Energy Research and Development Division

FINAL PROJECT REPORT

Improving Solar and Load Forecasts by Reducing Operational Uncertainty

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California Energy Commission

Gavin Newsom, Governor

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PREFACE

The California Energy Commission's Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

The California Public Utilities Commission established the Electric Program Investment Charge (EPIC) in 2012 to fund public investments in research to create and advance new energy solution, foster regional innovation and bring ideas from the lab to the marketplace. The California Energy Commission and the state's three largest investor-owned utilities – Pacific Gas and Electric Company, San Diego Gas and Electric Company and Southern California Edison Company –administered the EPIC funds and advance novel technologies, tools and strategies that provide benefits to their electric ratepayers.

The Energy Commission is committed to ensuring public participation in its research and development programs which promote greater reliability, lower costs and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

Improving Solar and Load Forecasts by Reducing Operational Uncertainty is the final report for the grant number CEC-EPC-14-001 conducted by Itron, Inc. dba in California as IBS. The information from this project contributes to Energy Research and Development Division's EPIC Program.

For more information about the Energy Research and Development Division, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

ABSTRACT

Homeowners and businesses in California have installed numerous solar photovoltaic (PV) systems because of California's Renewable Portfolio Standard requirements as well as the decreasing costs of PV. The California Independent System Operator (California ISO), who operates California's electric grid, does not measure behind-the-meter PV generation. The California ISO and the electric utilities are facing the uncertainty associated with PV generation profiles. The California ISO is conservatively forecasting and scheduling excess regulation and spinning reserves because of this PV uncertainty. They must extend their load forecast models to better predict when customers rely on the grid to meet their electricity requirements versus relying on their behind-the-meter PV generation.

This project addresses this issue by advancing the state of the art in solar energy forecasting as it relates to the operation of the California electric grid. It undertook four specific technical tasks:

1) Investigate supplementing the California ISO's current real-time solar data feeds.
2) Improve the California ISO's solar production forecasts.
3) Investigate alternative net load forecasting methods to improve integrating PV generation forecasts with an operational net load forecast, and
4) Estimate the monetary value of the alternative net load forecasts and develop a framework for optimizing their use.

This research identified improvements necessary for real-time solar data and forecasts, and alternative methods of net load forecasting that provide value to the grid and its stakeholders. The research team also identified additional areas of future research.

The California ISO has adopted the findings of this research and implemented these methods, providing savings for ratepayers and other stakeholders. In addition, the Australia Energy Market Operator, the New York Independent System Operator, and the Independent Electricity System Operator in Ontario Canada have implemented variations of these findings.

Keywords: Solar photovoltaics (PV), load forecasting, solar forecasting, forecast valuation

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EXECUTIVE SUMMARY

Introduction

Homeowners and businesses in California have installed numerous solar photovoltaic (PV) systems because of Renewable Portfolio Standard requirements and the decreasing costs of PV. The installed capacity of behind-the-meter solar in California is nearly 6 gigawatts, and researchers expect this capacity to increase substantially by 2020. Behind-the-meter generation supplies a portion of the electricity consumed by end-users (such as residential, commercial, industrial, agriculture, and other customers).

The California Independent System Operator (California ISO) operates California's electrical grid but does not measure behind-the-meter PV generation. As a result, that generation is not captured in the California ISO's load forecast models, which only include factors that affect gross end-user electricity consumption. With more behind-the-meter solar PV, these load forecast models will need to better predict when end users will rely on the grid to meet their electricity requirements versus relying on their solar generation. Additionally, the increasing number of larger scale PV plants is exacerbating variable electricity from renewable resources that the California ISO must then compensate for with conventional generating resources.

Uncertainty associated with PV generation profiles is the key challenge facing the California ISO and electric utilities as they integrate higher concentrations of PV into the grid. PV is inherently an intermittent, or irregular, resource, while utilities must maintain high system reliability at low costs. The California ISO's current scheduling of conventional generators like natural gas plants to maintain system stability is conservative and reflects the uncertainty in PV.

Project Purpose

Itron, Inc. proposed advancing the state of the art in solar energy forecasting as it relates to operating the California electric grid. Itron submitted its proposal under the Electric Program Investment Charge (EPIC) funds, with Clean Power Research, LLC identified as a major subcontractor.

While numerous efforts have attempted to improve predicting solar PV generation, they often failed to address one of the core challenges facing grid operators—uncertainty in net load forecasts. This project explored how to reduce the operational uncertainty in PV and net load forecasts with high accuracy forecasts and linking them to net load forecasts at more precise time intervals. Increased accuracy in estimating and incorporating PV into net load forecasts will enable better integration of intermittent PV generation in California and provide substantial savings in the associated wholesale energy market costs.

Project Process

Itron and Clean Power Research supplied the California ISO with solar forecasts and net load forecasts separately. The research team coordinated with the California ISO in implementing the approaches to their scheduling operations while developing the improved forecast methods. The team used 15-minute to two-hour forecast horizons in five-minute time intervals to evaluate the forecast performance improvements. In addition, the research team used a second set of forecast performance metrics to quantify the reduction of net load forecast uncertainty. The team used the error in the net load forecast to estimate how much excess generation California needed to ensure adequate power was available. Finally, the team used wholesale energy market cost analysis to further quantify savings from more accurate forecasts.

The research team used a series of four analyses to accomplish the research: data forecasting accuracy improvement; grid-connected and embedded PV fleet forecasting accuracy; improving short-term load forecasts by incorporating solar PV generation; and forecasting evaluation and framework analysis.

Data Forecasting Accuracy Improvement

The project investigated using real-time data taken from utility-scale and behind-the-meter resources to improve solar production forecasts. This data could potentially improve forecasts by providing a "true up" for calculated solar irradiance (solar energy as radiation) as well as an indication of individual power plant availability. The project sought a method for forecasting production from concentrating solar power resources. Concentrating solar power resource forecasting is more complicated than solar PV forecasting because output depends not only on the solar intensity, but also on the position of the sun. Concentrating solar power concentrates light, so it can only make use of direct “beam” irradiance, whereas non-concentrating PV uses three types of solar radiation: beam, diffuse (refracted throughout the sky and received from many directions) and reflected (such as from the ground).

Grid-Connected and Embedded Photovoltaic Fleet Forecasting Accuracy

The project analyzed potential methods for improving solar forecasts. Solar forecasting includes forecasting for individual, utility-scale resources and aggregated behind-the-meter "fleet" resources. Possible improvements to the solar forecasts include incorporating factors such as: age-related degradation, improvements in inverter modeling, incorporating ever-changing amounts of solar capacity, and handling real-world performance issues such as soiling, system outages, and shading.

Improving Short-Term Load Forecasts by Incorporating Solar Photovoltaic Generation

The California ISO Baseline Load Forecast Model provided forecasts of measured loads for forecast horizons of 15 minutes ahead to ten days ahead. The baseline modeling framework is composed of a set of 193 individual forecast models. None of these models included the impact of behind-the-meter solar PV on measured loads. The research team extended the existing California ISO load forecast models to capture the influence of behind-the-meter solar PV and predict an increasingly volatile load. This study evaluated three alternative model approaches for extending the California ISO load forecast framework.

1. Error Correction. The Error Correction approach implemented what many system operators did initially when faced with the problem of solar PV generation. They made ex post adjustments of the load forecast to account for forecasted values of solar PV generation.

2. Reconstituted Loads. Under the reconstituted loads approach, the research team reconstituted the historical time series of measured load by adding back estimates of solar PV generation. The team then re-estimated the load forecast model against the reconstituted loads. The team then adjusted, ex post, the reconstituted load forecasts by subtracting away forecasts of solar PV generation to form a forecast of measured loads.
3. Model Direct. Under this approach, the research team directly estimated the weight placed on the solar PV generation data by including these data as an explanatory variable in the load forecast models. The estimated coefficient on the solar PV generation variable is the weight.

To evaluate the forecast performance of the alternative model approaches, the study simulated a series of 24-hour ahead load forecasts. The research team compared the forecast errors to the corresponding baseline model load forecast errors. The study relied on two sources of behind-the-meter solar PV generation estimates—Clean Power Research's solar generation estimates and cloud-cover driven solar generation estimates.

Forecasting Valuation and Framework Analysis

The study considered how the monetary value associated with the alternative net load forecasts would affect stakeholder long-term and short-term costs. The research team developed alternative net load forecasts as short-term forecasts for the next-day and day-of wholesale electricity markets within California. Determining the short-term avoided costs associated with the alternative forecasts requires the use of short-term wholesale electricity prices and not long-term avoided capital costs.

The research team computed the avoided costs (valuation) of electricity associated with using the alternative forecasts over the California ISO's baseline forecasting models by costing the electricity from each forecast and then taking the difference. This difference in costs determines the value of using the alternative forecasts. The team performed the evaluation for each of the five zones (Pacific Gas and Electric (PG&E) Bay Area, PG&E Not Bay, Southern California Edison (SCE) Inland, SCE Coastal, and San Diego Gas and Electric (SDG&E)) used in the development of the alternative forecast methodology and at the total California ISO level (sum of the five zones).

This study examined highly influential factors in determining the value associated with the alternative net load forecasts. The team performed this examination as a precursor to developing a framework for using the alternate forecasts.

The research team did not find any clearly observable correlations. The team used three machine learning approaches to investigate the creation of a framework for optimizing the choice of forecasting method. These included a number of different machine learning techniques and approaches. The project team applied these algorithms to each of the five California ISO zones (PG&E Bay Area, PG&E Not Bay, SCE Inland, SCE Coastal, and SDG&E).

Project Results

Data Forecasting Accuracy Improvement

Using ground irradiance measurements from utility-scale resources was problematic because plants do not report global horizontal irradiance (the amount of radiation received on a surface horizontal to the ground), but irradiance measured on the tilted surface of the solar modules. The project developed a method to estimate how often solar power plants were online when the sun was shining. Finally, the project introduced an approach to forecasting concentrating solar power resources, but also identified forecast difficulties with some aspects of this approach.

Grid-Connected and Embedded Photovoltaic Fleet Forecasting Accuracy

The project incorporated several forecast improvements. The project team introduced a method for tracking system installation dates and added a correction for module degradation. The project advanced methods for determining system specifications and shading based on measured production inputs, rather than relying upon installer-supplied data which is not always accurate. Forecast improvements also included the use of model-specific inverter power curves; advanced ensemble methods leveraging forecasts from multiple sources. The project team evaluated a method to increase forecast performance using representative fleets and developed a process to automatically update FleetView™ (a software program developed by Clean Power Research) to incorporate monthly utility-reported behind-the-meter capacity increases. Sacramento Municipal Utility District (SMUD), SCE and PG&E held utility partner meetings to quantify the impact of distributed PV on the distribution grid.

Improving Short-Term Load Forecasts by Incorporating Solar Photovoltaic Generation

The team compared the baseline forecast to each of the six different forecasting methodologies: California ISO as a whole, the three investor owned utilities, and the five California ISO zones (PG&E Bay Area, PG&E Non-Bay Area, SCE Coastal, SCE Inland, and SDG&E). In general, the results showed that:

- Not adjusting the California ISO baseline forecast models will only lead to further erosion of forecast accuracy and a greater dispersion of forecast errors.
- Direct modelling performed better than the baseline and other methods in the near term (fifteen minutes to four hours in advance). The Reconstituted Load Approach performed better for longer time horizons from four hours through to day ahead horizons. That suggests that a hybrid or ensemble approach that combines these two methods is optimal.
- SDG&E showed better improvements from forecasts that integrated behind-the-meter PV forecasts than the California ISO or any of the other California ISO zones. This could be a result of a smaller geographic area combined with a higher penetration of behind-the-meter PV.
- Hourly cloud cover driven estimates of solar generation can provide benefit over doing nothing, however the detailed bottom-up approach implemented by Clean Power Research yields superior results.

- The findings also indicated that 1 megawatt of solar PV generation may not reduce what the California ISO measures as load by the same amount, 1 megawatt. A possible explanation for this counterintuitive finding is that the California ISO only measures what happens in front of the meter. Installing solar PV can result in fundamental behind-the-meter behavioral changes in how consumers use end-use equipment, which mutes the impact of solar PV generation on load.
- The model direct approach allows some investigation into how much of the solar PV generation results in net load increases associated with this type of behavioral change. Further research can determine the extent to which penetration of solar PV is leading to behavioral changes.

Forecasting Valuation and Framework Process and Analysis

The research team developed a method for estimating the avoided costs, or value, associated with the alternative forecasts. The team calculated the cost of acquiring electricity in the California wholesale markets for each of the forecasting methodologies and compared the alternative forecast to the existing baseline forecast. In general, the results show:

- In total, the alternative forecast method provides positive value at the California ISO level across all years.
- At the California ISO level, the valuation varies significantly in magnitude across years.
- At the individual zonal level, the alternative forecast does not provide positive value in all months or years.
- There does not appear to be a consistent pattern as to which months or zones will have a positive valuation.

Machine learning is the field of computer science where computers learn from data without being explicitly programmed. The project team developed and applied a framework to choose the least costly forecast method, which uses several data mining and machine learning algorithms. One of these machine learning algorithms did appear to improve results but was deemed to be too complicated to be actionable for system operators.

The research team recommends more research into machine learning before deciding on a more sophisticated framework.

Knowledge Transfer

The technology analyzed under this project is being used today by the California ISO to improve net load forecasts. Other Independent System Operators that have adopted at least some variation of the improved net load framework include New York ISO, ISO New England, IESO (Ontario, Canada), AEMO (Australia) and Western Power (Australia).

In addition, multiple conference presentations and papers were completed to disseminate the learnings form this analysis. The team also published an Energy Commission report on improving short-term load forecasts by incorporating solar PV generation to share these first-of-their-kind results with stakeholders and the international community interested in the subject (available at https://www.energy.ca.gov/2017publications/CEC-500-2017-031/CEC-500-2017-031.pdf.

Benefits to California

This research is important to stakeholders (California ISO, generation providers, utilities, and ratepayers) because it shows that improvements in solar and net load forecasting methods can provide positive financial impacts in the scheduling and procurement of electricity in the wholesale electric market within California. The results of this research have shown that, just in the period covered by this analysis, the potential savings to all stakeholders would have been about $9 million. With further growth in solar and improvements in integrating behind the meter solar into the California ISO net load forecasts, the team anticipates it can achieve even greater cost reductions. The California ISO adopted the findings demonstrated in this research and placed them in production. They are currently generating saving for ratepayers and other stakeholders. In addition, AEMO, the New York ISO, and IESO in Ontario Canada have all implemented in production variations of the models.

This research is also important to stakeholders because it sets the groundwork for further research into developing a framework to optimize the use of the alternative forecast method by the California ISO to develop its net load forecast. It may be possible to develop a framework for choosing when to use the alternative forecast to optimize its value to all stakeholders.

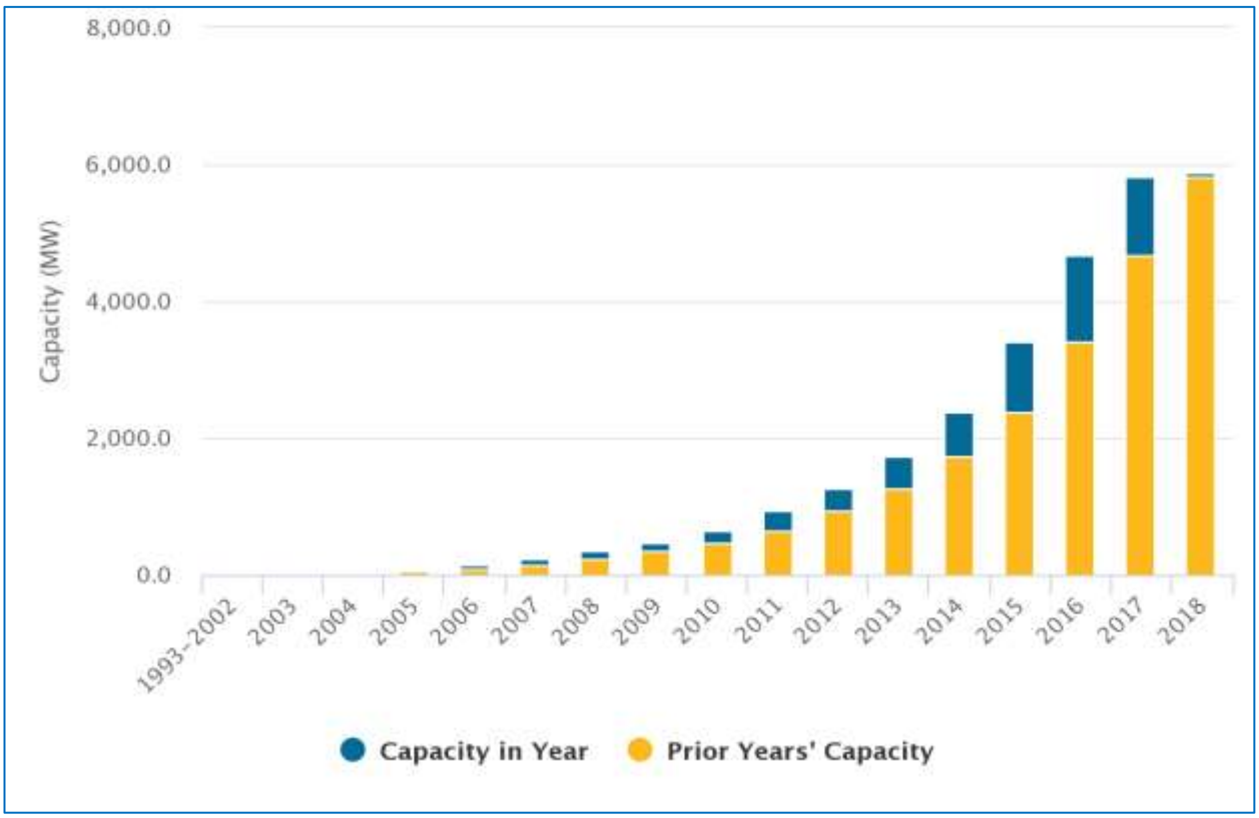
In additional to financial savings, emission savings should result from the reduction in the need for spinning reserves as part of this project. Finally, by reducing the need for resources to balance intermittent renewables, this project should enable a higher proportion of solar generation on California’s grid.

Chapter 1
Introduction

The key challenge facing the California Independent System Operator (California ISO) and the electric utilities as they integrate higher and higher concentrations of photovoltaics (PV) into the grid is the uncertainty associated with PV generation profiles. Figure 1 shows the growth of behind-the-meter (BTM) PV in California. PV generation is inherently an intermittent resource and utilities must maintain high system reliability at low costs. The California ISO's current scheduling of conventional generators and spinning reserves is conservative and reflects the uncertainty in PV. To reduce the reliance on regulation services and spinning reserves, the California ISO requires improved solar generation and measured load forecasts.

Itron, Inc., developed a proposal in June 2014 to the California Energy Commission (Energy Commission) to address this issue by advancing the state of the art in solar energy forecasting as it relates to the operation of the California electric grid. The Itron team submitted its proposal under the Electric Program Investment Charge (EPIC) funds, with Clean Power Research, LLC (CPR) identified as a major subcontractor. The Energy Commission awarded the project to the Itron/CPR team in February 2015.

Figure 1: California Statewide Behind-The-Meter Solar Generation Capacity



Source: https://www.californiadgstats.ca.gov/

California utilities and the California ISO have identified that increasing solar has led to a phenomena deemed the “duck curve.” As more solar generation comes onto the grid, net load drops in the middle of the day and ramps up much more quickly in the late afternoon and the sun goes down. The dip in the middle of the day forms the “belly” of the duck and the faster ramp in the late afternoon forms the “head” of the duck. This changing load shape and the increasing uncertainty associated with it make operation of California’s grid more challenging.

The objective of this project was to investigate reducing the operational uncertainty behind the duck curve by producing high accuracy forecasts for utilities and the California ISO and linking them to net loads. This increased fidelity and connection to net load forecasts will provide critical insights to better manage the rapidly evolving grid in California.

Technical Approach

This research attempts to holistically improve forecasts of solar generation and net load to utility and California ISO operations. The objectives of the tasks undertaken in this project were:

- Improve data acquisition capabilities, reliability, and cost effectiveness of ground-mounted solar instrumentation,
- Develop and refine current solar forecasting fools for grid connected solar generation,
- Develop and refine current solar forecasting tools for embedded solar generation,
- Improve net load forecast accuracy and metrics,
- Develop approach to value the improved net load forecasts, and
- Develop a forecasting framework to improve solar integration.

The research team grouped the project work into four primary tasks, discussed in the remainder of this report in greater detail.

Chapter 2: Data Forecasting Accuracy Improvement

Introduction and Background

The work described in this chapter discusses the use of existing real-time data to improve the solar generation forecasts. Forecasts include forecasts for output of individual utility-scale resources as well as aggregated forecasts of small BTM forecasts.

Prior to this project, CPR established a software system for providing forecasts to grid operators (SolarAnywhere® FleetView™ software product), but these forecasts solely rely upon knowledge of the installed PV resources and the forecasted irradiance/temperature at grid locations across the state. The California Solar Initiative (CSI) incentive program for BTM systems was the primary source for PV system hardware specifications—solar panel ratings, tilt and azimuth orientation, inverter specifications and the like. Data on transmission-connected resources came from various public data sources. Solar irradiance and temperature forecasts are available through FleetView™ directly.

The research team undertook this task to determine whether real-time data collected could be used to supplement the other two data sources. The team was particularly interested in two data feeds.

First, the metered systems, utility-scale PV systems, could collect plane-of-array solar irradiance, and one can use this data in real-time to provide state-of-the-art forecasts for the resources. The research team believed that this data could act as calibration source to supplement CPR's data, derived from satellite imagery.

In particular, aerosol optical depth (AOD) and cloud albedo (or reflectivity) are two physical parameters that govern availability of solar radiation at ground level. These parameters are not measurable or derivable from the satellite images, collected outside the atmosphere. Consequently, calibration of satellite-derived irradiance requires ground measured sources, and these are supplied by ground stations across the United States. Real-time collected ground irradiance measurements taken at various solar generating sites could potentially be used to obtain local values that could be incorporated into the irradiance forecasts. If this were possible, the measured data could help to calibrate the irradiance data in real time, and the improvement would apply to both metered and BTM forecasts.

Second, maintenance schedule of metered systems is a potential input to the forecasts. For example, taking an inverter or array out of service would reduce the available capacity of the resource. This requires scaling the production forecast for the reduced plant capacity to incorporate this into the forecast of solar production.

The intent of the task was to obtain the relevant data fields in real-time and evaluate their use in producing more accurate forecasts. Unfortunately, the California ISO did not grant CPR access to the real-time data due to the timing of the project and steps required. Security requires that plant-specific data be available only by permission from specific plant operators. CPR could have required getting approvals from solar plant operators, but this would have exceeded the time available under the project. Therefore, this task did not include a demonstration using real time irradiance but rather focused on a description of such a process and an analysis of the approach, for future consideration.

CPR developed software in preparation for uploading and processing of the real-time data. To be ready to accept a real-time feed of data and to incorporate this into the FleetView™ software, CPR focused development on SolarAnywhere® infrastructure. Also, CPR identified other sources of data and incorporated them into FleetView™ forecasts. CPR can now download new numerical weather prediction (NWP) models from their respective sources and uploaded them to their servers for use in FleetView™ with operational reliability.

SolarAnywhere FleetView Forecasting Model

Overview

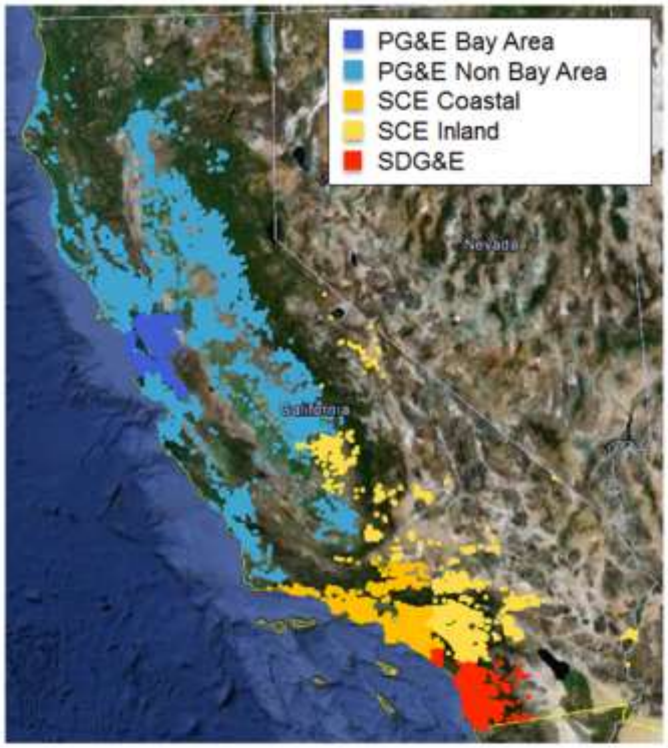
SolarAnywhere FleetView employs satellite-derived irradiance data in combination with patented fleet analysis methodologies to provide insight into the impact of PV on grid operations. As a hosted software solution, SolarAnywhere® FleetView™ serves as an ongoing platform for analysis, enabling rapid, dynamic and cost-effective intelligence as compared to traditional point-in-time studies.

FleetView™ uses satellite-derived irradiance data to generate PV performance data rather than using expensive ground sensors and communication networks. Using this data, FleetView™ can quantify PV variability to allow grid operators to conduct planning studies and forecast PV fleet output based on the design attributes and locations of individual PV systems. The model uses advanced algorithms for calculating PV plant correlation coefficients and quantifying geographic dispersion effects in a manner that is useful at the control area level.

Integral to the solution is the ability to enumerate, specify, catalog, and simulate fleets of PV systems, including providing PV power output forecasts. These software tools allow utility managers to understand PV system impact at macroscopic or granular levels, with virtual fleets being definable as a few systems on a single feeder or many thousands across an entire service territory. As a result, FleetView™ makes it possible for utilities, regional transmission operators (RTOs), and independent system operators (ISOs), such as the California ISO, to have an ongoing planning study to optimize PV siting while accounting for changes in distributed generation resource availability and other factors—all at a fraction of the cost and time associated with traditional planning studies.

To date, Energy Commission and California Public Utilities Commission (CPUC) contractors have performed simulations of fleets within California ISO. CPR collected most of the BTM resource data from the CSI. The project team divided the systems into five geographical territories according to the California ISO designations. The baseline CSI fleet includes 78,025 systems with a total rating of 773 MW-AC.[1] Figure 2 shows the mapping of all CSI systems in their respective fleets, including those at Pacific Gas and Electric (PG&E), Southern California Edison (SCE) and San Diego Gas and Electric (SDG&E).

Figure 2: Mapping of All ~78,000 Behind-the-meter Photovoltaic Systems in the California Independent System Operator



Source: Itron, Inc.

In addition to the BTM resources identified through CSI (and later through GoSolarCalifornia), the project included California ISO's metered systems (utility scale systems). CPR independently collected plant specifications for these systems. Data sources included available public information from the California ISO Open Access Same Time Information System (OASIS) site and various public records (for example, permits, press releases, and maps). These public sources provided the required hardware specifications.

Photovoltaic Simulation Methods

SolarAnywhere® produces a time series of PV system energy production using internal PV simulation models for use across a broad range of applications.

CPR began the simulation process by specifying inputs about how to perform the simulation, what to simulate, and what results are desired. To define how one performs the simulation, one selects among a variety of different electrical models for PV arrays and inverters as well as

[1] The industry rates systems here based on their alternating current (AC) capability rather than their direct current (DC) capability.

different models for shading and obstruction analysis. The simulation specification consists of a definition of the PV system configuration and weather data for the time span of interest.

Either latitude and longitude or by street address (for residential systems) defines the locational information. Just inputting a system zip code defines the location using a geographic centroid of the zip code to select the weather data and results in less accurate simulations.

PV array geometry includes inputs such as installation azimuth and tilt angle, as well as tracking algorithms (for example stationary, single-axis and dual-axis tracking). Collecting on site solar obstruction information reflects obstructions caused by surrounding objects, including trees or adjacent buildings, or obstructions caused by utility plant intra-row spacing. The specific equipment by manufacturer and model or generic system ratings determine the actual hardware efficiency of energy conversion, used in the PVForm power output model. The commissioning (installation) date can be estimated using year-by-year degradation. Also, a temperature coefficient that describes the reduction in output for higher temperatures (SolarAnywhere® supplies temperature data) can be used to identify modules.

Power Output Simulation

The project adapted SolarAnywhere® to accept multiple models throughout the different stages of simulation, hence making it customizable. The accuracy of the results is impacted by the selected model. This may require additional model-specific information about the PV system. The current PV power output option is an implementation of PVForm, with the Sandia PV Array and Inverter Performance Model under development. The user has the option to select either the Perez/Hoff shading model for the obstruction analysis or forgo obstruction analysis in cases where details about the surrounding obstructions are unknown. One can incorporate other model inputs, depending on the level of specification by the application.

It is necessary to define the PV simulation configuration after identifying the desired models. SolarAnywhere® can model a diverse range of system configurations. The configuration begins at the smallest scale with the PV array consisting of one or more PV modules having the same orientation. A PV subsystem is composed of one or more PV arrays each of which can have a different orientation, shading, and an arbitrary number of inverters. A PV system consists of one or more PV subsystems all at the same geographic location. A simulation consists of one or more PV systems all of which can be in different locations. In this way, SolarAnywhere® will accommodate the needs of any size system from the small residential scale up to large industrial PV systems or a fleet of PV systems distributed across different geographic locations.

SolarAnywhere's simulation accuracy depends on the level of detail and accuracy in specifying the PV system configuration and the models and data used to perform the simulation. SolarAnywhere® accommodates a minimal amount of configuration information (that is, location, orientation, and system rating) using a simple model for applications designed to provide a quick economic evaluation. SolarAnywhere® also accepts detailed information (such as detailed inverter and module specs, SolarAnywhere® time series data, specific shading information) for applications designed to produce performance guarantees requiring greater accuracy.

Sandia National Labs originally developed the PVForm Power Output Model in 1985. CPR originally developed PVForm through the Clean Power Estimator tool. Numerous solar agencies and solar manufacturer have built the tool into their websites. CPR has further developed this implementation into SolarAnywhere®.

Data Sources

Functionally, SolarAnywhere® is currently retrieving and processing data in real time throughout North America and Hawaii at Enhanced Resolution (1-kilometer [km] grid, 30-minute measurements) and contains historical measurements back to January 1, 1998. Research improvements have added the ability to capture higher resolution data. The user can match any current coverage area to the SolarAnywhere® high (1-km, 1-minute) resolution geographically. While the underlying satellite images have a resolution of 30 minutes, using cloud motion vector calculations to effectively interpolate irradiance during times between any two images, the user can obtain high resolution. To date, however, users have only processed at high resolution certain target regions, including the state of California.

SolarAnywhere® implements the latest satellite-to-solar irradiance model developed by Dr. Richard Perez at SUNY Albany by collecting half-hourly satellite visible and infrared (IR) images from GOES satellites operated by the National Oceanic and Atmospheric Administration (NOAA). NOAA owns and operates the GOES-15, responsible for images in the western half of North America and GOES-16, for images in the eastern half of North America. The Perez algorithm first extracts the cloud indices from the satellite's visible channel using a self-calibrating feedback process. This process can adjust for arbitrary ground surfaces. The cloud indices modulate physically-based radiative transfer models representative of localized clear sky conditions. The database incorporates Wind and ambient temperature data through collection of NOAA weather data on their standard 5-km grid.

Standardized logic in SolarAnywhere® calculates typical year data files. First, it sums sub-monthly time series data to compute the total available monthly energy specific to each 10-km or 1-km gridded tile location. SolarAnywhere® treats Global horizontal (GHI) and direct normal (DNI) irradiance as separate irradiance components. For each location, SolarAnywhere® calculates the average GHI or DNI by selecting the month with total energy closest to mean and concatenating the actual data into a final 12-month, 8760-hour typical irradiance file. Default settings in SolarAnywhere® select data based on data from the range January 1998 to December 2016.

For this project, the research team identified and evaluated several Numerical Weather Prediction (NWP) models for their usefulness in improving a solar forecast. Development work went into creating robust systems for downloading this data from their respective sources and then uploading to CPR servers.

Use of Data in Forecasts

Ground Irradiance Measurements

Initial investigation of historical (not real time) data revealed that many of the utility scale PV plants do not report Global Horizontal Irradiance (GHI) but the plane of array (POA) irradiance is available. However, POA is not as clearly related to AOD. Detectable issues, such as back tracking, can pollute any AOD signal. Additionally, there is uncertainty and error associated with any sort of POA to GHI transposition as well, which would also degrade any sort of AOD signal detected.

CPR concluded that GHI data is not available and POA data could not provide reliable real-time improvements in forecasting. It would be possible to install solar instrumentation at selected California ISO locations, but including such a demonstration was outside the project scope.

Plant Availability

CPR developed a procedure that could be used to incorporate plant production as an indicator of availability. This could be an approach where plant availability reporting is not provided. Given the plant technical specifications and recent (for example, the prior hour) irradiance measurements, it would be possible to compare the expected production with the actual production. If the actual production consistently was less than expected, the plant could be "de-rated" for a temporary period. A proof-of-concept plant database schema was developed to support such an approach, matching plant rating by date. This schema would be used for both ongoing forecasts (during the temporary outage) as well as serving as a record for later analysis using historical data.

Concentrating Solar Power Resources

The project was primarily concerned with forecasting solar PV production using the methods described above. However, concentrating solar power (CSP) resources are also present on the California grid, and the scope of work (SOW) required that CPR develop a description of an approach that could be used to forecast CSP resources.

CSP requires optical concentration of direct normal irradiance (DNI). Unlike non-concentrating PV, CSP is not able to capture radiant energy from diffuse sky regions. SolarAnywhere includes DNI, so it would be possible to use the SolarAnywhere DNI as a basis for forecasting, along with SolarAnywhere ambient temperature data, also a factor in CSP performance.

CPR developed a method for calculating power output as follows. Optical efficiency is complicated by the complex array of heliostats, each of which accept solar beam radiation at a different angle defined by their location in the field and the time-varying solar vector.

To model each heliostat individually requires knowledge of the heliostat geometrical attributes and the tower/receiver height to calculate the solar incidence angle on the receiver. Other plant attributes must also be specified and modeled, such as the heat transfer fluid thermal properties, loss factors, turbine parameters, and so forth. It is not possible to model the plant without these data, and it is not feasible to obtain the plant specifications without significant input from the system designer.

To overcome these difficulties, it may be possible to create a simplified model that correlates plant output with available SolarAnywhere irradiance and ambient temperature data. The approach taken by CPR was to perform this correlation as a function of sun position.

The heliostat field has a different optical efficiency (incident radiation on the received divided by incident radiation on the heliostat) for each sun position. For example, at solar noon the heliostats located to the north of the tower will have a small angle between the solar vector and the tower vector, so the incidence angle will be small. These northern heliostats will therefore have a higher efficiency than heliostats located in, say, the east. However, in the afternoon, the sun is located in the west. Therefore, heliostats located in the east will have higher efficiency than heliostats in the north.

Plant performance is therefore a function of sun position. At a given position, the optical efficiency is determined, and the potential plant output would be a function of the piping losses, turbine efficiency, and ambient temperature.

Also, unlike PV, CSP does not respond instantaneously with available irradiance. Instead, one may observe a lag time. This is consistent with the understanding that CSP plants have inherent thermal capacity in the piping, receiver, and other components. Such a thermal lag would lead to both slow startup time at sunrise and extended operation after sundown. One would need to build a time lag into the forecast model.

A final difficulty is that developers can design CSP plants with thermal storage. For example, developers can be design molten salt plants with storage subsystems which can retain salt at elevated temperatures, providing dispatchability to the plant. In these cases, output is decoupled from solar availability, and knowledge of storage dispatch is required to complete the forecast. It may be possible to forecast dispatch based on available radiation and market prices, that is, to assume an optimized dispatch to maximize revenue.

In sum, CPR believes that to fully incorporate CSP resources into the forecast, additional study is required. A more expansive study could incorporate data from multiple resources and an investigation into the dispatch of stored energy.

