

Improving Short-Term Load Forecasts by Incorporating Solar PV Generation

A Study conducted for the California Energy Commission

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PREFACE

The California Energy Commission Energy Research and Development Division supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

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ABSTRACT

Three different methods to integrate behind the meter (BTM) solar photovoltaic (PV) forecasts with an operational net load forecast are investigated. The purpose of this work is to determine how to best integrate rapidly growing BTM PV into net load forecasts for the California Independent System Operator (CAISO). The different methods are run from 2012 through mid-2015. Analysis of the improvements during 2014-2015 over a baseline net load forecast (that does not account for BTM PV) are analyzed to identify which method is best when and how much the forecasts are improved. The methods analyzed are being evaluated by the CAISO and are applicable for use by other System Operators experiencing rapid penetration of BTM PV.

Keywords: Solar Photovoltaics (PV), load forecasting, solar forecasting

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EXECUTIVE SUMMARY

Introduction

Incentives, increasing environmental concerns and the decreasing cost of photovoltaics (PV) are resulting in significant amounts of solar PV systems being installed in California. Currently, over 3.8 GW of Behind the Meter (BTM) solar PV capacity are installed in California. This capacity is expected to increase three- to five-fold by 2020. Uncertainty in solar PV output and its associated measured load impacts lead to overly conservative scheduling of regulation services and spinning reserves. To reduce the reliance on regulation services and spinning reserves, the California Independent System Operator (CAISO) requires improved measured load forecasts.

One effect of a high penetration of solar PV is that forecasts of measured load are becoming less reliable. This is especially true in the morning hours when loads appear to be driven more by the presence of clouds (e.g., marine layer) rather than temperatures. In contrast, afternoon loads still appear to be dominated by temperature changes that drive air conditioning loads. This may change over time when solar PV penetration reaches a critical mass, where the variation in solar PV generation is sufficiently large to outweigh the load variation due to variation in air conditioning loads.

Study Purpose

The CAISO Baseline Load Forecast Model is used to provide forecasts of measured loads for forecast horizons of 15 minutes ahead out to ten days ahead. The baseline modeling framework is composed of a set of 193 individual forecast models. None of these models include the impact of BTM solar PV on measured loads. To better predict an increasingly volatile load, the existing CAISO load forecast models need to be extended to capture the influence of BTM solar PV. This study evaluates the following three alternative model approaches (described in detail in Chapter 2: *Incorporating the Impact of Solar PV Generation in a Load Forecast*) for extending the CAISO load forecast framework.

- » 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, the adjustment is to lower the load forecast and on cloudy days, the load forecast is adjusted upward. The key advantage of the Error Correction Approach is the existing load forecast model can continue to be used without any changes. All that is needed is a means of forecasting solar PV generation.
- Reconstituted Loads. Under the Reconstituted Loads approach the historical time series of measured load is reconstituted by adding back estimates of solar PV generation. The load forecast model is then re-estimated against the reconstituted loads. The subsequent reconstituted load forecasts are then adjusted *ex post* by subtracting away forecasts of solar PV generation to form a forecast of measured loads. The advantage of this approach is any inherent bias that might be imposed on the estimated coefficients of a model of measured loads is controlled for by estimating the model coefficients against a time series of demand for power regardless of how it is sourced. The disadvantage is a historical time series of solar PV generation needs to be developed and maintained 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.
- » Model Direct. Under this approach, the weight placed on the solar PV generation data is estimated directly 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, by including solar PV generation as an explanatory variable, the coefficients on the remaining explanatory variables should not be biased. 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.

To evaluate the forecast performance of the alternative model approaches a series of 24 hour ahead load forecasts are simulated. The 15-minute ahead up to 24-hour ahead alternative model load forecasts errors are compared to the corresponding baseline model load forecast errors. The study purpose is to demonstrate that one or more of the alternative approaches outperforms the baseline load forecast by reducing both the average absolute forecast error and the associated forecast error variance. In other words, the load forecast errors are on average smaller and the width of the forecast error distribution is tighter. To conduct the simulations a historical time series of BTM solar PV generation is required. Unfortunately, direct metering of the generation output of the fleet of BTM PV installed in

California is not available. To address the lack of historical generation data, the study relies on the following two sources of BTM solar PV generation estimates (described in *Chapter 3: Solar PV Generation Estimates*):

- » Clean Power Research (CPR) Solar Generation Estimates. Itron's partner on this grant, Clean Power Research (CPR), is refining a forecast model that simulates each individual PV system in the CAISO. This forecast is based on an ensemble of models to estimate the amount of power each system will produce in any given hour. CPR combines an ensemble of techniques to do that ranging from vector decomposition of satellite imagery to vector decomposition of location specific cloud cover observations to numerical weather prediction models. This micro focus is most useful when the exact locations of the solar installations are known. For the case of the CAISO, 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.
- » 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. To provide a basis for comparison to the CPR results, BTM solar PV generation estimates are derived by combining hourly cloud cover data collected by weather station with aggregate estimates of installed capacity by load zone.

The detailed forecast performance of the six different forecasting methodologies (three alternative model frameworks x two solar PV generation estimates) are presented in *Chapter 5: Simulations Results Summary*. The findings are summarized below.

Study Results

Each of these six different forecasting methodologies was compared to the baseline forecast. This was done for CAISO as a whole, each of the three IOU's and each of the five CAISO zones (Pacific Gas and Electric Company (PG&E) Bay Area, PG&E Non-Bay Area, Southern California Edison (SCE) Coastal, SCE Inland, and San Diego gas and electric (SDG&E)). *Chapter 4: Forecast Simulations* describes the simulations and *Chapter 5: Simulations Results Summary* has detail on the results. In general:

- » Not adjusting the CAISO 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 BTM PV forecasts than the CAISO as a whole or any of the other CAISO zones. This could be a result of a smaller geographic area combined with a higher penetration of BTM PV.
- » Hourly cloud cover driven estimates of solar generation can provide benefit over doing nothing, however the detailed bottom-up approach implemented by CPR yields superior results.
- » The findings also indicate that one (1) MW of Solar PV generation may not reduce what the CAISO measures as load by one (1) MW. A possible explanation for this counter intuitive finding has to do with the fact that the CAISO only measures what happens in front of the meter. If the installation of solar PV leads to fundamental behind-the-meter behavioral changes in how consumers utilize end-use equipment the impact of solar PV generation on load will be muted. One possible behavioral change that will lead to offsetting load impacts is when consumers with solar PV keep their space conditioning equipment running during the day. Potentially they do this because the electricity from the solar PV is deemed to be 'free'. This type of behavioral change can lead to a net increase in both load levels and load weather sensitivity if the vast majority of these consumers were in the habit of turning off their air conditioning equipment during the day prior to investing in solar PV.
- » The model direct approach allows some investigation into how much of the solar PV generation actually results in net load increases associated with this type of behavioral change. Section 6 investigates this and shows that the statistically estimated impact of solar PV generation is less than one (1) MW of load reduction for one (1) MW of solar PV generation. Further, the trend in solar PV installations captures a net load increase in the shoulder periods (early morning and later afternoon) potentially as a result of behavioral changes after the installation of

solar PV. Further research is needed to determine the extent to which penetration of solar PV is leading to behavioral changes. If the research validates that behavioral changes are taking place, then the load forecasting problem will only become more complicated as deeper penetration of solar PV installations lead to more weathersensitive loads. In a similar fashion, developing a strong understanding of how consumer behavior can change with the adoption of electric vehicle charging and on-site storage will ultimately be required to maintain acceptable load forecast performance.

Study Benefits

This improved net load forecasts presented in the report will result in a number of benefits to California. The nearest term benefit is to reduce the cost of grid regulation required due to forecast errors. By reducing the mean absolute percentage error by just 0.1% (e.g., from 1.7% to 1.6%), the CAISO and California ratepayers can save over \$2 Million per year. As the installed capacity of BTM PV increases, the annual savings will likely increase. Further financial savings from more accurate forecasts may also be possible and will be investigated in Task 5 of this project.

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

^a Based on an average annual CAISO 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

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CHAPTER 1: INTRODUCTION

Renewable Portfolio Standard requirements and decreasing cost of photovoltaics (PV) are resulting in significant amounts of Behind-the-Meter (BTM) solar PV systems being installed in California. Currently, over 3.8 GW of BTM PV capacity are installed in California.² This capacity is expected to increase three- to five-fold by 2020. Uncertainty in BTM solar PV output and its associated measured load impacts lead to overly conservative scheduling or regulation services and spinning reserves. To reduce the reliance on regulation services and spinning reserves, the California Independent System Operator (CAISO) requires improved measured load forecasts.

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

Why does this matter? It matters because the statistical load forecast models are designed to capture the factors that impact end-user electricity consumption. With deeper penetration of BTM solar PV, load forecast models need to be extended to predict when end users will lean on the grid to meet their electricity requirements versus relying on their own generation. Prior to BTM solar PV, reliance on the grid was driven by traditional end-user consumption patterns that are well-studied and predictable. With BTM solar PV, reliance on the grid is driven both by end-user consumption patterns and the availability of BTM solar PV generation. The latter is driven by meteorological events not easily predicted.

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 when loads appear to be driven more by the presence of clouds (e.g., marine layer) rather than temperatures. In contrast, afternoon loads still appear to be dominated by temperature changes that drive air conditioning 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.

To better predict an increasing volatile load, the CAISO existing load forecast models need to be extended to capture the influence of BTM solar PV. This study evaluates three alternative model approaches for extending the CAISO load forecast framework. This report presents the alternative load forecast frameworks for incorporating BTM solar PV forecasts and the forecast simulations that were implemented to evaluate the performance of these approaches.

To put these approaches into context, below is a description of the existing CAISO load forecast model.

1.1 The CAISO Short-Term Load Forecast Model

The Baseline Load Forecast Model is used to provide forecasts of measured loads for forecast horizons of 15 minutes ahead out to ten days ahead. The CAISO load forecasting system produces 15-minute level load forecasts for forecast horizons of 15-minutes ahead out ten (10) days ahead. The load forecasts are updated 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 CAISO load zones: Pacific Gas and Electric (PG&E), Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E). In addition, the CAISO 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. The load forecasts are driven by hourly weather forecasts of temperature and humidity for approximately 24 weather stations located throughout the State of California. The weather forecasts are updated hourly and are available from multiple weather forecast service providers. This allows the CAISO to quantify the load forecast uncertainty due to weather forecast uncertainty. An ensemble of load forecast is then computed as a weighted average across the load forecast ensemble. The weighting scheme is based on the most recent forecast performance of each weather service provider.

For each load zone (i.e. 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. Each forecast model is designed to optimize the load forecast performance for specific forecast horizon. The 193 individual forecast models that define the CAISO baseline 15-minute load forecast modeling framework are:

² Go Solar California website https://www.californiasolarstatistics.ca.gov/

- » **Daily Energy Model**. A Neural Network Model of Daily Energy is used to capture daily swings in electricity demand as driven by changes in calendar and weather conditions.
- » **Day-Ahead Models.** Designed for forecast horizons of four hours ahead and longer. Is composed of 96, 15-Minute Regression Models that are 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.
- » 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.

The operational forecast that the CAISO utilizes is updated every 15 minutes and has a forecast horizon of the balance-of-the-day out ten days ahead. The operational forecast is generated with the following steps:

- » Generate a balance-of-the-day out ten days ahead forecast of Daily Energy using the Daily Energy model.
- » Generate a balance-of-the-day out ten days ahead forecast of quarter hour loads using the Day-Ahead models.
- » Generate a balance-of-the-day out ten days ahead forecast of quarter hour loads using the Hour-Ahead models.
- » Create 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, 100% weight is placed 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, 100% weight is placed on the Day-Ahead forecast.

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

- » Forecasts of Daily Energy capture the influence of a full day of weather conditions on loads. This influence is then channeled through to the Day-Ahead model forecasts via predicted Daily Energy values with day-of-the-week interaction terms.
- » The Day-ahead model forecasts are free to respond quickly to forecasted changes in weather conditions.
- » The Hour-Ahead models exploit the information contained in the most recent metered loads.
- » 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.

Daily Energy Model Specification. The Daily Energy Model is used to forecast total measured load for forecast horizons of balance-of-the-day to ten days ahead. The forecast values from the Daily Energy model are included as explanatory variables in the 96, 15-minute level Day-Ahead models. The reason for this is that the time series of Daily Energy tends to be smoother than the individual 15-minute load streams. This allows the development of very powerful Daily Energy models. Accurate forecasts of Daily Energy in turn are strong forecast drivers for the 15-minute Day-Ahead models.

The Daily Energy model utilizes Neural Network Techniques. Because Neural Network Techniques describe a broad range of model specifications it is useful to describe the specific adaptation that is implemented at the CAISO. The specific Neural Network Model that is used for the CAISO is a five (5) Node Neural Network Model with a single Hidden layer pointing to a single output. Translated to the language of a multivariate regression, the single output is the dependent variable of the model, namely Daily Energy which is computed as the sum of the 15-minute loads.³ A single layer means the predicted value is the weighted sum of the predicted value from each of the five nodes. The weights can be thought of as the estimated parameters from regressing the dependent variable (Daily Energy) on the predicted values from the five (5) nodes. Further, the predicted values from the nodes do not interact with the values from the other nodes. The nodes themselves have specific functional forms. The first node utilizes a linear activation function which means the predicted value from this node is a weighted sum of the explanatory variables included on

³ See J. S. McMenamin and Frank A. Monforte, *Short Term Energy Forecasting with Neural Networks,* The Energy Journal, Volume 19, Number 4 (1998) pages 43-61 for a comparison of regression and Neural Network modeling techniques for short term energy forecasting.

this node. Further, there are no interactions between the explanatory variables included on this node. The weights or coefficients are estimated as part of the model estimation process. The second through fifth nodes use a logistic or sigmoid activation function. This function form has proven to be extremely useful in applying Neural Network Techniques to the problem of load forecasting because it provides a continuous nonlinear approximation of the nonlinear response between loads and weather. This approximation is very similar to what regressing loads against a third order polynomial in weather would derive. Unlike a polynomial regression, where key interaction terms like weekend weather slope offsets would need to be constructed outside of the regression model and then added as additional explanatory variables, the mathematical properties of the sigmoid function allows for these interactions to be estimated directly as part of the model estimation process. Although, the explanatory variables (like weather and weekend binary variables) need to be included in the list of explanatory variables included on a Node for the interactions to be estimated. Like the linear node, the weights or coefficients of the nonlinear nodes (Node 2 through Node 5) are estimated as part of the model estimation process.

The model can be written generally as follows:

Equation 1. Daily Energy Neural Network Model

$$E_d^Z = \sum_{n=1}^N \phi_n^Z H_d^{Z,n} (A_d^{Z,n} \alpha^{Z,n}) + \epsilon_d^Z$$

Where,

 E_d^Z is the daily sum of the 96 15-minute load values for Load Zone (Z) on Day (d)

N is the number of Nodes in the Hidden Layer of the Neural Network Model. Node 1 (n=1) utilizes a Linear Activation Function. Nodes (2 through 5) utilize a Sigmoid Activation Function.

- $Ø_n^Z$ is the weight placed on Node (n)
- $H_d^{Z,n}(A_d^{Z,n}\alpha^{Z,n})$ is the nth Node in the Hidden Layer

 $A_d^{Z,n}$ is a vector of explanatory variables included on the nth Node in the Hidden Layer

 $\alpha^{Z,n}$ is a vector of weights placed on the explanatory variables included on the nth Node in the Hidden Layer

 ε_d^Z is the Neural Network model error for Load Zone (Z) on Day (d)

The Neural Network weights (\emptyset_n^Z and $\alpha^{Z,n}$) are estimated using Non-Linear Least Squares.

The explanatory variables included on the Nodes in the Hidden Layer are as follows.

Node 1: Linear Activation Function

- A set of Day Type Variables: (Sunday, Monday, Tuesday-Wednesday-Thursday (TWT), Friday, Saturday) by Month
- Day of the Week Variables
- Holiday Variables
- Linear Time Trend
- Hours of Light Variable

Node 2 and 3: Sigmoid Activation Function

- Night, Morning, Afternoon, and Evening Heating Degree Day Variables
- Night, Morning, Afternoon, and Evening Latent Heat Variables
- Night, Morning, Afternoon, and Evening Wind Speed Variables
- Prior Day Maximum and Minimum Temperature Variables

- Day-of-the-Week Variables
- Non-Winter Months, Monthly Binary Variables

Node 4 and 5: Sigmoid Activation Function

- Night, Morning, Afternoon, and Evening Cooling Degree Day Variables
- Night, Morning, Afternoon, and Evening Latent Heat Variables
- Night, Morning, Afternoon, and Evening Wind Speed Variables
- Prior Day Maximum and Minimum Temperature Variables
- Day-of-the-Week Variables
- Non-Summer Months, Monthly Binary Variables

The load forecasts generated from the Daily Energy Models can be written as follows.

Equation 2. Predicted Daily Energy

$$\widehat{E}_{d}^{Z,T+h} = \sum_{n=1}^{N} \widehat{\wp}_{n}^{Z} H_{d}^{Z,n,T+h} \big(A_{d}^{Z,n,T+h} \widehat{\alpha}^{Z,n} \big)$$

Where,

 $\widehat{E}_{d}^{Z,T+h}$ is the h-step ahead forecast of Daily Measured Load for Zone (Z) made at time (T) for forecast day (d)

T + h measures the number of time intervals in the forecast horizon for a forecast generated at time (T)

 $A_{d'}^{Z,n,T+h}$ contains the h-step ahead forecasted values of the explanatory variables made at time (T)

 $H_d^{Z,n,T+h}$ is the h-step ahead forecasted value for node (n) for Zone (Z) made at time (T),

 $\widehat{\emptyset}_n^Z$ is the vector of estimated Node weights

 $\widehat{\alpha}^{Z,n}$ is the vector of estimated Neural Network coefficients for Node (n)

Day-Ahead Model Specification. The 96 ,15-minute level Day-Ahead models can be described generically as:

Equation 3. 96, 15-Minute Level Day-Ahead Models

$$L_{d,i}^{Z} = F(X_{d,i}^{Z}\beta_{i}^{Z}) + u_{d,i}^{Z}$$

Where,

 $L_{d,i}^{Z}$ is the measured load for load zone (Z), on day (d), and 15-minute time interval (i). Load zones include PGE Total, PG&E Bay Area, PG&E Non-Bay Area, SCE Total, SCE Inland, SCE Coastal, and SDG&E

 $F(X_{d,i}^Z \beta_i^Z)$ is a generic representation of a regression model where $X_{d,i}^Z$ is a set of explanatory variables - excluding explicit treatment of Behind-the-Meter Solar Generation

 β_i^Z is a vector of model coefficients.

 u_{di}^{Z} is the forecast model error

The vector of mode coefficients (β_i^z) are estimated using Multivariate Least Squares.

The explanatory variables included in the models are as follows.

- A set of Day Type Variables: (Sunday, Monday, TWT, Friday, Saturday) by Month
- Day of the Week Variables
- Holiday Variables
- Linear Time Trend
- Variables that Measure the Fraction of the Morning/Evening Hours that are dark
- Coincident Heating Degree Day Variables
- Coincident Heating Degree Day Variables with Sunday and Saturday interactions
- Coincident Cooling Degree Day Variables
- Coincident Cooling Degree Day Variables with Sunday & Saturday interactions
- Prior Day Maximum and Minimum Temperature Variables
- Predicted Values from the Daily Energy Model interacted with Day-of-the-Week

The load forecasts generated from the Day-Ahead Models can be written as follows:

Equation 4. 96, 15-Minute level Day Ahead Predicted values

$$DayAhead_{\hat{L}_{d,i}^{Z,T+h}} = F(X_{d,i}^{Z,T+h}\hat{\beta}_{i}^{Z})$$

Where,

 $DayAhead_\hat{L}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Measured Load for Zone (Z), forecast day (d) and time interval (i) made at time (T)

h measures the number of forecast intervals ahead

 $X_{d\,i}^{Z,T+h}$ contains the h-step ahead forecasted values of the explanatory variables

 $\hat{\beta}_i^Z$ is the vector of estimated model coefficients

Hour-Ahead Model Specification. The 96, Hour-ahead models can be described generically as:

Equation 5. 96, 15-Minute level Hour Ahead Models

$$L_{d,i}^Z = G\big(X_{d,i}^Z\delta_i^Z\big) + \sum_{k=1}^K L_{d,i-k}^Z\gamma_k^Z + w_{d,i}^Z$$

Where,

 $L^{Z}_{d,i}$ is the measured load for load zone (Z), on day (d), and 15-minute time interval (i).

 $G(X_{d,i}^Z \delta_i^Z)$ is a generic representation of a regression model where $X_{d,i}^Z$ is a set of explanatory variables - excluding explicit treatment of Behind-the-Meter Solar Generation (BTMSG)

 δ_i^Z is the vector of model coefficients

 $L^{Z}_{d,i-k}$ is an autoregressive term of lag (i-k), where the maximum length of the autoregressive structure is (K)

 γ_k^Z is the coefficients for the autoregressive terms

 $w_{d,i}^{Z}$ is the forecast model error

The explanatory variables included in the models:

- A set of Day Type Variables: (Sunday, Monday, TWT, Friday, Saturday) by Month
- Day of the Week Variables
- Holiday Variables
- Linear Time Trend
- Variables that Measure the Fraction of the Morning/Evening Hours that are dark
- Coincident Heating Degree Day Variables
- Coincident Heating Degree Day Variables with Sunday and Saturday interactions
- Coincident Cooling Degree Day Variables
- Coincident Cooling Degree Day Variables with Sunday and Saturday interactions
- Prior Day Maximum and Minimum Temperature Variables
- A set of the prior five (K), 15-minute load values

In this case, the autoregressive terms replace the predicted value from the Daily Energy model.

The load forecasts generated from the Hour-Ahead Models can be expressed as follows:

Equation 6. 96, 15-Minute level Hour Ahead Predicted Values

$$\text{HourAhead}_{\hat{L}_{d,i}^{Z,T+h}} = G(X_{d,i}^{Z,T+h}\hat{\delta}_{i}^{Z}) + \sum_{k=1,T+h-k< T}^{K} L_{d,i-k}^{Z,T+h-k}\hat{\gamma}_{k}^{Z} + \sum_{k=1,T+h-k>T}^{K} \text{HourAhead}_{\hat{L}_{d,i-k}^{Z,T+h-k}}\hat{\gamma}_{k}^{Z}$$

Where,

 $HourAhead_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Measured Load for Zone (Z), forecast day (d) and time interval (i) made at time (T)

h measures 15-minute time intervals - if a forecast is generated at 08:00 then T equals 08:00 of day (d=0), the two hour-ahead Load forecast would then be indexed as T=08:00, d = 0, h = 8

 $X_{d\,i}^{Z,T+h}$ contains the h-step ahead forecasted values of the explanatory variables

 $\hat{\delta}^{Z}_{i}$ is the vector of estimated model coefficients

 $L_{di-k}^{Z,T+h-k}$ is observed Measured Load for Zone (Z), forecast day (d) and time interval (i) available at time (T)

 $\hat{\gamma}_k^Z$ is the estimated coefficients for the autoregressive terms

 $HourAhead_{L_{d,i-k}^{Z,T+h-k}}$ is the Hour Ahead forecasted Measured Load for Zone (Z), forecast day (d) and time interval (i-k) available at time (T+h)

Blended Load Forecast. 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. The blended forecast is constructed in steps.

Step 1. A 10-day ahead load forecast is generated using the Daily Energy Model. This ten day ahead forecast then feeds into the Day-Ahead Models.

