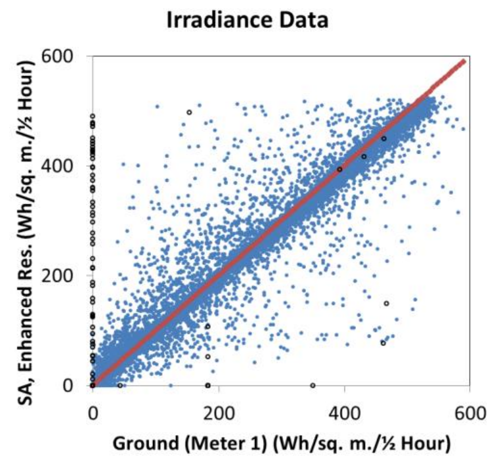
Appendix C:
Half-hour Irradiance Data for Six CAISO Locations



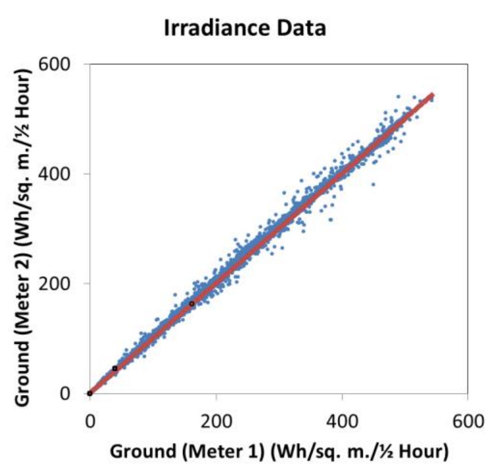


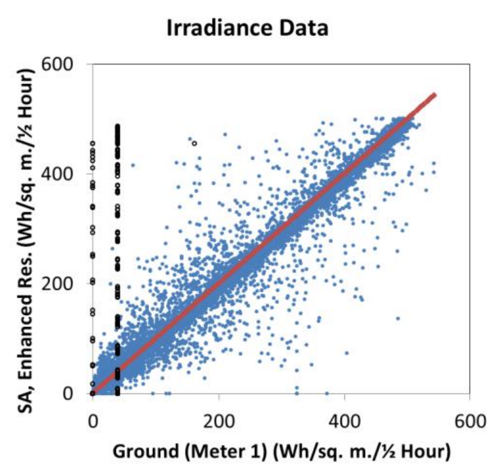
Site A



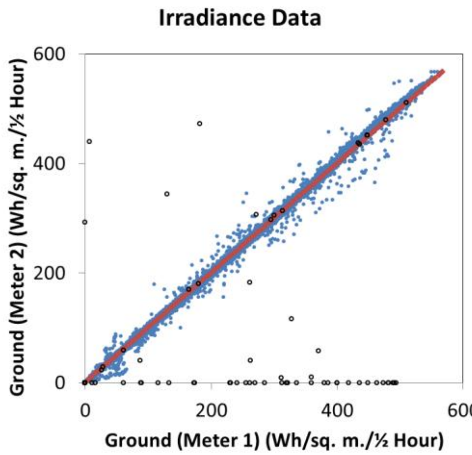


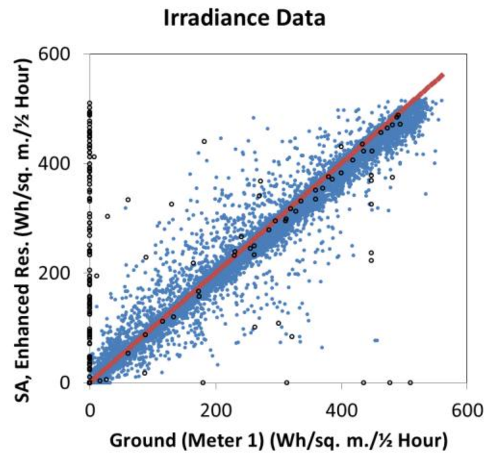
Site B



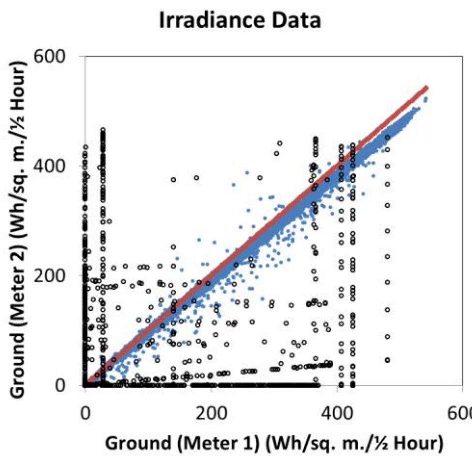


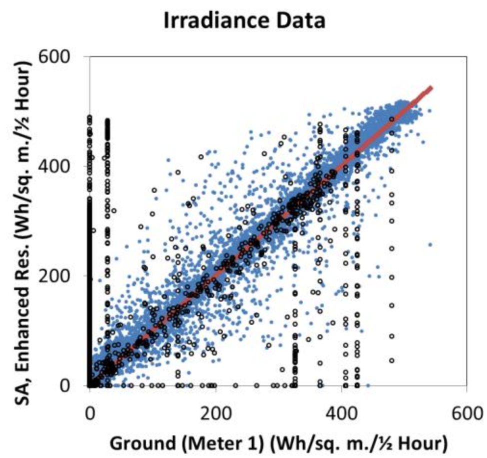
Site C



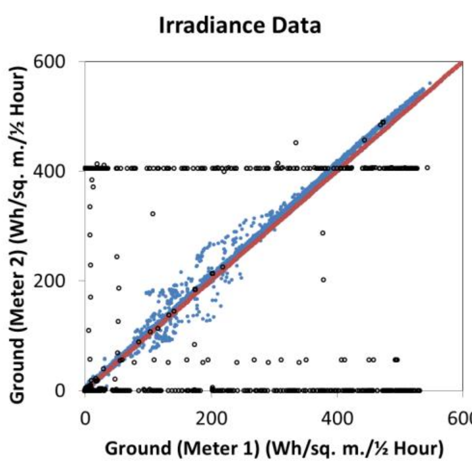


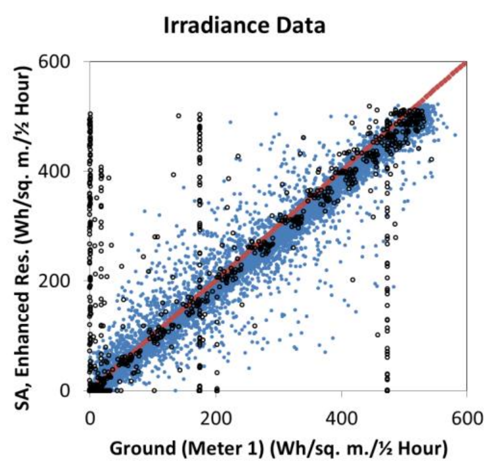
Site D





Site E





Site F

APPENDIX 2

Validation of SolarAnywhere FleetView Using Measured Production Data from More Than 2,000 PV Systems

Adam Kankiewicz, Thomas E. Hoff, and Tyler Codispoti

Draft June 4, 2012

Executive Summary

Understanding the behavior and errors associated with the simulation of fleet-wide PV system energy production is a critical step towards facilitating increased PV penetration into California's electricity system. Metered PV system data collected by the Sacramento Municipal Utility District (SMUD) provides a unique opportunity to evaluate the performance and errors observed during simulation of a fleet of more than 2,000 PV systems.

This report presents the results of a six-month simulation of the SMUD fleet of PV systems.
Results demonstrate an accuracy of 6.2 percent Mean Absolute Error relative to energy (rMAE) when all systems and all days are included. The error was reduced to 4.5 percent rMAE for a subset of well-behaved PV systems. Results further improve to 5.4 and 3.5 percent rMAE, respectively, when partly cloudy day conditions are removed. These results demonstrate that accurate simulations of a large fleet of PV systems are obtainable.

Improvement in the underlying PV simulation methodologies by further inspection of simulated and measured data at the hourly and sub-hourly level will improve accuracy. Additional work to better estimate PV modeling derate factors and to identify better ways to clean measured data and to identify and rectify faulty PV system specifications will further improve results.

