REPORT

2015 Load Impact Evaluation of the California Statewide Permanent Load Shifting Program

Public Version

April 1, 2016

Prepared for
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Abstract

This evaluation documents the ex post and ex ante load impact analysis and results for the California Statewide Permanent Load Shifting (PLS) program at Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E). The PLS program provides a one-time incentive payment ($875/kW shifted) to customers who install qualifying PLS-Thermal Energy Storage (TES) technology on typical central air conditioning units or process cooling equipment. The statewide PLS program design was finalized and adopted by the CPUC in May 2013.[1] Because of the long lead time involved in moving from submitting an application to completing a PLS installation, there is only one installation currently in place on which to base ex post impact estimates for 2015. As such, while the ex post evaluation is included in this report, the bulk of the report focuses on the 2016–2026 ex ante load impact estimates. As of January 2016, the utilities had a total of 17 active applications, with one operational installation. The peak hourly ex post load impact for the single operational project in the SCE service territory was [redacted] kW. The ex ante impact estimates rely on information in these applications along with the ex post analysis for the single operational installation to improve upon the analysis that was done for the 2014 program year evaluation. Nonetheless, this year's forecast must still rely on numerous assumptions about impacts and further enrollment in the program, which have a high degree of uncertainty. This uncertainty is explicitly acknowledged in this evaluation by including ex ante impact estimates for low, base, and high enrollment scenarios. In the base case scenario for the 2018 Utility-specific August monthly system peak day under 1-in-10 year weather conditions, the program is expected to deliver a 2.6 MW load impact for PG&E; a 7.8 MW load impact for SCE; and a 4.1 MW load impact for SDG&E—totaling 14.5 MW statewide. The peak load reduction for the program occurs under the Utility-specific July monthly system peak day under 1-in-10 year weather conditions, when the program is expected to deliver a 2.7 MW load impact for PG&E; a 7.9 MW load impact for SCE; and a 4.3 MW load impact for SDG&E—totaling 14.9 MW statewide.

[1] CPUC Resolution E-4586 issued on May 9, 2013.

1 Introduction

This evaluation documents the ex post and ex ante load impact analysis and results for the California Statewide Permanent Load Shifting (PLS) program at Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E). The statewide PLS program design and rules were finalized and adopted by the California Public Utility Commission (CPUC) in May 2013.[2] Due in part to the long lead time involved in moving from submitting an application to completing a PLS installation, there is only one installation on which to base ex post impact estimates for the 2015 program year (PY2015). As such, while the ex post evaluation is included in this report, the bulk of this evaluation focuses on the 2016–2026 ex ante load impact estimates because the ex post results from a single installation are not generalizable. Under the Statewide PLS program, utility customers are incentivized to install Thermal Energy Storage (TES) systems, which either eliminate or reduce on-peak period electric load for cooling by shifting chiller operation to off-peak periods. Shifting daily cooling loads to off-peak periods benefits the grid and distribution systems for regions with peaking characteristics that mirror those of the grid, and can reduce customer bills relative to applicable time-of-use rates. For installed TES technology projects, the total incentive is calculated as a multiple of the on-peak period load (kW) that is shifted to off-peak periods and equals $875/kW shifted, with a cap of $1.5 million per customer.

1.1 Background

Prior to development of the statewide program, each of the three IOUs had PLS pilots similar to the current program, but with different incentive levels, participation requirements, and technologies. These pilots arose out of CPUC Decision (D.) 06-11-049, Order Adopting Changes to 2007 Utility Demand Response Programs, which was a resolution of the 2006–2008 Demand Response Application (A.) 05-06-006, et. al. This Decision, among other things, ordered the IOUs to pursue requests for proposals and bilateral arrangements for PLS installations to promote system reliability during summer peak-demand periods. A four-year PLS pilot program was approved for all IOUs from 2008–2011. The details of those pilots are not revisited here; it should be noted that, although the pilots and programs have different characteristics, each IOU had experience with PLS pilots and technologies prior to rollout of the current program.

In November 2010, a Statewide PLS Study, authored by Energy + Environmental Economics (E3) and StrateGen, provided information to the utilities for use in developing a new PLS program. On April 30, 2012, D.12-04-045 ordered the utilities to work collaboratively to develop and propose a standardized, statewide PLS program. As part of the PLS program design process, the utilities incorporated many findings from the Statewide PLS Study into the 2012–2014 PLS program design. On July 30, 2012, the utilities submitted a joint PLS program design proposal to the Commission Staff. The Commission Staff sought feedback from interested parties by facilitating a PLS Workshop that was held on September 18, 2012. As a result of the PLS Workshop and comments received from interested parties, Energy Division (ED) provided the utilities with program design feedback on November 13, 2012. The IOUs incorporated ED's feedback in their final version of the program design proposal submitted

[2] CPUC Resolution E-4586 issued on May 9, 2013.

on January 14, 2013. The most noteworthy ED input resulted in limiting eligibility to mature thermal energy storage technologies for cooling and setting the incentive rate at $875/kw-shifted. On May 9, 2013, Resolution E-4586 adopted the PLS program rules, budget, and implementation details proposed by the IOUs, with modifications.

In May 2014, the CPUC issued a decision[3] to fund 2015 and 2016 as bridge funding years. This decision authorized a total program budget of $10M for PG&E, $9.3M for SCE, and $2M for SDG&E. The incentive portion of the budget was $9M for PG&E, $6.5M for SCE, and $2M for SDG&E. SDG&E later requested and received approval to shift $1.5M of unspent incentive funds from the 2013–14 funding cycle to the current 2015–16 bridge funding cycle to reach a total incentive budget of $3.5M. On December 4, 2014, D.14-12-024 stated that 2017 will also be a bridge year but there was no information regarding details on program budgets. A ruling by the assigned administrative law judge (ALJ) in this proceeding is expected to initiate the process to authorize a 2017 bridge funding period. However, as of the writing of this report, no 2017 funding has been authorized. Consequently, enrollment forecasts for future funding cycles will not be integrated into the load impact analysis until the budgets are formally authorized by the CPUC. It should be noted that the utilities are currently working to request funding for the 2017 bridge funding cycle.

1.2 Key Considerations for Program Year 2015 Load Impact Forecast

As previously noted, there is currently only one operational PLS installation in place for which ex post impacts can be estimated for PY2015 under the present approved program. While there are important lessons to be learned from evaluating this installation, including comparing the ex post results to peak load reductions from the feasibility study, it is not appropriate to generalize the findings from the single site to the rest of the PLS program. Despite that, the ex ante load impact estimates in this document conform to the timing and requirements of the CPUC Demand Response Load Impact Protocols for nonevent based programs.[4] Since the program rules have been finalized and customer feasibility studies and applications have been submitted, the ex ante impact estimates rely on the ex post results for the single operational customer in conjunction with information in these pipeline applications to improve upon the analysis that was done for the PY2014 evaluation. Nonetheless, this year's forecast still relies on numerous assumptions about how expected PLS load shifting changes under various weather conditions, and further enrollment in the program, which have a high degree of uncertainty. If future ex post evaluations from a wider variety of customers show that the PLS-TES technology works differently than expected or if enrollment proceeds at an unexpected pace, this forecast may not reflect the load impacts that the PLS program ultimately delivers. For example, this forecast assumes that each utility receives a certain number of PLS program applications for low, base case, and high scenarios. However, these assumptions carry a high degree of uncertainty because projecting uptake of any utility program depends on several factors and is inherently uncertain. This uncertainty is compounded by the fairly high initial capital investment and custom nature of each installation. The actual number of applications that each utility receives could be quite different than these projections.

[3] CPUC D.14-05-025 issued on May 19, 2014.

[4] CPUC D.08-04-050 issued on April 28, 2008 with Attachment A.

The current PLS program design specifies the data to be collected from participants to optimize TES system performance and to enable load impact evaluation. In future years, these measurements will be the basis for the ex post and ex ante impact evaluations. For this evaluation, ex ante estimates rely, in part, on information contained in the feasibility studies and applications submitted by the end of 2015 in addition to the ex post analysis. These applications do not exhaust the program budgets for PG&E and SCE. SDG&E applications have reserved all of the incentive funds. As such, ex ante estimates associated with the remaining budget were based on a method similar to the one used in last year's evaluation, which estimates impacts by dividing the program budgets expected to be spent by the incentive amount per kW that the utilities pay for PLS investments.

Estimates from program managers and evaluation, measurement and verification (EM&V) staff on budget scenarios, combined with knowledge of the proposed rules of the program and building simulation modeling, provided the foundation for the analysis. As the PLS program evolves and additional PLS-TES installations come online over the next few years, evaluators will gradually phase out the assumptions-driven approach and transition to a data-driven approach where actual PLS customer data is the basis for the analysis, which will reduce the uncertainty of future ex ante load impact estimates. While there is always statistical uncertainty in load impact estimation, the use of customer data from actual PLS operations rather than basing the analysis largely on utility assumptions—as is currently necessary due to lack of operational PLS installations—will dramatically reduce the level of uncertainty in the forecast. Currently, due to all of the assumptions—including how PLS systems will actually perform relative to the engineering estimates—and the high level of uncertainty regarding actual program participation rates, it isn't appropriate to assign statistical uncertainty such as confidence intervals to the ex ante estimates. This would actually imply a level of false precision that is inappropriate for a program at this stage in the development cycle. It is for this reason that high, medium (base case), and low scenarios are provided. Only when many more PLS customers are operational, and the customer participation rates are more predictable, will it be appropriate to assign statistical measures such as confidence intervals to quantify the level of uncertainty in the ex ante forecast.

1.3 Program Overview

The PLS program provides a one-time incentive payment ($875/kW shifted) to customers who install qualifying PLS-TES technology on typical central air conditioning units or process cooling equipment. Incentives are determined based on the designed load shift capability of the system and the project must undergo a feasibility study prepared by a licensed engineer. The load shift is typically accomplished through shifting of daytime chiller load to overnight hours. All electric customers on time-of-use electricity rates are eligible for the program, including residential, commercial, industrial, agricultural, direct access, and Community Choice Aggregation customers.

To qualify for the PLS program incentive payment, customers must go through the program application, approval and verification process, which includes all of the stages that are required for customers to apply for and receive a verified incentive amount. These stages are:

1. Customer submits complete application;
2. Customer submits feasibility study;

3. IOU reviews feasibility study prior to approval;
4. IOU conducts pre-installation inspection, including pre-installation M&V, and, if customer passes, approves application and sets aside incentive funds;
5. IOU and customer sign agreement (SCE only);
6. Customer submits project design;
7. Customer installs PLS-TES system;
8. Customer submits Commissioning Report;
9. IOU reviews commissioning report and conducts post-installation inspection, tests, cost, and any other verifications; and
10. Customer receives final PLS technology incentive.

After submitting an application, participating customers must provide, in advance of installation, a feasibility study prepared by a licensed engineer. This study must include an estimated cooling profile for each hour for a year based on building simulation models and input about building specifications, regional temperatures, occupancy, and other inputs. Both retrofit and new construction customers are subject to the energy modeling process unless utility approved cooling usage data is available.

The total incentive amount is determined using a customer's load shift on their maximum cooling demand day—based on the on-peak hours. A conversion factor[5] is used to convert the cooling load shift tons to electricity load shift (kW) for both full and partial storage systems. The incentive levels for the program are $875/kW-shifted for all IOUs.

The incentive payments are intended to offset a portion of the cost of installation, thereby making the system more attractive financially. Under the program rules, the incentive is the lesser of (1) the incentive reservation amount calculated from the approved feasibility study and post-installation approval; (2) 50% of the actual final installed project cost; or (3) $1.5 million. In addition, customers are required to be on a time-of-use electric rate and provide trend data to the IOU's about their TES system for the first five years after installation. In the participation component of the program, customers are required to run their TES system on summer weekdays for five years after installation, thereby realizing electric bill savings, and submit monitored system data to the IOU. The systems are expected to have a lifetime of about 20 years.

As mentioned above, the current incentive budgets from the '15-'16 Bridge funding cycle are $9 million for PG&E, $6.5 million for SCE, and $3.5 million for SDG&E.[6] These incentive budgets can be interpreted to represent an upper limit on the amount of peak period shifting from new applications that the program could ultimately provide as a result of funding during this program cycle.

[5] A conversion factor will be used to convert the cooling load shift (tons) to electricity load shift (kW) capacity. This calculation method is applied for both full and partial storage systems. A conversion factor of 0.7 kW/ton will be applied to water-cooled chillers and 1.2 kW/ton will be applied to air-cooled chillers.

[6] The original SDG&E 2015-16 bridge funding budget was $2M, but $1.5M of unspent funds were rolled over from the 2013-14 funding cycle to reach a total incentive budget of $3.5M.

Customers are required to shift load by running the TES system on weekdays during summer months, which are defined slightly differently for each utility. Table 1-1 shows the on-peak periods and summer months for each utility, as approved in the Statewide PLS Program Proposal.[7] PLS program participants are also encouraged to shift load during non-summer months to maximize their energy bill savings.

Table 1-1: On-peak Periods for Each Utility

Utility	Summer Months	On-peak Hours
PG&E	May 1–October 31	12–6 PM
SCE	June 1–September 30	12–6 PM
SDG&E	May 1–October 31	11 AM–6 PM

1.4 Current PLS Program Status

Table 1-2 provides the PLS program status as of January 2016 by utility and by stage in the PLS application and verification process. Combined, the 3 IOUs had 1 operational installation and 17 active applications that are likely to move forward in the verification process. Since these applications have already been received, they are referred to as identified projects in the ex ante forecast. If these 17 customers successfully install a PLS-TES system, these installations are expected to provide 9.1 MW of total load shift, resulting in incentives of around $7.9 million being spent across the three utilities. However, as these customers move through the verification process, the load shift amount is likely to change, so the 9.1 MW total load shift amount is simply an indicator based on the most recently available information. For example, SCE has received a total of 13 applications, but 6 applications have been temporarily or permanently being withdrawn. One project is operational, and the remaining six active applications all have completed feasibility studies. PG&E has approved five applications; however two applications have since been withdrawn. The remaining three active applications all have completed feasibility studies. SDG&E received eight applications, and all projects have completed the feasibility study submission stage. While this year's PLS evaluation benefits from this information on applications that have been received, it is important to recognize that there are six or seven time-consuming stages from the time an application is submitted by a customer to the time when the installation becomes operational. All of these stages are illustrated in Table 1-2. It can take from one to two years for applications to go through all of the stages and result in an installation depending on the size and complexity of the project. Based on the current applications, the time period for each project (application) is expected to vary with the size of the PLS-TES installation, from 8 months for small projects to 24 months for large projects. Therefore, the forecast for these identified projects is still uncertain, as the kW load shift can change during the verification process and customers may choose not to continue through the process.

[7] 2012–2014 Statewide Permanent Load Shifting Program Proposal. July 30, 2012. Jointly proposed by: Pacific Gas and Electric, San Diego Gas & Electric, and Southern California Edison Company.

Table 1-2: PLS Program Status by Utility and Stage in Verification Process (as of January 2016)

Stage #	Stage Description	PG&E Totals			SCE Totals			SDG&E Totals		
		Apps	Incentive	kW	Apps	Incentive	kW	Apps	Incentive	kW
1	Customer submits complete application							3	[redacted]	[redacted]
2	Customer submits feasibility study									
3	IOU reviews feasibility study and approves application	3	[redacted]	[redacted]	3	[redacted]	[redacted]			
4	IOU conducts pre-installation inspection and sets aside incentive funds							2	[redacted]	[redacted]
5	IOU and customer sign agreement (SCE only)									
6	Customer submits project design and installs PLS-TES system				3	[redacted]	[redacted]	2	[redacted]	[redacted]
7	Customer submits commissioning report									
8	IOU reviews commissioning report and conducts post-installation inspection, tests and cost verifications							1	[redacted]	[redacted]
9	Customer receives final PLS program incentive				1	[redacted]	[redacted]			
Total		**3**	[redacted]	[redacted]	**7**	[redacted]	[redacted]	**8**	[redacted]	[redacted]

1.5 Report Organization

The remainder of this report proceeds as follows. Section 2 summarizes the methodology for the ex post evaluation. Section 3 provides the ex post load impact estimates. Section 0 summarizes the methodology used for the ex ante evaluation. Section 5 provides a summary of key assumptions and the resulting enrollment forecast. Section 6 provides the ex ante load impact estimates by utility. Section 7 includes recommendations for future evaluations. Appendix A summarizes the methodology for developing the ex ante conversion factors, which are key inputs for the analysis.

2 Ex Post Methods and Validation

As in any demand response evaluation, the fundamental exercise is to estimate what usage would have been in the absence of the program. In this case, that entails estimating what a given premise's cooling system usage would have been if they had not installed the TES system.

In this document, we refer to both measured and estimated usage of the pre-TES cooling system as baseline usage. We believe the most reasonable assumption for baseline usage is that, in the absence of TES, the customer would have continued to operate their current cooling system as they had in the past. This may not always be accurate, but attempting to determine what alternative modifications they would have made in the absence of the PLS program would not likely yield generalizable robust results. With that assumption, and in a situation where cooling electric usage is measured, the ex post evaluation task involves estimating what the electrical usage of each customer's pre-TES cooling system would have been under the weather conditions that were observed over the ex post evaluation period. These estimates can be compared to actual measured usage over the same period.

In our evaluation of the PG&E PLS pilot, we found little scope for improvement upon the baseline models that were developed for the participating facilities under PG&E's pilot. The currently approved PLS program guidelines call for future sites to replicate the data collection done at those pilot sites over a three month pre-TES installation period, and for the five year post-TES installation period. As directed in the resolution approving the PLS program,[8] devices will be installed to monitor:

- OAT: 1) Outdoor ambient temperature;
- Cooling System Load: 2) Electric demand (kW) of all chilled water plant equipment (all plant chillers, pumps, and cooling tower fans); and
- Cooling Tons:
    - 3) Chilled water return temperature;
    - 4) Chilled water supply temperature; and
    - 5) Chilled water flow rate.