Step 2. The Day-Ahead Models are then used to generate a 10-day ahead load forecast at the 15-minute level of load resolution.

Step 3. The Hour Ahead Models are then used to construct a separate 15-minute level load forecast.

Step 4. A single blended load forecast is then constructed as follows:

Equation 7. 15-Minute level Blended Forecast

$$Blended_{L_{d,i}^{Z,T+h}} = \omega_{h}^{Z}HourAhead_{L_{d,i}^{Z,T+h}} + (1 - \omega_{h}^{Z})DayAhead_{L_{d,i}^{Z,T+h}}$$

Where,

Blended_ $\hat{L}_{d,i}^{Z,T+h}$ is the blended forecast of Measured Load for Zone (Z) made at time (T) for the fifteen minute time interval (T+h)

HourAhead_ $\hat{L}_{d,i}^{Z,T+h}$ is the Hour-Ahead forecast of Measured Load for Zone (Z) made at time (T) for the fifteen minute time interval (T+h)

 $DayAhead_{L_{d,i}^{Z,T+h}}$ is the Day-Ahead forecast of Measured Load for Zone (Z) made at time (T) for the fifteen minute time interval (T+h)

 ω_h^Z is the weight placed on the Hour-Ahead forecast for forecast period (T+h)

Load Forecast Errors. The Load Forecast errors are then computed as:

Equation 8. 15-Minute level Load Forecast Errors

$$\mathbf{e}_{d,i}^{Z,T+h} = \mathbf{L}_{d,i}^{Z} - \text{Blended}_{\hat{\mathbf{L}}_{d,i}}^{Z,T+h}$$

Where,

 $e_{d,i}^{Z,T+h}$ is the forecast error for Zone (Z) for day (d) and 15-minute time interval (i) from a h-step ahead forecast made at time (T)

1.2 The Impact of Solar PV on the CAISO Short-Term Load Forecast

The statistical models described above use linear least squares to estimate the model coefficients.⁴ 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 the averages are taken. 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 CAISO 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, the model coefficients are tuned 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 bump up in loads due to lower solar PV production.

⁴ The Neural Network model coefficients are estimated using the Levenberg-Marquardt algorithm, which is a specific application of Nonlinear Least Squares.

To help fix ideas, the following examples illustrate how solar PV generation can impact a load forecast. In these examples, assume the demand for electricity at noon, regardless of how it is sourced, is 1,300 MW.

No Solar PV Generation. Under this first example, there is no solar PV generation. As a result, Measured Load, which is the load that a system operator sees, equals actual Demand for electricity services. That is,

Equation 9. Measured Load at Noon vs. Actual Demand with no BTM Solar PV

$$L_d^{Noon} = D_d^{Noon}$$

Where,

 L_d^{Noon} is the telemetry measured load that the control room sees at Noon at day (d)

D^{Noon} is the Demand for electrical services at Noon on day (d)

Now consider developing a forecasting model of measured load. If there is a year's worth of measured load, the following regression model can be used.

Equation 10 Regression Model to Predict Load at Noon with no BTM Solar PV.

 $L_d^{Noon} = \beta_1 \text{ Intercept}_d + e_d^{Noon}$

Where,

Intercept_d is an explanatory variable that takes on the value 1.0 for every day (d)

 e_d^{Noon} is a random error with expected value of 0.0

 β_1 is the regression coefficient on the Intercept variable

In this case, the estimated coefficient on the Intercept variable will be equal to the average measured load, or 1,300 MW. As a result, the forecast from the estimated model will provide an accurate forecast of both measured load and actual demand.

That is,

Equation 11 Predicted Load at Noon with no BTM Solar PV.

 $\hat{L}_d^{Noon} = 1300 \text{ x Intecept}_d = 1300 = D_d^{Noon}$

Where,

 \hat{L}^{Noon}_d is the forecast of measured load for day (d) at Noon

With Constant Solar PV Generation. Now, assume that 100 MW of solar PV generation is produced every day at noon. The measured load can be re-written as follows:

Equation 12 Measured Load with Constant BTM Solar PV.

$$L_d^{Noon} = D_d^{Noon} - SG_d^{Noon}$$

Because measured load will be 100 MW lower, the estimated coefficient from regressing the new lower measured load on the Intecept variable will lead to an estimated coefficient of 1,200 MW. In this case, the resulting model forecast will accurately forecast measured load, but will under predict demand by 100 MW.

Equation 13 Regression Model to Predict Load with Constant BTM Solar PV.

 $\hat{L}_d^{Noon} = 1200 \text{ x Intercept}_d = 1200 < D_d^{Noon}$

From the perspective of system operations, the fact that the forecast model under predicts demand for electricity is not a concern, since in this unrealistic example, they can rely on the 100 MW of solar generation being there all the time.

With Volatile Solar PV Generation. In reality, solar PV generation is not as reliable as the above example suggests. One can introduce uncertainty into the amount of solar generation that is available by assuming that half the time cloud cover is thick enough to drive the solar generation to 0 MW. The other days are perfectly clear and the solar generation is 100 MW. This means that half the time measured load equals 1,200 MW and the other half of the time measured load equals 1,300 MW. If the cloudy and sunny days are equal in number, the average measured load over the year of data will be 1,250 MW. This implies the estimated coefficient on the Intercept variable will be equal to 1,250 MW. That is,

Equation 14 Regression Model to Predict Load with Variable BTM Solar PV.

$$L_d^{Noon} = 1250 \text{ x Intercept}_d$$

Now consider using this model on two types of days: a Cloudy Day and a Sunny Day. On a Cloudy Day, solar PV generation is 0 MW and measured load will be equal to 1,300 MW, computed as $(D_d^{Noon} - 0)$. In this case, the model forecast of 1,250 MW under predicts measured load. On a Sunny Day, solar PV generation is 100 MW giving a measured load of 1,200 MW, computed as $(D_d^{Noon} - 100)$. In this case, the model forecast will over predict measured load.

The variability in solar generation means that the statistical model that was fitted to measured load will under predict measured loads on cloudy days and over predict measured loads on sunny days. From the perspective of system operations, this means they will need additional spinning reserves available to cover the load variability and subsequent load forecast error introduced by the volatile solar PV generation. The inherent bias that arises from fitting statistical models to measured load implies that a growing penetration of solar PV generation will lead to an erosion of the forecast accuracy of load forecast models that do not account for this impact.

Accounting for Average Solar Generation. Is it possible to improve the accuracy of the load forecast? Assuming a perfect forecast of cloud over can be obtained, it is possible to accurately predict how much solar generation is going to be available tomorrow. It seems reasonable to adjust the baseline load forecast with the forecast of solar generation. Specifically, the adjusted forecast of measured load can be constructed as:

Equation 15 Predicted Load with Perfectly Forecasted BTM Solar PV.

$$\overline{\overline{L}}_{d}^{\text{Noon}} = \widehat{L}_{d}^{\text{Noon}} + (\overline{SG}^{\text{Noon}} - \widehat{SG}_{d}^{\text{Noon}})$$

Where,

 \bar{L}^{Noon}_d is the adjusted forecast of measure load

 \overline{SG}^{Noon} is the average solar PV generation over the model estimation period

 \widehat{SG}_{d}^{Noon} is the forecast of solar PV generation at Noon on day (d)

Following the example from above, the average solar PV generation over the model estimation period is equal to 50 MW, computed as (50% of the days at 0 MW + 50% of the days at 100 MW). On a sunny day, the forecast of measured load will be equal to the predicted value of 1,250 MW from the model of measured load plus (50 MW – 100 MW), or 1,200 MW. On a cloudy day, the forecast of measured load will be equal to the predicted value of 1,250 MW from the model of the predicted value of 1,250 MW from the model of measured load plus (50 MW – 00 MW), or 1,300 MW. On a sunny day, this approach lowers the forecast of measured load by 50 MW which is the additional solar generation that occurs on a sunny day versus an average day. Conversely, on a cloudy day, this approach raises the forecast of measured load by an additional 50 MW to account for no solar generation taking place on that day.

These examples illustrate that a statistical model of measured load will capture in the estimated model coefficients the average impact of solar generation. Accordingly, with volatile solar PV generation, the model-based forecast of measured load needs to be adjusted 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. This is followed by a discussion of the simulation framework that was developed to evaluate the potential to improve forecast accuracy by utilizing forecasts of solar PV generation. Findings based on a summary of the simulation results are then presented.

CHAPTER 2: INCORPORATING THE IMPACT OF SOLAR PV GENERATION IN A LOAD FORECAST

The existing CAISO 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 CAISO mid-day forecasts tend to be high on sunny days and low on cloudy days. The purpose of this study is develop alternative forecast frameworks that account for the load impact of solar PV generation. The study utilizes forecast simulations to compare the forecast accuracy of the existing CAISO forecast framework against the following three alternative modeling approaches.

- » 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, the adjustment is to lower the load forecast and on cloudy days, the load forecast is adjusted upward. The key advantage of the Error Correction Approach is the existing load forecast model can continue to be used without any changes. All that is needed is a means of forecasting solar PV generation.
- Reconstituted Loads. Under the Reconstituted Loads approach the historical time series of measured load is reconstituted by adding back estimates of solar PV generation. The load forecast model is then re-estimated against the reconstituted loads. The subsequent reconstituted load forecasts are then adjusted *ex post* by subtracting away forecasts of solar PV generation to form a forecast of measured loads. The advantage of this approach is any inherent bias that might be imposed on the estimated coefficients of a model of measured loads is controlled for by estimating the model coefficients against a time series of demand for power regardless of how it is sourced. The disadvantage is a historical time series of solar PV generation needs to be developed and maintained 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.
- » Model Direct. Under this approach, the weight placed on the solar PV generation data is estimated directly 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, by including solar PV generation as an explanatory variable, the coefficients on the remaining explanatory variables should not be biased. 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.

What follows is a description of these three frameworks.

2.1 Error Correction

As described above, the Error Correction approach provides an *ex post* (or after the event) adjustment to an existing load forecast. This framework is described 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. That is:

Equation 16. Day-Ahead Error Correction Forecast

$$DayAhead_{L_{d,i}}^{\overline{Z},T+h} = DayAhead_{L_{d,i}}^{Z,T+h} + \vartheta_{i}^{Z} [\overline{BTMSG}_{i}^{Z} - B\overline{TMSG}_{d,i}^{Z,T+h}]$$

Where,

DayAhead $\overline{L}_{di}^{Z,T+h}$ is the h-step ahead Error Corrected Day-Ahead Measured Load forecast made at time (T)

DayAhead $\hat{L}_{di}^{Z,T+h}$ is the h-step ahead Day-Ahead Model forecast of Measured Load made at time (T)

BTMSG_i^Z is the historical average of Behind-the-Meter Solar Generation for time interval (i)

 $\widehat{BTMSG}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Behind-the-Meter Solar Generation for Zone (Z) time interval (i) made at Time (T)

 ϑ_i^Z is a subjective adjustment weight which has a default value of 1.0 for all Load Zones (Z) and time intervals (i)

In this case, if the forecast of solar PV generation is higher than the historical average, then the Day-Ahead Load Forecast will be adjusted downward. For example, on a clear sunny day, the Day-Ahead Load Forecast will be adjusted 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, the Day-Ahead Load Forecast will be adjusted upwards.

Hour-Ahead Error Correction Forecast. The Hour-Ahead Forecast models are highly autoregressive. In principle, this means a certain amount of solar PV generation is reflected in the Measure Load values that are passed into the models as autoregressive terms. 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, the Hour-Ahead Forecast should be lifted if it is expected that there will be a drop in solar PV generation between 11:00 and 11:15. This suggests the following Error Correction:

Equation 17. Hour-Ahead Error Correction Forecast

$$HourAhead_{L_{d,i}^{Z,T+h}} = HourAhead_{L_{d,i}^{Z,T+h}} + \nabla_{i}^{Z} \Big[B\widehat{TMSG}_{d,i-1}^{Z,T+h-1} - B\widehat{TMSG}_{d,i}^{Z,T+h} \Big]$$

Where,

 $\operatorname{HourAhead}_{L_{d,i}}^{Z,T+h}$ is the h-step ahead Error Corrected Hour-Ahead Measured Load forecast for Zone (Z) made at time (T)

 $HourAhead_{L_{d,i}^{Z,T+h}}$ is the h-step ahead Hour-Ahead Model forecast of Measured Load for Zone (Z) made at time (T)

 $\widehat{BTMSG}_{d,i-1}^{Z,T+h-1}$ the (h-1) step ahead forecast of Behind-the-Meter Solar Generation for Zone (Z) made at Time (T)

 $\widehat{BTMSG}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Behind-the-Meter Solar Generation for Zone (Z) made at Time (T)

 ∇_i^Z is a subjective adjustment weight that has a default value of 1.0 for all Load Zones (Z) and time intervals (i)

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 forecast value $B\widetilde{TMSG}_{d,i-1}^{Z,T+h-1}$ would be replaced with the measurement value.

For this study, the adjustment weights $(\vartheta_i^Z, \nabla_i^Z)$ are assumed fixed at a default value of 1.0. In practice, as forecasters build experience, it is expected that the adjustments weights would be modified to account for the forecaster's confidence in the solar PV generation forecasts, as well as the forecast performance of the adjustments.

Error Corrected Measured Load Forecast. The Error Corrected Measured Load Forecast is then constructed as a weighted average of the Error Corrected Hour-Ahead and Day-Ahead forecasts. Formally,

Equation 18. Error Corrected Load Forecast

$$ErrorCorrection_Blended_\overline{L}_{d,i}^{Z,T+h} = \omega_h^Z HourAhead_\overline{L}_{d,i}^{Z,T+h} + (1 - \omega_h^Z) DayAhead_\overline{L}_{d,i}^{Z,T+h}$$

The load forecast errors from the Error Correction Model are then computed as:

Equation 19. Error Corrected Load Forecast Errors

ErrorCorrection_
$$e_{d,i}^{Z,T+h} = L_{d,i}^{Z} - ErrorCorrection_Blended_{L_{d,i}}^{Z,T+h}$$

Where,

 $ErrorCorrection_e_{d,i}^{Z,T+h}$ is the Load Forecast Error for Zone (Z) for day (d) and 15-minute time interval (i) from a h-step ahead forecast made at time (T)

2.2 Reconstituted Loads

Under the Reconstituted Loads approach, the historical time series of measured load is *reconstituted* by adding back estimates of solar PV generation. The load forecast model is then re-estimated against the reconstituted loads. The resulting reconstituted load forecast is then reduced by a forecast of solar PV generation to provide a forecast of measured load. This framework is described below.

Estimates of demand for power regardless of how it is sourced are created by adding estimates of solar PV generation to measured loads. Specifically,

Equation 20. Reconstituted Loads

Reconstituted_
$$L_{d,i}^{Z} = L_{d,i}^{Z} + BTMSG_{d,i}^{Z}$$

Where,

BTMSG^Z_{d,i} is the estimated BTM Solar Generation for load zone (Z), on day (d) and time interval (i)

The original CAISO baseline load forecast model is then re-estimated using the Reconstituted Loads as the dependent variable. That is,

Equation 21. Reconstituted Loads Daily Energy Model

$$\text{Reconstituted}_E_d^Z = \sum_{n=1}^N \phi_n^Z H_d^{Z,n} (A_d^{Z,n} \alpha^{Z,n}) + \epsilon_d^Z$$

Where,

Reconstituted E_d^Z is the daily sum of the 96 15-minute reconstituted load values for Load Zone (Z) on Day (d)

The load forecasts generated from the Daily Energy Model can be written as follows:

Equation 22. Forecast of Daily Reconstituted Energy

$$\text{Reconstituted}_{\underline{}}\widehat{E}_{d}^{Z} = \sum_{n=1}^{N} \widehat{\varrho}_{n}^{Z} H_{d}^{Z,n} (A_{d}^{Z,n} \widehat{\alpha}^{Z,n})$$

Where,

Reconstituted $L\widehat{E}_{d,}^{Z}$ is the forecast of Daily Reconstituted Load for Zone (Z) made at time (T) for forecast day (d)

Day-Ahead Model Specification. The 96, 15-minute level Day-Ahead models can be described generically as:

Equation 23. 96, 15-Minute Level Reconstituted Load Day-Ahead Models

Reconstituted_ $L_{d,i}^{Z} = F(X_{d,i}^{Z}\beta_{i}^{Z}) + u_{d,i}^{Z}$

Where,

Reconstituted $L_{d,i}^{Z}$ is the reconstituted load for load zone (Z), on day (d), and 15-minute time interval (i).

The load forecasts generated from the Day-Ahead Models can be written as follows:

Equation 24. 96, 15-Minute Level Day-Ahead Reconstituted Load Forecasts

DayAhead_Reconstituted_ $\hat{L}_{d,i}^{Z,T+h} = F(X_{d,i}^{Z,T+h}\hat{\beta}_{i}^{Z})$

Where,

 $DayAhead_Reconstituted_\hat{L}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Reconstituted Load for Zone (Z), forecast day (d) and time interval (i) made at time (T)

Day-Ahead Measured Load Forecast. To recast the forecasts of Reconstituted Loads into forecasts of Measured Loads, the following *ex post* adjustment is made to the Day-Ahead Reconstituted Load forecasts.

Equation 25. 96, 15-Minute Level Day-Ahead Measured Load Forecasts

DayAhead_MeasuredLoad_ $\vec{L}_{d,i}^{Z,T+h} = DayAhead_Reconstituted_<math>\hat{L}_{d,i}^{Z,T+h} - B\widehat{TMSG}_{d,i}^{Z,T+h}$

Where,

 $\label{eq:loss} DayAhead_MeasuredLoad_\bar{L}^{Z,T+h}_{d,i} \text{ is the h-step ahead forecast of Measured Load from the Day Ahead models}$

 $\label{eq:lag} DayAhead_Reconstituted_\hat{L}_{d,i}^{Z,T+h} \text{ is the h-step ahead Day-Ahead Model forecast of Reconstituted Load}$

 $\widehat{BTMSG}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Behind-the-Meter Solar Generation for Zone (Z) time interval (i) made at Time (T)

Hour-Ahead Model Specification. The 96, Hour-ahead models can be described generically as:

Equation 26. 96, 15-Minute Level Reconstituted Load Hour Ahead Models

Where,

 $\label{eq:reconstituted_L} \ensuremath{^Z_{d,i}}\xspace$ is the reconstituted load for load zone (Z), on day (d), and 15-minute time interval (i).

The load forecasts generated from the Hour-Ahead Models can be expressed as follows:

Equation 27. 96, 15-Minute Level Hour-Ahead Reconstituted Load Forecasts

$$\begin{split} \text{HourAhead}_\text{Reconstituted}_\hat{L}_{d,i}^{Z,T+h} \\ &= G\big(X_{d,i}^{Z,T+h}\hat{\delta}_{i}^{Z}\big) + \sum_{k=1,T+h-k < T}^{K} \text{Reconstituted}_L_{d,i-k}^{Z,T+h-k}\hat{\gamma}_{k}^{Z} \\ &+ \sum_{k=1,T+h-k > T}^{K} \text{HourAhead}_\text{Reconstituted}_\hat{L}_{d,i-k}^{Z,T+h-k}\hat{\gamma}_{k}^{Z} \end{split}$$

Where,

HourAhead_Reconstituted_ $\hat{L}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Reconstituted Load for Zone (Z), forecast day (d) and time interval (i) made at time (T)

$$\label{eq:hourAhead_Reconstituted_L} \begin{split} & {\rm HourAhead_Reconstituted_L} \hat{\rm L}_{d,i-k}^{Z,T+h-k} \text{ is the Hour Ahead forecasted Measured Load for Zone (Z), forecast day (d) and time interval (i-k) available at time (T+h) \end{split}$$

Hour-Ahead Measured Load Forecast. To recast the forecasts of Reconstituted Loads into forecasts of Measured Loads the following *ex post* adjustment is made to the Hour-Ahead Reconstituted Load forecasts.

Equation 28. 96, 15-Minute Level Hour-Ahead Measured Load Forecasts

HourAhead_MesasuredLoad_
$$\overline{L}_{d,i}^{Z,T+h}$$
 = HourAhead_Reconstituted_ $\hat{L}_{d,i}^{Z,T+h}$ - BTMSG_{d,i}^{Z,T+h}

Where,

 ${\rm HourAhead_MeasuredLoad_\bar{\vec{L}}_{d,i}^{Z,T+h}}$ is the h-step ahead forecast of Measured Load

HourAhead_Reconstituted $\hat{L}_{d i}^{Z,T+h}$ is the h-step ahead Hour-Ahead Model forecast of Reconstituted Load

 $\widehat{BTMSG}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Behind-the-Meter Solar Generation for Zone (Z) made at Time (T)

Measured Load Forecast from the Reconstituted Load Approach. The Measured Load Forecast is then constructed as a weighted average of the Adjusted Hour-Ahead and Day-Ahead forecasts. Formally,

Equation 29. 96, 15-Minute Level Blended Measured Load Forecasts

 $Reconstituted_Blended_\overline{L}_{d,i}^{Z,T+h} = \omega_{h}^{Z}HourAhead_MeasuredLoad_\overline{L}_{d,i}^{Z,T+h} + (1 - \omega_{h}^{Z})DayAhead_MeasuredLoad_\overline{L}_{d,i}^{Z,T+h}$

The load forecast errors from the Reconstituted Load Approach are then computed as:

Equation 30. 96, 15-Minute Level Load Forecast Errors

$$Reconstituted_e^{Z,T+h}_{d,i} = L^{Z}_{d,i} - Reconstituted_Blended_\overline{L}^{Z,T+h}_{d,i}$$

Where,

Reconstituted_ $e_{d,i}^{Z,T+h}$ is the Measured Load Forecast Error for Zone (Z) for day (d) and fifteen-minute time interval (i) from a h-step ahead forecast made at time (T)

2.3 Model Direct

Under this approach, the existing CAISO Baseline Load Forecast models are extended to include explanatory variables that are designed to capture the impact of solar PV generation on measured loads. The model framework is described below.

The revised load forecast model are:

Equation 31. Model Direct Daily Energy Model

$$E_d^Z = \sum_{n=1}^N \phi_n^Z H_d^{Z,n} \big(S_d^{Z,n} \alpha_?^{Z,n} \big) + \epsilon_d^Z$$

Where,

 E_d^Z is the daily sum of the 96 15-minute measured load values for Load Zone (Z) on Day (d)

N is the number of Nodes in the Hidden Layer of the Neural Network Model. Node 1 (n=1) utilizes a Linear Activation Function. Nodes (2 through 5) utilize a Sigmoid Activation Function.

