

2017 Load Impact Evaluation of the California Statewide Permanent Load Shifting Program

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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]](#footnote-2) There are currently seven installations across the three IOU’s that are currently in place with sufficient data on which to base ex post impact estimates for 2017. As of January 2018, the utilities had a total of 13 active applications, with 7 operational installations. The largest average monthly system peak impact for the three operational projects in SCE’s service territory was XXXXXX. For the single installation in PG&E’s territory, the largest average monthly system peak impact was XXXXX. The largest average monthly system peak impact for the three operational projects in SDG&E’s service territory was 888 kW.[[2]](#footnote-3) The ex ante impact estimates rely on information provided in the applications, along with the ex post analysis for the seven operational installations with sufficient data to improve upon the analysis that was done for the 2016 program year evaluation. Additionally, after Decision 17-12-003, the CPUC decided to phase out the PLS program, which will dramatically reduce the level of uncertainty in the ex ante forecast. Because each of three IOU’s are no longer accepting new applications to participate in PLS, the forecasted number of participants will exclusively be dependent on the number of current installations and applications. For those customers that have already applied and are awaiting approval, their PLS installation will be completed and run for the required 5 years. In 2020 under utility-specific August monthly system peak day 1‑in-10 year weather conditions, the program is projected to deliver XXX MW load impact for PG&E; a XXXXX load impact for SCE; and a 2.1 MW load impact for SDG&E—totaling XXXXXX statewide. 2020 is the last year that new installations are assumed to come online for SCE. The final installations for PG&E are expected to complete in 2019 and in 2018 for those in SDG&E’s territory.

# 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.[[3]](#footnote-4) Currently, there are seven installations with sufficient data on which to base ex post impact estimates for the 2017 program year (PY2017), a sharp increase from the two installations in PY2016. However, while the ex post evaluation is included in this report, a substantial portion of this evaluation focuses on the 2018–2028 ex ante load impact estimates because the ex post results from seven installations are not generalizable due to high variation in data sources and availability, as well external factors affecting performance at each of the different installation locations not captured in the data Nexant received from each of the three IOU’s. 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.

## 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 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; however, it should be noted that while 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 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[[4]](#footnote-5) 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. As of January 2017, the three IOUs have requested incentive funding for the 2017 bridge year, as well as funding for the 2018–2022 program years. For the 2017 bridge year, PG&E requested $2.05M, SCE requested $4.7M,[[5]](#footnote-6) and SDG&E requested $1.3M. For the 2018–2022 program years, PG&E requested $7.5M, SCE requested $5.2M, and SDG&E requested $6.5M. Finally, in 2017 the CPUC voted to end the PLS program, as recorded in Decision 17-12-003.

## Key Considerations for Program Year 2017 Load Impact Forecast

As previously noted, there are currently seven operational PLS installations in place with sufficient data for which ex post impacts can be estimated for PY2017 under the present approved program. While there are important lessons to be learned from evaluating these installations, including comparing the ex post results to peak load reductions from the feasibility study, it is not appropriate to generalize the findings from these sites to the rest of the PLS program as there are significant differences between sites’ data availability and quality, PLS performances, and external variables specific to each location. 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.[[6]](#footnote-7) 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 seven operational customers in conjunction with information in these pipeline applications to improve upon the analysis that was done for the PY2016 evaluation. Nonetheless, this year’s forecast still relies on numerous assumptions about how expected PLS load shifting changes under various weather conditions for sites which are not yet operational, which has 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, this forecast may not reflect the load impacts that the PLS program ultimately delivers.

The current PLS program design specifies the data to be collected from participants to optimize TES system performance and to enable load impact evaluation. These measurements were the basis for the ex post and ex ante impact evaluations for operational sites and will be used increasingly as more projects come online. For this evaluation, ex ante estimates rely, in part, on information contained in the feasibility studies and applications submitted by the beginning of 2018 in addition to the ex post analyses.

The 2017 CPUC decision to phase out the PLS program will significantly reduce the level of uncertainty in the ex ante forecast associated with future program enrollment as no new applications are being accepted. Customers that have already applied will be allowed to complete their PLS installation and are required to operate the equipment for 5 years..

## 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[[7]](#footnote-8) 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.

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.[[8]](#footnote-9) PLS program participants are also encouraged to shift load during non-summer months if doing so maximizes their energy bill savings.

Table ‑: 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 |

## Current PLS Program Status

Table 1‑2 provides the PLS program status as of January 2018 by utility and by stage in the PLS application and verification process. Combined, the 3 IOUs have 7 operational installations and 13 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 13 customers successfully install a PLS-TES system, these future installations combined with the 7 operational installations are projected to provide XXXX XX of total load shift, resulting in incentives of almost $13.0 million being spent across the three utilities. However, as these customers move through the verification process, the actual load shift amount is likely to change, so the XXXXXXX total load shift amount is simply an indicator based on the most recently available information. For example, SCE has received a total of 21 applications to date, but 12 applications have been withdrawn or deemed ineligible. One project has been operational since 2015 and a second project was installed in 2016; the third installation was completed in 2017 and 6 operations are in progress. Excluding the current installation, PG&E has received 6 applications, which consists of four that have been approved, one that is awaiting approval, and one application that has since been withdrawn. Of the four applications that have been approved by PG&E, one was installed as of May 2016 but has yet to submit their commissioning report, two are waiting for the IOU to conduct the pre-installation inspection and set aside incentive funds, and the remaining one is waiting for the utility to complete the feasibility study review. SDG&E has received 8 applications, but 3 have been withdrawn as of January 2018. Three installations have been completed to date and received incentives, and two installations are expected to come online in 2018. 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 to seven time-consuming stages between 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 eight 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.

Table ‑: PLS Program Status by Utility and Stage in Verification Process  
 (as of January 2018)

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 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 | 1 | XXXXXXXX | XXXX | 0 | - | - | 0 | - | - |
| 2 | Customer submits feasibility study | 0 | - | - | 0 | - | - | 0 | - | - |
| 3 | IOU reviews feasibility study and approves application | 1 | XXXXXXXX | XXXX | 2 | XXXXXXXX | XXXX | 0 | - | - |
| 4 | IOU conducts pre-installation inspection and sets aside incentive funds | 2 | XXXXXXXX | XXXX | 0 | - | - | 0 | - | - |
| 5 | IOU and customer sign agreement (SCE only) | 0 | - | - | 0 | - | - | 0 | - | - |
| 6 | Customer submits project design and installs PLS-TES system | 1 | XXXXXXXX | XXXX | 4 | XXXXXXXX | XXXX | 2 | $ 733,775 | 838.6 |
| 7 | Customer submits commissioning report | 0 | - | - | 0 | - | - | 0 | - | - |
| 8 | IOU reviews commissioning report and conducts post-installation inspection, tests and cost verifications | 0 | - | - | 0 | - | - | 0 | - | - |
| 9 | Customer receives final PLS program incentive | 1 | XXXXXXXX | XXXX | 3 | XXXXXXXX | XXXX | 3 | $ 1,854,667.5 | 1,631.09 |
| **Total** | | **6** | XXXXXXXX | XXXX | **9** | XXXXXXXX | XXXX | **5** | **$ 2,588,442.50** | **2,469.69** |

## Report Organization

The remainder of this report proceeds as follows. Section 2 summarizes the methodology for the ex post evaluation. Sections 3.1, 3.2, and 3.3 provide the ex post load impact estimates for SCE, PG&E, and SDG&E, respectively. Section 4 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. Finally, Section 7 includes recommendations for future evaluations.

# 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,[[9]](#footnote-10) 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, where U.S. gallons per minute (USgpm) denotes the unit to describe the water flow and water supply and return temperatures are measured in degrees Fahrenheit (°F);
* Cooling Tons = Flow (USgpm) × (oFin-oFout)/24
* Calculate the coefficient of performance (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/h)
* 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. Various model specifications are tested using standard regression diagnostics (e.g., accuracy metrics such as root-mean-square error, average percent error, adjusted R2, etc.), including out-of-sample testing;
* Use the regression model to estimate (i.e., the ratio of cooling tons to cooling system usage) for each hour of the summer based on the OAT observed during the post-TES installation period;
* Use the estimated and the observed post-installation cooling tons to estimate baseline cooling usage for each hour of the summer;
* , 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.

In developing the ex post methodology, one consideration was to simply estimate a baseline model of electric usage as a function of temperature; however the two-step process described above—estimating COP as a function of temperature and using the estimated values and the observed cooling tons to calculate baseline cooling usage—is a more accurate and transparent method. While directly estimating electric usage as a function of temperature would work and may potentially serve as a useful corroboration exercise, the proposed method will be more accurate in the ex post setting because a direct model of electric usage as a function of temperature would effectively ignore information provided from directly measuring post-installation cooling tons. The cooling tons provide valuable information about how hard the cooling system is working, and they are not perfectly correlated with temperature. Thus, using a model that excludes cooling tons would introduce an additional and unnecessary source of variance into the results.

In the 2015 and 2016 evaluations, there were data collection challenges at the only operational site installed in SCE’s territory. 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,[[10]](#footnote-11) 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 does not fully take advantage of 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.

This year, the methodology described above leveraging operational data was used to estimate the ex post impacts for the single PG&E installation. Since all three SCE installations only have post-installation data, the same methodology based on the premise level interval meter data used in the 2015 and 2016 evaluations was used to estimate the customer’s ex post impacts for this year’s evaluation. For the three operational sites within SDG&E’s service territory, a variety of data sources were used to calculate ex post impacts at each of the sites. These sources include operational data, premise level meter data, and operational data from select test days at one of the installation sites. The variation in data required differing analyses for each of the three installations, with the aggregate impacts being determined after the contrasting analyses were completed.

## PG&E Ex Post Model Selection

Since a complete panel of operational data was available for the PG&E installation, Nexant used the methodology described in Section 2. The operational data collected by the customer included:

* 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.

The data was collected over the three month pre-TES installation period spanning July to September 2015. The customer installed the TES system sometime in May 2016, and post‑installation data spanned May through October 2017

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, where U.S. gallons per minute (USgpm) denotes the unit to describe the water flow and water supply and return temperatures are measured in degrees Fahrenheit (°F)
  + Cooling Tons = Flow (USgpm) × (oFin-oFout)/24
  + Calculate the coefficient of performance (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/h)
* 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. Various model specifications are tested using standard regression diagnostics (e.g., accuracy metrics such as root-mean-square error, average percent error, adjusted R2, etc.), including out-of-sample testing.
* Use the regression model to estimate (i.e., the ratio of cooling tons to cooling system usage) for each hour of the summer based on the OAT observed during the post-TES installation period.
* Use the estimated and the observed post-TES cooling tons to estimate baseline usage for each hour of the summer.
* , 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.

The model selection process is summarized as follows:

1. Identified 12 days from the pre-installation period, July through September 2015 (4 days from each month) with the highest average noon to 6 PM cooling load to use as peak load days prior to the TES installation for out-of-sample testing.
2. Estimated 13 different regression models and used them to predict out-of-sample for the peak load days identified in step 1. This allowed for identification of 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.