Under the approved PLS program data collection requirements, the calculation of ex post baseline usage and ex post savings were expected to proceed as follows:

- Use the collected chilled water data to calculate actual ex post cooling tons for each TES system for each hour of the pre- and post-TES installation period in the summer;
    - $Cooling\ Tons = Flow\ (USgpm) \times ({}^{o}F_{in} - {}^{o}F_{out})/24$
- Calculate the COP for each hour of the pre-TES period for each system based on the hourly cooling tons and cooling system load;
    - $COP = Cooling\ Tons\ /\ Cooling\ System\ Load\ (kWh)$

[8] CPUC Resolution E-4586 issued May 13, 2013 approved as modified herein: Advice Letters SCE 2837-E, PG&E 4177-E, and SDG&E 2445-E jointly filed on January 14, 2013.

- Develop a regression model of the relationship between COP and OAT during the pre-TES period. Nexant will develop this model separately for each site since each pre-TES system was different. Most likely a simple linear or quadratic relationship between COP and outdoor air temperature will suffice. This model may require interactions with time of day or day-type since the customer's use of the cooling system, driving the cooling tons, may vary based on building occupancy schedules for space cooling, or production schedules for process cooling. Nexant will test various model specifications using our standard regression diagnostics, including out-of-sample testing;
- Use the regression model to estimate $\widehat{\mathrm{COP}}$ for each hour of the summer based on the OAT during the post-TES installation period;
- Use the estimated $\widehat{\mathrm{COP}}$ and the observed post-TES cooling tons to estimate baseline usage for each hour of the summer; and
  - $Baseline\ kWh_t = \frac{Cooling\ Tons_t}{\widehat{COP}_t}$, where t (time) is a specific hour on a specific day
- Subtract actual measured usage from baseline usage to produce estimated ex post savings. This is one reason for requiring the measurement of system electricity usage.
  - $Ex\ post\ impact\ kWh_t = Baseline\ kWh_t - Actual\ kWh_t$

There were data collection challenges at the only operational site in 2015. No pre-TES operational data was available because SCE waived the requirement for the customer, and the only post-TES installation operational data available was from the winter,[9] which doesn't correspond to the peak load shift season. Consequently, an alternative evaluation approach was developed that leverages the pre and post-TES installation premise level interval meter data and utility provided regional temperature data. We believe that the originally proposed method is likely to be more accurate and transparent because a direct model of electric usage as a function of temperature would essentially throw away the information provided by the directly measured ex post cooling tons. The cooling tons provide valuable information about how hard the cooling system is working and the cooling tons are not perfectly correlated with temperature, which means that using a model that eschews them introduces an additional and unnecessary source of variance into the results. However, the alternative approach based on the available data appears to produce reasonable results that provide valuable feedback to the utilities regarding operational performance relative to the expected load shift based off the incentive calculations.

Next year when the operational data should be available for the new sites expected to come online in 2016, the originally proposed methodology that relies on this operational data will be implemented, and the difference in estimated impacts based on the two data sources—operational and premise level meter data—will be evaluated. This information will be useful in determining if any of the TES system monitoring requirements may be relaxed without significantly impacting the quality of the impact evaluation results.

[9] The post-installation data was inadvertently overwritten by the customer's data logger. The issue has now been identified and resolved.

2.1 Ex Post Model Selection

A regression model was used to estimate the relationship between premise level hourly load data for the customer with the operational TES system and several explanatory variables expected to influence the load such as the temperature, time of day, day of the week, month, season, and year. Three years of data were used for model estimation—January 2013 through December 2015. The site became operational in March 2015, resulting in approximately two years of pre-TES installation data and nine months of post-TES installation data. March 2015 was excluded from the analysis to allow for the installation and testing period to not influence model estimation. Many model specifications were systematically evaluated via out-of-sample testing, as discussed below, and the best performing model was used to estimate the relationship between the explanatory variables such as weather and time during the pre-TES installation period. The relationships estimated from the pre-TES installation period were then applied to the observed data—temperature and time related variables—in the post-TES installation period to forecast the reference load; or what we would have expected the customer's load to be in the absence of TES under the specific weather conditions at that time. The load shift is then calculated as the difference between the predicted reference load and the actual observed load for each hour.

Impacts were calculated for every hour of every day in the post-TES installation period. However, the reporting of impacts is limited to the day types required by the load impact protocols—system peak days and the average weekday for each month—and the day with the largest estimated impact for each month. The peak usage for the customer didn't always align with SCE's monthly system peak day each month, so the day with the largest estimated impact was included in order to facilitate the identification of the largest estimated load shift; which allows for the comparison with the customer's incentive calculation based expected load shift.

The model selection process is summarized as follows:

1. Identified 10 days from 2013 and 2014 (5 from each year) with the highest hourly load to use as peak load days prior to TES installation for out of sample testing.
2. Estimated 28 different regression models and used them to predict out-of-sample for the peak load days identified in step 1. This allowed us to identify the regression model that produced the most accurate predictions for peak load days similar to when maximum load shifting is expected. The models vary with respect to how weather variables were defined and with the inclusion of time related variables such as day of the week, month, or season.
3. Selected the most accurate model specification based on out-of-sample testing metrics and used it to estimate the reference load after the TES system was installed.

Nexant first developed a set of candidate models to test. A candidate model could vary based on its specification. The model specifications tested were carefully selected with a focus on load magnitude and shape under peak load conditions when maximum load shifting is expected to occur. The set of candidate models were evaluated using a cross-validation process that assesses the quality of the model based on how well it predicts for excluded peak load days that were not used to estimate the model. The rationale for such a strategy is that, if a model accurately predicts load on peak load days prior to TES installation, it is expected to provide an accurate counterfactual for expected load in the absence of a TES system, after that system is installed.

A good model can be said to predict load accurately if it yields an unbiased and precise fit to that of the withheld peak load day. The evaluation used a quantitative model selection process that employs a method called *leave one out cross validation* (LOOCV) over a set of peak load days. That set of days, as noted in step 1 above, is selected to be as similar as possible to days when a maximum load shift is expected. LOOCV is outlined below:

1. For each of the m candidate models, conduct LOOCV over peak load days:
   a. For each of the n peak load days:
      i. Develop explanatory variables using data from all peak load days except the nth;
      ii. Fit mth model using explanatory variables and predict load based on the observed characteristics of the nth day;
      iii. Record predicted load and actual load on the nth peak load day not used to fit the model; and
2. Compute metrics to measure bias and goodness-of-fit for each model.

The quality of a model is evaluated based on the bias and precision of its prediction of load compared to the actual load on the excluded peak load days. Table 2-1 shows the metrics computed in step 2. All metrics were computed over the relevant PLS program hours, as that was the principal period over which we had to estimate load shifting.

Table 2-1: Control Group Accuracy Statistics

Statistic Type	Statistic Level	Statistic	Formula	Description	Typical Values
Bias	Program	Average Percent Error	$\frac{\sum \hat{y}_{i,t}}{\sum y_{i,t}} - 1$	Sums up predicted and actual value for peak load days for the customer; calculates error statistics from these values.	Expressed in percentage terms. Can be positive or negative. The closer to zero, the better.
Bias	Program	SD(APE)	$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(APE_t - \overline{APE})^2}$	Measures the average deviation in average percent error on individual peak load days.	Expressed in percentage terms. Can only be positive. The smaller the number, the better.
Goodness-of-fit	Program	Absolute Sum of Errors	$\sum \lvert \hat{y}_{i,t} - y_{i,t} \rvert$	Sums up absolute errors for peak days.	Expressed in kWh terms. Can only be positive. The smaller the number, the better.

The statistics above use the following nomenclature:

- y - observed kWh
- $\hat{y}$ - predicted kWh
- i - customer
- t - each individual peak load day
- n - total number of peak load days

The final model was selected on the basis of average percent error, taking into account both its absolute value and its deviation across the excluded days, provided that the absolute sum of errors was acceptable relative to other potential models. The final model and its associated explanatory variables are summarized below.

Mathematically, the regression can be expressed by:

$$kW_t = A + \sum_{i=1}^{24}\sum_{j=1}^{12} B_{ij} \times Hour_i \times Month_j + \sum_{i=1}^{24}\sum_{j=1}^{3} C_{ij} \times Hour_i \times DayType_j +$$

$$\sum_{i=1}^{24} D_i \times Hour_i \times CDD_t + \sum_{i=1}^{24} E_i \times Hour_i \times CDDsqr_t +$$
$$\sum_{i=1}^{24} F_i \times Hour_i \times CDH_t + \sum_{i=1}^{24} G_i \times Hour_i \times CDHsqr_t +$$
$$\sum_{i=1}^{24} H_i \times Hour_i \times Summer + \sum_{i=1}^{3} I_i \times Year_{it} +$$
$$J_i \times PLS_t \; + \; \varepsilon_t$$

Table 2-2: Description of Regression Model Variables

Variable	Definition
kW_t	Average hourly demand (kW) for each time period
A	Estimated constant term
B_{ij} through J_i	Regression model parameters
$Hour_i$	Series of binary variables for each hour, which account for the basic hourly load shape of the customer after other factors such as weather are accounted for
$DayType_j$	Series of binary variables representing three different day types (Mon, Tues-Thurs, Fri); weekends and holidays are excluded from the model
$Month_j$	Series of binary variables for each month designed to reflect seasonality in loads
CDD_t	Cooling Degree Day—the max of zero and the mean temperature of the day of the hourly observation less a base value of 60°F
$CDDsqr_t$	The square of Cooling Degree Day
CDH_t	Cooling Degree Hour—the max of zero and the hourly temperature value less a base value of 60°F
$CDHsqr_t$	The square of Cooling Degree Hour
$Summer_t$	Binary variable reflecting the summer months of July through October
PLS_t	Binary variable reflecting when the TES system is operational
e_t	Error term

3 Ex Post Impact Estimates

The single PLS installation that was completed in 2015 is located in SCE's service territory near the coast in the city of [redacted]. It is comprised of two, multi-story office buildings totaling over [redacted] square feet of office space. Figure 3-1 compares premise-level meter load for the pre- and post-PLS installation periods. The red dashed curve represents the average of the top five load days during the pre-PLS installation period and provides a good proxy for the upper-bound values of weather sensitive load without any storage system. Similarly, the green dashed line plots the average pre-PLS load for March, representing the lowest monthly average usage and providing a lower bound for weather sensitive load. Together, these two curves provide a weather sensitivity range of [redacted] kW for the scenario under no PLS. Figure 3-1 also plots the average load for the top five peak load days during the post-PLS installation period, the average pre- and post-installation loads for the month of September—orange dashed and solid lines, respectively—and the average load under the PLS system—gray dashed line.

Using this information, we see the largest estimated load shift—calculated as the difference between the pre-PLS top five load day average and the average PLS load—to be [redacted] kW occurring at hour ending [redacted]. This calculation is not intended to represent the actual estimated load shift, but rather to demonstrate the range of load shifting magnitude we should expect as a cross validation for the econometric modeling. Additionally, we see the minimum achieved loads under PLS to be lower than the pre-PLS March loads. The difference between pre-PLS March loads and average load with PLS is [redacted] kW. While the true driver of this difference is unknown, it could be that prior to the PLS installation, there was a base load of chillers running all the time. Another possible explanation is that more efficient blowers/fans were installed in the post-PLS period.

Figure 3-1: Premise Level Meter Load Pre and Post-PLS Installation

Redacted to protect confidential customer information

Figure 3-2 shows a comparison of load duration curves for all hours and for peak hours for the pre and post-PLS installation periods. The load duration curves plot the hourly load values, sorted highest to lowest, for the months of April to December for the pre and post-installation periods of 2014 and 2015, respectively. The peak hours from 12 to 6 PM are provided in addition to all hours of the day in order to show the impact of the program specifically during program hours when the system peak is expected to occur. The load duration curve is a useful tool for visualizing the impact a program has on the system peak load across an extended period of time. Typically, most load duration curves are for an entire year (8,760 hours); however, the PLS system was only installed in March 2015. Consequently, this load duration curve is restricted to only the months for which post-PLS installation data was available.

When evaluating the change in load between the pre and post-PLS installation periods for all hours, the difference isn't all that significant. In 2014, prior to the PLS installation, the peak hourly load was [redacted] kW, compared to [redacted] kW in 2015 after the PLS installation. The difference of only [redacted] kW is attributable to the relatively flat load shape during the day that reaches high load levels relative to the peak well before the peak hours; this can be observed in Figure 3-1. During peak hours the difference is much more significant. In 2014 the peak period maximum hourly load was still [redacted] kW; however, the 2015 maximum hourly load during the peak period was [redacted] kW, resulting in an annual peak load reduction of [redacted] kW.

It should be noted that 2015 had significantly hotter days than 2014, so it is likely that the peak load without PLS would have exceeded the peak load observed in 2014. This difference in year over year peak load is not the maximum load shift from the PLS system, which will be discussed later in this section. The shape of the all hours and peak hours load duration curves in 2015, after the PLS installation, both show a significant reduction across the top ranked load hours, as noted by the green lines (post-PLS) being below the blue lines (pre-PLS) for the top third of the hours. The higher load during the off-peak hours can be observed where the green line is higher than the blue line towards the right hand side of the graph. This is when the PLS system is recharging at night and in the early morning.

Figure 3-2: Load Duration Curve: April through December—Peak vs All Hours

Redacted to protect confidential customer information

The California Demand Response Load Impact Evaluation Protocols require the reporting of load impacts for the system peak days and the average weekday for each month. Figure 3-3 plots the customer's daily peak load against the SCE system daily peak load for June through September for 2013 and 2014, prior to the PLS system being installed. The '+' symbol represents the regular days, and the '▲' symbol represents the monthly system peak days. The peak usage for the customer didn't always align with SCE's monthly system peak day each month. In September, the customer's peak load was fairly well aligned with the SCE system peak load days; however, the other summer months didn't consistently align. Given that the PLS program incentives are based on the expected maximum hourly peak load shift, which may not necessarily align with the monthly system peak day, the day with the largest estimated load shift (impact) in each month was included in the ex post load impact tables. This facilitates the comparison of the largest estimated load shift with the customer's incentive calculation based expected load shift in Section 3.1.

Figure 3-3: Daily Peak and Monthly System Peak Day Load—June through September

Redacted to protect confidential customer information

Figure 3-4 shows the results of the best model from the out-of-sample testing from the model selection process on the top 10 peak load days in the 2 years prior to the PLS installation.[10] Each day shows the predicted hourly load from the model in red, and the actual load from each day in blue. Predicting hourly load at the premise level for a single customer based only on observable data such as the time of day, day of the week, month, and temperature based values is very challenging given the inherent random energy usage variation observed at the individual customer level. Typically, aggregation across thousands of customers is used in reference load estimation for load impact evaluations. The difference between the predicted and observed load is fairly balanced between being positive and negative during the program operational hours indicating minimal bias; however, on most individual days there is a noticeable difference between the predicted and observed load. The difference between

[10] The model specification is provided in Section 2.1.

the predicted and observed load is captured by the modeling estimation process, and is later reflected in the confidence intervals around the load impact estimation.

Figure 3-4: Predicted & Observed Load on Individual Peak Load Days Iteratively Withheld for Out of Sample Testing

Redacted to protect confidential customer information

Figure 3-5 shows the average predicted and observed load across the 10 days presented in Figure 3-4. The aggregation across days acts to smooth out the variation observed at the daily level, and provides an estimate of how well the model will predict load for an average peak load day. Given that the estimation is only for a single customer, the model appears to predict load very well. As noted earlier, the uncertainty in the reference load estimation is reflected in the confidence intervals surrounding the load impact estimate.

Figure 3-5: Predicted & Observed Load across Average of Peak Load Days Iteratively Withheld for Out of Sample Testing

Redacted to protect confidential customer information

Figure 3-6 shows the ex post load impact table for the day with the highest estimated hourly load impact in 2015. The largest impact of [redacted] kW occurred in the hour ending [redacted]. Hour ending [redacted] also had the highest reference load of the year at [redacted] kW. It should be noted that the estimated reference load exceeded all previously observed hourly load values from the pre-PLS period in 2013 and 2014. However, the average temperature between midnight and 5 PM, also known as mean17,[11] was also three degrees higher than any value observed during the pre-PLS period. Consequently, it is entirely plausible that the estimated reference load reflects what would have occurred in the absence of the PLS system.

As noted above, the upper and lower confidence intervals on the graph (green dashed lines) represent the uncertainty surrounding the load impact estimate. The uncertainty in the load impact estimation is a direct result of estimating the reference load, which reflects what load would have likely been in the absence of the PLS system. The upper and lower bounds of the 90% confidence interval are [redacted] kW and [redacted] kW, respectively. This range represents the point estimate of the load impact plus or minus 22%. Most demand response load impact evaluations exhibit much narrower confidence intervals; however, that is also the result of

[11]Mean17 is a variable that helps to capture overnight heat buildup and is often used for load modeling.

including hundreds or thousands of customers in the estimation process. Confidence intervals for a single customer will always be relatively wide compared to a larger population.

Figure 3-6: Ex Post Load Impact Table—Largest Hourly Impact

Redacted to protect confidential customer information

Table 3-1 compares the monthly system peak day impact with the maximum impact estimated for each month. The average impact across the peak hours and the maximum hourly impact are also presented. In the months of May, August, and October, the monthly maximum impact coincided with the monthly system peak day. However, the impacts in April, June, July, and September were not the highest on the monthly system peak days for those months. The largest difference in the maximum hourly impact between the monthly maximum and the system peak day occurred in September and was [redacted] kW, or approximately [redacted] %.