 $Ø_n^Z$ is the weight placed on Node (n)

 $H_d^{Z,n}(S_d^{Z,n}\alpha_2^{Z,n})$ is the nth Node in the Hidden Layer

 $S_d^{Z,n}$ is a vector of explanatory variables included on the nth Node in the Hidden Layer which equals the original vector of explanatory variables plus the time series of Behind-the-Meter Solar Generation ($S_d^{Z,n} = A_d^{Z,n}$ augmented with BTMSG^Z_d)

 $\alpha_2^{Z,n}$ is a vector weights placed on the explanatory variables included on the nth Node in the Hidden Layer

 ε_{d}^{Z} is the Neural Network model error for Load Zone (Z) on Day (d)

The load forecasts generated from the Daily Energy Model can be written as follows:

Equation 32. Model Direct Daily Energy Forecast

$$\text{ModelDirect}_\widehat{E}_{d}^{Z} = \sum_{n=1}^{N} \widehat{\varnothing}_{n}^{Z} H_{d}^{Z,n} (S_{d}^{Z,n} \widehat{\alpha}^{Z,n})$$

Where,

 $ModelDirect_{d}^{Z}$ is the forecast of Daily Measured Load for Zone (Z) made at time (T) for forecast day (d)

Day-Ahead Model Specification. The 96 15-minute level Day-Ahead models can be described generically as:

Equation 33. 96, 15-Minute Level Model Direct Day-Ahead Models

$$L_{d,i}^{Z} = F(X_{d,i}^{Z}\beta_{i}^{Z}) + \vartheta_{i}^{Z}BTMSG_{d,i}^{Z} + u_{d,i}^{Z}$$

Where,

 $L_{d\,i}^{Z}$ is the measured load for load zone (Z), on day (d), and 15-minute time interval (i)

 $BTMSG_{d,i}^{Z}$ is the estimated Behind-the-Meter Solar Generation for load zone (Z), on day (d) and time interval (i)

 ϑ_i^Z is the model coefficient for the Behind-the-Meter Solar Generation time series

The load forecasts generated from the Day-Ahead Models can be written as follows:

Equation 34. 96, 15-Minute Level Model Direct Day-Ahead Load Forecasts

$$DayAhead_ModelDirect_\hat{L}_{d,i}^{Z,T+h} = F(X_{d,i}^{Z,T+h}\hat{\beta}_{i}^{Z}) + \hat{\vartheta}_{i}^{Z}B\widehat{TMS}G_{d,i}^{Z,T+h}$$

Where,

 $DayAhead_ModelDirect_\hat{L}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Measured Load for Zone (Z), forecast day (d) and time interval (i) made at time (T)

 $\widehat{BTMSG}_{d,i}^{Z,T+h}$ is the h-step ahead forecast of Behind-the-Meter Solar Generation for Zone (Z), forecast day (d) and time interval (i) made at time (T)

Hour-Ahead Model Specification. The 96 Hour-Ahead models can be described generically as:

Equation 35. 96, 15-Minute Level Model Direct Hour-Ahead Models

$$L_{d,i}^{Z} = G(X_{d,i}^{Z}\delta_{i}^{Z}) + \nabla_{i}^{Z}(BTMSG_{d,i-1}^{Z} - BTMSG_{d,i}^{Z}) + \sum_{k=1}^{K} L_{d,i-k}^{Z}\gamma_{k}^{Z} + w_{d,i}^{Z}$$

Where,

 $L^{Z}_{d,i}$ is the measured load for load zone (Z), on day (d), and 15-minute time interval (i).

 $BTMSG_{d,i}^{Z}$ is the estimated Behind-the-Meter Solar Generation for load zone (Z), on day (d) and time interval (i)

 $BTMSG_{d,i-1}^{Z}$ is the estimated Behind-the-Meter Solar Generation for load zone (Z), on day (d) and time interval (i-1)

 ∇_i^Z is the estimated coefficient or weight placed on the 15-minute ramp in Behind-the-Meter Solar Generation

The Hour-Ahead Model mimics the approach utilized in the Error Correction Approach in that the solar PV generation enters into the model as the difference between the current interval and the prior fifteen minute interval value. When cast in this fashion, the revised Hour-Ahead Model provides a means for statistically estimating the weight that should be placed on this difference. That is, the adjustment weight that is judgmentally imposed under the Error Correction Approach is estimated directly under this approach.

The load forecasts generated from the Hour-Ahead Models can be expressed as follows:

Equation 36. 96, 15-Minute Level Model Direct Hour-Ahead Forecasts

HourAhead_ModelDirect_ $\hat{L}_{d,i}^{Z,T+h}$

$$= G(X_{d,i}^{Z,T+h}\widehat{\delta}_{i}^{Z}) + \nabla_{i}^{Z}(B\widehat{TMS}G_{d,i-1}^{Z} - B\widehat{TMS}G_{d,i}^{Z}) + \sum_{k=1,T+h-k
$$+ \sum_{k=1,T+h-k>T}^{K} HourAhead_ModelDirect_{L_{d,i-k}}^{Z,T+h-k}\widehat{\gamma}_{k}^{Z}$$$$

Where,

 $\label{eq:hourAhead_ModelDirect_L^{Z,T+h}_{d,i} is the h-step ahead forecast of Measured Load for Zone (Z), forecast day (d) and time interval (i) made at time (T)$

HourAhead_ModelDirect_ $\hat{L}_{d,i-k}^{Z,T+h-k}$ is the Hour Ahead forecasted Measured Load for Zone (Z), forecast day (d) and time interval (i-k) available at time (T+h)

Measured Load Forecast from the Direct Model Approach. The Measured Load Forecast is then constructed as a weighted average of the Hour-Ahead and Day-Ahead forecasts.

Formally,

Equation 37. Model Direct Blended Measured Load Forecast

 $ModelDirect_Blended_\bar{\bar{L}}_{d,i}^{Z,T+h} = \omega_h^Z HourAhead_ModelDirect_\bar{\bar{L}}_{d,i}^{Z,T+h} + \left(1 - \omega_h^Z\right) DayAhead_ModelDirect_\bar{\bar{L}}_{d,i}^{Z,T+h} + \left$

The load forecast errors from the Model Direct are then computed as:

Equation 38. Model Direct Measured Load Forecast Errors

$$ModelDirect_e_{d,i}^{Z,T+h} = L_{d,i}^{Z} - ModelDirect_Blended_\overline{L}_{d,i}^{Z,T+h}$$

Where,

 $ModelDirect_e_{d,i}^{Z,T+h}$ is the Load Forecast Error for Zone (Z) for day (d) and 15-minute time interval (i) from a h-step ahead forecast made at time (T)

CHAPTER 3: SOLAR PV GENERATION ESTIMATES

This chapter presents the two alternative sources for solar generation that are used to evaluate the forecast performance of the Error Correction, Reconstituted Loads, and Direct Modeling approaches described above. The first source of solar generation data is developed by Clean Power Research (CPR), which has a detailed database of solar installations in the PG&E, SCE, and SDG&E service territories. These detailed data are combined with satellite imagery to construct bottom-up estimates of solar generation by the PG&E Bay Area, PG&E Non Bay Area, SCE Coastal, SCE Inland and SDG&E load zones. 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, the hourly cloud cover data collected by weather stations are combined 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 that can be expected when the solar generation estimates/forecasts are sourced from a commercial vendor like CPR.

3.1 CPR Solar Generation Estimates

Much of the focus in the area of solar generation forecasting 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. This analysis is geared 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 CAISO, 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. These estimates are used to evaluate the forecast performance of the alternative load forecast approaches described above.

The solar capacity and generation data compiled by CPR for this study are summarized in Table 1 and Table 2 below.

- » Total solar capacity is estimated to have grown from 653.0 MW at the beginning of 2010 to 4,081.5 MW by June 2015. Maximum solar generation output in June has grown by over a factor of seven, from 369 MWh in 2010 to 2,665 MWh in 2016.
- » PG&E accounts for 2,050.7 MW, or about half of the installed capacity in June 2015. Approximately 70% of the PG&E installations have been the Non Bay Area portion of the service territory. The 2,050.7 MW of installed capacity generated at its maximum an estimated 1,320.8 MWh of electricity.
- » SCE accounts for about 38% of the total installed capacity, or 1,556.2 MW. Approximately 57% of this capacity has been installed in the Inland portion of SCE's service territory. The 1,556.2 MW of installed capacity led to a maximum of 1,028.5 MWh of solar generation.
- » SDG&E accounts for 474.6 MW of installed capacity, which is approximately 12% of the total. Maximum solar generation in June has grown from an estimated value of 44.2 MWh in 2010 to 316.0 MWh in 2015, which is a growth of over seven times.

Table 1. Estimated Installed B	8TM Solar Ca	pacity (MW)
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CAISO Tota	1											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	653.0	660.4	669.9	681.9	695.9	712.0	729.9	749.9	771.2	794.2	818.6	844.4
2011	872.0	899.5	928.1	958.8	990.6	1,023.4	1,057.2	1,092.6	1,128.3	1,164.8	1,202.2	1,240.5
2012	1,280.2	1,319.5	1,359.5	1,401.0	1,443.3	1,486.4	1,530.4	1,576.0	1,621.7	1,668.4	1,716.0	1,764.6
2013	1,815.0	1,864.1	1,914.2	1,967.3	2,021.6	2,077.2	2,134.3	2,193.8	2,254.0	2,315.8	2,379.4	2,445.0
2014	2,513.6	2,580.9	2,650.3	2,724.3	2,800.8	2,879.9	2,961.7	3,047.7	3,135.5	3,226.4	3,320.6	3,418.3
2015	3,521.4	3,623.1	3,728.6	3,841.8	3,959.4	4,081.5						
PG&E Total	I											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	383.9	389.7	396.5	404.5	413.4	423.1	433.7	445.2	457.3	470.1	483.5	497.6
2011	512.6	527.4	542.7	559.0	575.8	593.1	610.9	629.4	648.0	667.1	686.6	706.4
2012	727.0	747.3	767.9	789.2	811.0	833.1	855.5	878.8	902.0	925.7	949.8	974.3
2013	999.6	1,024.2	1,049.2	1,075.6	1,102.5	1,129.9	1,158.0	1,187.1	1,216.3	1,246.3	1,276.9	1,308.3
2014	1,341.1	1,373.0	1,405.7	1,440.5	1,476.2	1,512.9	1,550.7	1,590.2	1,630.3	1,671.5	1,714.1	1,758.0
2015	1,804.1	1,849.3	1,896.0	1,945.9	1,997.4	2,050.7						
PG&E Bay A	Area											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	130.5	131.4	132.7	134.4	136.6	139.1	142.1	145.4	149.0	152.9	157.2	161.7
2011	166.6	171.5	176.7	182.3	188.1	194.2	200.4	207.0	213.7	220.5	227.6	234.7
2012	242.2	249.6	257.1	264.9	272.8	280.8	288.9	297.3	305.7	314.1	322.7	331.3
2013	340.2	348.7	357.4	366.3	375.4	384.6	393.8	403.2	412.6	422.1	431.6	441.2
2014	451.1	460.6	470.1	480.0	490.1	500.2	510.4	520.9	531.4	541.9	552.6	563.4
2015	574.5	585.2	596.0	607.3	618.8	630.5						
PG&E Non	Bay Area											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	253.4	258.4	263.9	270.1	276.8	284.0	291.6	299.8	308.3	317.1	326.4	335.9
2011	346.0	355.8	365.9	376.7	387.7	398.9	410.4	422.4	434.4	446.6	459.0	471.7
2012	484.8	497.7	510.8	524.4	538.2	552.3	566.6	581.5	596.4	611.6	627.1	643.0
2013	659.4	675.5	691.9	709.3	727.1	745.4	764.2	783.8	803.7	824.2	845.3	867.1
2014	890.0	912.4	935.6	960.4	986.1	1,012.7	1,040.2	1,069.3	1,098.9	1,129.6	1,161.5	1,194.6
2015	1,229.6	1,264.2	1,300.0	1,338.5	1,378.6	1,420.2						
SCE Total												
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	195.9	196.2	197.4	199.6	202.7	206.8	211.6	217.4	223.8	230.9	238.7	247.1
2011	256.3	265.6	275.4	286.1	297.3	308.9	321.1	333.8	346.8	360.2	374.0	388.2
2012	403.1	417.8	432.9	448.7	464.8	481.4	498.3	516.0	533.7	552.0	570.6	589.8
2013	609.7	629.2	649.2	670.4	692.2	714.6	737.7	761.9	786.4	811.7	837.8	864.8
2014	893.1	921.0	949.8	980.6	1,012.6	1,045.7	1,080.0	1,116.2	1,153.2	1,191.7	1,231.6	1,273.1
2015	1,316.9		1,405.2	1,453.6	1,503.9	1,556.2						
		1,360.2	2,10012									
SCE Coasta		1,500.2	2,10012									
												-
2010	Jan	Feb	Mar	Apr	May	Jun	lut	Aug	Sep	Oct	Nov	Dec
2010	Jan 87.0	Feb 86.1	Mar 85.9	86.5	87.8	89.7	92.3	95.5	99.1	103.3	107.9	113.0
2011	Jan 87.0 118.6	Feb 86.1 124.2	Mar 85.9 130.2	86.5 136.7	87.8 143.4	89.7 150.5	92.3 157.7	95.5 165.4	99.1 173.1	103.3 180.9	107.9 189.0	113.0 197.2
2011 2012	Jan 87.0 118.6 205.6	Feb 86.1 124.2 213.9	Mar 85.9 130.2 222.3	86.5 136.7 231.0	87.8 143.4 239.7	89.7 150.5 248.5	92.3 157.7 257.4	95.5 165.4 266.5	99.1 173.1 275.5	103.3 180.9 284.6	107.9 189.0 293.8	113.0 197.2 303.0
2011 2012 2013	Jan 87.0 118.6 205.6 312.4	Feb 86.1 124.2 213.9 321.5	Mar 85.9 130.2 222.3 330.6	86.5 136.7 231.0 340.2	87.8 143.4 239.7 349.8	89.7 150.5 248.5 359.5	92.3 157.7 257.4 369.4	95.5 165.4 266.5 379.5	99.1 173.1 275.5 389.7	103.3 180.9 284.6 400.0	107.9 189.0 293.8 410.4	113.0 197.2 303.0 421.1
2011 2012 2013 2014	Jan 87.0 118.6 205.6 312.4 432.2	Feb 86.1 124.2 213.9 321.5 442.9	Mar 85.9 130.2 222.3 330.6 453.9	86.5 136.7 231.0 340.2 465.6	87.8 143.4 239.7 349.8 477.5	89.7 150.5 248.5 359.5 489.8	92.3 157.7 257.4	95.5 165.4 266.5	99.1 173.1 275.5	103.3 180.9 284.6	107.9 189.0 293.8	113.0 197.2 303.0
2011 2012 2013	Jan 87.0 118.6 205.6 312.4	Feb 86.1 124.2 213.9 321.5	Mar 85.9 130.2 222.3 330.6	86.5 136.7 231.0 340.2	87.8 143.4 239.7 349.8	89.7 150.5 248.5 359.5	92.3 157.7 257.4 369.4	95.5 165.4 266.5 379.5	99.1 173.1 275.5 389.7	103.3 180.9 284.6 400.0	107.9 189.0 293.8 410.4	113.0 197.2 303.0 421.1
2011 2012 2013 2014 2015	Jan 87.0 118.6 205.6 312.4 432.2	Feb 86.1 124.2 213.9 321.5 442.9	Mar 85.9 130.2 222.3 330.6 453.9	86.5 136.7 231.0 340.2 465.6	87.8 143.4 239.7 349.8 477.5	89.7 150.5 248.5 359.5 489.8	92.3 157.7 257.4 369.4	95.5 165.4 266.5 379.5	99.1 173.1 275.5 389.7	103.3 180.9 284.6 400.0	107.9 189.0 293.8 410.4	113.0 197.2 303.0 421.1
2011 2012 2013 2014	Jan 87.0 118.6 205.6 312.4 432.2 588.5	Feb 86.1 124.2 213.9 321.5 442.9 604.1	Mar 85.9 130.2 222.3 330.6 453.9 620.3	86.5 136.7 231.0 340.2 465.6 637.8	87.8 143.4 239.7 349.8 477.5 656.0	89.7 150.5 248.5 359.5 489.8 674.9	92.3 157.7 257.4 369.4 502.5	95.5 165.4 266.5 379.5 515.8	99.1 173.1 275.5 389.7 529.3	103.3 180.9 284.6 400.0 543.2	107.9 189.0 293.8 410.4 557.7	113.0 197.2 303.0 421.1 572.6
2011 2012 2013 2014 2015 SCE Inland	Jan 87.0 118.6 205.6 312.4 432.2 588.5	Feb 86.1 124.2 213.9 321.5 442.9 604.1 Feb	Mar 85.9 130.2 222.3 330.6 453.9 620.3 Mar	86.5 136.7 231.0 340.2 465.6 637.8 Apr	87.8 143.4 239.7 349.8 477.5 656.0 May	89.7 150.5 248.5 359.5 489.8 674.9	92.3 157.7 257.4 369.4 502.5	95.5 165.4 266.5 379.5 515.8 Aug	99.1 173.1 275.5 389.7 529.3 Sep	103.3 180.9 284.6 400.0 543.2 Oct	107.9 189.0 293.8 410.4 557.7	113.0 197.2 303.0 421.1 572.6 Dec
2011 2012 2013 2014 2015 SCE Inland 2010	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0	Feb 86.1 124.2 213.9 321.5 442.9 604.1 Feb 110.1	Mar 85.9 130.2 222.3 330.6 453.9 620.3 Mar 111.4	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0	92.3 157.7 257.4 369.4 502.5 Jul 119.3	95.5 165.4 266.5 379.5 515.8 Aug 121.9	99.1 173.1 275.5 389.7 529.3 Sep 124.6	103.3 180.9 284.6 400.0 543.2 Oct 127.6	107.9 189.0 293.8 410.4 557.7 Nov 130.7	113.0 197.2 303.0 421.1 572.6 Dec 134.1
2011 2012 2013 2014 2015 SCE Inland 2010 2011	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8	Feb 86.1 124.2 213.9 321.5 442.9 604.1 Feb 110.1 141.4	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 Mar 111.4 145.3	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1
2011 2012 2013 2014 2015 SCE Inland 2010 2011 2012	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5	Feb 86.1 124.2 213.9 321.5 442.9 604.1 604.1 Feb 110.1 141.4 203.9	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 620.3 111.4 145.3 210.6	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5 217.7	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1 286.8
2011 2012 2013 2014 2015 SCE Inland 2010 2010 2011 2012 2013	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5 297.3	Feb 86.1 124.2 213.9 321.5 442.9 604.1 Feb 110.1 141.4 203.9 307.7	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 620.3 620.3 8 111.4 145.3 210.6 318.5	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5 217.7 330.2	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9 355.1	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9 427.4	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1 286.8 443.7
2011 2012 2013 2014 2015 SCE Inland 2010 2011 2012 2013 2014	Jan 87.0 118.6 205.6 312.4 432.2 8 8 9 109.0 137.8 197.5 297.3 461.0	Feb 86.1 124.2 213.9 321.5 442.9 604.1 Feb 110.1 141.4 203.9 307.7 478.1	Mar 85.9 130.2 222.3 330.6 433.9 620.3 620.3 Mar 111.4 145.3 210.6 318.5 495.9	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5 217.7 330.2 515.1	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4 535.1	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9 355.1 555.9	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1 286.8
2011 2012 2013 2014 2015 SCE Inland 2010 2011 2012 2013	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5 297.3	Feb 86.1 124.2 213.9 321.5 442.9 604.1 Feb 110.1 141.4 203.9 307.7	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 620.3 620.3 8 111.4 145.3 210.6 318.5	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5 217.7 330.2	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9 355.1	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9 427.4	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1 286.8 443.7
2011 2012 2013 2014 2015 SCE Inland 2010 2010 2011 2012 2013 2014 2015	Jan 87.0 118.6 205.6 312.4 432.2 8 8 9 109.0 137.8 197.5 297.3 461.0	Feb 86.1 124.2 213.9 321.5 442.9 604.1 Feb 110.1 141.4 203.9 307.7 478.1	Mar 85.9 130.2 222.3 330.6 433.9 620.3 620.3 Mar 111.4 145.3 210.6 318.5 495.9	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5 217.7 330.2 515.1	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4 535.1	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9 355.1 555.9	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9 427.4	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1 286.8 443.7
2011 2012 2013 2014 2015 SCE Inland 2010 2011 2012 2013 2014	Jan 87.0 118.6 205.6 312.4 422.2 588.5 Jan 109.0 137.8 197.5 297.3 461.0 728.4	Feb 86.1 124.2 213.9 321.5 442.9 604.1 100.1 141.4 203.9 307.7 478.1 756.1	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 620.3 620.3 820.6 318.5 410.6 318.5 455.9 784.9	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5 217.7 330.2 515.1 815.8	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4 535.1 847.9	89.7 150.5 248.5 359.5 499.8 674.9 Jun 117.0 158.5 232.9 355.1 555.9 881.3	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3 577.5	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3 600.5	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7 624.0	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7 648.5	107.9 189.0 293.8 410.4 557.7 130.7 185.1 276.9 427.4 673.9	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1 286.8 443.7 700.4
2011 2012 2013 2014 2015 SCE Inland 2010 2011 2012 2013 2014 2015 SDGE	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5 297.3 461.0 728.4	Feb 86.1 124.2 213.9 321.5 442.9 604.1 110.1 141.4 203.9 307.7 478.1 756.1 Feb	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 620.3 111.4 145.3 210.6 318.5 495.9 784.9	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5 217.7 330.2 515.1 815.8 Apr	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4 535.1 847.9 May	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9 355.1 555.9 881.3	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3 577.5	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3 600.5	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7 624.0 Sep	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7 648.5	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9 427.4 673.9 Nov	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1 286.8 443.7 700.4 Dec
2011 2012 2013 2014 2015 SCE Inland 2010 2011 2012 2012 2012 2013 2014 2015 SDGE 2010	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5 297.3 461.0 728.4 Jan 73.2	Feb 86.1 124.2 213.9 321.5 442.9 604.1 10.1 141.4 203.9 307.7 478.1 756.1	Mar 85.9 130.2 222.3 330.6 453.9 620.3 Mar 111.4 145.3 210.6 318.5 495.9 784.9 784.9 Mar 140.1 14	86.5 136.7 231.0 340.2 465.6 637.8 Apr 113.1 149.5 217.7 330.2 515.1 815.8 Apr 77.8	87.8 143.4 239.7 349.8 477.5 656.0 114.9 153.9 225.2 342.4 535.1 847.9 May 79.8	89.7 150.5 248.5 359.5 489.8 674.9 Jun 1170.5 232.9 355.1 555.9 881.3 Jun 82.1	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3 577.5 Jul 84.6	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3 600.5 Aug 87.3	99.1 173.1 275.5 389.7 529.3 529.3 124.6 173.8 258.2 396.7 624.0 58ep 90.2	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7 648.5 Oct 93.2	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9 427.4 673.9 Nov 96.4	113.0 197.2 303.0 421.1 572.6 Dec 134.1 191.1 286.8 443.7 700.4 Dec 99.7
2011 2012 2013 2014 2015 2010 2010 2011 2012 2013 2014 2015 2014 2015 2014 2015	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5 297.3 461.0 728.4 Jan 73.2 103.1	Feb 86.1 124.2 213.9 321.5 442.9 604.1 10.1 141.4 203.9 307.7 478.1 756.1 307.7 478.1 756.1	Mar 85.9 130.2 222.3 330.6 433.9 620.3 Mar 111.4 145.3 210.6 318.5 495.9 784.9 Mar 78.0 110.0	86.5 136.7 231.0 340.2 455.6 637.8 113.1 149.5 217.7 330.2 515.1 815.8 815.8 Apr 77.8 113.7	87.8 143.4 239.7 349.8 477.5 656.0 114.9 153.9 225.2 342.4 353.9 225.2 342.4 342.4 342.4 847.9 847.9 May	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9 355.1 555.9 881.3 Jun 82.1 121.4	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3 577.5 Jul 84.6 125.3	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3 600.5 Aug 87.3 129.3	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7 624.0 Sep 90.2 133.4	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7 648.5 Oct 93.2 137.5	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9 427.4 673.9 Nov 96.4 141.6	113.0 197.2 303.0 421.1 572.6 134.1 191.1 286.8 443.7 700.4 Dec 99.7 145.8
2011 2012 2013 2014 2015 SCE Inland 2010 2010 2011 2012 2013 2014 2015 SDGE 2010 2011 2011 2012	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5 297.3 461.0 728.4 Jan 73.2 103.1 150.2	Feb 86.1 124.2 213.9 321.5 442.9 604.1 100.1 141.4 203.9 307.7 478.1 756.1 Feb 74.5 106.5 154.4	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 620.3 620.3 620.3 820.6 318.5 495.9 784.9 784.9 784.9 784.9	86.5 136.7 231.0 340.2 465.6 637.8 113.1 149.5 217.7 330.2 515.1 815.8 Apr 77.8 113.7 163.0	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4 535.1 847.9 May 79.8 117.5 167.5	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9 355.1 555.9 881.3 Jun 82.1 121.4 121.4	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3 577.5 Jul 84.6 125.3 176.5	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3 600.5 Aug 87.3 129.3 181.2	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7 624.0 Sep 90.2 133.4 185.9	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7 648.5 Oct 93.2 137.5 190.7	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9 427.4 673.9 Nov 96.4 141.6 195.6	113.0 197.2 303.0 421.1 572.6 134.1 191.1 286.8 443.7 700.4 Dec 99.7 145.8 200.5
2011 2012 2013 2014 2015 SCE Inland 2010 2011 2012 2013 2014 2015 SDGE 2010 2011 2011 2012 2012 2013	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5 297.3 461.0 728.4 Jan 73.2 103.1 150.2 205.7	Feb 86.1 124.2 213.9 321.5 442.9 604.1 100.1 141.4 203.9 307.7 478.1 756.1 Feb 74.5 106.5 154.4 210.7	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 620.3 130.6 453.9 620.3 130.6 318.5 455.9 784.9 784.9 Mar 76.0 110.6 158.6 215.8	86.5 136.7 231.0 340.2 455.6 637.8 Apr 113.1 149.5 217.7 330.2 515.1 815.8 Apr 77.8 113.7 163.0 221.3	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4 535.1 847.9 May 79.8 117.5 167.5 226.9	89.7 150.5 248.5 359.5 499.8 674.9 Jun 117.0 158.5 232.9 355.1 555.9 881.3 Jun 82.1 121.4 121.4 121.4 122.4	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3 577.5 Jul 84.6 125.3 176.5 238.6	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3 600.5 Aug 87.3 129.3 181.2 244.8	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7 624.0 Sep 90.2 133.4 185.9 251.2	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7 648.5 Oct 93.2 137.5 190.7 257.8	107.9 189.0 293.8 410.4 557.7 185.1 276.9 427.4 673.9 Nov 96.4 141.6 145.6 264.7	113.0 197.2 303.0 421.1 572.6 134.1 191.1 286.8 443.7 700.4 Dec 99.7 145.8 200.5 271.8
2011 2012 2013 2014 2015 SCE Inland 2010 2010 2011 2012 2013 2014 2015 SDGE 2010 2011 2011 2012	Jan 87.0 118.6 205.6 312.4 432.2 588.5 Jan 109.0 137.8 197.5 297.3 461.0 728.4 Jan 73.2 103.1 150.2	Feb 86.1 124.2 213.9 321.5 442.9 604.1 100.1 141.4 203.9 307.7 478.1 756.1 Feb 74.5 106.5 154.4	Mar 85.9 130.2 222.3 330.6 453.9 620.3 620.3 620.3 620.3 620.3 820.6 318.5 495.9 784.9 784.9 784.9 784.9	86.5 136.7 231.0 340.2 465.6 637.8 113.1 149.5 217.7 330.2 515.1 815.8 Apr 77.8 113.7 163.0	87.8 143.4 239.7 349.8 477.5 656.0 May 114.9 153.9 225.2 342.4 535.1 847.9 May 79.8 117.5 167.5	89.7 150.5 248.5 359.5 489.8 674.9 Jun 117.0 158.5 232.9 355.1 555.9 881.3 Jun 82.1 121.4 121.4	92.3 157.7 257.4 369.4 502.5 Jul 119.3 163.3 240.9 368.3 577.5 Jul 84.6 125.3 176.5	95.5 165.4 266.5 379.5 515.8 Aug 121.9 168.5 249.5 382.3 600.5 Aug 87.3 129.3 181.2	99.1 173.1 275.5 389.7 529.3 Sep 124.6 173.8 258.2 396.7 624.0 Sep 90.2 133.4 185.9	103.3 180.9 284.6 400.0 543.2 Oct 127.6 179.3 267.4 411.7 648.5 Oct 93.2 137.5 190.7	107.9 189.0 293.8 410.4 557.7 Nov 130.7 185.1 276.9 427.4 673.9 Nov 96.4 141.6 195.6	113.0 197.2 303.0 421.1 572.6 134.1 191.1 286.8 443.7 700.4 Dec 99.7 145.8 200.5