California Independent System Operator Real-time Data Feed

Description

The Statement of Work also called for CPR to describe the real-time data feed at California ISO, data structure formats, and API. To accomplish this, CPR reviewed publicly available data provided by California ISO's specification documentation. This documentation is available to the public by downloading it from the California ISO website. The following is a summary of the relevant information.

In March 2016, this research indicated that the California ISO provided such real-time data through the Participating Intermittent Resource Program (PIRP) application programming interface (API), but this method of access was in the process of being deprecated in favor of the Plant Information Service-Oriented Architecture (PISOA) API.[2]

To obtain access to the data provided through PIRP the authorized Point of Contact (POC) submits an Application Access Request Form (AARF) through the California ISO's Customer Inquiry and Dispute Information (CIDI) system. Applications specify both the resource identifier (ID) and the Scheduling Coordinator ID (SCID). PISOA provides access to near real-time measurements of wind speed, plane of array irradiance, wind direction, MW generated, barometric pressure, ambient air temperature, and back of (PV) panel temperature for the requested Variable Energy Resource (VER).

Access to the service is via hypertext transfer protocol (HTTP) over secure sockets layer (SSL) (HTTPS) using an SSL certificate signed by a California ISO Certificate Signing Authority. The app_pisoa_ver_measurements role must be associated with the certificate used by application retrieving the VER measurements.

Data Application Programming Interface and Structure Formats

The PISOA service has one operation for getting VER measurements with three message types. All input and output messages are in XML format. The operation for making a data request is RetrieveVERMeasurements_PISOAv2_AP. The input message for the RetrieveVERMeasurements_PISOAv2_AP operation is RequestVERMeasurements_v1. This message can include an optional message header, but it is the message payload that contains the required start and end time to indicate the period that the returned measurements will cover.

The output message for this operation is Meter Measurement Data. Although the PISOA Interface Specification is unclear in this regard, it appears that meter measurement data includes the PI tag associated with the VER, the VER registered name, the type of measurement, the metered value, and the timestamp associated with the end time of the measured value.

If there is an error in processing or in the input message header or payload, a fault type message will be returned. Fault return data is documented in the PISOA Interface Specification.

[2] http://www.caiso.com/Documents/BusinessRequirementsSpecification-ForecastingandDataTransparency.pdf

Chapter 3: Grid-Connected and Embedded Photovoltaic Fleet Forecasting Accuracy

Introduction and Background

The key challenge facing California ISO and the electric utilities as they integrate higher and higher concentrations of PV into the grid is the uncertainty associated with PV generation profiles. PV is inherently a variable resource and utilities are charged with maintaining high system reliability at low costs. The uncertainty in PV is reflected in conservative scheduling of regulation and spinning reserves.

The work described in this chapter covers Task 3 of the project related to improvements in forecasting accuracy for behind-the-meter (BTM) (embedded) PV and utility-scale (grid-connected) systems. This work covers a broad range of activities that led directly to improvements in CPR's ability to efficiently and accurately produce solar production forecasts for the California electric grid.

Itron used the forecasts in two ways: (1) embedded system fleet forecasts are delivered to Itron as inputs to net-load forecasts; and (2) grid-connected system forecasts can be used by California ISO to schedule units for delivering the net forecasted load. Both use CPR's SolarAnywhere FleetView software product, into which the improved methods are incorporated.

Project Partnerships

As part of the project, the team held utility partner meetings to gather input on applicability beyond the ISO. The team held project meetings with partners SMUD, SCE and PG&E. The team identified key areas of interest to be the use of the PV simulation tools for quantifying the impact of distributed PV on the distribution grid and more regionalized BTM PV forecast for utility load modeling.

The specific use case for PG&E was the PV modeling for distribution grid planning. As the number and capacity of distributed PV continues to grow in PG&E territory, the cost of and uncertainty around operating the distribution grid is growing. Distributed PV can create a number of problems at the distribution level. The problems largely arise when the PV capacity becomes a significant portion of the regional load. PG&E was seeking to quantify the regional, feeder-level capacity and energy contribution of distributed PV. This project demonstrated that the PV modeling tools were useful in demonstrating capacity and energy contribution. The team encountered challenges, however, when system shading information was not recorded. Activities included:

- Held meetings with project partners SMUD, SCE, and PG&E
- Refined utility partner BTM/utility-scale PV fleet grouping capabilities
- Performed in-depth PG&E and SCE sub-fleet modeling analysis.

Enhancements Using Embedded System Production Data

Several forecast improvements relied upon a data set of individually metered production systems from a third-party source. The research team used this data to gauge the effectiveness of the new methods in improving simulation accuracy and, by extension, forecast accuracy, which relies on the simulations. Improvements include the incorporation of module degradation effects, module soiling, system availability, and the accuracy of system design specifications.

Prior to this project, SolarAnywhere FleetView treated systems as if they were newly installed: they were always available for service (that is, they were on-line), they operated as newly installed, there was no age-induced module degradation, and they were free from dust and dirt. In reality, none of these assumptions are true. CPR developed and evaluated methods to incorporate these real-world effects into the forecasts.

Module Degradation

Although CPR's PV modeling tools have long applied module degradation, the team generally applied this effect starting at the beginning of the simulation period. In other words, if you specify a degradation rate of 0.5 percent per year, and simulate the period from January 1, 2015 to January 1, 2016, the team reduces the module's rating as of January 1, 2016 by exactly 0.5 percent from its value on January 1, 2015. When working with newly installed or hypothetical systems, this is exactly the behavior desired. However, when modeling output for a 10-year-old system, the team already reduced the module rating by 5 percent on January 1, 2015 and an additional 0.5 percent by January 1, 2016.

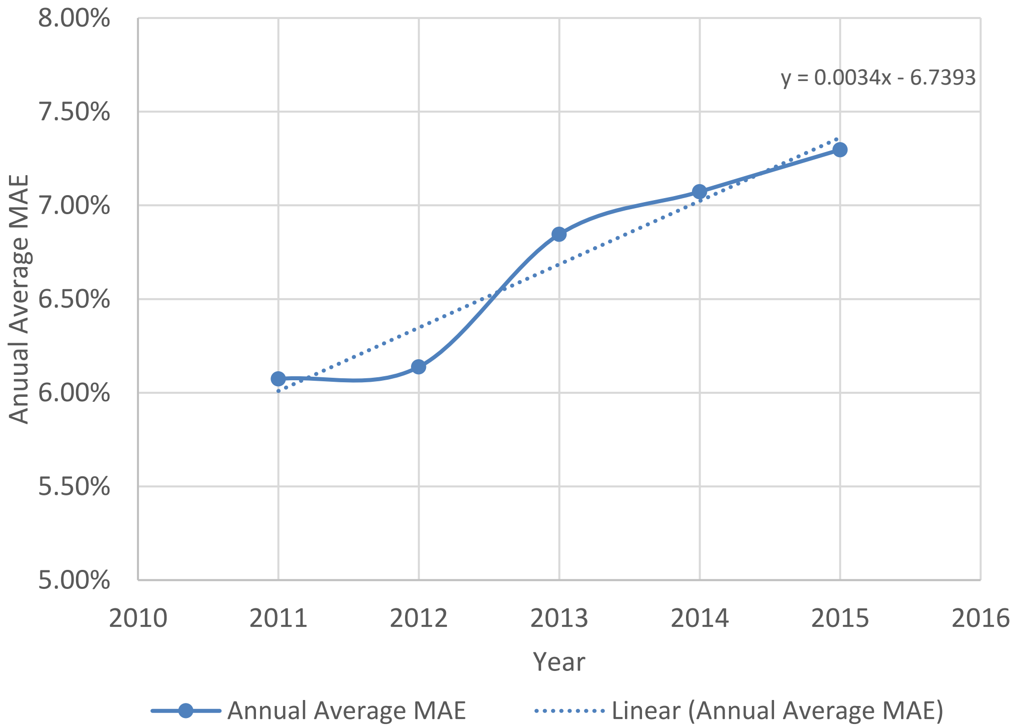
CPR added a commissioning date to all system specifications, which was not previously available in FleetView. The team can now calculate the module degradation at the specified rate beginning on that date, regardless of the period simulated.

To estimate the effect that this change might have in a real-world application, CPR simulated the SDG&E BTM fleet of approximately 14,000 systems for a single day (July 4, 2013) using a 0.5 percent annual degradation rate and a per-system commissioning date based on the system's California Solar Initiative (CSI) incentive payment date. Systems were installed as early as 2008, but typical age was about 2-3 years. Note that 2013 was a transition year, CSI was no longer funding new installations, so CPR performed this analysis for mid-2013 where reliable data was available.

Total daily fleet energy production without degradation was 883 MWh and peak power was 113 MW AC. With degradation, total daily energy production dropped to 874 MWh and peak power was 112 MW AC. The relative Mean Absolute Error in power production over the course of the day was 1.03 percent.

CPR observed an increase in average mean absolute error (MAE) for all systems between 2011 to 2015. This increase, when only taking the 2011 and 2015 into account, results in a 0.42 percent per year increase in average MAE for all systems. This rate is lower than the rough estimate of 1 percent per year, going by the typical 80 percent of capacity after 20 years of use. Comparing the results to the measured degradation of solar panels of about 0.5 percent year, puts the result of 0.42 percent annually - well within a reasonable range (Figure 3).

Figure 3: Relationship Between Average Mean Absolute Error for 207 Sites Selected from the Itron Data that Both have Five Years of Data and Annual Mean Absolute Error less than 20 percent

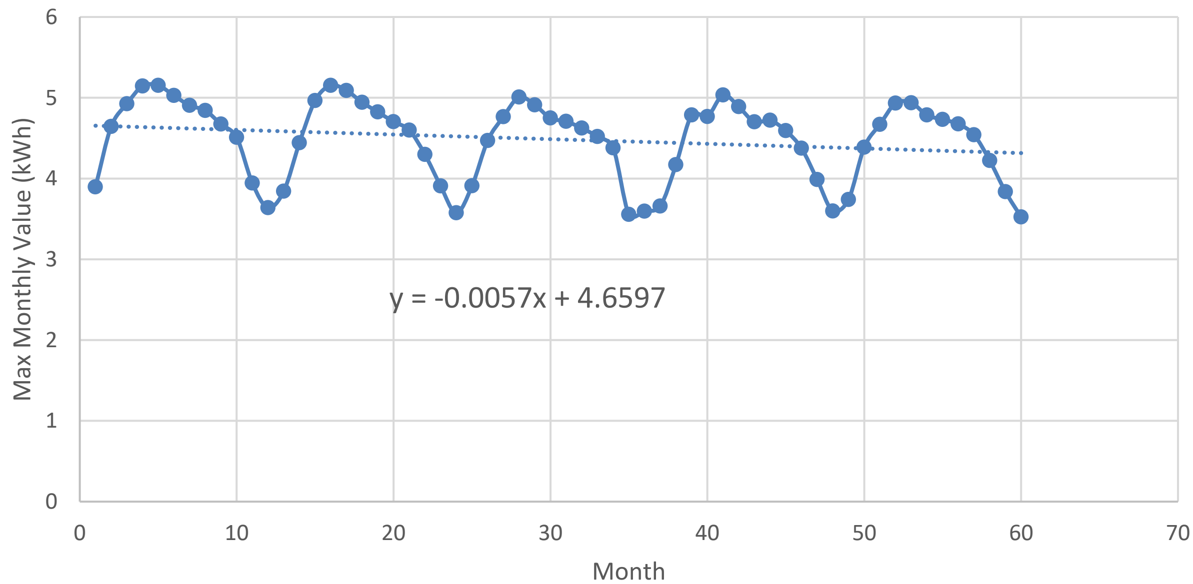


Source: Clean Power Research

CPR interpreted the annual increase in average MAE for all systems as degradation (Figure 4). The increase is on the expected order of magnitude and in expected direction. The team expected the increase in MAE because the SolarAnywhere power simulations do not currently take degradation into account. This would lead to a small increase in simulation error over time as PV panels degrade. A linear line of best fit has a slope of +0.0034 which, when divided by the average power of the 207 systems, results in an annual degradation rate of 0.32 percent.

CPR employed a second approach to identify degradation. CPR averaged the monthly maximum energy generation over five years for the same 207 filtered systems, resulting in 60 average monthly maximum values. CPR then applied a linear line of best fit trend line. The resulting slope was -0.0057 kWh. CPR then divided this by the average system power output, of 1.053 kWh, for an annual degradation rate of 0.54 percent.

Figure 4: Degradation via Monthly Max Values



Source: Clean Power Research

Both approaches result in similar results and are consistent with industry studies reporting 0.5 percent degradation. Comparable results from both the satellite simulations relative to ground and using the ground information indicates consistency in the satellite data prior to applying degradation and builds confidence in applying a modeled degradation approach to better predict the real-world PV fleet output.

Soiling

The soiling algorithm allows SolarAnywhere power simulation to take soiling of PV panels into account. Not considering module soiling losses during PV simulations can lead to systemically high biases in PV power. The soiling algorithm is a function of time and precipitation. The algorithm assumes that soiling increases at a constant temporal rate and is reduced by precipitation events. There are two categories of precipitation events; major and minor events. Major precipitation events remove more soil from PV modules than minor events do. CPR has custom-designed this soiling algorithm to work with daily precipitation data from the Snow Data Assimilation System (SNODAS) dataset, which is produced using a reanalysis with measured input to the base numerical model. The team shows the results and improvement with mean bias error (MBE) and mean absolute error (MAE) with and without the soiling model applied.

The results show hourly data from the 500-system Itron-metered PV fleet for five years (Table 1). CPR used one year of BTM data from a major solar installer to firm up the soiling rate calculations (Figure 5).

Table 1: Soiling Analysis Results

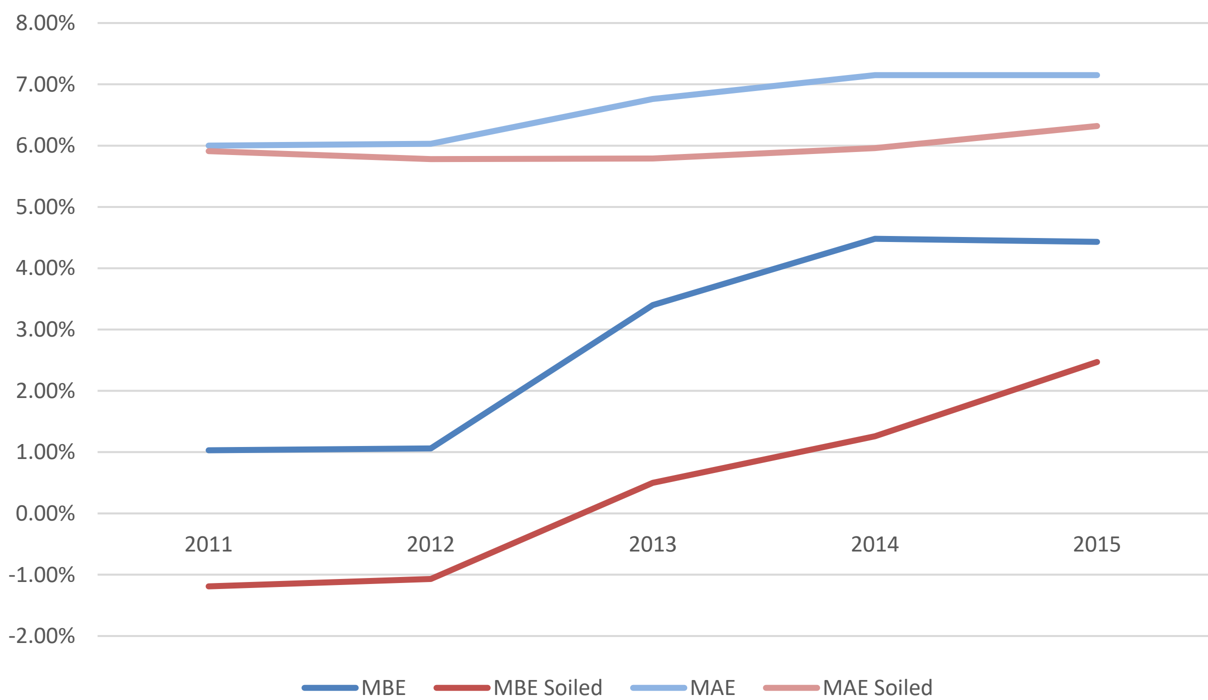
Soiling Results		
Average MAE Unsoiled	Average MAE Soiled	Absolute % Difference
6.62%	5.95%	0.67%

Relative Percent Improvement	10.12%

Yearly stats	2011	2012	2013	2014	2015
MBE	1.03%	1.06%	3.40%	4.48%	4.43%
MBE Soiled	-1.19%	-1.07%	0.50%	1.26%	2.47%
MAE	6.00%	6.03%	6.76%	7.15%	7.15%
MAE Soiled	5.91%	5.78%	5.79%	5.96%	6.32%

Source: Clean Power Research

Figure 5: Soiling by Year



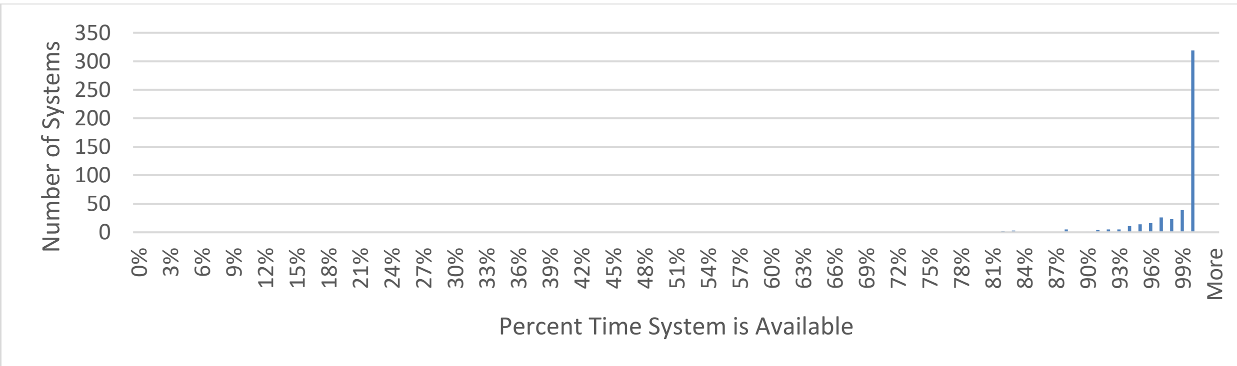
Source: Clean Power Research

System Availability

Forecasts should account for the fact that not all systems are on-line at any given time. Some may be unavailable due to any number of factors, such as fuse/breaker trips, maintenance, and line power disturbances (which cause the units to trip offline). It is not possible the research team to monitor every system in the fleet for availability, so CPR used an overall factor to represent average outage rates. CPR then applied the factor to the fleet as a whole.

Overall, systems had high availability. The average of all 476 systems was 98.27 percent availability. 319 systems had 100 percent availability. Figure 6 shows the distribution of system availability in the fleet. The trend is highly biased towards near 100 percent availability.

Figure 6: Histogram of System Availability



Source: Clean Power Research

Table 2 depicts additional statistics on the fleets availability.

Table 2: Fleet Availability Statistics

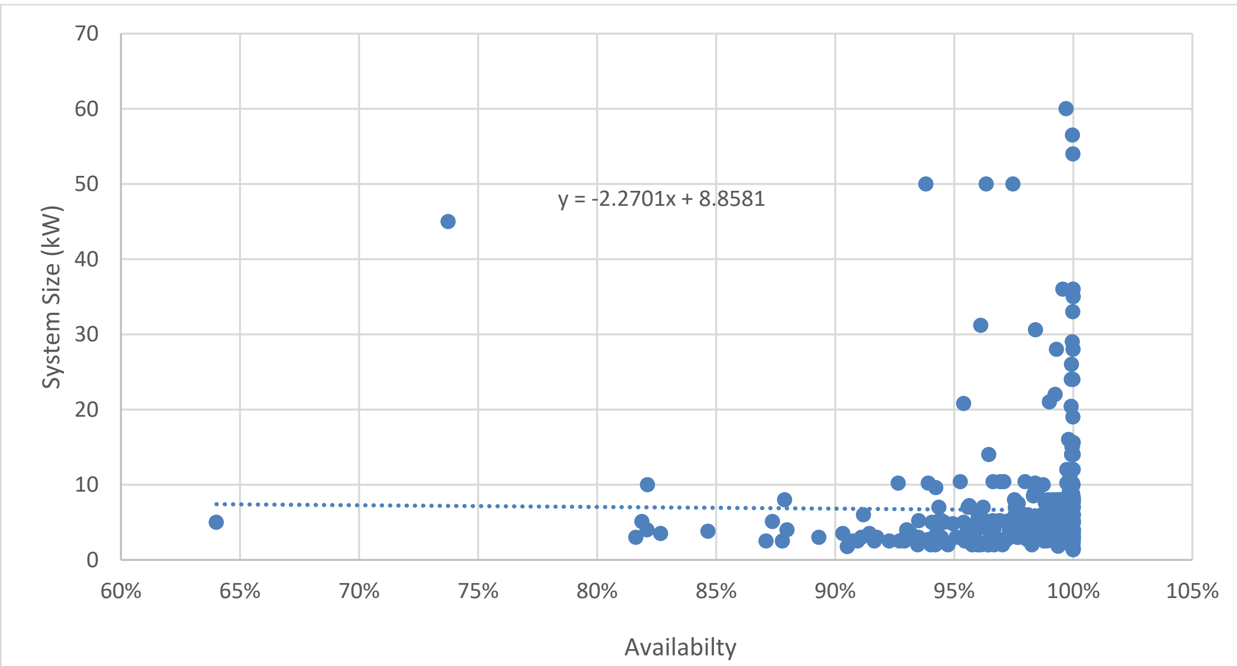
Statistics	
Average	98.27%
Max	100.00%
Min	64.01%
Mode	100.00%
Median	99.84%
Standard Deviation	3.56%

Source: Clean Power Research

One aspect of availability that the research team did not consider is partial system availability. This can occur when a single module or an inverter in the system is not functioning properly. This would result in decreased power output from the system but would not result in the system be reported as unavailable, rather it might be interpreted as degradation or soiling. Since the system is not reporting zeros, this aspect of availability remains unmeasured. This partial availability would be seen in increased error between the power simulations, and actual ground data. This error would be difficult to systematically identify.

Additionally, CPR investigated the relationship between system size and availability. CPR hypothesized that larger systems have a higher availability because they are more likely to be carefully monitored and maintained. Figure 7 shows that relationship, however the sample size is small enough that this relationship may be obscured. Finally, the available data skewed heavily towards single family residential systems.

Figure 7: Availability as a Function of System Size



Source: Clean Power Research

Improving System Specifications by Inference

With more than 5 GW of utility-scale PV capacity, the California ISO's ability to forecast output from large PV plants is becoming increasingly important.[3] CPR has learned that detailed system specifications improve the accuracy of modeled PV output. Unfortunately, these specifications are difficult to obtain because most of these plants are privately owned. It is CPR's hypothesis that it should be possible to use historical weather data and measured system output to infer some or all of a PV system's specifications automatically. The same approach might also be used to determine BTM system specifications.

The goal for this part of the project was to develop a command-line tool that would compare measured PV production data with the simulated output from candidate systems with various

[3] http://www.eia.gov/todayinenergy/detail.php?id=24852.

tilt and azimuth combinations. It would then identify the candidate system whose output resulted in the best fit to the measured data.

To simplify the problem somewhat, exact system location (latitude and longitude) is a required input. Also, the first version of the tool would only attempt to infer tilt, azimuth, and alternative current (AC) and direct current (DC) system ratings for fixed (that is non-tracking) systems. Furthermore, to reduce the overall error in candidate system output, CPR used a baseline specification would provide any known system details such as commissioning date, row count, row spacing, or solar obstructions.

CPR obtained measured PV production data for the period from March 1, 2013 through March 31, 2014 for several utility-scale PV plants. The team focused on three of the smaller plants, designated Plant A, B, and C. CPR used publicly available information to determine actual plant specifications manually. CPR supplemented this information with satellite imagery to determine the approximate number of rows of modules, number of inverters, and the array orientation. CPR used that information as the basis for a baseline system to be used as a template for each of the candidate systems whose simulated output would be compared to measured.

Figures 8 shows measured output for two of the PV plants studied. Based on the increases in maximum power output, it appears that the plant was undergoing construction from March through July 2013. Starting in August 2013, maximum power output remains flat, in spite of seasonal changes that would normally cause a drop-in output. From this, it can be deduced that the plant has a DC to AC ratio high enough to allow its maximum power output to remain relatively constant throughout the year.

Figure 8: Measured Photovoltaic Output, Example One

Source: Clean Power Research

CPR has clipped the plant's output shown in Figure 9 due to a high DC to AC ratio. However, the ratio is not high enough to permit its maximum power output to remain constant throughout the year and there is a drop in maximum power output from October through January. Also worth noting is the lack of data in mid-January 2014. This could be either a reporting error or a plant outage. It is impossible to know from the measured data alone.

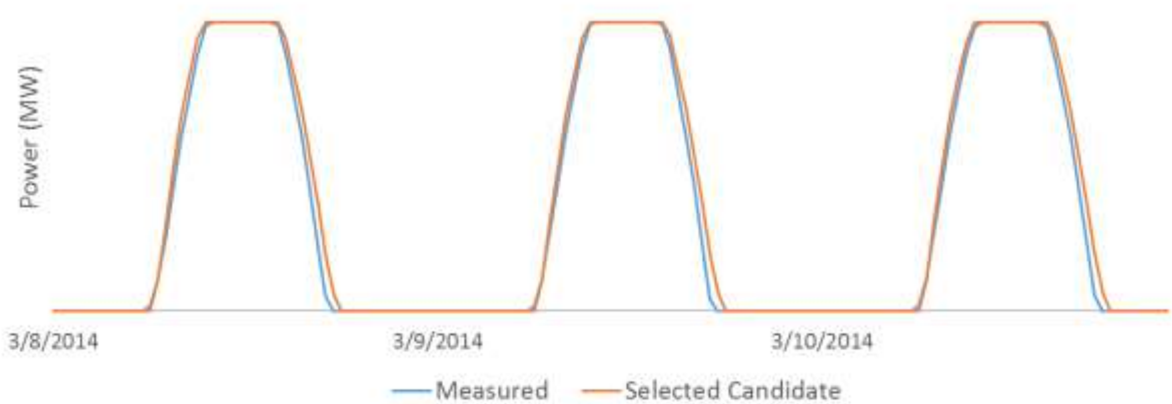
Figure 9: Measured Photovoltaic Output, Example Two

Source: Clean Power Research

These two measured data examples illustrate some of the challenges in deriving system specifications from measured data: Changes in plant capacity, inverter clipping and lack of seasonal output changes due to high DC to AC ratios, missing data, and unknown PV plant operational status.

When automatically inferring specifications, the tool correctly identified the gross capacity changes over time but had difficulty during transitional periods where capacity changed on an almost daily basis. Once capacity had stabilized, the simulated output from the selected candidate system matched the measured output reasonably well (Figure 10).

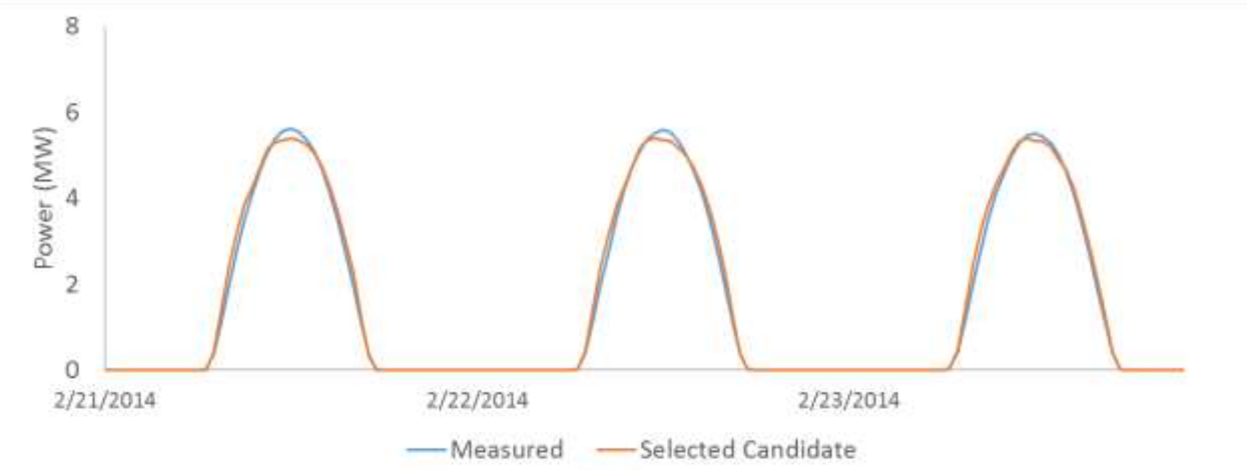
Figure 10: Measured and Simulated Photovoltaic Output for Selected Days, Example One



Source: Clean Power Research

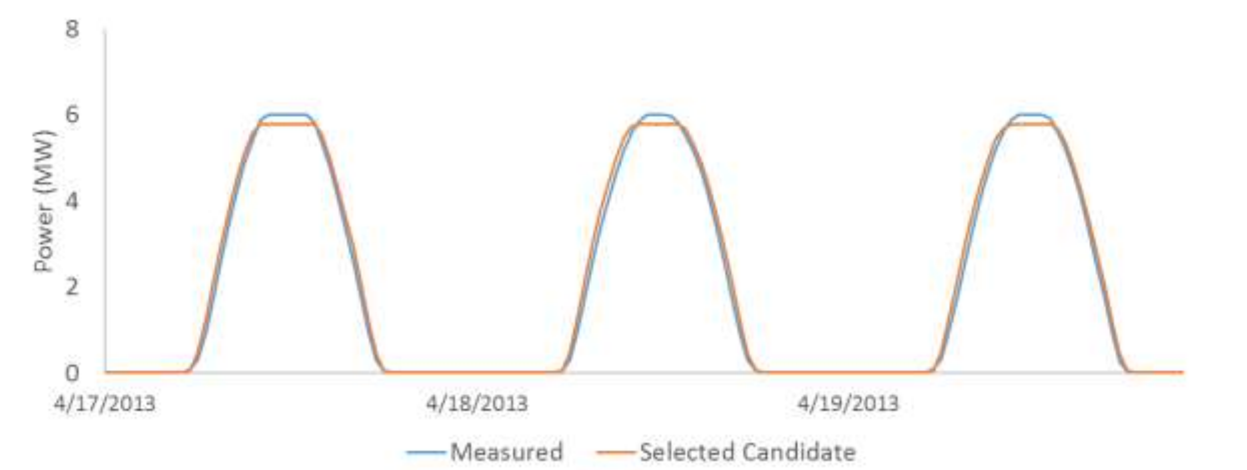
For the output, CPR slightly underestimated the AC capacity by the spec inference tool (Figure 11) and overestimated the DC to AC ratio (Figure 12).

Figure 11: AC Capacity Underestimated, Example Two



Source: Clean Power Research

Figure 12: DC to AC Ratio Overestimated, Example Two



Source: Clean Power Research

Table 3 summarizes the system specifications inferred for three sets of measured data. Information about these three systems was readily available online for these systems and in two cases, the baseline system yielded the lowest relative mean absolute error. However, the process identified a much better candidate for Plant A, reducing error significantly.

Table 3: Summary of Results for Three Systems

		Plant A	Plant B	Plant C
Baseline				
	Rating (MW DC-PTC)	7.733	19.668	20.703
	Rating (MW AC with Losses)	6.821	17.347	18.260
	Tracking	none (fixed)	none (fixed)	none (fixed)
	Azimuth	180	180	180
	Tilt	20	20	20
	DC to AC Ratio	1.22	0.98	0.98
	rMAE	23.0%	12.6%	12.8%
Selected Candidate				
	Rating (MW DC-PTC)	7.772	19.668	20.703
	Rating (MW AC with Losses)	7.402	17.347	18.260
	Tracking	none (fixed)	none (fixed)	none (fixed)
	Azimuth	180	180	180
	Tilt	25	20	20
	DC to AC Ratio	1.05	0.98	0.98
	rMAE	6.2%	12.6%	12.8%

Source: Clean Power Research

Clean Power Research made significant progress in creating an automated tool for inferring PV system specifications using measured PV output data. Due to the complexities inherent in interpreting such data, the team believes that additional accuracy is possible. For example, the project team did not account for solar obstructions, soiling, module degradation and other factors that decrease DC output. Consideration of such details were outside of the scope of this project, but the team hopes to continue development of this tool and the algorithms it implements.

CPR could apply preliminary versions of the tool when implemented in software to a system that improves the quality of reported PV system specifications in PowerClerk (the system of record for PV specifications under CSI), by incorporating measured production data from PV systems within a utility or ISO territory.

Other Forecast Improvements

Inverter Power Curve

Historically, when modeling PV system output, CPR has relied on the Energy Commission-weighted average efficiency rating to determine the output of an inverter relative to its DC input. CPR has used this single number in conjunction with an inverter power curve that is the same regardless of inverter make or model. In an effort to improve model accuracy, CPR has implemented two new ways to specify the inverter power curve.

The first method allows the system specification to contain a list of power level/efficiency pairs. Using this method, you could, for example, specify the five power levels for which the CEC publishes inverter test results and the inverter efficiency at each level.

The second method implemented for specifying the inverter curve is to list a set of coefficients and exponents used in a formula to calculate AC power output for a given DC input. This method facilitates precise mathematical control over the shape of the output curve.

To estimate the effect of a more accurate inverter curve on modeled output, the project team simulated output for a one-year period from two 5 kW systems that were identical in every way except for the inverter curve. Using the CPR default inverter curve yielded a maximum power output of 4.51 kW and a total of 9,042 kWh for the year, while using an inverter specified by a list of power level/efficiency pairs yielded a maximum power output of 4.388 kW and a total of 8,786 kWh for the year. The relative Mean Absolute Error was 2.9 percent.

Figure 13 shows the results of using this approach versus the default inverter power curve used in CPR's simulation model.

Figure 13: Actual Inverter Power Curve versus Existing Default

Source: Clean Power Research

Ensemble Methods

Additional work focused on improving the operational SolarAnywhere forecast models at both the short-term (hour ahead) and longer-term (day ahead) time horizons by using advanced ensemble methods leveraging forecasts from multiple sources.

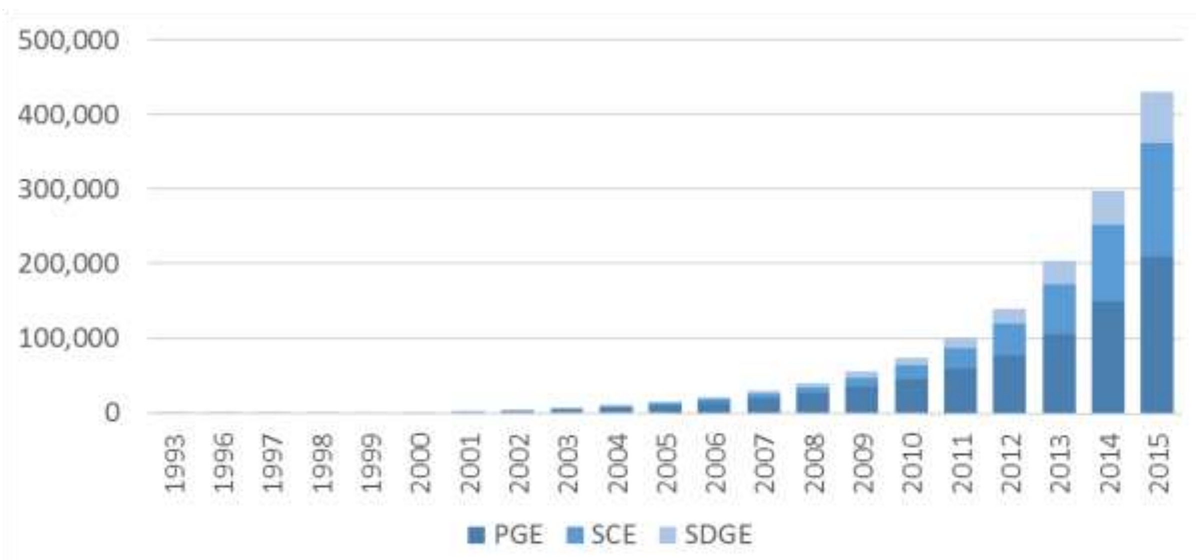
Representative Photovoltaic System Fleets

As the number of BTM PV systems in California continues to grow, tracking the capacity and forecasting the output from those systems becomes more important to grid operators and balancing authorities. At the same time, while simulating and aggregating power output from individual systems provides greater accuracy, it also requires ever-increasing computing resources. However, CPR can combine system capacity from multiple systems in nearby locations with similar orientations to create representative systems, thereby reducing the number of simulations of distinct systems in a fleet while retaining the diversity of locations and orientations that characterize the fleet's power production. While these "Representative PV Fleets" introduce some level of error into the modeling process, the decrease in simulation time may prove to be a worthwhile trade-off. In addition, CPR could apply representative fleet concepts in a top-down manner to extrapolate PV fleet production in areas where the detailed specification of individual resources is unknown.