While different model specifications were tested for PG&E, the overall ex post model selection process was identical to that used to select the model for SCE that was based on premise meter data and described in Section 2.1. 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:

Table 2-1: Description of Regression Model Variables

| Variable | Definition |
| --- | --- |
| kWt | Average hourly demand (kW) for each time period |
| A | Estimated constant term |
| Bij through Di | Regression model parameters |
| Houri | 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 |
| DOWj | Series of binary variables representing weekdays (Mon-Fri); weekends and holidays are excluded from the model |
| Monthj | Series of binary variables for each month designed to reflect seasonality in loads |
| Mean17t | Mean17—the average temperature between midnight to 5 PM |
| et | Error term |

The regression model specified above use the observed temperatures in the post-installation period to estimate ex post COP. The estimated COP was combined with the observed ex post cooling tons to calculate baseline usage, as described in the methodology above. Because the pre-installation data spanned July through September and generally represented higher temperatures, the model estimated very small, but nonzero values of hourly COP for cooler temperatures during the post-installation period. Since the baseline usage is calculated as the ratio between the observed post-installation cooling tons and the estimated COP, these very small, nonzero estimates of COP caused the estimates of baseline usage to approach infinity. In order to create upper bounds on the baseline usage, the estimated values of COP were replaced with zero for the hours between 11 PM and 8 AM, which is consistent with the observed COP values in the pre-installation data. In order to create a continuous load profile, in every hour where the COP was zero, the cooling load was replaced with the average baseline cooling load from the pre-installation period.

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. It should be noted the peak usage for the customer didn’t always align with PGE’s monthly system peak day each month. Additionally, because the COP calculation relied on the presence of multiple variables, including total cooling system load and chilled water temperature and rates, impacts could only be determined for hours with all input variables present. For two system peak days, June and August, the data was incomplete. Accordingly, the second highest system peak days were reported in the ex post table impact generator.

## SCE Ex Post Model Selection

This year, SCE had three installations that were analyzed by Nexant. All of the installations were analyzed separately using premise-level data and then the results were combined at the end. The same model specification used in 2016 was used to estimate the 2017 ex post impacts for the SCE installation that was evaluated in 2016. The 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. For two of the three locations, Nexant received two channels of data: “Delivered” and “Received.” After discussions with SCE’s contracted engineering firm responsible for managing meter data one of the locations, Nexant determined that the received meter is offloading some demand from the main meter (“delivered”), and the received meter is not an “outbound” meter. From our combined analysis, it appears as though the generation is being metered individually. For the second site, the “Received” data was dropped from the analysis as nearly all observations (99.96% of observations) were zero. In contrast, to analyze impacts for the third customer location and calibrate an energy model for the campus, the combined consumption on both meters was utilized (received kilowatts plus delivered kilowatts). However, to verify that the facility has enough demand on the grid at any time to substantiate the approved kilowatt load shift, only the main meter (delivered) was used.

To construct the model, at least two years of data were used for estimation— ranging from January 2013 through December 2017. The first site became operational in March 2015, resulting in approximately two years of pre-TES installation data and two years 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. The second site became operational in August 2016, resulting in approximately 2 years of pre-TES installation data from January 2014 through October 2017 and one year of post-TES installation data. July 2016 was excluded from the analysis to allow for the installation and testing period to not influence model estimation. The third site became operational in in March 2017, resulting in approximately three years of pre-installation data from January 2014 through March 2017. For the third site, on-site generation made the average daily loads inconsistent between the three pre-installation years. To make sure that the pre-installation data conditions were as similar to the post-installation data as possible, only 2016 summer data was used for the analysis. This resulted in 4 months of pre-installation data and 4 months of post-installation data being used for analysis.

Many model specifications were systematically evaluated via out-of-sample testing, 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 the pre-installation data (5 from each year or 10 from 1 year depending on available data) 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 was 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 candidate models, conduct LOOCV over peak load days:
   1. For each of the peak load days:
      1. Develop explanatory variables using data from all peak load days except the;
      2. Fit model using explanatory variables and predict load based on the observed characteristics of the day;
      3. Record predicted load and actual load on the 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 2-2 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 2-2: Control Group Accuracy Statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Statistic Type | Statistic Level | Statistic | Formula | Description | Typical Values |
| Bias | Program | Average Percent Error |  | 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) |  | 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 |  | 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:

* - observed kWh
* - predicted kWh
* - customer
* - each individual peak load day

- 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. An example of the final model and its associated explanatory variables are summarized below. The models for the other customers can be found in Appendix A.

Mathematically, the regression can be expressed by:

Table 2-3: Description of Regression Model Variables

| Variable | Definition |
| --- | --- |
| kWt | Average hourly demand (kW) for each time period |
| A | Estimated constant term |
| Bij through Ji | Regression model parameters |
| Houri | 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 |
| DOWj | Series of binary variables representing weekdays (Mon-Fri); weekends and holidays are excluded from the model. Energy use immediately before or after a weekend may be different compared to load in the middle of the week |
| Monthj | Series of binary variables for each month designed to reflect seasonality in loads |
| CDDt | 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 |
| CDDsqrt | The square of Cooling Degree Day |
| CDHt | Cooling Degree Hour—the max of zero and the hourly temperature value less a base value of 60°F |
| CDHsqrt | The square of Cooling Degree Hour |
| Summert | Binary variable reflecting the summer months of July through October |
| PLSt | Binary variable reflecting when the TES system is operational |
| et | Error term |

To estimate the 2016 ex post load impacts, a regression model such as the one specified in the above equation was applied to premise meter data from 2017, specifically to the summer months (June 1–September 30) the customer was required to shift load. Nexant conducted an additional analysis to refine the base temperature used to calculate the cooling degree day and cooling degree hour variables. Based on the results of testing the correlation between several base temperatures (50°F to 70°F in increments of five degrees) and pre-installation period load data, a base temperature of 60°F was chosen for both cooling degree days and cooling degree hours, compared to the base temperature of 55°F used in the 2015 evaluation.

## SDG&E Ex Post Model Selection

This year, SDG&E had three operational customers enrolled in the PLS program. Each customer was analyzed separately using a different methodology and then the results of the three analyses were combined.

The first customer was analyzed last year after the April 1 filing and presented several data problems. After determining that there was no change in the customer’s status from the previous year, Nexant used the same methodology as last year to estimate the ex post impacts for its first customer, outlined below.

The first customer’s installation in SDG&E’s territory presented several challenges to estimating ex post impacts. Records from SDG&E indicate the building with the TES installation changed owners or tenants around the time of the installation. This makes it difficult to find pre-installation data that can be used to generate a reference loads for comparison with observed premise meter data during the post-installation period. Additionally, the building is only partially occupied, so the TES system is not being run at full capacity. This makes it difficult to detect the PLS signature in the premise meter data, as the TES system is being run below the maximum incentivized capacity of 306 kW. In this situation where the PLS signature is small relative to the base load, it is ideal to use operational data directly from TES system; however, the building conducts classified[[11]](#footnote-12) activities, which limited the access of the third-party contractor to collect operational data and conduct operational tests.

In order to demonstrate system performance and calculate the final incentive amount for this customer, the third-party contractor ran the fully charged TES system to depletion on two test days, June 8 and June 9, 2016, and recorded the total ton-hours.[[12]](#footnote-13) The total ton-hours were divided by the seven hour load-shifting period (11 AM to 6 PM) to calculate the average tons the TES system would shift during the on-peak period. The maximum average on-peak tons measured over the two test days was 255 tons, or 306 kW (255 tons \* 1.2 kW/ton = 306).

Given the TES system’s small signature in the premise meter data, the lack of pre-installation premise data for the current customer, and the lack of operational data, Nexant identified approximately 10 proxy days each from June 2014 and non-test days in June 2016 based on similar weather conditions. Proxy days were selected based on their similarity to each test day based on mean17, overnight cooling degree hour (CDH),[[13]](#footnote-14) and cooling degree day (CDD).[[14]](#footnote-15) A simple propensity score model was used to calculate the likelihood that a proxy day had the same weather conditions as the test days. The model was run separately for each test day and each weather metric. Each run identified up to 10 nearest neighbor matches from the group of weekdays in June 2014 and the non-test weekdays in June 2016. The final 2014 and 2016 proxy days were selected if the day was identified as a top ten match across two of the three weather metrics. Figure 2‑1 shows a side-by-side comparison of the average 2014 and 2016 proxy day loads with the observed load on the June 8 test day. Figure 2‑2 shows the same set of graphs for the June 9 test day.

Figure ‑: Average 2014 and 2016 June Proxy Days and Observed Load –

June 8, 2016 Test Day

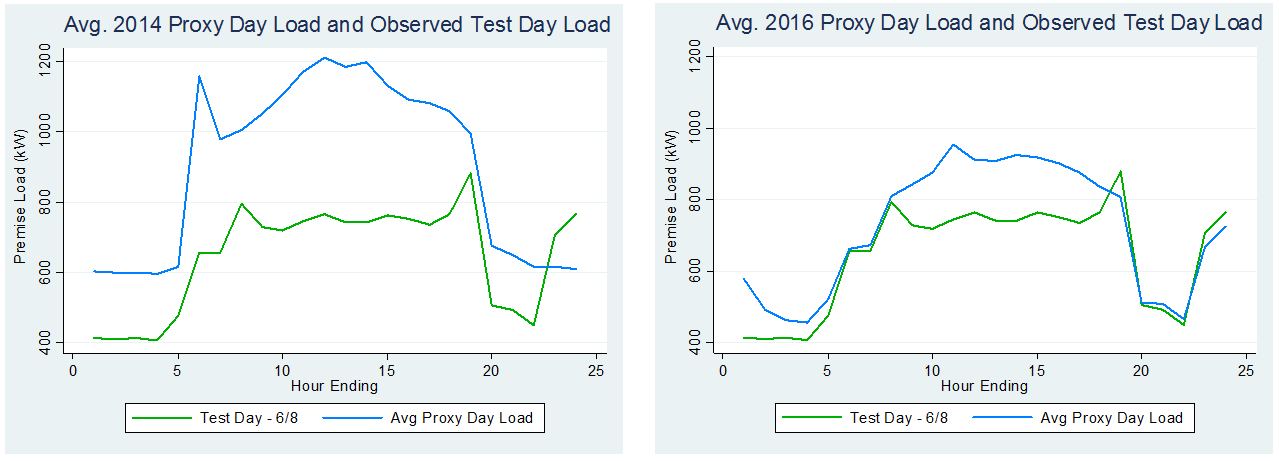
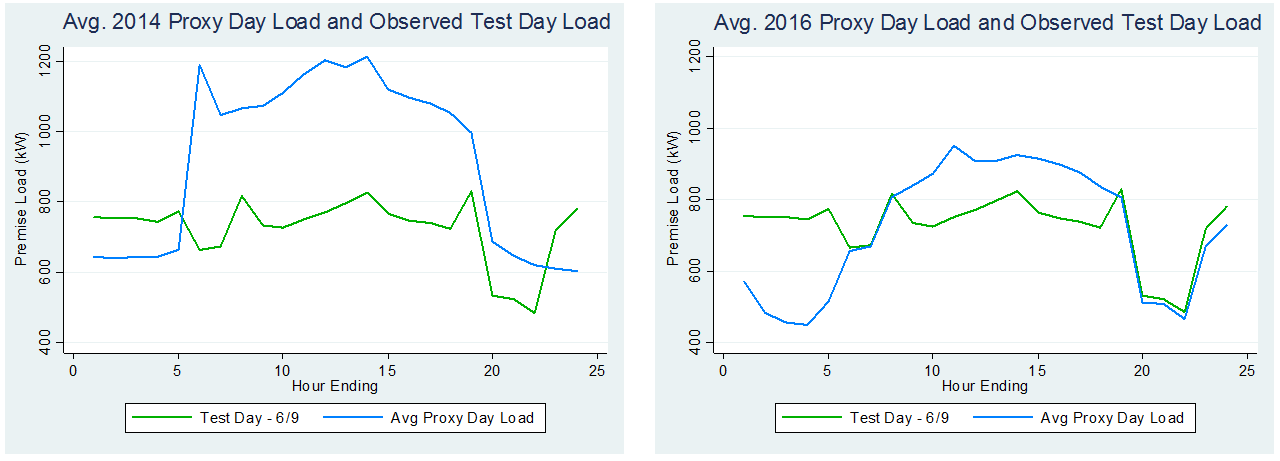


Figure ‑: Average 2014 and 2016 June Proxy Days and Observed Load –

June 9, 2016 Test Day



The difference between the reference and observed loads using the average 2014 and 2016 proxy days represent the upper and lower bounds of the load shift, respectively. The range for the average on-peak shift for the June 8 test day is 146.3 kW to 384 kW and 129.5 kW to 369.5 kW for the June 9 test day.