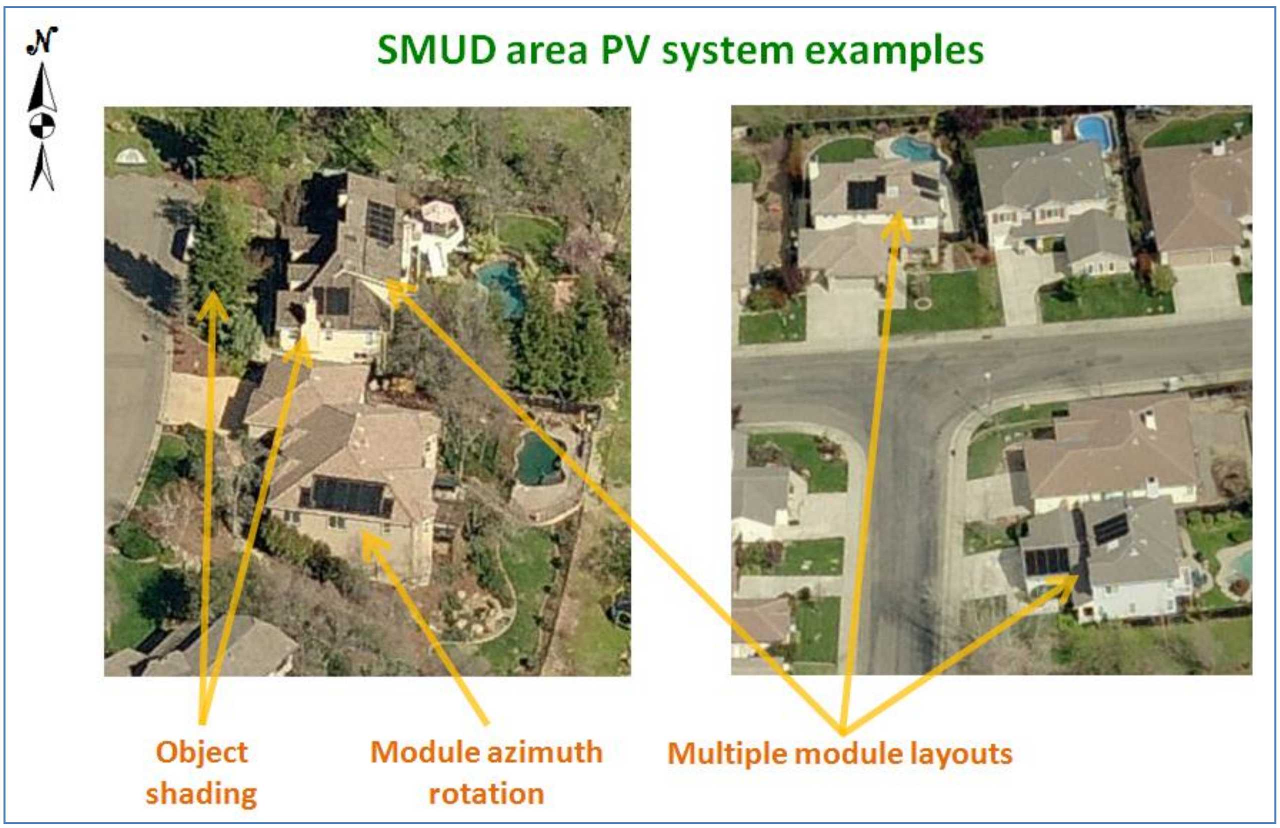
A key next step of the work is to perform this analysis using forecasted rather than historical solar resource data.

Introduction

Background

It is challenging to obtain accurate estimates of photovoltaic (PV) system energy production. Factors such as irradiance, shading, soiling, and system configuration can greatly influence the performance of an installed PV system. Figure 1 illustrates some of the challenges that must be addressed to obtain accurate production estimates of PV energy production.

Figure 1: Depiction of several rooftop PV solar systems from the Folsom, CA area and associated challenges identified which, when improperly accounted for, can thwart accurate PV performance simulations.

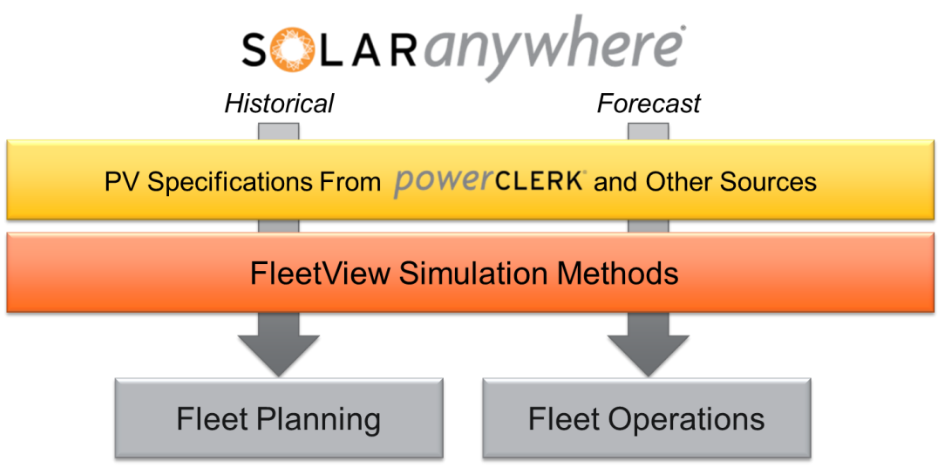


Understanding how accurately one can simulate existing PV system energy production is a critical step towards facilitating increased PV penetration into California's electricity system. The California Solar Initiative (CSI) partially funded the development of an enhanced resolution satellite-based solar resource database for the state of California. It is referred to as SolarAnywhere® Enhanced Resolution [1]. The database has a one-km spatial resolution and half-hour temporal resolution, using the native spatial and temporal resolution of the US geostationary satellites. This data set has been further expanded to have a one-km spatial, one-minute temporal resolution by applying intra-interval short-term forecasting. It is referred to as SolarAnywhere High Resolution [1]. These data sets have the potential to provide the solar resource data required to address the PV simulation challenges described above.

FleetView Power Prediction Method

Clean Power Research (CPR) has developed the SolarAnywhere® FleetView™ software service to predict PV fleet power production. FleetView uses inputs of satellite-derived solar resource data and the design attributes and locations of PV systems. It combines these inputs with advanced algorithms to predict PV fleet power production as illustrated in Figure 2.

Figure 2. PV fleet simulation procedure.



Objective

The objective of this report is to validate FleetView simulation results using detailed measured PV production data from SMUD. This report compares the accuracy of the FleetView simulations with corresponding measured SMUD PV system data over a six-month time period (4/16/2012 - 10/10/2012) at hourly time intervals using a historical time perspective. Results are presented for both individual locations (i.e., single solar systems) and various ensembles of those locations (i.e., a fleet of solar systems).

Validation Definition

Accuracy validation often means different things to different people. As such, it is useful to begin with a definition of how accuracy is quantified.

Three fundamental questions need to be answered in order to provide a clear definition of how accuracy is quantified.

1. What is the data source?
2. What are the time attributes?
3. What is the evaluation metric?

Data Source

The first step is to identify the data that is being evaluated. Options include irradiance data or PV power production simulated using irradiance data and other parameters. In addition, the analysis can be performed for individual locations or fleets (i.e., multiple locations).

This report uses PV power data. The analysis is performed for both individual locations and fleets.

Time Attributes

The second step is to specify the required time attributes. These include:

- **Time period**: total amount of data included in the analysis. This can range from a few minutes to many years.
- **Time interval**: how the data in the time period is binned. This can range from a few seconds to annually. For example, if the time period is one year and the time interval is one hour, the time period would be binned into 8,760 time increments.
- **Time perspective**: when the predicted observation is reported. This can range from historical (backward looking) to forecasted a few hours ahead to forecasted multiple days ahead (forward looking).

This report uses time attributes of historical data for a six-month time period for hourly time intervals.