Table 3-1: Monthly System Peak Day and Maximum Impact Day

Month	Monthly System Peak Day (kW)		Maximum Monthly Impact Day (kW)	
	Average Hourly Impact	Maximum Hourly Impact	Average Hourly Impact	Maximum Hourly Impact
April	Redacted to protect confidential customer information			
May				
June				
July				
August				
September				
October				

4 Ex Ante Methodology

Although the statewide PLS program currently has 17 applications in the pipeline, only a single program-funded TES installation has been completed that allows for modeling ex post load impacts. Due to the customized nature of each PLS installation, the findings from a single customer are not appropriate to generalize to the broader PLS program for ex ante forecasting purposes. Each utility had a pilot PLS program from 2008 through 2011, but the design of the Pilots differed from the current program design, therefore the PLS-TES installations completed under the Pilots cannot be used as the basis for forecasting load impacts for this program. To produce load impact estimates for the PY2015 PLS evaluation, Nexant relied on assumptions from the program managers and EM&V staff at each utility to forecast the budget scenarios, timing of when projects would become operational, and additional aspects related to the number, size, and geographic distribution of future projects in combination with the ex post results from the operational installation. These assumptions have a high degree of uncertainty because projecting uptake of any utility program is inherently uncertain, especially when there are multiple stages in the application and verification process that may require up to 18 months or more to complete.[12] To date, there is not enough data to predict how many projects will be installed, how big those projects will be, where they will be located or when they will start up. This uncertainty is compounded by the fairly high investment cost and custom nature of each installation. Without a detailed assessment of any given site, it is hard to know whether it would be a good candidate for PLS-TES installation.

The 2014 evaluation attempted to reflect this high degree of uncertainty in the forecast by providing low case, base case, and high case enrollment and load impact scenarios. The base case is the expected[13] value as drawn from discussions that Nexant had with utility program staff. The low case is a forecast in which PLS program uptake is around 50% lower and the high case is around 50% higher than the base case, for PG&E. For SCE, the low case is a forecast in which PLS program uptake is around 40% lower and the high case is around 40% higher than the base case. Finally, SDG&E has reserved all $3.5M of their incentive budget, so there is no need for scenarios. To the extent any scenarios are presented at the statewide results level, the SDG&E results will be consistent under each scenario. Even this range may not fully cover the outcomes that the program could experience. In a case like this with such great uncertainty, it is likely that other stakeholders may make different projections or consider different assumptions to be reasonable. To allow other stakeholders to understand how different assumptions may produce different values, this evaluation is as transparent as possible about all of the assumptions and about how the assumptions lead to the reported load impact forecasts. Therefore, a concise summary of assumptions that drove the PY2015 evaluation by utility is provided in Section 5. All of the assumptions are based on the most recent information on program enrollment and the current status of projects that have been identified and are in the application/verification stages of the process.

[12] The steps in the application and verification process are described in detail in the Statewide PLS Program Handbook (September 2014).

[13] Note that these "expected values" are not expected values in a statistical sense. They are literally just what utility program staff express as reasonable expectations. The uncertainty expressed in the high and low values are also just opinions, not statistical measurements.

This evaluation forecasts load impacts for three different types of projects:

- **Operational**—customers with installed and operational PLS systems;
- **Identified**—those for which customers have completed an application or feasibility study; and
- **Unidentified**—applications that are expected to be submitted during the current funding cycle.

Applications are submitted by potential PLS participants to initiate their enrollment in the program. Each application includes an initial estimate of the proposed PLS-TES installation's load shifting capacity. Feasibility studies are more in-depth analyses conducted by qualified engineers and include a technical and cost analysis of the proposed project. Completion of a feasibility study is the next step in the PLS approval process after the initial application has been submitted and approved. As of this writing, a total of 26 applications have been received by the 3 IOUs, 8 have been withdrawn, 17 projects have completed feasibility studies, and 1 installation is operational.

For identified projects, the ex ante load impacts were allocated to specific local capacity areas[14] (LCAs) because the location of the PLS-TES system installation was known. While this information on where identified projects will be installed reduces some uncertainty in the forecast, there is still substantial uncertainty regarding whether the project will successfully go through the entire verification process given that, as of January 2016, only a single project has completed the actual installation stage and started operation. The identified projects also have an expectation of the installation date—either in the application or the feasibility study, if available—but those dates may change throughout the verification process.

Load impacts for unidentified projects are based on assumptions developed with the utility PLS program managers and EM&V staff, as discussed above. The forecast of unidentified projects is based on the number of applications that are expected to be submitted by the end of 2016, when "bridge" funding for the PLS program's incentives expire. Currently, the bridge funding budget is only approved for 2015–2016. On December 4, 2014, D.14-12-024 stated that 2016–17 will also be a bridge year but there was no information regarding details on program budgets. A ruling by the assigned ALJ in this proceeding is expected to initiate the process to authorize a 2017 bridge funding period. However, as of the writing of this report, no 2017 funding has been authorized. The budgets for each IOU have been updated accordingly to reflect the currently authorized incentive funding levels.

For unidentified projects, the number and size of the installations have been estimated for a range of scenarios based on an expected[15] percentage of each utility's incentive budget that will be spent—similar to last year's approach. However, additional assumptions are needed to estimate the pace of project startups and the allocation of load impacts across different LCAs, given load impacts are location and weather dependent.

[14] LCA is the CAISO-defined term that represents each transmission-constrained load pocket in the California IOU service territories.

[15] Note that these "expected values" are not expected values in a statistical sense. They are literally just what utility program staff express as reasonable expectations. The uncertainty expressed in the high and low values are also just opinions, not statistical measurements.

Because the number and size of identified projects varies between each IOU, the approach used to evaluate program impacts was tailored to the amount of information that was available for each IOU. Primarily, the number and diversity of applications determines the methodology used to generate load impacts for identified projects. The methodology for determining load impacts from unidentified projects was uniform across the three IOUs, although the specific assumptions for these impacts did vary and were partially informed by the applications that each IOU had received.

The following subsections describe the methodology that was used to estimate ex ante load impacts for operational, identified, and unidentified projects.

4.1 Operational Projects

The task for ex ante estimation for the operational site is based off the ex post estimation, but contains three extra modeling steps—developing a model to estimate the relationship between temperature and the ex post load shift; predict the reference load under ex ante conditions using the same model used for ex post; and predict the ex ante load impacts based on the ex ante weather conditions—all as functions of outdoor air temperature and time. Therefore, to estimate ex ante savings, Nexant took the following steps:

The model selection process is summarized as follows:

1. Identified 10 days from 2013 and 2014 (5 from each year) with the highest hourly load to use as peak load days prior to TES installation for out of sample testing.
2. Estimated 28 different regression models and used them to predict out-of-sample for the peak load days identified in step 1. This allowed us to identify the regression model that produced the most accurate results on peak load days similar to when a maximum load shifting is expected. The models vary in how weather variables were defined, and in the inclusion of time related variables such as day of the week, month, or season.
3. Selected the most accurate model specification based on out-of-sample testing metrics and used it to estimate the reference load after the TES system was installed.
4. Calculate estimated ex post load impacts based on subtracting the observed load from the estimated reference load during the post-PLS installation period.
5. Develop a model of the relationship between temperature, time, and ex post load impacts.
6. Forecast reference load under ex ante weather conditions based on model from step 3.
7. Forecast ex ante impacts based on model developed in step 5 under ex ante weather conditions, and combine with reference load to create to create ex ante load impacts.

4.2 Identified Projects

The PY2015 PLS program evaluation used a single, consistent, methodology across the IOUs for estimating ex ante load impacts for identified projects. This approach is similar to that for unidentified projects, except that the installation date and location were based on each specific project. At the time of the evaluation, PG&E had three active projects, SCE had six, and SDG&E had eight. All 17 of these projects had reached the feasibility study stage in the application and verification process. The projects range in size from approximately 30 kW up to 1.5 MW. Ex ante conversion factors (discussed in the next report section) were used to convert the expected load shift from the application/feasibility study to ex ante weather conditions. This methodology is nearly identical to Step 2 and Step 3 in the methodology used for unidentified projects discussed in Section 4.3, except that the incentive amount was taken from the latest available information for that project—the application or feasibility study. In addition, considering that the location and installation date were provided in the application for identified projects, the forecast for identified projects incorporates this information by having the project come online on the expected installation date and by assigning the ex ante load impacts for that project to the customer's LCA.

4.3 Unidentified Projects

This year's methodology for unidentified projects was similar to that used for the PY2014 ex ante PLS evaluation, as they both attempt to quantify load impacts for customers whose building characteristics, location, project timing, and load patterns are unknown. As in last year's PLS evaluation, because the main uncertainty was the number and size of projects that will be included in the program, a range of scenarios has been generated for each IOU.

Figure 4-1 summarizes the three stage methodology for estimating ex ante load impacts for unidentified PLS projects:

1. Involves forecasting the available amount of incentive dollars that will be spent on unidentified projects for each IOU. The first key input for this calculation was the total PLS incentive budget for each IOU. The budget that has been awarded to operational projects or committed to identified projects was subtracted from the total incentive budget amount. Then, the remaining budget for unidentified projects was multiplied by the percentage of each IOU's budget that will be committed to projects by the end of 2016, under the low, base case, and high scenarios.[16] This produced the forecast of incentives available to be spent on unidentified projects.
2. Converts the incentive dollar forecast into the ex ante load impact estimates. To do this, the forecast of incentive dollars spent on unidentified projects was divided by the incentive amount per kW load shift ($875/kW). This kW load shift amount represents the peak load shift[17] that can be expected under hot, maximum cooling load, weather conditions. The kW load shift was multiplied by the ex ante conversion factors,[18] which converted the load shift under the incentive payment, maximum cooling load,

[16] The percent budget commitment does not necessarily reflect the amount that will ultimately be spent, since some projects may drop from the PLS program prior to installation—for instance, if the feasibility study indicates that the project would not be cost-effective for the customer. To account for this, the forecast assumes a drop off rate between projects committed and projects actually installed. In the PY2015 evaluation, the assumed drop off rate was 10%.

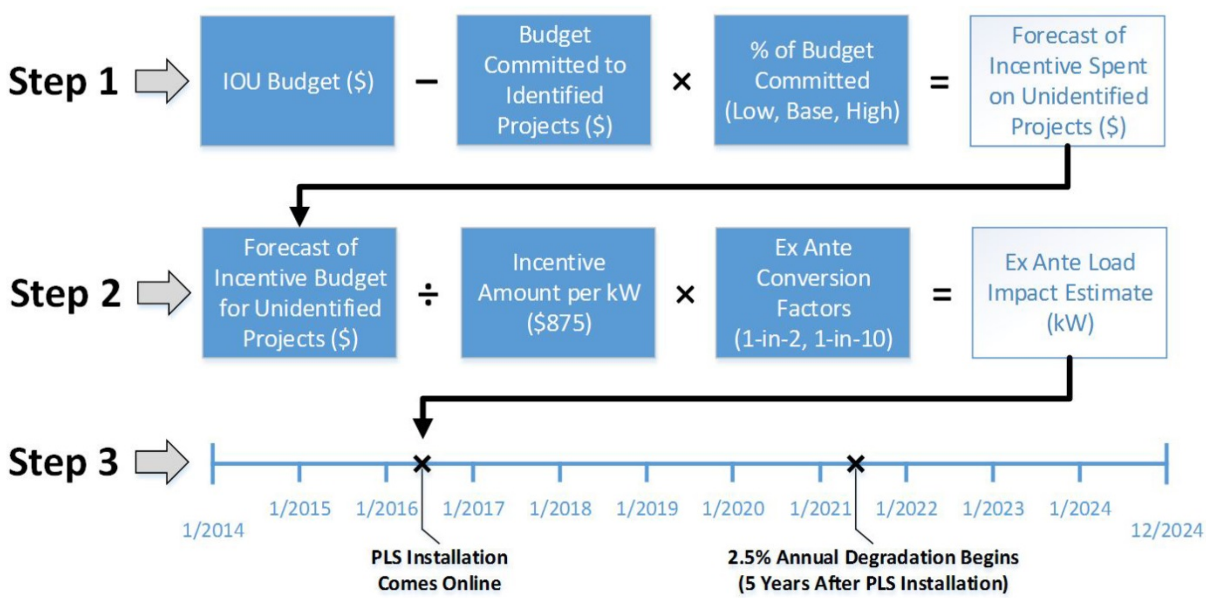
[17] This peak load shift value is the amount of demand shifting that each utility expects to pay incentives for. This means that these are expected output from the model used in the engineering feasibility study for each site. Although we do not know with certainty what conditions the engineers performing the study used to represent peak yearly conditions, the new building simulation models were calibrated such that the 1-in-10 peak day conditions for the hottest month in each LCA represented the maximum cooling load conditions. Because the models creating the conversion factors used the weather from the hottest 1-in-10 peak day to set the maximum cooling load, and consequently the maximum peak load shift, the hottest 1-in-10 peak weather day can also be used as a proxy for weather conditions under which the incentive would be calculated. See Appendix A for additional discussion.

[18] The ex ante conversion factors are described in detail on the following page. In summary: ex ante conversion factors were used to convert the load shift under the incentive payment, maximum cooling load, and weather conditions to the load shift that can be expected under the various ex ante temperature scenarios.

and weather conditions to the ex ante load impact estimates for monthly system peak days and average weekdays under 1-in-2 year and 1-in-10 year weather conditions—as per the California DR Load Impact Protocols. The conversion factors were re-estimated for the PY2014 evaluation based on updated building simulation models and newly developed 1-in-2 and 1-in-10 year weather data that addressed the new requirement for reporting results for the CAISO system peak in addition to the IOU system peak.

3. Forecasts when each PLS-TES installation is expected to come online based on slightly different assumptions for each utility (described below). The time between when an application is received and when the installation and verification are completed varies from 8 to 24 months, so projects are not expected to come online until 2016 or later. Over time, the load shifting capacity of the PLS-TES technologies is expected to degrade as the system ages. The forecasts assume that five years after each forecasted PLS-TES installation, the ex ante impacts begin to degrade at a rate of 2.5% per year.[19] This assumption was made in consultation with program managers and it is consistent with last year's evaluation.

Figure 4-1: Methodology for Estimating Ex Ante Load Impacts of Unidentified PLS Projects



The ex ante conversion factors were used to convert the load shift under the incentive payment, maximum cooling load, and weather conditions to the load shift that can be expected under the various ex ante temperature scenarios. The ex ante temperature scenarios include the monthly system peak days and average weekdays under 1-in-2 year and 1-in-10 year weather conditions for the utility specific and CAISO peak. Essentially, the conversion factors facilitate the estimation of the PLS-TES load impacts under a variety of different weather conditions with ease and efficiency. The methodology for developing the conversion factors is described

19 This estimate of 2.5% degradation was developed as a mutually agreed upon value by the IOUs based on past experience in energy efficiency program implementation. The operational data being collected and evaluation will help to refine this estimate in the future.

in Appendix A. In the appendix, Nexant provides evidence that it is not necessary to know the specific building characteristics, and that conversion factors may be used for this evaluation. The analysis shows that relative usage values across different weather conditions are basically insensitive to building characteristics, and the ratio for a given ex ante condition hardly changes as the building characteristics vary substantially. This relationship is a critical factor in the evaluation, and the current conversion factor approach would need to be modified if this weren’t the case.

It is important to note that these conversion factors were developed with building simulation models of space cooling installations. Some of the applications that have been received thus far also include process cooling installations, which have load profiles that frequently differ from the typical space cooling profile. Unfortunately, the process cooling installations do not make good candidates for generalized modeling because they are highly customized by industry and location; in addition, while space cooling loads exhibit significant seasonality due to temperature variation, process cooling loads may vary seasonally by temperature and changes in the underlying production process. For example, agricultural customer process cooling loads tend to follow the harvest schedule in addition to being temperature sensitive. The weather sensitivity of the currently modeled process cooling applications was analyzed, and the range of sensitivity in terms of the percentage difference in cooling load between 1-in-2 and 1-in-10 monthly peak days exhibit similar upper and lower limits to commercial AC cycling programs. For the sake of simplicity, lack of generalizability of the process cooling installations, and similarity in weather sensitivity ranges; space cooling building simulation models were used to develop the conversion factors applied to both space cooling and process cooling installations.

The forecast of incentive dollars spent on unidentified projects was used to estimate PLS program enrollment, which is defined as the number of PLS-TES installations that have come online. Before a project comes online, customers must go through the application and verification process, during which some customers may drop off. Therefore, customers are not defined as enrolled until their PLS-TES installation has come online. Nonetheless, for each IOU, the applications that have been received were used to inform assumptions about the following:

- Peak load shift of typical unidentified projects;
- Number of projects of each size; and
- Expected project installation and verification timeline—the time between when an application is received and when the installation and verification are completed.

These assumptions are IOU-specific and were informed by the current applications for identified projects. Section 5 provides a summary of the assumptions from the PY2015 evaluation. The PY2015 evaluation refined these assumptions based on the most recent information on budget, program enrollment, the current status of identified projects, and the most recently revised and adopted Statewide PLS Program Handbook (June 2015).

Finally, because local weather conditions influence the load shift that is actually experienced, the ex ante load impacts are dependent on the specific geographic region in which an installation is located. As such, it was necessary to allocate the unidentified projects to

LCAs within each utility's service area. Without any information on where these projects will actually be located, the aggregate peak load shift was allocated to each LCA in proportion to the distribution of C&I customers with annual maximum demand greater than 200 kW for PG&E and 1 MW for SCE located in each LCA. The 200 kW and 1 MW thresholds were determined based on the existing pool of applications. SDG&E has only a single LCA, so no population weighting was necessary. Considering that the utilities have received applications from customers that are located in LCAs that are not usually associated with having high cooling load, the expectation regarding where these PLS-TES installations will be located is unclear. Essentially, with process cooling being eligible for PLS program incentives, the program is viable in many different climates, as the current applications have shown.

4.4 Estimating Ex Ante Weather Conditions

The CPUC Load Impact Protocols[20] require that ex ante load impacts be estimated assuming weather conditions associated with both normal and extreme utility operating conditions. Normal conditions are defined as those that would be expected to occur once every 2 years (1-in-2 conditions) and extreme conditions are those that would be expected to occur once every 10 years (1-in-10 conditions). Since 2008, the IOUs have based ex ante weather on system operating conditions specific to each individual utility. However, ex ante weather conditions could alternatively reflect 1-in-2 and 1-in-10 year operating conditions for the California Independent System Operator (CAISO) rather than the operating conditions for each IOU. While the protocols are silent on this issue, a letter from the CPUC Energy Division to the IOUs dated October 21, 2014 directed the utilities to provide impact estimates under two sets of operating conditions starting with the April 1, 2015 filings: one reflecting operating conditions for each IOU and one reflecting operating conditions for the CAISO system.