The reference load for the average 2014 proxy day is assumed to represent the pre-installation load for the current customer if the building were fully occupied. Given the similarity in load shapes during the off-peak periods for the test days and 2014 proxy days, it is reasonable to assume that the 2014 proxy days represent the typical pre-installation premise loads for the current customer. The 2016 proxy days were selected to generate a lower bound on the impact estimates. Since the customer is not currently running the TES system to its full capacity, it is reasonable to assume that the load on similar, non-test days represent the typical load profile for the customer under the limited occupancy conditions.

The final ex post impact is calculated using the average of the 2014 and 2016 proxy day loads for each test day and for an average test day.

For the second and third customer’s installation 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.

To construct the model for the second customer, at least four years of premise-level data were used for estimation. The first site became operational between January and May 2016, resulting in approximately two years of pre-TES installation data and two years of post-TES installation data. The time from January 2016 through May 2016 was excluded from the analysis to allow for the installation and testing period to not influence model estimation.

For the third customer, Nexant was unable to use premise-level data for the ex post analysis because additional buildings had been added after the time of the pre-installation data, and therefore the load shape had changed too much to separate out the impact of the PLS system. Because of this, Nexant used operational data for the analysis. This means that the aggregate impact of the PLS system includes both premise-level data and end-use data, and so the percent impact of the PLS system is not well defined because the data type is not consistent across all three sites.

The operational data for SDGE’s third customer presented several data challenges. Pre-installation data indicated that the cooling system had three chillers, but one of the chillers was not being used at full capacity during the 2012-2013 time interval in which Nexant was provided with pre-installation data. To ensure only the PLS system impact was captured in the analysis, Nexant excluded the third chiller from the analysis, since its use had changed independently of the installation of the PLS system. Nexant was also provided with auxiliary load in pre-installation data, but not in the post-installation data, and so was not able to include auxiliary data in the analysis. Therefore, Nexant analyzed the impact of the PLS system on two of the customer’s chillers. The chiller load was given the same treatment as premise-level load in the model selection and analysis.

The customer’s operational data for July also only included five days that could be used for analysis. Of these five days, two days had a significantly higher load than all other post-operational data provided. In order to prevent these outliers from influencing the monthly predictions in the ex ante analysis, Nexant created a model that estimated impacts without including the month as a variable.

To construct the model for the third customer, twelve months of data were used for estimation—April 2012 through July 2012, April 2013 through July 2013, and April 2017 through July 2017. The other months were excluded from the analysis because Nexant did not receive post-installation data for the other months. The site became operational October 2016, resulting in approximately eight months of pre-TES installation data and four months of post-TES installation data.

For both customers, 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 model selection process is summarized as follows:

1. Identified 10 days from 2012 and 2013 (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 was 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 candidate models, conduct LOOCV over peak load days:
   1. For each of the peak load days:
      1. Develop explanatory variables using data from all peak load days except the;
      2. Fit model using explanatory variables and predict load based on the observed characteristics of the day;
      3. Record predicted load and actual load on the 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 2-4 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 2-4: Control Group Accuracy Statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Statistic Type | Statistic Level | Statistic | Formula | Description | Typical Values |
| Bias | Program | Average Percent Error |  | 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) |  | 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 |  | 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:

* - observed kWh
* - predicted kWh
* - customer
* - each individual peak load day

- 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:

# Ex Post Impact Estimates

## PG&E Ex Post Impacts

The single installation in PG&E’s territory was installed in May 2016 and is located in XXXX XXX. The installation site comprises a single, mixed-use industrial building that houses office, manufacturing, warehouse, and laboratory facilities and totals over XXXXX square feet. Coincident with the PLS installation, the customer also installed a solar generation system, which makes it impossible to estimate the ex post impacts from the PLS TES installation based on premise level meter data without additional information about the customer’s solar generation profiles. Since this information was unavailable, Nexant used the operational data from the TES system to estimate a relationship between the coefficient of performance (i.e., the ratio of cooling tons to cooling system load) and temperature.

The PLS program is designed to shift cooling load using the TES system during the on-peak summer hours (12 to 6 PM May through October) rather than reduce overall cooling load. Figure 3‑1 shows the cooling system load for the average August weekday during the pre- and post-installation periods. The figure clearly shows the load shift occurring during the post-installation period where the load from approximately HE 13 to HE 19 drops to XXX kW compared to approximately XXX kW for the same period in the pre-installation period. Additionally, the graph shows an expected increase in post-installation cooling load during the nighttime and early morning hours as the system is recharging and creating ice for cooling during the day. While Figure 3‑1 does not take into account day-to-day variation or the relationship between cooling load, cooling tons, and temperature, it provides the average load shapes and the order of magnitude of load impacts we would expect to see in the post-installation period.

Figure ‑: Comparison of Pre- and Post-installation Cooling System Load for the Average August Weekday



Figure 3‑2 shows the results of the best model from the out-of-sample testing from the model selection process averaged across the 12 peak load days in the pre-installation period that were used for out-of-sample testing.[[15]](#footnote-16) The average predicted hourly COP from the model is shown in blue, and the actual COP averaged across the 12 peak load days is shown in green. 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 the hourly variation of COP and that the estimation is only for a single customer, the model appears to predict COP relatively well. The difference between the predicted and observed COP is fairly balanced between being positive and negative over the course of the average peak load day; however, the model consistently overestimates COP during the program operational hours (noon to 6 PM). Assuming accuracy in the measured post-installation cooling ton data, this will have the effect of slightly underestimating baseline usage, defined as ratio of the observed cooling tons to the estimated COP, and consequently underestimating ex post impacts. The difference between the predicted and observed COP is captured by the modeling estimation process, and is later reflected in the confidence intervals around the load impact estimation.

**Figure 3‑2: Average Predicted & Observed COP across the Peak Load Days Iteratively Withheld for Out-of-sample Testing**



The final driver of estimated ex post baseline cooling load is the observed cooling tons for the post-installation period.

Figure 3‑3 through Figure 3‑5 show the average observed cooling tons and cooling load in the pre-installation period compared to the observed cooling tons and estimated cooling load for the overlapping post-installation period. The figures clearly show a marked increase in average cooling tons in the post-installation period, which consequently drives higher baseline cooling loads on average. The figures also demonstrate a change in the building’s cooling capacity needs from the pre- to post-installation period.

Figure ‑: Comparison of the Pre- and Post-installation Cooling Tons and Baseline Cooling Load for the July Average Weekday



Figure ‑: Comparison of the Pre- and Post-installation Cooling Tons and Baseline Cooling Load for the August Average Weekday



Figure ‑: Comparison of the Pre- and Post-installation Cooling Tons and Baseline Cooling Load for the September Average Weekday

Figure 3‑6 shows the ex post load impact table for the August system peak day, which shows an average load shift of XXXX kW. According to the customer’s feasibility study, the TES system would provide a maximum load shift of approximately XXX kW. It should be noted that the estimated reference load, with a maximum value of over XXXXX kW occurs in hour ending 17 exceeded all previously observed hourly load values from the pre-installation period. While the average temperature between midnight and 5 PM, also known as mean17,[[16]](#footnote-17) was within the range of values observed during the pre-installation period,

Figures 3‑3 through 3-5 indicate the building’s cooling capacity needs differed from the pre- and post-installation period. One explanation could be that the previous cooling system wasn’t being used at full capacity under the conditions captured in the three months of pre-installation data. Consequently, it is entirely plausible that the estimated reference load reflects what would have occurred in the absence of the PLS system.

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 largest hourly load shift on the August system peak day shown in Figure 3‑6 was XXXX kW, which occurred in hour ending 17. The upper and lower bounds of the 90% confidence interval are XXXXX kW and XXXX kW, respectively. This range represents the point estimate of the load impact plus or minus 38%. Most demand response load impact evaluations exhibit much narrower confidence intervals; however, that is also the result of including hundreds or thousands of customers in the estimation process. Confidence intervals for a single customer will always be relatively wide compared to regression estimates from a larger population. In this case, the confidence intervals are also quite wide relative to other regression estimates because the regression model estimates COP, so the variance is captured at the COP estimate level. In order to calculate baseline cooling load, the observed cooling tons are divided by the estimated COP. Consequently, the estimated variance must also be scaled to reflect the uncertainty of the baseline usage in kWh. The scaled variance is proportional to the cooling tons, the original variance from the COP estimation, and the inverse of the estimated COP to the fourth power. As many of the COP estimates are less than one, the above relationship drives the large confidence intervals. It should also be noted that the confidence interval is narrower when observing results for the average weekday versus the monthly system peak day. This is due to having approximately 20 average weekday observations for the estimation whereas there is only a single monthly system peak day.

Figure ‑: Ex Post Load Impact Table—August Monthly System Peak



Table 3‑1 compares the monthly system peak day impact with the average weekday impact estimated for each month. The average impact across the peak hours and the maximum hourly impact are also presented. The August monthly system peak saw the highest impacts with an average shift of nearly XXXX kW and an hourly maximum of almost XX MW. Because PLS is not an event based program and the TES system runs at all hours during the program operational months, the average weekday impacts are more indicative of the day-to-day usage. The highest average weekday impact of XXXX kW was observed in July. The largest difference in the maximum hourly impact between the average weekday and the system peak day occurred in May and was XXXX kW, or approximately XX%.

Table ‑: Comparison of Monthly System Peak Day[[17]](#footnote-18) and Average Weekday Impacts

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Month** | **Monthly System Peak Day (kW)** | | **Average Weekday (kW)** | |
| **Average Hourly Impact** | **Maximum Hourly Impact** | **Average Hourly Impact** | **Maximum Hourly Impact** |
| May | XXXX | XXXX | XXXX | XXXX |
| June | XXXX | XXXX | XXXX | XXXX |
| July | XXXX | XXXX | XXXX | XXXX |
| August | XXXX | XXXX | XXXX | XXXX |
| September | XXXX | XXXX | XXXX | XXXX |
| October | - | - | XXXX | XXXX |

### Comparison between 2016 and 2017 Ex Post Results

The average weekday impacts were very comparable between 2016 and 2017. In 2016 the average hourly impacts across July and August was XXXX kW. The similarly calculated value for 2017 was XXXX - which was nearly identical.