CPR produced BTM PV fleet power forecasts every 30 minutes for five load regions[4] in the territories of California's three investor-owned utilities (IOUs). The California ISO identified these five load regions. CPR produced these forecasts using satellite-derived irradiance values from SolarAnywhere at 1 km x 1 km spatial resolution. CPR used system specifications such as latitude, longitude, tilt and azimuth, PV module and inverter efficiency ratings, obtained from IOUs, the Energy Commission and CSI, to model power output from approximately 186,000 systems. CPR aggregated the power output from these individual systems to provide fleet power output. These systems, however, only represent about 43 percent of the total systems online.

According to the CPUC California Solar Statistics web site,[5] homeowners and businesses have installed more than 440,000 behind the meter PV systems in California IOU territories. That number appears to be growing steadily, with more than 30 percent of the systems installed in 2015 (Figure 14).

Figure 14: Cumulative Installed Behind-the meter Systems in California



Source: Clean Power Research

[4] These regions are SDG&E, SCE Inland, SCE Coastal, PG&E Bay Area, and PG&E Non-Bay Area.

[5] https://www.californiasolarstatistics.ca.gov/.

In addition to the increased computing horsepower required to model such large numbers of systems, specifications for the systems in the publicly available data are inexact or missing altogether. For example, locations are anonymized by providing only the systems' zip code. Furthermore, system orientation (tilt and azimuth) is only available for 30 percent of the systems. Rather than creating generic systems and guessing at their orientation and exact location, the team scaled the modelled PV fleet power output on the assumption that the locations and system orientations of new systems will have a distribution similar to that of the current fleet captured in PowerClerk. In a way, this is one of the simplest methods for creating a bottom-up representative PV fleet.

Method

To investigate methods for reducing the computational resources required for modelling large PV fleets and to better quantify the margin of error that generalizing the locations and orientation of systems in such fleets might introduce, CPR created various representative fleets using the CSI systems in the PG&E Non-Bay Area load region behind-the-meter fleet as a baseline for comparison. CPR spread this baseline fleet, consisting of the 34,562 PV systems, across a large portion of California and has a wide variety of system orientations. CPR simulated the 30-minute power output from each of these systems for a one-year period from January 1, 2014 through December 31, 2014 and aggregated results to produce the baseline fleet output every 30 minutes during the period. CPR binned the capacity in a baseline fleet with known system specifications to create "Bottom-up" representative fleets. CPR calculated the relative Mean Absolute Error (rMAE)[6] for each of the representative (test) fleets to compare to the output of this baseline (reference) fleet.

Geographic Bin Selection

CPR selected site locations for the representative fleets using one of two methods. In the first method, CPR created a grid, by evenly dividing the rectangle bounding the systems in the baseline fleet. The method used six different spatial resolutions. The first five spatial resolutions tested were 1.6° latitude and longitude (approximately 160 x 160 kilometers), 0.8°, 0.4°, 0.2°, and 0.1° latitude and longitude (approximately 10 x 10 kilometers).

CPR mapped capacity for each system to the nearest location on the grid, then further binned by orientation (tilt, azimuth, and tracking). **Error! Reference source not found.** shows the s elected geographic bins and how

CPR combined them with the orientation bins (described in the next section) to create the systems in each representative fleet. The map in Figure 15 shows the locations for one representative fleet. Each location included multiple systems, sized to represent the capacity of the actual systems in each orientation bin.

[6] Thomas E. Hoff, J. K. (2012). Reporting of Irradiance Model Relative Errors. Proc. ASES Annual Conference. Raleigh, NC: American Solar Energy Society.

For example, in the fleet shown in Figure 15, among the 32 systems created at 37.942° latitude, -120.593° longitude, there would be a south-facing system, with a 22.5° tilt, rated at 798.8 kW AC.

Table 4: Number of Systems in Representative Fleets by Spatial Resolution and Orientation Bin

Number of systems				
Spatial resolution	Azimuth/Tilt Increments			
	10°/5°	20°/10°	30°/15°	Single Orientation
Single Location	362	130	73	-
Zip Codes	15,305	8,824	6,302	601
160 x 160 km	1,926	730	418	-
80 x 80 km	4,020	1,707	1,025	-
40 x 40 km	6,818	3,329	2,077	-
20 x 20 km	11,119	6,091	4,022	-
10 x 10 km	16,276	9,986	6,841	-

Source: Clean Power Research

CPR combined them with the orientation bins (described in the next section) to create the systems in each representative fleet. The map in Figure 15 shows the locations for one representative fleet. Each location included multiple systems, sized to represent the capacity of the actual systems in each orientation bin.

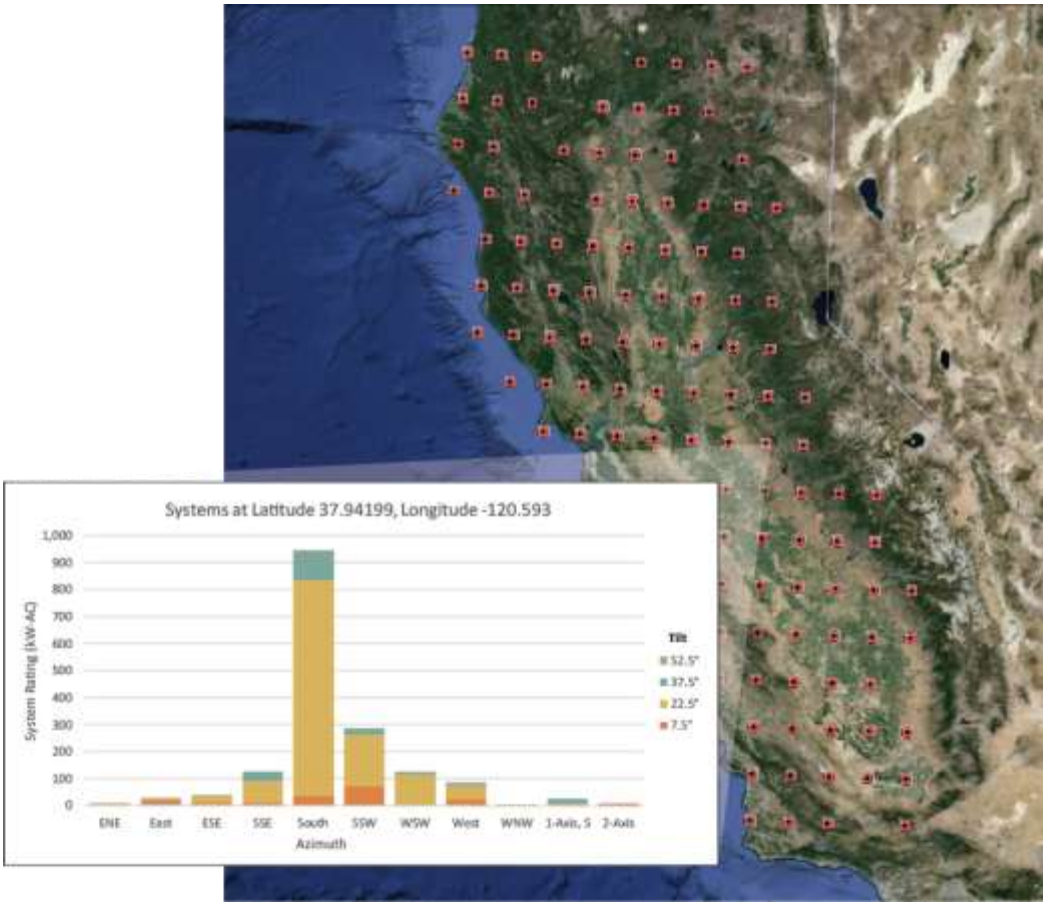
For example, in the fleet shown in Figure 15, among the 32 systems created at 37.942° latitude, -120.593° longitude, there would be a south-facing system, with a 22.5° tilt, rated at 798.8 kW AC.

For the sixth spatial resolution, the fleet had all capacity mapped to a single location, then binned by orientation. The location selected was the capacity-weighted geographic center of the baseline fleet.

Note that SolarAnywhere Enhanced Resolution data has a spatial resolution of 1 km x 1 km. This implicitly bins the systems in the baseline fleet by location to the nearest 1 km, with no binning by orientation. This implicit binning has the effect of reducing the number of actual locations from 35,562 to 10,866.

With the second method for representative fleet creation, mapped each system's capacity was mapped based on the zip code of the PV site and used the geographic center of the zip code as the location, then further binned the capacity based on the system's orientation. Finally, in a variation of the zip code-based method, CPR mapped each system's capacity based on the zip code but created a single system with all of the zip code's capacity, located it at the geographic center of the zip code, and used the baseline fleet’s capacity-weighted azimuth and tilt (17˚ and 175˚, respectively) as that system’s orientation.

Figure 15: Representative Fleet with System Locations at 0.4° Latitude/Longitude Spacing



Source: Clean Power Research

Orientation Bin Selection

In addition to binning system capacity by location, when creating the representative fleets, CPR binned the capacity of the actual systems by tilt, azimuth and tracking to capture the diversity in system orientations at each location typical in large PV fleets. System orientation bins were based on 10˚ azimuth and 5˚ tilt increments (648 bins), 20˚, azimuth and 10˚ tilt increments (162 bins), or 30˚ azimuth and 15˚ tilt increments (72 bins). Dual-axis tracking systems, where azimuth and tilt vary continuously throughout the day, constituted an additional bin.

For each location, CPR assigned the capacity for each array[7] to the bin that most closely matched the azimuth and tilt of that array. For example, in the case where CPR used 30˚ azimuth and 15˚ tilt increment bins, capacity for arrays with azimuths that were +/- 15˚ from

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[7] CPR analyzed capacity at the array level rather than the system level to properly account for systems with multiple arrays.

south (165˚ to 195˚) with tilts between 22.5˚ and 37.5˚ it would have added to the 180˚ azimuth/30˚ tilt capacity bin.

System Creation and Simulation

CPR determined the total capacity for each location/orientation bin and created systems with the appropriate capacity. Table 4 shows the number of systems in each of the 22 representative fleets created by combining spatial and orientation bins.

CPR calculated the maximum power rating for the inverter used for each system based on the capacity-weighted DC to AC ratio for the baseline fleet of 1.027 as recorded for actual systems. CPR set inverter efficiency for each system to 96.2 percent - also based on the capacity-weighted inverter efficiency rating of the baseline fleet – and set other DC losses to 11 percent - once again using the capacity-weighted DC losses of the baseline fleet. After creating the systems, CPR simulated power output for each system for every 30-minute period from January 1, 2014 through December 31, 2014 and aggregated the results to produce 30-minute interval fleet power. CPR then compered those results to the output from the baseline fleet.

Effect of Spatial Resolution and Orientation Bin Count on Relative Mean Absolute Error

The amount of error introduced by using bottom-up representative PV fleets with regular geographic dispersion, rather than fleets consisting of individual systems with exact system specifications varied from 4.2 percent for the coarsest spatial resolution and smallest number of orientation bins, to 1.1 percent for the fleet with 10 km x 10 km spatial resolution and the largest number of orientation bins. As shown in Figure 16, the greatest impact on error was due to spatial resolution, rather than the number of orientations considered. However, further increases in spatial resolution would likely have proportionally less impact.

The rMAE for the representative fleets with a single location had significantly higher error than the other fleets, ranging from 10.1 percent to 10.7 percent.

The representative fleet based on multiple orientations at each zip code fared reasonably well with rMAE ranging from 2.2 percent to 2.4 percent. However, the zip code-based fleet that used a single orientation at each zip code had a much higher rMAE at 6.6 percent. While a multi-orientation zip code-based fleet may be appropriate when exact system locations are unknown, performance is only slightly better than the representative fleets with the highest number of orientation bins and spatial resolution, and error is approximately double.

The graphs in Figure 17 show the correlation between the 30-minute power values for selected representative fleets versus the baseline fleet. At the same spatial resolution, there was little difference between fleets with different numbers of orientation bins, so CPR omitted these.

Figure 16: Relative Mean Absolute Error for Representative Fleets

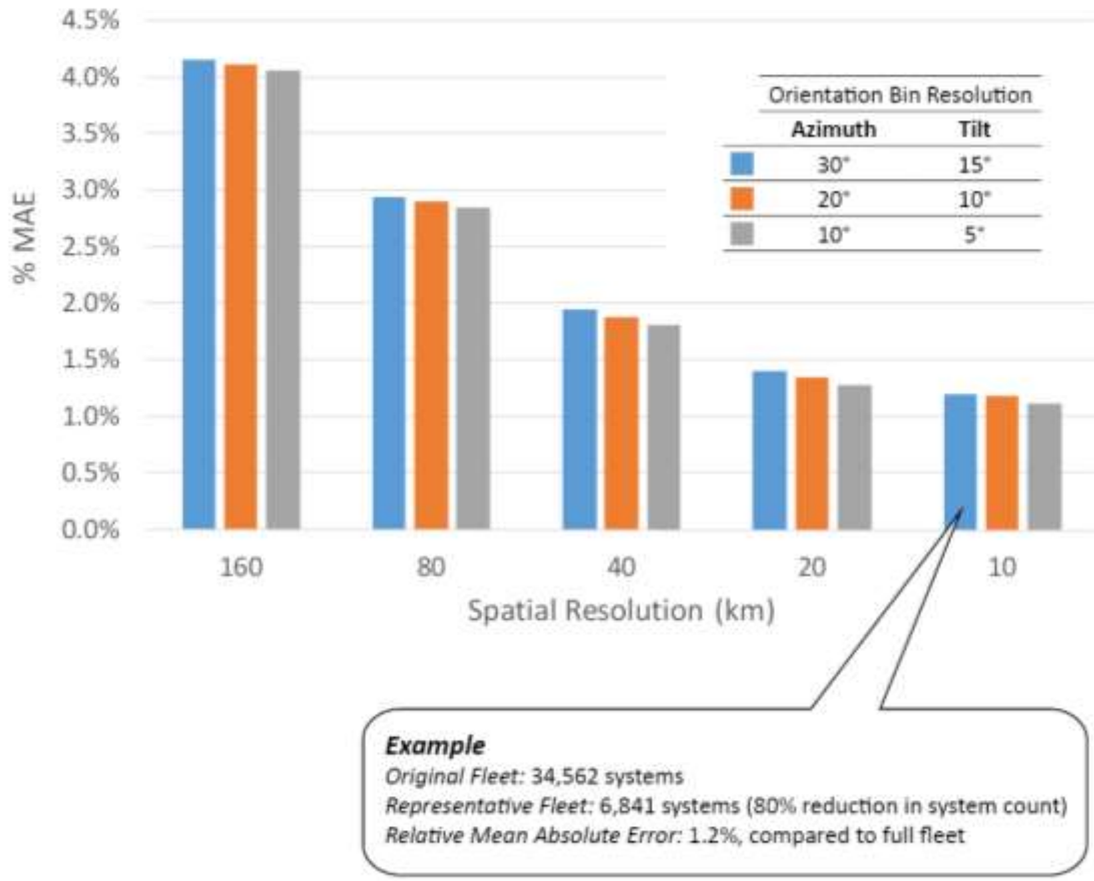
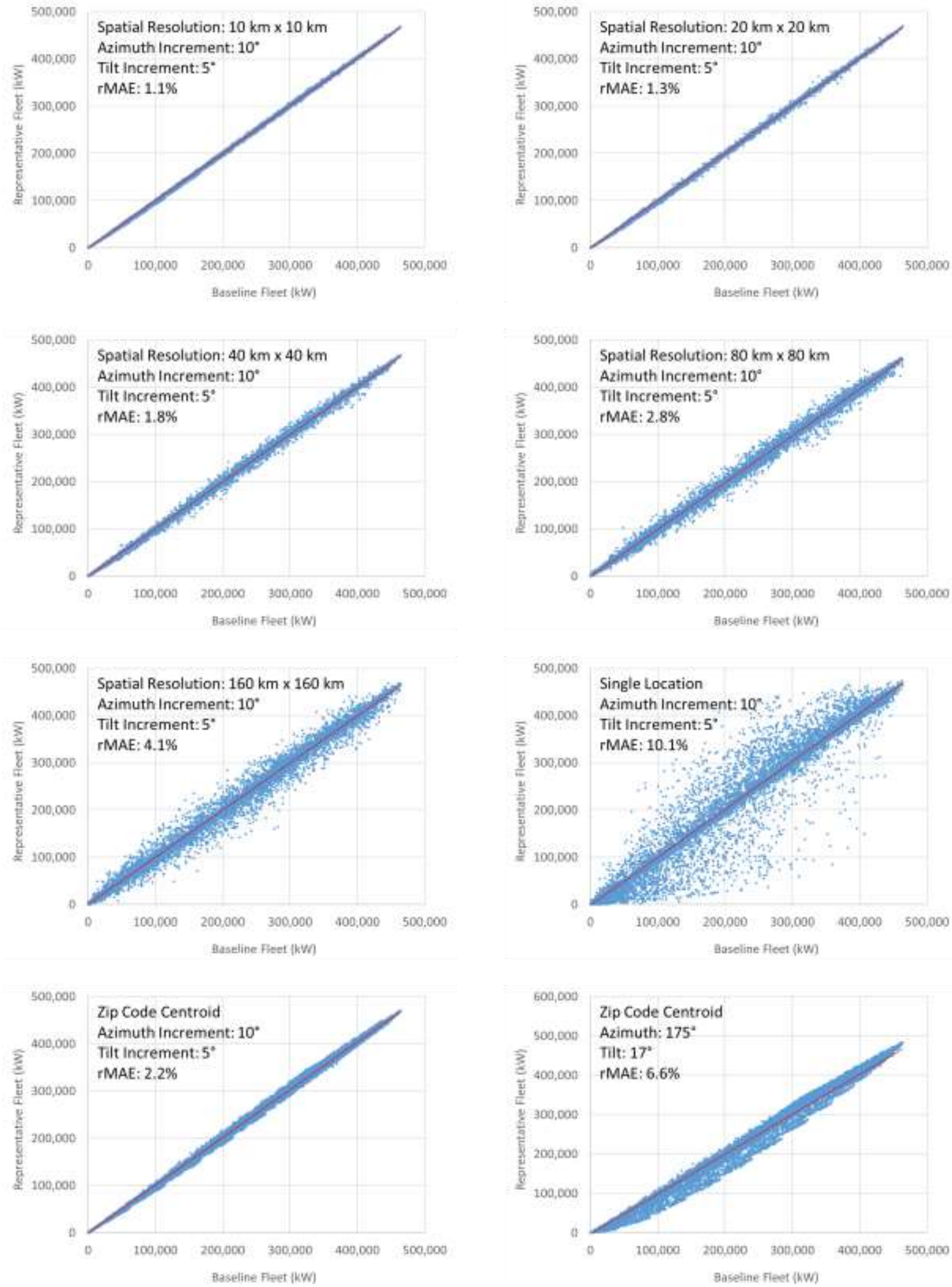


Figure 17: Thirty-Minute Power Value Correlation



Source: Clean Power Research

Performance Benefits

In general, the amount of time it takes to simulate a PV fleet scales linearly with the number of simulated systems. CPR found that when there are many systems to be simulated at a single location, there is approximately an 8 percent additional reduction in time. Although CPR tracked simulation times for the representative and baseline fleets, the team believes that the actual times, which vary greatly depending on computer system load and data transmission speeds over the Internet, should not be considered when evaluating performance. Instead, based on the number of locations and systems, Table 5 shows the hypothetical reduction in time required to simulate these representative fleets relative to the baseline fleet. Even at the highest spatial resolution and the largest number of orientation bins evaluated, CPR reduced the simulation times by 63.5 percent. However, fewer orientation bins at the same high spatial resolution adds only 0.1 percent error, while yielding an 83.4 percent reduction in simulations time.

Table 5: Estimated Reduction in Simulation Times for Representative Fleets Relative to Baseline Fleet

	Azimuth/Tilt Increments			
	10°/5°	20°/10°	30°/15°	Single Orientation
Single Location	99.2%	99.7%	99.8%	
Zip Codes	66.3%	80.0%	85.3%	98.6%
160 x 160 km	95.9%	98.4%	99.1%	
80 x 80 km	91.4%	96.3%	97.7%	
40 x 40 km	85.5%	92.9%	95.5%	
20 x 20 km	75.7%	86.3%	90.7%	
10 x 10 km	63.5%	76.8%	83.4%	

Source: Clean Power Research

Using bottom-up representative PV fleets, created by generalizing the location and orientation of a set of individual systems with known specifications, can reduce computing resource requirements by more than 80 percent in modelling fleet output, while introducing as little as 1.2 percent rMAE on an annual basis. By applying scaling factors to the known historical California BTM PV fleet, this was the approach used for the trial of this project with California ISO.

Zip code based representative fleets, which make use of known individual system orientation data can reduce computing resource requirements by more than 65 percent, while introducing as little as 2.2 percent rMAE on an annual basis.

Representative fleets that make use of a single location exhibit more than 10 percent rMAE and have a fairly inaccurate power production curve on a daily basis, despite short simulation times. At 6.6 percent rMAE, zip code fleets that use a single system orientation have less error than single location fleets, but typically exhibit a narrower daily production curve with a higher peak. CPR found that it is necessary to account for loss of accuracy and ensure that any avoidable error is not introduced when applying this approach correctly as the size of the PV fleet continues to grow.

Dynamic Regional Fleet Capacity Updates

The equipment comprising BTM PV systems do not always remain in service on a continuous basis. Owners sometimes replace system components such as the inverter. They also may add or remove modules. They sometime built utility-scale systems in phases, with capacity growing over time. In addition, outages – both planned and unplanned – can cause capacity to drop. As part of this project, CPR has implemented the ability to track changes in system capacity over time and use that information when simulating system output.

California leads the nation in BTM PV installations – systems whose production, for the most part, utilities do not track. To provide an accurate estimate of the power produced by these systems, it is important to have detailed information about each system's configuration: location, installation date, orientation of each array in the system, the model's and quantities of installed modules and inverters, and the elevation of any solar obstructions, such as buildings and trees surrounding the system that are above the bottom edge of the panels. Modeling software produces a reasonably accurate estimate of the system's production[8] when combined with accurate weather data, whether historical or forecast

Beginning in 2007, PowerClerk collected detailed specifications for systems incentivized under the CSI, an online software service from CPR. CPR also collected specifications for non-CSI BTM systems incentivized under Self Generation Incentive Program (SGIP), the Emerging Renewables Program (ERP). By the end of 2014, CPR team had collected detailed specifications for more than 140,000 CSI systems and 43,000 non-CSI systems. CPR used these system specifications, with a combined capacity over 2.1 GW, in the creation of five of the BTM fleets used in the California ISO forecast.

As incentives available through the CSI began to run out, utilities gradually discontinued tracking interconnections in PowerClerk. This was especially true in PG&E and SDG&E territories, and CPR began to look for ways to keep the capacity of its PV fleets up to date.

Initially, CPR experimented with capacity data provided to California ISO by the IOUs. However, the poor quality (for example redundant and missing data) of data prevented its use. Next, the project team obtained market research data from GTM Research. Although the data quality was better, reporting was only by quarter for the entire state, rather than by IOU or region.

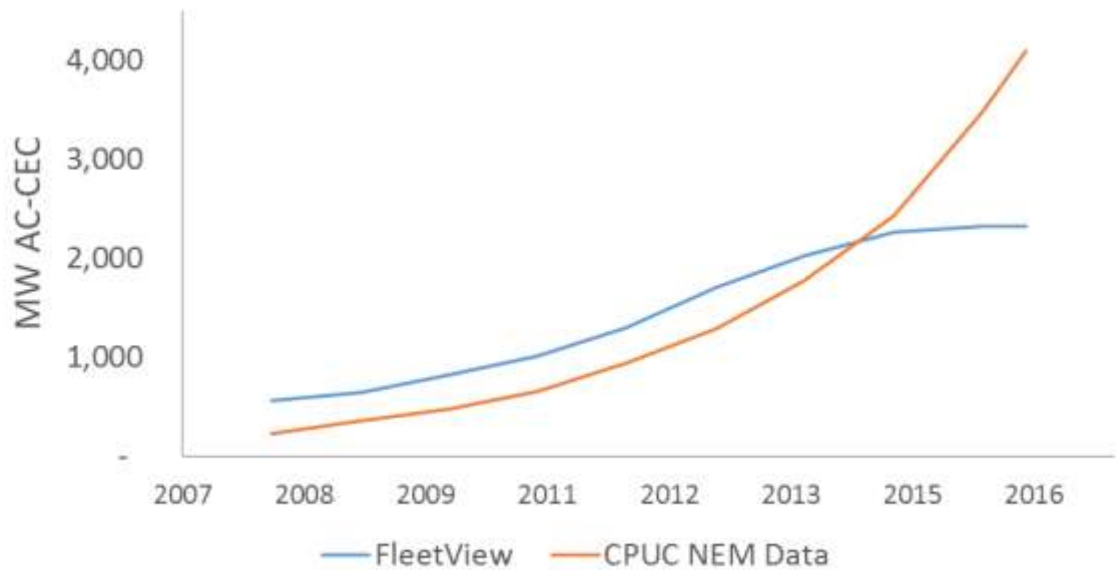
In July 2015, the CPUC began posting monthly editions of the net energy metered (NEM) Currently Interconnected Data Set (CIDS) on the California Solar Statistics web site.[9] This data

[8] https://www.nrel.gov/analysis/sam/pdfs/2008_sandia_ieee_pvsc.pdf.

[9] http://www.californiadgstats.ca.gov/downloads/.

set is useful for estimating total installed capacity. However, it is of limited usefulness as a source for detailed system specifications due to anonymized locations (only zip codes) and missing data (tilt and azimuth) is available for only 30 percent of the systems. Figure 18 shows the capacity of the systems tracked in CSI ("FleetView") and systems recorded in the CIDS database ("CPUC Net Energy Metering (NEM) Data").

Figure 18: California Behind-the meter Fleet Capacity 2008 to 2016



Source: Clean Power Research

By using capacity data from the NEM Interconnection Applications Data Set in conjunction with the detailed system specifications in FleetView, CPR was able to develop the time-dependent scaling factors and apply them to the historical simulations of the five California ISO BTM fleets. Itron used the simulation output to train its load forecasting software. Furthermore, FleetView now automatically recalculates the scaling factors when the CPUC publishes CIDS updates, then projects to future dates and applies to the California ISO BTM fleet forecasts.

Determination of Fleet Historical Scaling Factors

Since CPR believes the NEM CIDS contains only those systems that are currently online, and not decommissioned, CPR evaluated the NEM Interconnection Applications Data Set to get a complete picture of historical capacity over time. Figure 18 depicts the complete picture of historical capacity.

Determination of Fleet Forecast Scaling Factors

For forecasting, CPR derived a linear formula for the scaling factor growth trend for each California ISO zonal fleet, defined by this project, using CIDS and FleetView capacities for the most recent two months. CPR dynamically calculates monthly scaling factors using those formulas, based on the time elapsed since the beginning of the growth trend period and applied to the PV production forecast. Technically, coefficients only need to be updated if the growth rate of the scaling factors change. However, CPR monitors CIDS and automatically updates the coefficients whenever the CPUC updates the CIDS.

The scaling factors and consequent fleet ratings calculated for November 20, 2015 6:00 PM, for example, would be as follows in Table 6.

Table 6: Fleet Scaling Factors and Ratings

Fleet	Scaling Factor	Scaled CEC-AC Capacity (MW)
Non-Metered: PG&E Bay Area	1.3002497	520.2
Non-Metered: PG&E Non-Bay Area	1.5414869	1,179.2
Non-Metered: SCE Coastal	1.1985151	557.3
Non-Metered: SCE Inland	1.2929136	572.2
Non-Metered: SDG&E	1.66500428	422.0
Total		**3,251.8**

Source: Clean Power Research

Historical Behind-the-meter Photovoltaic Fleet Production Modeling

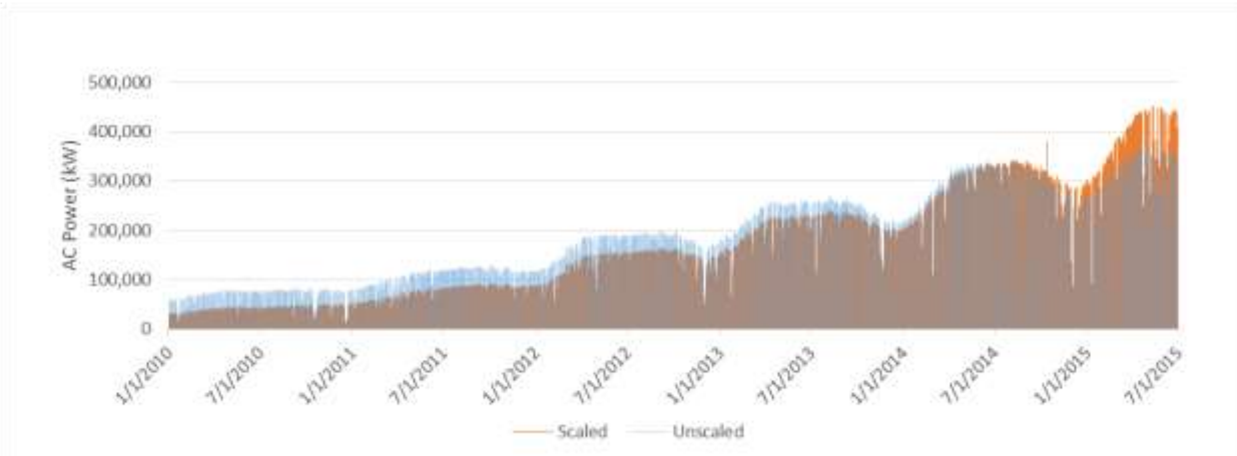
Estimated PV production is one of the available inputs to the load forecasting model produced by Itron for the California ISO. For this project, the California ISO has identified five zonal fleets for which they require separate forecasts: PG&E Bay Area, PG&E Non-Bay Area, SCE Coastal, SCE Inland, and SDG&E.

Using CSI data, CPR had previously created fleets of individual systems for each of the five zones. As more non-CSI systems began to come online, those fleets were no longer representative of the actual California PV fleet capacity. However, the large number of systems in these fleets did provide a representative sample of geographic distribution, diversity of orientations, and other system characteristics such as DC to AC sizing and inverter efficiency.[10] Therefore, CPR simulated historical PV fleet production for each of those five fleets for the period from Jan. 1, 2010 through December 31, 2015 using SolarAnywhere Enhanced Resolution data, which has a temporal resolution of 30 minutes. The method used interpolation to calculate 15-minute interval values. It then scaled PV production to match monthly capacity derived by combining the non-CSI portion of CIDS capacity as of June 30, 2015 with CSI capacity data obtained from PowerClerk. CPR interpolated scaling factors for the periods between each month. CPR the CSV-format PV production data files for each fleet to Itron via a File Transfer Protocol (FTP) server. The charts below show the scaled versus unscaled PV

[10] This method assumes that geographic diversity of capacity and other system characteristics remained unchanged beyond the time at which systems incented under CSI began to comprise a smaller share of the total fleet.

production for each of the five California ISO fleets. As illustrated in Figure 19, CPR's estimate of non-CSI capacity in the SCE Coastal Region before 2014 was higher than that reported in the CIDS. These results assume that the CIDS is the best source for capacity available.

Figure 19: Southern California Edison Coastal Photovoltaic Production



Source: Clean Power Research

Robustness of the California Independent System Operator Forecast Delivery

To improve availability and accuracy of the forecasts provided to California ISO during this project, CPR made the following operational changes to the forecast production and delivery:

1. Add distributed processing support to process larger fleets more quickly.
2. Run forecasts on a scalable cloud-based platform that permits better monitoring and increases reliability.
3. Automatically detect changes to the NEM Currently Interconnected Data Set and, trigger an automatic update of the scaling factors applied to the baseline fleet output.

Real-time Data Feedback

The use of feedback from real time production data have the potential to also improve forecasts. By using the current conditions and knowledge of the clear sky profile, it would be possible to advance the current observed clearness index along the clear sky profile to produce a "persistence forecast." This assumes that the cloud conditions will not vary from the current conditions, or in other words that the current conditions will persist. However, it is difficult to obtain real time data, fast enough to produce a forecast and disseminate for decision making.

The approach taken in this project was to focus on the use of production data from distributed rooftop systems. This requires a large number of systems, particularly if the systems did not report data reliably, were out of service, or they were reporting bad data. These are all possible factors for distributed systems.

Itron provided near real-time access to data from approximately 30 systems in the Bay Area. Time delay in the readings was inevitable: the process required data transmission from the PV system itself to Itron's database, followed by ingesting into the forecast system. CPR developed and demonstrated a proof-of-concept system for retrieving and ingesting the data, and the process typically took 20 minutes when working correctly.

CPR demonstrated the process for a period of about one month. The system used real time data to modify the CPR solar forecast. During this period, CPR evaluated the modified forecasts and observed small forecast improvements in the modified forecast of PV system power for each of the 30 PV systems. CPR expected this since it proved that persistence, at least for short time scales, adds skill to the forecast. However, for forecasts beyond three hours CPR observed no improvement in forecast skill.

After a month, the cellular carrier phased out support of the modems that collected the data. This prevented a comprehensive evaluation. The use of data from these distributed systems is also costly, so a more complete evaluation would not only have to determine whether a forecast improvement was possible on a consistent basis, but also whether any such improvement would justify ongoing maintenance costs at scale. CPR is not clear how many systems would provide a meaningful impact state-wide. A more complete evaluation could become cost-prohibitive.

Chapter 4: Improving Short-term Load Forecasts by Incorporating Solar Photovoltaic Generation

Background

Itron developed the load forecasts that the California ISO relies on for real-time system operations using statistical models of five-minute measured loads. The California ISO collects these data in real time based on measurement points at each grid-connected generation resource, as well as, inter-region tie lines. It is important to note that at the time of this study, the California ISO does not measure either in real time or ex post BTM solar PV generation. This means measured load does not equal actual end-user (that is, residential, commercial, industrial, agriculture, and other customer segments) consumption of electricity, since BTM solar PV generation supplies some portion of the consumption.

The net effect of a deep penetration of BTM solar PV is that forecasts of measured load are becoming less reliable. This is especially true in the morning hours because the presence of clouds (for example, marine layer) rather than temperatures appear to drive loads. In contrast, temperature changes that drive air conditioning loads appear to dominate afternoon loads. This may change over time when BTM solar PV penetration reaches a critical mass, where the variation in BTM solar PV generation is sufficiently large to outweigh the load variation due to variation in air conditioning loads.

The California ISO must extend the existing load forecast models to capture the influence of BTM solar PV and better predict an increasing volatile load. This study evaluates three alternative model approaches for extending the California ISO load forecast framework. This report presents the alternative load forecast frameworks for incorporating BTM solar PV forecasts and the forecast simulations that Itron implemented to evaluate the performance of these approaches.

To put these approaches into context, following is a description of the existing California ISO load forecast model.

California Independent System Operator Short-Term Load Forecast Model

Itron used the Baseline Load Forecast Model provide forecasts of measured loads for forecast horizons of 15 minutes ahead out to ten days ahead. The California ISO load forecasting system produces 15-minute level load forecasts for forecast horizons of 15-minutes ahead out ten (10) days ahead. The load forecasts update automatically every 15-minutes to support generation scheduling and dispatching. A separate set of load forecast models are used for each of the three major California ISO load zones: PG&E, SCE and SDG&E. In addition, the California ISO develops sub-region forecasts for five (5) climatic zones: PGE& Bay Area, PG&E Non-Bay Area, SCE Coastal, and SCE Inland load zones and SDG&E. Hourly weather forecasts of temperature and humidity for approximately 24 weather stations located throughout the State of California drive the load forecasts. Itron updated the weather forecasts hourly from multiple weather forecast service providers.