Evaluation Metric

The third step is to select the evaluation metric. Mean Absolute Error (MAE) relative to available energy has been shown to be a good method to measure relative dispersion error (see [5] and [15] for details). This is referred to as the relative MAE or rMAE. rMAE is defined to be the sum of the absolute error between simulated and measured energy for each time interval over the time period and divided by total available energy. Appendix A illustrates how to calculate rMAE.

$$rMAE = \frac{Total\ Absolute\ Error}{Total\ Energy} = \frac{\sum_{t=1}^{N} \left| E_t^{Simulated} - E_t^{Measured} \right|}{\sum_{t=1}^{N} E_t^{Measured}} \qquad (1)$$

where $E_t^{Simulated}$ and $E_t^{Measured}$ are the simulated and measured energy over time interval *t* and *N* is the number of time intervals.

Note that while rMAE is a consistent measure of error, results must be interpreted correctly. For example, consider a comparison of the daily rMAE for a clear day vs. a cloudy day. Suppose that both days have the same total absolute error (1 kWh) but that the PV system produces twice as much energy on the clear day as on the cloudy day (10 kWh vs. 5 kWh). According to Equation (1), rMAE is 10 percent for the clear day while it is 20 percent for the cloudy day.

Relative Mean Bias Error (rMBE) is additionally used as a measure of overall bias error or systematic error.

$$rMBE = \sum_{i=1}^{N} \frac{E_t^{Simulated} - E_t^{Measured}}{E_t^{Measured}} \qquad (2)$$

Approach

Data Set Correlation

SMUD provided historical PV data for 2,550 distinct PV systems. The data contained a timestamp, measured energy production, duration of the measurement (time increments from 5 minutes up to hourly), and the system's Distributed Generation number (DG number).

PowerClerk® is used as the primary record for all PV systems in SMUD's service territory. PowerClerk contains detailed system specifications, including inverter type and quantity, PV module type and quantity, array tilt, azimuth orientation, and shading. PowerClerk identifies each system by its DG number.

The measured production data set and system specifications data set were linked using the DG number. The systems were assumed to be the same if the DG numbers matched. Random spot checks confirmed this was a valid assumption.

Matches were obtained for 2,338 of the 2,550 PV systems (i.e., 92 percent of the systems). No DG number match could be found in PowerClerk for approximately 212 of the systems.

PV Production Simulation

Hourly energy was estimated by performing hourly simulations for each system using FleetView by combining system specifications with the SolarAnywhere Enhanced Resolution (1km) hourly data that corresponded to the system's latitude/longitude. (Note: performing the simulation using two half-hour observations rather than one hourly observation would probably improve accuracy).

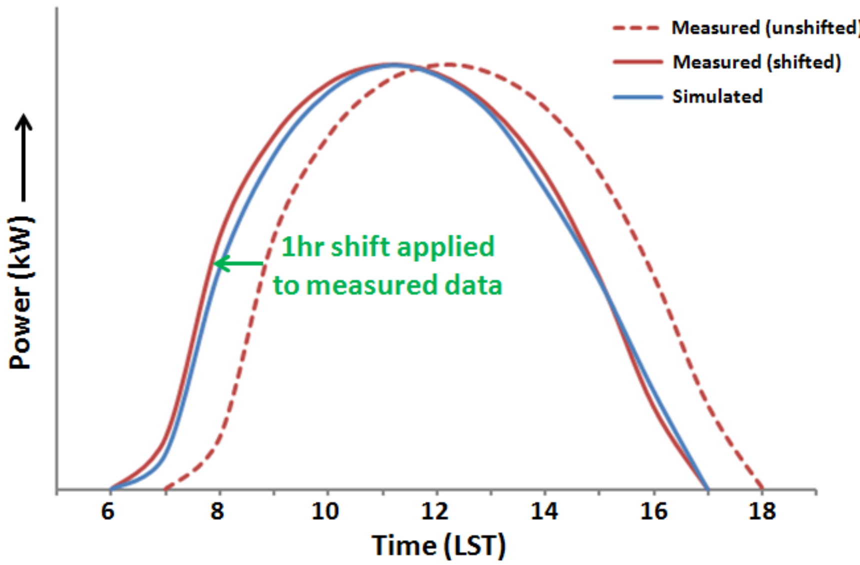
Measured data that contained sub-hourly time intervals were converted to hourly time intervals.

Simulated and measured data were time-correlated (i.e., matched up by date and time). Records were discarded where either the simulated or measured data was missing.

Data Quality Issues

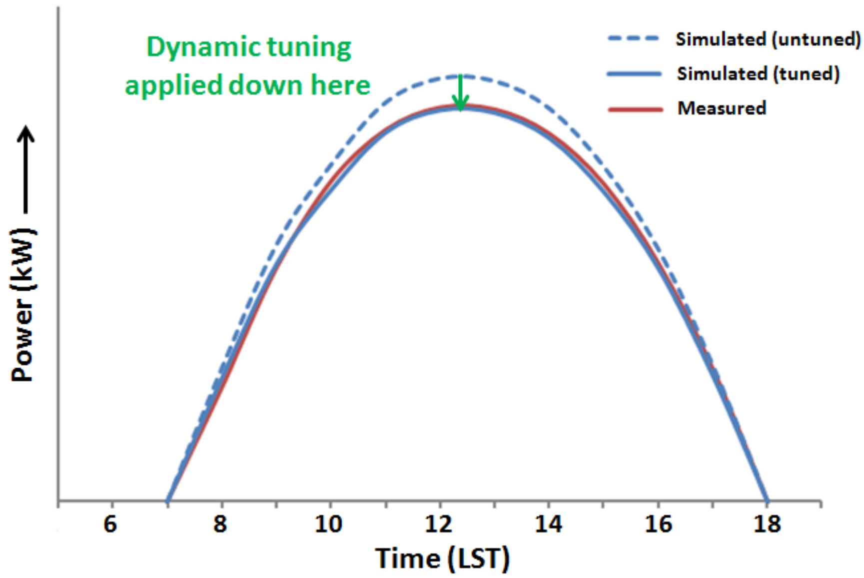
It was determined that some of the measured data did not properly time-correlate with the simulated data. This was corrected by shifting the measured data backward or forward up to 60 minutes in 15 minute intervals (-60,-45,-30, -15, 0, +15, +30, +45,+60). rMAE was calculated for each time shift. The time shift that resulted in the lowest rMAE was assumed to be the most correct for the measured data. Figure 3 illustrates this measured data time shift procedure for one day for one system.

Figure 3: Illustration of CPR's measured data time shift correction process (one hour in this case). Measured power is individually checked for spurious time shifts for each production system in the SMUD PV fleet.



Site-specific tuning was applied to PV simulation results using CPR's dynamic tuning process once the simulated and measured data were time-correlated over the period of examination. A scale factor was selected that minimized certain error characteristics. Figure 4 illustrates the results of the dynamic tuning process for one day for one system.

Figure 4: Illustration of CPR's dynamic tuning methodology. Simulated power is uniquely tuned (down in this case) for each production system in the SMUD PV fleet.



Results

Individual PV Systems

This section presents results for two individual systems: a well characterized PV site simulation and a challenging PV site simulation.

Well-Characterized PV Site Simulation

First, consider a well-characterized PV site simulation. This system (RR-00201) is a residential PV solar installation consisting of thirty-two Evergreen PV solar modules and one SMA power inverter. It has an CEC-AC System Rating of 5.186 kW. A dynamically-derived scaling factor of 0.96307 was applied to this site for final PV production tuning purposes.

Figure 5 presents examples of the hourly simulated and measured production data from this site. Clear day simulations are handled well. Cloudy day simulations exhibit higher error due to the challenge of accurately predicting ground irradiance under cloudy conditions. Figure 6 presents the daily rMAE over the 177 day observation period. Higher daily rMAE spikes during this period are associated with the cloudy day simulations.

Figure 7 further clarifies the cloudy vs. clear day simulation challenges by breaking down the hourly simulated vs. observed statistics in: (a) all conditions; (b) clear day conditions; and (c) cloudy day conditions. Significantly more scatter is clearly visible under cloudy day conditions.

Figure 5: Simulated (red line) and observed (blue line) production at the RR-00201 site over a four day period in August. August 18th shows production on a partly cloudy day.