## SCE Ex Post Impacts

There were three PLS installations within SCE’s territory available to be evaluated for PY2017. The first PLS installation in SCE’s service territory was completed in 2015 and is located near the coast in the city of XXXXXXXX. It is comprised of two, multi-story office buildings totaling over XXXXXX square feet of office space. The second PLS installation, completed in 2016, was installed inside a XXXXXXXXXXXXXXXXXXX In total, the XXXXXX consists of XXXXXX gross square feet, of which XXXXXX square feet are assignable (ASF). Facility cooling currently consists XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX XXXXXX. The feasibility study lists that XXXXXX XXXXXX XXXXXX square feet are served by the central plant. The third PLS installation was completed in 2017 and is also comprised of a XXXXXXXXXXXXXXXXXXXXXXXXXXXX. The campus consists of XXXXXX Assignable Square Feet (ASF). XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

For the first site, the same model specification used in 2015 and 2016 was used to estimate the 2017 ex post impacts. A detailed explanation of the model selection process and the performance of the selected model was included in the 2015 load impact evaluation report.[[18]](#footnote-19) The detailed approach to the analysis for the second two sites is covered in the methodology section. At a high level, premise level data was analyzed in a manner similar to the first site.

Figure 3‑7 shows the aggregated ex post load impact table for September system peak day, which experienced the highest average load shift of XXXXX kW. 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 largest hourly load shift on the September system peak day shown in Figure 3‑7 was XXXXX kW which occurred in hour ending 16, the middle hour of the operational load shifting period. The upper and lower bounds of the 90% confidence interval are XXXXX kW and XXXXX kW, respectively. This range represents the point estimate of the load impact plus or minus 17%. Most demand response load impact evaluations exhibit much narrower confidence intervals; however, that is also the result of 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. Similarly, Figure 3-8 shows the average customer ex post load impacts for the September peak day, which experienced the highest load shift of XXXXX kW. The largest hourly load shift on the September system peak day shown in Figure 3-8 was XXXXX kW which occurred in hour ending 16, the middle hour of the operational load shifting period. The upper and lower bounds of the 90% confidence interval are XXXXX kW and XXXX kW, respectively

Figure ‑: Ex Post Load Impact Table—Aggregate September Monthly System Peak Day



Figure ‑8: Ex Post Load Impact Table—Average Customer September Monthly System Peak Day



Table 3‑2 compares the monthly system peak day aggregate impact with the average weekday impact estimated for each month the customer is required to shift load (June 1 to September 30). The average impact across the peak hours and the maximum hourly impact are also presented. The September monthly system peak saw the highest impacts with an average shift of nearly XXXXX kW and an hourly maximum of over XX MW. Because PLS is not an event based program and the TES system runs at all hours during the program operational months, the average weekday impacts are more indicative of the day-to-day usage. The highest average weekday impact of XXXXX kW was observed in September. The largest difference in the maximum hourly impact between the average weekday and the system peak day occurred in June and was XXXXX kW, or approximately 48%.

Table ‑: Comparison of Monthly System Peak Day and Average Weekday Impacts

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Month** | **Monthly System Peak Day (kW)** | | **Average Weekday (kW)** | |
| **Average Hourly Impact** | **Maximum Hourly Impact** | **Average Hourly Impact** | **Maximum Hourly Impact** |
| June | XXXXXX | XXXXXX | XXXXXX | XXXXXX |
| July | XXXXXX | XXXXXX | XXXXXX | XXXXXX |
| August | XXXXXX | XXXXXX | XXXXXX | XXXXXX |
| September | XXXXXX | XXXXXX | XXXXXX | XXXXXX |

### Comparison between 2016 and 2017 Ex Post Results

The significant enrollment increase from a single customer up to three customers between 2016 and 2017 limits the value of comparing impacts between the program years. The 2017 ex post impacts are significantly larger, as would be expected. However, year over year comparison won’t be meaningful until the enrolled population is stable.

## SDG&E Ex Post Impacts

There were three PLS installations within SDG&E’s territory that were available for evaluation this year. The first installation in SDG&E’s territory was installed in March 2015, however due to the ownership change for the building and its classified status, the final post-installation activities and commissioning report were not completed until spring 2016. The installation is located in San Diego, and the installation site comprises a single building that is part of a larger office park. The second installation was installed in May 2016, and is comprised of a 40,000 square foot laboratory facility. The third installation was installed in October 2016 and is comprised of a 10,350 square foot building that is part of a college campus located in San Diego.

Due to a lack of post-operational data, the results for the 2017 evaluation only include all three utilities in the average June weekday results. Two customers are included for the months of April through July for both average weekdays and monthly system peak days, and one customer is included in all of the result months. Figure 3-9 shows the aggregate ex post load impact table for an average June weekday where all three customers are included. An average June weekday experienced an aggregate load shift of 899 kW and a maximum hourly load shift of 934 kW occurring in hour ending 14. The load impact is likely larger in the hotter peak summer months, but the data availability challenges limit what can be reported in the ex post section of the report. Modeling techniques will be applied for the ex ante analysis that help to reflect the full load shifting potential of the program during the months not included in the ex post.

The upper and lower confidence intervals on the graph (green dashed lines) represent the uncertainty around the load impact estimate. The upper and lower bounds of the 90% confidence interval are 1,076/]p[ kW and 793 kW, respectively. This range represents the point estimate of the load impact plus or minus 18%. Similarly, Figure 3-10 shows the ex post load impact for the average customer on an average June weekday. On an average June weekday the average PLS customer experienced a load shift of 300 kW and a maximum hourly load shift of 311 kW during hour ending 14. The upper and lower bounds of the 90% confidence interval are 359 kW and 264 kW, respectively.