For each load zone (PG&E, PG&E Bay Area, PG&E Non Bay Area, SCE, SCE Inland, SCE Coastal, and SDG&E), the baseline 15-minute load forecast modeling framework is composed of 193 individual forecast models. The 193 individual forecast models that define the California ISO baseline 15-minute load forecast modeling framework are:

1. Daily energy model. Itron used a Neural Network Model of Daily Energy to capture daily swings in electricity demand as driven by changes in calendar and weather conditions.
2. Day-ahead models. Designed for forecast horizons of four hours ahead and longer. Composed of 96, 15-Minute Regression Models driven by the forecasts from the Daily Energy Model, as well as by forecasted calendar and weather conditions. Because the Day-Ahead models do not contain autoregressive terms, they are quick to react to changing weather conditions.
3. Hour-ahead models. Designed for forecast horizons of up to four to six hours ahead. Is composed of a second set of 96, 15-Minute Regression Models that launch off the most recent meter data through inclusion of autoregressive terms in addition to forecasted calendar and weather conditions.

Itron updated the operational forecast that the California ISO utilizes every 15 minutes which has a forecast horizon of the balance-of-the-day out ten days ahead. Itron created a single quarter hour load forecast by taking a weighted average of the Day-Ahead and Hour-Ahead forecasts. For forecast horizons of up to two hours ahead, Itron placed 100 percent weight on the Hour-Ahead forecasts. Between two and four hours ahead, the weight cascades away from the Hour-Ahead forecast and towards the Day-Ahead forecast. For forecast horizons of four hours ahead and longer, Itron placed 100 percent weight on the Day-Ahead forecast.

This framework offers the following advantages over the use of a single set of 96, quarter hour models.

1. Forecasts of daily energy capture the influence of a full day of weather conditions on loads. Itron channeled this influence through to the Day-Ahead model forecasts via predicted daily energy values with day-of-the-week interaction terms.
2. The day-ahead model forecasts are free to respond quickly to forecasted changes in weather conditions.
3. The hour-ahead models exploit the information contained in the most recent metered loads.
4. The blended forecast balances the value of autoregressive terms over near-term forecast horizons with the value of forecasted weather conditions over longer-term forecast horizons in a single forecast.

A total of eight separate models make up this framework. The Task 4 full report[11] provides a more detailed description of the California ISO's forecasting models.

The Impact of Solar Photovoltaic on the California Independent System Operator Short-Term Load Forecast

The statistical models described above use linear least squares to estimate the model coefficients. At a very high level, the process of estimating the model coefficients is an averaging of the historical load data, where the explanatory variables segment the load data over which Itron takes the averages. While this is not an exact description of the least squares approach, it is a useful metaphor when describing how solar PV impacts the estimated coefficients of the California ISO short-term load forecast models. Over time, an increased penetration of solar PV has the net effect of reducing on average measured load. This implies that the estimated model coefficients embody this reduction in measured loads. That is, Itron tunes the model coefficients to measured load under average solar PV production that occurred over the model estimation period. As a result, the short-term load forecasts produce a forecast under average solar PV production conditions. The challenge is on any given day actual solar PV production will not necessarily align with the average solar PV production. On cloudy days when solar PV production is smaller than average, the load forecast will under forecast loads because the model fails to reflect the bump up in loads due to lower solar PV production. On sunny days when solar PV production is greater than average, the load forecast will over forecast loads because the model fails to reflect the drop-in loads due to higher solar PV production.

The issue is that a statistical model of measured load will capture the average impact of solar generation in the estimated model coefficients. Accordingly, with volatile solar PV generation, Itron adjusts the model-based forecast of measured load to account for the solar PV generation not already accounted for by the estimated model coefficients. A key objective of this study is to develop a means for improving the short-term load forecast by incorporating forecasts of solar PV generation into the forecast framework. The next section describes three alternative frameworks for incorporating the impact of solar PV generation into a forecast of measured loads.

Incorporating the Impact of Solar Photovoltaic Generation in a Load Forecast

The existing California ISO short-term load forecast models do not include explicit treatment of solar PV generation. As such, the forecasts are subject to the type of forecast bias described above. In particular, the existing California ISO mid-day forecasts tend to be high on sunny days and low on cloudy days. This study developed alternative forecast frameworks that account for the load impact of solar PV generation. The study uses forecast simulations to compare the

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[11] Monforte, Dr. Frank A.; Fordham, Christine; Blanco, Jennifer; Barsun, Stephan (Itron, Inc.) Kankiewicz, Adam; Norris, Ben (Clean Power Research). 2016. *Improving Short-Term Load Forecasts by Incorporating Solar PV Generation.* California Energy Commission, https://www.energy.ca.gov/2017publications/CEC-500-2017-031/CEC-500-2017-031.pdf.

forecast accuracy of the existing California ISO forecast framework against the three alternative modeling approaches; Error Correction, Reconstituted Loads, and Model Direct.

What follows is a brief description of these three frameworks.

Error Correction

The Error Correction approach implements what many System Operators do initially when faced with the problem of solar PV generation. Namely, they make ex post adjustments of the load forecast to account for forecasted values of solar PV generation. On sunny days, Itron lowers the load forecast and on cloudy days, Itron adjusts the load forecast upward. The key advantage of the Error Correction Approach is that Itron can continue to use the existing load forecast model without any changes. All Itron needs is a means of forecasting solar PV generation. This report describes the framework below.

Day-Ahead Error Correction Forecast. The Day-Ahead Error Corrections recognize that the Day-Ahead model coefficients capture the average amount of solar PV generation that existed over the model estimation period. Since the load forecast already reflects a certain level of solar PV generation the *ex post* error correction makes an adjustment based on how much the current solar PV generation differs from the historical average solar PV generation.

In this case, if the forecast of solar PV generation is higher than the historical average, then Itron adjusts the Day-Ahead Load Forecast downward. For example, on a clear sunny day, Itron adjusts the Day-Ahead Load Forecast downward to account for greater than average solar PV generation. On the other hand, on cloudy days when solar PV generation forecasts are lower than the historical average, Itron adjusts the Day-Ahead Load Forecast upwards.

Hour-Ahead Error Correction Forecast. The Hour-Ahead Forecast models are highly autoregressive. In principle, this means the Measure Load values passed into the models as autoregressive terms reflect a certain amount of solar PV generation. For example, the load forecast made at 11:00 for 11:15 launches off measured loads at 11:00, 10:45, 10:30, 10:15, and 10:00. If it is a sunny day, these measured loads are lower than average due to the higher than average solar PV generation. Conversely, on a cloud day these measured loads are higher than average due to a lower than average solar PV generation. If at 11:15 one expects that the solar PV generation is going to be higher than what it was at 11:00, then one would want to adjust down the Hour-Ahead Forecast. On the other hand, if one expects that there will be a drop in solar PV generation between 11:00 and 11:15, the Hour-Ahead Forecast should be lifted.

This approach uses the difference of forecasts of solar PV generation to make the error correction because real-time measurement of solar PV generation does not exist. Real-time measurement data makes it possible to use measured values instead of forecast values.

Error Corrected Measured Load Forecast. Itron constructed the Error Corrected Measured Load Forecast as a weighted average of the Error Corrected Hour-Ahead and Day-Ahead forecasts.

Reconstituted Loads

Itron reconstitutes the historical time series of measured load under the Reconstituted Loads approach by adding back estimates of solar PV generation. Itron then re-estimates the load forecast model against the reconstituted loads. Itron adjusts the subsequent reconstituted load forecasts ex post by subtracting away forecasts of solar PV generation to form a forecast of measured loads. By estimating the model coefficients against a time series of demand for power regardless of how it is sourced, one controls for any inherent bias on the estimated coefficients of a model of measured loads. The disadvantage is one must develop and maintain an historical time series of solar PV generation to estimate the load forecast model coefficients. Further, this approach assumes that the historical solar PV generation time series is accurate. This may not necessarily be true, in which case this approach places too high of a weight on the solar PV generation values.

This approach uses the difference of forecasts of solar PV generation to make the error correction because real-time measurement of solar PV generation does not exist. If real-time measurement data become available, then the measured value replaces forecast value.

Model Direct

Under this approach, one directly estimates the weight placed on the solar PV generation data by including these data as an explanatory variable in the load forecast models. The estimated coefficient on the solar PV generation variable is the weight. Also, in principle, no bias on the remaining explanatory variables should be introduced by including solar PV generation as an explanatory variable. This approach also provides a direct forecast of measured loads that accounts for solar PV generation, thus avoiding any ex post processing of the load forecast. Like the Reconstituted Load Approach, this approach requires developing and maintaining an historical time series of solar PV generation.

Solar Photovoltaic Generation Estimates

This study uses two alternative sources for solar generation to evaluate the forecast performance of the Error Correction, Reconstituted Loads, and Direct Modeling approaches described above. CPR developed the first source of solar generation data and a detailed database of solar installations in the PG&E, SCE, and SDG&E service territories. The second source of solar generation mimics what a number of system operators have used as starting point for addressing the impact of solar generation on their loads, which is to leverage the cloud cover data they already collect. Under this approach, Itron combines the hourly cloud cover data collected by weather stations with estimates of installed capacity to estimate solar generation by load zone. The purpose of developing this second source is to provide a basis for comparison to the forecast improvements when the solar generation estimates/forecasts come from a commercial vendor like CPR.

Clean Power Research Solar Generation Estimates

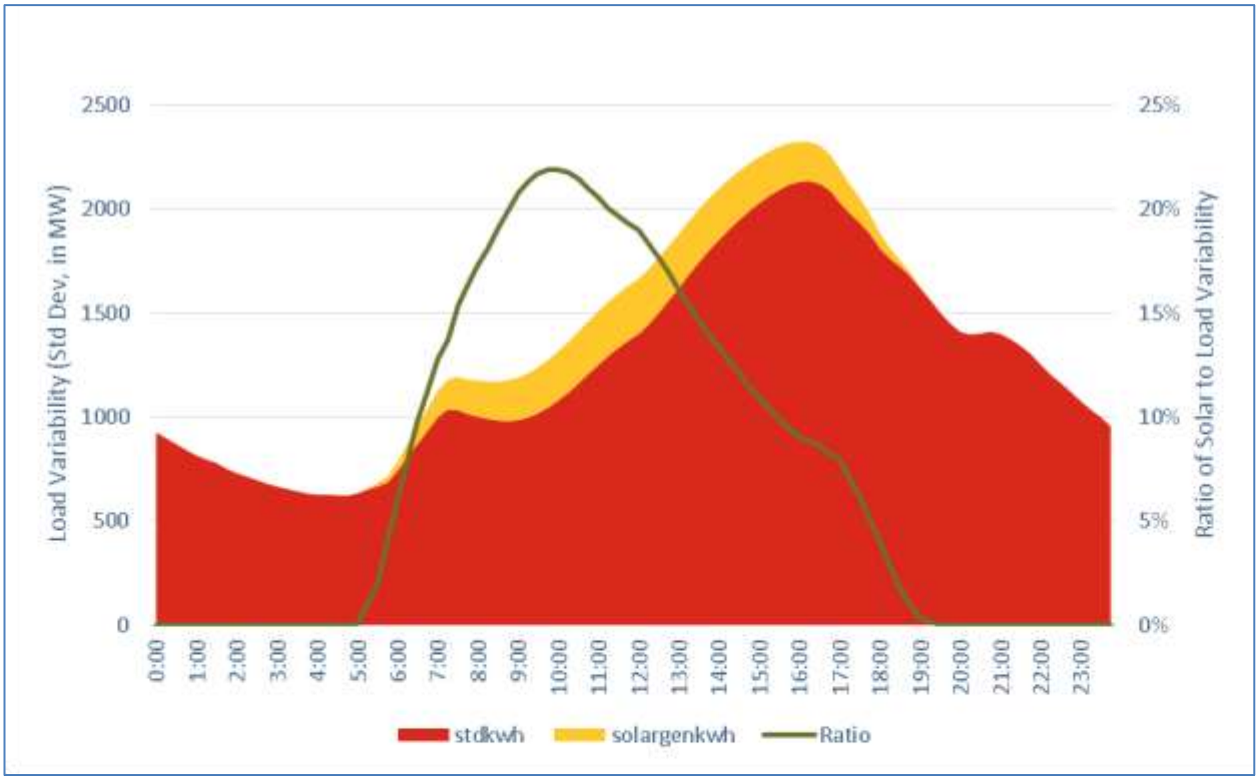
Much of the solar generation forecasting focus is on developing accurate forecasts of panel-level solar irradiance. The techniques range from vector decomposition of satellite imagery to vector decomposition of location specific cloud cover observations. Itron has geared this analysis for forecasting generation at utility solar installations and/or solar generation over a small geographic footprint. This micro focus is most useful when the exact locations of the solar installations are known. For the case of the California ISO, CPR has combined this micro level approach with a detailed database of solar PV installations to construct a rich time series of non-utility scale solar generation estimates by load zone. Itron used these estimates to evaluate the forecast performance of the alternative load forecast approaches described above.

Increased penetration of solar PV can lead to growing load volatility that in turn will lead to eroding load forecast performance. To put the solar generation data derived by CPR into a load forecasting context, it is useful to consider what fraction of load volatility could be associated with solar generation volatility. Figure 20 presents the ratio of solar generation volatility to load volatility for the total PG&E service territory. Here, Itron measured the solar generation volatility by the standard deviation (stdkwh) of the estimated solar generation output (solargenkwh), gold area in the chart, by time interval. Itron measured the load volatility by the standard deviation of loads (red area in the chart) by time interval. The green line in Figure 20 is the ratio of these two volatility measures. For the case of PG&E. the ratio of solar generation volatility to PG&E load volatility peaks around 10 am at a value of 0.22. This is in stark contrast to SCE (Figure 21), which also peaks mid-morning but at a much lower value of 0.13. As shown in Figure 22, SDG&E has a similar volatility profile as PG&E, with the ratio of solar generation volatility to SDG&E load volatility peaking mid-morning with a value of 0.20. Figure 23 presents a comparison the ratios for PG&E, SCE, and SDG&E.

From a model perspective, the greater the proportion of load volatility that can be associated with or explained by the volatility of solar generation, the more improvement in model fit that one can expect when adding solar generation as an explanatory variable in a model. To help fix ideas, consider a simple analogy of trying to measure (predict) the depth of a lake. If the lake is relatively shallow, accurately predicting the height of the waves is relatively important. In contrast, wave height is noise when considering trying to measure the depth of a lake as deep such as Lake Tahoe. In load forecasting, the volatility of solar generation is the measurement of the height of the waves. The load volatility is the measurement of the depth of the lake. The smaller the ratio of solar volatility (that is, the waves) to load volatility (depth of the lake) the less weight a statistical model will place on the solar generation variables. As a result, it is less likely that adding forecasts of solar generation will improve the load forecast. Conversely, the higher the ratio the more likely one will have forecast performance gains from adding forecasts of solar generation to the model.

The data in Figure 23 suggest that the forecast performance improvements were less for SCE than for PG&E and SDG&E because of the lower ratio. Further, Itron anticipated that there would be bigger performance gains in the mid-morning hours than the afternoon hours. Finally, Itron expected little to no forecast gains for the dawn and dusk hours when solar generation output was at its lowest.

Figure 20: Ratio of Solar Generation Volatility to Load Volatility (Pacific Gas & Electric Total)



Source: Clean Power Research

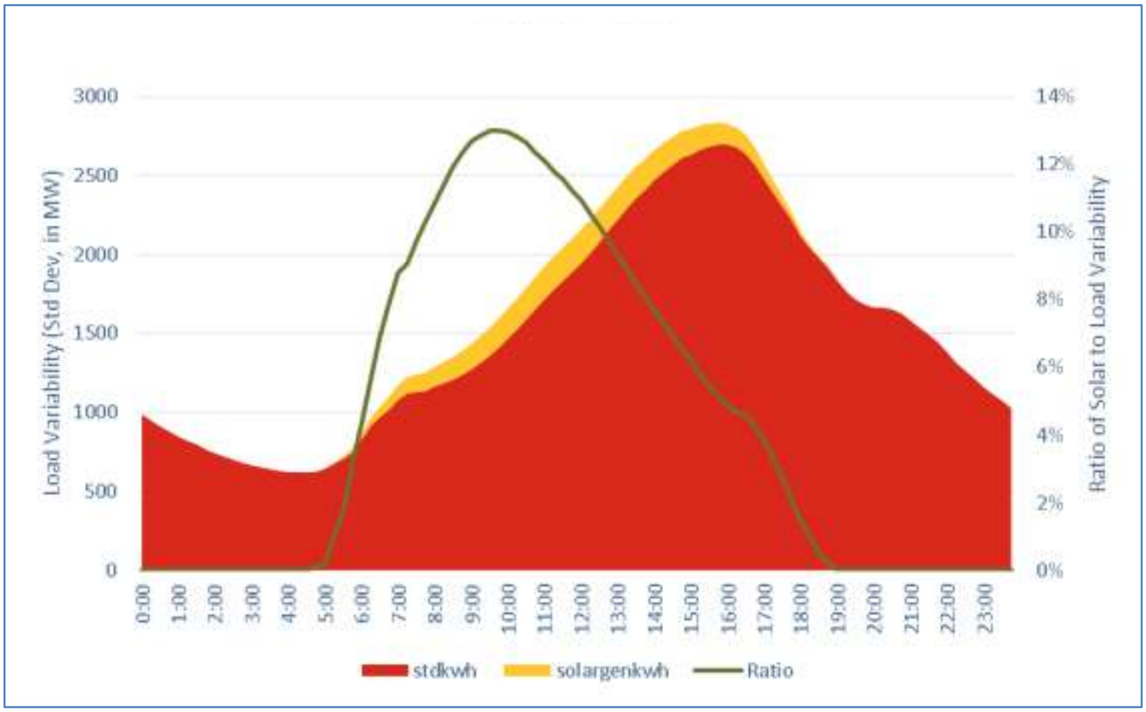
In this and subsequent figures, "stdkwh" is the estimated load variability (using the Standard Deviation of Measured Loads in MW), "solargenkwh" is the estimated solar PV generation variability (using Standard Deviation of BTM solar PV generation in MW), and "Ratio" is the ratio of solargenkwh to stdkwh.

Cloud Cover Driven Solar Generation Estimates

Unfortunately, not all system operators have access to the detailed installation data that CPR has gathered for the state of California. In many cases, a system operator will have at best good estimates of the total installed capacity by transmission zone and/or possibly by postal code. Further, most system operators only have access to hourly cloud cover data for the weather stations they use to forecast loads. For years, load forecasters have lived by the assumption that hourly weather data for a handful of weather stations was sufficient to produce accurate short-term load forecasts. This begs the question, is having an estimate of total installed capacity by transmission zone coupled with hourly cloud cover data for a handful of weather stations that span the load zone sufficient to capture the overall impact of solar PV generation on loads?

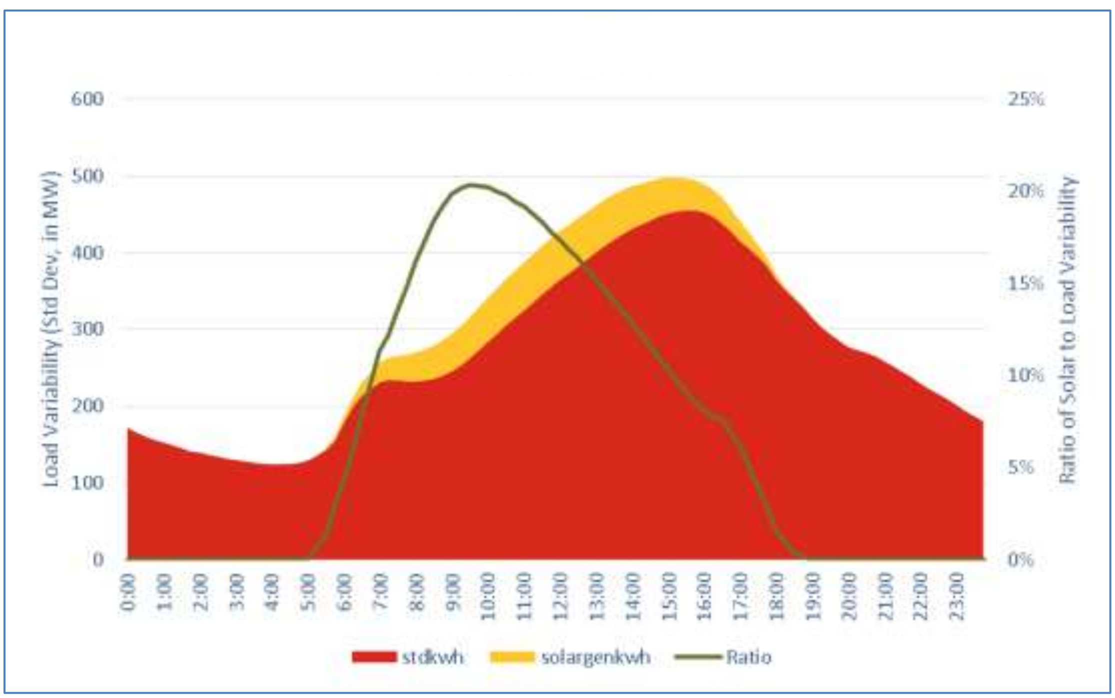
To answer this question, Itron developed an alternative time series of solar PV generation by combining the total installed solar PV capacity estimates by load zone developed by CPR with the hourly cloud cover observations for the weather stations that the California ISO uses to drive their load forecasts. The result was a time series of solar PV generation for the load zones: PG&E, PG&E Bay Area, PG&E Non Bay Area, SCE, SCE Coastal, SCE Inland, and SDG&E.

Figure 21: Ratio of Solar Generation Volatility to Load Volatility: Southern California Edison Total



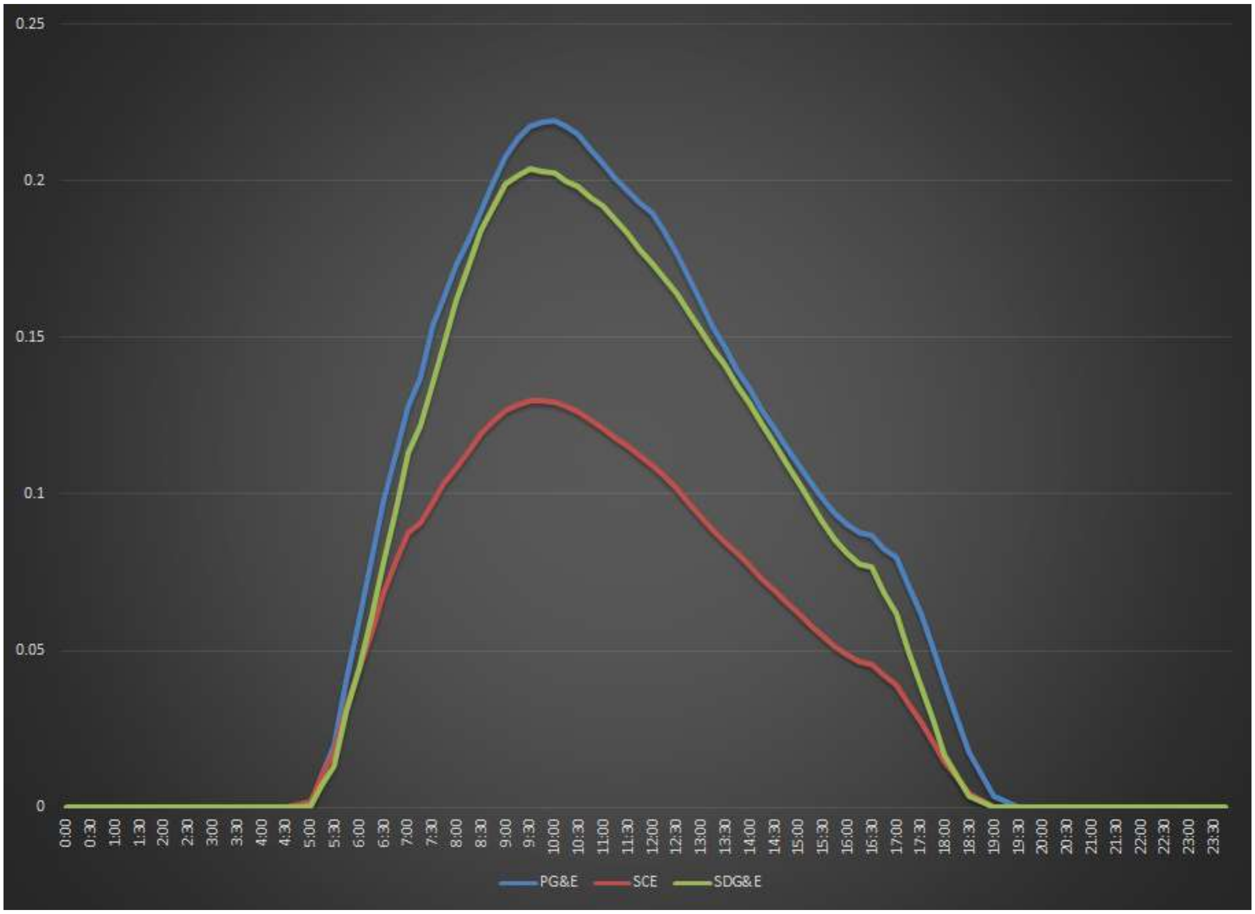
Source: Clean Power Research

Figure 22: Ratio of Solar Generation Volatility to Load Volatility: San Diego Gas & Electric



Source: Clean Power Research

Figure 23: Ratio of Solar Generation Volatility to Load Volatility: Investor-owned Utility Comparison



Source: Clean Power Research

One can quantify the benefit of doing "something" over doing "nothing" by comparing the forecast performance of the short-term load forecasts with and without cloud cover driven solar PV generation. Further, one can establish a baseline of short-term load forecast performance against which the short-term load forecast using CPR's detail bottom-up solar PV generation estimates can be evaluated. The remainder of this section, Itron describes how to develop forecasts (estimates) of solar PV generation by load zone by combining hourly cloud cover with solar PV capacity estimates.

Itron's approach used to develop cloud cover solar PV generation estimates was necessarily simple given the limited information available:

- Total Installed solar PV capacity (MW) by day and load zone, and
- Hourly Cloud Cover in percentage terms by hour, day and weather station.

Listed below are the practical steps used to develop the historical time series of solar PV generation by load zone.

Step 1. Construct an Historical Time Series of Solar Insolation. Given the above engineering relationship, how does one predict the amount of solar energy that will reach the surface of a solar panel for any location and time? For this study, Itron used the National Oceanic & Atmospheric Administration (NOAA) solar calculation spreadsheet[12] to derive estimates of solar insolation by location and day of year for roughly the geographic midpoint (measured as latitude/longitude) for the following load zones: PG&E Bay Area, PG&E Non Bay Area, SCE Coastal, SCE Inland and SDG&E. This step provided daily estimates of solar insolation at Solar Noon for the period January 1, 2010 through December 31, 2015.

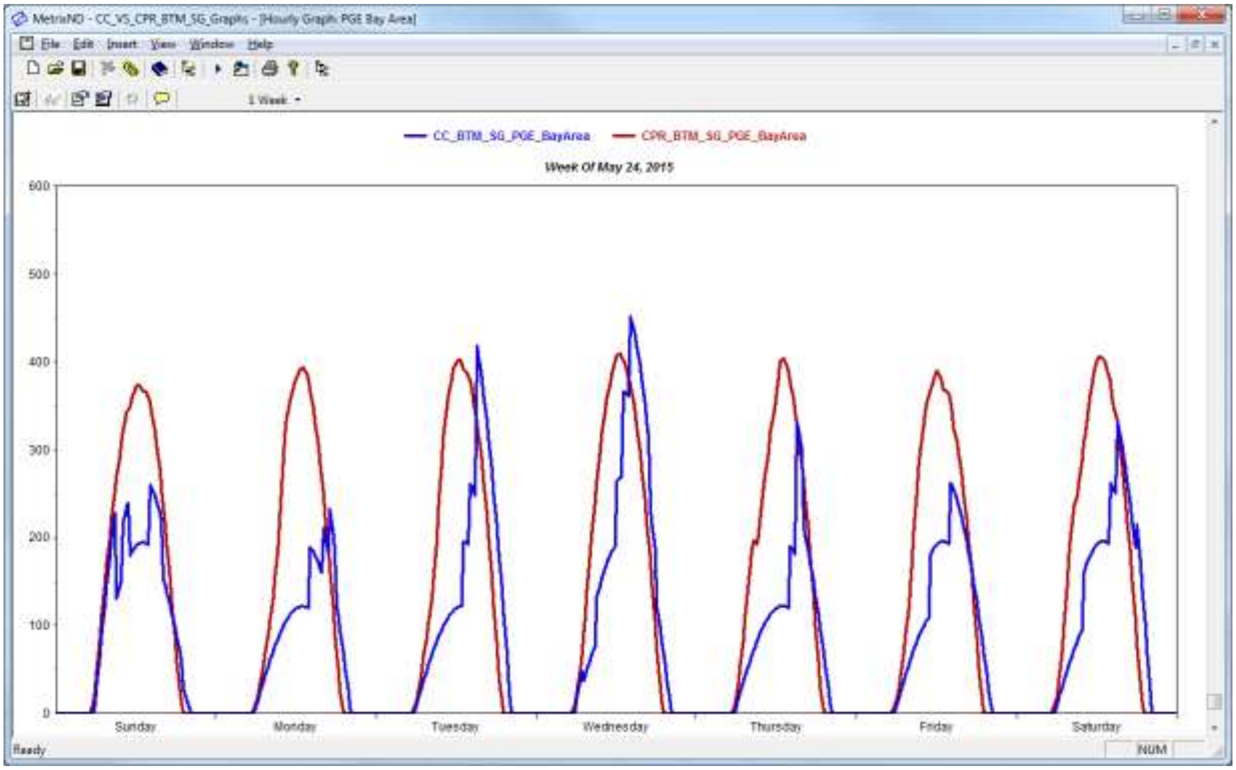
To compute a value of solar insolation for a specific time-of-the-day, it is important to know the Solar Altitude Angle for that time point. Again, Itron used the information available on the NOAA spreadsheet which gives an estimate of the time of Solar Noon that corresponds to a Solar Altitude Angle of 90 degrees. This spreadsheet also provides estimated sunrise and sunset times. Since the Solar Altitude Angle at the time of sunrise and sunset is 0 degrees, one can back into the average decay per minute in the Solar Altitude Angle.

Step 2. Constructing Estimates of Solar PV generation Capacity. For this study, Itron used the CPR-developed historical time series of solar installations by load zone to develop the solar PV generation estimates.

Step 3. Cloud Cover Driven Solar PV Generation. Next, Itron used hourly cloud cover and temperature values from the weather stations assigned to each load zone to derive estimates of solar PV generation which it will use in the load forecasting models. Figure 24 through Figure 28 present a comparison of the Cloud Cover solar generation estimates to the CPR estimates for the week of May 24, 2015. In general, the CPR estimates are smoother than the Cloud Cover driven estimates. This reflects the data smoothing inherent in the bottom-up approach implemented by CPR versus the hourly choppiness that comes with hourly cloud cover observations for a small number of weather stations. Itron anticipated that the smoother CPR estimates would lead to less volatile measured load forecasts than the cloud-cover driven estimates. If this observation proves true, then that is a distinct advantage of the CPR approach because adding load forecast uncertainty is not desirable.