Source: Clean Power Research

Table 2. Estimated Maximum BTM Solar Generation (MWh)

CAISO Total												
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	273.7	307.6	341.9	363.6	367.7	369.0	376.5	382.4	386.1	381.9	366.4	370.6
2011	394.5	467.3	508.5	551.3	559.0	570.2	584.7	596.7	605.8	605.2	577.7	561.
2012	620.8	723.8	793.7	858.2	888.7	902.0	907.8	915.6	924.1	907.5	853.8	837.
2013	943.4	1,077.6	1,190.6	1,273.4	1,306.9	1,315.7	1,323.7	1,350.0	1,341.3	1,341.3	1,240.5	1,190.
2014	1,303.3	1,513.5	1,693.4	1,831.4	1,860.0	1,891.2	1,895.2	1,915.1	1,911.2	1,904.2	1,774.2	1,712.
2015	1,844.2	2,181.2	2,442.7	2,606.1	2,646.6	2,665.4						
PG&E Total	I											
I GUL IOUI	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	160.4	185.3	208.3	223.6	227.2	227.2	231.5	234.3	234.6	229.3	217.6	216.
2011	229.7	275.0	303.6	330.7	331.2	335.4	345.8	351.8	353.4	348.7	328.4	313.
2012	346.0	409.1	442.2	487.4	504.1	511.5	510.7	515.7	518.5	500.7	459.4	448.
2013	508.9	587.0	646.5	696.2	718.6	719.6	714.8	731.1	723.5	720.0	651.4	621.
2014	673.3	785.4	872.4	960.9	971.8	980.5	985.0	985.2	977.4	954.2	880.8	844.
2015	932.5	1,080.0	1,229.6	1,298.9	1,310.9	1,320.8						
PG&E Bay A	lroa											
F Got Day A	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	56.9	66.1	71.7	77.1	78.1	77.3	79.3	79.5	79.0	76.4	71.8	71.
2011	76.9	89.4	101.9	110.2	112.7	113.6	117.2	120.3	119.7	117.8	108.3	104.5
2012	118.6	139.4	154.5	169.6	177.4	181.0	181.6	181.0	182.8	173.2	161.0	154.8
2013	173.5	203.0	224.8	243.0	252.4	253.7	253.7	256.6	251.1	246.7	223.0	209.
2014	237.1	266.7	296.7	329.7	331.4	334.1	334.3	334.2	327.5	313.2	287.9	273.
2015	299.0	343.5	393.3	416.1	421.8	420.9						
	D A											
PG&E Non I	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2010	103.5	119.2	136.5	146.4	149.1	149.8	152.2	154.8	155.6	152.9	145.9	144.9
2011	152.8	185.7	201.7	220.5	218.5	221.8	228.5	231.5	233.7	230.9	220.1	208.
2012	227.3	269.7	287.7	317.8	326.6	330.5	329.1	334.7	335.8	327.4	298.5	293.4
2013	335.4	384.0	421.7	453.2	466.2	466.0	461.2	474.5	472.4	473.4	428.4	411.
2014	436.1	518.7	575.7	631.2	640.4	646.4	650.7	651.0	649.8	641.0	593.0	570.
2015	633.5	736.6	836.3	882.8	889.1	900.0						
SCE Total												
	lan	Feb	Mar	Apr	May	lun	Iul	Aug	Sen	Oct	Nov	Dec
2010	Jan 80.3	Feb 85.9	Mar 92.5	Apr 97.0	May 96,9	Jun 97.7	Jul 99.7	Aug 101.6	Sep 104.2	Oct 104.9	Nov 103.1	Dec 106.9
2010 2011	Jan 80.3 114.1	Feb 85.9 133.5	92.5	Apr 97.0 154.5	May 96.9 159.8	Jun 97.7 164.6	Jul 99.7 168.5	Aug 101.6 173.0	104.2	Oct 104.9 181.5	Nov 103.1 177.6	106.9
	80.3	85.9		97.0	96.9	97.7	99.7	101.6	-	104.9	103.1	106.9 177.5
2011	80.3 114.1	85.9 133.5	92.5 142.2	97.0 154.5	96.9 159.8	97.7 164.6	99.7 168.5	101.6 173.0	104.2 178.4	104.9 181.5	103.1 177.6	106.9 177.9 286.4
2011 2012	80.3 114.1 195.7	85.9 133.5 225.5	92.5 142.2 253.5	97.0 154.5 269.4	96.9 159.8 280.4	97.7 164.6 285.7	99.7 168.5 290.8	101.6 173.0 292.7	104.2 178.4 298.2	104.9 181.5 300.3	103.1 177.6 289.8	106.9 177.5 286.4 429.4
2011 2012 2013	80.3 114.1 195.7 322.3	85.9 133.5 225.5 365.1	92.5 142.2 253.5 404.9	97.0 154.5 269.4 431.9	96.9 159.8 280.4 441.4	97.7 164.6 285.7 447.9	99.7 168.5 290.8 457.2	101.6 173.0 292.7 466.2	104.2 178.4 298.2 466.5	104.9 181.5 300.3 466.8	103.1 177.6 289.8 443.5	106.9 177.5 286.4 429.4
2011 2012 2013 2014 2015	80.3 114.1 195.7 322.3 475.1 687.6	85.9 133.5 225.5 365.1 552.1	92.5 142.2 253.5 404.9 623.0	97.0 154.5 269.4 431.9 665.8	96.9 159.8 280.4 441.4 681.1	97.7 164.6 285.7 447.9 700.0	99.7 168.5 290.8 457.2	101.6 173.0 292.7 466.2	104.2 178.4 298.2 466.5	104.9 181.5 300.3 466.8	103.1 177.6 289.8 443.5	Dec 106.9 177.5 286.4 429.4 661.6
2011 2012 2013 2014 2015	80.3 114.1 195.7 322.3 475.1 687.6	85.9 133.5 225.5 365.1 552.1 842.5	92.5 142.2 253.5 404.9 623.0 927.5	97.0 154.5 269.4 431.9 665.8 1,004.7	96.9 159.8 280.4 441.4 681.1 1,022.9	97.7 164.6 285.7 447.9 700.0 1,028.5	99.7 168.5 290.8 457.2 697.6	101.6 173.0 292.7 466.2 713.6	104.2 178.4 298.2 466.5 715.1	104.9 181.5 300.3 466.8 730.8	103.1 177.6 289.8 443.5 683.1	106.9 177.5 286.4 429.4 661.0
2011 2012 2013 2014 2015 SCE Coastal	80.3 114.1 195.7 322.3 475.1 687.6	85.9 133.5 225.5 365.1 552.1	92.5 142.2 253.5 404.9 623.0	97.0 154.5 269.4 431.9 665.8	96.9 159.8 280.4 441.4 681.1	97.7 164.6 285.7 447.9 700.0	99.7 168.5 290.8 457.2	101.6 173.0 292.7 466.2	104.2 178.4 298.2 466.5	104.9 181.5 300.3 466.8	103.1 177.6 289.8 443.5	106.9 177.5 286.4 429.4 661.0 Dec
2011 2012 2013 2014 2015 SCE Coastal 2010	80.3 114.1 195.7 322.3 475.1 687.6	85.9 133.5 225.5 365.1 552.1 842.5	92.5 142.2 253.5 404.9 623.0 927.5 Mar	97.0 154.5 269.4 431.9 665.8 1,004.7	96.9 159.8 280.4 441.4 681.1 1,022.9 May	97.7 164.6 285.7 447.9 700.0 1,028.5	99.7 168.5 290.8 457.2 697.6	101.6 173.0 292.7 466.2 713.6 Aug	104.2 178.4 298.2 466.5 715.1 Sep	104.9 181.5 300.3 466.8 730.8	103.1 177.6 289.8 443.5 683.1 Nov	106.9 177.5 286.4 429.4 661.0 Dec 50.0
2011 2012 2013 2014 2015 SCE Coastal 2010 2011	80.3 114.1 195.7 322.3 475.1 687.6 Jan 35.7	85.9 133.5 225.5 365.1 552.1 842.5 Feb 38.8	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8	97.0 154.5 269.4 431.9 665.8 1,004.7 Apr 43.3	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5	99.7 168.5 290.8 457.2 697.6 Jul 44.9	101.6 173.0 292.7 466.2 713.6 Aug 45.8	104.2 178.4 298.2 466.5 715.1 Sep 47.2	104.9 181.5 300.3 466.8 730.8 Oct 47.9	103.1 177.6 289.8 443.5 683.1 Nov 47.3	106.: 177 286 429 661 Dec 50 92
2011 2012 2013 2014 2015 SCE Coastal 2010 2010 2011 2012	80.3 114.1 195.7 322.3 475.1 687.6 Jan 35.7 55.2	85.9 133.5 225.5 365.1 552.1 842.5 Feb 38.8 63.9	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5	97.0 154.5 269.4 431.9 665.8 1,004.7 Apr 43.3 76.2	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8	106. 177. 286. 429. 661. Dec 50. 92. 149.
2011 2012 2013 2014 2015 SCE Coastal 2010 2010 2011 2012 2013	80.3 114.1 195.7 322.3 475.1 687.6 Jan 35.7 55.2 101.7	85.9 133.5 225.5 365.1 552.1 842.5 Feb 38.8 63.9 119.3	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5	97.0 154.5 269.4 431.9 665.8 1,004.7 Apr 43.3 76.2 145.7	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5 151.4	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9 160.8	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2	106.9 177.9 286.4 429.4 661.0 Dec 50.0 92.4 149.7 209.8
2011 2012 2013 2014 2015 SCE Coastal 2010 2010 2011 2012 2013	80.3 114.1 195.7 322.3 475.1 687.6 Jan 35.7 55.2 101.7 167.9	85.9 133.5 225.5 365.1 552.1 842.5 Feb 38.8 63.9 119.3 190.2	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1	97.0 154.5 269.4 431.9 665.8 1,004.7 Apr 43.3 76.2 145.7 224.6	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5 151.4 229.1	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1 232.5	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0 239.5	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9 160.8 233.4	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0	106.9 177.9 286.4 429.4 661.0 Dec 50.0 92.4 149.7 209.8
2011 2012 2013 2014 2015 SCE Coastal 2010 2010 2011 2012 2013 2014 2015	80.3 114.1 195.7 322.3 475.1 687.6 Jan 35.7 55.2 101.7 167.9 232.3	85.9 133.5 225.5 365.1 552.1 842.5 Feb 38.8 63.9 119.3 190.2 270.3	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1 306.3	97.0 154.5 269.4 431.9 665.8 1,004.7 Apr 43.3 76.2 145.7 224.6 320.5	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5 151.4 229.1 326.7	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1 232.5 333.7	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0 239.5	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9 160.8 233.4	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0	106.9 177.5 286.4 429.4 661.6
2011 2012 2013 2014 2015 SCE Coastal 2010 2010 2011 2012 2013 2014	80.3 114.1 195.7 322.3 475.1 687.6 755.2 101.7 167.9 232.3 319.8	85.9 133.5 225.5 365.1 552.1 842.5 Feb 38.8 63.9 119.3 190.2 270.3 375.3	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1 306.3 414.9	97.0 154.5 269.4 431.9 665.8 1,004.7 43.3 76.2 145.7 224.6 320.5 445.3	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5 151.4 229.1 326.7 452.3	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1 232.5 333.7 454.3	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5 332.1	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0 239.5 337.9	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6 336.0	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9 160.8 233.4 349.4	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0 310.7	106.5 177.5 286.4 429.6 661.0 Dec 50.0 92.6 149.7 209.8 296.5
2011 2012 2013 2014 2015 SCE Coastal 2010 2010 2011 2012 2013 2014 2015 SCE Inland	80.3 114.1 195.7 322.3 475.1 687.6 Jan 35.7 55.2 101.7 167.9 232.3 319.8 Jan	85.9 133.5 225.5 365.1 552.1 842.5 Feb 38.8 63.9 119.3 190.2 270.3 375.3	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1 306.3 414.9 Mar	97.0 154.5 269.4 431.9 665.8 1,004.7 Apr 43.3 76.2 145.7 224.6 320.5 445.3 Apr	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5 151.4 229.1 326.7 452.3 May	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1 232.5 333.7 454.3 Jun	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5 332.1	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0 239.5 337.9 Aug	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6 336.0 Sep	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9 160.8 233.4 349.4 Oct	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0 310.7	106. 177. 286. 429. 661. Dec 50. 92. 149. 209. 296. 296.
2011 2012 2013 2014 2015 SCE Coastal 2010 2011 2012 2012 2013 2014 2015 SCE Inland 2010	80.3 114.1 195.7 322.3 475.1 687.6 87.6 35.7 55.2 101.7 167.9 232.3 319.8 319.8 Jan 44.6	85.9 133.5 225.5 365.1 842.5 Feb 38.8 63.9 119.3 190.2 270.3 375.3 Feb 47.1	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1 306.3 414.9 Mar 51.7	97.0 154.5 269.4 431.9 665.8 1,004.7 43.3 76.2 145.7 224.6 320.5 445.3 320.5 445.3	96.9 159.8 280.4 441.4 661.1 1,022.9 May 43.0 80.5 151.4 229.1 326.7 452.3 May 54.0	97.7 164.6 285.7 447.9 700.0 1,028.5 44.6 155.1 232.5 333.7 454.3 Jun 54.1	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5 332.1 Jul 54.8	101.6 173.0 292.7 466.2 713.6 Aug 455.8 89.7 159.0 239.5 337.9 Aug 55.8	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6 336.0 Sep 56.9	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9 160.8 233.4 349.4 349.4	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0 310.7 310.7	106.5 177.5 286.4 429.4 661.0 Dec 50.0 92.0 149.5 209.3 296.5 Dec 56.5
2011 2012 2013 2014 2015 SCE Coastal 2010 2011 2012 2013 2014 2015 SCE Inland 2010 2010 2011	80.3 114.1 195.7 322.3 475.1 687.6 755.2 101.7 167.9 232.3 319.8 Jan 44.6 58.9	85.9 133.5 225.5 365.1 842.5 Feb 38.8 63.9 119.3 190.2 270.3 375.3 Feb 47.1 69.6	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1 306.3 414.9 Mar 5 1.7 72.7	97.0 154.5 269.4 431.9 665.8 1,004.7 43.3 76.2 145.7 224.6 320.5 320.5 3245.3 445.3	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5 151.4 29.1 326.7 452.3 May 54.0 79.2	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1 232.5 333.7 454.3 Jun 54.1 79.9	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5 332.1 Jul 54.8 81.4	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0 239.5 337.9 Aug 55.8 83.3	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6 336.0 Sep 56.9 85.1	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9 160.8 233.4 349.4 349.4 Oct 57.0 86.7	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0 310.7 Nov 55.8 84.8	106.: 177.: 286.: 429.: 661.: 50.: 92.: 149.: 209.: 296.: 296.: Dec 56.: 84.:
2011 2012 2013 2014 2015 SCE Coastal 2010 2011 2012 2013 2014 2015 SCE Inland 2020 2021	80.3 114.1 195.7 322.3 475.1 687.6 755.2 101.7 167.9 232.3 319.8 Jan 44.6 58.9 94.0	85.9 133.5 225.5 365.1 552.1 842.5 Feb 38.8 63.9 119.3 190.2 270.3 375.3 Feb 47.1 69.6 106.2	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1 306.3 414.9 Mar 51.7 72.7 116.0	97.0 154.5 269.4 431.9 665.8 1,004.7 43.3 76.2 145.7 224.6 320.5 445.3 445.3 Apr 53.7 78.3 123.7	96.9 159.8 280.4 441.4 681.1 1,022.9 43.0 80.5 151.4 229.1 326.7 452.3 May 54.0 79.2 128.9	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1 232.5 333.7 454.3 Jun 54.1 79.9 130.6	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5 332.1 Jul 54.8 81.4 132.9	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0 239.5 337.9 Aug 55.8 83.3 133.8	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6 336.0 Sep 56.9 85.1 137.8	104.9 181.5 300.3 466.8 730.8 0ct 47.9 94.9 160.8 233.4 349.4 349.4 0ct 57.0 86.7 139.5	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0 310.7 Nov 55.8 84.8 137.6	106.: 177.: 286.4 429.6 661.0 50.0 92.1 149.2 209.4 209.4 209.4 296.5 Dec 56 84.4 84.3 137.3
2011 2012 2013 2014 2015 SCE Coastal 2010 2010 2011 2012 2013 2014 2015 SCE Inland 2010 2011 2011 2011 2012 2013	80.3 114.1 195.7 322.3 475.1 687.6 687.6 7 55.2 101.7 167.9 232.3 319.8 Jan 44.6 58.9 94.0 154.4	85.9 133.5 225.5 365.1 552.1 842.5 Feb 119.3 190.2 270.3 375.3 Feb 47.1 610.6 91.6 91.6 91.6 91.6 91.6 91.6 91.6 91	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1 306.3 414.9 Mar 51.7 72.7 7116.0 191.8	97.0 154.5 269.4 431.9 665.8 1,004.7 43.3 76.2 145.7 224.6 320.5 445.3 Apr 53.7 78.3 123.7 207.2	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5 151.4 229.1 326.7 452.3 May 54.0 79.2 128.9 212.3	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1 232.5 333.7 454.3 Jun 54.1 79.9 130.6 215.4	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5 332.1 Jul 54.8 81.4 132.9 221.7	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0 239.5 337.9 Aug 55.8 83.3 133.8 133.8 226.7	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6 336.0 Sep 56.9 85.1 137.8 229.0	104.9 181.5 300.3 466.8 730.8 Oct 47.9 94.9 160.8 233.4 349.4 Oct 57.0 86.7 139.5 233.4	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0 310.7 Nov 55.8 84.8 84.8 81.37.6 224.6	106.: 177.: 286. 429. 661.0 50.0 92.1 149.: 209.3 209.3 296.: 209.5 296.: 56.: 84.3 137.: 219.0
2011 2012 2013 2014 2015 SCE Coastal 2010 2010 2011 2012 2013 2014 2015 SCE Inland 2010 2010 2011 2012 2013 2014	80.3 114.1 195.7 322.3 475.1 687.6 755.2 101.7 167.9 232.3 319.8 Jan 44.6 58.9 94.0 154.4 242.7	85.9 133.5 225.5 365.1 582.1 842.5 Feb 38.8 63.9 119.3 190.2 270.3 375.3 Feb 47.1 69.6 106.2 174.9 281.8	92.5 142.2 253.5 404.9 623.0 927.5 Mar 40.8 69.5 137.5 213.1 306.3 414.9 Mar 51.7 72.7 116.0 191.8 316.7	97.0 154.5 269.4 431.9 665.8 1,004.7 Apr 43.3 76.2 145.7 224.6 320.5 445.3 Apr 53.7 78.3 123.7 78.3 123.7 207.2 345.3	96.9 159.8 280.4 441.4 681.1 1,022.9 May 43.0 80.5 151.4 229.1 326.7 452.3 May 54.0 79.2 128.9 212.3 354.4	97.7 164.6 285.7 447.9 700.0 1,028.5 Jun 43.5 84.6 155.1 232.5 333.7 454.3 Jun 54.1 79.9 130.6 215.4 366.2	99.7 168.5 290.8 457.2 697.6 Jul 44.9 87.1 157.9 235.5 332.1 Jul 54.8 81.4 132.9	101.6 173.0 292.7 466.2 713.6 Aug 45.8 89.7 159.0 239.5 337.9 Aug 55.8 83.3 133.8	104.2 178.4 298.2 466.5 715.1 Sep 47.2 93.3 160.4 237.6 336.0 Sep 56.9 85.1 137.8	104.9 181.5 300.3 466.8 730.8 0ct 47.9 94.9 160.8 233.4 349.4 349.4 0ct 57.0 86.7 139.5	103.1 177.6 289.8 443.5 683.1 Nov 47.3 92.8 152.2 219.0 310.7 Nov 55.8 84.8 137.6	106.5 177.5 286.4 429.4 661.6 Dec 50.0 92.6 149.1 209.8 296.5 Dec 56.5 84.5 84.5 219.6
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Source: Clean Power Research

As illustrated 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 1 presents the ratio of solar generation volatility to load volatility for the total PG&E service territory. Here, solar generation volatility is measured by the standard deviation (stdkwh) of the estimated solar generation output (solargenkwh), gold area in the chart, by time interval. Load volatility measures by the standard deviation of loads (red area in the chart) by time interval. The ratio of these two volatility measures is given by the green line in the chart. 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 (shown in Figure 2), which also peaks mid-morning but at a much lower value of 0.13. As shown in Figure 3, 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. A comparison the ratios for PG&E, SCE, and SDG&E is presented in Figure 4.