In order to meet this new requirement, California's IOUs contracted with Nexant to develop ex ante weather conditions based on the peaking conditions for each utility and for the CAISO system. The previous ex ante weather conditions for each utility were developed in 2009 and were updated in 2015 along with the development of the new CAISO based conditions. Both sets of estimates used a common methodology, which was documented in a report delivered to the IOUs.[21]

The extent to which utility-specific ex ante weather conditions differ from CAISO ex ante weather conditions largely depends on the correlation between individual utility and CAISO peak loads. Figure 4-2 shows the correlations between each of the three California investor-owned utilities' daily peaks and CAISO system-wide daily peaks. Because the focus was on peaking conditions, the graph includes the 25 days with the highest CAISO loads in each year from 2006–2013—25 days per year for 8 years, leaving 200 observations per utility.

SCE peak loads are more closely related to CAISO peak loads than are PG&E or SDG&E peak loads. Part of the explanation is simply that SCE constitutes a larger share of CAISO load than do the other two utilities and therefore has more influence on the overall CAISO loads.

[20] See CPUC Rulemaking (R.) 07-01-041 Decision (D.) 08-04-050, "Adopting Protocols for Estimating Demand Response Load Impacts" and Attachment A, "Protocols."

[21] See *Statewide Demand Response Ex Ante Weather Conditions*. Nexant, Inc. January 30, 2015.

However, there are additional reasons for the differences. PG&E's northern California service territory experiences different weather systems and is more likely to peak earlier in the year than the overall CAISO system. SDG&E weekday loads and weather patterns are also unique. A larger share of SDG&E's load is residential and less of it is industrial. Temperatures peak earlier in the day than load does at SDG&E and the diurnal swing between overnight and peak temperatures is smaller.

While IOU and CAISO loads do not peak at the same time all the time, the relationship between CAISO loads and utility peaking conditions has been weakest when CAISO loads have been below 45,000 MW. For example, CAISO loads often reach 43,000 MW when Southern California loads are extreme but Northern California loads are moderate (or vice-versa). However, whenever CAISO loads have exceeded 45,000 MW, loads typically have been high across all three IOU's.

**Figure 4-2: Relationship between CAISO and Utility Peak Loads
CAISO Top 25 Peak Days per Year (2006–2013)**

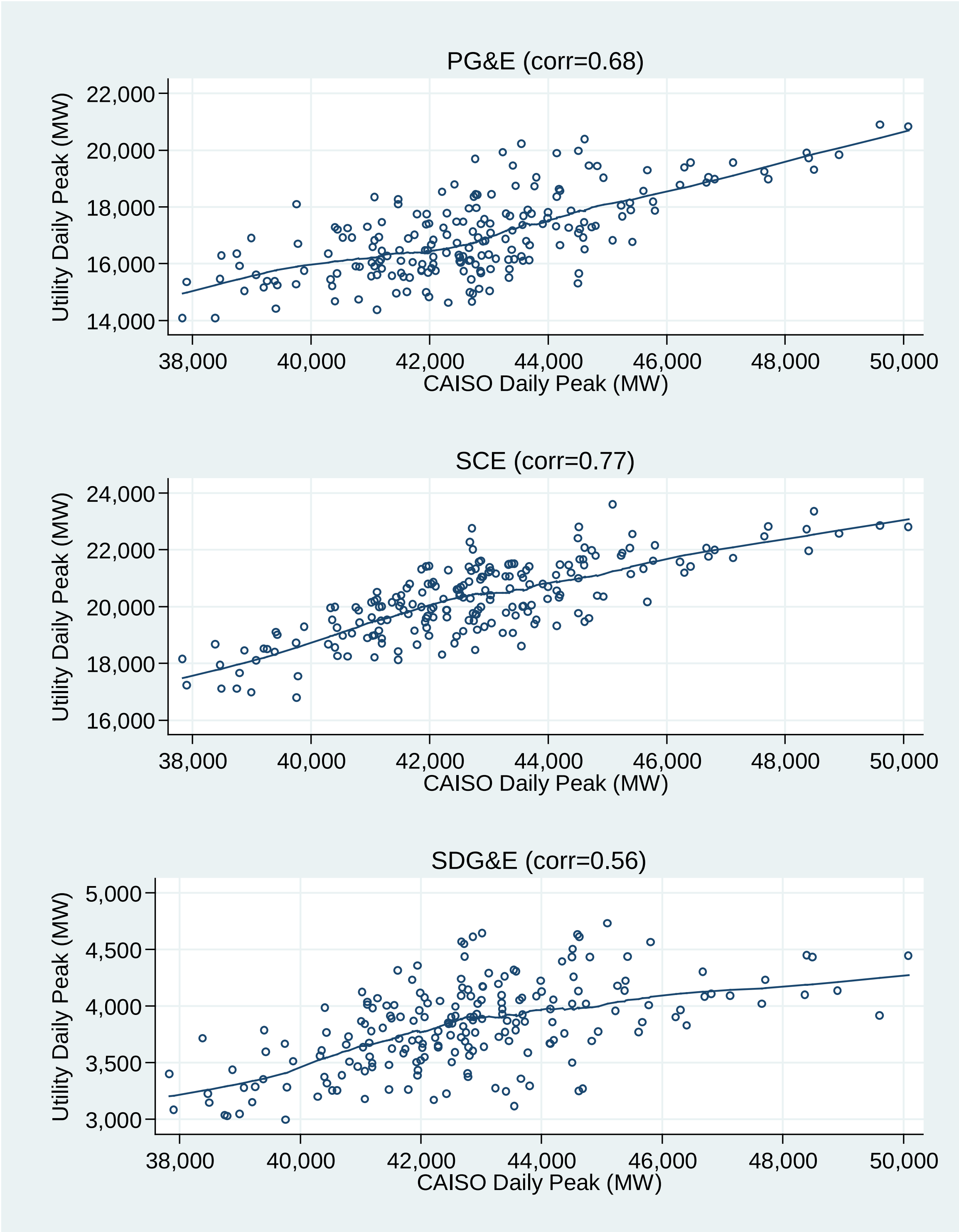


Table 4-1 through 4-3 show the values for each weather scenario, weather year and month for a variable equal to the average temperature from midnight to 5 PM (referred to as mean17) for each day type. For the typical event day, the CAISO weather is lower on average than the utility specific weather for PG&E for both 1-in-2 and 1-in-10 year weather conditions. For SCE, CAISO values are hotter than the utility-specific scenarios under normal weather conditions and nearly equal under extreme weather conditions for the typical event day. For SDG&E, the CAISO weather is slightly warmer under 1-in-2 year weather and slightly cooler under 1-in-10 year conditions. There are instances for both PG&E and SDG&E where the CAISO 1-in-2 weather conditions are higher temperature than the CAISO 1-in-10 weather conditions for the average weekday. This is driven by the process of how the CAISO weather conditions are selected, and the relationship between the CAISO peaking conditions and the local utility weather.[22]

Table 4-1: PG&E Enrollment Weighted Ex Ante Weather Values (mean17)

Day Type		PG&E Based Weather		CAISO Based Weather	
		1-in-2	1-in-10	1-in-2	1-in-10
Typical Event Day		77.8	81.4	75.5	78.5
Peak Day	May	71.6	80.5	70.5	74.8
	June	78.1	82.3	77.6	77.8
	July	78.1	82.9	76.9	81.2
	August	78.1	81.5	74.1	79.3
	September	77.0	79.0	73.4	75.7
	October	69.7	75.7	69.5	73.2
Average Weekday	May	64.2	68.8	65.6	64.3
	June	68.5	71.3	67.2	69.5
	July	71.8	74.3	73.2	72.2
	August	71.4	73.4	71.8	71.2
	September	68.3	71.5	68.9	71.7
	October	62.5	65.2	62.5	64.5

[22] SCE peak loads are more closely related to CAISO peak loads than are PG&E or SDG&E peak loads. Part of the explanation is simply that SCE constitutes a larger share of CAISO load than do the other two utilities and therefore has more influence on the overall CAISO loads. However, there are additional reasons for the differences. PG&E's northern California service territory experiences different weather systems and is more likely to peak earlier in the year than the overall CAISO system. SDG&E weekday loads and weather patterns are also unique. A larger share of SDG&E's load is residential and less of it is industrial. Temperatures peak earlier in the day and the diurnal swing between overnight and peak temperatures is smaller.

Table 4-2: SCE Enrollment Weighted Ex Ante Weather Values (mean17)

Day Type		SCE Based Weather		CAISO Based Weather	
		1-in-2	1-in-10	1-in-2	1-in-10
Typical Event Day		75.7	80.1	77.1	80.0
Peak Day	May	69.6	77.9	68.2	76.5
	June	72.1	76.5	72.8	77.0
	July	75.7	79.8	78.9	79.3
	August	79.4	81.6	78.6	80.9
	September	75.7	82.3	78.0	82.7
	October	74.2	76.8	70.6	77.1
Average Weekday	May	63.6	68.7	63.6	63.4
	June	65.2	70.5	66.7	70.5
	July	73.1	73.8	72.4	73.8
	August	74.2	76.4	72.6	76.4
	September	69.4	72.9	71.1	72.9
	October	63.5	65.9	64.5	67.9

Table 4-3: SDG&E Enrollment Weighted Ex Ante Weather Values (mean17)

Day Type		SDG&E Based Weather		CAISO Based Weather	
		1-in-2	1-in-10	1-in-2	1-in-10
Typical Event Day		72.5	77.3	73.1	75.8
Peak Day	May	67.6	75.8	64.4	72.7
	June	68.1	73.1	68.7	72.9
	July	71.8	77.8	71.5	73.5
	August	74.9	78.5	75.9	76.4
	September	75.0	80.0	76.2	80.5
	October	70.8	75.9	68.3	74.7
Average Weekday	May	62.3	66.2	63.0	62.3
	June	65.2	69.3	64.1	67.2
	July	68.7	70.4	69.3	69.2
	August	70.0	72.8	70.0	73.7
	September	68.1	71.4	69.6	71.4
	October	65.2	67.7	65.4	67.7

5 Summary of Assumptions and Enrollment Forecast

Table 5-1 provides a summary of the ex ante forecast assumptions by utility. The table is included to provide transparency to the types of assumptions that must be made in the PY2015 evaluation. The assumed time period for incentive commitments ends in 2016 for all three IOUs. With incentives available to be committed through 2016, it may be reasonable to assume that projects come online as late as 2018 given that it is expected to take around two years for some projects to become operational. As in the PY2014 evaluation, the uncertainty associated with the percent of the total budget to be committed is reflected in the base case, low, and high scenarios. The assumed percent of total budget to be committed in each scenario and the other remaining assumptions were discussed with each utility and are documented in **Error! Reference source not found.**.

Table 5-1: Summary of Ex Ante Forecast Assumptions by Utility

Assumption		PG&E	SCE	SDG&E
Total ‘12-‘14 PLS Incentive Budget		$13,500,000	$12,690,000	$3,000,000
Completed Projects from ‘12-‘14 PLS Incentive Budget		[redacted]	[redacted]	[redacted]
$ Committed to Existing Applications from ‘12-‘14 Budget		[redacted]	[redacted]	[redacted]
Total ‘15-’16 PLS Bridge Funding Incentive Budget		$9,000,000	$6,533,333	$2,000,000
$ Committed to Existing Applications from ‘15-‘16 Bridge Funding		[redacted]	[redacted]	[redacted]
Total $ for Existing Applications		[redacted]	[redacted]	[redacted]
Budget Remaining for Unidentified Projects		[redacted]	[redacted]	[redacted]
% of Total Budget to be Committed by Scenario	Low	10%	30%	100%
	Base	20%	50%	100%
	High	30%	70%	100%
Time Period of Budget Commitment		2015-2016	2015-2016	2015-2016
Annual % Degradation (After Year 5)		2.5%		
Installation Size (kW)		400 kW	675 kW	N/A
Timing of When Projects Come Online	Identified	Based on most recent information regarding proposed project		
	Unidentified	2017-18	2017-18	N/A
Location of Installations		Distributed by LCA, proportional to C&I population		

In the base scenario, PG&E assumed 20% of the uncommitted PLS incentive budget as the amount that will be committed to unidentified projects by the end of 2016;[23] SCE projects committing 50% of its uncommitted budget by the end of 2016; and SDG&E had already committed its entire $3.5M PLS incentive budget by the end of 2015. The uncertainty associated with the percent of the total budget to be committed is reflected in the low and high scenarios. Using the applications that have been received thus far as a guide, PG&E assumes each unidentified project will produce a 400kW load shift. In the base case, PG&E projects 4.6 installations, in addition to the current identified projects. PG&E projects 2.3 installations in the low case and 6.9 installations in the high case, in addition to the current identified projects. SCE assumed a typical installation size of 675 kW, which was informed by their somewhat homogenous mix of applications thus far. In the base case, this assumption yielded 4.1 additional projects for SCE. Regardless of the assumed installation sizes, the total ex ante load impact estimates are primarily a function of the percent of the total budget to be committed by scenario. Therefore, while the project size assumption will not ultimately be accurate, it does not affect the main results of interest—the ex ante load impact estimates.

As discussed in Section 2.1, five years after each forecasted PLS-TES installation, the ex ante impacts are assumed to degrade at a rate of 2.5% per year. This assumption was made in consultation with program managers and is consistent with last year's evaluation. In addition, without any information on where these projects will be located, the aggregate peak load shift was allocated to each LCA in proportion to the distribution of commercial and industrial customers with an annual maximum demand of greater than 200 kW located in each LCA. Considering that the utilities have received applications from customers that are located in LCAs that are not usually associated with having high cooling load, the expectation regarding where these PLS-TES installations will come online is unclear. Ultimately, with process cooling being eligible for PLS program incentives, the program is viable in many different climates as the current applications have indicated.

Based on these assumptions, Figure 5-1 provides the enrollment forecast by utility and type of project for the base scenario. As discussed in Section 0, customers are not defined as enrolled until their PLS-TES installation has come online. Most of the identified projects for all three IOUs are expected to come online in 2016 and 2017. Enrollment reaches a steady state in 2018, with around 26 projects in the Statewide PLS program. Again, this evaluation only includes projects that the IOUs commit to through 2016, so if the PLS incentive budget expands or if funding is extended past the current deadlines, the program will have higher enrollment potential.

[23] The cost-effectiveness analysis filed along with the Statewide PLS program proposal (D.12-04-045 and Resolution E-4586) assumed that the total incentive budget would be spent by end of 2014. The assumptions made in this evaluation differ significantly from that scenario, and are based on the best available information at this time.

Figure 5-1: Enrollment Forecast by Utility and Type of Project – Base Scenario

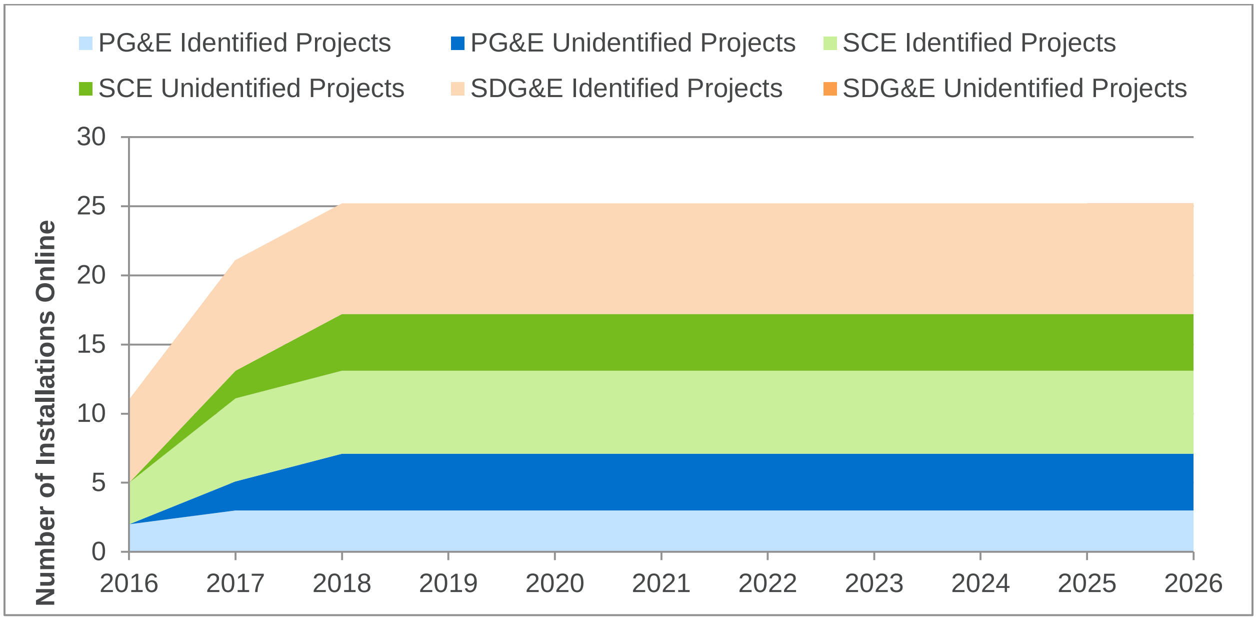


Table 5-2 provides the PLS program enrollment forecast by utility and LCA for each year until a steady state is reached for the current budget timeline. Of all the LCAs in California, the greatest number of PLS program installations is expected to occur in the LA Basin LCA—10 of 26 installations. The Greater Bay Area and SDG&E are the only other LCAs in California that are forecasted to have more than two PLS program installations. Within several of the LCAs, the expected number of PLS program installations that forecasted to come online is less than one. While fractions of installations are not possible in reality, these projected enrollment numbers properly reflect the uncertainty of the forecast. In this case, the realistic expectation is that every LCA has a chance of ultimately having a PLS program installation. However, because several of the LCAs are so small in terms of the number of IOU customers that are located there, the expected number of installations is less than one in those LCAs. A second factor that also results in fractions of installations is that a typical size per installation is assumed. If the assumed system size were scaled down small enough there is presumably a scenario where fractions of installations could be avoided. However, a large number of small installations doesn't reflect the pool of applications received to date. The fractions ultimately convey the inherent uncertainty in the forecast of the location, size, and number[24] of PLS systems.