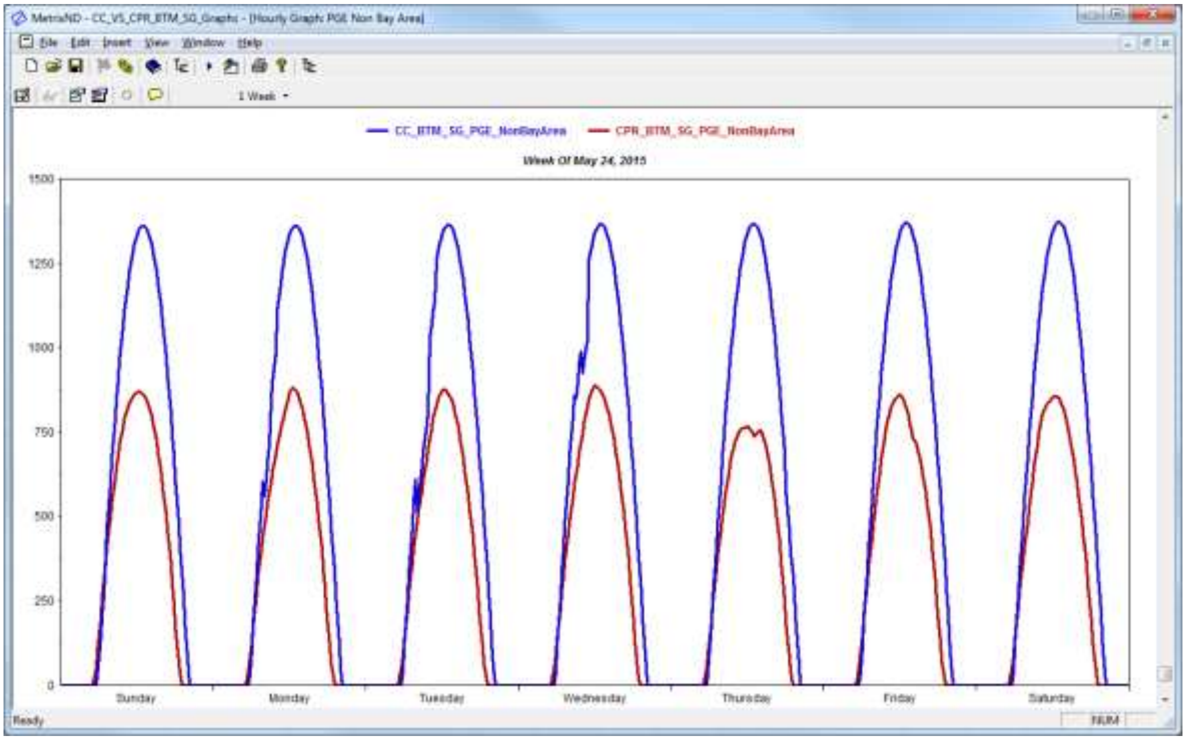
12 http://www.esrl.noaa.gov/gmd/grad/solcalc/calcdetails.html

Figure 24: CPR versus Cloud Cover Solar Generation (MWh): Pacific Gas & Electric Bay Area



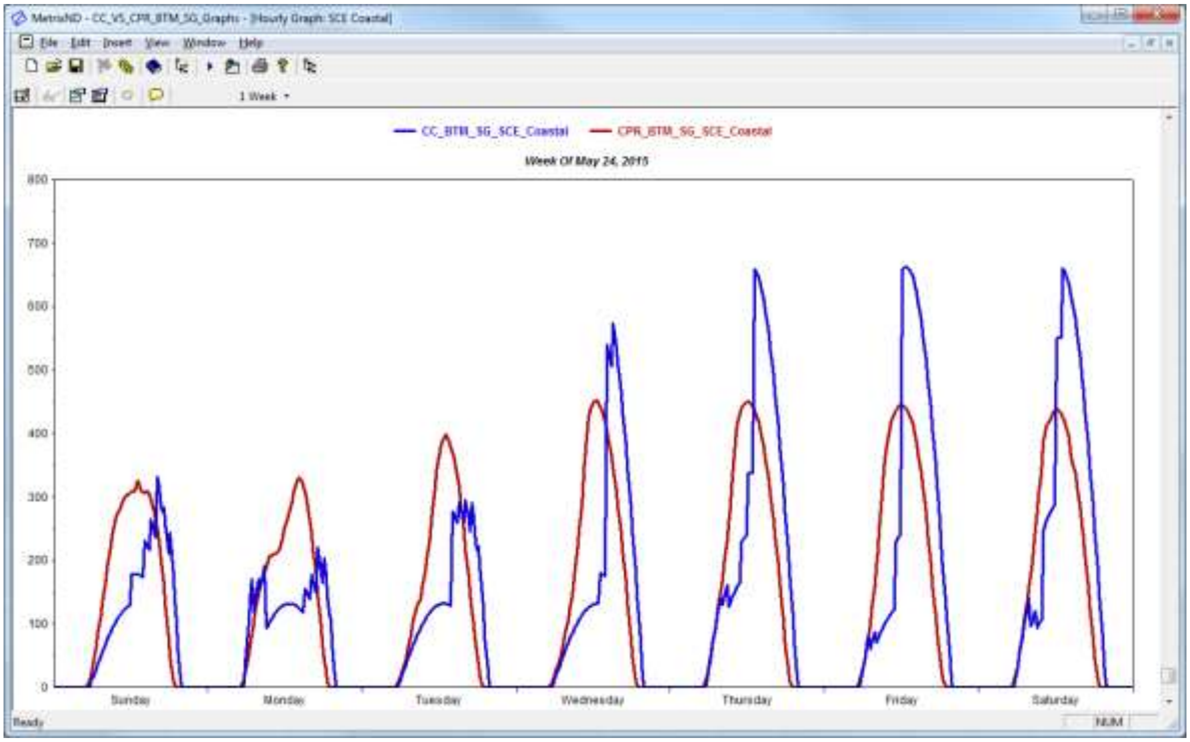
Source: Clean Power Research

Figure 25: CPR versus Cloud Cover Solar Generation (MWh): Pacific Gas & Electric Non Bay Area



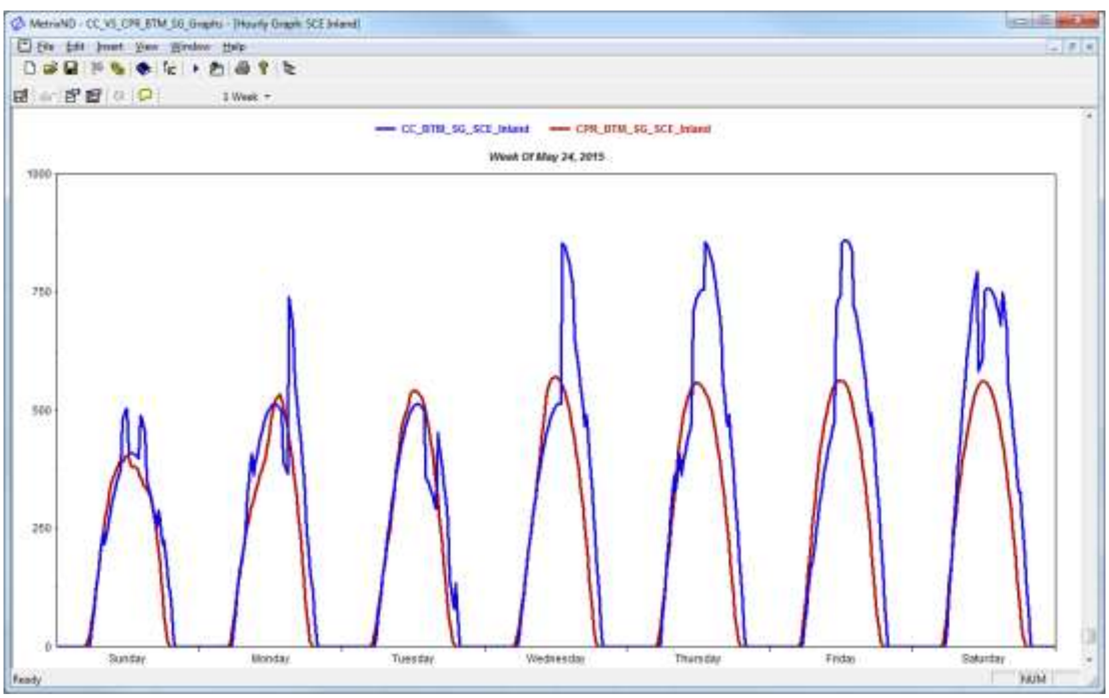
Source: Clean Power Research

Figure 26: CPR versus Cloud Cover Solar Generation (MWh): Southern California Edison Coastal



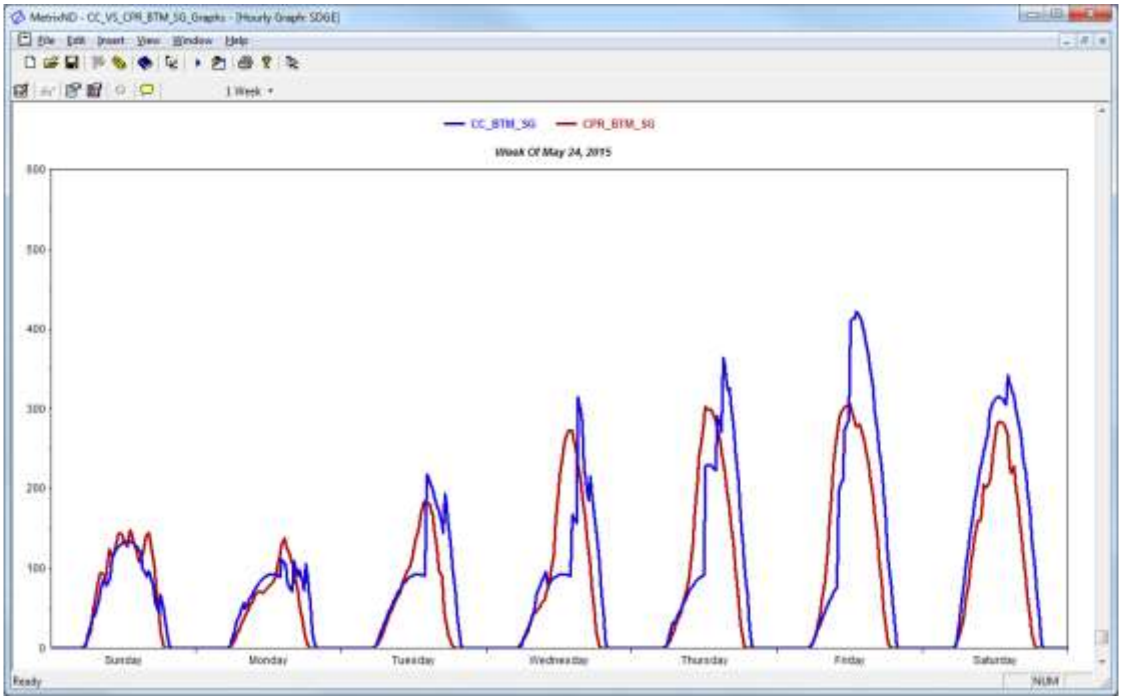
Source: Clean Power Research

Figure 27: CPR versus Cloud Cover Solar Generation (MWh): Southern California Edison Inland



Source: Clean Power Research

Figure 28: CPR versus Cloud Cover Solar Generation (MWh): San Diego Gas & Electric



Source: Clean Power Research

Forecast Simulations

To evaluate the accuracy of load forecast improvements, the research team computed a series of h-step ahead forecast simulations for each of the four modeling approaches: (1) California ISO Baseline Model, (2) Error Correction, (3) Reconstituted Loads, and (4) Model Direct. The simulation date range was from January 1, 2012 through June 8, 2015.

The process steps in the simulation are:

1. Start at midnight of January 1, 2012,
2. Import Metered Load data through the top of the simulation hour,
3. Import weather data for the forecast horizon,
4. Import solar PV generation estimates for the forecast horizon,
5. Generate a 48-hour ahead forecast of measured loads by Load Zone (PG&E, PG&E Bay Area, PG&E Non Bay Area, SCE, SCE Coastal, SCE Inland, SDG&E) and Forecast Method (Baseline, Error Correction, Reconstituted, Model Direct),
6. Store to an analysis database the: 15, 30, 45, 60, 90, 120, 180, 240, 300, 360 minute ahead and 24-hour ahead measured load forecasts by Load Zone and Forecast Approach, and
7. Increment to the next hour in the simulation horizon and repeat steps 2 through 7.

The data available to the models at the time of the forecast are:

- Actual 15-Minute level measured loads through the end of the prior hour,

- Hourly observed weather data by weather station for all weather concepts, including: Temperature, Dew Point, Cloud Cover, Wind Speed, and Wind Direction, and
- Estimated (Forecasted) 15-Minute level solar PV generation.

Itron used observed weather conditions to eliminate load forecast error driven by weather forecast errors.

The research team used the two sets of estimated solar PV generation in the simulations: (a) cloud cover driven and (b) CPR detailed bottom-up estimates. The use of cloud cover based solar generation estimates mimic the initial approach many system operators have implemented as a first pass at trying to improve their eroding load forecasts. A comparison of the results from the different estimates should demonstrate the benefit of the more detailed approach implemented by CPR.

Forecast Performance Measurements

A common metric used to evaluate load forecast performance is the Mean Absolute Percentage Error (MAPE). This metric represents the average percentage error in absolute terms expected from a load forecast model. In general, load forecast MAPEs become bigger the longer the forecast horizon.

To facilitate identifying improvements in forecast performance relative to the baseline forecast the forecast MAPE values represent the percentage change relative to the baseline MAPE. In this case, a negative percent change in the forecast MAPE of the alternative approach represents an improvement in forecast performance over the baseline forecast.

A second metric for evaluating forecast accuracy improvements is Forecast Skill. This is a commonly used statistic in renewable energy forecasting studies, which tend to compare the performance of an alternative approach relative to a baseline approach such as a persistence forecast. Forecast Skill metrics also avoid a problem inherent in the use of MAPE for evaluating the forecast performance of solar and wind generation that occurs when the observed generation value run close to zero. Small generation values tend to be associated with large percentage forecast errors not necessarily because there are large absolute forecast errors, but rather the error is divided by a small number.

For this study, Forecast Skill measures the percentage of forecast simulations that the candidate forecast approach produced, a smaller in absolute terms load forecast error than the baseline load forecast. In this case, if the Forecast Skill is greater than 50 percent of the time, a forecast approach will lead to an improvement on average in load forecast accuracy.

These first two metrics focus on the first moment of the forecast error distribution. In addition to reducing forecast errors on average, Itron was interested in testing whether or not the alternative forecast approaches reduce the overall dispersion of forecast errors. In this case, Itron measured the forecast error dispersion using the Forecast Standard Deviation.

To ease comparisons, Itron constructed the change in the Standard Deviation of the forecast errors of each approach relative to the baseline Standard Deviation. In this case, a negative percent change in the forecast Standard Deviation of the alternative approach represents an improvement in forecast performance over the baseline forecast.

Collectively, the team looked to evaluate whether or not the alternative approaches reduced not only the mean or average forecast error, but also the dispersion of forecast errors.

Simulation Results Summary

The results of forecast simulations for January 1, 2015 through June 30, 2015 are below. Itron selected this period since it represents the most recent data and the period which PV installations were at their highest. The results from earlier periods are less applicable to the forecast problem currently faced by the California ISO because the earlier periods had significantly lower penetration of PV relative to 2016 values.

The exhibits present the forecast MAPE, Skill, and Error Standard Deviation by:

- Forecast Horizon
  - 15 Minutes Ahead
  - 30 Minutes Ahead
  - 45 Minutes Ahead
  - 60 Minutes Ahead
  - 90 Minutes Ahead
  - 120 Minutes Ahead (2 Hours Ahead)
  - 180 Minutes Ahead (3 Hours Ahead)
  - 240 Minutes Ahead (4 Hours Ahead)
  - 300 Minutes Ahead (5 Hours Ahead)
  - 360 Minutes Ahead (6 Hours Ahead)
  - 720 Minutes Ahead (12 Hours Ahead)
  - 1440 Minutes Ahead (24 Hours Ahead)
- Forecast Approach
  - Baseline Load Forecast Model with no Behind-the-Meter Solar Generation
  - Error Correction Approach using Cloud Cover driven Solar Generation estimates
  - Model Direct Approach using Cloud Cover driven Solar Generation estimates
  - Reconstituted Loads Approach using Cloud Cover driven Solar Generation estimates
  - Error Correction Approach using CPR's Solar Generation estimates
  - Model Direct Approach using CPR's Solar Generation estimates
  - Reconstituted Loads Approach using CPR's Solar Generation estimates

The results are presented for the following segmentations:

- Load Zones:

    - California ISO Total
    - PG&E Bay Area
    - PG&E Non Bay Area
    - SCE Coastal
    - SCE Inland
    - SDG&E Total
- Seasons:
    - Winter (October through March)
    - Summer (April through September)
- Cloud Cover Conditions
    - Clear: average cloud cover percentage less than 75 percent
    - Cloudy: average daily cloud cover percentage greater than or equal to 75 percent

Figure 29 through Figure 40 summarize the results. On each figure, the values highlighted in green represent an improvement over the baseline load forecast.

California Independent System Operator Total Simulation Results

- Figure 29 through Forecast Horizons of 12 Hours Ahead to 24 Hours Ahead. For longer-term forecast horizons of 12 hours ahead to 24 hours ahead, the Reconstituted Load approach combined with CPR solar generation estimates significantly reduced both the forecast MAPE and error dispersion. Over this same forecast horizon, the Error Correction approach combined with either Cloud Cover or CPR solar generations estimates outperformed the baseline load forecast. This suggests that imposing an a priori weight of -1.0 on the solar generation estimates works well for these longer forecast horizons.
- Seasonal Differences. The conclusions do not change substantially when the forecast results are segmented between the winter and summer seasons. The Model Direct approach utilizing the CPR solar generation estimates improves the load forecast performance for forecast horizons of 15 minutes ahead to five hours ahead. For longer forecast horizons, the Reconstituted Load approach out performs the baseline load forecast. The main difference between the seasonal results and the overall results is the Model Direct approach using Cloud Cover driven solar generation estimates only performed well during the summer season while this approach performed well for forecast horizons from 15 minutes ahead to four hours ahead over the winter season.
- Cloud Cover. The alternative approaches appear to work best under varying cloud conditions. Most notably, combining CPR solar generation estimates reduces the forecast error dispersion across most forecast horizons under the Model Direct and Reconstituted Load approaches.

Figure 30 presents the results for the California ISO total (that is, the sum of all the PG&E, SCE, and SDG&E zone loads) across all seasons, and cloud cover conditions.

- Improvement over Baseline. A mix or "ensemble" of the different approaches can result in a reduction in forecast accuracy. Although these improvements are largely in the single (relative) percentage points, the improvements still have measurable potential savings to California of approximately $2 million per year. [13]
- Forecast Horizons of 15 Minutes Ahead to Four Hours Ahead. For forecast horizons of up to four hours ahead, the Model Direct approach consistently outperformed the baseline load forecast model with both a reduced MAPE and smaller dispersion of forecast errors. Further, the Model Direct approach performed better than the baseline forecast when using both Cloud Cover and CPR computed solar generation estimates. However, the Model Direct approach when combined with the CPR solar generation estimates outperformed the same approach combined with the Cloud Cover driven solar generation estimates.
- Forecast Horizons of Five Hours Ahead to Six Hours Ahead. For forecast horizons of five hours ahead to six hours ahead, the results are mixed between the Model Direct combined with CPR solar generation estimates and the Reconstituted Loads approach combined with CPR solar generation estimates. Using Forecast Skill as a metric, the Reconstituted Loads approach outperformed the baseline forecast. However, the forecast error dispersion grew with this approach.

[13] Based on an average annual California ISO load of 26 GW and an average regulation cost of $9/MWh per MacDonald e. al 'Demand Response Providing Ancillary Services A Comparison of Opportunities and Challenges in the US Wholesale Markets', Grid-Interop Forum 2012

Figure 29: California Independent System Operator Total, All Seasons, All Cloud Cover Conditions

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	12.91%	-0.55%	28.94%	9.56%	-1.23%	1.94%
30	7.71%	-0.57%	22.15%	5.30%	-1.79%	1.22%
45	15.08%	-0.43%	19.28%	17.15%	-2.47%	1.33%
60	16.06%	-0.48%	21.89%	2.31%	-2.93%	1.17%
90	2.17%	-0.40%	15.85%	1.96%	-3.41%	-0.34%
120	7.71%	-0.26%	15.78%	1.73%	-3.89%	-0.29%
180	4.81%	-0.42%	12.14%	1.76%	-4.55%	-1.11%
240	3.20%	-0.38%	9.07%	1.40%	-4.03%	-2.02%
300	1.07%	1.04%	13.44%	-0.48%	-1.51%	2.40%
360	-0.18%	2.83%	13.40%	-2.16%	0.99%	2.08%
720	-0.08%	5.39%	4.80%	-3.65%	4.56%	-6.44%
1440	-0.36%	4.93%	4.05%	-3.89%	4.07%	-5.92%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	36.6%	51.3%	40.3%	37.8%	52.0%	48.5%
30	38.9%	51.4%	40.9%	40.1%	52.6%	49.2%
45	39.7%	51.6%	41.2%	40.3%	53.4%	49.4%
60	39.7%	51.5%	41.4%	43.3%	53.8%	49.6%
90	42.5%	51.2%	42.4%	42.6%	53.7%	50.4%
120	42.1%	50.6%	42.6%	43.4%	54.0%	50.4%
180	43.4%	50.8%	43.9%	43.7%	54.7%	50.8%
240	46.0%	50.2%	44.7%	46.1%	53.3%	51.3%
300	47.8%	48.6%	44.3%	48.9%	50.7%	51.0%
360	47.7%	47.2%	44.1%	49.7%	48.8%	50.9%
720	44.5%	46.0%	47.6%	47.5%	46.6%	54.3%
1440	44.6%	46.4%	48.0%	47.5%	47.1%	54.4%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	7.2%	-0.3%	19.6%	4.5%	-0.7%	0.1%
30	5.1%	-0.3%	14.6%	3.2%	-0.9%	0.2%
45	15.5%	-0.2%	12.9%	16.9%	-1.2%	0.6%
60	12.1%	-0.2%	16.0%	1.4%	-1.6%	0.7%
90	1.6%	-0.2%	10.9%	1.2%	-1.8%	-0.2%
120	5.6%	-0.1%	11.7%	0.8%	-2.2%	0.0%
180	3.4%	-0.2%	9.2%	0.9%	-2.5%	-0.2%
240	2.6%	-0.1%	6.7%	1.0%	-2.0%	-1.0%
300	1.1%	0.9%	9.2%	-0.3%	-0.3%	2.0%
360	-0.5%	1.8%	8.1%	-2.1%	1.1%	1.0%
720	-3.1%	3.1%	-0.6%	-5.1%	2.8%	-7.6%
1440	-3.3%	2.9%	-0.7%	-5.3%	2.7%	-7.1%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

- Forecast Horizons of 12 Hours Ahead to 24 Hours Ahead. For longer-term forecast horizons of 12 hours ahead to 24 hours ahead, the Reconstituted Load approach combined with CPR solar generation estimates significantly reduced both the forecast MAPE and error dispersion. Over this same forecast horizon, the Error Correction approach combined with either Cloud Cover or CPR solar generations estimates outperformed the baseline load forecast. This suggests that imposing an a priori weight of -1.0 on the solar generation estimates works well for these longer forecast horizons.
- Seasonal Differences. The conclusions do not change substantially when the forecast results are segmented between the winter and summer seasons. The Model Direct approach utilizing the CPR solar generation estimates improves the load forecast performance for forecast horizons of 15 minutes ahead to five hours ahead. For longer forecast horizons, the Reconstituted Load approach out performs the baseline load forecast. The main difference between the seasonal results and the overall results is the Model Direct approach using Cloud Cover driven solar generation estimates only performed well during the summer season while this approach performed well for forecast horizons from 15 minutes ahead to four hours ahead over the winter season.
- Cloud Cover. The alternative approaches appear to work best under varying cloud conditions. Most notably, combining CPR solar generation estimates reduces the forecast error dispersion across most forecast horizons under the Model Direct and Reconstituted Load approaches.

Figure 30: California Independent System Operator Total, All Seasons, Clear

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	15.39%	-0.64%	24.02%	10.27%	-1.05%	1.71%
30	8.90%	-0.63%	18.93%	5.40%	-1.37%	1.24%
45	17.28%	-0.45%	16.74%	18.54%	-1.84%	1.31%
60	14.15%	-0.48%	20.02%	1.73%	-2.17%	1.53%
90	1.76%	-0.25%	14.63%	1.32%	-2.66%	0.38%
120	6.29%	-0.11%	15.16%	1.04%	-3.01%	0.71%
180	3.55%	-0.16%	11.84%	1.14%	-3.65%	0.28%
240	2.12%	-0.21%	9.02%	1.07%	-3.26%	-0.55%
300	0.27%	1.15%	13.32%	-0.54%	-0.98%	3.39%
360	-1.00%	2.91%	12.90%	-2.09%	1.42%	2.35%
720	-1.16%	5.54%	3.94%	-3.86%	4.92%	-7.03%
1440	-1.52%	5.02%	3.09%	-4.08%	4.39%	-6.54%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	36.1%	51.2%	41.1%	38.0%	51.6%	48.7%
30	39.1%	50.9%	41.6%	40.8%	52.2%	49.2%
45	40.1%	51.4%	41.8%	41.2%	52.7%	49.4%
60	41.0%	51.3%	41.9%	44.7%	53.1%	49.4%
90	44.1%	50.3%	42.8%	44.5%	52.9%	50.0%
120	43.7%	49.9%	42.6%	45.2%	53.4%	49.8%
180	45.2%	50.2%	43.9%	45.6%	54.1%	50.1%
240	47.1%	49.7%	44.4%	47.2%	52.8%	50.4%
300	48.4%	48.6%	44.5%	49.3%	50.4%	50.5%
360	48.0%	47.3%	44.8%	49.7%	48.6%	51.0%
720	44.4%	46.4%	48.4%	47.3%	46.6%	54.7%
1440	44.5%	46.7%	48.9%	47.2%	47.1%	54.8%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	8.3%	-0.3%	15.3%	4.8%	-0.7%	0.1%
30	5.8%	-0.4%	11.9%	3.3%	-0.7%	0.4%
45	18.2%	-0.2%	10.8%	19.2%	-0.9%	0.8%
60	10.1%	-0.2%	14.3%	1.2%	-1.1%	1.1%
90	1.4%	-0.1%	9.9%	0.8%	-1.3%	0.5%
120	3.9%	0.0%	10.5%	0.3%	-1.7%	1.0%
180	2.0%	-0.1%	8.3%	0.4%	-2.0%	0.9%
240	1.5%	0.1%	6.4%	0.7%	-1.4%	0.2%
300	0.3%	1.3%	9.2%	-0.4%	0.4%	2.9%
360	-1.1%	2.5%	8.1%	-2.1%	1.9%	1.8%
720	-3.6%	4.1%	-0.9%	-5.3%	3.9%	-7.0%
1440	-3.9%	3.9%	-1.0%	-5.4%	3.7%	-6.6%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Pacific Gas & Electric Bay Area Simulation Results

Figure 31 through Figure 32 presents the results for PG&E Bay Area across all seasons, and cloud cover conditions.

- Forecast Horizons of 15 Minutes Ahead to Four Hours Ahead. For forecast horizons of up to four hours ahead, the Model Direct approach consistently outperformed the baseline load forecast model with both a reduced MAPE and smaller dispersion of forecast errors. Further, the Model Direct approach performed better than the baseline forecast when using both Cloud Cover driven estimates and CPR computed solar generation estimates. However, the Model Direct approach when combined with the CPR solar generation estimates outperformed the same approach combined with the Cloud Cover driven solar generation estimates.
- Forecast Horizons of Five Hours Ahead to Six Hours Ahead. For forecast horizons of five hours ahead to six hours ahead, the Error Correction approach combined with CPR solar generation estimates outperformed all other approaches.
- Forecast Horizons of 12 Hours Ahead to 24 Hours Ahead. For longer-term forecast horizons of 12 hours ahead to 24 hours ahead, the baseline model forecasts were on average more accurate, but the Error Correction approach combined with the CPR solar generation estimates led to a tighter distribution of forecast errors.
- Seasonal Differences. The main difference between the winter and summer seasons is the Model Direct approach when combined with the CPR solar generation estimates reduced the forecast error dispersion during the winter months across all forecast horizons. This improvement is limited to the forecast horizons of 15 minutes ahead to four hours ahead during the summer season.
- Cloud Cover. The alternative approaches appear to work best under varying cloud conditions. Most notably, combining the CPR solar generation estimates reduced the forecast error dispersion across most forecast horizons under the Model Direct and Reconstituted Load approaches.

Figure 31: Pacific Gas & Electric Bay Area, All Seasons, All Cloud Cover Conditions

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	4.60%	-1.06%	24.00%	5.85%	-1.77%	1.66%
30	2.99%	-0.79%	19.55%	3.25%	-2.19%	1.72%
45	6.58%	-0.44%	16.96%	9.52%	-2.47%	1.96%
60	13.93%	-0.56%	21.48%	1.56%	-2.79%	1.31%
90	0.76%	-0.53%	15.96%	0.87%	-3.26%	0.55%
120	6.99%	-0.30%	16.51%	0.94%	-3.53%	-0.15%
180	4.67%	-0.68%	14.16%	0.92%	-4.29%	-1.53%
240	3.05%	-0.24%	11.90%	0.36%	-2.60%	-2.53%
300	1.45%	2.17%	18.48%	-0.72%	1.92%	4.23%
360	0.90%	5.63%	19.45%	-1.16%	6.14%	5.83%
720	1.74%	11.63%	13.54%	-0.22%	12.11%	0.37%
1440	1.56%	10.79%	13.01%	-0.36%	11.28%	0.15%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	38.9%	51.7%	41.5%	37.6%	52.6%	49.0%
30	39.4%	51.9%	41.5%	39.5%	54.0%	49.7%
45	39.7%	51.9%	42.1%	38.4%	54.0%	49.8%
60	36.9%	52.0%	41.1%	41.2%	54.1%	50.8%
90	41.2%	52.4%	42.5%	41.0%	55.2%	50.2%
120	38.7%	51.4%	43.1%	41.3%	54.7%	51.1%
180	40.3%	52.3%	43.6%	41.8%	55.4%	52.2%
240	43.8%	50.3%	43.2%	44.9%	53.0%	52.3%
300	45.4%	46.0%	40.3%	47.7%	46.4%	48.9%
360	45.5%	42.6%	38.4%	48.1%	42.6%	46.7%
720	44.1%	39.2%	39.7%	44.7%	39.2%	48.0%
1440	44.3%	39.8%	40.1%	44.7%	39.7%	48.2%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	3.1%	-0.9%	20.6%	3.5%	-1.3%	1.2%
30	2.0%	-0.6%	14.6%	1.9%	-1.4%	0.9%
45	4.9%	-0.2%	12.6%	7.5%	-1.6%	1.0%
60	11.5%	-0.2%	17.7%	0.7%	-1.8%	0.6%
90	0.4%	-0.2%	12.4%	0.3%	-2.4%	-0.1%
120	5.5%	0.0%	13.8%	0.2%	-2.7%	-0.4%
180	3.2%	-0.1%	11.7%	0.1%	-3.1%	-1.4%
240	1.8%	-0.4%	8.8%	-0.4%	-2.5%	-2.6%
300	0.8%	-0.1%	12.0%	-1.2%	-0.6%	1.3%
360	0.4%	0.7%	11.3%	-1.5%	1.0%	1.4%
720	0.7%	2.6%	3.0%	-1.2%	3.2%	-5.2%
1440	0.7%	2.5%	2.8%	-1.3%	3.1%	-5.2%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Figure 32: Pacific Gas & Electric Bay Area, All Seasons, Clear

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	5.33%	-1.08%	25.97%	5.77%	-1.40%	0.94%
30	3.14%	-0.58%	21.34%	3.06%	-1.30%	1.64%
45	7.69%	-0.18%	18.95%	10.33%	-1.64%	2.02%
60	15.72%	-0.19%	24.80%	1.09%	-1.67%	1.60%
90	0.48%	-0.17%	18.50%	0.13%	-2.28%	1.05%
120	7.90%	0.15%	20.02%	0.23%	-2.17%	0.57%
180	5.17%	-0.04%	17.18%	0.34%	-2.87%	-0.21%
240	3.48%	0.69%	14.33%	-0.01%	-1.08%	-0.66%
300	1.61%	3.85%	20.57%	-0.80%	4.07%	6.57%
360	1.03%	7.80%	20.67%	-1.04%	8.81%	7.83%
720	1.86%	14.71%	13.87%	-0.26%	15.55%	2.06%
1440	1.58%	13.71%	12.96%	-0.49%	14.52%	1.68%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	39.2%	50.7%	41.2%	38.2%	51.8%	49.7%
30	40.5%	51.0%	41.1%	40.2%	53.4%	50.0%
45	40.6%	50.9%	41.6%	40.0%	53.5%	50.0%
60	37.9%	50.9%	40.2%	43.0%	53.1%	50.8%
90	43.0%	51.2%	41.6%	43.1%	54.4%	50.1%
120	40.3%	50.2%	41.4%	43.9%	53.8%	50.3%
180	41.6%	51.1%	42.4%	44.2%	54.2%	51.4%
240	44.1%	49.1%	42.0%	46.5%	51.7%	51.2%
300	45.6%	45.8%	40.2%	48.5%	45.5%	47.9%
360	45.4%	42.5%	39.0%	48.0%	42.0%	46.3%
720	43.9%	39.4%	41.8%	44.2%	39.3%	47.8%
1440	44.0%	39.9%	42.4%	44.1%	39.8%	48.1%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	3.7%	-1.0%	22.0%	3.6%	-1.2%	0.5%
30	2.3%	-0.5%	15.4%	1.8%	-1.0%	0.5%
45	6.0%	-0.1%	13.5%	8.5%	-1.0%	0.9%
60	13.0%	0.1%	19.9%	0.4%	-1.0%	0.5%
90	0.1%	0.0%	13.9%	-0.2%	-1.5%	0.2%
120	6.2%	0.4%	15.9%	-0.3%	-1.5%	0.2%
180	3.5%	0.5%	13.5%	-0.4%	-1.8%	-0.4%
240	1.8%	0.7%	11.0%	-0.7%	-0.9%	-0.9%
300	0.7%	2.5%	15.3%	-1.4%	2.1%	4.5%
360	0.2%	4.9%	15.7%	-1.7%	5.1%	6.3%
720	0.3%	10.0%	9.3%	-1.8%	10.6%	2.2%
1440	0.3%	9.7%	8.8%	-1.9%	10.3%	2.0%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Pacific Gas & Electric Non Bay Area Simulation Results

Figure 33 through Figure 34 presents the results for PG&E Non Bay Area across all seasons, and cloud cover conditions.

- Forecast Horizons of 15 Minutes Ahead to Four Hours Ahead. For forecast horizons of up to four hours ahead, the Model Direct approach consistently outperformed the baseline load forecast model with both a reduced MAPE and smaller dispersion of forecast errors. Further, the Model Direct approach performed better than the baseline forecast when using both Cloud Cover driven estimates and CPR computed solar generation estimates. However, the Model Direct approach when combined with the CPR solar generation estimates outperformed the same approach combined with the Cloud Cover driven solar generation estimates.
- Forecast Horizons of Five Hours Ahead to Six Hours Ahead. For forecast horizons of five hours ahead to six hours ahead, the Error Correction approach combined with CPR solar generation estimates outperformed all other approaches.
- Forecast Horizons of 12 Hours Ahead to 24 Hours Ahead. For longer-term forecast horizons of 12 hours ahead to 24 hours ahead, the baseline model forecasts were on average more accurate.
- Seasonal Differences. The main difference between the winter and summer seasons is the Reconstituted Load approach when combined with the CPR solar generation estimates performed better with the longer forecast horizons during the summer season than the winter season.
- Cloud Cover. The alternative approaches appear to work best under varying cloud conditions. Most notably, combining the CPR solar generation estimates reduced the forecast error dispersion across most forecast horizons under the Model Direct and Reconstituted Load approaches.

Figure 33: Pacific Gas & Electric Non Bay Area, All Seasons, All Cloud Cover Conditions

Change in Forecast Mean Absolute Percentage Error (%)

Forecast Horizon Minutes Ahead	Behind-the-Meter Solar Generation Source: Cloud Cover — Error Correction	Model Direct	Reconstituted Loads	Behind-the-Meter Solar Generation Source: Clean Power Research — Error Correction	Model Direct	Reconstituted Loads
15	26.52%	-1.12%	24.29%	15.42%	-2.61%	1.61%
30	16.65%	-1.77%	18.39%	8.95%	-3.04%	0.90%
45	26.37%	-1.85%	16.72%	25.86%	-3.68%	0.91%
60	16.95%	-1.82%	17.92%	2.51%	-4.28%	1.23%
90	2.71%	-2.69%	11.64%	1.26%	-5.55%	-1.26%
120	7.67%	-2.60%	11.98%	0.81%	-6.09%	-0.99%
180	4.65%	-3.23%	8.10%	0.33%	-7.12%	-2.67%
240	1.38%	-2.03%	5.83%	-0.96%	-6.55%	-3.11%
300	0.12%	3.66%	13.40%	-2.08%	-0.81%	5.25%
360	1.52%	9.52%	17.28%	-1.86%	5.49%	8.61%
720	8.83%	18.46%	17.69%	0.97%	15.82%	6.30%
1440	8.29%	16.88%	16.16%	0.77%	14.23%	5.50%

Forecast Skill (%)

Forecast Horizon Minutes Ahead	Behind-the-Meter Solar Generation Source: Cloud Cover — Error Correction	Model Direct	Reconstituted Loads	Behind-the-Meter Solar Generation Source: Clean Power Research — Error Correction	Model Direct	Reconstituted Loads
15	31.1%	52.0%	43.8%	35.5%	52.9%	48.9%
30	34.5%	52.8%	44.1%	38.3%	53.5%	49.7%
45	36.4%	53.7%	43.8%	38.1%	54.6%	49.6%
60	39.4%	53.6%	44.5%	43.5%	54.2%	48.8%
90	43.0%	54.7%	45.8%	44.8%	54.8%	50.6%
120	43.5%	53.8%	44.6%	46.3%	54.9%	50.2%
180	45.9%	54.7%	46.2%	48.0%	56.4%	50.8%
240	49.7%	51.9%	47.6%	52.3%	54.7%	50.9%
300	49.7%	47.1%	44.8%	52.8%	49.4%	49.5%
360	46.3%	43.5%	43.2%	51.0%	45.8%	48.3%
720	33.7%	40.7%	40.9%	41.7%	42.0%	50.9%
1440	33.7%	41.5%	41.4%	41.7%	42.9%	51.6%

Change in Forecast Error Standard Deviation (MW)

Forecast Horizon Minutes Ahead	Behind-the-Meter Solar Generation Source: Cloud Cover — Error Correction	Model Direct	Reconstituted Loads	Behind-the-Meter Solar Generation Source: Clean Power Research — Error Correction	Model Direct	Reconstituted Loads
15	17.4%	-0.9%	22.1%	9.3%	-2.6%	-0.5%
30	11.1%	-1.4%	15.1%	5.6%	-2.9%	-0.8%
45	35.0%	-1.2%	13.1%	35.4%	-3.1%	-0.2%
60	14.9%	-1.2%	15.1%	2.3%	-3.6%	-0.4%
90	2.2%	-1.9%	9.3%	0.9%	-4.5%	-2.0%
120	6.1%	-1.9%	9.0%	0.4%	-5.0%	-1.8%
180	3.5%	-2.4%	6.2%	0.1%	-5.5%	-2.7%
240	1.6%	-1.8%	4.6%	-0.4%	-4.8%	-2.8%
300	1.2%	1.5%	10.5%	-0.9%	-1.3%	4.1%
360	2.1%	5.0%	13.0%	-0.8%	2.3%	6.7%
720	6.5%	11.6%	12.3%	0.7%	9.7%	4.6%
1440	6.1%	10.9%	11.6%	0.5%	8.8%	4.0%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Figure 34: Pacific Gas & Electric Non Bay Area, All Seasons, Clear

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	31.54%	-1.16%	14.96%	17.75%	-2.47%	2.69%
30	19.42%	-1.59%	11.91%	9.57%	-2.53%	2.07%
45	32.19%	-1.62%	11.48%	31.26%	-2.77%	1.52%
60	11.47%	-1.76%	12.03%	1.81%	-3.29%	1.65%
90	2.29%	-2.34%	8.36%	0.73%	-4.07%	0.09%
120	4.01%	-2.36%	8.73%	0.18%	-4.69%	0.14%
180	1.87%	-2.67%	6.05%	-0.17%	-5.32%	-1.00%
240	-0.55%	-1.75%	4.02%	-1.04%	-4.88%	-1.99%
300	-0.95%	2.91%	11.23%	-1.78%	-0.14%	3.83%
360	0.40%	8.01%	15.12%	-1.54%	5.02%	4.86%
720	7.77%	16.02%	16.72%	0.90%	13.80%	0.58%
1440	6.96%	14.15%	14.70%	0.65%	11.94%	-0.39%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	31.2%	51.9%	45.5%	36.1%	52.3%	47.8%
30	35.2%	52.3%	45.6%	39.7%	52.7%	49.0%
45	37.2%	53.4%	44.9%	39.0%	53.1%	49.3%
60	41.9%	53.7%	45.5%	45.3%	53.0%	48.6%
90	45.0%	54.1%	46.1%	46.9%	53.2%	49.7%
120	45.8%	53.8%	45.2%	48.1%	54.2%	49.6%
180	48.4%	54.6%	46.6%	49.8%	55.4%	50.3%
240	51.1%	51.8%	47.9%	52.1%	53.8%	50.2%
300	50.4%	48.1%	45.9%	52.0%	49.1%	50.0%
360	46.8%	45.1%	44.6%	50.7%	46.1%	50.1%
720	33.8%	43.3%	41.9%	42.9%	44.0%	53.2%
1440	33.8%	44.3%	42.7%	43.1%	45.1%	54.0%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	20.1%	-0.8%	13.3%	10.7%	-2.4%	0.5%
30	12.5%	-1.1%	9.4%	5.9%	-2.5%	0.1%
45	41.0%	-0.8%	8.4%	41.2%	-2.4%	0.3%
60	10.1%	-0.9%	10.1%	1.9%	-2.8%	0.3%
90	1.9%	-1.5%	6.7%	0.4%	-3.4%	-0.8%
120	3.0%	-1.5%	7.0%	-0.1%	-3.6%	-0.2%
180	1.2%	-1.8%	5.6%	-0.3%	-3.8%	-0.5%
240	0.3%	-1.0%	4.9%	-0.3%	-2.7%	-0.4%
300	1.2%	2.3%	11.5%	0.1%	0.7%	5.4%
360	2.8%	5.9%	14.6%	0.7%	4.1%	7.5%
720	7.6%	12.2%	13.8%	2.6%	10.8%	4.2%
1440	7.2%	11.4%	12.8%	2.5%	9.9%	3.5%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Southern California Edison Coastal Simulation Results

Figure 35 through Figure 36 presents the results for SCE Coastal across all seasons, and cloud cover conditions.