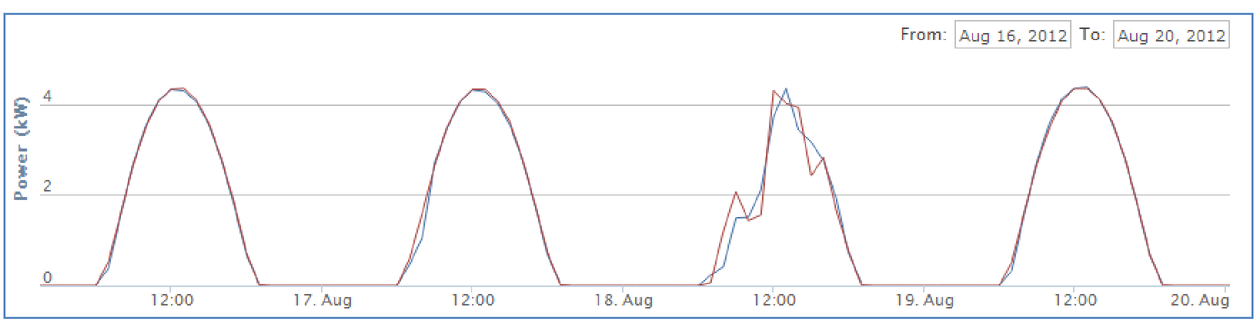


Figure 6: Daily rMAE statistics for site RR-00201 over the observation period from 4/16/2012 - 10/10/2012. Higher rMAE spikes are associated with cloudy days during the observation period.

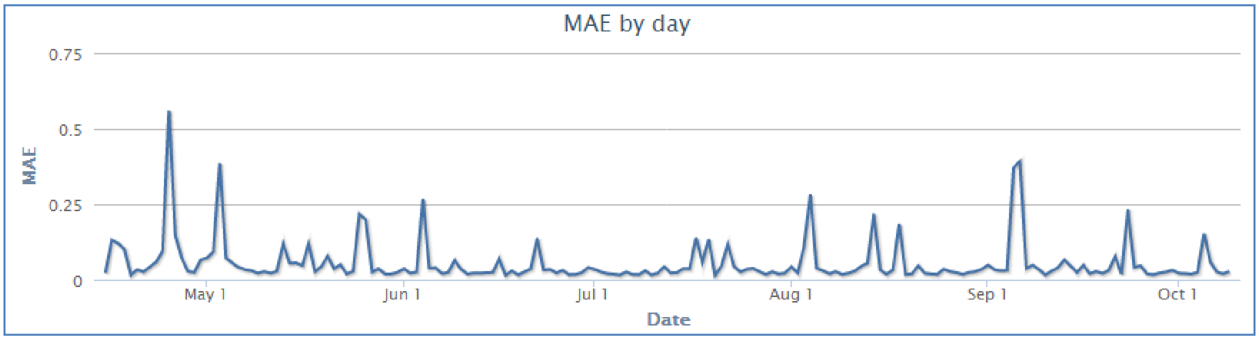


Figure 7: Scatter plot of simulated vs. measured hourly energy production for site RR-00201 from 4/16/2012 - 10/10/2012 for: (a) all day conditions; (b) clear days; and (c) and cloudy days.

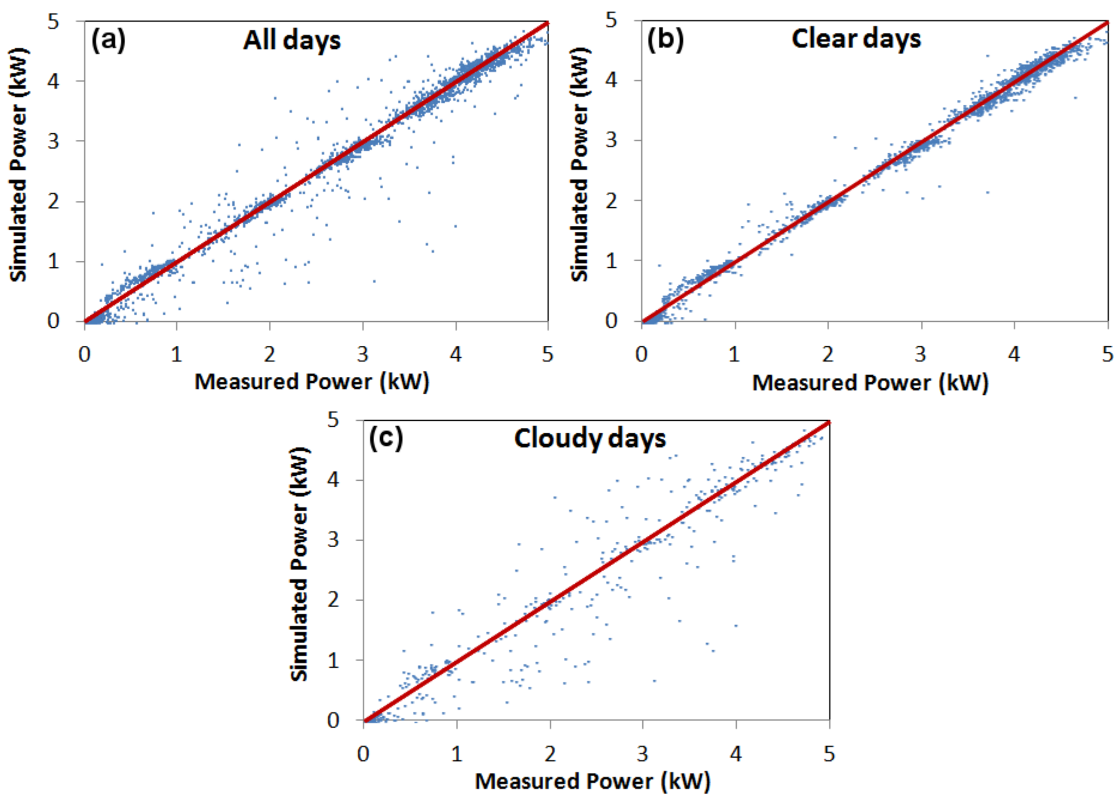


Table 1 presents error statistics for this single system over the six-month period (4/16/2012-10/10/2012). Overall rMAE is 4.9 percent during this observational period under all conditions. Error drops to 3.3 percent when only clear days are included due to the exclusion of higher error prone cloudy days. Error increases to 13.6 percent for cloudy days.

Table 1: rMAE for site RR-00201.

	Clear Days	Cloudy Days	All Days
rMAE	**3.3%**	**13.6%**	**4.9%**
Ave Daily Energy	**34.5 kWh**	**28.1 kWh**	**33.3 kWh**
Number of Days	**145 days**	**32 days**	**177 days**

Challenging PV Site Simulation

Next, consider a challenging PV site simulation. This system (RR-01452) is a residential PV solar installation consisting of nine Sharp PV solar modules and one Power-One power inverter. It has an overall CEC-AC System Rating of 3.290 kW. A dynamically-derived scaling factor of 0.97615 was applied to this site for final PV production tuning purposes.

Figure 8 presents hourly simulated and measured production data for this site. The hourly PV simulations show significantly more error in the morning than during the afternoon. This systematic error in simulation (in the form of over predication) is better illustrated in Figure 9. The hourly MBE averaged over the entire production period has a significant systematic bias present during mid-morning. This corresponds to the mismatch in simulated and measured production illustrated in Figure 8. This over-prediction is most likely due to improper system shading specifications provided to FleetView simulation software. Further evidence of the shading influence can be seen in Figure 10 by the gradual upward trend in daily MAE as one moves later in the observation period when the sun is lower in the sky and shading effects are increased. Figure 11 further clarifies the cloudy vs. clear day simulation challenges by breaking down the hourly simulated vs. measured statistics in: (a) all conditions; and (b) clear day conditions. Both figures show significant scatter due to the miss-characterized morning simulations and further illustrate the challenges inherent to rooftop PV simulations.

Figure 8: Example simulated (red line) and measured (blue line) production at the PC RR-01452 site over a four day period in September. Significant over prediction in the simulations can be seen in the morning hours. August 5th shows comparisons on a mostly cloudy day.