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 can be expected 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 height 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 height of a lake as deep as, say, Lake Tahoe. In load forecasting, the waves are the measured by the volatility of solar generation. The depth of the lake is measured by the load volatility. The smaller the ratio of solar volatility (i.e., the waves) to load volatility (i.e., 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 there will be forecast performance gains from adding forecasts of solar generation to the model.

The data in Figure 4 suggest that the forecast performance improvements will be less for SCE than for PG&E and SDG&E because of the lower ratio. Further, it is anticipated that there will be bigger performance gains in the midmorning hours than the afternoon hours. Finally, the forecast gains are expected to be little to none for the dawn and dusk hours when solar generation output is at its lowest values.

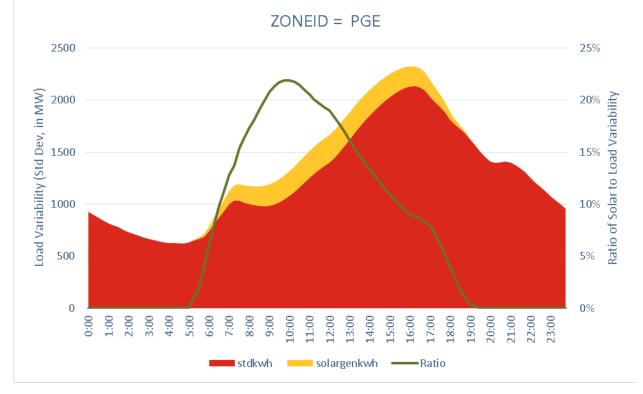


Figure 1: Ratio of Solar Generation Volatility to Load Volatility: PG&E Total

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)

Ratio is the ratio of solargenkwh to stdkwh

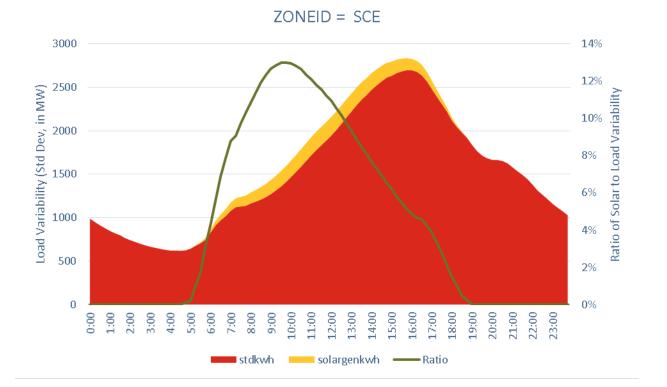


Figure 2: Ratio of Solar Generation Volatility to Load Volatility: SCE Total

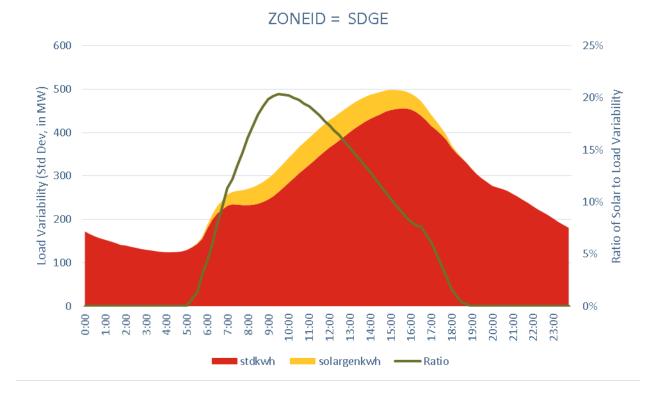


Figure 3: Ratio of Solar Generation Volatility to Load Volatility: SDG&E

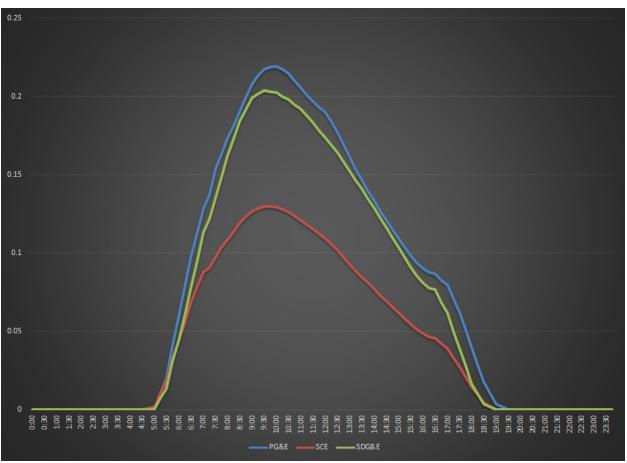


Figure 4: Ratio of Solar Generation Volatility to Load Volatility: IOU Comparison

3.2 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, an alternative time series of solar PV generation is developed 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 CAISO uses to drive their load forecasts. The result is 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. By comparing the forecast performance of the short-term load forecasts with and without cloud cover driven solar PV generation, the benefit of doing "something" over doing "nothing" can be quantified. Further, a baseline of short-term load forecast performance is established, 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 describes how hourly cloud cover is combined with solar PV capacity estimates to develop forecasts (estimates) of solar PV generation by load zone.

The approach used to develop cloud cover solar PV generation estimates is necessarily simple given the information available is limited to:

» Total Installed solar PV capacity (MW) by day and load zone, and

» Hourly Cloud Cover in percentage terms by hour, day and weather station.

Given this limited set of data, begin with the following simplified engineering relationship.

Equation 39. Simplified Solar Generation Forecast Model

 $SolarGeneration_{d,i} = SolarInsolation_{d,i} \times SolarPanelCapacity_d \times SolarPanelEfficiency_{d,i}$

Where,

SolarGeneration_{d,i} is the electricity generated on day (d) time interval (i) in Watts Out

SolarInsolation_{d,i} is the solar energy delivered to the panel in $\frac{\text{Watts In}}{m^2}$

SolarPanelCapacity_d is the installed capacity in m²

SolarPanelEfficiency_{d,i} is the solar panel efficiency in $\frac{Watts Out}{Watts In}$

To help fix ideas, assume solar insolation at noon of June 12 is 1,000 Watts/m², installed BTM solar PV capacity is 2.5 kW, and the BTM solar PV system efficiency (Sunlight to AC) is 15%. If one assumes 150 Watts/m² for the average panel size, the solar panel area would be approximately 16.66 m² (computed as 2500 Watts over 150 Watts/m²). With these numbers you have:

Equation 40. Solar Generation Forecast Example

SolarGeneration = 2500 Watts = $1000 \text{ Watts}/\text{m}^2 \times 16.667 \text{m}^2 \times 0.15$

Factoring in Temperature Impacts. The hotter a solar panel becomes, the less efficient it is in converting sun energy into useful electricity. This leads to the following adjustment to the solar panel efficiency.

Equation 41. Temperature Driven Solar Panel Efficiency Equation

 $SolarPanelEfficiency_{d,i} = RatedEfficiency \times (1 - [MAX(Temp_{d,i} - ThresholdTemp, 0) \times \nabla])$

Where,

 $SolarPanelEfficiency_{d,i}$ is the solar panel operating efficiency for day (d) and time interval (i)

RatedEfficiency is the peak output efficiency

Temp_{d,i}is the temperature of the panel

ThresholdTemp is the temperature above which the efficiency of the panel degrades

 ∇ is the rate of efficiency degradation per degree (-0.48% Per °C or - 0.27% Per °F).

Factoring in Cloud Cover. Cloud cover lowers the output of a solar panel by reducing the amount of solar energy (i.e solar insolation) reaching the panel. While the exact impact of cloud cover on a particular location is difficult to measure, one can assume that at 100% cloud cover, only about 20% of the solar flux reaches Earth's surface. That is, the cloud albedo is 80% at 100% cloud cover. This information can be used to adjust the engineering estimate of solar insolation by incorporating the following relationship.

Equation 42. Cloud Driven Solar Insolation

 $CloudAlbedo_{d,i} = CloudCoverPercentage_{d,i} \times 80\%$

SolarInsolation_{di} = SolarFlux_d×COS(ϕ_d^i)×(1 - CloudAlbedo_{di})

Where,

 $SolarFlux_d$ is the amount of solar radiation hitting the Earth's *atmosphere* on any day of the year and is measured in Watts/m². Solar Flux equals the Solar Constant Output of 1367 Watts/m² adjusted for seasonal variation due to the annual cycle in the distance between Earth and Sun.

 $COS(\phi_d^i)$ is the solar zenith angle which is used to adjust the amount of solar energy striking a horizontal plane on Earth's *surface* for any location and time of day

The final engineering model of solar generation can then be written as follows:

Equation 43. Solar Generation Output

SolarGeneration_{d.i}

= SolarFlux_{d,i}×COS(\emptyset_d^i)×(1 - CloudAlbedo_{d,i})×SolarCapacity_d ×(1 - [MAX(Temp_{d,i} - ThresholdTemp, 0)× ∇])

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 energ that will reach the surface of a solar panel for any location and time? For this study, the National Oceanic & Atmospheric Administration (NOAA) solar calculation spreadsheet is used 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 provides 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, one needs to know the Solar Altitude Angle for that time point. Again, information available on the NOAA spreadsheet is used, which gives an estimate of the time of Solar Noon that corresponds to a Solar Altitude Angle of 90 degrees. Estimated sunrise and sunset times are also provided. 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. Specifically:

Equation 44. Computing Solar Altitude Angle

Angle Lost Per Minute_d = $\frac{90^{\circ}}{(\text{Time of Solar Noon}_d - \text{Time of Sun Rise}_d)}$

Typically, the value for the Angle Lost Per Minute will range between 0.2 and 0.31 degrees per minute, with the average value of approximately 0.25 degrees per minute; or about 4 minutes for every degree.

Given this value, the Solar Altitude Angle for any period can be computed as:

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

Equation 45. Solar Altitude Angle

SolarAltitudeAngle_{d,i} = 90° – (Angle Lost Per Minute_d × |Time of Solar Noon_d – Time of Interval of the day_d |)

Where, the absolute value function returns the number of minutes between the time of Solar Noon and the time of the time interval (i) under study.

Given the Solar Insolation at Solar Noon, the Solar Insolation for time interval (i) can be computed as follows:

Equation 46. Computing Solar Insolation by day and time interval

SolarInsolation_{d i} = SolarInsolation_d^{SolarNoon}×COS(SolarAltitudeAngle_{d i} - 90°)

Applying these equations to the solar insolation data for PG&E Bay Area, PG&E Non Bay Area, SCE Coastal, SCE Inland, and SDG&E results in 15-minute level solar insolation values for each 15-minute interval from January 1, 2010 through December 31, 2015.

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

Step 3. Cloud Cover Driven Solar PV Generation. Next, hourly cloud cover and temperature values from the weather stations assigned to each load zone are used to derive estimates of solar PV generation that will be used in the load forecasting models. The list of weather stations used by the CAISO and their mapping to the five CAISO load zones are presented in Table 3. A comparison of the Cloud Cover solar generation estimates to the CPR estimates for the week of May 24, 2015 are presented in Figure 5 through Figure 9. 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. It is anticipated that the smoother CPR estimates will lead to less volatile measured load forecasts than the cloud-cover driven estimates. If this observation is proven true, then that is a distinct advantage of the CPR approach because adding load forecast uncertainty is not desirable.

Load Zone	Sub Load Zone	Weather Station
PG&E	PG&E Bay Area	Concord
PG&E	PG&E Bay Area	Livermore
PG&E	PG&E Bay Area	Oakland
PG&E	PG&E Bay Area	San Francisco
PG&E	PG&E Bay Area	San Jose
PG&E	PG&E Non Bay Area	Bakersfield
PG&E	PG&E Non Bay Area	Marysville
PG&E	PG&E Non Bay Area	Merced
PG&E	PG&E Non Bay Area	Paso Robles
PG&E	PG&E Non Bay Area	Redding
PG&E	PG&E Non Bay Area	Santa Rosa
SCE	SCE Coast	Fullerton
SCE	SCE Coast	Los Angeles Civic Center
SCE	SCE Coast	March AFB
SCE	SCE Coast	Ontario
SCE	SCE Coast	Van Nuys
SCE	SCE Inland	Daggett
SCE	SCE Inland	Lancaster
SCE	SCE Inland	Palm Springs
SCE	SCE Inland	Riverside Municipal
SDG&E	SDG&E Coast	Lindberg
SDG&E	SDG&E Coast	Oceanside
SDG&E	SDG&E Inland	Miramar
SDG&E	SDG&E Inland	Ramona

Table 3: Mapping of Weather Stations to CAISO Load Zones

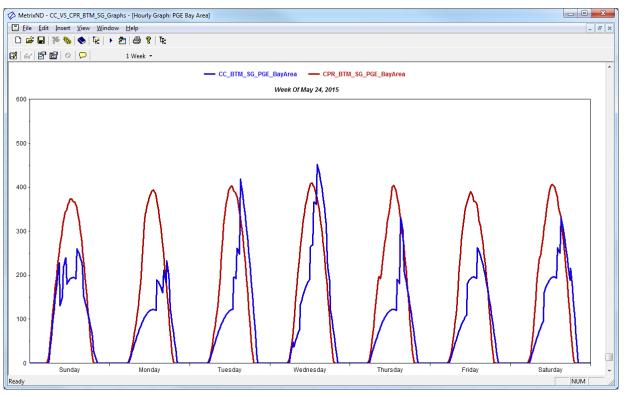
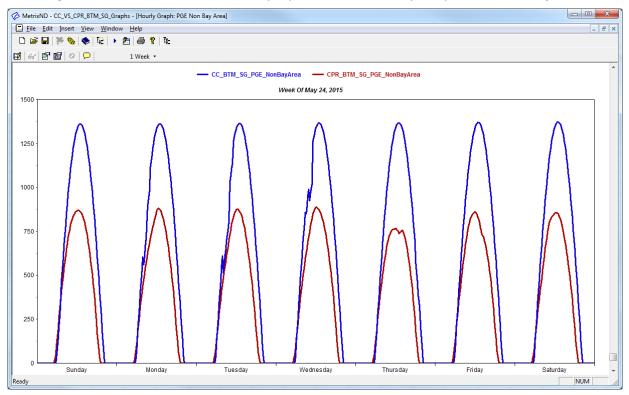


Figure 5: CPR versus Cloud Cover (CC) Solar Generation (MWh): PG&E Bay Area

Figure 6: CPR versus Cloud Cover (CC) Solar Generation (MWh): PG&E Non Bay Area



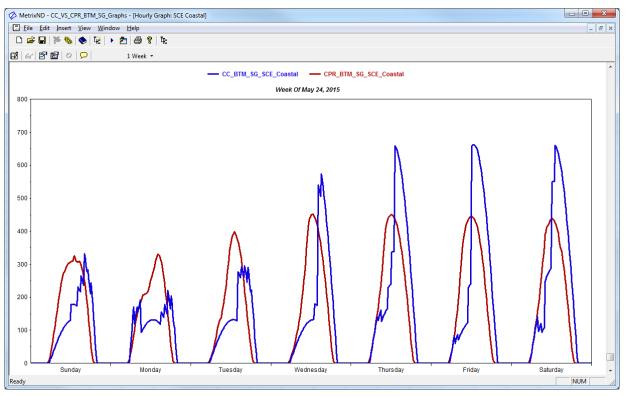
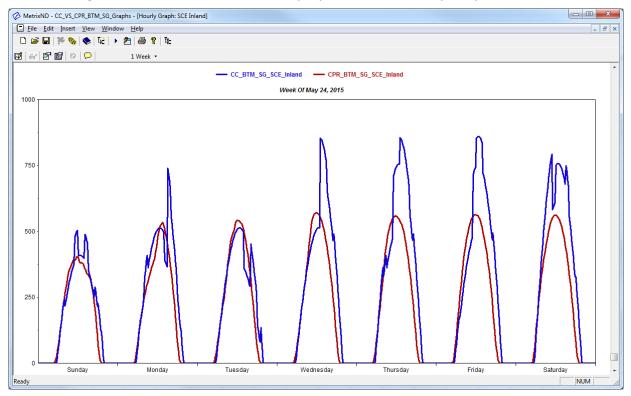


Figure 7: CPR versus Cloud Cover (CC) Solar Generation (MWh): SCE Coastal

Figure 8: CPR versus Cloud Cover (CC) Solar Generation (MWh): SCE Inland



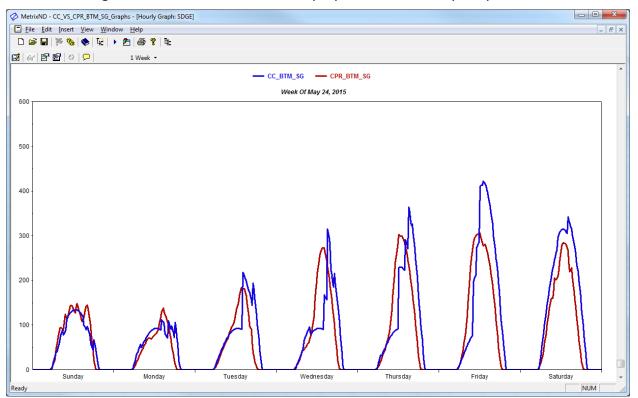


Figure 9: CPR versus Cloud Cover (CC)Solar Generation (MWh): SDG&E

CHAPTER 4: FORECAST SIMULATIONS

A key objective of this study is to evaluate the load forecast accuracy improvements that can be expected by incorporating forecasts of solar PV generation into the load forecast framework. To meet this study objective, a series of h-step ahead forecast simulations are computed for each of the four modeling approaches: (a) CAISO Baseline Model, (b) Error Correction, (c) Reconstituted Loads, and (d) Model Direct. The simulation date range is 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,
- 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 24hour 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.

Observed weather conditions are used to eliminate load forecast error driven by weather forecast errors.

Solar PV Generation Forecasts. Two sets of estimated solar PV generation are used 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.

The list of simulations that were run are presented in Table 4 below.

Table 4: List of Forecast Simulations

Method/Load Zone	Description
Method_1_PGE	Baseline No Behind-the-Meter Solar Generation
Method_1_SCE	Baseline No Behind-the-Meter Solar Generation
Method_1_SDGE	Baseline No Behind-the-Meter Solar Generation
Method_2_PGE	Error Correction: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_2_PGEBayArea	Error Correction: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_2_PGENonBayArea	Error Correction: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_2_SCE	Error Correction: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_2_SCECoastal	Error Correction: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_2_SCEInland	Error Correction: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_2_SDGE	Error Correction: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_3_PGE	Model Direct: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_3_PGEBayArea	Model Direct: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_3_PGENonBayArea	Model Direct: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_3_SCE	Model Direct: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_3_SCECoastal	Model Direct: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_3_SCEInland	Model Direct: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_3_SDGE	Model Direct: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_4_PGE	Reconstituted Loads: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_4_PGEBayArea	Reconstituted Loads: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_4_PGENonBayArea	Reconstituted Loads: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_4_SCE	Reconstituted Loads: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_4_SCECoastal	Reconstituted Loads: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_4_SCEInland	Reconstituted Loads: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_4_SDGE	Reconstituted Loads: Cloud Cover Based Behind-the-Meter Solar Generation Estimates
Method_5_PGE	Error Correction: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_5_PGEBayArea	Error Correction: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_5_PGENonBayArea	Error Correction: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_5_SCE	Error Correction: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_5_SCECoastal	Error Correction: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_5_SCEInland	Error Correction: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_5_SDGE	Error Correction: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_6_PGE	Model Direct: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_6_PGEBayArea	Model Direct: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_6_PGENonBayArea	Model Direct: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_6_SCE	Model Direct: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_6_SCECoastal	Model Direct: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_6_SCEInland	Model Direct: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_6_SDGE	Model Direct: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_7_PGE	Reconstituted Loads: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_7_PGEBayArea	Reconstituted Loads: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_7_PGENonBayArea	Reconstituted Loads: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_7_SCE	Reconstituted Loads: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_7_SCECoastal	Reconstituted Loads: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_7_SCEInland	Reconstituted Loads: Clean Power Research Based Behind-the-Meter Solar Generation Estimates
Method_7_SDGE	Reconstituted Loads: Clean Power Research Based Behind-the-Meter Solar Generation Estimates

4.1 Forecast Performance Measurements

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

Equation 47. Mean Absolute Percentage Error

$$MAPE_{h}^{Z,A} = \frac{\sum_{d=1}^{D} \sum_{i=1}^{I} \frac{\left|L_{d,i}^{Z} - F_{h,d,i}^{Z,A}\right|}{L_{d,i}^{Z}} \times 100}{D \times I}$$

Where,

 $MAPE_h^{Z,A}$ is the Mean Absolute Percentage Error for Load Zone (Z) for the h-step ahead load forecast (h) using forecast approach (A)

 $L_{d,i}^{Z}$ is measured load for Load Zone (Z), day (d), and time interval (i)

 $F_{d,i}^{Z,h,A}$ is the h step ahead forecast of measured load for Load Zone (Z), day (d) and interval (i) use forecast approach (A)

I is the number of non-dark time intervals (i) over which the forecast MAPE is computed

D is the number of days in forecast simulation

To facilitate identifying improvements in forecast performance relative to the baseline forecast the forecast MAPE values are presented as a percentage change relative to the baseline MAPE. Specifically,

Equation 48. Percentage Change in MAPE Relative to the Baseline MAPE

$$PercentMAPEChange_{h}^{Z,A} = \frac{\left(MAPE_{h}^{Z,A} - MAPE_{h}^{Z,Baseline}\right)}{MAPE_{h}^{Z,Baseline}} \times 100$$

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, a forecast approach can be said to lead to an improvement on average in load forecast accuracy if the Forecast Skill is greater than 50% of the time. Formally, Forecast Skill is computed as:

Equation 49. Forecast Skill

$$Skill_{h}^{Z,A} = \frac{\sum_{d=1}^{D} \sum_{i=1}^{I} (|ForecastErrorBaseline_{d,i}^{Z,h}| > |ForecastErrorApproach_{d,i}^{Z,h,A}|)}{D \times I} \times 100$$

Where,

 ${\rm Skill}_{h}^{Z,A}$ is the percentage of time that the h-step ahead forecast for Load Zone (Z) from the alternative approach (A) was more accurate than the baseline forecast

 $(|ForecastErrorBaseline_{d,i}^{Z,h}| > |ForecastErrorApproach_{d,i}^{Z,h,A}|)$ returns a value of 1.0 if the baseline forecast error is greater in absolute value than the forecast error of the alternative model approach, otherwise returns 0.0

These first two metrics focus on the first moment of the forecast error distribution. In addition to reducing forecast errors on average, it is of interest to test whether or not the alternative forecast approaches reduce the overall dispersion of forecast errors. In this case, forecast error dispersion is measured by the Forecast Standard Deviation. Formally, the Forecast Standard Deviation is computed as:

Equation 50. Forecast Standard Deviation

$$\sigma_{h}^{Z,A} = \sqrt{\frac{1}{D \times I} \sum_{d=1}^{D} \sum_{i=1}^{I} (L_{d,i}^{Z} - F_{d,i}^{Z,h,A})^{2}}$$

Where,

 $\sigma_h^{Z\!,A}$ is the Standard Deviation of the forecast errors for the h-step ahead load forecast for Load Zone (Z) using load forecast approach (A)

To ease comparisons the change in the Standard Deviation of the forecast errors of each approach relative to the baseline Standard Deviation is constructed as follows:

Equation 51. Percent Change in Forecast Error Volatility

$$PercentStandardDeviationChange_{h}^{Z,A} = \frac{\left(\sigma_{h}^{Z,A} - \sigma_{h}^{Z,Baseline}\right)}{\sigma_{h}^{Z,Baseline}} \times 100$$

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 is looking to evaluate whether or not the alternative approaches reduce not only the mean or average forecast error, but also the dispersion of forecast errors.