[24] Under a fixed budget scenario such as this program, the number of installations is a function of their size. There could be many small installations, or fewer larger ones equaling the same aggregate MW.

Table 5-2: PLS Program Enrollment Forecast by Utility and LCA – Base Scenario

Utility	LCA	2016	2017	2018–2025
PG&E	Greater Bay Area	1.0	1.9	2.7
	Greater Fresno	0.0	0.3	0.5
	Humboldt	0.0	0.0	0.0
	Kern	0.0	0.3	0.5
	Northern Coast	1.0	1.1	1.2
	Other	0.0	1.4	1.7
	Sierra	0.0	0.1	0.1
	Stockton	0.0	0.1	0.2
	Total (PG&E)	*2.0*	*5.1*	*7.1*
SCE	LA Basin	4.0	8.5	10.2
	Outside LA Basin	0.0	0.1	0.3
	Ventura	0.0	0.3	0.6
	Total (SCE)	*4.0*	*9.0*	*11.1*
SDG&E		6.0	8.0	8.0
Total (Statewide)		**12.0**	**22.1**	**26.2**

6 Ex Ante Impact Estimates

This section provides the ex ante impact estimates for peak period conditions for the program operational months of May through October. In accordance with the Resource Adequacy window, the peak period is defined as 1 to 6 PM, even though PLS program participants are required to shift load from 12 to 6 PM (for SCE and PG&E) or 11 AM to 6 PM (for SDG&E). Estimates for average weekdays can be found in the Excel load impact tables, which are available upon request.[25] The results are provided separately for each utility. A comparison to last year's ex ante forecast is also provided for each utility. The forecast runs from May 2016 through October 2026.

Load impacts during the months of November through March are expected to be zero or nearly zero due to a lack of significant cooling load in most areas during those months. In addition, because customers will not be required to run their systems during those months, it is best to assume that the impacts are zero until further information becomes available. Therefore, estimates have not been developed for those months. In the future, if installations occur in areas where there is significant winter cooling load and if customers appear to be shifting during those times, it may make sense to estimate impacts for those months.

Similarly, customers technically do not have to run their systems during April and SCE customers do not have to run their systems during May or October (see Table 1-1). Regardless, customers may choose to simply run their systems when the cooling season begins. It is uncertain whether that pattern will develop, and it depends on how easy and financially advantageous it is for customers to run their systems when they are not required to do so. For that reason, April impacts are also excluded from the analysis until empirical data is available to support load impacts outside of the specified program guidelines. May and October impacts for SCE have been included in the evaluation to provide consistency in results across the utilities. However, those months include more uncertainty than the others due to being outside of the regular SCE program season.

It is also important to note that these impacts represent load that is shifted, not eliminated. The evaluation assumes that all avoided peak period load, plus an additional 5%, is consumed during the hours from 9 PM to 6 AM. PLS systems are required to use no more than 5% additional energy than the baseline system. Because not all cooling load comes during the peak period and we have only added 5% to the shifted peak period load, our assumption implies that the 5% limit will be binding for many, but not all, sites.

Finally, each installation is expected to last a minimum of five years, after which we have assumed a degradation in load impacts of about 2.5% per year, which corresponds to an expected life of about 20 years for each installation.[26] We have assumed the same degradation factor for each month within a given year so that the percentage difference measured May over May would be identical to the difference measured June over June and so forth. The

[25] Due to the confidentiality concerns described in Section 1, these load impact tables are not available publicly.

[26] The actual assumed trajectory is for a constant amount of absolute shifting capacity loss each year after the fifth year, such that the expected total life is 20 years and the maximum total life is 35 years. If the program becomes a major part of the energy savings portfolio, then more nuanced assumptions for shift capacity degradation will be in order.

degradation factor is a major simplification of what will likely become a complex issue if the program continues over the next decade. Similar to the issue of projecting PLS enrollment, this is primarily an empirical question that is unlikely to be determined accurately in advance. PLS-TES systems are too complex and their continued function is based on too many variables for a theoretical analysis to have any serious hope of accuracy. Therefore, we have chosen a simple set of values for degradation that dovetail with the assumptions that utility staff consider reasonable; and we recognize the significant uncertainty associated with these projections.

6.1 PG&E Results

Table 6-1 provides the ex ante load impact estimates for monthly system peak days in May through October of 2016, under the utility specific 1-in-2 and 1-in-10 year weather conditions for the base scenario. The single project scheduled to come online in early 2016 is expected to yield approximately 30 kW of load reduction during the summer season under the utility specific 1-in-10 conditions.[27] PG&E's two remaining identified projects are forecasted to become operational in July 2016 and March 2017. Two unidentified projects are expected to come online in 2017, followed by an additional two unidentified projects in 2018, resulting in a total of seven projects ultimately yielding a peak load shift of 2.7 MW on a utility specific July 1-in-10 peak day in 2018. Table 6-2 shows results from 2017, which is a transition year when additional projects are expected to come online. Table 6-3 provides results for PG&E in 2018 when enrollment reaches the steady state under the currently approved funding cycle. The base case scenario load impact for the utility specific August 1-in-10 peak day reaches 2.6 MW. The Greater Bay Area LCA accounts for the largest share of load impacts, comprising approximately 57% of the total. It is important to note that the Greater Bay Area includes many hot areas with large commercial and industrial facilities, including Silicon Valley, Concord, and San Ramon.

[27] Tables for 2015 are not included due to the results pertaining to only a single customer.

Table 6-1: PG&E Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days for May-October 2016 (kW) Utility Specific Peak – Base Scenario

LCA	May		June		July		August		September		October	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Greater Bay Area	Redacted to protect confidential customer information											
Greater Fresno	0	0	0	0	0	0	0	0	0	0	0	0
Humboldt	0	0	0	0	0	0	0	0	0	0	0	0
Kern	0	0	0	0	0	0	0	0	0	0	0	0
Northern Coast	Redacted to protect confidential customer information											
Other	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Stockton	0	0	0	0	0	0	0	0	0	0	0	0
Total	Redacted to protect confidential customer information											

Table 6-2: PG&E Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days for May-October 2017 (kW) Utility Specific Peak – Base Scenario

LCA	May		June		July		August		September		October	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Greater Bay Area	1,019	1,141	1,089	1,174	1,140	1,216	1,124	1,184	1,118	1,152	1,004	1,045
Greater Fresno	85	87	95	95	99	101	95	103	91	92	82	81
Humboldt	8	9	8	9	9	10	9	9	9	9	8	9
Kern	96	76	101	99	101	106	101	105	97	99	87	89
Northern Coast	64	71	69	76	73	75	70	75	69	73	64	67
Other	281	305	307	319	319	333	310	331	302	313	266	280
Sierra	20	21	22	22	22	24	22	23	21	21	18	19
Stockton	36	38	39	40	41	43	41	42	37	39	32	34
Total	**1,611**	**1,749**	**1,734**	**1,836**	**1,804**	**1,908**	**1,776**	**1,876**	**1,746**	**1,799**	**1,561**	**1,623**

Table 6-3: PG&E Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days for May-October 2018 (kW) Utility Specific Peak – Base Scenario

LCA	May		June		July		August		September		October	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Greater Bay Area	1,304	1,459	1,393	1,503	1,459	1,556	1,438	1,515	1,430	1,474	1,285	1,337
Greater Fresno	166	170	186	186	193	197	186	201	177	179	161	157
Humboldt	15	17	16	18	18	19	18	18	17	18	15	17
Kern	187	149	198	193	197	207	198	204	189	192	170	173
Northern Coast	100	111	109	120	114	117	110	118	108	115	100	106
Other	404	438	441	458	458	479	446	476	434	449	381	403
Sierra	39	41	42	43	43	46	42	44	40	41	36	37
Stockton	71	75	76	77	80	83	80	81	73	76	62	66
Total	**2,290**	**2,460**	**2,468**	**2,600**	**2,563**	**2,707**	**2,523**	**2,664**	**2,473**	**2,547**	**2,211**	**2,296**

Figure 6-1 illustrates how the August 1-in-10 load impact estimates vary by forecast year and scenario. Figure 6-2 shows the same results for August 1-in-2 weather conditions. Across the forecast years and scenarios, the impacts are slightly higher under August 1-in-10 weather conditions but the difference is less than 0.2 MW. As described in Section 3, the three scenarios correspond to different forecasts of the percent of the total PLS program incentive budget that will be committed by the end of 2016, with 10% assumed under the low scenario, 20% under the base scenario, and 30% under the high scenario. The different percentages of the total PLS program incentive budget being committed translate into different enrollment forecasts across the three scenarios. We consider these scenarios to be about the best that can be done to estimate the uncertainty associated with these estimates, since the estimation method was not statistical in nature and therefore there are no standard errors to report. As a result of this uncertainty, the aggregate load reduction of the program varies substantially. When the aggregate impact peaks in 2018—before the 2.5% annual degradation begins—the PLS program is expected to deliver from 1.9 MW in the low scenario to nearly 3.5 MW in the high scenario. At 2.7 MW, the aggregate impact for the base scenario is in the middle.

Figure 6-1: PG&E August 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM) by Forecast Year and Scenario

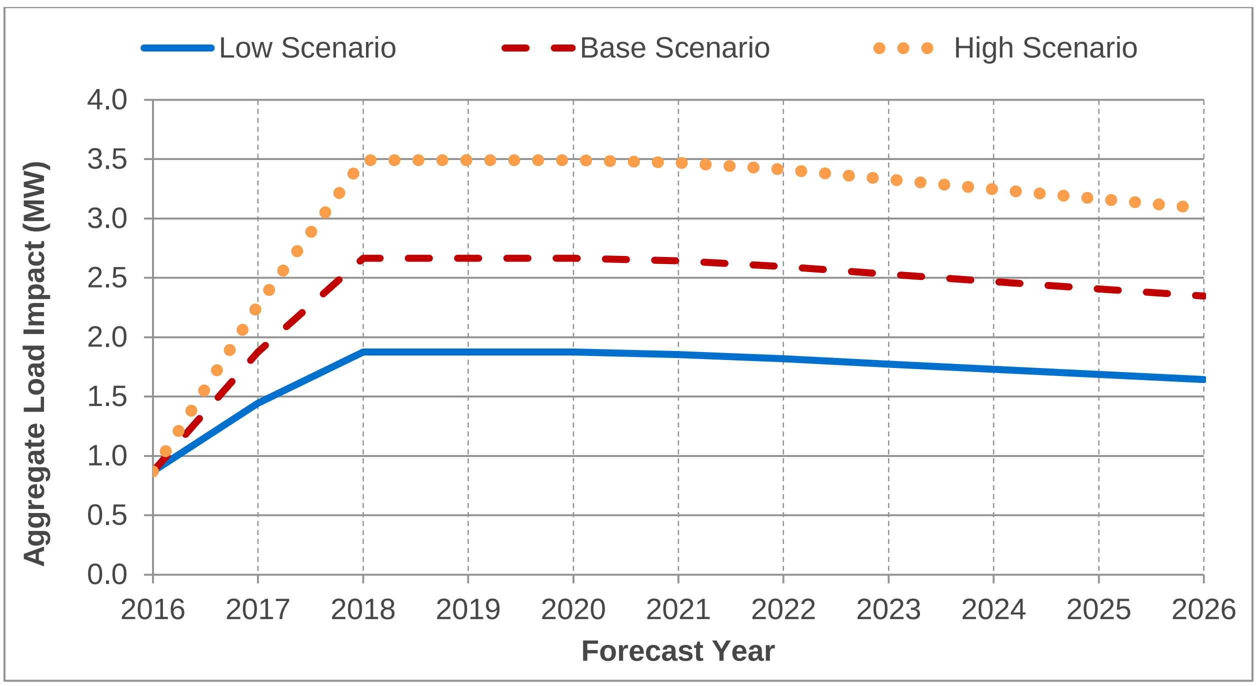


Figure 6-2: PG&E August 1-in-2 Monthly System Peak Day Load Impacts (1 to 6 PM) by Forecast Year and Scenario

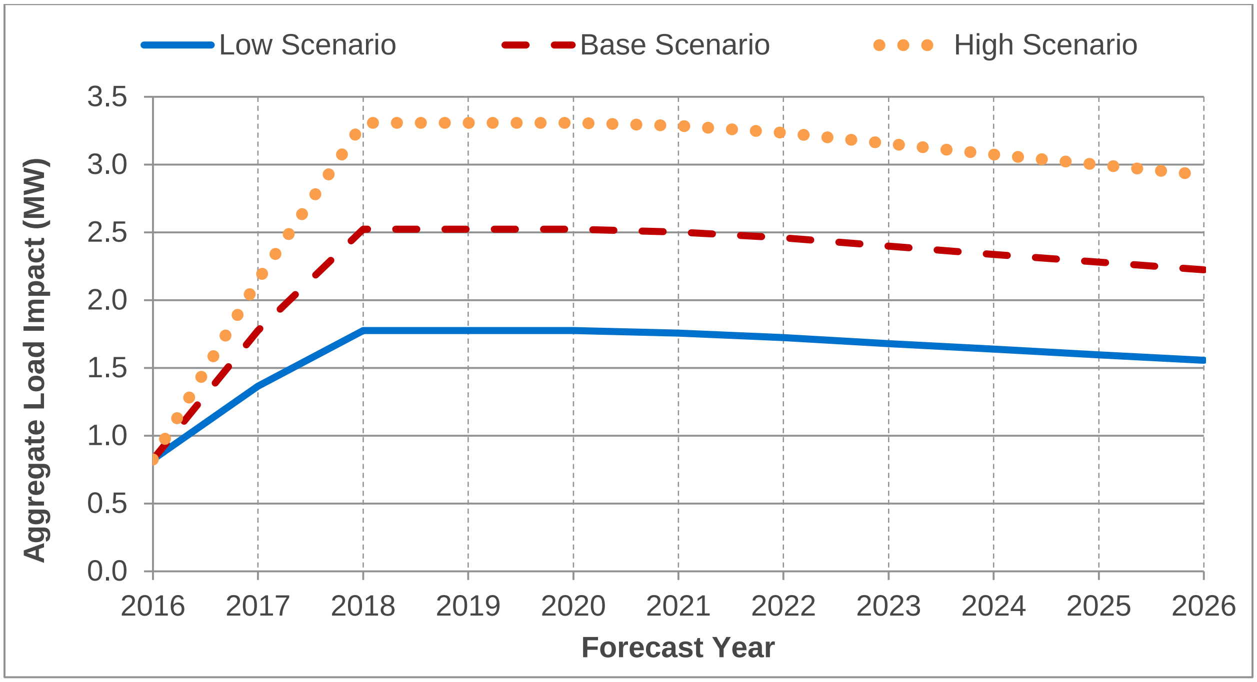


Table 6-4 shows the expected trajectory of load impacts under August 1-in-10 weather conditions from 2015 through 2026 by LCA for both the utility specific and CAISO specific weather conditions. Table 6-5 shows the same results for August 1-in-2 conditions. The Greater Bay Area and Other LCAs combined account for a majority of load impacts throughout the forecast horizon under both 1-in-10 and 1-in-2 year weather conditions for both CAISO and utility specific peaks. Outside of the Greater Bay Area LCA, only the 'Other' LCA comprises more than 10% of load impacts. As a result of the assumed 2.5% annual degradation in load impacts after year five, the aggregate load reduction decreases from around 2.7 MW in 2018 under 1-in-10 year, utility-specific weather conditions to 2.3 MW in 2026. Similarly, the CAISO-specific impacts decrease from 2.6 MW in 2018 to 2.3 MW in 2026.