Figure 3-9: Aggregate Impact June Average Weekday

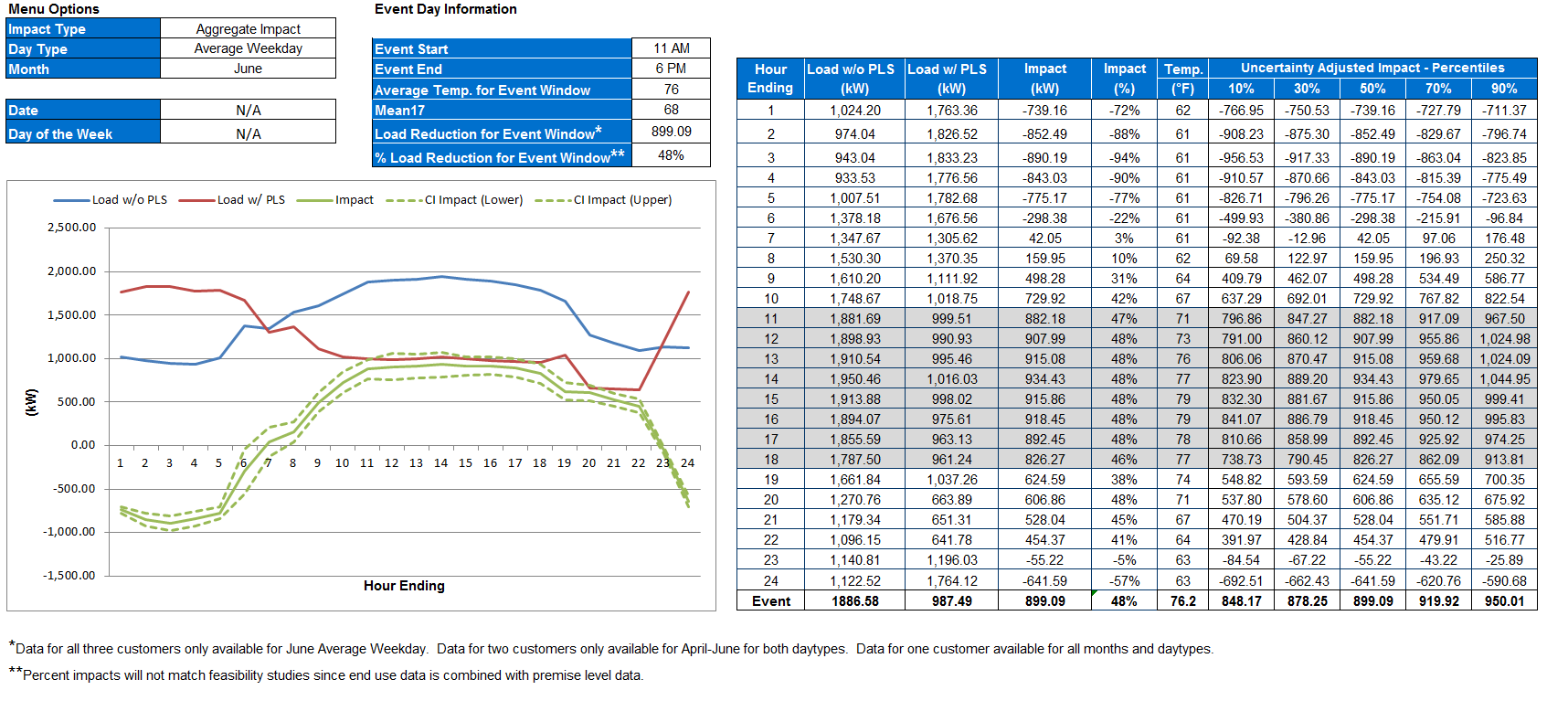


Figure 3-10: Average Customer Impact June Average Weekday

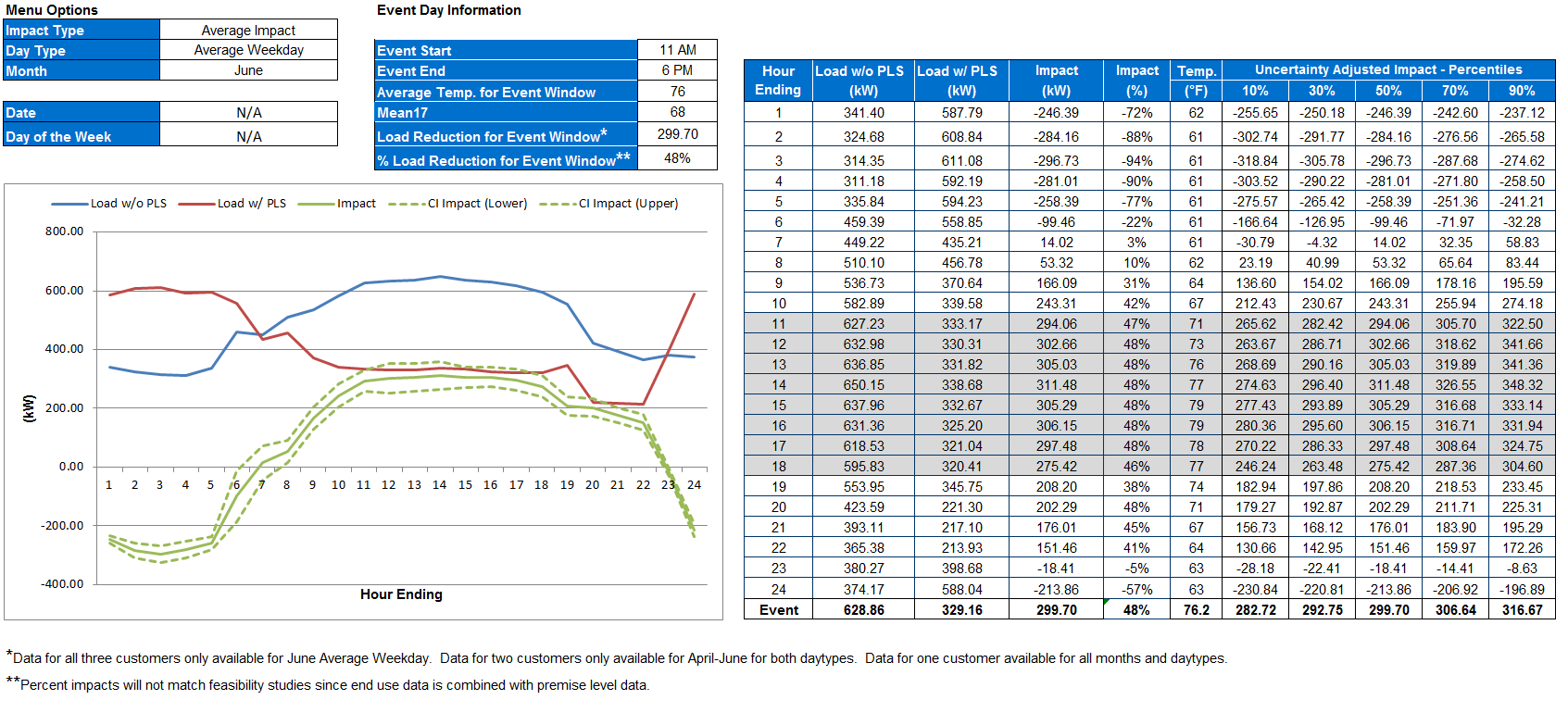


Table 3-3 compares the monthly system peak day aggregate impact with the average weekday impact estimated for each month the customer is required to shift load (June 1 to September 30). The average impact across the peak hours and the maximum hourly impact are also presented. The July monthly system peak saw the highest impacts with an average shift of 1,100 kW and an hourly maximum of 1,134 kW. Because PLS is not an event based program and the TES system runs at all hours during the program operational months, the average weekday impacts are more indicative of the day-to-day usage. The highest average weekday impact of 899 kW was observed in June. It should again be noted that only June average weekdays represent all three customer loads, and August and September only represent the load impacts of one customer.

Table ‑3: Comparison of Monthly System Peak Day and Average Weekday Impacts (aggregate)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Month** | **Monthly System Peak Day (kW)** | | **Average Weekday (kW)** | |
| **Average Hourly Impact** | **Maximum Hourly Impact** | **Average Hourly Impact** | **Maximum Hourly Impact** |
| June | 934.67 | 1,089.18 | 899.09 | 934.43 |
| July | 1,101.81 | 1,134.65 | 652.77 | 715.11 |
| August | 151.19 | 259.06 | 137.57 | 189.11 |
| September | 132.17 | 280.23 | 156.09 | 197.37 |

### Comparison between 2016 and 2017 Ex Post Results

The significant enrollment increase from a single customer up to three customers between 2016 and 2017 limits the value of comparing impacts between the program years. The 2017 ex post impacts are significantly larger, as would be expected. However, year over year comparison won’t be meaningful until the enrolled population is stable.

# Ex Ante Methodology

The statewide PLS program currently has 13 applications in the pipeline and 7 program-funded TES installations have been completed that allowed 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. Because the PLS program is no longer open to new applications, there is little uncertainty about the number of future installations that will come online. Accordingly, Nexant relied on the expected peak load reduction and timing of when projects would become operational from the current application pipeline in combination with the ex post results from the operational installations to produce ex ante load impact estimates for the PY2017 PLS evaluation.

A concise summary of assumptions that drove the PY2017 evaluation by utility is provided in Section 5 in order to be as transparent as possible. 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.

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

* **Operational**—customers with installed and operational PLS systems; and
* **Identified**—those for which customers have completed an application or feasibility study.

In past years, Nexant has analyzed impacts for both identified projects, those for which customers have already completed an application or feasibility study, and unidentified projects, or projects in which applications are projected to be submitted during the funding cycle. Because the PLS program is not open to new applicants, Nexant only analyzed identified and operational projects in the PY2017 evaluation.

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 30 applications have been received by the 3 IOUs, 10 have been withdrawn, 1 project is awaiting approval, 12 projects have completed feasibility studies, and 7 installations are operational.

For identified projects, the ex ante load impacts were allocated to specific local capacity areas[[19]](#footnote-20) (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 2018, seven projects have become operational. 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.

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

## Operational Projects

There were two similar methods used for ex ante estimation for operational sites[[20]](#footnote-21), depending on whether ex post estimation used premise level meter data or operational data. The following sections summarize the two different methodologies.

### Ex Post Based on Premise Level Data

The methodology for ex ante estimation for the operational sites using premise level data 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 predicting the ex ante load impacts based on the ex ante weather conditions—all as functions of outdoor air temperature and time. This methodology was used to estimate ex ante for the three operational installations in SCE’s territory as well as two installations in SDG&E’s territory[[21]](#footnote-22) and includes the following steps:

1. Identify 10 days from the two most recent pre-installation years (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. Estimate 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. Select the most accurate model specification based on out-of-sample testing metrics (same as those used in the ex post model selection) and use the selected model to estimate the reference load after the TES system was installed.
4. Calculate the estimated ex post load impacts based by 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 the selected model from Step 3.
7. Forecast ex ante impacts based on the model developed in Step 5 under ex ante weather conditions, and combine with reference load to create to create ex ante load impacts.

### Ex Post Based on Operational Data

The methodology for ex ante estimation for the operational site using operational data is based off the ex post estimation, but contains two extra modeling steps—developing a model for cooling tons and developing a model for post-installation cooling system usage—both as functions of outdoor air temperature and time. These models need to be developed because neither cooling tons nor post-installation usage is observable under ex ante conditions. This methodology was used to estimate ex ante impacts for the one operational site in PG&E’s territory and includes the following steps:

1. Identify 10 days in the pre- and post-installation period (5 from each year) with the highest average noon to 6 PM cooling load to use as peak load days   
   for out-of-sample testing.
2. Estimate 13 regression models of cooling tons as a function of temperature. These models can use as inputs for both the pre-installation and post-installation cooling tons because we are assuming that the building’s cooling needs are static. The models will account for possible differences in cooling intensity at different times of day and on different days of the week by allowing the temperature coefficients to vary across hours of the day and between weekends and weekdays.
3. Estimate 13 regression models of post-TES cooling system load as a function of temperature. As with the case above, we will allow the effect of temperature to vary across hours and day-types.
4. Select the most accurate model specifications for estimating cooling tons and post-installation cooling load based on out-of-sample testing metrics (same as those used in the ex post model selection).
5. Use the three regression models (including the COP model developed for the ex post analysis) to estimate COP, cooling tons, and post-installation cooling usage for all ex ante weather conditions.
6. Use estimated COP and the estimated cooling tons to estimate the baseline cooling load for all ex ante weather conditions, similar to the process in ex post.
7. Subtract estimated post-installation load from the calculated baseline load to produce ex ante impact estimates for all ex ante weather conditions.

## Identified Projects

The PY2017 PLS program evaluation used the same single, consistent, methodology as the 2016 evaluation to estimate ex ante load impacts for identified projects across the IOUs. This approach is based on the fact that the size, installation date, and location were known for each specific project. At the time of the evaluation, PG&E had five active projects, SCE had six, and SDG&E had two. Of these 13 projects that are currently in progress, 12 projects have reached the feasibility study stage in the application and verification process and had their application approved while one application is waiting to be approved. The projects range in size from approximately 30 kW up to 1.5 MW. Ex ante conversion factors (discussed in detail in the next report section) were used to convert the expected load shift from the application/feasibility study to ex ante weather conditions.

This kW load shift amount represents the peak load shift that can be expected under hot, maximum cooling load, weather conditions. The kW load shift was multiplied by the ex ante conversion factors, which converted the load shift under the incentive payment, maximum cooling load, 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 are the same as those used in PY2015 and PY2016. These 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.

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. This assumption was made in consultation with program managers and it is consistent with last year’s evaluation.

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 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, likely due to building codes that establish standard materials for window insulation and other weatherization factors, and that the ratio for a given ex ante condition hardly changes even 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.

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. 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.

## Estimating Ex Ante Weather Conditions

The CPUC Load Impact Protocols[[22]](#footnote-23) 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 for all three utilities. There were updated again in 2017 for SDG&E 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.[[23]](#footnote-24) The PY2017 PLS program evaluation uses the most recently developed ex ante weather conditions that are available for each utility, which means that 2017 updates for SDG&E’s ex ante weather conditions were incorporated for its operational projects where the ex ante impacts were based off the ex post results. However, identified (not yet operational) projects that rely on building simulation models to calculate the ex ante impacts are all based on the 2015 ex ante weather conditions. Building simulation models are based on specific sets of weather data, and are not simple updates, requiring extensive calibration and quality checks. Given the uncertainty regarding these identified sites actually completing installation, and the final specifications of the installation (which often vary compared to the initial application and feasibility study), the benefit of creating new building simulation models for the two SDG&E applicants isn’t enough to outweigh the costs of creating the model. This is especially the case now that the program has been closed, as the cost of the previous building simulation models were able to be spread out across several years of evaluations. Based on all of these factors, Nexant has recommended the original building simulation models based on the 2015 ex ante weather data be used because the newer data wouldn’t necessarily improve the accuracy or precision of the forecast, nor would it be an efficient use of the evaluation budget.

Table 4‑1 through 4‑4 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 almost the same as the utility-specific scenarios under normal weather conditions and slightly cooler than the utility-specific scenarios under extreme weather conditions for the typical event day. For SDG&E, the CAISO weather is cooler under both 1-in-2 year and 1-in-10 year weather 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.[[24]](#footnote-25)

Table ‑: 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 | | 73.0 | 78.7 | 70.4 | 73.9 |
| Peak Day | May | 67.4 | 78.9 | 64.6 | 70.4 |
| June | 72.6 | 81.3 | 73.5 | 73.4 |
| July | 72.3 | 78.2 | 69.9 | 76.4 |
| August | 73.5 | 77.3 | 69.3 | 74.2 |
| September | 73.6 | 77.8 | 68.8 | 71.8 |
| October | 68.0 | 74.8 | 67.9 | 69.7 |
| Average Weekday | May | 61.2 | 64.9 | 62.4 | 60.8 |
| June | 63.5 | 66.4 | 62.2 | 64.3 |
| July | 66.3 | 67.7 | 69.2 | 66.7 |
| August | 67.4 | 67.5 | 65.8 | 64.5 |
| September | 66.2 | 68.8 | 66.5 | 67.6 |
| October | 61.5 | 64.3 | 61.5 | 63.4 |

Table ‑: 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 | | 75.5 | 80.3 | 75.3 | 78.6 |
| Peak Day | May | 69.1 | 79.2 | 66.5 | 75.3 |
| June | 72.5 | 78.2 | 73.0 | 76.0 |
| July | 74.9 | 79.5 | 76.3 | 78.2 |
| August | 78.3 | 81.3 | 76.2 | 79.8 |
| September | 76.4 | 82.3 | 75.9 | 80.5 |
| October | 73.8 | 77.8 | 71.1 | 75.5 |
| Average Weekday | May | 61.8 | 67.6 | 62.1 | 62.1 |
| June | 64.3 | 69.2 | 64.7 | 68.5 |
| July | 70.3 | 71.2 | 71.4 | 71.0 |
| August | 72.2 | 73.9 | 70.6 | 72.9 |
| September | 68.8 | 71.6 | 70.0 | 71.1 |
| October | 63.5 | 66.6 | 64.5 | 67.6 |