CHAPTER 5: SIMULATION RESULTS SUMMARY

The results of forecast simulations for January 1, 2015 through June 30, 2015 are presented below. This period was selected since it represents the most recent data and the period over which PV installations were at their highest. The results from earlier periods are less applicable to the forecast problem currently faced by the CAISO 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:
 - CAISO Total
 - PG&E Total
 - PG&E Bay Area
 - PG&E Non Bay Area
 - SCE Total
 - 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%
 - Cloudy: average daily cloud cover percentage greater than or equal to 75%

The results are summarized in Figure 10 through Figure 49. On each figure, values that represent an improvement over the baseline load forecast are highlighted in green.

5.1 CAISO Total Simulation Results

Figure 10 through Figure 14 presents the results for the CAISO total (i.e., the sum of 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.⁶
- » 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 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.
- » 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 driven or the 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 perform well during the summer season while this approach performed will 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, the forecast error dispersion is reduced across most forecast horizons under the Model Direct and Reconstituted Load approach when combined with the CPR solar generation estimates.

Based on an average annual CAISO 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

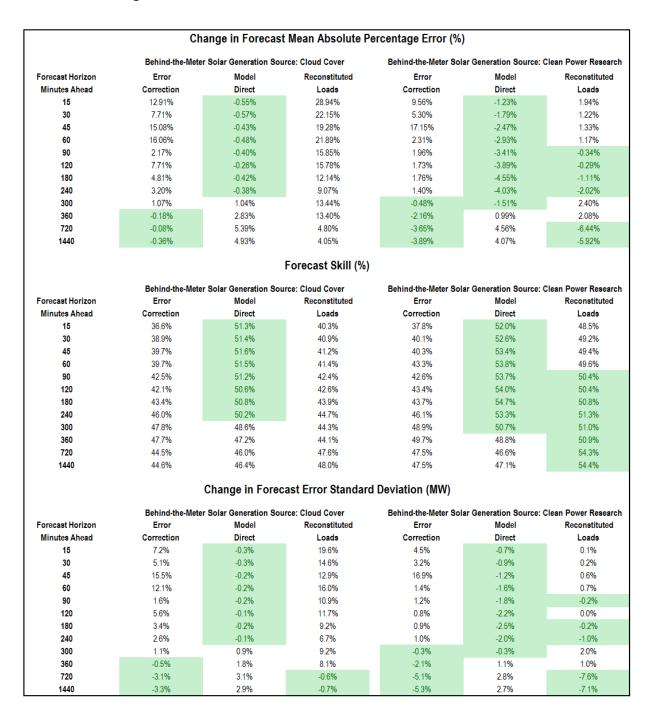


Figure 10: CAISO Total, All Seasons, All Cloud Cover Conditions

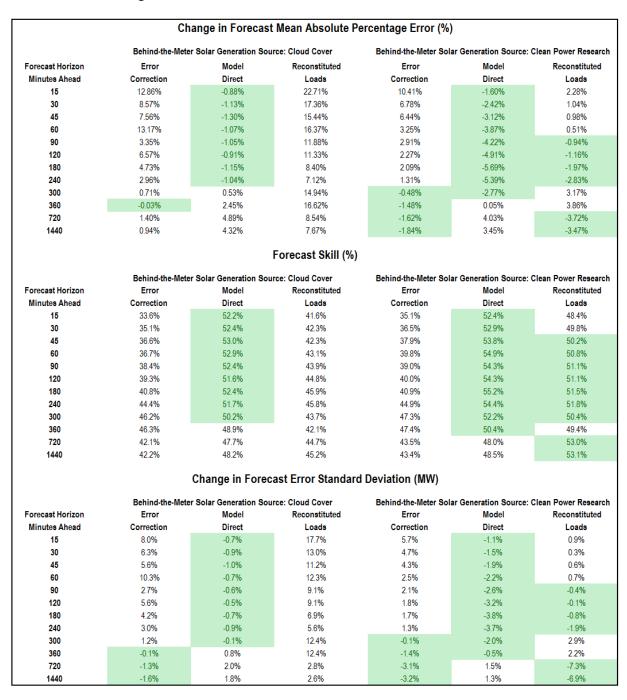


Figure 11: CAISO Total, Winter, All Cloud Cover Conditions

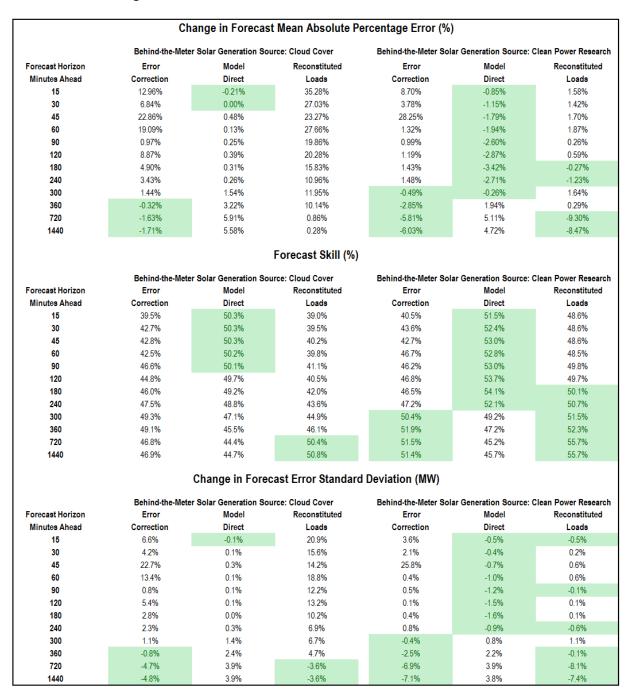


Figure 12: CAISO Total, Summer, All Cloud Cover Conditions

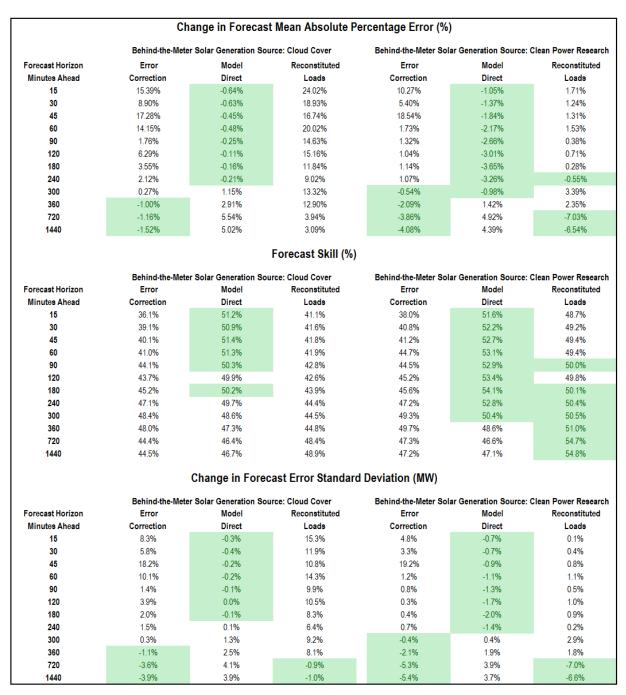


Figure 13: CAISO Total, All Seasons, Clear

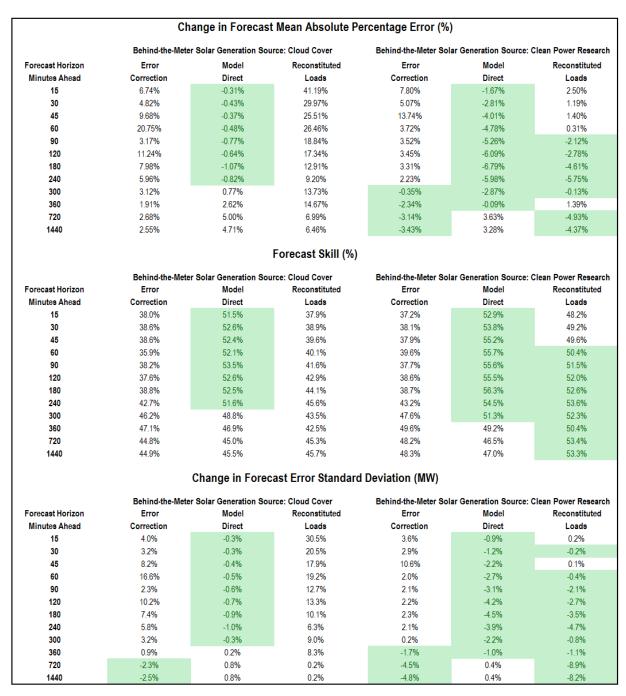


Figure 14: CAISO Total, All Seasons, Cloudy

5.2 PG&E Total Simulation Results

Figure 15 through Figure 19 presents the results for PG&E total 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 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 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 perform well during the summer season while this approach performed will 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, the forecast error dispersion is reduced across most forecast horizons under the Model Direct and Reconstituted Load approach when combined with the CPR solar generation estimates.

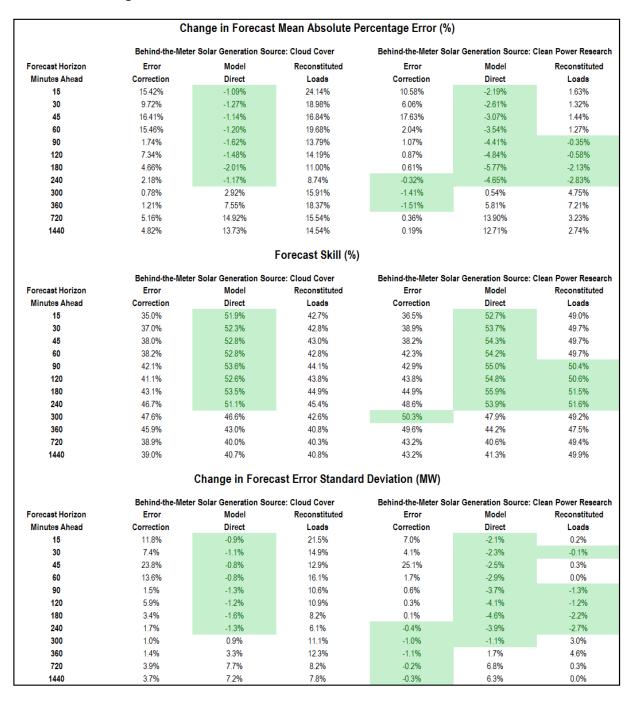


Figure 15: PG&E Total, All Seasons, All Cloud Cover Conditions

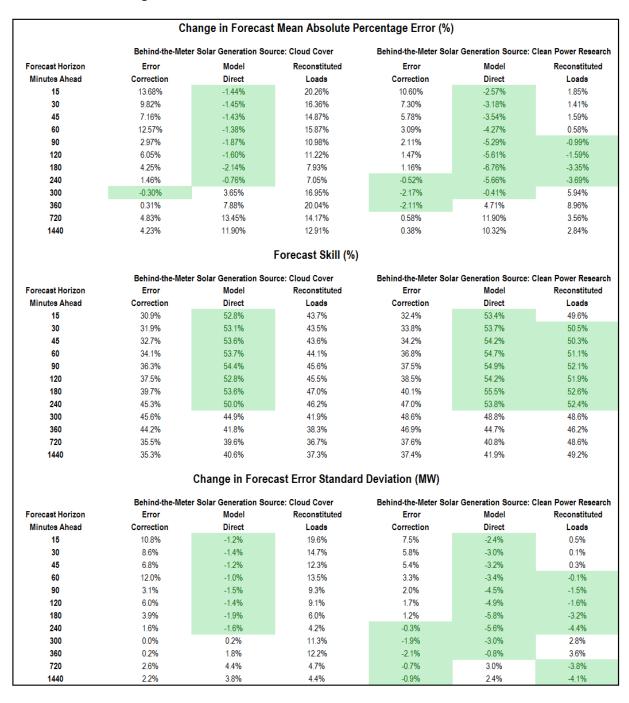


Figure 16: PG&E Total, Winter, All Cloud Cover Conditions

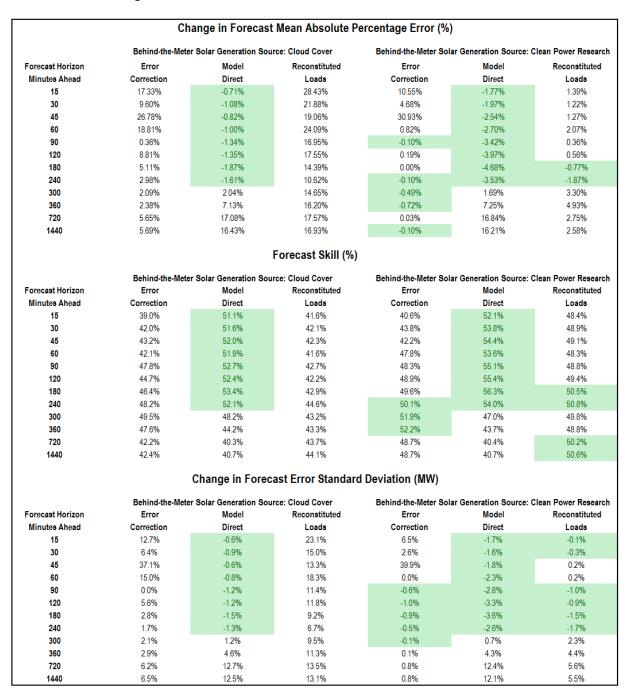


Figure 17: PG&E Total, Summer, All Cloud Cover Conditions

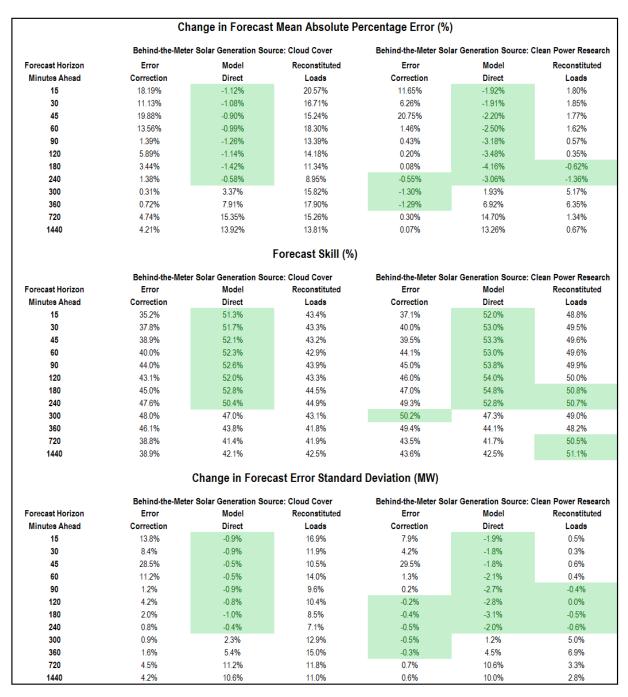


Figure 18: PG&E Total, All Seasons, Clear

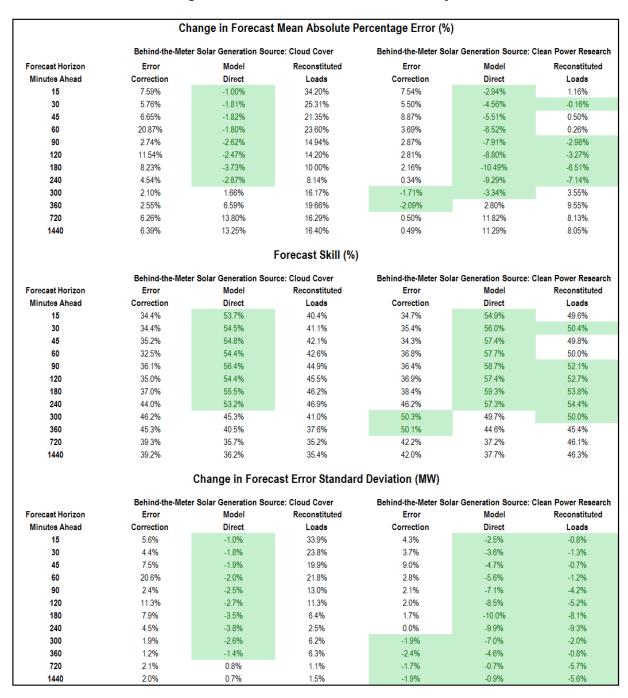


Figure 19: PG&E Total, All Seasons, Cloudy

5.3 PG&E Bay Area Simulation Results

Figure 20 through Figure 24 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 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 reduce 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, the forecast error dispersion is reduced across most forecast horizons under the Model Direct and Reconstituted Load approach when combined with the CPR solar generation estimates.

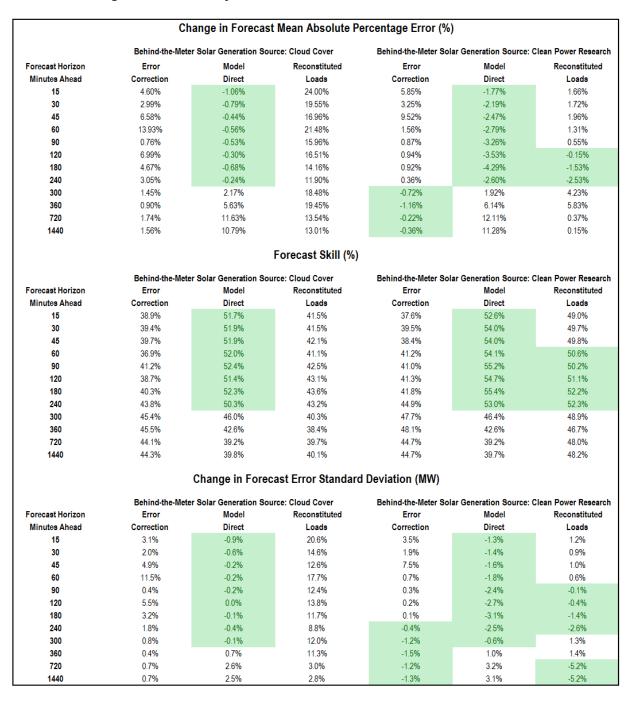


Figure 20: PG&E Bay Area, All Seasons, All Cloud Cover Conditions

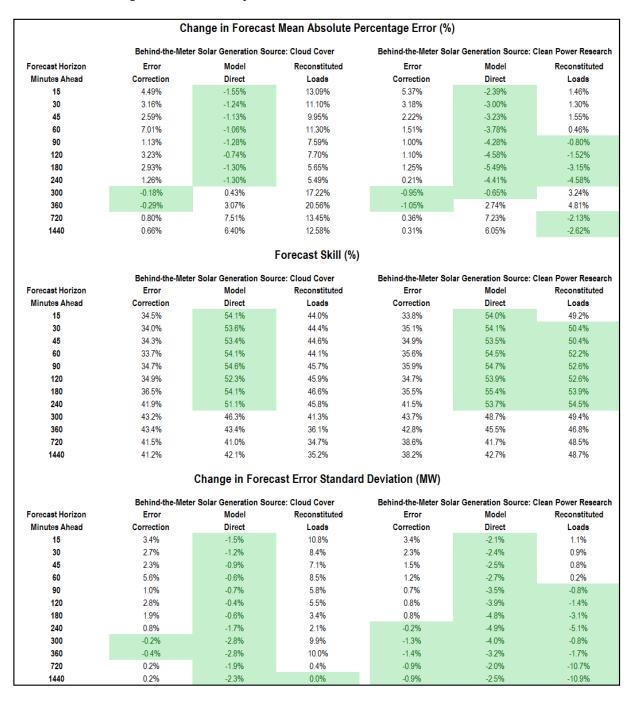


Figure 21: PG&E Bay Area, Winter, All Cloud Cover Conditions

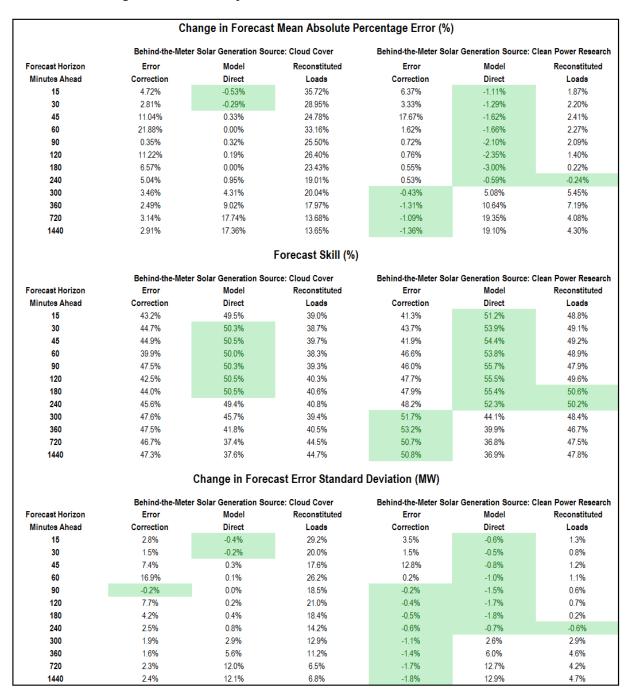


Figure 22: PG&E Bay Area, Summer, All Cloud Cover Conditions

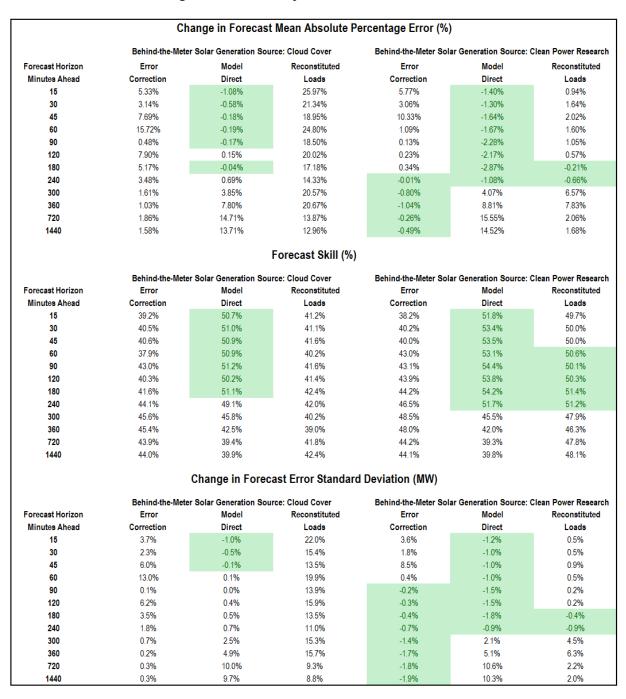


Figure 23: PG&E Bay Area, All Seasons, Clear

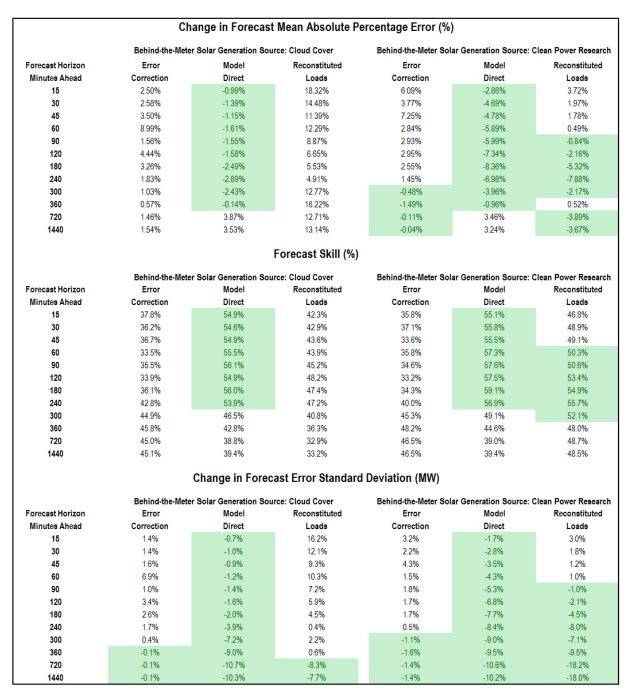


Figure 24: PG&E Bay Area, All Seasons, Cloudy

5.4 PG&E Non Bay Area Simulation Results

Figure 25 through Figure 29 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 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, the forecast error dispersion is reduced across most forecast horizons under the Model Direct and Reconstituted Load approach when combined with the CPR solar generation estimates.