- Forecast Horizons of 15 Minutes Ahead to Four Hours Ahead. For forecast horizons of one-hour ahead up to four hours ahead, only the Model Direct approach combined with the CPR solar generation estimates outperformed the baseline load forecast model. For forecast horizons of less than one-hour ahead the baseline load forecast outperformed the alternative approaches.
- Forecast Horizons of Five Hours Ahead to Six Hours Ahead. For forecast horizons of five hours ahead to six hours ahead, the Model Direct approach combined with CPR solar generation estimates outperformed all other approaches.
- Forecast Horizons of 12 Hours Ahead to 24 Hours Ahead. For longer-term forecast horizons of 12 hours ahead to 24 hours ahead, the Error Correction and Reconstituted Load approaches were on average more accurate than the baseline load forecast.
- Seasonal Differences. The main difference between the winter and summer seasons is the Model Direct approach when combined with the CPR solar generation estimates performed during the winter season for forecast horizons of 30 minutes ahead to 24 hours ahead. In contrast, the Model Direct approach did not outperform the baseline model during the summer season across all forecast horizons.
- Cloud Cover. In contrast to other load zones, the alternative approaches appear to work best under clear cloud conditions. Most notably, the Model Direct approach when combined with the CPR solar generation estimates outperformed the baseline load forecast over forecast horizons of 30 minutes ahead to 24 hours ahead.

Figure 35: Southern California Edison Coastal, All Seasons, All Cloud Cover Conditions

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	11.40%	0.58%	24.66%	9.09%	0.97%	1.26%
30	7.53%	0.76%	19.49%	5.76%	0.41%	0.50%
45	11.98%	0.93%	17.80%	12.13%	0.16%	0.64%
60	15.10%	0.88%	22.95%	3.90%	-0.15%	0.97%
90	5.21%	1.74%	16.74%	5.09%	-0.29%	0.01%
120	10.20%	2.01%	19.29%	4.86%	-0.55%	0.76%
180	8.18%	2.27%	16.42%	5.62%	-0.61%	1.03%
240	6.25%	1.50%	11.34%	5.30%	-0.65%	-0.56%
300	0.61%	0.83%	13.75%	0.24%	-0.53%	4.20%
360	-3.80%	0.77%	11.00%	-4.35%	-0.34%	2.43%
720	-9.46%	0.76%	-3.11%	-10.61%	0.17%	-9.55%
1440	-9.55%	0.61%	-2.65%	-10.70%	0.01%	-6.89%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	37.8%	48.9%	39.4%	39.1%	47.9%	48.2%
30	39.6%	48.9%	40.1%	41.0%	49.3%	48.8%
45	41.0%	49.2%	39.9%	42.2%	50.5%	48.5%
60	40.9%	49.5%	40.5%	43.8%	51.5%	49.8%
90	40.0%	47.2%	41.1%	40.0%	49.8%	50.1%
120	40.0%	47.1%	40.5%	40.6%	50.7%	49.8%
180	40.0%	46.2%	41.4%	39.2%	51.1%	49.0%
240	42.0%	46.8%	42.3%	41.0%	49.1%	50.1%
300	49.1%	48.1%	45.4%	49.8%	49.0%	51.8%
360	53.0%	48.7%	46.8%	53.6%	49.1%	52.3%
720	57.4%	48.6%	54.2%	57.5%	49.8%	57.9%
1440	57.7%	48.9%	53.7%	57.6%	50.2%	56.9%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	5.8%	0.5%	16.4%	4.2%	0.5%	0.5%
30	4.9%	0.8%	12.4%	3.9%	0.7%	0.4%
45	8.1%	0.7%	11.4%	7.9%	0.5%	0.4%
60	10.6%	0.6%	16.7%	2.2%	0.1%	0.8%
90	3.1%	1.1%	12.0%	2.9%	0.2%	0.3%
120	6.4%	1.4%	14.5%	2.6%	-0.2%	1.0%
180	5.5%	1.7%	12.9%	3.6%	-0.1%	1.3%
240	5.8%	1.7%	10.0%	4.6%	0.5%	0.0%
300	1.9%	1.5%	11.4%	1.1%	1.0%	2.9%
360	-2.3%	1.3%	7.9%	-3.1%	1.0%	0.5%
720	-9.0%	0.9%	-4.7%	-10.0%	0.7%	-10.1%
1440	-9.2%	0.8%	-4.5%	-10.1%	0.6%	-8.3%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Figure 36: Southern California Edison Coastal, All Seasons, Clear

Change in Forecast Mean Absolute Percentage Error (%)

Forecast Horizon	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	13.28%	0.34%	21.79%	9.80%	0.71%	0.82%
30	8.23%	0.15%	17.35%	5.98%	-0.09%	-0.21%
45	13.27%	0.43%	15.98%	12.57%	-0.15%	-0.17%
60	14.70%	0.47%	21.71%	4.00%	-0.49%	0.80%
90	5.19%	1.55%	16.20%	5.02%	-0.69%	0.19%
120	9.63%	1.75%	18.87%	4.63%	-1.06%	0.85%
180	7.54%	1.92%	16.10%	5.37%	-1.19%	1.16%
240	5.63%	0.89%	11.45%	5.21%	-1.49%	0.04%
300	-0.25%	0.24%	13.52%	0.07%	-1.48%	4.63%
360	-4.98%	0.30%	10.65%	-4.64%	-1.14%	2.27%
720	-11.14%	0.48%	-3.48%	-11.29%	-0.20%	-10.68%
1440	-11.12%	0.32%	-2.94%	-11.27%	-0.35%	-7.94%

Forecast Skill (%)

Forecast Horizon	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	36.9%	48.7%	40.1%	39.0%	48.0%	48.6%
30	39.6%	49.0%	40.7%	41.5%	49.6%	49.5%
45	41.3%	49.3%	40.5%	42.5%	50.9%	48.6%
60	41.0%	49.8%	40.5%	43.8%	51.7%	49.7%
90	40.9%	46.9%	41.1%	40.8%	49.9%	49.8%
120	40.7%	47.1%	40.3%	41.2%	51.3%	49.7%
180	40.4%	46.0%	41.5%	39.5%	51.7%	48.6%
240	42.6%	47.0%	41.8%	41.7%	49.9%	49.4%
300	50.1%	48.7%	45.6%	50.3%	50.0%	51.2%
360	53.8%	49.2%	46.9%	53.8%	49.9%	52.2%
720	58.0%	48.7%	54.2%	57.3%	49.5%	58.4%
1440	56.2%	49.1%	53.6%	57.4%	49.9%	57.4%

Change in Forecast Error Standard Deviation (MW)

Forecast Horizon	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	6.3%	0.3%	15.0%	4.3%	0.4%	0.5%
30	5.3%	0.5%	11.7%	4.0%	0.5%	0.3%
45	9.0%	0.3%	11.0%	8.1%	0.3%	0.4%
60	10.6%	0.3%	16.8%	2.4%	-0.1%	1.0%
90	3.1%	0.8%	11.7%	2.9%	-0.1%	0.5%
120	5.7%	1.0%	13.8%	2.3%	-0.7%	1.0%
180	4.7%	1.2%	12.0%	3.0%	-1.0%	1.1%
240	4.8%	1.4%	9.5%	3.9%	-0.4%	0.0%
300	1.1%	1.5%	11.4%	0.4%	0.6%	3.2%
360	-2.9%	1.4%	7.9%	-3.8%	0.9%	0.8%
720	-9.4%	1.1%	-5.3%	-10.5%	0.8%	-10.4%
1440	-9.5%	1.0%	-5.0%	-10.5%	0.7%	-8.6%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Southern California Edison Inland Simulation Results

Figure 37 through Figure 38 presents the results for SCE Inland across all seasons, and cloud cover conditions.

- Forecast Horizons of 15 Minutes Ahead to Four Hours Ahead. For forecast horizons of one-hour ahead up to four hours ahead, only the Model Direct approach combined with CPR's and the Cloud Cover driven estimates of solar generation outperformed the baseline load forecast model.
- Forecast Horizons of Five Hours Ahead to Six Hours Ahead. For forecast horizons of five hours ahead to six hours ahead, the Model Direct approach combined with CPR solar generation estimates outperformed all other approaches.
- Forecast Horizons of 12 Hours Ahead to 24 Hours Ahead. For longer-term forecast horizons of 12 hours ahead to 24 hours ahead, the Error Correction and Reconstituted Load approaches were on average more accurate than the baseline load forecast.
- Seasonal Differences. The main difference between the winter and summer seasons is the Error Correction approach when combined with the CPR solar generation estimates performed well during the summer season, but not so in the winter season.
- Cloud Cover. In general, the alternative approaches combined with the CPR solar generation estimates worked better under Cloudy conditions.

Figure 37: Southern California Edison Inland, All Seasons, All Cloud Cover Conditions

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	7.39%	-0.58%	26.94%	5.58%	-0.57%	1.30%
30	4.46%	-0.62%	19.70%	3.14%	-1.12%	0.93%
45	14.59%	-0.58%	16.69%	15.29%	-1.86%	1.33%
60	13.75%	-0.46%	16.80%	1.11%	-2.24%	1.44%
90	1.02%	-0.28%	11.59%	0.86%	-2.10%	0.73%
120	5.30%	-0.29%	10.59%	0.34%	-2.33%	0.71%
180	2.59%	-0.22%	7.17%	0.32%	-2.53%	0.54%
240	1.92%	-0.34%	5.12%	0.52%	-2.12%	-0.13%
300	1.01%	0.42%	11.16%	-0.05%	-0.33%	2.37%
360	-0.15%	1.10%	11.44%	-1.17%	0.94%	-0.28%
720	-1.17%	1.56%	1.01%	-2.34%	1.61%	-12.49%
1440	-1.91%	1.54%	0.89%	-3.08%	1.55%	-12.90%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	41.1%	51.4%	40.4%	42.9%	51.5%	48.5%
30	42.9%	51.0%	41.3%	45.0%	50.7%	48.8%
45	42.8%	51.8%	41.4%	45.1%	51.5%	49.3%
60	42.3%	50.7%	41.7%	47.6%	52.0%	48.8%
90	46.1%	50.2%	42.8%	47.6%	51.6%	49.3%
120	46.1%	50.0%	42.7%	48.3%	51.8%	48.7%
180	47.2%	49.9%	44.9%	48.3%	51.8%	49.0%
240	48.9%	51.2%	46.0%	49.6%	51.2%	50.3%
300	49.4%	49.6%	46.3%	49.9%	50.3%	51.8%
360	50.7%	48.4%	46.4%	51.3%	48.7%	53.1%
720	50.8%	46.5%	53.2%	51.7%	46.2%	59.7%
1440	51.4%	46.3%	53.4%	52.4%	46.1%	60.2%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	3.6%	-0.3%	18.2%	2.1%	-0.4%	-0.6%
30	2.7%	-0.5%	14.3%	1.6%	-0.7%	0.2%
45	12.4%	-0.4%	12.8%	13.8%	-1.1%	0.9%
60	10.7%	-0.4%	13.6%	0.4%	-1.3%	1.1%
90	0.8%	-0.1%	9.3%	0.4%	-1.2%	0.4%
120	4.4%	-0.2%	9.4%	0.0%	-1.6%	0.6%
180	2.1%	-0.2%	7.2%	0.0%	-1.8%	0.7%
240	1.5%	-0.2%	4.6%	0.1%	-1.4%	0.0%
300	0.6%	0.4%	5.7%	-0.7%	-0.1%	0.7%
360	-0.8%	1.1%	4.2%	-2.0%	1.0%	-1.8%
720	-3.4%	1.5%	-4.2%	-4.4%	1.9%	-12.0%
1440	-3.6%	1.7%	-4.0%	-4.6%	2.0%	-12.2%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Figure 38: Southern California Edison Inland, All Seasons, Clear

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	8.70%	-0.65%	20.57%	5.82%	-0.40%	1.71%
30	5.09%	-0.68%	15.76%	3.23%	-0.61%	1.76%
45	15.56%	-0.59%	13.44%	16.04%	-1.04%	2.37%
60	10.26%	-0.44%	14.42%	0.51%	-1.48%	2.63%
90	0.46%	-0.20%	9.71%	0.30%	-1.46%	2.08%
120	2.87%	-0.24%	9.43%	-0.26%	-1.53%	2.71%
180	0.61%	-0.09%	6.64%	-0.18%	-1.91%	2.80%
240	0.22%	-0.27%	5.35%	0.25%	-1.76%	1.92%
300	-0.10%	0.42%	10.89%	-0.12%	-0.23%	3.97%
360	-0.80%	1.10%	10.13%	-1.07%	1.04%	1.01%
720	-1.51%	1.60%	-1.53%	-2.43%	1.68%	-11.78%
1440	-2.38%	1.59%	-1.60%	-3.20%	1.65%	-12.23%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	40.3%	52.1%	41.4%	43.0%	51.2%	48.3%
30	42.0%	50.7%	41.6%	44.9%	49.6%	48.1%
45	42.2%	51.7%	41.9%	45.4%	49.6%	48.5%
60	44.2%	50.6%	42.5%	48.7%	51.1%	47.5%
90	47.4%	49.3%	43.9%	49.1%	50.6%	48.6%
120	47.6%	49.2%	43.1%	49.7%	50.8%	47.4%
180	48.9%	49.5%	44.6%	49.7%	50.7%	47.6%
240	50.6%	51.2%	45.3%	50.4%	50.9%	48.8%
300	50.1%	49.5%	46.7%	50.4%	50.6%	50.9%
360	50.7%	48.5%	47.7%	51.1%	48.5%	53.0%
720	50.1%	47.0%	55.8%	51.3%	46.5%	60.2%
1440	50.8%	46.6%	56.0%	51.8%	46.4%	60.8%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	4.1%	-0.3%	12.5%	2.1%	-0.3%	-0.7%
30	3.2%	-0.5%	10.7%	1.7%	-0.5%	0.6%
45	13.2%	-0.4%	9.6%	14.4%	-0.6%	1.4%
60	7.5%	-0.3%	11.2%	0.0%	-0.8%	1.8%
90	0.4%	0.0%	7.7%	0.0%	-0.6%	1.6%
120	1.9%	0.0%	7.4%	-0.4%	-0.9%	2.2%
180	0.3%	0.0%	5.4%	-0.3%	-1.3%	2.1%
240	0.0%	-0.1%	3.5%	-0.2%	-1.1%	1.2%
300	-0.8%	0.4%	4.4%	-1.0%	0.0%	1.5%
360	-2.1%	1.1%	2.3%	-2.3%	1.1%	-1.3%
720	-4.6%	1.7%	-6.6%	-4.9%	2.1%	-11.5%
1440	-4.8%	1.8%	-6.4%	-5.1%	2.2%	-11.8%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

San Diego Gas & Electric Total Simulation Results

Figure 39 through Figure 40 presents the results for SDG&E across all seasons, and cloud cover conditions.

- Forecast Horizons of 15 Minutes Ahead to Four Hours Ahead. For forecast horizons of up to four hours ahead, the Model Direct approach consistently outperformed the baseline load forecast model with both a reduced MAPE and smaller dispersion of forecast errors. Further, the Model Direct approach performed better than the baseline forecast when using both Cloud Cover driven estimates and CPR computed solar generation estimates. However, the Model Direct approach when combined with the CPR solar generation estimates outperformed the same approach combined with the Cloud Cover driven solar generation estimates.
- Forecast Horizons of Five Hours Ahead to Six Hours Ahead. For forecast horizons of five hours ahead to six hours ahead, the Model Direct approach combined with both Cloud Cover driven and CPR solar generation estimates outperformed the baseline load forecast in terms of both accuracy and reduction of forecast error dispersion.
- Forecast Horizons of 12 Hours Ahead to 24 Hours Ahead. For longer-term forecast horizons of 12 hours ahead to 24 hours ahead, again the Model Direct approach combined with both Cloud Cover driven and CPR solar generation estimates outperformed the baseline load forecast in terms of both accuracy and reduction of forecast error dispersion.
- Seasonal Differences. The main difference between the winter and summer seasons is that the performance of the Reconstituted Loads approach degrades during the summer season.
- Cloud Cover. There were no substantial differences between the alternative approaches performance under cloudy versus sunny conditions.

Figure 39: San Diego Gas & Electric Total, All Seasons, All Cloud Cover Conditions

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	17.83%	-0.83%	48.70%	14.05%	-3.10%	4.52%
30	8.51%	-0.82%	36.03%	6.25%	-3.97%	2.42%
45	16.97%	-0.47%	29.75%	25.13%	-5.43%	1.99%
60	21.53%	-0.78%	31.77%	2.51%	-6.03%	0.88%
90	0.79%	-0.85%	25.08%	1.34%	-7.28%	-2.33%
120	8.82%	-0.60%	22.01%	1.57%	-8.36%	-2.44%
180	4.26%	-0.85%	16.55%	1.39%	-10.00%	-4.21%
240	3.18%	-1.40%	12.95%	1.04%	-10.48%	-5.35%
300	2.85%	-2.30%	10.81%	-0.27%	-11.02%	-7.08%
360	4.37%	-2.91%	8.24%	-1.23%	-10.96%	-9.42%
720	17.67%	-4.46%	2.35%	0.96%	-8.72%	-14.51%
1440	18.91%	-4.75%	-4.64%	1.70%	-9.32%	-14.59%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	34.1%	52.2%	36.1%	33.9%	54.9%	48.0%
30	38.3%	52.3%	37.4%	36.7%	55.6%	49.0%
45	38.7%	51.6%	38.8%	37.7%	56.3%	49.9%
60	38.8%	51.9%	39.3%	40.4%	57.3%	50.2%
90	42.3%	51.4%	40.0%	39.7%	56.9%	51.8%
120	42.1%	50.7%	42.3%	40.7%	57.9%	52.2%
180	43.8%	51.0%	43.6%	41.3%	58.8%	52.9%
240	45.4%	50.9%	44.5%	42.6%	58.3%	52.8%
300	45.2%	52.2%	44.6%	44.0%	58.3%	52.8%
360	43.3%	52.9%	45.9%	44.4%	57.7%	53.8%
720	36.3%	55.0%	50.1%	42.0%	55.8%	55.2%
1440	35.9%	55.4%	51.6%	41.2%	56.4%	55.2%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	10.5%	-0.4%	41.9%	7.6%	-1.8%	3.0%
30	6.3%	-0.4%	31.4%	4.0%	-2.5%	2.3%
45	15.1%	-0.1%	26.0%	29.0%	-3.6%	3.0%
60	20.5%	-0.4%	29.5%	1.6%	-4.1%	2.4%
90	0.8%	-0.4%	23.0%	0.6%	-5.0%	-1.2%
120	8.1%	-0.3%	21.1%	0.3%	-6.4%	-1.0%
180	3.1%	-0.3%	15.6%	0.2%	-7.4%	-2.3%
240	1.9%	-0.4%	12.1%	-0.3%	-7.6%	-3.5%
300	2.0%	-0.9%	10.1%	-1.4%	-7.8%	-5.0%
360	3.9%	-1.5%	9.0%	-2.1%	-7.8%	-7.2%
720	16.2%	-3.8%	10.7%	0.1%	-7.2%	-12.9%
1440	17.2%	-4.1%	-4.8%	0.6%	-7.7%	-13.3%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Figure 40: San Diego Gas & Electric Total, All Seasons, Clear

Change in Forecast Mean Absolute Percentage Error (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	22.81%	-0.92%	42.26%	14.99%	-2.63%	2.84%
30	10.64%	-0.66%	31.87%	5.90%	-3.21%	1.12%
45	19.63%	-0.45%	26.37%	25.82%	-4.64%	0.71%
60	20.48%	-0.75%	29.87%	0.99%	-4.78%	0.69%
90	-0.25%	-0.56%	23.10%	-0.34%	-6.16%	-2.46%
120	7.88%	-0.15%	21.10%	-0.01%	-6.96%	-1.78%
180	3.08%	-0.24%	15.56%	-0.18%	-8.78%	-2.99%
240	1.83%	-0.91%	11.93%	0.09%	-9.16%	-3.85%
300	2.05%	-1.97%	10.77%	-0.45%	-10.09%	-5.69%
360	3.40%	-2.85%	8.67%	-0.60%	-10.17%	-8.16%
720	15.33%	-4.23%	3.41%	2.64%	-7.34%	-12.72%
1440	16.45%	-4.29%	-4.10%	3.64%	-7.62%	-12.64%

Forecast Skill (%)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	32.7%	52.6%	37.1%	33.8%	55.1%	48.9%
30	38.2%	51.7%	38.5%	37.7%	55.8%	49.6%
45	39.4%	51.5%	39.8%	39.0%	56.6%	50.5%
60	40.2%	51.5%	40.6%	42.5%	57.0%	50.4%
90	44.2%	49.9%	40.9%	42.2%	56.8%	52.0%
120	44.4%	48.8%	42.8%	43.2%	57.5%	52.1%
180	46.7%	49.4%	44.4%	44.6%	58.8%	52.8%
240	47.4%	49.3%	45.1%	44.8%	58.3%	52.6%
300	45.5%	50.8%	44.4%	45.0%	57.7%	52.6%
360	42.9%	52.0%	45.8%	44.4%	57.5%	54.0%
720	35.7%	54.4%	49.1%	40.5%	54.8%	54.1%
1440	35.2%	54.5%	50.6%	39.4%	55.1%	54.0%

Change in Forecast Error Standard Deviation (MW)

	Behind-the-Meter Solar Generation Source: Cloud Cover			Behind-the-Meter Solar Generation Source: Clean Power Research		
Forecast Horizon Minutes Ahead	Error Correction	Model Direct	Reconstituted Loads	Error Correction	Model Direct	Reconstituted Loads
15	13.6%	-0.8%	36.0%	8.3%	-1.5%	1.7%
30	8.1%	-0.5%	27.4%	4.0%	-1.9%	1.5%
45	19.5%	-0.1%	22.9%	32.1%	-2.9%	2.3%
60	19.5%	-0.5%	27.4%	0.6%	-3.2%	2.3%
90	0.2%	-0.3%	20.7%	-0.9%	-4.2%	-0.4%
120	7.0%	-0.1%	19.6%	-0.8%	-5.2%	-0.1%
180	1.9%	0.1%	14.1%	-1.0%	-6.5%	-0.9%
240	0.3%	0.0%	11.1%	-1.3%	-6.8%	-1.9%
300	-0.2%	-0.6%	10.1%	-2.0%	-7.1%	-3.8%
360	0.4%	-1.3%	10.0%	-2.4%	-7.0%	-5.7%
720	8.1%	-3.7%	13.6%	-0.4%	-5.8%	-11.5%
1440	7.7%	-3.9%	-4.5%	-0.2%	-6.3%	-11.9%

*** Values that represent an improvement over the baseline load forecast are highlighted in green.**

Source: Clean Power Research

Statistical Estimates of Solar Photovoltaic Load Impacts

A benefit of the Model Direct approach is that it allows the statistical models through the process of model estimation to determine the forecasted load impact of a MW of Solar PV generation. Engineering principles suggest that every 1 MW of Solar PV generation directly offsets 1 MW of load. Based on these principles, one expects the estimated coefficients on the Solar PV variables to be equal to or very close to -1.0. In fact, the coefficients on the Solar PV variables in the Error Correction and Reconstituted Load approaches were explicitly set equal to -1.0 for just this very reason. Engineering principles, however, do not account for behavioral changes that may have taken place with the penetration of Solar PV. A plausible behavioral change is the increased use of air conditioning equipment post installation of Solar PV. Prior to installing Solar PV, consumers may not have run their air conditioners when they were at work to save money. Post Solar PV installation, the idea that they now have “free” electricity might lead consumers to leave their air conditioners on all the time regardless of whether they are home or not. In this example, 1 MW of Solar PV generation still offsets 1 MW of load, but that reduction may be masked by a load increase driven by the behavioral change. As a result, one may not realize an engineering-based *a priori* value of -1.0 for the estimated coefficient on the Solar PV variable.

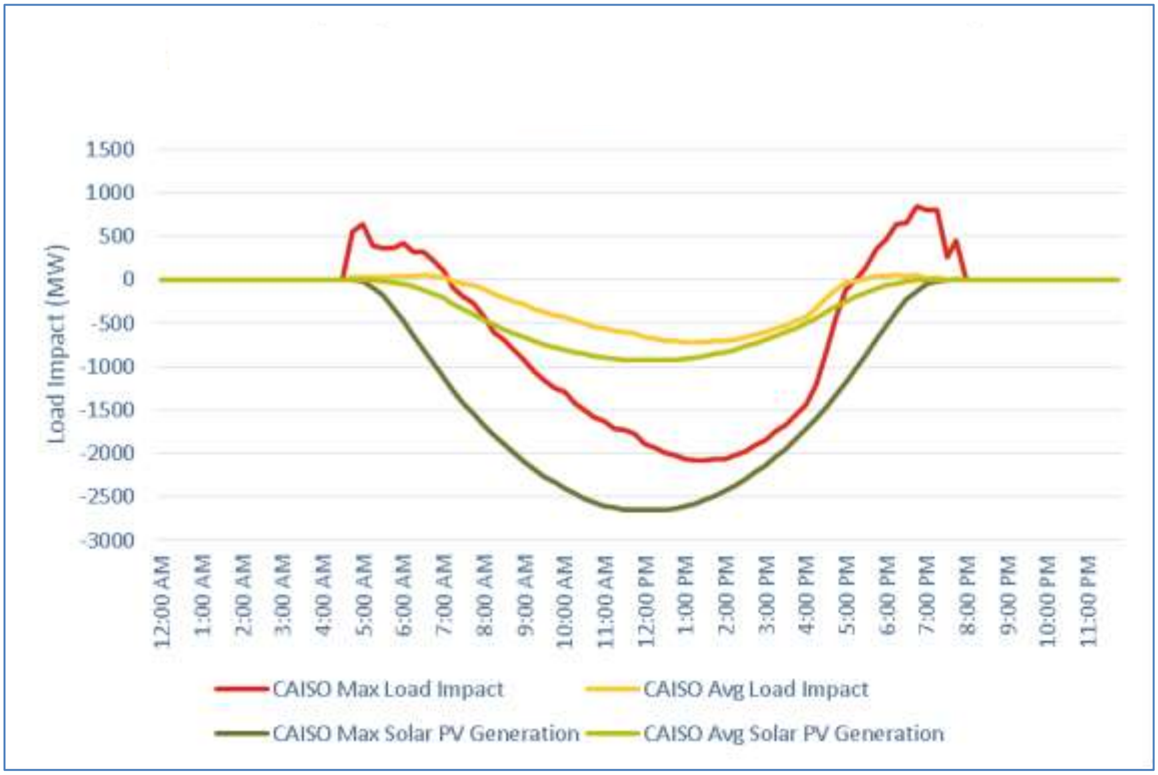
Other confounding factors include prevailing weather conditions and the mix of space heating and space conditioning that exists in the load zone. A hot, cloudy day may offset the lower Solar PV generation value with higher air conditioning loads especially in load zones that have high penetrations of air conditioning. That same hot, cloudy day in an area with low air conditioning saturations may have the full impact of the Solar PV generation because of the lack of offsetting air conditioning loads. In a similar fashion, a cold, cloudy morning might lead to the compounding of a load increase associated with lower Solar PV generation by an increase in electric space heating loads.

In general, weather and behavioral driven utilization of space conditioning equipment will complicate the observed load impact of Solar PV generation. Without detailed measurement of end-use equipment loads, it is difficult for a statistical model to isolate the impact of Solar PV generation on measured loads. Unfortunately, the challenge of isolating the impact of Solar PV on measured loads will only become more complex with saturation of electric vehicle charging and behind-the-meter storage, which will provide consumers flexibility with when they will use the electricity generated by their solar panels. In this soon-to-be-here world, the 1 MW of solar generation at Noon may offset 1 MW of vehicle charging at midnight. This type of behavioral change will further mask the load impact of Solar PV generation.

Presented in Figures 41-44 are the statistically estimated load impacts under average solar and maximum solar conditions for the California ISO total and each of the load zones. In the figures, the dashed yellow line represents CPR’s estimate of maximum Solar PV generation over the 2014-2015 period. The blue dashed line represents CPR’s estimate of average Solar PV Generation over the same period. The solid gold line is the statistically adjusted maximum Solar PV generation impact that Itron computed as the product the CPR’s maximum Solar PV generation and the estimated coefficient on the Solar PV variable from each of the 96 Day-

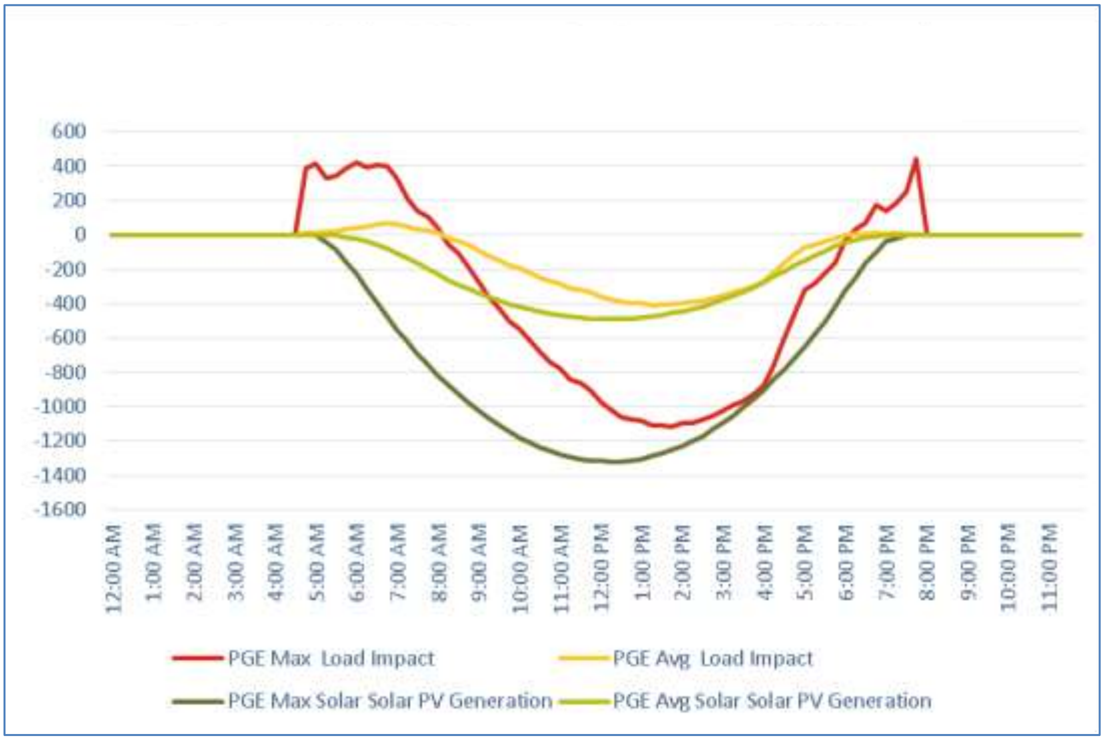
Ahead models. The solid blue line is the statistically adjusted average Solar PV generation impact that Itron computed as the product the CPR's average Solar PV generation and the estimated coefficient on the Solar PV variable from each of the 96 Day-Ahead models.