Table 6-4: PG&E August 1-in-10 Monthly System Peak Day Load Impacts (1–6 PM) by LCA and Forecast Year – Base Scenario

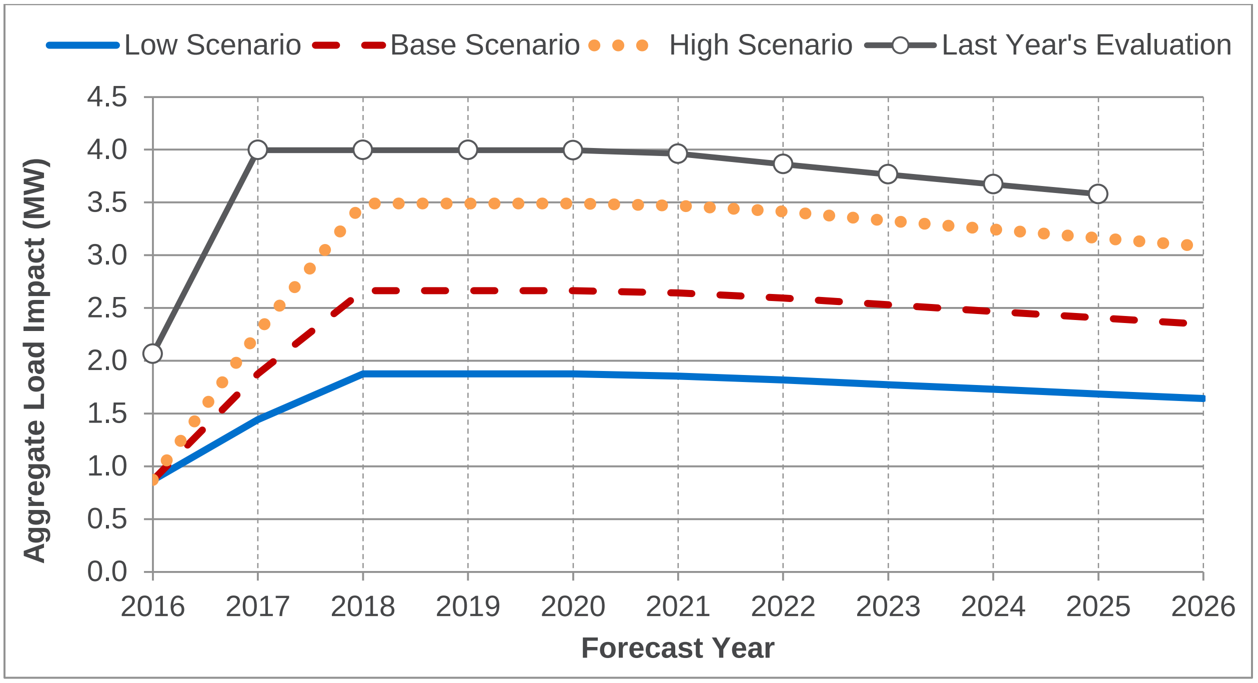
Peak Type	LCA	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
Utility Specific	Greater Bay Area	Redacted to protect confidential customer information	1,184	1,515	1,515	1,515	1,494	1,464	1,428	1,392	1,357	1,323
	Greater Fresno		103	201	201	201	201	198	193	188	184	179
	Humboldt		9	18	18	18	18	18	18	17	17	16
	Kern		105	204	204	204	204	202	197	192	187	182
	Northern Coast		75	118	118	118	117	115	112	109	107	104
	Other		331	476	476	476	476	468	456	445	434	423
	Sierra		23	44	44	44	44	44	42	41	40	39
	Stockton		42	81	81	81	81	80	78	76	74	73
	Total		**1,876**	**2,664**	**2,664**	**2,664**	**2,642**	**2,596**	**2,531**	**2,468**	**2,406**	**2,346**
CAISO Specific	Greater Bay Area		1,125	1,439	1,439	1,439	1,419	1,391	1,356	1,323	1,289	1,257
	Greater Fresno		100	195	195	195	195	192	188	183	178	174
	Humboldt		9	18	18	18	18	17	17	17	16	16
	Kern		104	204	204	204	204	201	196	191	186	182
	Northern Coast		71	112	112	112	111	109	107	104	101	99
	Other		322	463	463	463	463	455	444	433	422	411
	Sierra		22	43	43	43	43	43	42	41	40	39
	Stockton		41	80	80	80	80	78	77	75	73	71
	Total		**1,798**	**2,559**	**2,559**	**2,559**	**2,539**	**2,494**	**2,432**	**2,371**	**2,312**	**2,254**

Table 6-5: PG&E August 1-in-2 Monthly System Peak Day Load Impacts (1 to 6 PM) by LCA and Forecast Year – Base Scenario

Peak Type	LCA	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
Utility Specific	Greater Bay Area	Redacted to protect confidential customer information	1,124	1,438	1,438	1,438	1,418	1,391	1,356	1,322	1,289	1,257
	Greater Fresno		95	186	186	186	186	184	179	175	170	166
	Humboldt		9	18	18	18	18	18	17	17	16	16
	Kern		101	198	198	198	198	195	190	186	181	176
	Northern Coast		70	110	110	110	109	107	105	102	99	97
	Other		310	446	446	446	446	438	427	417	406	396
	Sierra		22	42	42	42	42	42	41	40	39	38
	Stockton		41	80	80	80	80	79	77	75	74	72
	Total		**1,776**	**2,523**	**2,523**	**2,523**	**2,502**	**2,458**	**2,397**	**2,337**	**2,279**	**2,222**
CAISO Specific	Greater Bay Area		1,098	1,405	1,405	1,405	1,386	1,359	1,325	1,292	1,260	1,229
	Greater Fresno		88	173	173	173	173	171	166	162	158	154
	Humboldt		8	16	16	16	16	16	15	15	15	14
	Kern		92	180	180	180	180	178	174	169	165	161
	Northern Coast		67	104	104	104	104	102	100	97	95	92
	Other		292	419	419	419	419	412	402	392	382	372
	Sierra		20	39	39	39	39	38	37	36	36	35
	Stockton		36	71	71	71	71	70	68	66	65	63
	Total		**1,701**	**2,408**	**2,408**	**2,408**	**2,388**	**2,346**	**2,287**	**2,231**	**2,175**	**2,121**

Figure 6-3 compares the ex ante load impact estimates from this evaluation to those from last year's PLS program evaluation, for the August 1-in-10 monthly system peak day. In general, the load impact estimates are significantly lower than those of last year's evaluation. The main reasons for these differences are 1) an application for a large project was withdrawn; and 2) the percentage of the remaining budget expected to be spent decreased from 30% to 20% in the medium scenario due to the limited amount of time remaining for applications to be submitted. This change is a conservative estimate and was based on the most recent information available, including the applications that PG&E has received at the time of this evaluation. These changes result in the base scenario forecast this year being roughly 35% lower than the estimates in last year's evaluation.

Figure 6-3: PG&E Comparison of August 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM) to Base Scenario from Last Year's PLS Program Evaluation



6.2 SCE Results

Table 6-6 provides the ex ante load impact estimates for monthly system peak days in May through October of 2016, under SCE-specific, 1-in-2 and 1-in-10 year weather conditions for the base scenario. Table 6-7 and 6-8 provide results for 2017 and 2018, respectively. SCE had one project become operational in 2015. Three identified projects and no unidentified projects are expected to come online in 2016. The remaining three identified projects and two additional unidentified projects are forecast to become operational in 2017. Finally, two additional unidentified projects are expected to come online in 2018. The steady state peak load shift level of projects under the current budget scenario is expected to be reached in 2018 with a total of 10.1 installations and 7.9 MW under SCE-specific, July 1-in-10 monthly peak conditions.

All of the currently identified applications are located within the LA Basin LCA. The majority of any future applications and related impacts are expected to also remain in the LA Basin LCA given that more than 75% of SCE's nonresidential customers with annual maximum demand greater than 1 MW are located within that LCA. Impacts are also reported at the South Orange County and South of Lugo regions. These regions within the LA Basin LCA are required to be reported separately as they are constrained circuits in the area affected by the closure of the San Onofre Nuclear Generating Station (SONGS). In 2018, under SCE-specific August 1-in-10 year conditions, the expected impacts for the constrained circuits are 1.2 MW and 3.6 MW for South Orange County and South of Lugo respectively. The South of Lugo impact is significant at more than 45% of SCE's aggregate load impact.

CAISO specific impacts are covered in greater detail below. For comparison purposes, the CAISO impact for August 1-in-10 monthly peak conditions is 7.8 MW, or approximately 1% lower than the comparable utility specific monthly peak. As noted in the ex ante weather description in Section 4.4 above, the CAISO and SCE utility specific peaks have the highest correlation among the three IOUs.

Table 6-6: SCE Ex Ante Load Impact Estimates (1–6 PM) on Monthly Peak Days for May–October 2016 (kW) – Base Scenario

LCA	May		June		July		August		September		October	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
LCA - LA Basin	Redacted to protect confidential customer information											
Region - South Orange County												
Region - South of Lugo												
LCA - Outside LA Basin												
LCA - Ventura												
Total												

Table 6-7: SCE Ex Ante Load Impact Estimates (1–6 PM) on Monthly Peak Days for May–October 2017 (kW) – Base Scenario

LCA	May		June		July		August		September		October	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
LCA - LA Basin	4,283	4,517	4,884	5,262	5,433	5,782	5,446	5,757	5,309	5,747	4,782	5,097
Region - South Orange County	119	126	574	618	631	671	632	669	616	667	555	592
Region - South of Lugo	2,761	2,912	2,858	3,079	3,141	3,343	3,149	3,329	3,069	3,323	2,765	2,947
LCA - Outside LA Basin	79	80	82	85	91	99	88	95	81	87	73	77
LCA - Ventura	168	176	180	194	195	212	189	204	177	192	165	180
Total	**4,527**	**4,775**	**5,146**	**5,544**	**5,720**	**6,097**	**5,727**	**6,065**	**5,570**	**6,029**	**5,021**	**5,354**

Table 6-8: SCE Ex Ante Load Impact Estimates (1–6 PM) on Monthly Peak Days for May -October 2018 (kW) – Base Scenario

LCA	May		June		July		August		September		October	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
LCA - LA Basin	6,008	6,336	6,219	6,700	6,836	7,275	6,852	7,244	6,679	7,231	6,017	6,413
Region - South Orange County	1,010	1,065	1,045	1,126	1,149	1,223	1,152	1,218	1,123	1,216	1,011	1,078
Region - South of Lugo	3,054	3,221	3,162	3,406	3,475	3,699	3,484	3,683	3,395	3,676	3,059	3,260
LCA - Outside LA Basin	161	164	168	175	187	202	180	195	165	179	150	158
LCA - Ventura	344	361	368	397	399	435	387	417	364	393	339	370
Total	**6,510**	**6,863**	**6,756**	**7,276**	**7,422**	**7,917**	**7,423**	**7,865**	**7,210**	**7,804**	**6,504**	**6,940**

Figure 6-4 illustrates how the August 1-in-10 year load impact estimates vary by forecast year and scenario. Figure 6-5 shows the same results for August 1-in-2 year weather conditions. Across the forecast years and scenarios, the impacts are approximately 6% higher under August 1-in-10 year weather conditions. As described in Section 4.3, the three scenarios correspond to different forecasts of the percent of the total PLS program incentive budget that will be committed by the end of 2016, with 30% assumed under the low scenario, 50% under the base scenario, and 70% under the high scenario. When the aggregate impact peaks in 2018, the PLS program is expected to deliver from 6.7 MW in the low scenario to nearly 8.9 MW in the high scenario, under August 1-in-10 weather conditions. The base case scenario forecasts a 7.9 MW load reduction.

Figure 6-4: SCE August 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM) by Forecast Year and Scenario

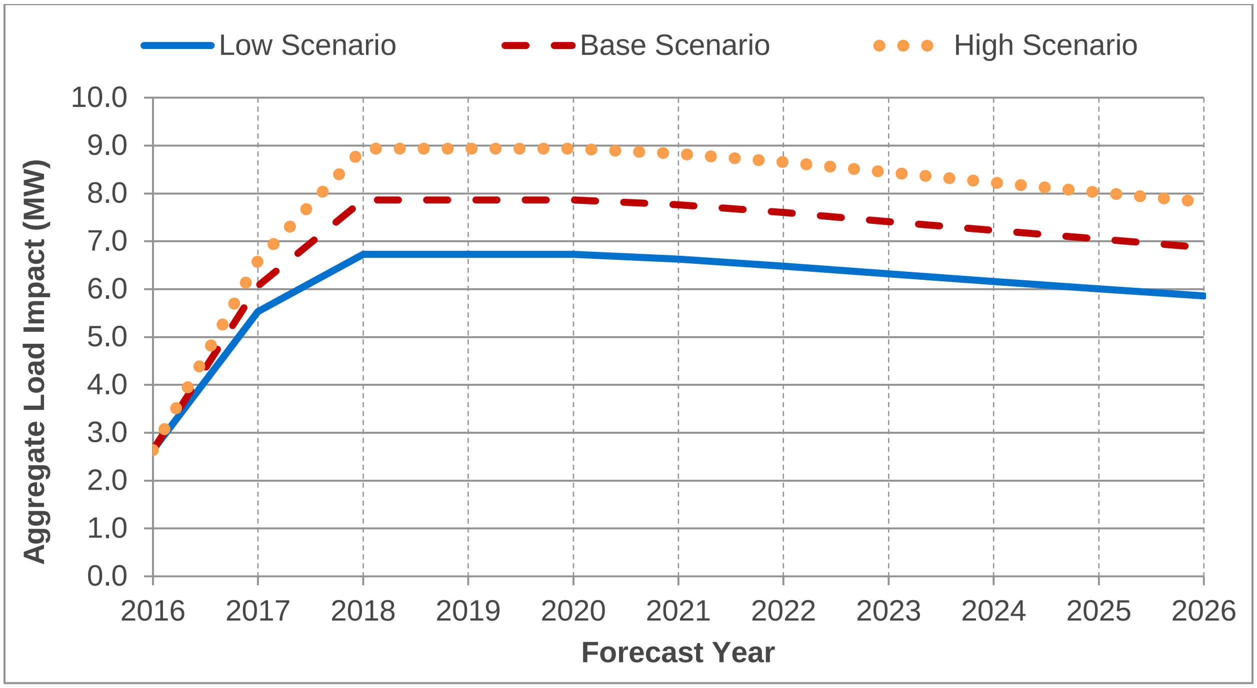


Figure 6-5: SCE August 1-in-2 Monthly System Peak Day Load Impacts (1 to 6 PM) by Forecast Year and Scenario

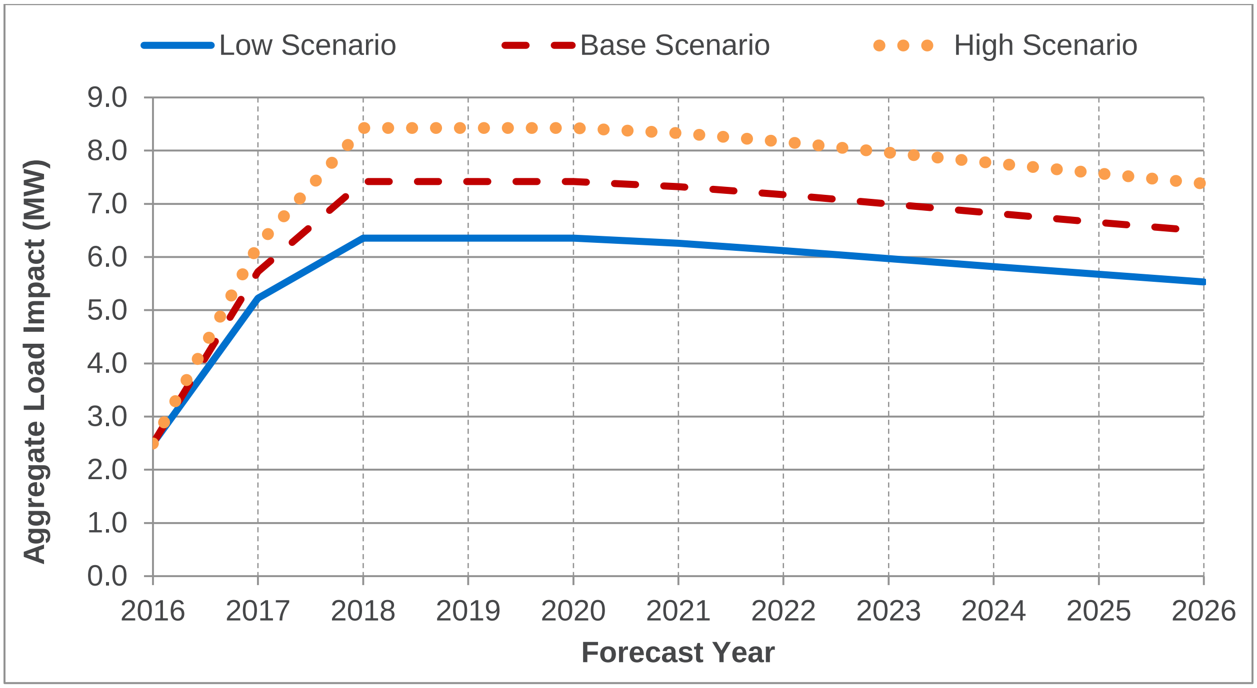


Table 6-9 shows the expected trajectory of load impacts under August 1-in-10 year weather conditions from 2016 through 2026 by LCA for the utility and CAISO specific peaks. Table 6-10 shows the same results for August 1-in-2 conditions. The LA Basin LCA accounts for at least 92% of load impacts over the forecast horizon under both 1-in-10 and 1-in-2 year weather conditions. As a result of the assumed 2.5% annual degradation in load impacts after year five, the aggregate load reduction decreases from around 7.9 MW in 2018 under 1-in-10 year weather conditions to 6.8 MW in 2026. As mentioned above, the CAISO-specific peak is very similar to the SCE utility specific peak and maintains a consistent relationship across all of the years in the forecast. The difference between the utility specific and the CAISO specific peak is approximately 1% under 1-in-10 conditions, and 2% under 1-in-2 conditions, with the utility peak being consistently higher.