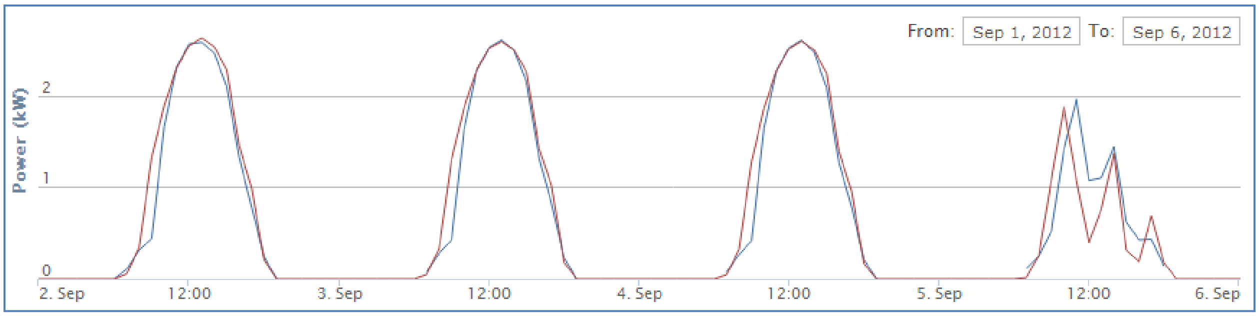


Figure 9: Hourly-averaged MBE measured over the observation period from 4/16/2012 - 10/10/2012. Note significant bias present at 9 AM due to mischaracterized PV system specifications.

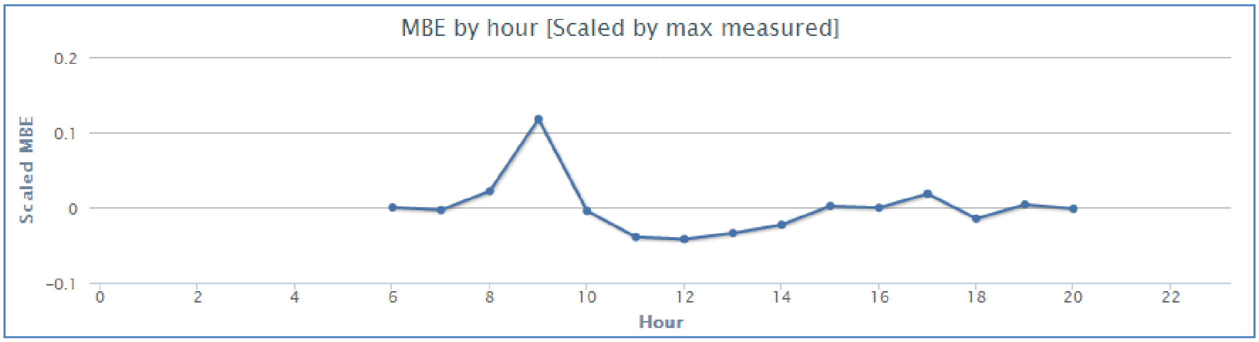


Figure 10: rMAE per day statistics for site RR-01452 over the observation period from 4/16/2012 - 10/10/2012. Higher daily MAE values are associated with cloudy days during the observation period.

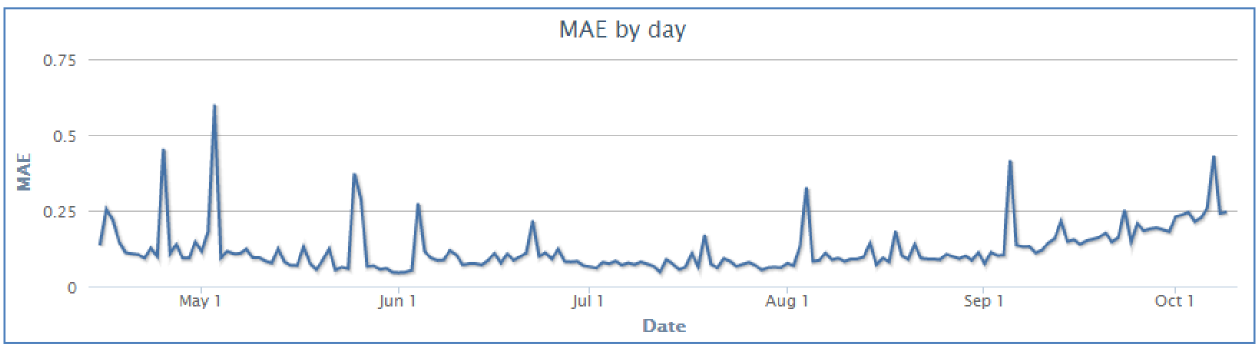


Figure 11: Scatter plot of simulated vs. measured hourly energy production for site RR-01452 from 4/16/2012 - 10/10/2012 for all day conditions (a) and clear days (b).

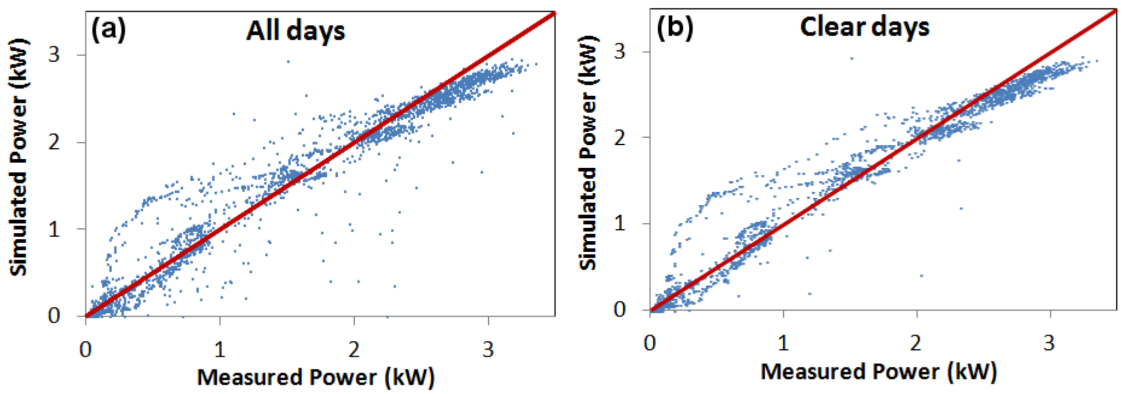


Table 2 presents error statistics for this single system over the six-month period (4/16/2012 - 10/10/2012. Overall rMAE is 11.1 percent during this observational period under all conditions. This error drops to 9.7 percent when only clear days are included due to the exclusion of higher error prone cloudy days which exhibit 18.8 percent error on their own.

Table 2. rMAE for site RR-01452.

	Clear Days	Cloudy Days	All Days
rMAE	**9.7%**	**18.8%**	**11.1%**
Ave Daily Energy	**20.5 kWh**	**16.6 kWh**	**19.8 kWh**
Number of Days	**145 days**	**32 days**	**177 days**

Fleet of Systems

This section presents results based on the fleet of systems.

Fleet of All PV Systems

CPR completed successful simulations of 2,338 SMUD PV systems of which 132 systems were excluded due to various missing or erroneous measured data issues. Results from the 2,206 remaining PV system simulations are presented here.

The time shift correction (illustrated in Figure 3) was applied to the measured data and the dynamic tuning analysis procedures (illustrated in Figure 4) was applied to simulated results for each PV system. Figure 12 presents the distribution of time shift analysis results for all measured PV system. The majority of systems required little or no time correction.

Figure 12: Distribution of time shift corrections applied to all locations (2206) derived from the six months of simulated vs. measured production data.

The dynamic tuning methodology was applied to each PV system simulation. The distribution of results is presented in Figure 13. While the peak in scaling factors applied is centered about zero, there is strong asymmetry present towards the downscaling side of the distribution. This unevenness in the distribution is likely due to influences which tend to lead to PV system underperformance. These effects can include system soiling, module mismatch and degradation, and enhanced rooftop-related temperature losses.

Figure 13 suggests that, in practice, it is more common for a PV system to underperform than to over perform.

Figure 13: Distribution of dynamic scaling factors applied to all locations (2206) derived from the six months of simulated vs. measured production data.