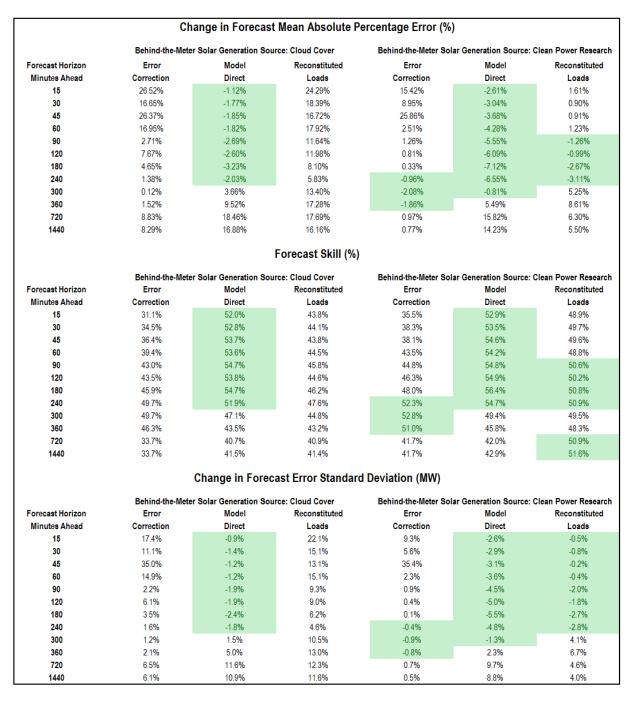


Figure 25: PG&E Non Bay Area, All Seasons, All Cloud Cover Conditions

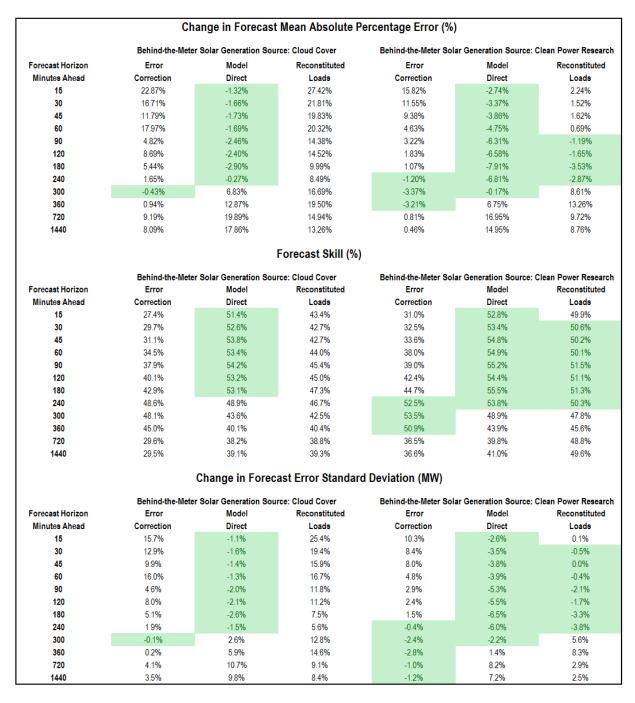


Figure 26: PG&E Non Bay Area, Winter, All Cloud Cover Conditions

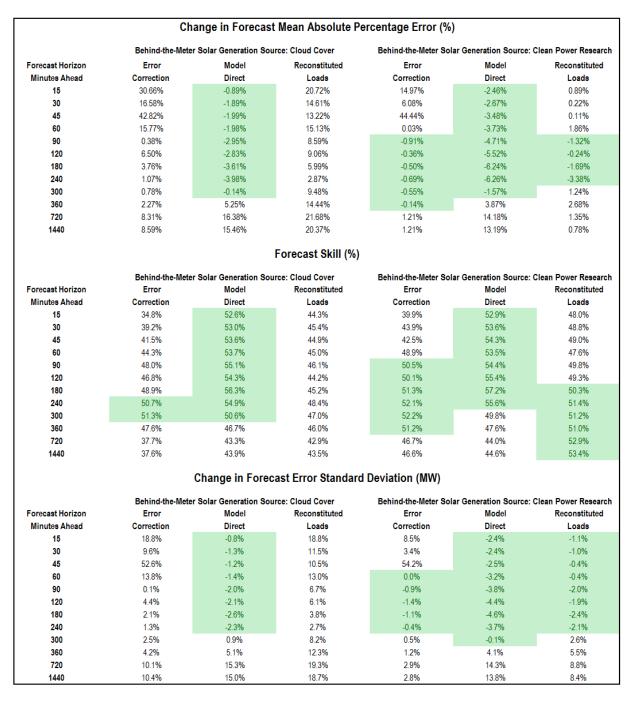


Figure 27: PG&E Non Bay Area, Summer, All Cloud Cover Conditions

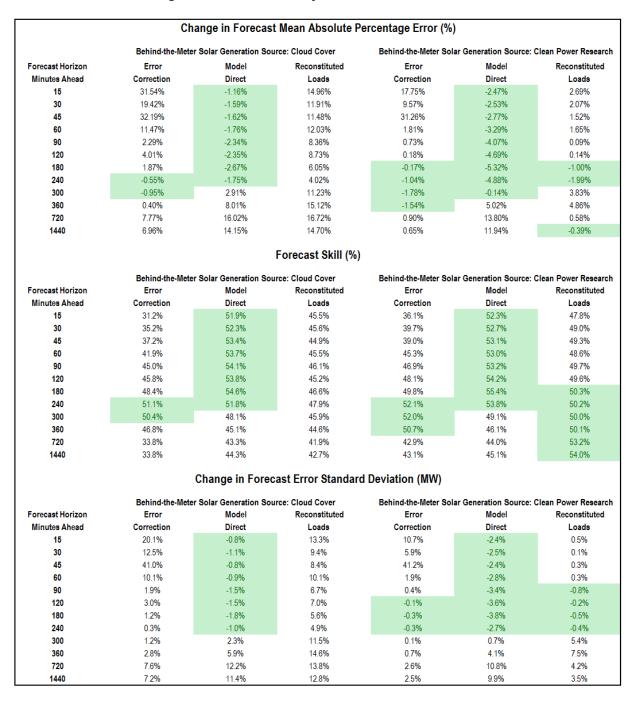


Figure 28: PG&E Non Bay Area, All Seasons, Clear

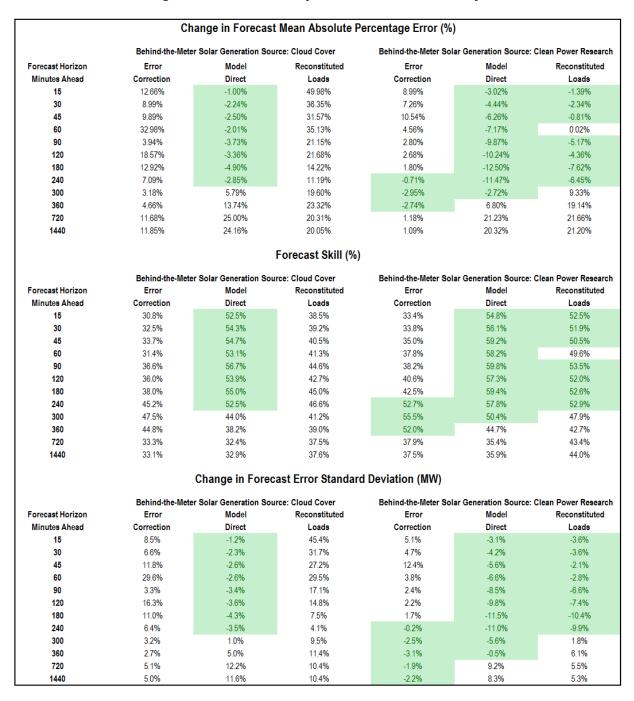


Figure 29: PG&E Non Bay Area, All Seasons, Cloudy

5.5 SCE Total Simulation Results

Figure 30 through Figure 34 presents the results for SCE Total 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 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 Model Direct approach when combined with the CPR solar generation estimates performed during the winter season for forecast horizons of 15 minutes ahead to six-hours ahead. In contrast, the Model Direct approach outperformed the baseline model during the summer season for forecast horizons up to four-hours ahead.
- » Cloud Cover. The alternative approaches appear to work best under varying cloud conditions. Most notably, the forecast error dispersion is reduced across most forecast horizons under the Model Direct and Reconstituted Load approach when combined with the CPR solar generation estimates.

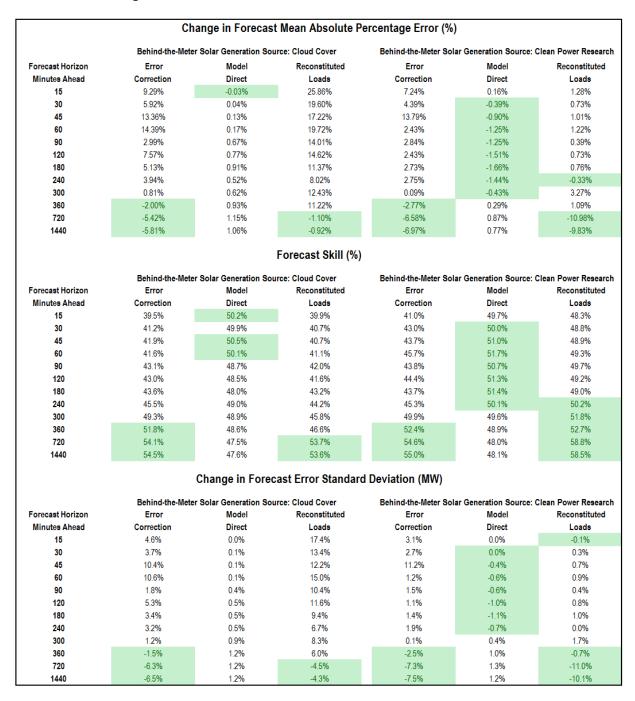


Figure 30: SCE Total, All Seasons, All Cloud Cover Conditions

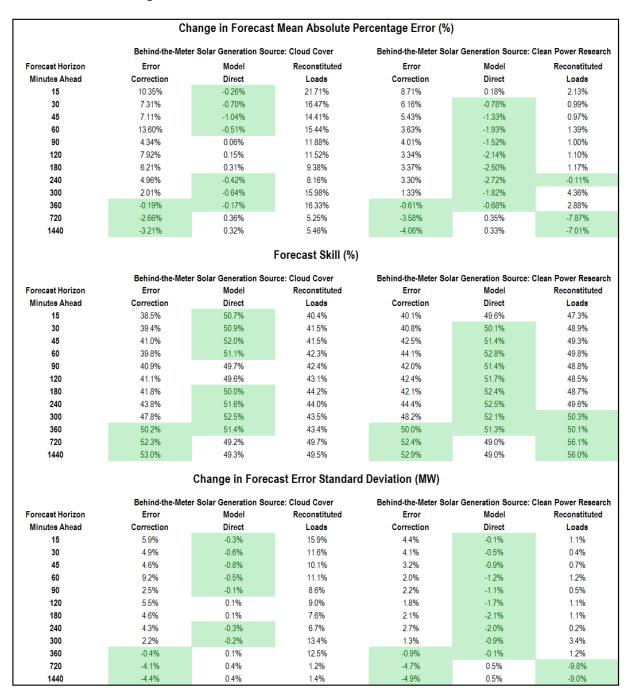


Figure 31: SCE Total, Winter, All Cloud Cover Conditions

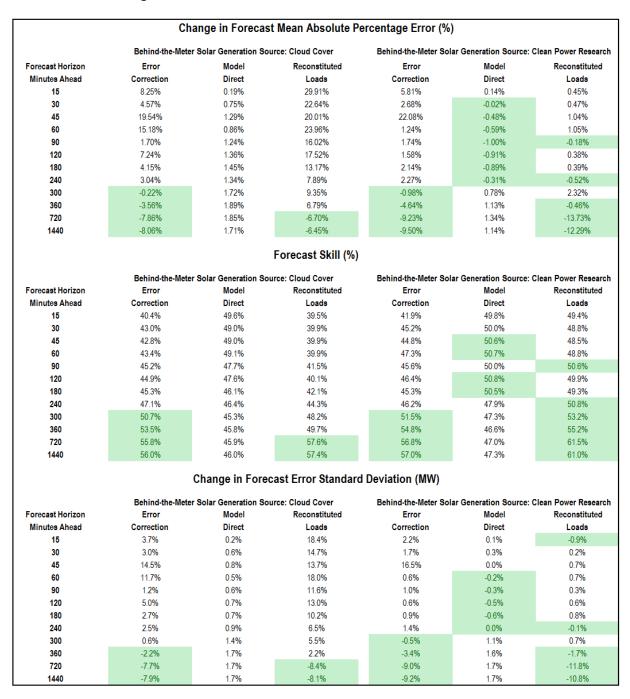


Figure 32: SCE Total, Summer, All Cloud Cover Conditions

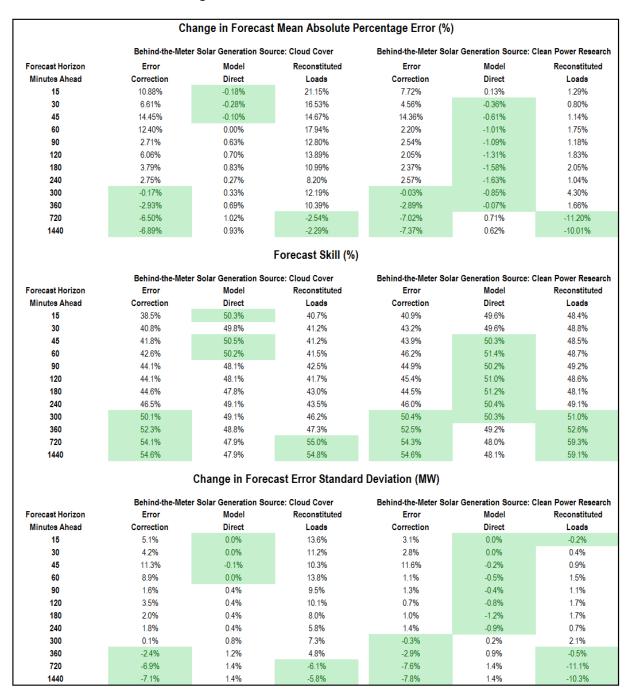


Figure 33: SCE Total, All Seasons, Clear

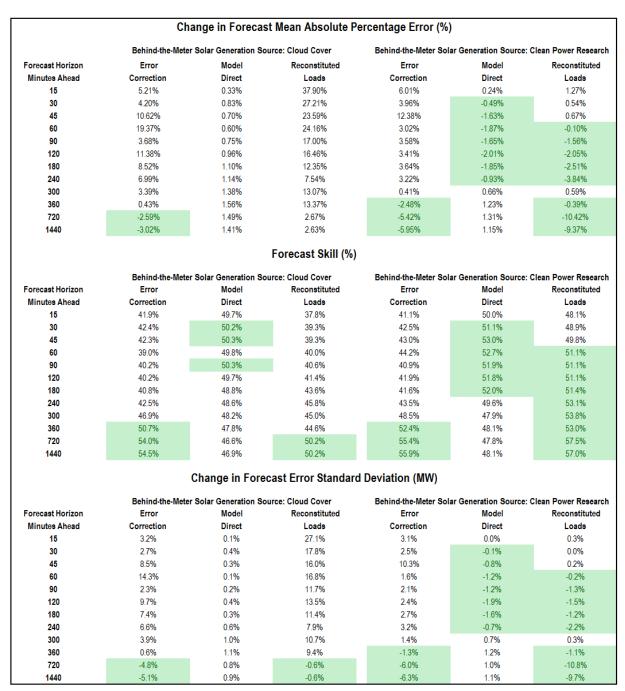


Figure 34: SCE Total, All Seasons, Cloudy

5.6 SCE Coastal Simulation Results

Figure 35 through Figure 39 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 outperformed 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.

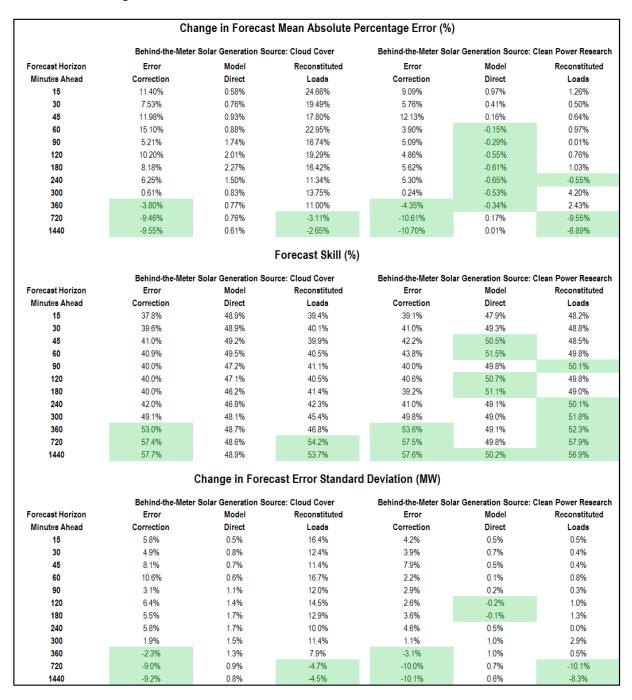


Figure 35: SCE Coastal, All Seasons, All Cloud Cover Conditions

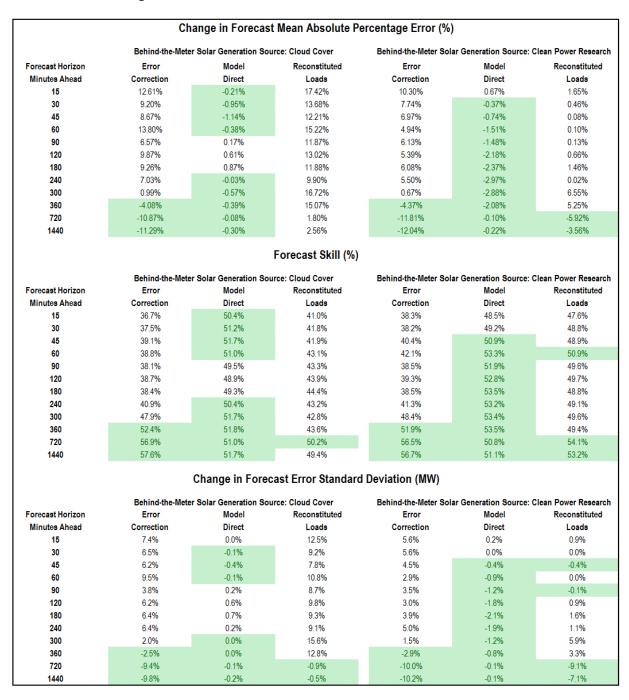


Figure 36: SCE Coastal, Winter, All Cloud Cover Conditions

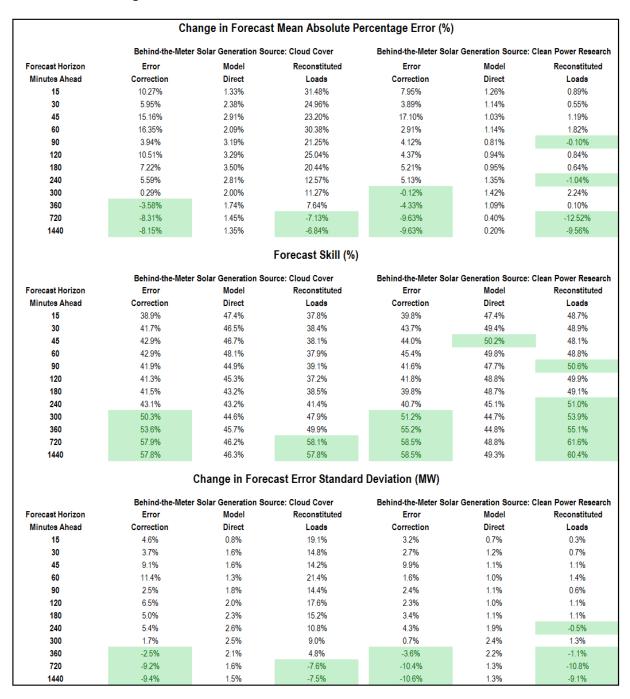


Figure 37: SCE Coastal, Summer, All Cloud Cover Conditions

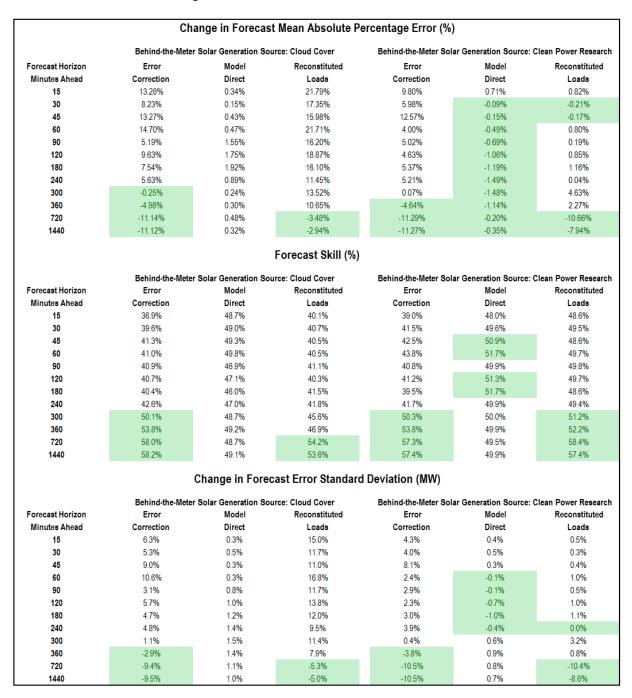


Figure 38: SCE Coastal, All Seasons, Clear

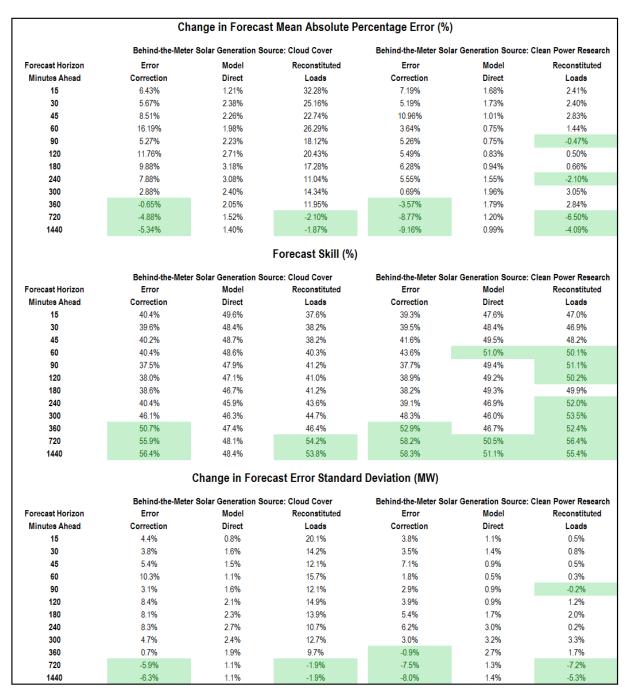


Figure 39: SCE Coastal, All Seasons, Cloudy

5.7 SCE Inland Simulation Results

Figure 40 through Figure 44 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.