Table ‑: 2015 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 | | 73.1 | 79.0 | 72.3 | 75.7 |
| Peak Day | May | 68.0 | 78.1 | 64.7 | 72.2 |
| June | 70.3 | 77.8 | 71.2 | 73.6 |
| July | 72.7 | 78.7 | 70.9 | 75.4 |
| August | 74.2 | 78.7 | 73.5 | 76.0 |
| September | 75.0 | 80.7 | 73.6 | 77.6 |
| October | 70.0 | 76.3 | 68.0 | 72.6 |
| Average Weekday | May | 61.6 | 65.7 | 62.1 | 61.4 |
| June | 63.7 | 67.3 | 63.5 | 65.6 |
| July | 67.4 | 69.2 | 70.5 | 68.2 |
| August | 68.5 | 70.3 | 67.6 | 69.5 |
| September | 67.1 | 70.4 | 67.8 | 69.8 |
| October | 63.2 | 66.0 | 63.1 | 65.5 |

Table ‑: 2017 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 | | 75.7 | 79.8 | 75.1 | 78.8 |
| Peak Day | May | 69.7 | 77.0 | 66.7 | 75.6 |
| June | 67.5 | 77.2 | 67.3 | 79.7 |
| July | 75.0 | 76.6 | 72.0 | 75.6 |
| August | 78.0 | 81.1 | 79.3 | 78.5 |
| September | 82.2 | 84.0 | 81.9 | 81.4 |
| October | 74.9 | 78.7 | 72.4 | 77.9 |
| Average Weekday | May | 62.8 | 65.0 | 63.5 | 63.5 |
| June | 64.9 | 68.6 | 64.6 | 68.6 |
| July | 69.5 | 72.15 | 70.6 | 72.2 |
| August | 71.9 | 74.0 | 73.0 | 74.0 |
| September | 70.4 | 74.9 | 70.4 | 74.9 |
| October | 65.4 | 69.5 | 64.5 | 69.5 |

# Summary of Assumptions and Enrollment Forecast

Section 5 provides a summary of the assumptions for the PY2017 evaluation, which refines the assumptions used in the PY2016 evaluation based on the most recent information on budget, program enrollment, and the current status of identified projects. Since the PLS program is no longer accepting new applications, the enrollment forecast is based upon active applications and existing installations only.

The PLS program is now closed to new applicants, and as such all expected new customers are customers that have already submitted an application and are expected to come online in the next few years. Once these projects come online the enrollment will be constant for the remainder of the forecast horizon. Since there are no new applicants, Nexant did not include unidentified projects in the evaluation this year and did not look at different enrollment scenarios.

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.

Figure 5‑1 provides the enrollment forecast by utility. As discussed in Section 3, customers are not defined as enrolled until their PLS-TES installation has come online and the post installation validation has been completed. Most of the identified projects for all three IOUs are expected to come online between 2018 and 2019, with two SCE projects projected to come online in 2020. This results in a total of 20 projects in the Statewide PLS program at the end of 2028.

Figure ‑: Enrollment Forecast by Utility

Table 5‑1 provides the PLS program enrollment forecast by utility and LCA for each year of the forecast horizon. Of all the LCAs in California, the greatest number of PLS program installations is projected to occur in the LA Basin LCA— with 9 of the 20 installations by the end of the forecast horizon. The Greater Bay Area and SDG&E are the only other LCAs in California that are forecasted to have more than three PLS program installations.

Table ‑: PLS Program Enrollment Forecast by Utility and LCA

|  |  |  |  |
| --- | --- | --- | --- |
| **Utility** | **LCA** | **2018** | **2019 - 2028** |
| PG&E | Greater Bay Area | 2 | 4 |
| Greater Fresno | 0 | 0 |
| Humboldt | 0 | 0 |
| Kern | 0 | 0 |
| Northern Coast | 2 | 2 |
| Other | 0 | 0 |
| Sierra | 0 | 0 |
| Stockton | 0 | 0 |
| *Total (PG&E)* | 4 | 6 |
| SCE | LA Basin | 6 | 9 |
| Outside LA Basin | 0 | 0 |
| Ventura | 0 | 0 |
| *Total (SCE)* | 6 | 9 |
| SDG&E | | 5 | 5 |
| **Total (Statewide)** | | **15** | **20** |

# 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,[[25]](#footnote-26) 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.[[26]](#footnote-27) 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 2018 through October 2028.

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.

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 also not been included since they are outside of the 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% of additional energy relative to the baseline system. Because not all cooling load occurs 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.[[27]](#footnote-28) 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 degradation factor is a major simplification of what is expected to occur in the next decade. PLS-TES systems are too complex and their continued function is based on too many variables for a theoretical analysis to accurately reflect the actual state of system operations. 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.

## PG&E Results

Table 6‑1 provides the ex ante load impact estimates for monthly system peak days in May through October of 2018, under the utility specific 1-in-2 and 1-in-10 year weather conditions. These load impacts are based on the ex post impacts from the single installation that came online in May 2016 and the three identified projects that are expected to come online in 2018. PG&E’s five identified projects are projected to become operational in May 2018, July 2018, August 2018, April 2019, and June 2019, respectively. In 2018, there are four total projects that provide a maximum peak load shift of nearly 2.4 MW under the utility specific August 1-in-10 weather conditions.

Table 6‑2 shows results from 2019, which is a transition year when the remaining identified projects come online. With the addition of these new installations, the maximum peak shift is estimated to be approximately 4.0 MW, occurring under the utility specific July 1-in-10 weather conditions. Table 6‑3 provides results for PG&E in 2028, the final year of the forecast horizon. The largest estimated load shift for the utility specific July 1‑in‑10 peak day drops to about 3.5 MW due to expected degradation. The Greater Bay Area LCA accounts for the largest share of load impacts, comprising approximately 97% of the total. It is important to note that the Greater Bay Area also includes many hot areas with large commercial and industrial facilities, including Silicon Valley, Concord, and San Ramon.

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

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **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 | XXX | XXX | XXX | XXX | XXX | XXX | 2,133 | 2,234 | 2,023 | 2,051 | 1,830 | 1,934 |
| 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 | XXX | XXX | XXX | XXX | 116 | 119 | 111 | 119 | 110 | 117 | 102 | 107 |
| 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** | **636** | **673** | **687** | **708** | **964** | **991** | **2,244** | **2,353** | **2,133** | **2,168** | **1,932** | **2,041** |

Table ‑: PG&E Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days for May-October 2019 (kW)   
Utility Specific Peak

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **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 | 1,960 | 2,156 | 3,336 | 3,564 | 3,651 | 3,862 | 3,577 | 3,755 | 3,460 | 3,532 | 3,121 | 3,277 |
| 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 | 102 | 113 | 110 | 122 | 116 | 119 | 111 | 119 | 110 | 117 | 102 | 107 |
| 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** | **2,062** | **2,269** | **3,446** | **3,686** | **3,767** | **3,981** | **3,688** | **3,874** | **3,570** | **3,649** | **3,223** | **3,384** |

Table ‑: PG&E Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days for May-October 2028 (kW)   
Utility Specific Peak

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **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 | 2,793 | 3,087 | 2,992 | 3,194 | 3,296 | 3,482 | 3,227 | 3,386 | 3,111 | 3,172 | 2,810 | 2,951 |
| 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 | 87 | 97 | 95 | 105 | 100 | 102 | 96 | 103 | 94 | 101 | 88 | 92 |
| 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** | **2,880** | **3,184** | **3,087** | **3,299** | **3,396** | **3,584** | **3,323** | **3,489** | **3,205** | **3,273** | **2,898** | **3,043** |

Figure 6‑1 illustrates how the July 1-in-10 monthly system peak day load impact estimates vary by forecast year. Figure 6‑2 shows the same results for July 1-in-2 weather conditions. Across the forecast years and scenarios, the impacts are slightly higher under July 1-in-10 weather conditions, but the difference is about 0.2 MW on average. At the end of the forecast horizon, the program is projected to deliver nearly 3.6 MW for the July 1-in-10 peak day. The confidence interval is wider on monthly system peak days compared to average weekdays. This is driven in part by using the ex post analysis as the basis for the ex ante analysis, and by the extremely small number of customers. In the ex post evaluation, there are typically about 20 days that can be used to estimate load impacts for the average weekday in a given month, but there is only a single monthly system peak day. The higher numbers of observations for the average weekday result in smaller standard errors, and a narrower confidence intervals. In contrast, the monthly system peak day has only a single day per month, and as a result, the standard errors are much larger and the confidence interval is wider. These values pass through to the ex ante estimates as well, and are reflected in the wide confidence intervals on monthly system peak days observed below.

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

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

Table 6‑4 shows the projected trajectory of load impacts under July 1-in-10 weather conditions from 2018 through 2028 by LCA for both the utility specific and CAISO specific weather conditions. Table 6‑5 shows the same results for July 1-in-2 conditions. The Greater Bay Area accounts 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 Northern Coast LCA is expected to have load impacts from the PLS program. As discussed above, the load impacts decrease over time even as enrollment remains steady due to the assumed 2.5% annual degradation in load impacts starting in the fifth year after a project is installed.

Table ‑: PG&E July 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM)  
by LCA and Forecast Year – (kW)

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Peak Type** | **LCA** | **2018** | **2019** | **2020** | **2021** | **2022** | **2023** | **2024** | **2025** | **2026** | **2027** | **2028** |
| Utility Specific | Greater Bay Area | XXX | 3,862 | 3,862 | 3,859 | 3,855 | 3,852 | 3,774 | 3,698 | 3,624 | 3,552 | 3,482 |
| Greater Fresno | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Humboldt | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Kern | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Northern Coast | 119 | 119 | 119 | 119 | 119 | 116 | 113 | 110 | 107 | 105 | 102 |
| Other | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sierra | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Stockton | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | 991 | 3,981 | 3,981 | 3,978 | 3,974 | 3,968 | 3,887 | 3,808 | 3,731 | 3,657 | 3,584 |
| CAISO Specific | Greater Bay Area | XXX | 3,846 | 3,846 | 3,843 | 3,839 | 3,836 | 3,759 | 3,683 | 3,609 | 3,537 | 3,466 |
| Greater Fresno | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Humboldt | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Kern | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Northern Coast | 120 | 120 | 120 | 120 | 120 | 117 | 114 | 112 | 109 | 106 | 103 |
| Other | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sierra | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Stockton | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | 982 | 3,966 | 3,966 | 3,963 | 3,959 | 3,953 | 3,873 | 3,795 | 3,718 | 3,643 | 3,569 |

Table ‑: PG&E July 1-in-2 Monthly System Peak Day Load Impacts (1 to 6 PM)  
by LCA and Forecast Year – (kW)

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Peak Type** | **LCA** | **2018** | **2019** | **2020** | **2021** | **2022** | **2023** | **2024** | **2025** | **2026** | **2027** | **2028** |
| Utility Specific | Greater Bay Area | XXX | 3,651 | 3,651 | 3,648 | 3,644 | 3,641 | 3,569 | 3,498 | 3,429 | 3,361 | 3,296 |
| Greater Fresno | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Humboldt | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Kern | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Northern Coast | 116 | 116 | 116 | 116 | 116 | 113 | 110 | 107 | 105 | 102 | 100 |
| Other | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sierra | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Stockton | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | **964** | **3,767** | **3,767** | **3,764** | **3,760** | **3,754** | **3,679** | **3,605** | **3,534** | **3,463** | **3,396** |
| CAISO Specific | Greater Bay Area | XXX | 3,512 | 3,512 | 3,509 | 3,506 | 3,503 | 3,433 | 3,364 | 3,297 | 3,231 | 3,168 |
| Greater Fresno | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Humboldt | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Kern | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Northern Coast | 111 | 111 | 111 | 111 | 111 | 108 | 106 | 103 | 100 | 98 | 95 |
| Other | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sierra | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Stockton | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | **909** | **3,623** | **3,623** | **3,620** | **3,617** | **3,611** | **3,538** | **3,467** | **3,397** | **3,329** | **3,263** |

### Relationship between Ex Post and Ex Ante Estimates

Table 6‑6 compares the current ex post results from the 2017 program year evaluation with last year’s 2016 program year ex ante forecast for 2017. This comparison shows how similar or different the forecast was from what actually took place. The forecast for 2017 did not expect any new programs to become operational, which is consistent with what was observed in the ex post evaluation. Since the ex ante was based off of this one installation, the ex post and ex ante estimates are very similar, with any variation explained by variations in temperature for the days being compared.