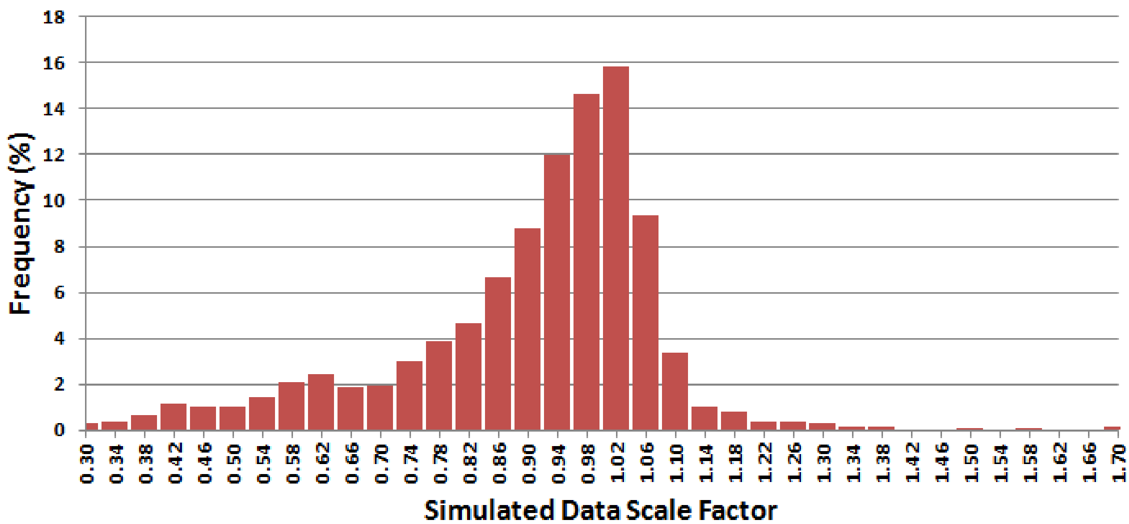


Figure 14 presents several days of the aggregate fleet hourly simulation and measured production data for all systems. Overall, the fleet PV simulations line up with production better than at the individual level due to system wide smoothing effects. As noted before, simulations for clear days tend to line up better with measured data than those for cloudy days. The daily rMAE statistics in Figure 15 confirm that there is lower error on sunny days. There is also less error observed on cloudy days due to aggregating of fleet production.

Figure 16 presents the hourly-averaged MBE. It suggests that at a fleet-level the simulations tend to slightly over predict energy during the morning and late afternoon timeframes while under predicting energy during the peak sunshine part of the day. It is likely that this can be corrected through improvements to the inverter power curve modeling.

Figure 17 illustrates the cloudy vs. clear day simulation aspects of the fleet simulations by breaking down the hourly simulated vs. measured statistics in: (a) all conditions; (b) clear day conditions; and (c) cloudy day conditions. The systematic morning/later afternoon over prediction and midday under prediction tendencies are well illustrated here.

Figure 14: Example simulated (red line) and measured (blue line) production for all systems (2206) over a five day period in May. May 25-26 illustrate comparisons on a partly cloudy days.

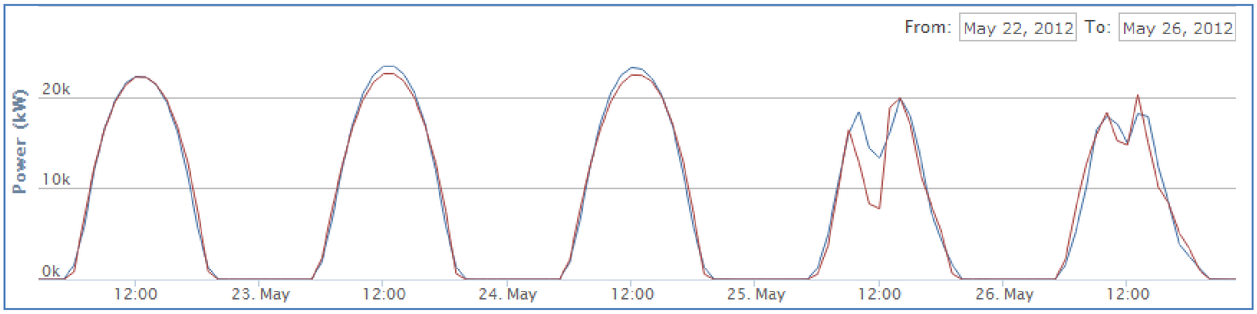


Figure 15: Aggregate MAE per day for all 2,206 systems from 4/16/2013 - 10/10/2013. The spikes in MAE are associated with cloudy day conditions.

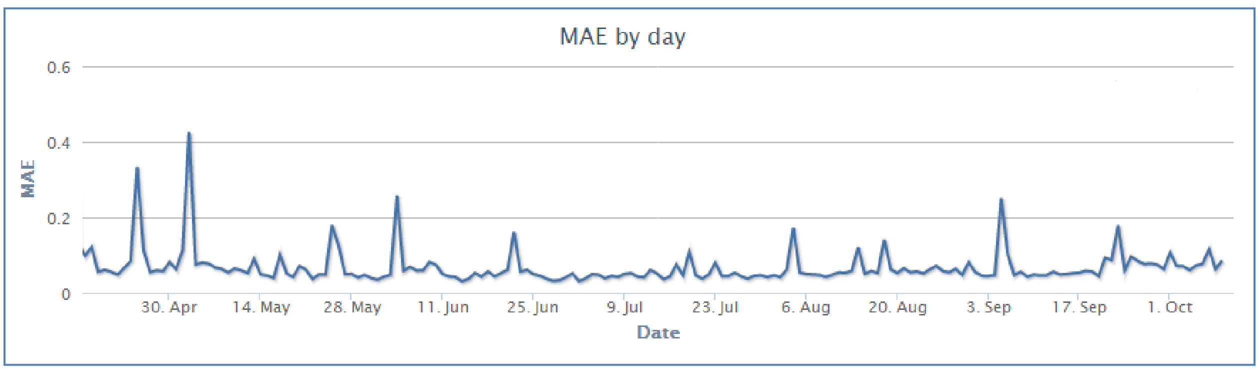


Figure 16: MBE by hour for all 2,206 systems. The overall tendency is towards a morning and late afternoon over prediction of energy with a slight under prediction of energy during the peak of the day.

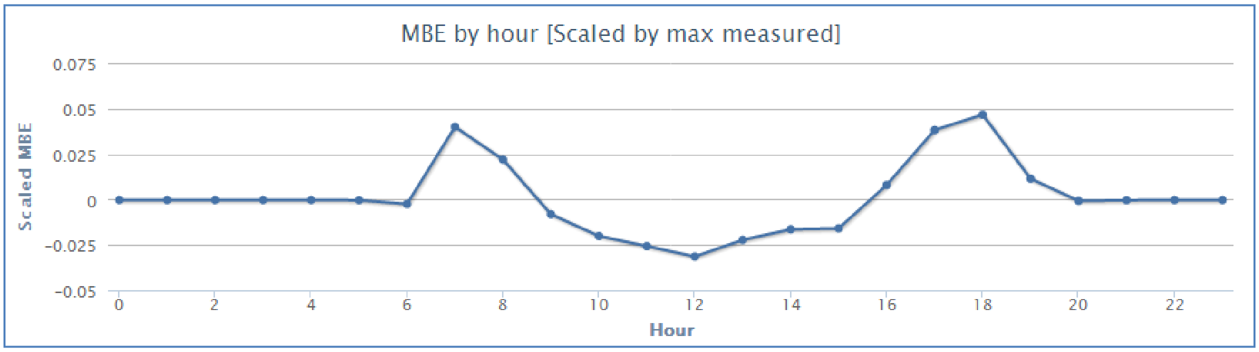


Figure 17: Scatter plot of simulated vs. measured hourly energy production for all 2,206 systems from 4/16/2012 - 10/10/2012 for all day conditions (a), clear days (b) and cloudy days (c).