Table 6-9: SCE August 1-in-10 Monthly System Peak Day Load Impacts (1-6 PM) by LCA and Forecast Year – Base Scenario

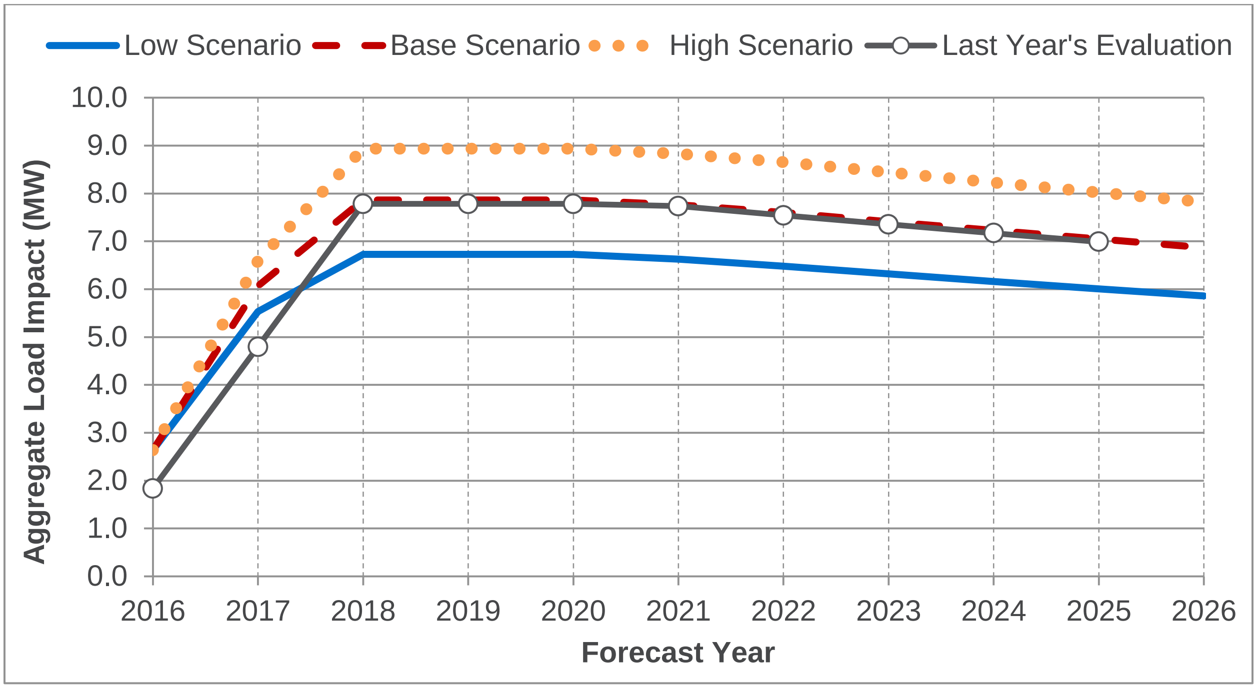
Peak Type	LCA	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
Utility Specific	LCA - LA Basin	Redacted to protect confidential customer information	5,757	7,244	7,244	7,244	7,140	6,988	6,813	6,642	6,476	6,313
	Region - South Orange County		669	1,218	1,218	1,218	1,218	1,191	1,161	1,132	1,104	1,076
	Region - South of Lugo		3,329	3,683	3,683	3,683	3,607	3,526	3,437	3,351	3,267	3,185
	LCA - Outside LA Basin		95	195	195	195	195	192	188	183	178	174
	LCA – Ventura		204	417	417	417	417	412	402	392	382	373
	Total		**6,065**	**7,865**	**7,865**	**7,865**	**7,761**	**7,602**	**7,412**	**7,226**	**7,045**	**6,869**
CAISO Specific	LCA - LA Basin		5,695	7,165	7,165	7,165	7,063	6,914	6,741	6,573	6,408	6,248
	Region - South Orange County		661	1,204	1,204	1,204	1,204	1,178	1,149	1,120	1,092	1,065
	Region - South of Lugo		3,293	3,642	3,642	3,642	3,569	3,488	3,401	3,316	3,233	3,152
	LCA - Outside LA Basin		94	193	193	193	193	191	186	181	177	173
	LCA – Ventura		202	415	415	415	415	410	400	390	380	371
	Total		**5,995**	**7,777**	**7,777**	**7,777**	**7,675**	**7,518**	**7,330**	**7,148**	**6,969**	**6,795**

Table 6-10: SCE August 1-in-2 Monthly System Peak Day Load Impacts (1-6 PM) by LCA and Forecast Year – Base Scenario

Peak Type	LCA	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
Utility Specific	LCA - LA Basin	Redacted to protect confidential customer information	5,446	6,852	6,852	6,852	6,755	6,612	6,447	6,286	6,130	5,977
	Region - South Orange County		632	1,152	1,152	1,152	1,152	1,127	1,099	1,071	1,044	1,018
	Region - South of Lugo		3,149	3,484	3,484	3,484	3,413	3,336	3,253	3,172	3,093	3,015
	LCA - Outside LA Basin		88	180	180	180	180	178	174	169	165	161
	LCA – Ventura		189	387	387	387	387	382	373	363	354	345
	Total		**5,727**	**7,423**	**7,423**	**7,423**	**7,325**	**7,175**	**6,997**	**6,822**	**6,652**	**6,487**
CAISO Specific	LCA - LA Basin		5,319	6,692	6,692	6,692	6,597	6,457	6,296	6,139	5,986	5,836
	Region - South Orange County		618	1,125	1,125	1,125	1,125	1,100	1,073	1,046	1,020	994
	Region - South of Lugo		3,075	3,402	3,402	3,402	3,333	3,258	3,177	3,097	3,020	2,945
	LCA - Outside LA Basin		88	181	181	181	181	179	174	170	166	161
	LCA – Ventura		189	387	387	387	387	382	372	363	354	345
	Total		**5,599**	**7,263**	**7,263**	**7,263**	**7,168**	**7,021**	**6,846**	**6,675**	**6,509**	**6,346**

Figure 6-6 compares the ex ante load impact estimates from this evaluation to those from last year's PLS program evaluation for the SCE-specific, August 1-in-10 monthly system peak day. From 2018 onwards, the load impact estimates for the base scenario are very similar to those of last year's evaluation. The main difference in this year's evaluation is that it forecasts projects coming online at a slightly faster pace. This change is based on the current status and expected installation dates of the identified PLS program applications.

Figure 6-6: SCE Comparison of August 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM) to Base Scenario from Last Year's PLS Program Evaluation



6.3 SDG&E Results

Table 6-11 provides the ex ante load impact estimates for 2016–2026 monthly system peak days in May through October for SDG&E-specific and CAISO 1-in-2 and 1-in-10 year weather conditions for the base scenario. SDG&E's service territory only has one LCA so the results are not divided geographically. In the base scenario, six SDG&E identified projects come online in 2016 and two additional unidentified projects comes online in 2017 to reach the steady state enrollment under the current budget scenario at eight installations producing 4.3 MW of load reduction in 2018. Table 6-11 also shows the expected trajectory of load impacts through 2026. As a result of the assumed 2.5% annual degradation in load impacts after year five of each installation, the aggregate load reduction under August 1-in-10 weather conditions decreases from around 4.3 MW in 2018 to 3.7 MW in 2026.

The difference between utility specific and CAISO peaks tend to vary by month. Impacts range from the CAISO-specific, September 1-in-2 monthly peak day in 2018 being 17% greater than the utility specific comparable peak at 3.5 MW and 4.2 MW respectively; to the utility specific

July 1-in-10 monthly peak day in 2018 being 24% greater than the CAISO specific comparable peak at 4.3 MW and 3.5 MW respectively. Year over year, the difference between the utility specific peak and the CAISO peak appears to remain fairly constant. For example, the utility specific August 1-in-10 monthly peak load impact is typically around 4% higher than the comparable CAISO specific impact.

**Table 6-11: SDG&E Ex Ante Load Impact Estimates (1 to 6 PM)
on Monthly Peak Days for May-October 2016-2026 (kW) – Base Scenario**

Peak Type	Forecast Year	May		June		July		August		September		October	
		1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
	2016												
	2017												
	2018												
	2019												
	2020												
Utility Specific	2021	Redacted to protect confidential customer information											
	2022												
	2023												
	2024												
	2025												
	2026												
	2016												
	2017												
	2018												
	2019												
	2020												
CAISO Specific	2021	Redacted to protect confidential customer information											
	2022												
	2023												
	2024												
	2025												
	2026												

Figure 6-7 illustrates how the August 1-in-10 load impact estimates vary by forecast year. As noted earlier, SDG&E has received applications that exhaust all incentive funding, and therefore there is no need to forecast enrollment scenarios. In this case, all three scenarios are made identical to the base case scenario. When the aggregate impact peaks in 2018—before the 2.5% annual degradation begins—the PLS program is expected to deliver approximately 4.3 MW under August 1-in-10 year weather conditions.

Figure 6-7: SDG&E August 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM) by Forecast Year and Scenario

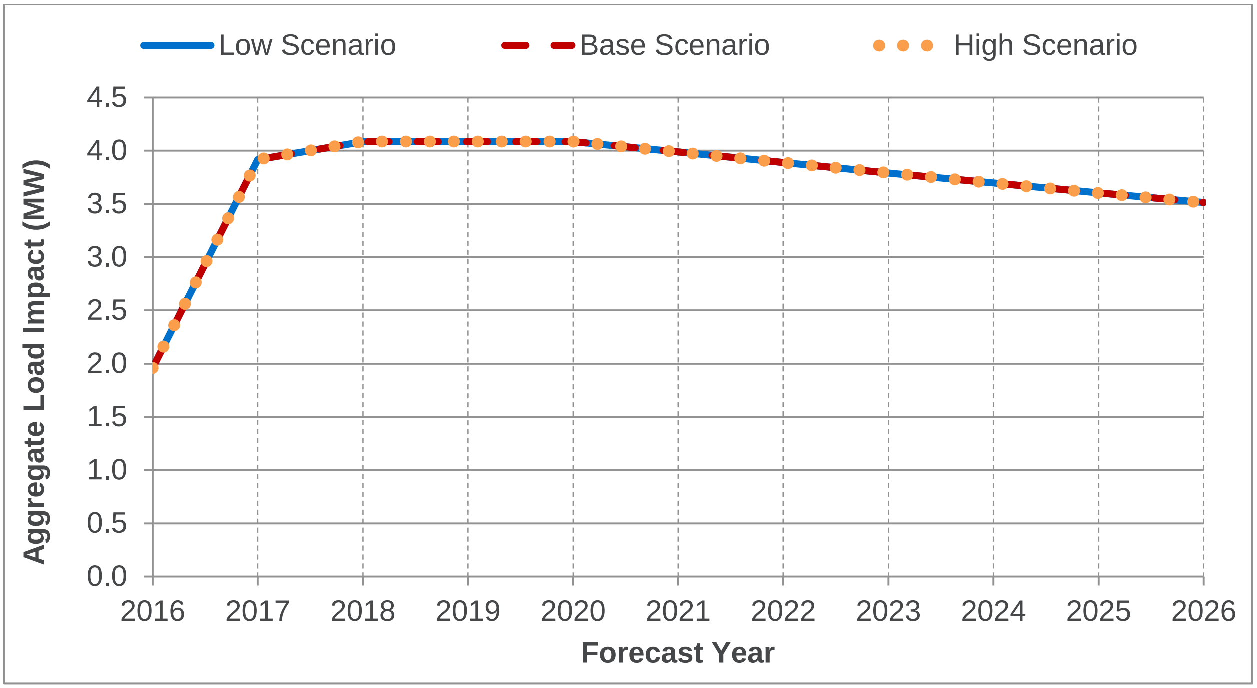


Figure 6-8 shows the same results for August 1-in-2 weather conditions. Across the forecast years, the impacts are roughly 11% higher under August 1-in-10 year weather conditions. When the aggregate impact peaks in 2018—before the 2.5% annual degradation begins—the PLS program is expected to deliver nearly 3.7 MW under August 1-in-2 year weather conditions.

Figure 6-8: SDG&E August 1-in-2 Monthly System Peak Day Load Impacts (1 to 6 PM) by Forecast Year and Scenario

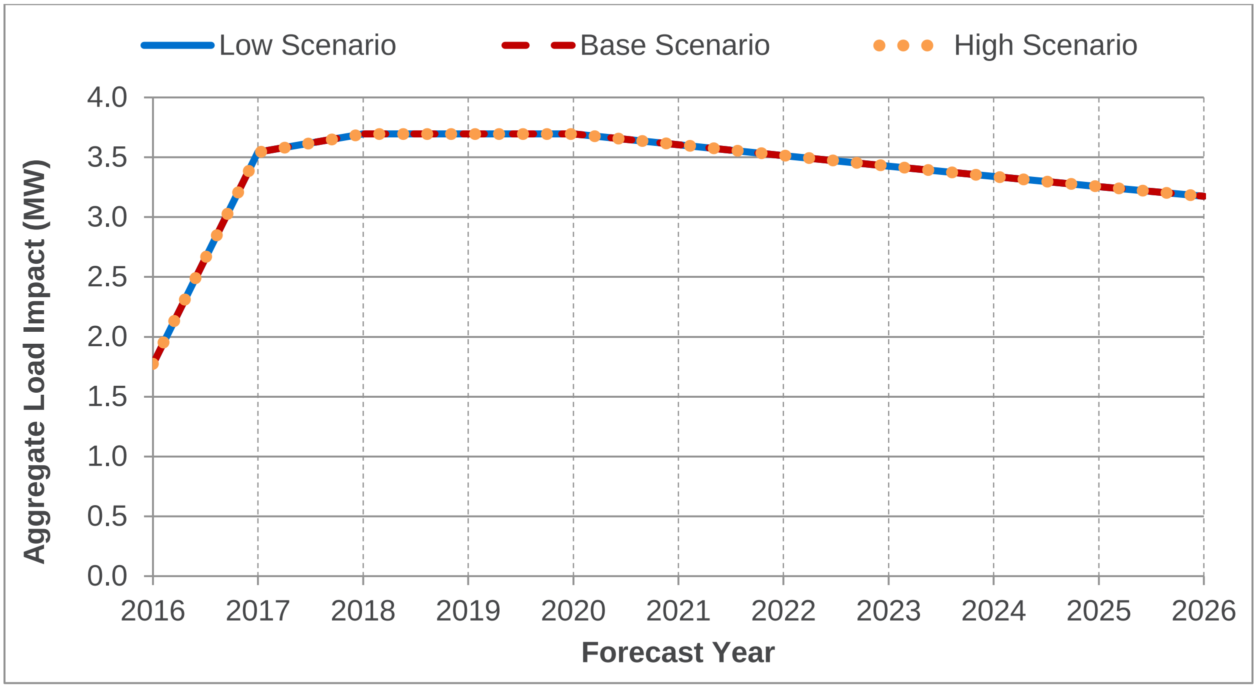
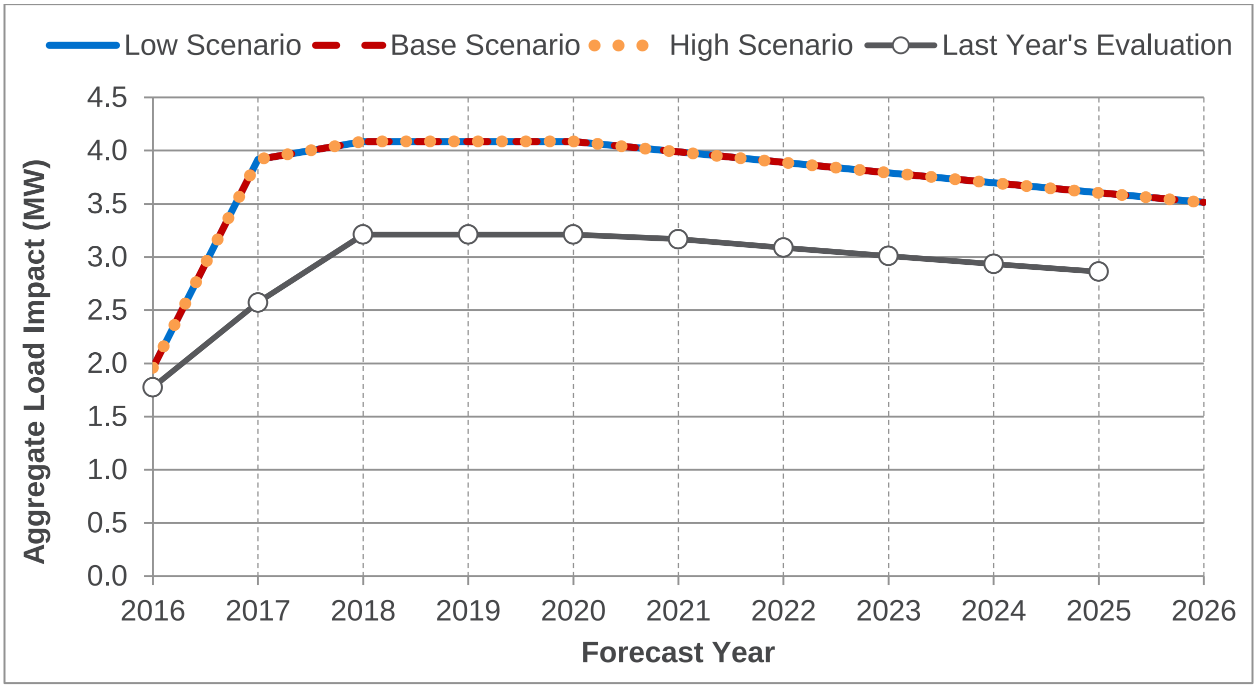


Figure 6-9 compares the ex ante load impact estimates from this evaluation to those from last year's PLS program evaluation, for the August 1-in-10 monthly system peak day. In all years the ex ante load impact from this evaluation are higher than those of last year's. This change is based on the number of applications SDG&E has received over the last year. From 2018 onwards, the load impact estimates for the base scenario are approximately 27% higher than those of last year's evaluation.

Figure 6-9: SDG&E Comparison of August 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM) to Base Scenario from Last Year's PLS Program Evaluation



7 Recommendations

The pre-operational data collection waiver and partial availability of post installation operational data due to data logger issues from SCE’s first site limited the methodological approaches that could be used to evaluate the load shift to only those using premise level data rather than focusing specifically on the cooling system data. This method may limit measurement of the load shift specifically provided by the TES system. As more PLS program installations are scheduled to come online, it is important to ensure that each of the utilities has a process in place to collect and store the post-installation operation data from customers. It is also recommended that pre-installation data be collected for customers whenever feasible. As additional projects are completed and the post installation operational data becomes available, it will be important to determine how consistent the load impact estimations are between premise level data and the cooling system specific data. If the impacts are generally consistent, it may be possible to relax some of the data collection requirements, which are a burden to customers and could potentially be negatively affecting program adoption rates.

Appendix A Methodology for Developing Ex Ante Conversion Factors

As described in Section 4.3, the PLS program kW load shift amount for incentive calculations for unidentified projects represents the peak load shift that can be expected under 1-in-10 year peak weather conditions. In order to comply with the California DR Load Impact Protocols, this evaluation must convert the forecasted load shift under 1-in-10 peak weather conditions to the ex ante load impact estimates for monthly system peak days and average weekdays under 1-in-2 and 1-in-10 year weather conditions.

At a high level, this is accomplished by 1) developing new generalized building simulation models calibrated to the weather conditions in each LCA; 2) applying updated localized ex ante weather data to the models; and 3) calculating the conversion factors based on the building simulation model output for each LCA from the ratio between chiller load under ex ante weather conditions to peak chiller load under the weather conditions used to calculate the program incentive. The following sections discuss each of the steps in further detail and document the key assumptions and challenges associated with the exercise.

A.1 Development of New Building Simulation Models

Due to new evaluation requirements to report load impacts by CAISO system peak in addition to the utility system peak, Nexant and the IOUs determined the best approach would be to use new building simulation model runs to develop updated conversion factors. For this building simulation modeling to work, the evaluation team used the Quick Energy Simulation Tool (eQUEST), which is a software package designed in collaboration with the Department of Energy (DOE) and Lawrence Berkeley National Laboratory (LBNL).[28] This software is used extensively throughout the industry to simulate building energy use for a wide variety of climates, building types, and cooling technologies—including various TES designs.