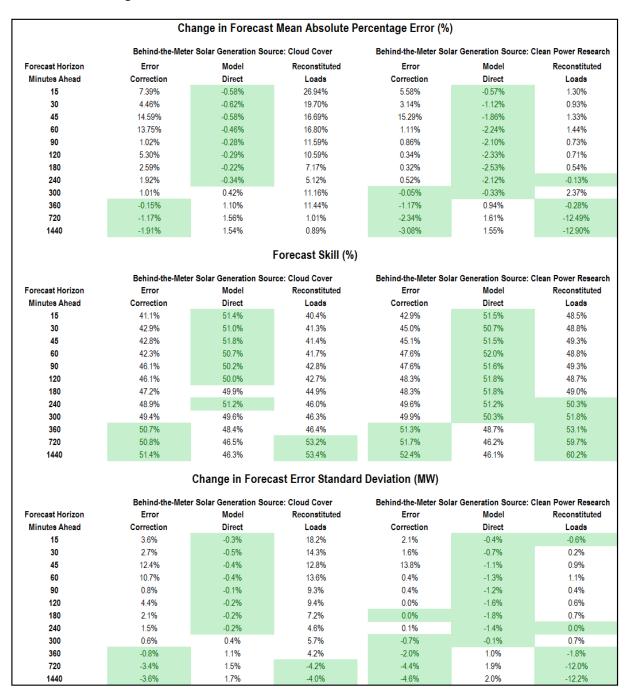


Figure 40: SCE Inland, All Seasons, All Cloud Cover Conditions

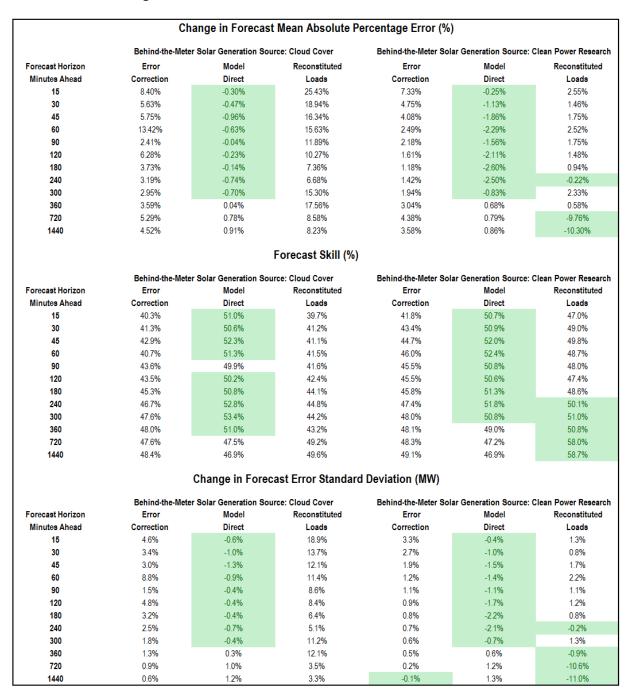


Figure 41: SCE Inland, Winter, All Cloud Cover Conditions

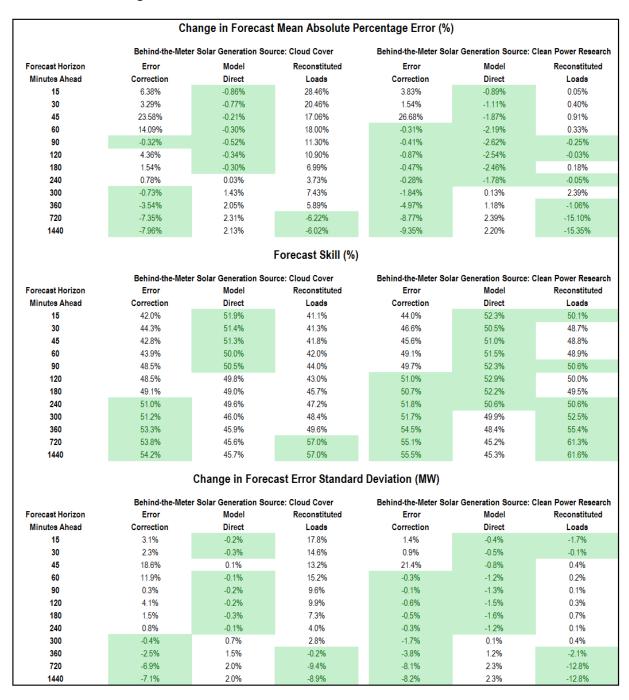


Figure 42: SCE Inland, Summer, All Cloud Cover Conditions

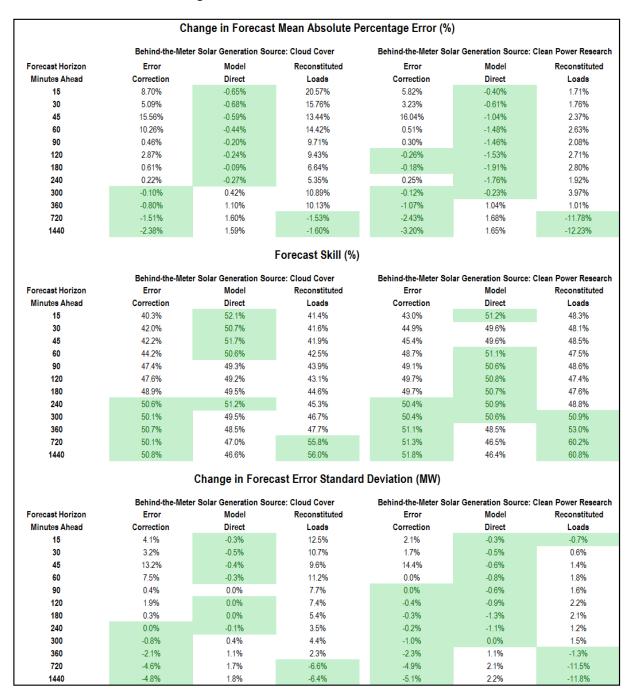


Figure 43: SCE Inland, All Seasons, Clear

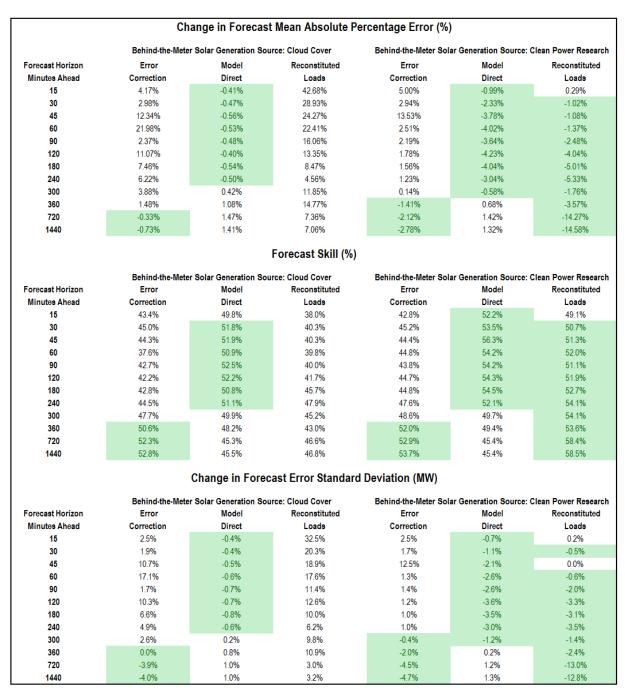


Figure 44: SCE Inland, All Seasons, Cloudy

5.8 SDG&E Total Simulation Results

Figure 45 through Figure 49 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 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 is no substantial differences between the alternative approaches performance under cloudy versus sunny conditions.

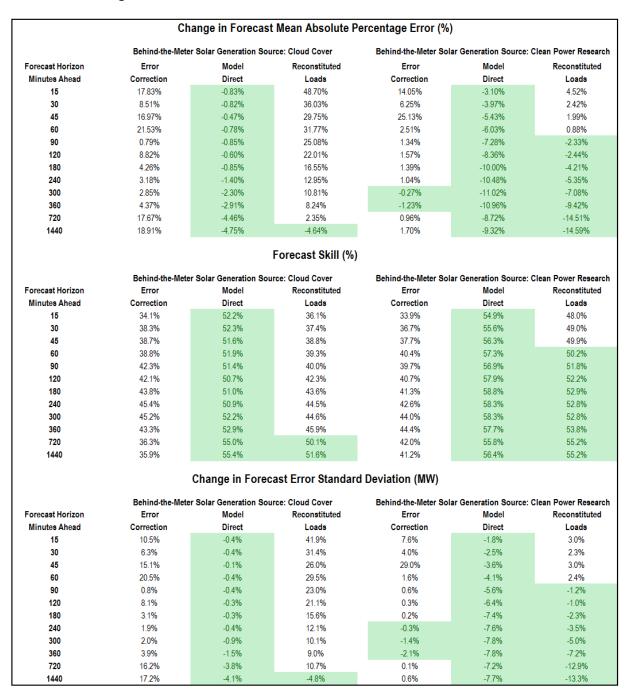


Figure 45: SDG&E Total, All Seasons, All Cloud Cover Conditions

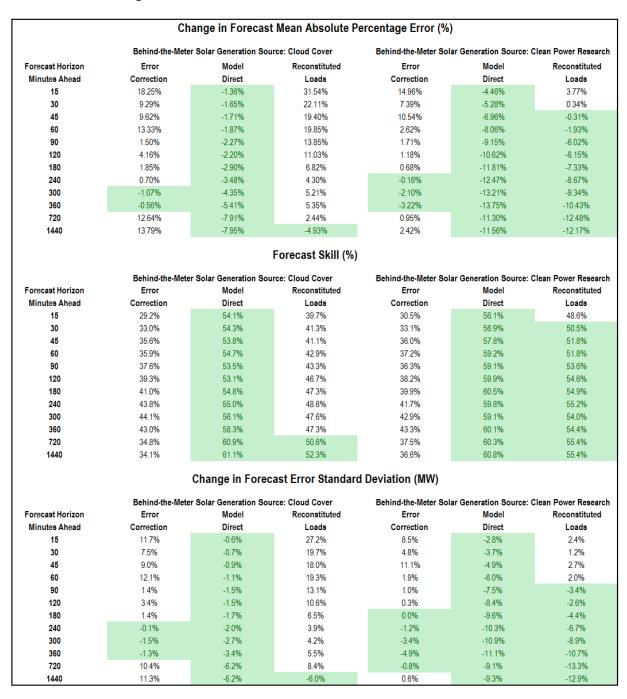


Figure 46: SDG&E Total, Winter, All Cloud Cover Conditions

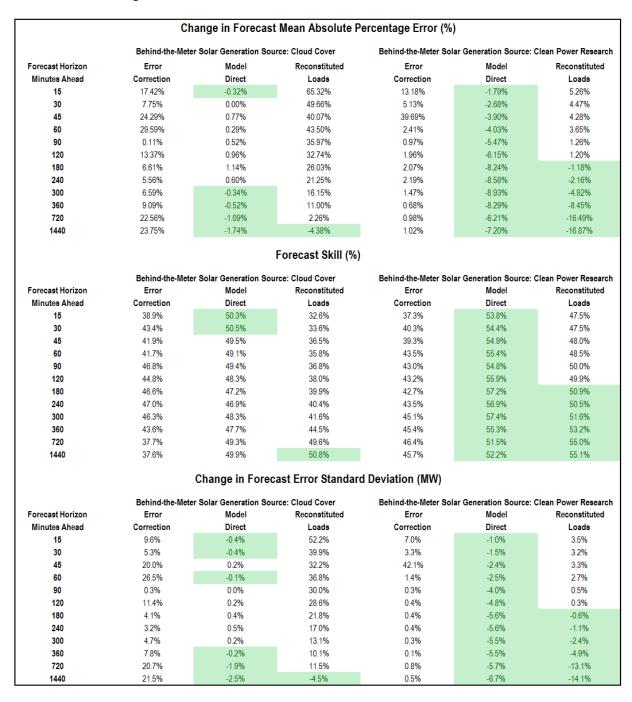


Figure 47: SDG&E Total, Summer, All Cloud Cover Conditions

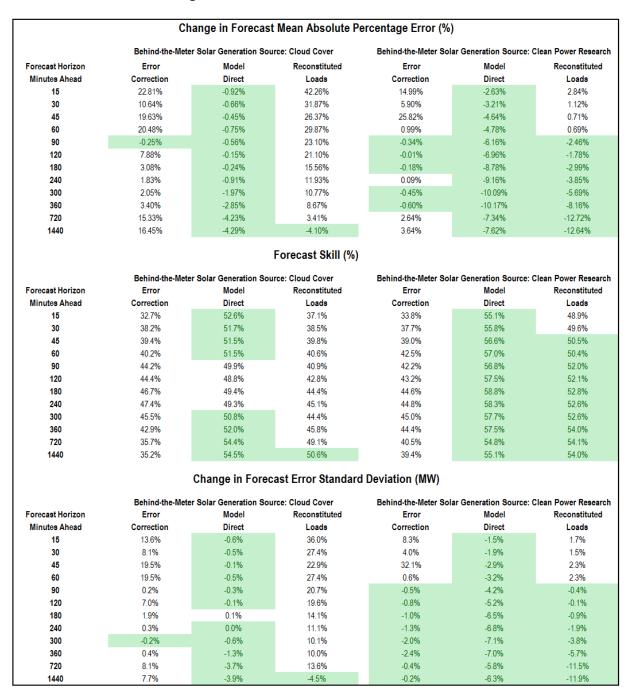


Figure 48: SDG&E Total, All Seasons, Clear

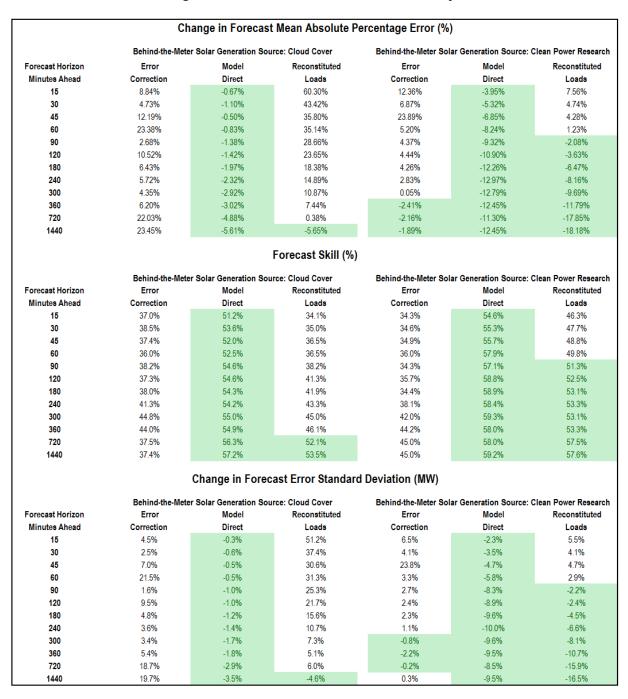


Figure 49: SDG&E Total, All Seasons, Cloudy

CHAPTER 6: STATISTICAL ESTIMATES OF SOLAR PV 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, the estimated coefficients on the Solar PV variables are expected 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 are 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, an engineering-based *a priori* value of -1.0 for the estimated coefficient on the Solar PV variable may not be realized.

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 lead to the lower Solar PV generation value being offset by 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 load increase associated with lower Solar PV generation being compounded by an increase in electric space heating loads.

In general, the observed load impact of Solar PV generation will be complicated by weather and behavioral driven utilization of space conditioning equipment. 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 Figure 50 through Figure 53 are the statistically estimated load impacts under average solar and maximum solar conditions for the CAISO 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 is computed as the product the CPR's maximum Solar PV generation 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 is computed as the product the the PCR's maximum Solar PV generation and the estimated coefficient on the Solar PV generation impact that is computed as the product the OPR's average Solar PV generation and the estimated coefficient on the Solar PV generation impact that is computed as the product the OPR's average Solar PV generation and the estimated coefficient on the Solar PV generation impact that is 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.

Observations about these data are outlined below.

- » 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, the load forecast is adjusted down by approximately 50% of the Solar PV generation estimate. In the mid-afternoon hours, the load forecast is adjusted down by approximately 77% 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 is leading to higher forecasted loads in both these periods. This impact is most pronounced under maximum solar conditions with an estimated impact of a little over 840 MW at 19:00. Under average solar conditions, the late afternoon pick up in loads is estimated 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 is a little over 540 MW. Under average solar conditions the average load impact at 19:00 is 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 is a little over 170 MW. Under average solar conditions, the average load impact at 19:00 is 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 is a little over 120 MW. Under average solar conditions, the average load impact at 19:00 is 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 is a similar forecasted rise in loads associated with penetration in Solar PV. This impact is most pronounced with PG&E with an estimated load impact of about 400 MW under maximum solar conditions. The impact on SCE early morning hours is estimated 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, the engineering-based *a priori* value for the estimated coefficient on the Solar PV generation variable of -1.0 is rejected. 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, to the extent penetration of Solar PV leads to behavioral changes whereby people are taking advantage of "free" electricity, then the estimated coefficients on the Solar PV generation variables will be skewed to account for these behavioral changes. While it would be nice to have all of the estimated coefficients with a value close to -1.0, the goal is 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.

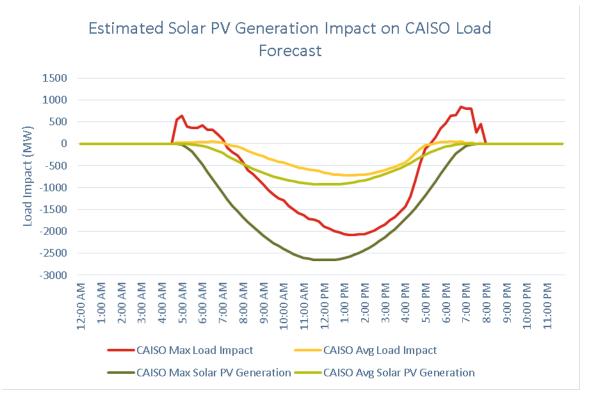


Figure 50: Estimated Load Impact of Solar PV Generation: CAISO Total

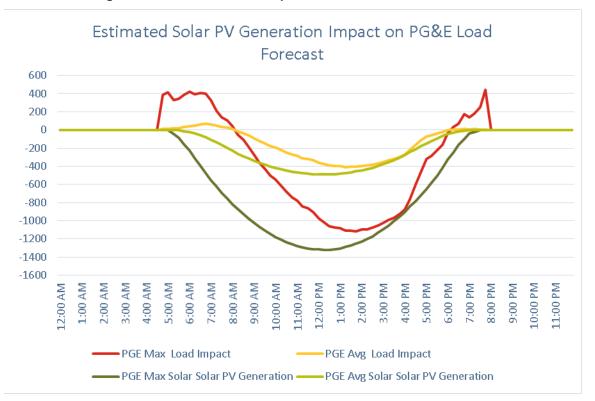
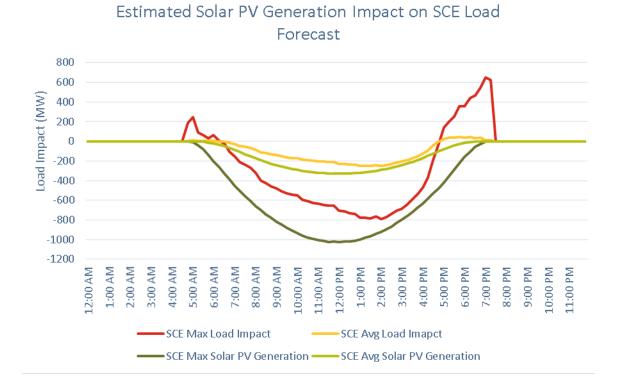


Figure 51: Estimated Load Impact of Solar PV Generation: PG&E Total

Figure 52: Estimated Load Impact of Solar PV Generation: SCE Total



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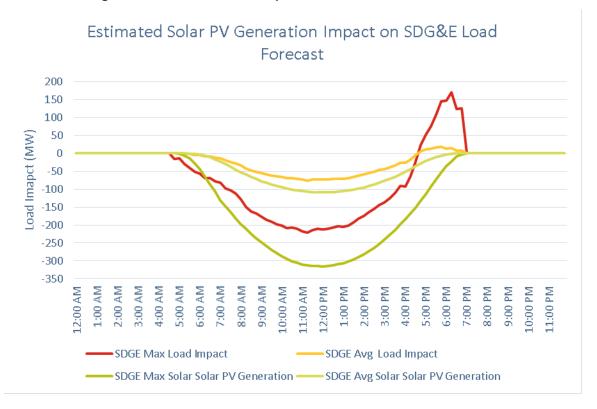


Figure 53: Estimated Load Impact of Solar PV Generation: SDG&E Total

CHAPTER 7: CONCLUSIONS

This study set out to determine if there was a way of improving the load forecast accuracy of the CAISO's existing load forecast models by incorporating forecasts of solar PV generation. Three alternative modeling approaches are presented. 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 CAISO 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.

Further research is needed to determine the extent to which penetration of solar PV is leading to behavioral changes. 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 micro grids.

GLOSSARY

Term	Definition
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
CAISO	California Independent System Operator – the organization that manages the three IOU's electricity grid in California
сс	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 s 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.[1] Irradiance is usually measured in W/m2.
EPIC	Electric Program Investment Charge
Global Horizontal Irradiance (GHI)	Global Horizontal Irradiance is the total amount of shortwave radiation received from above by a horizontal surface.

Term	Definition
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 CAISO zone, IOU, or CAISO level
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).

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