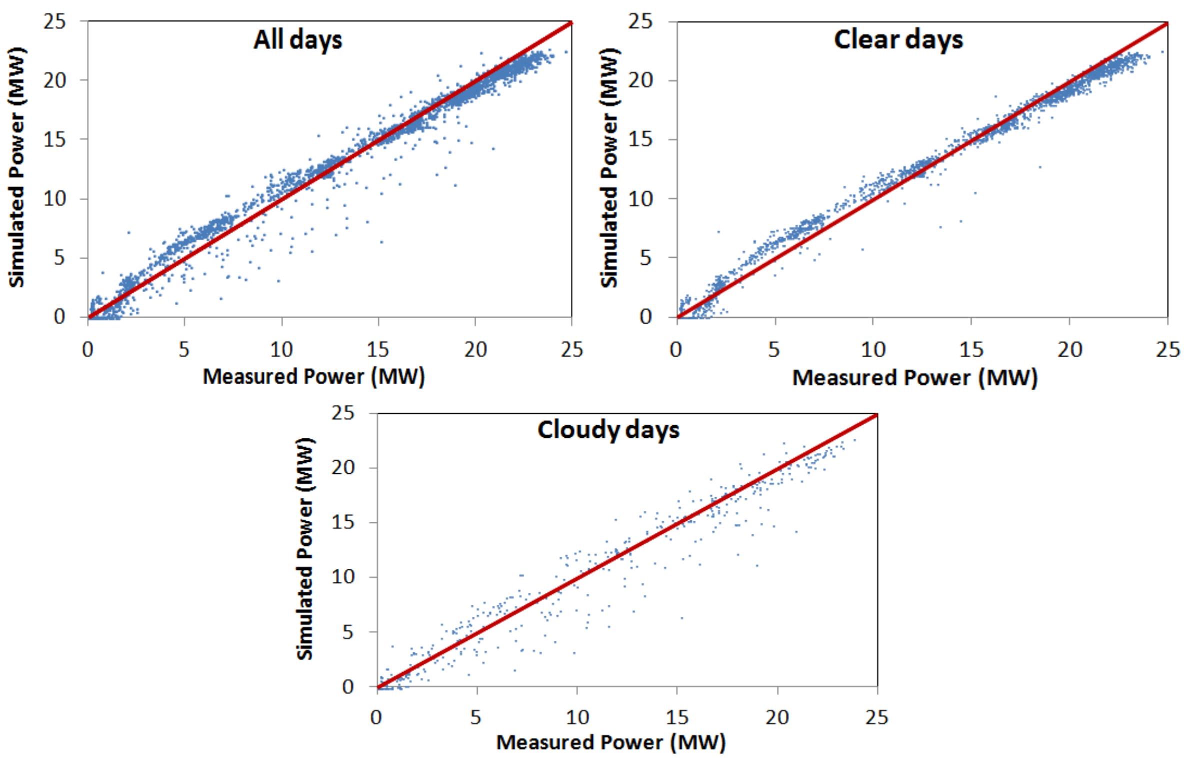


Table 3 presents error statistics for the fleet of 2,206 systems over a six-month period from 4/16/2012 - 10/10/2012. Overall rMAE is 6.2 percent during this observational period under all conditions. This error drops to 5.4 percent when only clear days are included due to the exclusion of higher error prone cloudy days which exhibit 11.1 percent error on their own.

Table 3: rMAE for all 2,206 systems.

	Clear Days	Cloudy Days	All Days
rMAE	**5.4%**	**11.1%**	**6.2%**
Ave Daily Energy	**185.8 MWh**	**143.9 MWh**	**178.2 MWh**
Number of Days	**145 days**	**32 days**	**177 days**

Fleet of Well-Behaved PV Systems

Further full fleet PV system simulation results are presented now. PV systems were removed with reported six-month MAE statistics higher than 10 percent to filter out some of the noise present in the fleet simulation process. This reduced the simulation pool to 1,102 systems.

Figure 18 presents examples of the trimmed down aggregate fleet hourly simulation and measured production data. Good partly cloudy day alignment can be see with mostly cloudy days still presenting challenges. The daily rMAE statistics in Figure 19 confirm the presence of lower error on sunny days with less error also observed on cloudy days due to the aggregation of fleet PV production. The highest noted daily rMAE error day (May 3) is presented in Figure 18. Heavy overcast cloud conditions dominated the SMUD-footprint region on May 3 which resulted in lower energy simulations due to the under prediction of surface irradiance.

The improvement in fleet error statistics is further illustrated in the hourly-averaged MBE presented in Figure 20. There is less morning and afternoon error while the previously noted midday under prediction error almost disappears. Figure 21 further illustrates the cloudy vs. clear day simulation aspects of the fleet simulations by breaking down the hourly simulated vs. measured statistics during: (a) all conditions; (b) clear day conditions; and (c) cloudy day conditions.

Figure 18: Example simulated (red line) and measured (blue line) production for 1,102 well-behaved systems over a four day period in May. May 1, 2 and 4 are partly cloudy days. May 3 is a heavy overcast day on which the highest measured daily MAE occurred during this observation period.

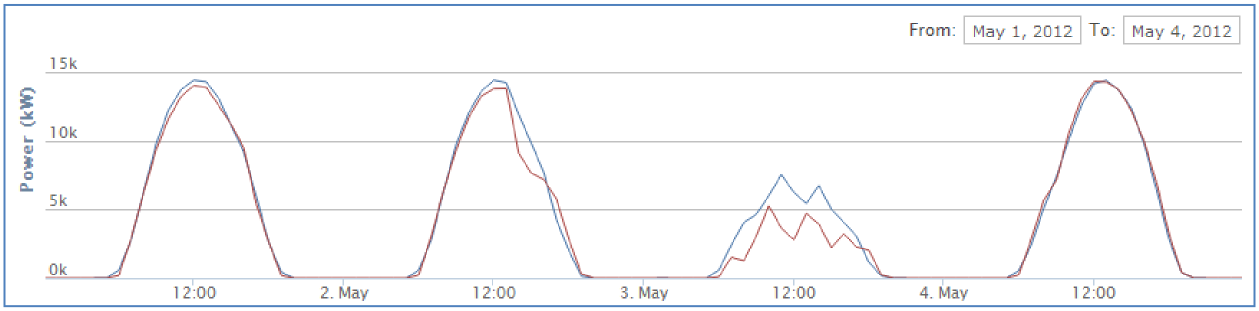


Figure 19: Aggregate MAE per day statistics for well, behaved systems (1102) over the observation period from 4/16/2012 - 10/10/2012. Higher daily MAE values are associated with cloudy days during the observation period.

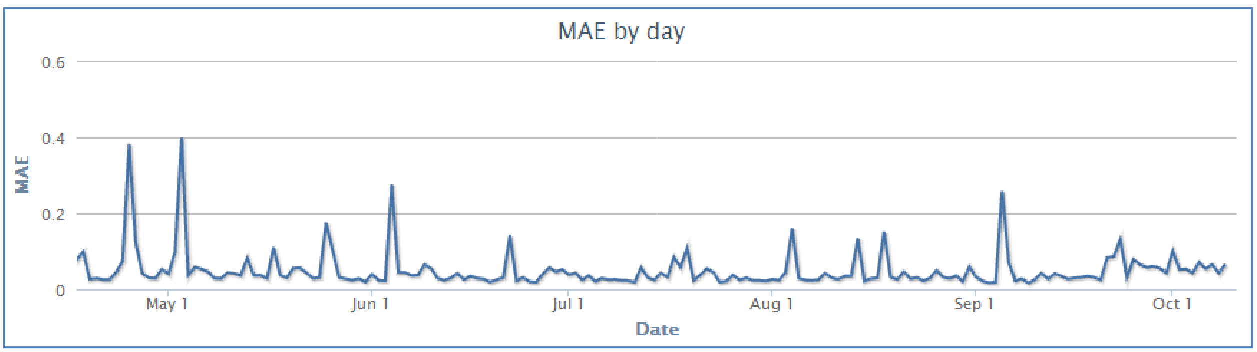


Figure 20: MBE by hour for 1,102 well behaved systems. The overall tendency is towards a morning and late afternoon over prediction of energy with a slight under prediction of energy during the peak of the day.

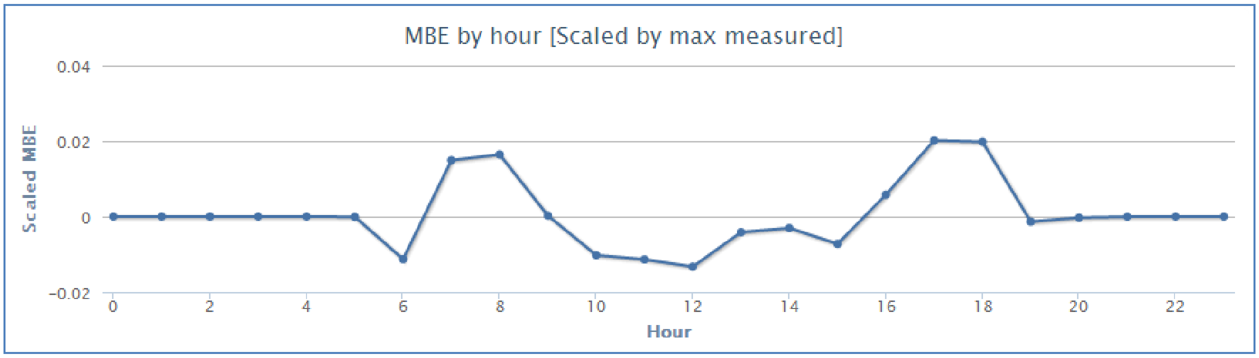


Figure 21: Scatter plot of simulated vs. measured hourly energy production for 1,102 well-behaved sites from 4/16/2012 - 10/10/2012 for all day conditions (a), clear days (b) and cloudy days (c).