Figure 41: Estimated Load Impact of Solar Photovoltaic Generation: California Independent System Operator Total



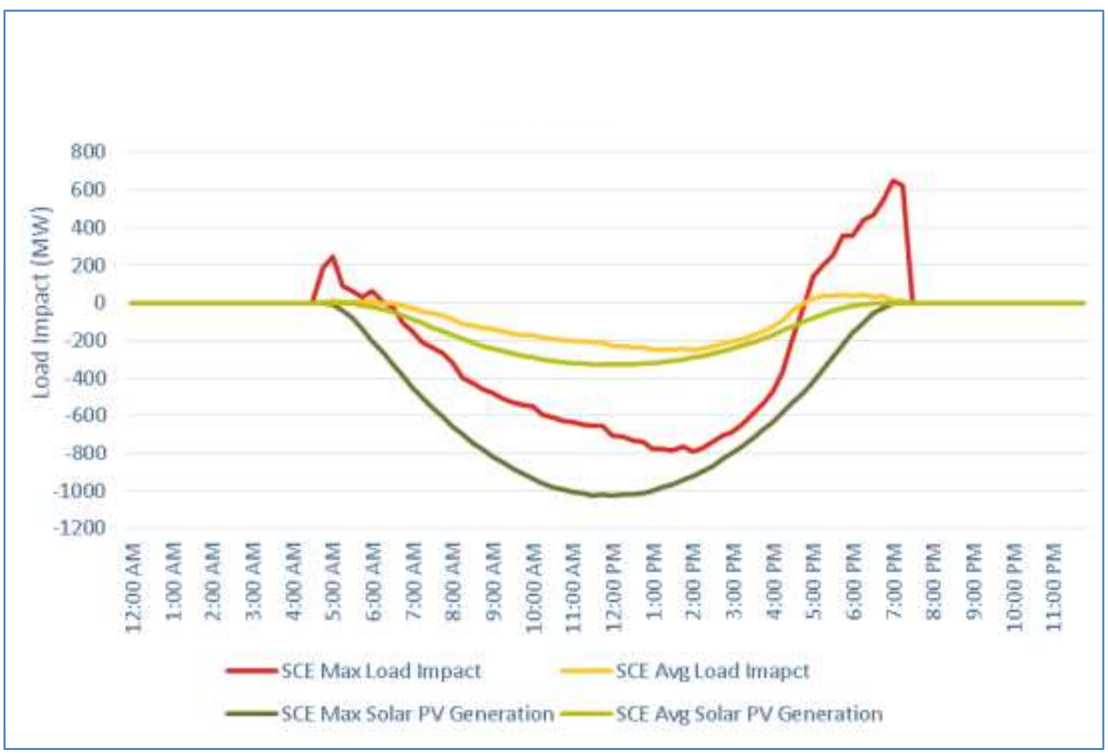
Source: Clean Power Research

Figure 42: Estimated Load Impact of Solar Photovoltaic Generation: Pacific Gas & Electric Total



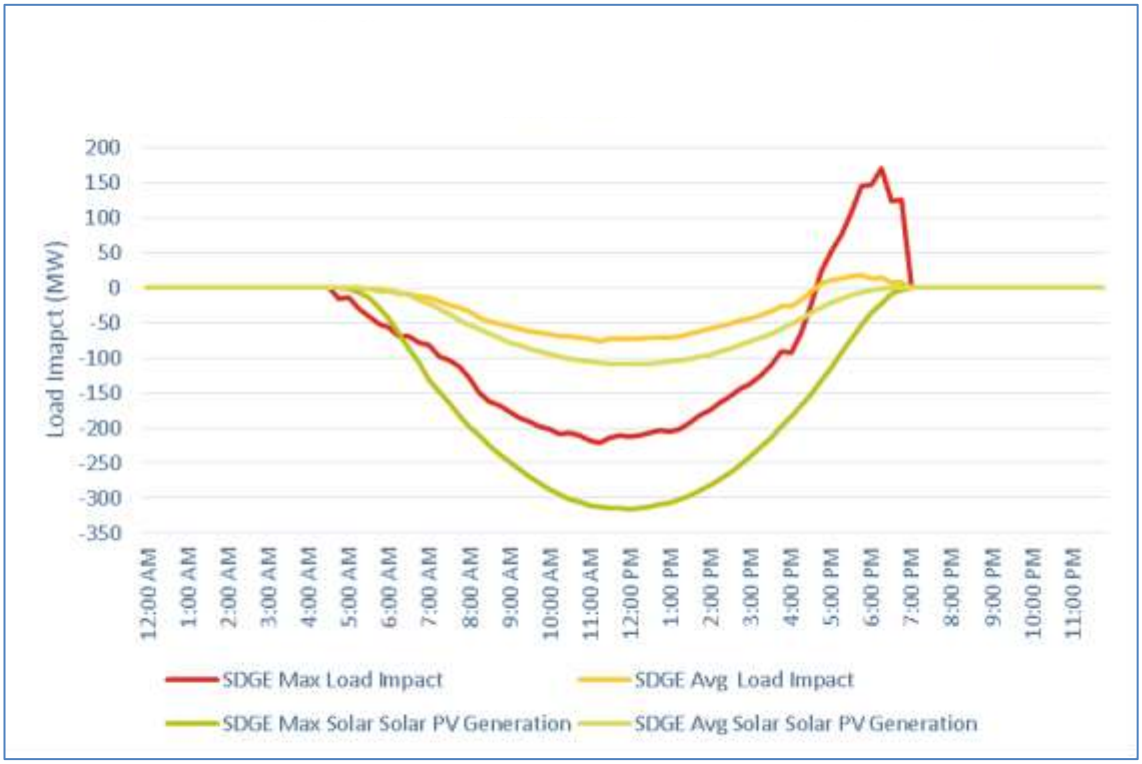
Source: Clean Power Research

Figure 43: Estimated Load Impact of Solar Photovoltaic Generation: Southern California Edison Total



Source: Clean Power Research

Figure 44: Estimated Load Impact of Solar Photovoltaic Generation: San Diego Gas & Electric Total



Source: Clean Power Research

Observations about these data include:

- On average, the estimated coefficients place less weight on the Solar PV generation in the mid-morning hours (08:00 to Noon) than the mid-afternoon hours (Noon to 16:00). During the mid-morning hours, Itron adjusted the load forecast down by approximately 50 percent of the Solar PV generation estimate. In the mid-afternoon hours, Itron adjusted the load forecast down by approximately 77 percent of the Solar PV estimate.
- The estimated coefficients on the early morning (pre 08:00) and late afternoon (post 16:45) potentially indicate a behavioral change associated with the trend in Solar PV installations that was leading to higher forecasted loads in both these periods. This impact was most pronounced under maximum solar conditions with an estimated impact of a little over 840 MW at 19:00. Under average solar conditions, Itron estimated the late afternoon pick up in loads to be about 60 MW. This leads to the potential swing in forecasts of late afternoon loads of about 780 MW.
- All three IOUs display a bump up in loads post 16:45 that is associated with the penetration of Solar PV. At 19:00, SCE estimated impact under maximum solar conditions was a little over 540 MW. Under average solar conditions the average load impact at 19:00 was about 30 MW. This implies a potential swing in forecasted loads

between a maximum solar condition day and an average solar condition day of about 510 MW.

- At 19:00, PG&E estimated impact under maximum solar conditions was a little over 170 MW. Under average solar conditions, the average load impact at 19:00 was about 15 MW. This implies a potential swing in forecasted loads between a maximum solar condition day and an average solar condition day of about 160 MW.
- At 19:00, PG&E estimated impact under maximum solar conditions was a little over 120 MW. Under average solar conditions, the average load impact at 19:00 was about 5 MW. This implies a potential swing in forecasted loads between a maximum solar condition day and an average solar condition day of about 115 MW.
- In the early morning hours (pre-08:00) there was a similar forecasted rise in loads associated with penetration in Solar PV. This impact was most pronounced with PG&E with an estimated load impact of about 400 MW under maximum solar conditions. Itron estimated the impact on SCE early morning hours to be a little over 200 MW under maximum solar conditions. SDG&E does not have this type impact.

The results highlight another operational challenge in that the impact of Solar PV generation varies not only in magnitude across the three IOUs, but also the timing of the maximum impact. This reflects the fact that the time at which the sun is at its zenith depends on where the loads are located. The geographic distance between the PG&E, SCE and SDG&E is sufficient to lead to differences in when the solar generation impact will be at its highest. This in turn implies the timing and order of magnitude of the late afternoon ramp-up in loads associated with a ramping down of Solar PV generation will vary across the year and across the three IOU loads.

The analysis of the statistically adjusted load impact of Solar PV generation reflects the challenge with the Model Direct approach. In all cases, one rejects the engineering-based *a priori* value for the estimated coefficient on the Solar PV generation variable of -1.0. This does not mean that one (1) MW of Solar PV generation does not reduce load by one (1) MW. Rather models of measured load are challenged in isolating the impact of Solar PV generation from other potentially highly correlated factors that drive weather sensitive loads. Further, the estimated coefficients on the Solar PV generation variables will be skewed to account for these behavioral changes to the extent penetration of Solar PV leads to behavioral changes whereby people are taking advantage of "free" electricity. While it would be nice to have all of the estimated coefficients with a value close to -1.0, the goal was to improve the load forecast. To that end, the statistical models optimize the coefficient values to reduce load forecast errors. By not imposing *a priori* constraints on the estimated coefficients, the models are able to capture the net impact of a growing penetration of Solar PV.

Chapter 5: Forecasting Valuation and Framework Analysis

Introduction and Background

The goals of this research task are 1) to analyze costs to determine the value of utilizing improved PV solar forecasts to utilities, grid operators, and California investor-owned utility (IOU) ratepayers; and 2) to leverage the improved forecasts and data from the earlier tasks to help utilities and the California ISO better integrate increasing amounts of renewables on the grid with lower costs. This section discusses these goals.

The valuation of any increased accuracy of the net load forecast from an alternative forecast method over the California Independent System Operator (California ISO) baseline forecast is dependent on the timeframe of the forecast. In the case of the research14 demonstrated in Task 4 that this cost analysis applies to, the timeframe is the day-ahead and day-of. This is important because it determines what costs are relevant in determining the value of an alternative forecast method.

Valuation of Alternative Forecast Method

The fundamental premise with using short term market pricing is that the forecast (Baseline or Alternative) used doesn't matter because at the end of the day, the actual electricity consumed is the same. Therefore, the valuation is dependent on three components; 1) the cost of reserving resources the day-ahead to supply the forecasted load, 2) the cost of making day-of adjustments to the forecasted load, and 3) the cost of making final adjustments to cover the difference between the forecasted load and the actual load.

The first element of the valuation is the calculation of the cost to reserve supply the day ahead based on each of the respective day ahead forecasts. Itron used the day ahead market (DAM) locational marginal price (LMP) to value the differences between the Baseline and Alternative forecasts. The size of these forecast differences was relatively small compared to the total forecasted net load. It is reasonable to use DAM LMP prices to value the forecast differences because the total amount of energy associated with the differences in the forecasts can reasonably be purchased in the DAM.

The second element of the valuation is the calculation of the cost to adjust the reserved supply in the day-of based on the day-of forecasts. The California ISO Trues-up the forecast in the day-of market. These are purchased in the hour ahead scheduling process (HASP) at HASP LMP

[14] Monforte, Dr. Frank A.; Fordham, Christine; Blanco, Jennifer; Barsun, Stephan (Itron, Inc.) Kankiewicz, Adam; Norris, Ben (Clean Power Research). 2016. Improving Short-Term Load Forecasts by Incorporating Solar PV Generation. California Energy Commission.

prices. The team used the differences between the day-ahead and the day-of forecasts multiplied by the HASP LMP for this valuation element.

Note, the team chose not to include the congestion charges associated with DAM LMP and HASP LMP. The team did not include congestion charges because they are very locational and too granular for this analysis.

The third element of the valuation is a little more complex due to the nature of the market that handles forecast error. The California ISO handles forecasting errors in the Ancillary Services (AS) markets through Regulation Up (RU) and Regulation Down (RD). The California ISO purchases most of regulation capacity in the DAM with true-ups in the hour ahead market. To simplify the calculation, the team assumed final regulation prices are established in the DAM.

Valuation Methodology

The valuation analysis used two Baseline hourly forecasts (24 hours ahead and two hours ahead) and two alternative hourly forecasts (Reconstituted Load with Clean Power Research's (CPR) estimates at 24 hours ahead and Model Direct w/ CPR estimates at 120 minutes or two hours ahead). The DA LMP cost calculations used the 24 hours ahead forecasts. The HASP LMP cost calculations used the difference between the 24 hours ahead forecasts and the two hours ahead forecasts, and the regulation costs used the two hours ahead forecasts. The actual or real-time costs used the ancillary services pricing and took into consideration whether the two hours ahead forecast was over or under predicting the actual load. Itron used regulation down pricing if the forecast was too high and regulation up pricing if the forecast was too low. These three-time periods coincide with the associated ISO settlement markets.

The team computed the total valuation by summing the day ahead costs, the day-of costs and the regulation costs for each forecast (baseline and then taking the difference between them daily). The difference in costs will be the value of the improved net load forecast. This calculation used the following equation:

$$Value_h = \sum_{h=1}^{24} \Big[\big((LMP_h \times BDAF_h) + \big(HASPLMP \times (BDOF_h - BDAF_h)\big) + \big(AS_h \times (AL_h - BDOF_h)\big) \big) \\ - \big((LMP_h \times ADAF_h) + \big(HASPLMP \times (ADOF_h - ADAF_h)\big) + \big(AS_h \times (AL_h - ADOF_h)\big) \big) \Big]$$

Where:

Value$_h$ =	**Hourly Valuation**
LMP$_h$ =	Locational Marginal Price for hour h
HASPLMP$_h$	Hour Ahead Scheduling Process Locational Marginal Price for hour h
BDAF$_h$ =	Baseline Day-Ahead Forecast for hour h
BDOF$_h$	Baseline Day-of Forecast for hour h
AS$_h$ =	Ancillary Services Price (Regulation Up or Regulation Down) for hour h

AL_h =	Actual Load for hour h
$ADAF_h$ =	Alternative Day-Ahead Forecast for hour h
$ADOF_h$	Alternative Day-of Forecast for hour h

The project team evaluated each of the five California ISO subzones (PG&E Bay Area, PG&E Non-Bay Area, SCE Coastal, SCE Inland, and SDG&E) and for the California ISO. The date range for conducting the valuation analysis goes from January 1, 2012 through June 8, 2015.

To better understand the influence of market prices on the forecast valuation, the following sub-sections summarize them and their associated seasonality and volatility.

Locational Marginal Prices

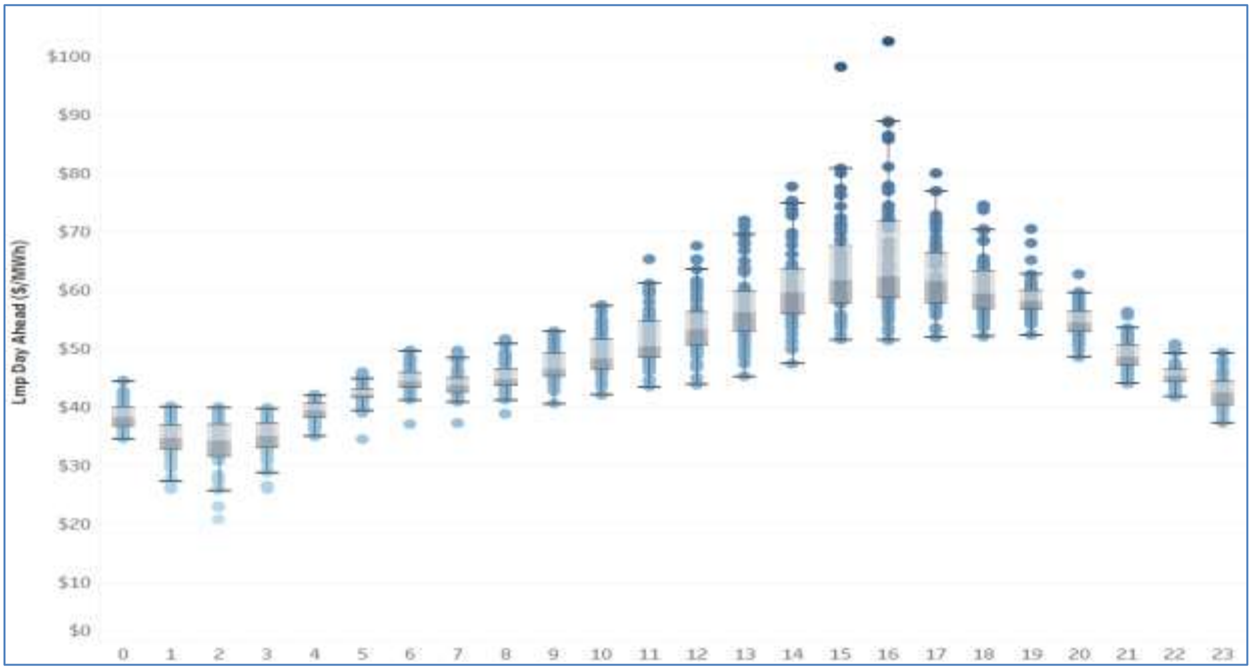
The DAM provides the LMP for all nodes managed by the California ISO. These nodal LMPs have three components. The first is the energy component, the second is the congestion charge for that location, and the third is associated with line loses. The energy component is the same for all nodes. Only the energy component for the valuation analysis was used.

Figure 45 and Figure 46 show the range of hourly LMPs for the summer 2014 and the spring 2015 respectively using box-and-whisker plots. Box and whisker plots illustrate the degree of dispersion, skewness and general variability of the data. There is a box representing each hour of all days in the period. The line in the center of each greyed box is the median price value and the ends of the box are the interquartile value (IQR)[15] in distance from the center line. The spread of one IQR on either side of the center line represents the spread where 50 percent of the values lie. The lines or whiskers further outside the box on either end are 1.5 times the IQR.

During the summer season, the LMP profile looks much like the system load profile with the greatest variation in price occurring at the system peak hours. During the other seasons, the average LMPs during the mid-day hours are relatively flat, but the day to day prices range widely for a given hour.

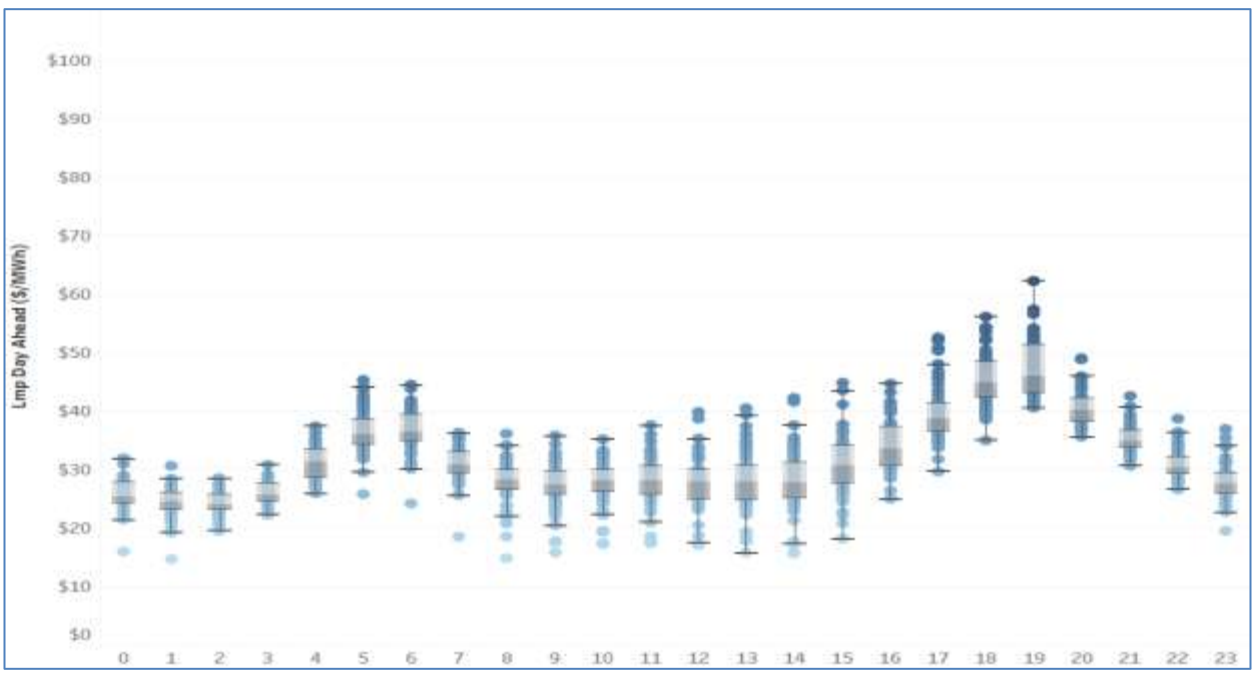
[15] See: https://en.wikipedia.org/wiki/Interquartile_range

Figure 45: Weekday Hourly Locational Marginal Price Prices – Summer 2014



Source: California ISO Open Access Same-time Information System (OASIS)

Figure 46: Weekday Hourly Locational Marginal Price Prices – Spring 2015



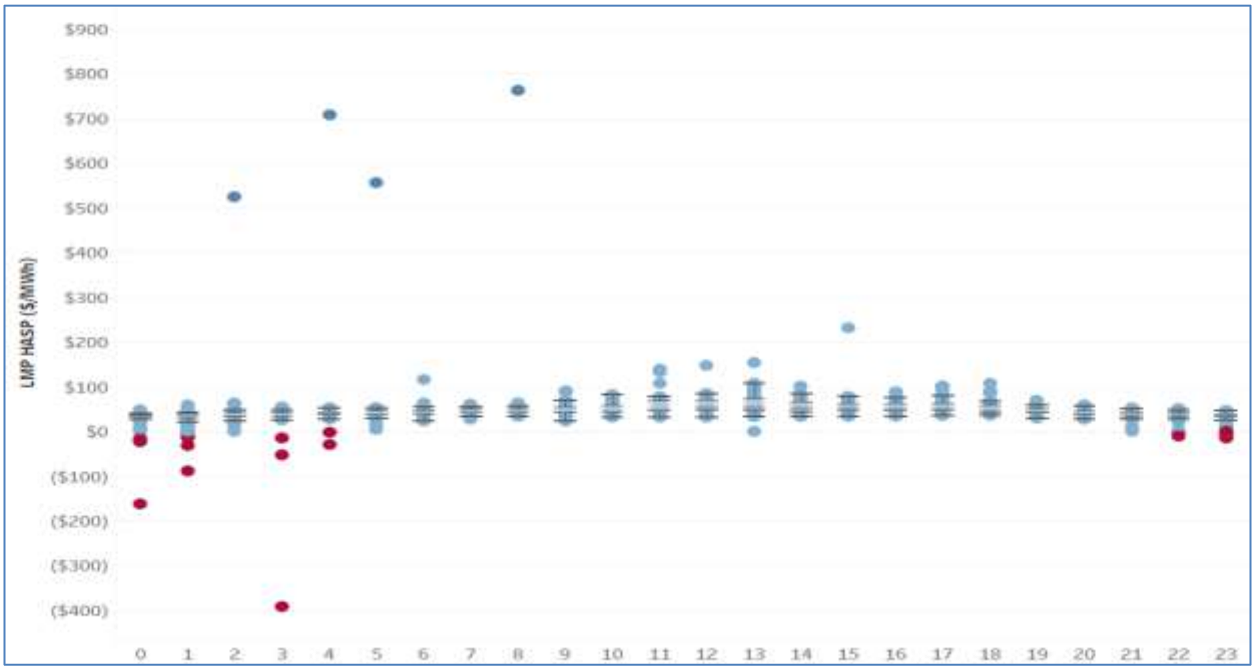
Source: California ISO Open Access Same-time Information System (OASIS)

Hour Ahead Locational Marginal Prices

The team used the HASP LMP prices for the day-of valuation analysis. As in the DA market, the HASP LMPs have three components. The valuation analysis only used the energy price component because it was the same across all nodes.

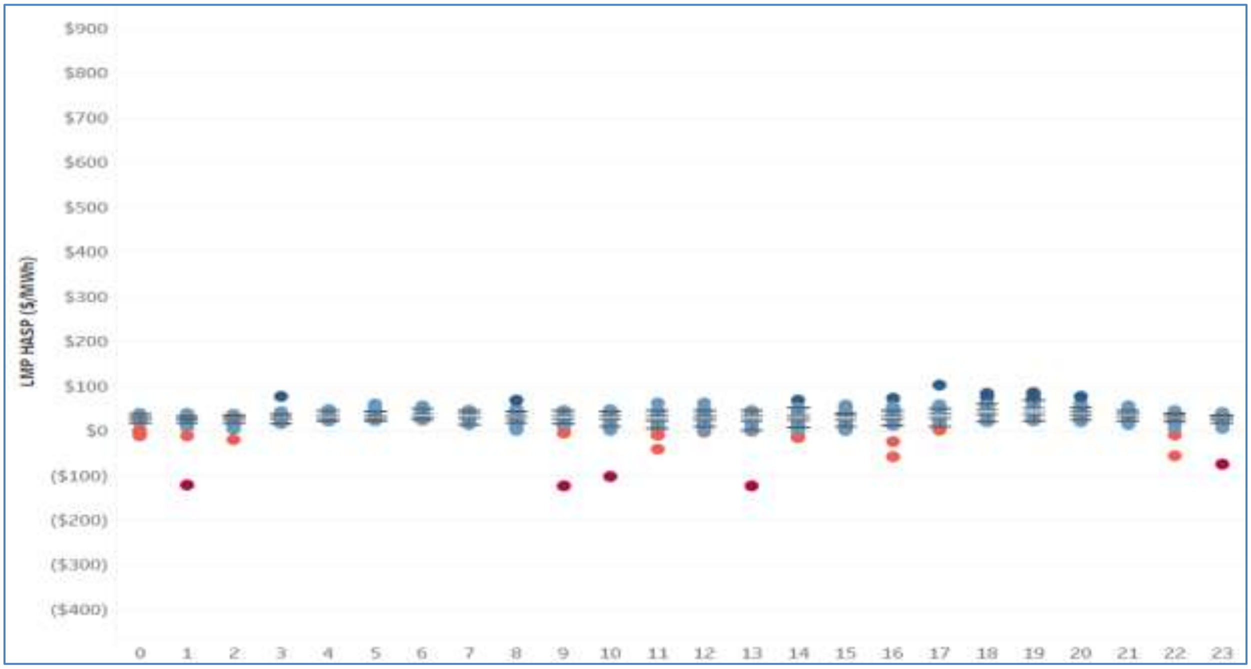
During all the seasons, the HASP LMP profile was relatively flat with occasional price spikes in both the positive and negative directions. Figure 47 and Figure 48 show the range of hourly LMPs for the summer 2014 and the spring 2015, respectively, using box-and-whisker plots. The spread in the prices was slightly greater in the middle of the day as opposed to mornings and evenings. However, the spikes can be extreme compared to the IQR.

Figure 47: Weekday Hourly Hour Ahead Scheduling Process Locational Marginal Price – Summer 2014



Source: California ISO Open Access Same-time Information System (OASIS)

Figure 48: Weekday Hourly Hour Ahead Scheduling Process Locational Marginal Price – Spring 2015



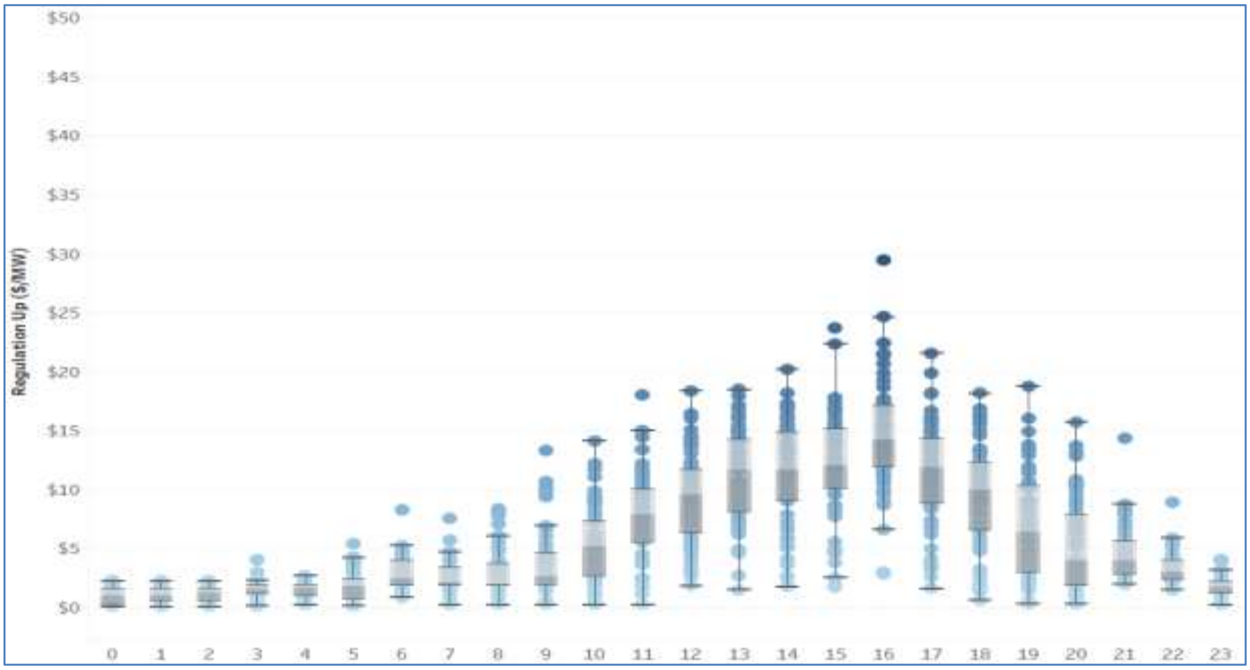
Source: California ISO Open Access Same-time Information System (OASIS)

Ancillary Services Prices

Regardless of the season, the regulation down (RD) prices are smaller than the regulation up (RU) prices particularly in the middle of the day. The price profile for RU and RD are noticeably different. In the summer, RU prices peak in the afternoon whereas RD tends to peak more in the early morning. In the spring, RU prices tend to peak in the morning and then again in the evening, whereas RD prices tend to be highest in the middle of the day and lowest in the morning and the evening, except for winter. Peak RU prices have been anywhere from double to four times greater than the RD prices. To illustrate this, the range of RU and RD prices during the summer 2014 and the spring 2015 using box and whisker graphs in Figure 49 through Figure 52, respectively.

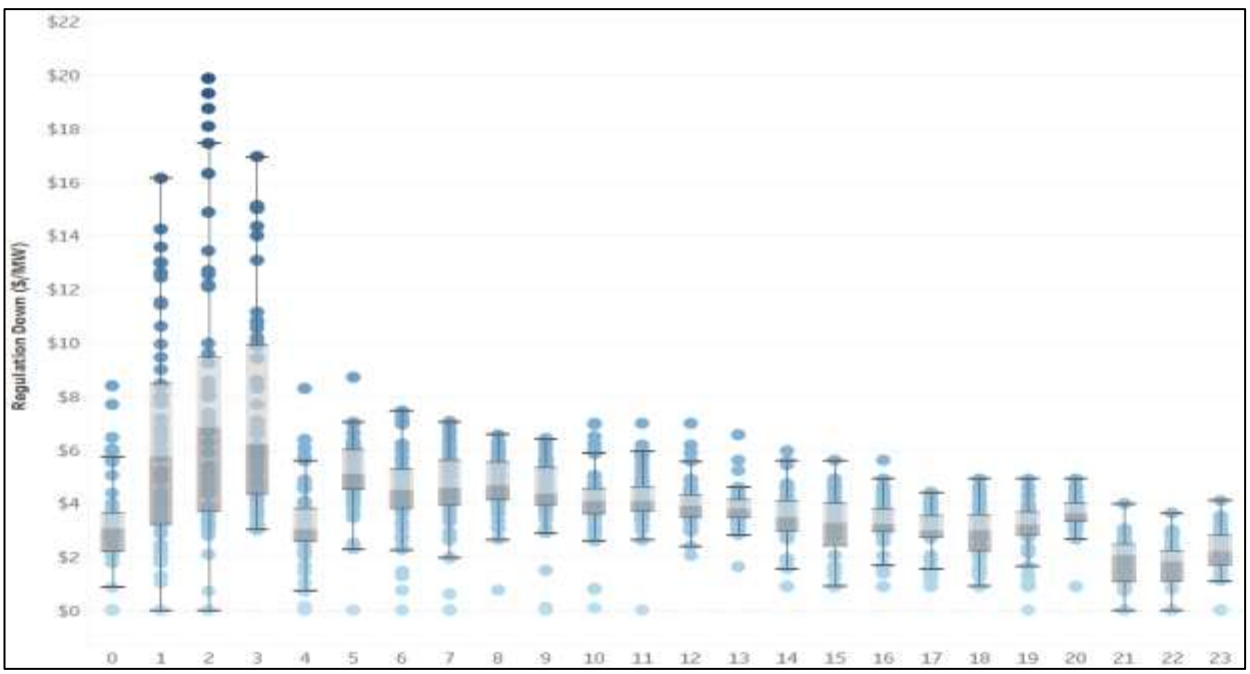
The range of RU prices in any given hour can be significant. Except for summer, the range in RU prices was relatively low over the hours where solar generation occurs. In the spring, the highest RU prices happen later in the day with the peak happening at 9 p.m.

Figure 49: Weekday Regulation Up Prices – Summer 2014



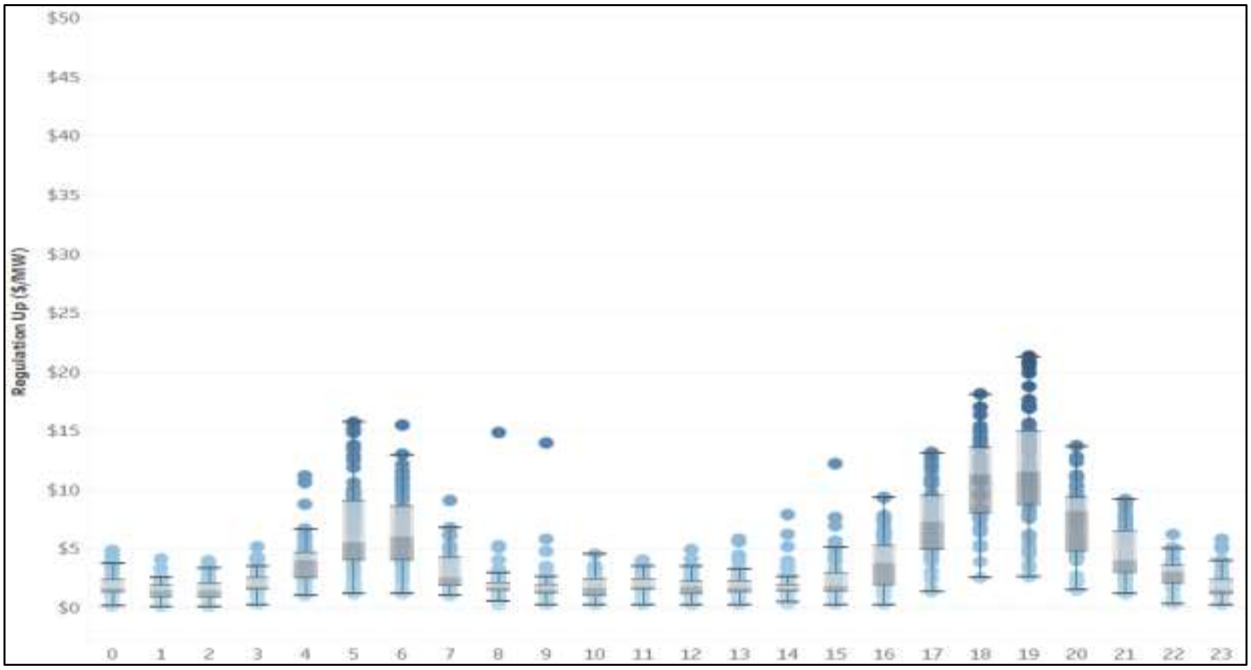
Source: California ISO Open Access Same-time Information System (OASIS)

Figure 50: Weekday Regulation Down Prices – Summer 2014



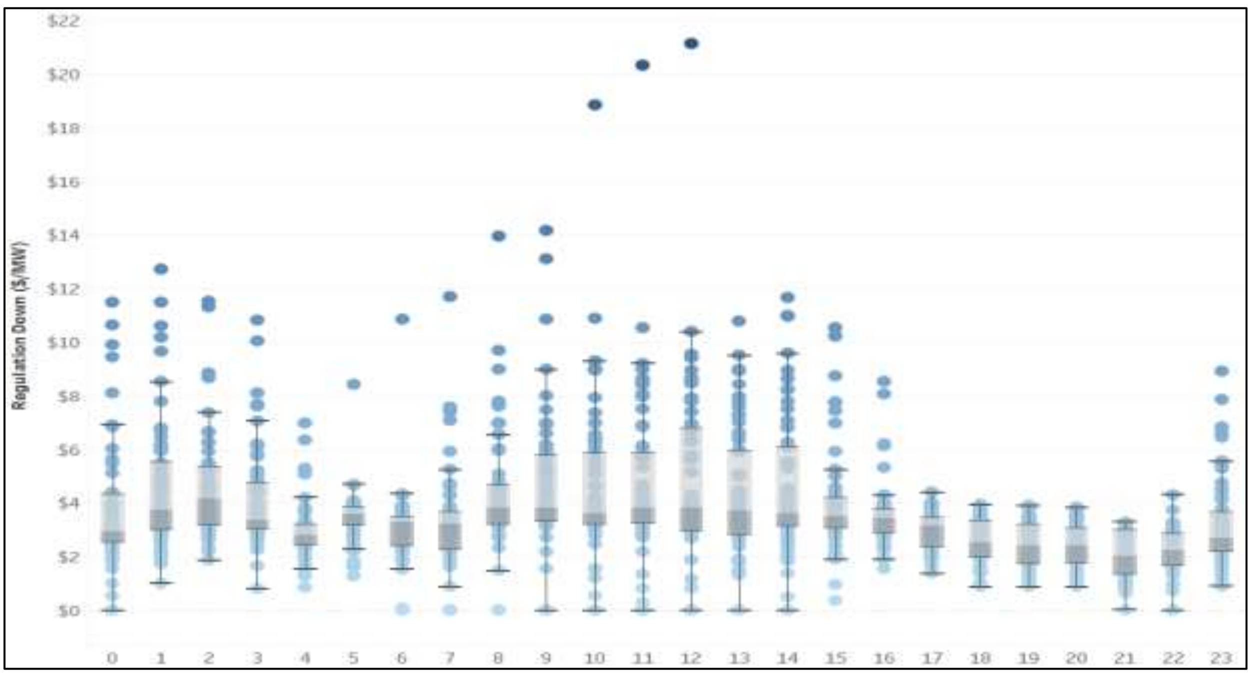
Source: California ISO Open Access Same-time Information System (OASIS)

Figure 51: Weekday Regulation Up Prices – Spring 2015



Source: California ISO Open Access Same-time Information System (OASIS)

Figure 52: Weekday Regulation Down Prices – Spring 2015



Source: California ISO Open Access Same-time Information System (OASIS)

Valuation Results Summary

The team performed the valuation calculations for each hour over the forecasting period (January 1, 2012 through June 7, 2015). Table 7 summarizes these results for the last 12 months. The team has aggregated valuation components (day-ahead, day-of, and real-time) within each zone and further aggregated by month. Positive valuations indicate that the alternative forecasts provided a financial improvement over the baseline forecasts.