A.1.1 Building Specifications

A single, 2008 vintage Title 24 compliant building simulation model was developed to represent large C&I customers in California. Based on analysis of the applications received to date, the initial model was designed to represent a 3-story commercial office building sized at 500,000 square feet. As is discussed later in this section, the specific characteristics of the initial building model are not critical. The model was calibrated such that the cooling load for the building simulation was appropriately sized for the climatic conditions in each of the 12 LCAs across the three IOUs. The eQUEST software allows Nexant to predict total building cooling load for a chilled water system—including both chiller and fan—based on specified weather conditions, building size, number of stories, orientation—North, South, etc.—the amount of glazing and location.

Fortunately, not knowing specific building characteristics does not affect the accuracy of the load impact estimates by noting that the designed peak shift values, not the raw building simulation model output, were used as the main anchor for load impacts. Nexant only used the simulation software to determine what the ratios were between the cooling load under

28 eQUEST, <http://www.doe2.com/equest/>

conditions used to determine the incentive payment, and under the ex ante weather conditions for a given building. At no point in the analysis did Nexant directly use simulation software to estimate the overall level of demand shifting at a given site. These values were assumed in the enrollment forecast. The simulation software was only used to answer questions such as, “if I have a site that provides 100 kW of shifting under the incentive payment calculation conditions, then how much does the same site provide under July 1-in-2 conditions?” The ex ante conversion factors answered this question.

Nexant provides evidence that it is not necessary to know the specific building characteristics in Table A-1, which shows that relative usage values across different weather conditions are basically insensitive to building characteristics. The table shows the ratio of average chiller load from 1 to 6 PM between the indicated temperature profile and August 1-in-10 peak conditions for a variety of building characteristics—which are provided in more detail in Table A-2. The point of Table A-1 is that the ratio for a given ex ante condition hardly changes as the building characteristics vary substantially. For example, the ratio of the average chiller load under September 1-in-10 conditions to the average chiller load under August 1-in-10 conditions only varies from 0.89 to 0.91, depending on whether the building is half its original size or twice its original size, whether it has its original window-to-wall ratio or twice that ratio, or whether it has one story versus four stories. This suggests that relative usage levels in the tool are determined primarily by temperature conditions, with the building characteristics driving the overall level of usage. There is only one major deviation from this pattern, under May 1-in-2 conditions, where the values vary from 0.82 to 0.70. Given the uncertainty associated with the other inputs into the estimates, this small inconsistency seems minor.

Having established that it is possible to use the building simulation models to determine relative usage levels without regard to the specific building characteristics, the next key assumptions are focused on the attributes of TES installations to be modeled.

Table A-1: Conversion Factors for a Variety of Building Characteristics under Each Set of Ex Ante Peak Weather Conditions[29]

	Baseline*	1 in 2 Typical	1 in 2 May	1 in 2 Jun.	1 in 2 Jul.	1 in 2 Aug.	1 in 2 Sep.	1 in 10 Typical	1 in 10 May	1 in 10 Jun.	1 in 10 Jul.	1 in 10 Aug.	1 in 10 Sep.
Original Building	0.46	0.92	0.80	0.86	0.98	0.92	0.93	0.97	0.90	0.93	1.02	1.00	0.90
Twice the Size	0.48	0.92	0.80	0.87	0.98	0.91	0.95	0.98	0.91	0.95	1.01	1.00	0.91
Half the Size	0.44	0.92	0.82	0.87	0.96	0.92	0.93	0.96	0.90	0.93	1.01	1.00	0.90
Four Floors	0.46	0.92	0.70	0.83	0.99	0.91	0.94	0.96	0.89	0.93	1.02	1.00	0.89
Twice the Window to Wall Ratio	0.45	0.92	0.80	0.87	0.98	0.92	0.93	0.97	0.90	0.93	1.02	1.00	0.90

Ex ante conversion factor = average kWh usage between 1–6 PM divided by average kWh usage during 1–6 PM on a typical August 1-in-10 day.

*Baseline is the default temperature profile on July 1 for California Climate Zone 12. It is not a monthly peak day.

29 This table and the associated conversion factors are from the PY2013 evaluation, and provided for comparative purposes in this appendix only.

Table A-2: Characteristics of Buildings in Table A-1[30]

Building Type	Footprint (sq. ft)	Stories	Orientation	Window to Wall Ratio				Climate Zone
				North	*East*	*South*	*West*	
Original Building	10,568	1	North	0.16	0.28	0.20	0.23	12
Twice the Size	21,141	1	North	0.16	0.28	0.20	0.23	12
Half the Size	5,329	1	North	0.16	0.28	0.20	0.23	12
Four Floors	10,568	4	North	0.16	0.28	0.20	0.23	12
Twice the Window to Wall Ratio	10,568	1	North	0.32	0.56	0.40	0.46	12

A.1.2 Treatment of Space and Process Cooling Installations

The utilities have received a combination of space and process cooling applications to date. The ideal situation would be to develop generalized models for both space and process cooling installations. However, process cooling installations are each unique to their specific industry, and may also exhibit seasonality in industries related to agriculture or food processing. The load shapes from the building simulation models for the existing PG&E applications were reviewed and confirm both industry specific load shapes and seasonality. Figure A-1 is an example of a food processing facility with limited energy consumption between November and March. Figure A-2 is an example of a winery with twice the typical load during the harvest season. Due to these factors, existing process cooling installations do not make good candidates for generalized modeling that could represent all future process cooling applications.

30 This table and the associated conversion factors are from the PY2013 evaluation, and provided for comparative purposes in this appendix only.

Figure A-1: Seasonal Load Shape

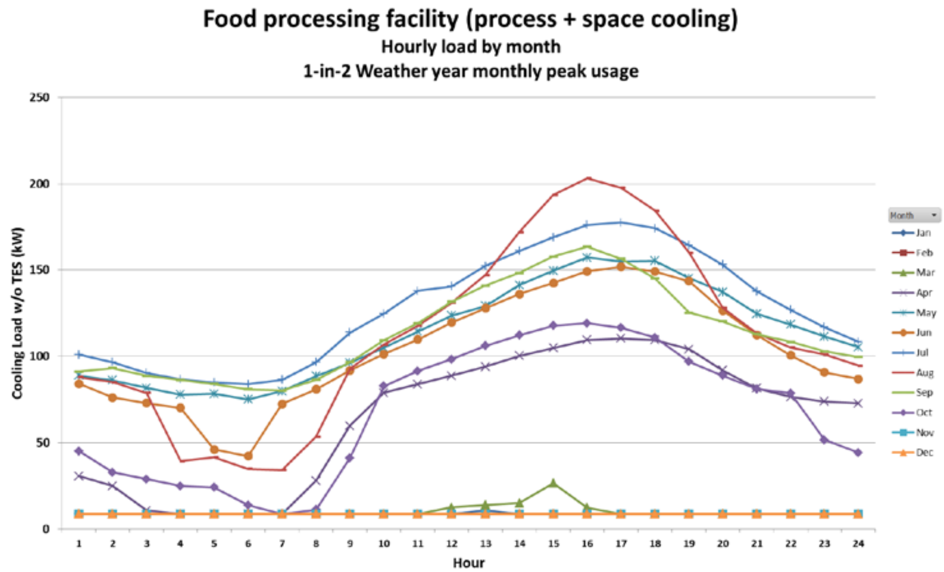
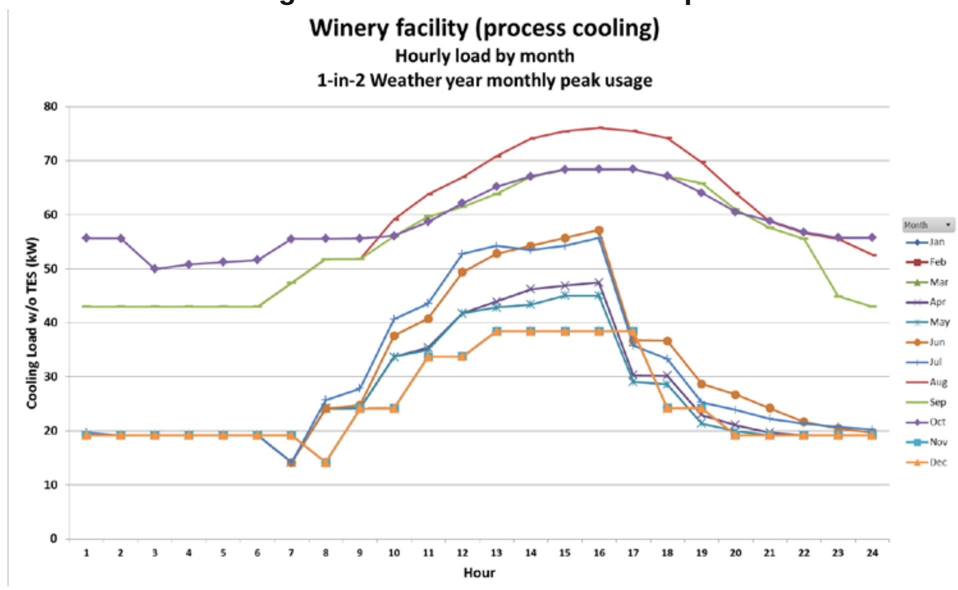


Figure A-2: Seasonal Load Shape



To determine the best method to account for process cooling installations, the weather sensitivity of the existing applications was analyzed. The customer usage data forecast from the building simulation models under 1-in-2 and 1-in-10 monthly IOU system peak conditions was calculated. The percentage difference in hourly usage under the 1-in-2 and 1-in-10 conditions was then calculated to determine the level of weather sensitivity of the process cooling load. A range of results up to approximately 20% was observed, indicating that process cooling load is weather sensitive. To provide a basis for comparison, PG&E's commercial SmartAC program exhibits a similar upper bound of approximately a 20% difference in cooling load between 1-in-2 and 1-in-10 monthly system peak conditions.

Due to the industry-specific load shape and seasonality of process cooling installations not being generalizable, and the weather sensitivity being comparable to commercial space cooling, it was reasonable to apply the conversion factors developed for the unidentified space cooling projects to the unidentified process cooling installations.

A.1.3 Percentage of TES Offset to Total Cooling Load

TES system capacity can vary based on the individual need for each project site. Previous evaluations have assumed that the TES system for unidentified projects is sized to offset the full chiller load under peak conditions. An alternative possibility is that the system is designed to shift only part of the chiller load under peak conditions. This distinction is referred to as full versus partial storage.

Now that feasibility studies are available for several project applications, assumptions are being revisited and updated as necessary. Based on the combination of applications and feasibility studies available for review, 7 of the 9 projects with available information are designed to shift between 95% and 100% of the maximum peak cooling load. For example, if the maximum cooling load for a building is 100 tons, a TES system designed for a 100% offset would be sized at approximately 600-ton hours to offset the cooling load of 100 tons for the required 6 hour period.

At this time, none of the projects have been completed, and most are still in the planning stages. When additional data on the type of projects that are actually installed becomes available, it will be good to revisit this assumption. However, at this time there is not enough evidence to warrant changing the expected offset from the full to the partial storage scenario.

To the extent that the partial storage alternative is applicable for some sites, the ex ante impact estimates for cooler weather conditions might be understated because under the current assumptions, load shift falls as temperature and the corresponding load decreases. Under partial storage, the load shift might be constant over some range of ex ante weather conditions at the hotter end of the weather spectrum. Because Nexant began with the designed peak shift as the main input, and because the designed peak shift takes place under conditions similar to the hottest ex ante conditions, the assumption is unlikely to have a significant effect on the accuracy of load impact estimates under the hottest weather conditions. Additionally, to the degree that it is inaccurate for cooler conditions, the results are conservative and tend to understate load impacts under those conditions. Given the uncertainty of the other components of the forecast such as the type and number of applicants, it was reasonable to maintain the full storage assumption until additional information becomes available.

A.2 Updated Ex Ante Weather Conditions

Nexant developed updated ex ante weather conditions to meet the new requirement for reporting load impacts by CAISO system peak in addition to the utility system peak. The new ex ante weather data incorporated the most recent weather data available and was used for inputs in all of the building simulation models.

The building simulation modeling was completed at the LCA level, requiring ex ante weather data that accurately represented conditions in each LCA. Some LCAs had multiple weather stations, and in those cases, Nexant developed a weighted ex ante weather file based on the proportion of customers similar in size to existing PLS applicants assigned to each weather station within an LCA. Aggregating and weighting the weather before running the model rather than running the building simulation models for each weather station minimized the number of costly building simulation runs.

The cooling load for each LCAs building simulation model was calibrated using the new ex ante weather data such that the modeled cooling equipment was appropriate for the local weather conditions. The 1-in-10 peak conditions for each LCA was the hottest weather input, and thus determined the maximum cooling load and associated peak load shift for each simulation model. This enabled the 1-in-10 peak day weather conditions to stand as a proxy for the conditions an engineer would have used to determine the maximum peak load shift for the incentive calculation. In other words, incentives would have always been calculated based on the peak load shift on the hottest day for a facility, and by design, the 1-in-10 peak day represented those conditions in the building simulation model.

A.3 Building Simulation Runs

Nexant used the building simulation model described in section A.1.1 along with the assumptions discussed in the remainder of appendix A and applied it as the representative building for determining relative usage levels under different conditions. Nexant then estimated cooling load for that building under the following conditions for each LCA:

- 1-in-10 maximum impact utility specific peak day as a proxy for incentive payment calculation conditions; and
- Ex ante weather conditions for each month of the year, for system peak day and average weekday, for 1-in-2 years and 1-in-10 years, for the utility and for CAISO.

A.4 Conversion Factor Calculations

The output from the eQUEST model was the estimated chiller load for each hour of the day under each of the conditions listed in A.3. Since these estimates were for a representative building, they do not necessarily bear any relation to the projected peak shifting values from the enrollment forecast. Nexant then applied the ratio of the eQUEST predicted loads under each set of ex ante conditions to the eQUEST predicted loads under the 1-in-10 peak day—as a proxy for incentive payment calculation conditions. These ratios were used as the conversion factors described in Section 2. To ensure load reductions in the ex ante tables did not exceed the maximum load impact specified under the incentive payment conditions, the conversion factor ratios were restricted to a maximum value of 1.

Table A-3: Summary of Ex Ante Conversion Factors for 1-in-2 and 1-in-10 Monthly System Peak Days (Ratios between peak PLS impact under ex ante conditions and Utility Specific annual maximum 1-in-10 monthly system peak day PLS impact)

Peak Type	Utility	LCA	May		June		July		August		September		October	
			1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Utility Specific	PG&E	All	0.84	0.91	0.91	0.96	0.94	1.00	0.93	0.98	0.91	0.94	0.81	0.84
		Greater Bay Area	0.84	0.94	0.90	0.96	0.93	1.00	0.92	0.98	0.92	0.95	0.82	0.86
		Greater Fresno	0.83	0.85	0.93	0.92	0.96	0.99	0.93	1.00	0.88	0.89	0.80	0.79
		Humboldt	0.80	0.89	0.85	0.95	0.93	1.00	0.95	0.96	0.92	0.95	0.78	0.87
		Kern	0.90	0.71	0.95	0.92	0.94	1.00	0.94	0.98	0.91	0.92	0.81	0.83
		Northern Coast	0.84	0.93	0.91	1.00	0.95	0.98	0.92	0.98	0.91	0.96	0.84	0.88
		Other	0.84	0.92	0.92	0.95	0.95	1.00	0.93	0.99	0.91	0.94	0.80	0.84
		Sierra	0.84	0.90	0.92	0.93	0.93	1.00	0.92	0.95	0.88	0.90	0.77	0.81
		Stockton	0.84	0.90	0.91	0.93	0.96	1.00	0.96	0.97	0.88	0.90	0.74	0.79
	SCE	All	0.81	0.86	0.85	0.91	0.93	1.00	0.93	0.99	0.90	0.97	0.81	0.87
		LA Basin	0.82	0.87	0.85	0.92	0.94	1.00	0.94	1.00	0.92	1.00	0.83	0.88
		Outside LA Basin	0.80	0.82	0.83	0.87	0.92	1.00	0.89	0.96	0.82	0.89	0.75	0.79
		Ventura	0.79	0.83	0.84	0.91	0.92	1.00	0.89	0.96	0.84	0.90	0.78	0.85
	SDG&E		0.74	0.84	0.77	0.83	0.76	0.98	0.85	0.93	0.80	1.00	0.85	0.87
CAISO Specific	PG&E	All	0.84	0.88	0.93	0.93	0.93	1.00	0.88	0.94	0.87	0.90	0.82	0.84
		Greater Bay Area	0.84	0.89	0.93	0.94	0.90	1.00	0.90	0.92	0.85	0.89	0.86	0.84
		Greater Fresno	0.86	0.87	0.90	0.92	0.96	0.99	0.86	0.97	0.88	0.91	0.75	0.83
		Humboldt	0.81	0.83	0.88	0.88	0.88	1.00	0.84	0.93	0.85	0.86	0.79	0.83
		Kern	0.86	0.89	0.94	0.91	0.97	1.00	0.86	0.98	0.90	0.88	0.78	0.85
		Northern Coast	0.80	0.90	0.94	0.93	0.92	1.00	0.87	0.94	0.88	0.92	0.84	0.85
		Other	0.85	0.86	0.92	0.94	0.94	1.00	0.87	0.96	0.87	0.91	0.80	0.86
		Sierra	0.83	0.84	0.90	0.91	0.94	0.98	0.84	0.94	0.85	0.86	0.77	0.82
		Stockton	0.87	0.83	0.92	0.92	0.95	0.98	0.85	0.95	0.87	0.87	0.73	0.80
	SCE	All	0.82	0.87	0.87	0.91	0.99	1.00	0.91	0.98	0.92	0.97	0.80	0.90
		LA Basin	0.82	0.87	0.87	0.92	0.99	1.00	0.92	0.98	0.94	0.99	0.81	0.91
		Outside LA Basin	0.82	0.81	0.87	0.89	0.99	0.99	0.89	0.96	0.86	0.87	0.75	0.83
		Ventura	0.82	0.87	0.88	0.91	0.97	1.00	0.89	0.95	0.90	0.93	0.78	0.85
	SDG&E		0.65	0.88	0.72	0.85	0.81	0.78	0.86	0.90	0.97	1.00	0.77	0.88