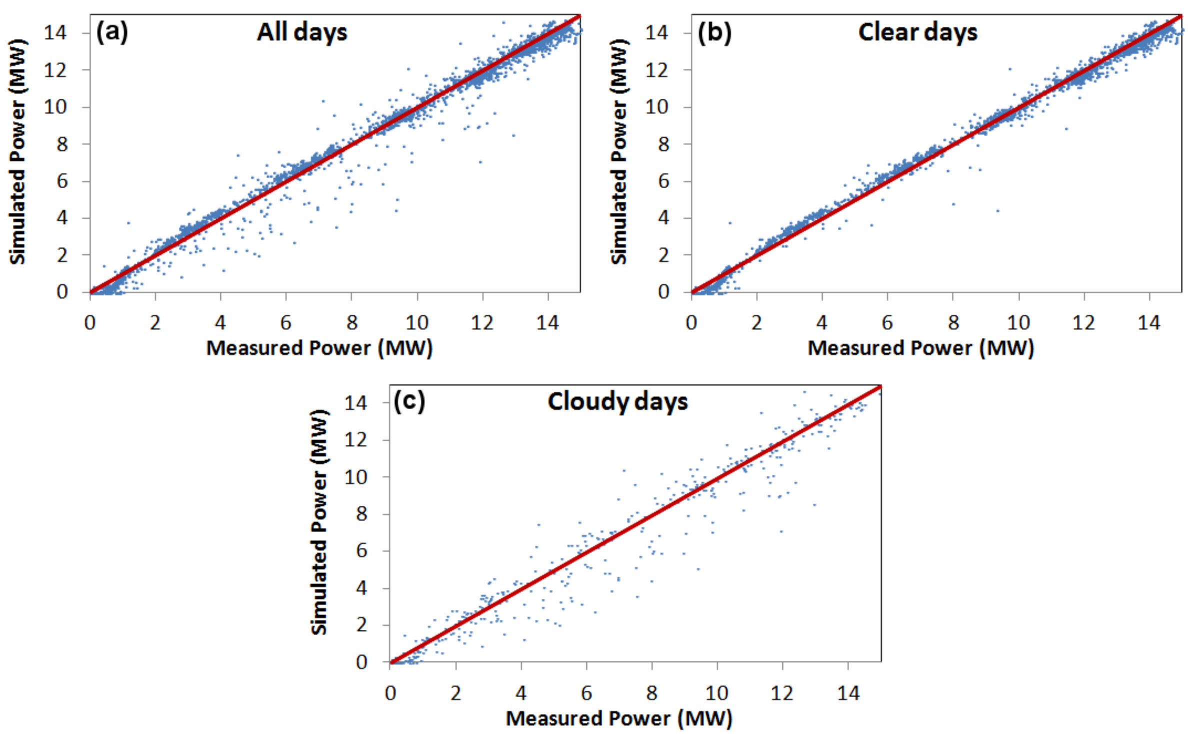


Table 4 presents error statistics for the fleet of 1,102 well-behaved systems over a six-month period from 4/16/2012 - 10/10/2012. Overall rMAE is 4.5 percent during this observational period under all conditions. This error drops down to 3.5 percent when only clear days are included due to the exclusion of higher error prone cloudy days which exhibit 10.0 percent error on their own.

Table 4: rMAE for 1,102 well-behaved systems.

	Clear Days	Cloudy Days	All Days
rMAE	**3.5%**	**10.0%**	**4.5%**
Ave Daily Energy	**112.8 MWh**	**88.3 MWh**	**108.4 MWh**
Number of Days	**145 days**	**32 days**	**177 days**

Conclusions and Future Research

Understanding the accuracy at which one can simulate fleet wide PV system energy production is a critical step towards facilitating increased PV penetration into California's electricity system. Factors such as irradiance, shading, soiling, and system configuration greatly influence the performance of an installed PV system. Proper characterization of these factors is important to the simulation of PV system energy.

Results demonstrated an accuracy of 6.2 percent rMAE when all systems and all days are included. The error was reduced to 4.5 percent rMAE for a subset of well-behaved PV systems. Results further improve to 5.4 and 3.5 percent rMAE, respectively, when partly cloudy day conditions are removed. These results demonstrate that accurate simulations of a large fleet of PV systems are obtainable.

Improvement in the underlying PV simulation methodologies by further inspection of simulated and measured data at the hourly and sub-hourly level will improve accuracy. Additional work will also be done to understand better application of PV modeling derate factors. One aspect highlighted in this report is the common mischaracterization of PV system specifications (i.e., system layout, orientation, shading, etc.) that can lead to poor system performance simulations. Better data tuning and measured data cleaning methods would help identify and rectify faulty PV system specifications and help improve simulations. Finally, the incorporation of a weather-driven PV module soiling model might help improve the overall PV fleet simulations.

A key next step of the work is to perform this analysis using forecasted rather than historical solar resource data.

Acknowledgements

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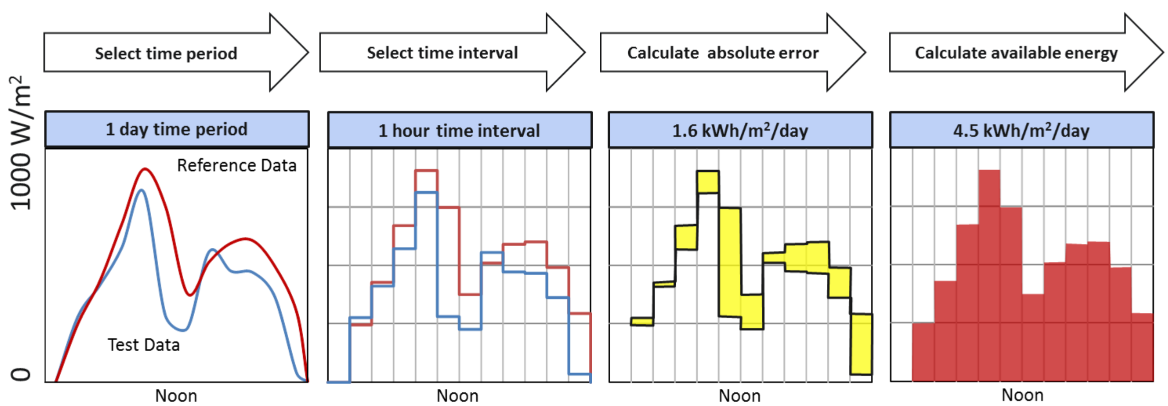
Appendix A

This appendix provides a hypothetical example of how to calculate rMAE. A short time period (one day) is selected in order to graphically illustrate the calculations; the actual calculations in this report use a six-month time period.

As presented in , the process is follows:

- Select time period: 1 day.
- Select time interval: 1 hour.
- Calculate absolute error for each hour and sum the result as described in the top part of Equation (1): 1.6 kWh/m^2/day.
- Calculate available energy for each hour from reference data and sum the result as described in the bottom part of Equation (1): 4.5 kWh/m^2/day.
- Calculate rMAE: 36% (i.e., 1.6/4.5).

Figure 22. rMAE calculation example.



It is important to note that a more often reported measurement of error is MAE relative to generating capacity. In the above example, however, it is unclear over what time period the generating capacity should be selected. Should it be capacity during daylight hours or capacity over the entire day, including night time hours? MAE relative to daytime capacity is about 13.3% (i.e., 1.6/12) while Mean Absolute Error relative to full day capacity is about 6.6% (i.e., 1.6/24).

It is due to this sort of ambiguity, as well as the fact that rMAE is a much more stringent metric (e.g., in this example, rMAE is 6 times higher than MAE relative to daily generation capacity).