Table ‑: Comparison of 2017 Ex Post to Prior Year Ex Ante Estimates   
(July Average Weekday – Utility Specific)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Analysis** | **Accounts** | **Reference Loads (MW)** | **Percent Reductions** | **Aggregate Impacts (MW)** |
| 2017 Ex Post | 1 | XXX | XXX | XXX |
| 2017 Ex Ante 1-in-2 | 1 | XXX | XXX | XXX |
| 2017 Ex Ante 1-in-10 | 1 | XXX | XXX | XXX |

Table 6‑7 provides an analysis of how the current ex ante results differ from the current ex post results. Four key factors contribute to the differences between the ex post and the ex ante forecast. The weather and event window provide small differences. However, the enrollment and methodology are interrelated and provide more significant differences. Given PLS is a growing program with low enrollment rates, yet a large impact per customer, very small changes to the enrollment forecast can have a large influence on program MW. The program enrollment is projected to expand further in 2018 and 2019. After that point, there is expected to be significant departure from the ex post results observed this year. The other factor related to the methodology is the specific analysis method used for the estimation of load impacts. In 2017 ex post data was available for the single operational customer; however, no such data exists for the projects projected to come online in the future. To address this, generalizable building simulation models and assumptions about the number and size of future projects are necessary. This is meant to represent the best estimate from program staff, but also involves a significant amount of uncertainty.

Table ‑: Summary of Factors Underlying Differences between 2017 Ex Post and 2018 Ex Ante Impacts   
(July Average Weekday – Utility Specific)

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex Post | Ex Ante | Expected Impact |
| Weather | Average weekday Mean17 = 68  Note: Mean17 is the average temperature between midnight and 5pm (hour ending 17). This metric helps to account for heat buildup during the day, which can affect cooling load. | Program specific Mean17 for 1-in-2 average weekday = 67 and 70 for PG&E and CAISO weather, respectively  Program specific mean17 for 1-in-10 average weekday = 68 and 67 for PG&E and CAISO weather, respectively | Ex ante estimates are sensitive to temperature– impacts will be lower based on 1-in-2 PG&E weather and similar based on 1-in-10 PG&E weather and CAISO weather |
| Event window | Program hours from 12 to 6 PM | Resource adequacy window is from 1 to 6 PM | In some cases average ex ante impacts will be lower because in many cases the impacts are largest in the 12-1 PM hour that isn’t included |
| Enrollment | Single customer | 2018+ includes additional identified customers | Ex ante estimates will start to increase in 2018+ as the program is projected to grow |
| Methodology | 2017 impacts based on operational data of single customer | 2018+ combines impacts based on operational data and building simulations for identified and unidentified customers | 2018+ rely on a variety of assumptions and a different approach. Results are not directly comparable |

### Comparison of 2016 and 2017 Ex Ante Estimates

Table 6‑8 provides a comparison of how the current ex ante results from the 2017 program year evaluation differ from last year’s ex ante forecast. The three years in the table were selected because 2018 and 2019 represent the years when enrollment is still expected to change for the program and 2027 is the last year common to both forecasts. In this year’s ex ante forecast for 2018, three customers are expected to be enrolled in the program for both 2016 and 2017 estimates, and as such the expected impacts of the program in 2018 are relatively similar. In 2019, an additional project is expected to come online for the 2017 forecast, so the impacts are higher for the 2017 forecast than the 2016 forecast. In 2027 the 2016 forecasted impact is more than twice the 2017 expected impact. This difference is due to the fact that in 2016 the program was still expecting new customers to apply and enroll in the program and included impacts from unidentified projects. Since the program is now closed to future applicants, 2017 estimates only include impacts from identified projects. The 2017 enrollment forecast for 2027 is therefore less than half of the number of customers from the 2016 forecast. Had the 2016 predictions only included identified projects, the ex ante estimates would be much more similar in 2027.

Table ‑: Comparison of Current Ex Ante Estimates to Prior Year Estimates   
(July Average Weekday – Utility Specific)

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Year** | **Year** | **Accounts** | | **Reference Loads (MW)** | | **Percent Reductions** | | **Aggregate Impacts (MW)** | |
| **2016 Estimates** | **2017 Estimates** | **2016 Estimates** | **2017 Estimates** | **2016 Estimates** | **2017 Estimates** | **2016 Load Impact (MW)** | **2017 Load Impact (MW)** |
| 1-in-2 | 2018 | 3 | 3 | 1.01 | 0.97 | 87% | 88% | 0.88 | 0.86 |
| 2019 | 5 | 6 | 2.90 | 3.56 | 95% | 97% | 2.77 | 3.44 |
| 2027 | 13 | 6 | 8.53 | 3.56 | 95% | 89% | 8.09 | 3.16 |
| 1-in-10 | 2018 | 3 | 3 | 1.05 | 1.01 | 88% | 88% | 0.92 | 0.89 |
| 2019 | 5 | 6 | 3.04 | 3.72 | 96% | 97% | 2.91 | 3.60 |
| 2027 | 13 | 6 | 8.98 | 3.72 | 95% | 89% | 8.52 | 3.30 |

## SCE Results

Table 6‑9 provides the ex ante load impact estimates for monthly system peak days in June through September of 2018[[28]](#footnote-29), under SCE-specific, 1-in-2 and 1-in-10 year weather conditions for the base scenario. Table 6‑10 and Table 6‑11 provide results for 2020 and 2028, respectively. SCE had one project become operational in 2015, one project become operational in 2016, and one project become operational in 2017. Three identified projects are expected to come online in 2018, one identified project is expected to come online in 2019, and two projects are expected to come online in 2020. After all of the identified projects have been installed the total enrollment will be 9 customers and the peak load shift is expected to be XX MW under SCE-Specific, September 1-in-10 monthly peak conditions.

All of the currently identified applications are located within the LA Basin LCA. All of the future applications and related impacts are also remain in the LA Basin 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 September 1-in-10 year conditions, the projected impacts for the constrained circuits are XX MW and XX MW for South Orange County and South of Lugo, respectively. The South of Lugo impact is significant, as the region contributes more than 86% of SCE’s aggregate load impact under the 2018 SCE September 1-in-10 weather conditions.

CAISO specific impacts are covered in greater detail below. For comparison purposes, the CAISO impact for 2028 September 1-in-10 monthly peak conditions is XX MW, which is less than 1% higher than the comparable utility specific monthly peak. As detailed in the 2015 evaluation report,[[29]](#footnote-30) the CAISO and SCE utility specific peaks have the highest correlation among the three IOUs.

Table ‑: SCE Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days   
for June – September 2018 (kW)[[30]](#footnote-31)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| LCA | June | | July | | August | | September | |
| 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 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South Orange County | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South of Lugo | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| LCA - Outside LA Basin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| LCA - Ventura | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |

Table ‑: SCE Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days   
for June-September 2020 (kW)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| LCA | June | | July | | August | | September | |
| 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 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South Orange County | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South of Lugo | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| LCA - Outside LA Basin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| LCA - Ventura | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |

Table ‑: SCE Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days   
for June-September 2028 (kW)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **LCA** | **June** | | **July** | | **August** | | **September** | |
| **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 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South Orange County | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South of Lugo | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| LCA - Outside LA Basin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| LCA - Ventura | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |

Figure 6‑3 illustrates how the September 1-in-10 year load impact estimates vary by forecast year and scenario. Figure 6‑4 shows the same results for September 1-in-2 year weather conditions. Across the forecast years, the impacts are approximately 8% higher under September 1-in-10 year weather conditions. When all of the projects are installed by 2020 the program is expected to deliver up to XX MW. By 2028 this impact is expected to drop to XX MW due to the annual 2.5% degradation. The confidence interval is wider on monthly system peak days compared to average weekdays. This is driven in part by using the ex post analysis as the basis for the ex ante analysis, and by the extremely small number of customers. In the ex post evaluation, there are typically about 20 days that can be used to estimate load impacts for the average weekday in a given month, but there is only a single monthly system peak day. The higher number of observations for the average weekday result in smaller standard errors, and a more narrow confidence interval. In contrast, the monthly system peak day has only a single day per month, and as a result, the standard errors are much larger and the confidence interval is wider. These values pass through to the ex ante estimates as well, and are reflected in the wide confidence intervals on monthly system peak days observed below. One customer in particular had very inconsistent load and load impacts in the ex post analysis. This high level of variation also passed through to the ex ante and contributed to the level of uncertainty of the load impacts.

Figure ‑: SCE September 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM)  
by Forecast Year



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



Table 6‑12 shows the projected trajectory of load impacts under September 1-in-10 year weather conditions from 2018 through 2028 by LCA for the utility and CAISO specific peaks. Table 6‑13 shows the same results for September 1-in-2 conditions. As mentioned above, the LA Basin LCA accounts for 100% 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 XX MW in 2020 under 1-in-10 year weather conditions to XX MW in 2028. 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 less than 1% under 1-in-10 conditions, and approximately 2% under 1-in-2 conditions, with the utility peak being higher under the 1-in-10 conditions and lower under 1-in-2 conditions.