Table 7: Monthly Valuation of Alternative Forecasts by California-Independent System Operator Zone

Month/ Year	PG&E Bay Area	PG&E Not Bay	SCE Coastal	SCE Inland	SDG&E	Cal-ISO Wide
June 2014	$167,972	$512,106	($731,286)	($1,279,170)	($43,975)	($1,374,354)
July 2014	$197,775	$169,896	$294,169	($10,413)	($152,045)	$499,382
Aug. 2014	$22,374	$65,074	($251,585)	($725,651)	($2,175)	($891,963)
Sept. 2014	($277,101)	$792,538	($105,638)	$563,551	$27,722	$1,001,071
Oct. 2014	$13,252	$537,854	$331,019	($445,311)	$48,961	$485,775
Nov. 2014	($114,001)	$165,564	($59,593)	$115,254	$64,305	$171,529
Dec. 2014	($6,937)	($210,752)	($174,131)	$195,612	$93,515	($102,693)
Jan. 2015	$352,915	($754,727)	$542,642	($117,595)	($22,201)	$1,033
Feb. 2015	$110,455	$73,400	($220,525)	($252,391)	$99,926	($189,134)
March 2015	$209,837	($78,685)	$293,500	$379,385	$29,403	$833,439
April 2015	($21,374)	($164,870)	$204,330	($196,302)	$43,754	($134,461)
May 2015	$31,924	$224,990	$275,443	($146,355)	$63,164	$449,166
Total	$687,091	$1,332,388	$398,345	($1,919,386)	$250,354	$748,790

Source: Itron Valuation Analysis

The performance of the alternative forecasts varies significant by month and across zones. At the zonal level, the alternative forecasts can be positive or negative across months and across years. The same was true at the total ISO level. However, at the total ISO level, each year ends with a positive valuation suggesting that at a minimum the alternative forecasts do provide an annual net benefit to the system. Table 8 summarizes the valuation for each zone at an annual level of aggregation. In general, the alternative forecast tended to be less costly, and therefore had a positive valuation, compared to the baseline forecast.

Since Itron performing the original forecasting research, the amounts of BTM solar has increased significantly. It is just conjecture, but the value of using the alternative forecasts will likely increase with greater PV penetration.

Table 8: Annual Valuation of Alternative Forecasts by California Independent System Operator Zone

Year	PG&E Bay Area	PG&E Not Bay	SCE Coastal	SCE Inland	SDG&E	Cal-ISO Wide
2012	$1,393,854	($1,659,008)	($2,973,766)	$3,290,775	$55,386	$107,241
2013	$2,132,599	$4,059,191	$1,862,615	($1,746,753)	$735,379	$7,043,032
2014	$1,423,229	$1,565,879	($3,081,437)	$2,294,784	($691,664)	$1,510,790
2015	$689,004	($762,631)	$919,519	($441,993)	$171,932	$575,832
Total	$5,638,686	$3,203,431	($3,273,069)	$3,396,814	$271,032	$9,236,894

Source: Itron Valuation Analysis

Costing Period Components

To get a better picture of which of the costing period components (day-ahead, hour-ahead, and regulation) are more significant to the overall valuation, they are shown in Table 9 and Table 10 by baseline and alternative forecast respectively for the PG&E Bay Area zone. The day-ahead component was by far the largest cost component followed by the hour-ahead and then the regulation cost components. This same pattern of cost magnitude exists across all the forecasting zones.

Table 9: Pacific Gas & Electric Bay Area Baseline Forecast Costing Period Components

Month & Year	Day-Ahead-Base Cost	Hour-Ahead Base Cost	Regulation Base Cost	Total Base Cost
June 2014	$148,625,381	$2,811,642	$287,258	$151,724,282
July 2014	$184,272,895	$2,999,219	$249,384	$187,521,498
August 2014	$178,833,076	$3,187,751	$225,596	$182,246,422
September 2014	$177,941,290	$4,747,989	$234,721	$182,924,001
October 2014	$122,008,465	$4,175,888	$242,596	$126,426,949
November 2014	$53,108,720	$1,598,932	$81,544	$54,789,195
December 2014	$125,946,041	$3,731,631	$212,649	$129,890,320
January 2015	$122,415,932	$1,368,015	$187,335	$123,971,282
February 2015	$101,194,214	$3,405,808	$152,302	$104,752,324
March 2015	$112,263,892	$363,099	$134,047	$112,761,038
April 2015	$95,718,062	$2,160,373	$163,304	$98,041,739
May 2015	$100,938,058	$680,025	$167,625	$101,785,708
Grand Total	$1,523,266,023	$31,230,374	$2,338,361	$1,556,834,758

Source: Itron Valuation Analysis

Table 10: Pacific Gas & Electric Bay Area Alternative Forecast Costing Period Components

Month & Year	Day-Ahead Alternative Cost	Hour-Ahead Alternative Cost	Regulation Alternative Cost	Total Alternative Cost
June 2014	$149,006,811	$2,270,814	$278,684	$151,556,310
July 2014	$183,473,775	$3,601,809	$248,139	$187,323,723
August 2014	$178,419,254	$3,582,755	$222,039	$182,224,048
September 2014	$179,929,939	$3,039,088	$232,075	$183,201,102
October 2014	$122,892,932	$3,276,006	$244,760	$126,413,697
November 2014	$54,052,230	$765,608	$85,359	$54,903,197
December 2014	$125,755,596	$3,937,017	$204,645	$129,897,257
January 2015	$120,771,392	$2,671,963	$175,011	$123,618,367
February 2015	$102,596,993	$1,902,449	$142,427	$104,641,869
March 2015	$111,866,415	$556,150	$128,636	$112,551,201
April 2015	$95,962,370	$1,941,639	$159,103	$98,063,113
May 2015	$100,356,784	$1,236,519	$160,481	$101,753,784
Grand Total	$1,525,084,492	$28,781,817	$2,281,359	$1,556,147,667

Source: Itron Valuation Analysis

It would appear from these cost summaries that the day-ahead forecast costs are the most important until one computes the valuation for each of the individual period components.

Table 11 shows the difference between baseline and alternative costs (that is valuation) for each period component for the last 12 complete months of alternative forecasts. Both the day-ahead and the hour-ahead valuation components are of similar absolute magnitude. The difference in regulation costs, however, are much smaller and therefore less significant. Even with the California ISO's change in regulation procurement beginning in February of 2016, the impact of regulation on valuation was still small. This examination of the period components may provide some guidance in developing a forecasting framework.

Table 11: Pacific Gas & Electric Bay Area Alternative Forecast Valuation by Period Component

Month & Year	Day-Ahead Alternative Valuation	Hour-Ahead Alternative Valuation	Regulation Alternative Valuation	Total Alternative Forecast Valuation
June 2014	($381,430)	$540,828	$8,574	$167,972
July 2014	$799,120	($602,590)	$1,245	$197,775
August 2014	$413,822	($395,004)	$3,557	$22,374
September 2014	($1,988,650)	$1,708,902	$2,647	($277,101)
October 2014	($884,467)	$899,882	($2,163)	$13,252
November 2014	($943,510)	$833,324	($3,816)	($114,001)
December 2014	$190,445	($205,386)	$8,004	($6,937)
January 2015	$1,644,539	($1,303,948)	$12,324	$352,915
February 2015	($1,402,780)	$1,503,360	$9,876	$110,455
March 2015	$397,477	($193,051)	$5,411	$209,837
April 2015	($244,308)	$218,734	$4,201	($21,374)
May 2015	$581,274	($556,494)	$7,145	$31,924
Grand Total	($1,818,468)	$2,448,557	$57,003	$687,091

Source: Itron Valuation Analysis

To really determine if there was a trend in any given factor that may be driving the results of the valuation, it was necessary to go down to the hourly level and see what if anything was consistently driving the resulting valuation in a positive or negative direction. The team addresses this in the next section on developing a forecasting framework.

Forecasting Framework Overview

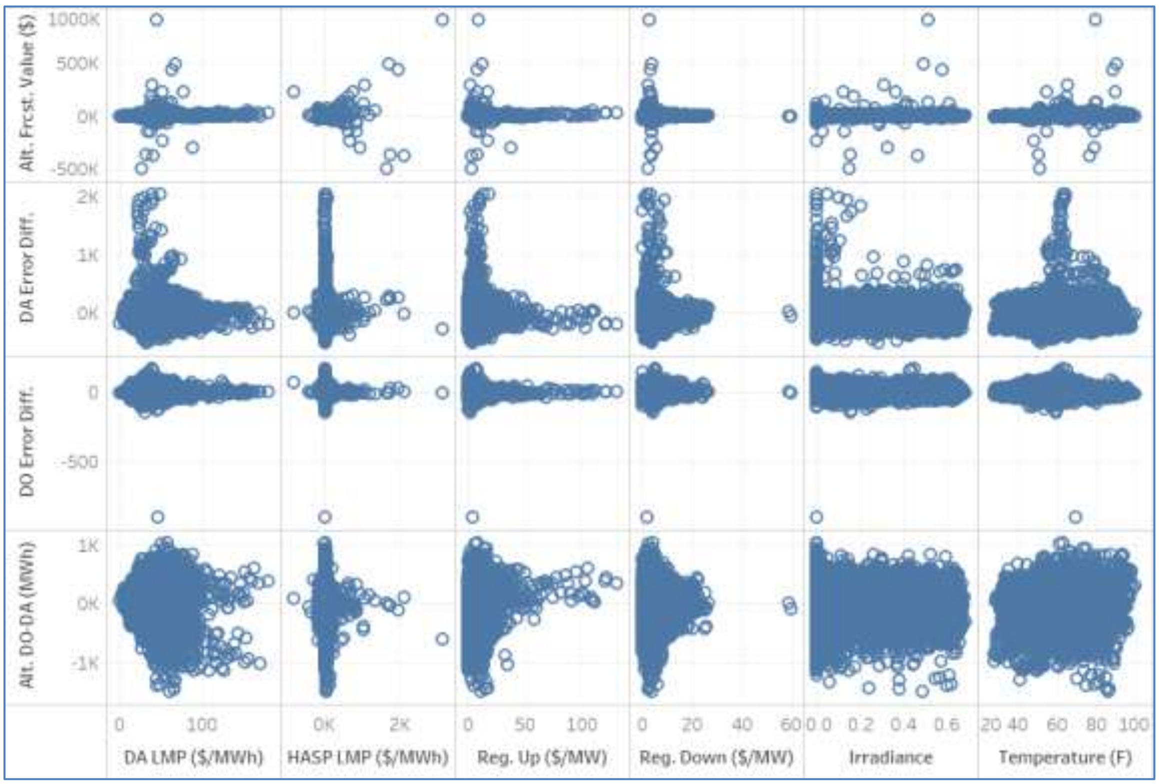
In general, the alternative forecasts would have resulted in a lower cost of energy on a statewide basis. However, the alternative forecasts are not always least costly suggesting that it may be possible to develop a forecasting framework for choosing the least costly forecasting approach. The goal here was to establish a framework for optimizing the use of the alternative forecasts. The team's objective was to leverage the improved forecasts and data from the earlier tasks to help the utilities and the California ISO better integrate increasing amounts of renewables on the grid with lower costs.

Examination of External Factors and Value

The project team first undertook a visual inspection of the valuation (difference between the alternate forecast cost and the baseline forecast cost) versus the influential factors like market prices, irradiance, and temperature. Using the stream of calculated hourly and daily valuations, the team examined the alternative forecasts under various conditions that might indicate when they provide the most value.

There are many factors at work that influence the valuation and identifying a simple forecasting framework may not be possible. To explore this visually, project team first developed several plots of the valuation versus influential factors. The influential factors examined included market prices, irradiance, and temperature. Figure 53 shows scatter plots of the calculated hourly valuations and how they relate to the various potentially influential factors (LMP, HASP LMP, RU, RD, irradiance, and temperature.)

Figure 53: Pacific Gas & Electric Bay Area – Alternative Forecasts Valuation vs. Prices, Irradiance and Temperature



Source: Clean Power Research

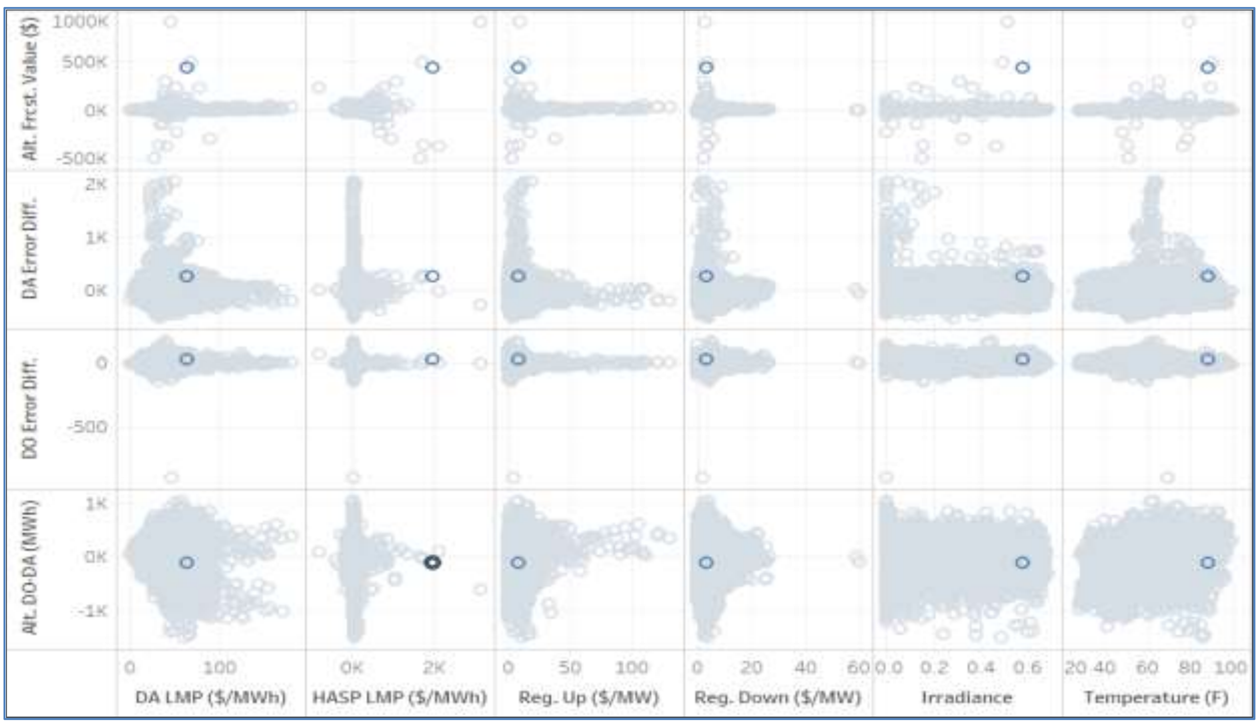
Figure 53 also examines several potential key indicators against these influential factors. These include the day ahead alternative forecast errors (the difference between the day ahead forecast and the actual load), the day-of alternative forecast errors (the difference between the day-of forecast and the actual load), and the difference between the day ahead and day-of alternative forecasts. In all cases, there were no clear or consistent correlations between influential factors and key indicators and the alternative forecast valuations. For example, one would think irradiance[16] would be an influential factor in explaining when the alternative forecast was less costly than the baseline forecast. If irradiance was a reliably predictor, something like a slanted line running through the plots could be seen. When the team looked at the irradiance column of

[16] The power per unit area received from the sun.

plots in Figure 53, no clear pattern of predictability reveals itself. For the most part, the range of irradiance values do not seem to have any influence on the Alternative Forecast value, the forecasts' errors, or the difference between the Alternative and Baseline forecasts.

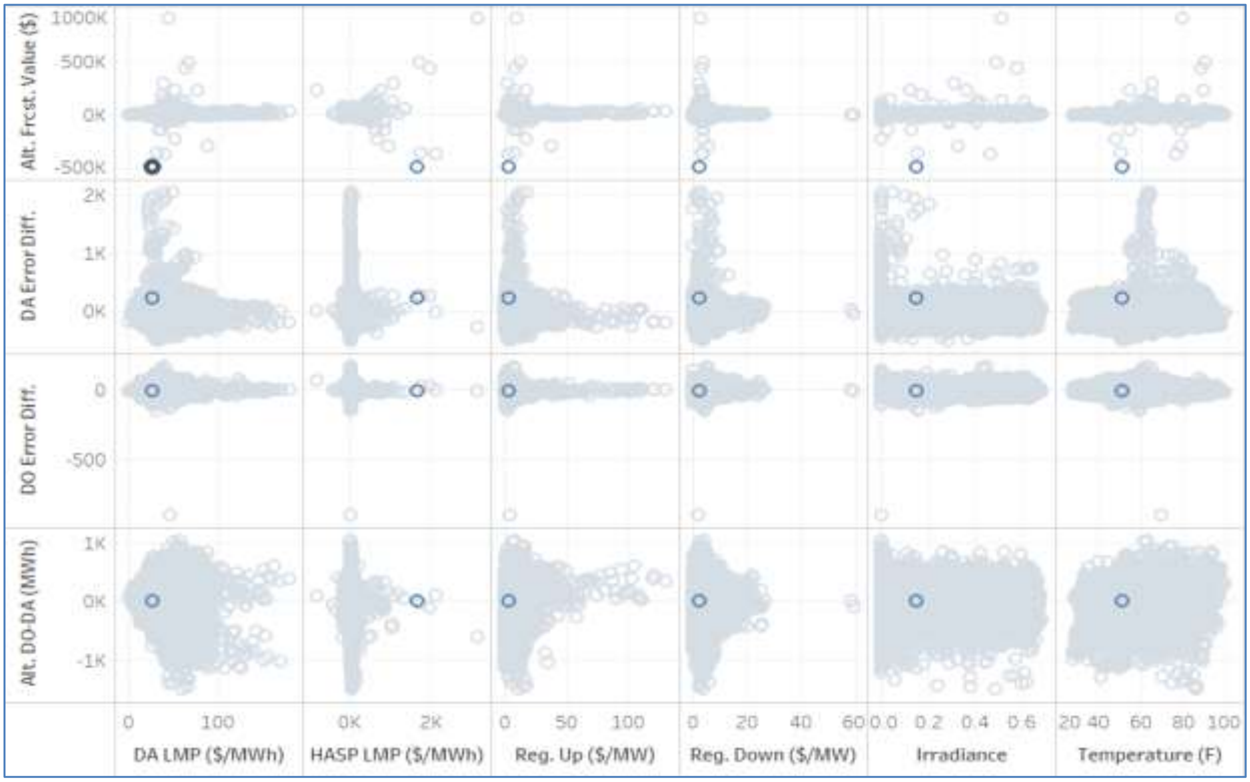
In Figure 54 and Figure 55, the project team further illustrates the lack of consistent correlations by highlighting the valuation for a couple of hours and the corresponding values for all the potential influential variables. This closer examination reveals that in some instances the influential factors can have virtually the same value, but the alternative forecast value goes from positive to negative. For example, the HASP LMP is a little less than $2,000 per MWh in both Figure 54 and Figure 55, but the alternative forecast value is positive in the first and negative in the second. Interestingly, HASP LMP shows some evidence of being positively and negatively correlated at certain times.

Figure 54: Pacific Gas & Electric Bay Area – Alternative Forecasts Valuation vs. Prices, Irradiance and Temperature



Source: Clean Power Research

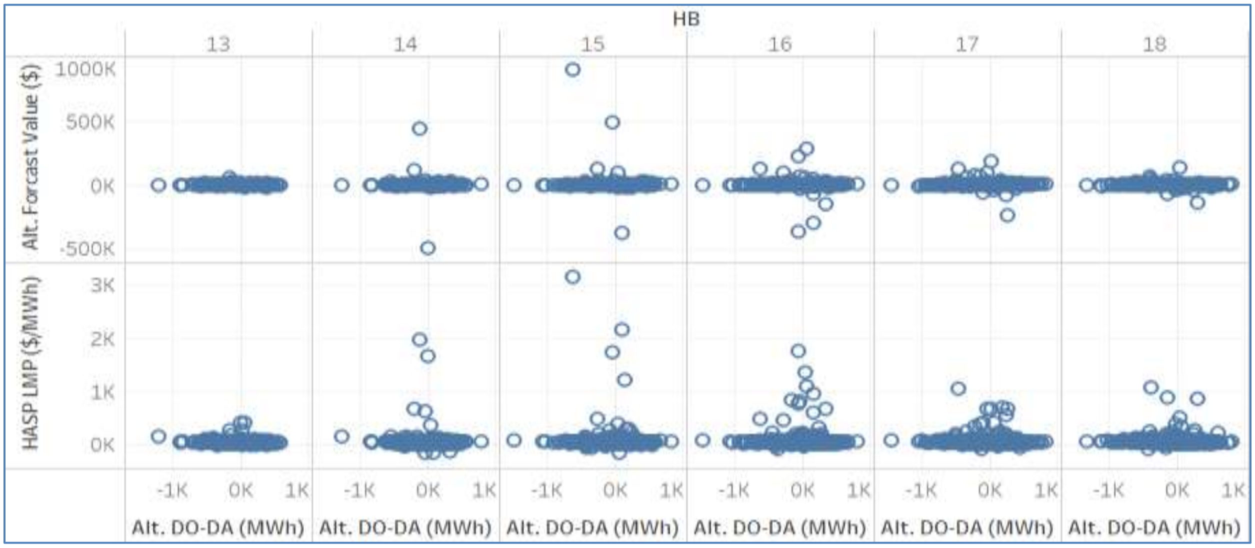
Figure 55: Pacific Gas & Electric Bay Area – Low Alternative Forecasts Valuation vs. Prices, Irradiance and Temperature



Source: Clean Power Research

Figure 56 drills down farther by examining the alternative forecast valuations versus the differences between the alternative and baseline forecasts across several mid-day hours (1 p.m. through 6 p.m.) Figure 56 also shows the corresponding HASP LMP for each of the hours beginning (HB). There does not appear to be any consistent association between forecast differences and the size of the valuation. There are a few instances of more extreme valuations, both positive and negative, that occur across some of these hours. With this view it is difficult to determine if HASP LMP or the differences between the day-of and day-ahead forecasts was the driver.

Figure 56: Pacific Gas & Electric Bay Area – Alternative Forecasts Valuation vs. Difference Between Day-of and Day-Ahead Forecasts



Source: Clean Power Research

The team concluded from this visual examination is that to develop a framework, a more sophisticated analysis would be necessary to uncover any conditions that may exist under which it could more reliably prescribe the alternative forecast over the baseline forecast to maximize its value.

Forecasting Framework Analysis

The goals of this chapter are to lay out several data mining and machine learning approaches used to come up with a framework to choose a forecast. The team utilized three approaches and applied them to the five zones individually.

Algorithmic Framework Exploration

The project team first started with a non-parametric method for classification: K-Nearest Neighbors (k-NN). The idea behind it was to classify the 2 forecasts based on the underlying features. The output of a k-NN is a classification by a majority vote of its neighbors. The model's object being to make an assignment to the forecast based on the most common result among the "k" nearest neighbors. The k-NN method is amongst the simplest machine learning techniques because the function is only approximated locally, and all computation occurs after the classification is complete.

The project team then turned to another popular classification algorithm: Decision Trees. Decision tree learning is one of the most widely used and practical methods for inductive inference. A Decision tree classifier repeatedly divides the sample space into sub parts by identifying the nodes or features that influence the outcome. Learned trees can also represent a series of "if-then" rules to improve human readability. The algorithm classifies instances by sorting them down the tree from the "root" to some "leaf" node, which provides the classification of the instance. Each node in the tree specifies a test of some feature or attribute of the instance, and each branch descending from the node corresponds to one of the possible values of the attribute.[17]

Lastly, the project team developed a Random Forest model. Random Forests are an ensemble learning method for classification that operate by constructing a multitude of decision trees at training time and outputting the forecast that is the mode (most common) of both the forecasts. They are a much more sophisticated and complex machine learning algorithm than the decision trees and correct for the overfitting bias in the decision trees. The Random Forest models grow out decision trees much deeper (more nodes) than the decision stumps shown above (from the decision tree algorithm), in fact the default behavior is to grow out each tree as far as possible (recall that to simply matters, the decision tree was reduced to one node). There is a direct relationship between the number of trees in the forest and the results it can get: the larger the number of decision trees, the more accurate the result.

Framework Analysis Summary

Summary of Results

Using these Machine Learning approaches, the researchers calculated the cost to purchase energy in the California ISO markets associated with each forecast. Table 12 shows the cost associated with the forecast chosen based on each of these Machine Learning models developed. While the research team believes there is merit in the Machine Learning approaches taken to understand the conditions under which a forecast should be chosen, the underlying data was very noisy and depended on too many features which makes it difficult to fit simple and interpretable Machine Learning models.

17 http://www.cs.princeton.edu/courses/archive/spr07/cos424/papers/mitchell-dectrees.pdf

Table 12: Energy Cost Summary by Machine Learning Models

Zone	Decision Tree 1: Terciles of Cloud Cover Day	Decision Tree 2: Median of Cloud Cover Day	Random Forest	Base Only	Alternate Only
PGE Bay Area	Model Doesn't Converge	Model Doesn't Converge	$5,452,381,322	$5,454,978,197	$5,462,543,775
PGE Non Bay Area	$7,404,465,618	$7,404,718,472	$7,402,354,186	$7,408,860,169	$7,406,205,706
SCE Coastal Area	$6,616,844,473	$6,618,151,250	$6,611,298,768	$6,616,443,563	$6,620,451,510
SCE Inland Area	Model Doesn't Converge	Model Doesn't Converge	$6,000,287,702	$6,006,418,114	$6,003,756,104
SDGE	Model Doesn't Converge	Model Doesn't Converge	$2,919,744,263	$2,921,159,545	$2,925,463,396

Source: Itron Valuation Analysis

Clearly the Random Forest model outperforms the Decision Tree based model, the Base only, and the Alternate only forecasts from a valuation standpoint. Essentially, the Random Forest model predicts which forecast to use given a condition (Cloud cover, temperature, irradiance, etc.) 60 percent of the time. Using the Random Forest algorithm-based framework to determine which forecast to use could save millions of dollars over the entire forecasting horizon over just using the Base or the Alternate forecasts. However, Random Forest models are very hard to interpret given the size and number of decision trees constructed to get higher accuracy. Using the Decision Tree based framework also is beneficial for the zones that the model converges. One can visualize and interpret decision trees as a set of IF-THEN-ELSE rules easily put into production. However, they come with their own disadvantages of overfitting and not converging for all the zones. Therefore, there exists a tradeoff between accuracy and interpretability for the machine learning-based frameworks.

Chapter 6: Conclusions and Recommendations

Data Forecasting Accuracy Improvement

Conclusions

The use of real time data for forecasting plant output shows promise, and warrants further pursuit. Plant availability would be of particular interest; however, the inclusion of security protocols would require close coordination with California ISO and possibly the individual plant operators.

Recommendations

A test of CSP forecasting may also prove valuable. One could develop Forecasts for CSP resources without storage (the simplest case), but one could also develop methods for storage dispatch using defined objectives, such as revenue maximization.

Grid-Connected and Embedded Photovoltaic Fleet Forecasting Accuracy

Conclusions

The research team has shown many of the methods to improve forecasting which have been implemented in software (or are ready for implementation). These relate to module degradation, fleet-level availability, improving the inverter power curve, ensemble methods, and dynamic fleet capacity tracking. Some insights gained from this work suggests additional investigation may yield further forecast accuracy benefits.

Recommendations

The accuracy of assessing system specifications by inference requires some additional study, as does assessing the importance of shading, and the lack of shading data from the original site installation. These could be topics for future research.

Improving Short-Term Load Forecasts by Incorporating Solar Photovoltaic Generation

Conclusions

This study set out to determine if there was a way of improving the load forecast accuracy of the California ISO's existing load forecast models by incorporating forecasts of solar PV generation. The research team presents three alternative modeling approaches. These approaches were subject to a forecast simulation using solar PV generation driven by hourly cloud cover for a handful of weather stations and solar PV generation estimates developed by

CPR using a detailed database of solar PV installations combined with satellite imagery. The conclusions from this study include the following outlined below.

- Not adjusting the California ISO baseline forecast models will only lead to further erosion of forecast accuracy and a greater dispersion of forecast errors.
- For forecast horizons of 15 minutes ahead to four hours ahead, the Model Direct approach, when combined with the CPR estimates of solar generation, provides improved forecast accuracy and reduced forecast error dispersion over the baseline load forecast model. This finding indicates the benefit of relaxing the assumption that 1 MW of BTM solar PV generation leads to a 1 MW reduction in measured load which is a key assumption of both the Reconstituted Load and Error Correction approaches. These approaches assume both: (1) no underlying behavioral changes take place as a result of the installation of solar PV and (2) the BTM solar PV estimates are correct. In contrast, the Direct Model through the process of model estimation is able to capture the influence of behavioral changes on the estimated BTM solar PV generation impact, as well as make statistical adjustments for incorrect BTM solar PV estimates. This finding also provides evidence of the benefit of CPR's more granular approach to developing BTM solar PV generation over the use of a cloud cover driven forecast for a handful of weather stations.
- For longer term forecast horizons of six hours ahead to 24 hours ahead, the Reconstituted Load approach, combined with the CPR estimates of solar generation, provide improvements in both forecast accuracy and reduced forecast error dispersion over the baseline load forecast model.
- This suggests a hybrid forecast framework that leverages the forecasts from the Model Direct approach for forecast horizons of 15 minutes ahead to four hours ahead and then switches to the Reconstituted Load approach for forecasts horizons of fours-ahead and longer.
- Hourly cloud cover driven estimates of solar generation can provide benefit over doing nothing, however the detail bottom-up approach implemented by CPR yields superior results.
- The fact the results vary by season and cloud cover conditions suggest introducing seasonal and cloud cover interaction terms in the Model Direct approach. This would allow the load impact of the solar generation variable to vary by season and cloud cover conditions.
- Other interaction terms including Day-of-the-Week and possibly temperature conditions may also prove useful in improving the accuracy of the Model Direct approach.
- The estimated coefficients of the Model Direct models provide evidence for the potential of long-run behavioral changes associated with the increased penetration of solar PV. If true, then the Error Correction and Reconstituted Load approaches will lose forecast skill over time as the assumption that the coefficient on the solar PV generation variable should be -1.0 becomes invalid.

Recommendations

With further research the extent to which penetration of solar PV is leading to behavioral changes can be determined. As part of the upcoming California Solar Initiative Final Impact Evaluations, Itron will be starting to investigate this question. If the answer is yes, then the load forecasting problem will only become more complicated with further penetration of solar PV combined with growth in electric vehicle charging, on-site electricity storage, and integration into emerging models such as microgrids.

Forecast Valuation & Framework Analysis

Conclusions

Calculating the value of the alternative forecasting approach that incorporates solar forecasts, requires using a valuation method that uses appropriate costs. Short-term load forecast estimates do not affect longer-term capital investments. Therefore, the research team believes that it is best to calculate the proper costs using the publicly available market prices used for settlement purposes by the California ISO in its day-ahead, hour-ahead and regulation markets.

The value of the alternative forecasts is in general positive, suggesting that they perform better financially than the California ISO baseline forecasts. Not all periods show this to be the case and it varies across all zones examined as well. It may be possible to develop a forecasting framework that specifies when to use either the alternative or the baseline forecasts thereby optimizing the value associated with the alternative forecasts.

Even though there is an economic value in using these machine learning approaches, the models are very difficult to interpret and operationalize in real conditions. At the total ISO level, each year ends with a positive valuation suggesting that, at a minimum, the alternative forecasts do provide an annual net benefit to the system if used all the time.

Recommendations

To improve the Machine Learning approaches, there needs to be more research in three areas.

- Influential factors
- Increasing the size of the training dataset
- Other machine learning algorithms
- Testing with recent alternative forecasting model results

First, there must be research to identify the best influential factors to use. The team limited this research to just those factors that were available to the alternative forecast method development. There may be better factors that were not available for this research. For example, because the zones cover large geographic areas, it may be better to use irradiance values averaged across a number of monitoring locations.

Second, increasing the size of the training dataset could increase the prediction accuracy. In most studies of classification, there is a rising accuracy curve with respect to the size of the training dataset. Therefore, increasing the forecast horizon to include more years would lead to a bigger training dataset that could ultimately increase the prediction accuracy.

Third, research into other types of Machine Learning algorithms must be done.[18] This research only attempted three types. There are numerous other algorithms worthy of consideration. Some of these include Linear Discriminant Analysis, Naïve Bayes, Learning Vector Quantization, Support Vector Machines, and Boosting. Some of these models may perform better and may be easier to operationalize. This would improve the chances stakeholders would accept and use them.

Lastly, the research team used the alternative forecasts developed for a forecast horizon that may not be relevant to today's conditions. BTM solar has grown substantially since the beginning of 2015. Examination of the impacts of this on the alternative forecasts' accuracy and ability to better perform than the California ISO's baseline forecasts is warranted. In addition, Itron has made improvements to its body of knowledge concerning forecasting models that incorporate BTM solar. These improved models should be considered.as replacements for those developed during this project.

18 https://machinelearningmastery.com/a-tour-of-machine-learning-algorithms/.

GLOSSARY AND ACRONYMS

Term	Definition
EPIC	Electric Program Investment Charge
Azimuth	The horizontal angular distance between the vertical plane containing a point in the sky and true north.
Behind the Meter (BTM)	Generation connected on the customer side of the meter that impacts net load
California ISO	California Independent System Operator – the organization that manages the three IOU's electricity grid in California
CC	Cloud Cover, for the report, a cloud cover based model of BTM PV solar forecasts and generation
CPR	Clean Power Research, Itron's partner on this grant that is refining detailed and granular BTM PV solar forecasts
Direct Normal Irradiance (DNI)	The amount of solar radiation received per unit area by a surface that is always held perpendicular (or normal) to the rays that come in a straight line from the direction of the sun at its current position in the sky. Typically, you can maximize the amount of irradiance annually received by a surface by keeping it normal to incoming radiation. Irradiance is usually measured in W/m2.
Global Horizontal Irradiance (GHI)	Global Horizontal Irradiance is the total amount of shortwave radiation received from above by a horizontal surface.
Insolation	A measure of solar radiation energy received on a given surface area in a given time. It is commonly expressed as kilowatt-hours per square meter per day (kWh/(m2·day)).
Inverter	An electric conversion device that converts direct current (DC) electricity into alternating current (AC) electricity.
Inverter Efficiency	The AC power output of the inverter divided by the DC power input.
IOU	Investor Owned Utility; in California there are three; PG&E, SCE, and SDG&E
Net Load	The load seen at the customer meter, or the actual load minus any generation. For this report, this refers to the aggregate of al customer net load at either the California ISO zone, IOU, or California ISO level

Term	Definition
Orientation	The azimuth and tilt of a PV system.
PG&E	Pacific Gas and Electric; the IOU that provides natural gas and electricity to much of Northern California
SCE	Southern California Edison; the IOU that provides electricity to much of Southern California outside of San Diego
SDG&E	San Diego Gas and Electric; the IOU that provides natural gas and electricity to San Diego and the surrounding area
Solar Irradiance	Radiant energy emitted by the sun, particularly electromagnetic energy.
Solar Noon	The moment when the sun appears highest in the sky (nearest zenith), compared to its positions during the rest of the day. It occurs when the sun is transiting the celestial meridian.
Solar PV	Solar Photovoltaic; a technology that uses semiconductors to convert solar irradiance into DC electrical power. This DC electrical power is usually converted to AC electrical power uses inverter(s).
HASP	Hour Ahead Scheduling Process (HASP) is a process for scheduling energy and ancillary services based on the bids submitted.
LMP	Locational Marginal Pricing (LMP) is a way for wholesale electric energy prices to reflect the value of electric energy at different locations, accounting for the patterns of load, generation, and the physical limits of the transmission system.
DAM	Day Ahead Market (DAM) is a financial market where market participants purchase and sell electric energy at financially binding day-ahead prices for the following day.

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