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

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Peak Type** | **LCA** | **2018** | **2019** | **2020** | **2021** | **2022** | **2023** | **2024** | **2025** | **2026** | **2027** | **2028** |
| Utility Specific | LCA - LA Basin | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South Orange County | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South of Lugo | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| LCA - Outside LA Basin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| LCA – Ventura | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| CAISO Specific | LCA - LA Basin | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South Orange County | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South of Lugo | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| LCA - Outside LA Basin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| LCA – Ventura | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |

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

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Peak Type** | **LCA** | **2018** | **2019** | **2020** | **2021** | **2022** | **2023** | **2024** | **2025** | **2026** | **2027** | **2028** |
| Utility Specific | LCA - LA Basin | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South Orange County | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South of Lugo | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| LCA - Outside LA Basin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| LCA – Ventura | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| CAISO Specific | LCA - LA Basin | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South Orange County | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| Region - South of Lugo | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| LCA - Outside LA Basin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| LCA – Ventura | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |

### Relationship between Ex Post and Ex Ante Estimates

Table 6‑14 compares the current ex post results from the 2017 program year evaluation with last year’s 2016 program year ex ante forecast for 2017. This comparison shows how similar or different the forecast was from what actually took place. The forecast for 2017 expected three additional projects to come online, however only two additional projects were added to the program. Most of the differences observed between the 2017 forecast and the 2017 ex post evaluation are due to the differences in evaluation methodology. For the ex post evaluation, Nexant evaluated load impacts based on premise-level data. The ex ante estimates on the other hand, were based off of a combination of premise-level data and building simulations for identified projects, which are discussed further below.

Table ‑: Comparison of 2017 Ex Post to Prior Year Ex Ante Estimates   
(July Average Weekday – Utility Specific)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Analysis** | **Accounts** | **Reference Loads (MW)** | **Percent Reductions** | **Aggregate Impacts (MW)** |
| 2017 Ex Post | 3 | XXXX | XXXX | XXXX |
| 2017 Ex Ante 1-in-2 | 5 | XXXX | XXXX | XXXX |
| 2017 Ex Ante 1-in-10 | 5 | XXXX | XXXX | XXXX |

Table 6‑15 provides an analysis of how the current ex ante results differ from the current ex post results. Four key factors contribute to the differences between the ex post and the ex ante forecast. The weather and event window provide small differences. However, the enrollment and methodology are interrelated and provide more significant differences. Technically, the enrollment forecast is a function of the methodology for forecasting program growth based on anticipated utilization of available budgets. Given PLS is a growing program with low enrollment rates, yet a large impact per customer, very small changes to the enrollment forecast can have a large influence on program MW. The program enrollment is projected to expand further in 2018 through 2020. After that point, there is expected to be significant departure from the ex post results observed this year. The other factor related to the methodology is the specific analysis method used for the estimation of load impacts. In 2017 ex post data was available for the three operational customers; however, no such data exists for the projects projected to come online in the future. To address this, generalizable building simulation models and assumptions about the number and size of future projects are necessary. This is meant to represent the best estimate from program staff, but also involves a significant amount of uncertainty.

Table ‑: Summary of Factors Underlying Differences between 2017 Ex Post and 2018 Ex Ante Impacts   
(July Average Weekday – Utility Specific)

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex Post | Ex Ante | Expected Impact |
| Weather | Average weekday Mean17 = 76  Note: Mean17 is the average temperature between midnight and 5pm (hour ending 17). This metric helps to account for heat buildup during the day, which can affect cooling load. | Program specific Mean17 for 1-in-2 average weekday = 69 and 71 for SCE and CAISO weather, respectively  Program specific mean17 for 1-in-10 average weekday = 70 and 70 for SCE and CAISO weather, respectively | Ex ante estimates are sensitive to temperature– impacts will be lower based on both 1-in-2 and 1-in-10 SCE weather and CAISO weather |
| Event window | Program hours from 12 to 6 PM | Resource adequacy window is from 1 to 6 PM | In some cases average ex ante impacts will be lower because in many cases the impacts are largest in the 12-1 PM hour that isn’t included |
| Enrollment | Three customers | 2018+ includes additional identified customers | Ex ante estimates will increase significantly in 2018+ as the program is projected to grow |
| Methodology | 2017 impacts based on premise-level data for three customers | 2018+ combines impacts based on premise-level data and building simulations for identified and unidentified customers | 2018+ rely on a variety of assumptions and a different approach. Results are not directly comparable |

### Comparison of 2016 and 2017 Ex Ante Estimates

Table 6‑16 provides a comparison of how the current ex ante results from the 2017 program year evaluation differ from last year’s ex ante forecast. The three years in the table were selected because 2018 and 2020 represent the years when enrollment is still expected to change for the program and 2027 is the last year common to both forecasts. In the ex ante forecast for 2018, 6.4 customers were expected to be enrolled in the program for PY2016 estimates and 6 customers are expected to be enrolled in the program for PY2017 estimates. However, as the forecasts are based off of different assumptions for each customer for each estimate there is a difference between estimated impacts and reference loads. By 2020, nine customers are forecasted to be enrolled for both estimates, but again because of the different assumptions there is a difference in both estimated impacts and reference loads. By 2027, the 2016 forecast predicted that 11.8 customers would be enrolled in the program. This year’s forecast predicts that the number of customers enrolled in the program will not change after 2020. Therefore, the assumed 2.5% degradation is not offset by new customers enrolling in the program in the 2017 forecast. The impacts are therefore much smaller for the 2017 forecast than for the 2016 forecast.

Table ‑: Comparison of Current Ex Ante Estimates to Prior Year Estimates   
(July Average Weekday – Utility Specific)

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Year** | **Year** | **Accounts** | | **Reference Loads (MW)** | | **Percent Reductions** | | **Aggregate Impacts (MW)** | |
| **2016 Estimates** | **2017 Estimates** | **2016 Estimates** | **2017 Estimates** | **2016 Estimates** | **2017 Estimates** | **2016 Load Impact (MW)** | **2017 Load Impact (MW)** |
| 1-in-2 | 2018 | 6.4 | 6 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| 2020 | 9 | 9 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| 2027 | 11.8 | 9 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| 1-in-10 | 2018 | 6.4 | 6 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| 2020 | 9 | 9 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |
| 2027 | 11.8 | 9 | XXXX | XXXX | XXXX | XXXX | XXXX | XXXX |

## SDG&E Results

SDG&E’s service territory only has one LCA so the results are not divided geographically. Table 6‑17 provides the ex ante load impact estimates for monthly system peak days in May through October of 2018, under SDG&E-specific, 1-in-2 and 1-in-10 year weather conditions for the base scenario. Table 6‑18 and Table 6‑19 provide results for 2019 and 2028, respectively. SDG&E has three operational projects. The remaining two identified projects are expected to become operational in 2018. Once the remaining identified projects are installed SDG&E is projected to have a 2.3 MW load shift under SDG&E specific, September 1-in-10 monthly peak conditions

CAISO specific impacts are covered in greater detail below. For comparison purposes, the CAISO impact for the 2024 September 1-in-10 monthly peak conditions is 2.1 MW, which is about 5% lower than the comparable utility specific monthly peak.

Table ‑: SDG&E Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days   
for May–October 2018 (kW)

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 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 |
| SDG&E (Total) | 1,082 | 1,337 | 989 | 1,343 | 1,677 | 1,971 | 1,863 | 2,092 | 2,049 | 2,305 | 1,902 | 2,035 |

Table ‑: SDG&E Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days   
for May–October 2019 (kW)

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 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 |
| SDG&E (Total) | 1,528 | 1,846 | 1,451 | 1,843 | 1,677 | 1,971 | 1,863 | 2,092 | 2,049 | 2,305 | 1,902 | 2,035 |

Table ‑: SDG&E Ex Ante Load Impact Estimates (1 to 6 PM) on Monthly Peak Days   
for May–October 2028 (kW)

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 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 |
| SDG&E (Total) | 1,368 | 1,637 | 1,288 | 1,624 | 1,471 | 1,732 | 1,631 | 1,831 | 1,806 | 2,025 | 1,698 | 1,809 |

Figure 6‑5 illustrates how the September 1-in-10 year load impact estimates vary by forecast year. Figure 6‑6 shows the same results for September 1-in-2 year weather conditions. Across the forecast years, the impacts are approximately 11% higher under September 1-in-10 year weather conditions. In 2019 the program is expected to deliver a 2.3 MW shift. By 2028, the assumed 2.5% annual degradation is expected to reduce that shift to 2 MW with the same number of customers still enrolled in the program. The confidence interval is wider on monthly system peak days compared to average weekdays. This is driven in part by using the ex post analysis as the basis for the ex ante analysis, and by the extremely small number of customers. In the ex post evaluation, there are typically about 20 days that can be used to estimate load impacts for the average weekday in a given month, but there is only a single monthly system peak day. The higher numbers of observations for the average weekday result in smaller standard errors, and a more narrow confidence interval. In contrast, the monthly system peak day has only a single day per month, and as a result, the standard errors are much larger and the confidence interval is wider. These values pass through to the ex ante estimates as well, and are reflected in the wide confidence intervals on monthly system peak days observed below.

Figure ‑: SDG&E September 1-in-10 Monthly System Peak Day Load Impacts

(1 to 6 PM) by Forecast Year

Figure ‑: SDG&E September 1-in-2 Monthly System Peak Day Load Impacts (1 to 6 PM)  
by Forecast Year

Table 6‑20 shows the impacts for the 1-in-2 and 1-in-10 utility-specific and CAISO weather conditions for the May through October system peak days. 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 9% greater than the utility specific comparable peak at 2.2 MW and 2.0 MW, respectively, to the utility specific July 1-in-10 monthly peak day in 2018 being 10% greater than the CAISO specific comparable peak at 2.0 MW and 1.8 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 September 1-in-10 monthly peak load impact is typically around 4% higher than the comparable CAISO specific impact.

Table ‑: SDG&E Ex Ante Load Impact Estimates (1 to 6 PM)   
on Monthly Peak Days for May–October 2017–2027 (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** |
| Utility Specific | 2018 | 1,082 | 1,337 | 989 | 1,343 | 1,677 | 1,971 | 1,863 | 2,092 | 2,049 | 2,305 | 1,902 | 2,035 |
| 2019 | 1,528 | 1,846 | 1,451 | 1,843 | 1,677 | 1,971 | 1,863 | 2,092 | 2,049 | 2,305 | 1,902 | 2,035 |
| 2020 | 1,528 | 1,846 | 1,451 | 1,843 | 1,677 | 1,971 | 1,863 | 2,092 | 2,049 | 2,305 | 1,902 | 2,035 |
| 2021 | 1,523 | 1,836 | 1,446 | 1,832 | 1,665 | 1,960 | 1,850 | 2,077 | 2,033 | 2,289 | 1,893 | 2,023 |
| 2022 | 1,512 | 1,821 | 1,436 | 1,815 | 1,649 | 1,943 | 1,832 | 2,056 | 2,013 | 2,266 | 1,878 | 2,006 |
| 2023 | 1,487 | 1,788 | 1,410 | 1,781 | 1,618 | 1,906 | 1,796 | 2,016 | 1,976 | 2,223 | 1,846 | 1,971 |
| 2024 | 1,462 | 1,756 | 1,384 | 1,748 | 1,587 | 1,869 | 1,761 | 1,977 | 1,940 | 2,182 | 1,815 | 1,937 |
| 2025 | 1,438 | 1,725 | 1,359 | 1,716 | 1,557 | 1,834 | 1,727 | 1,939 | 1,905 | 2,141 | 1,785 | 1,904 |
| 2026 | 1,414 | 1,695 | 1,335 | 1,685 | 1,527 | 1,799 | 1,694 | 1,902 | 1,871 | 2,101 | 1,755 | 1,871 |
| 2027 | 1,391 | 1,666 | 1,311 | 1,654 | 1,499 | 1,765 | 1,662 | 1,866 | 1,838 | 2,063 | 1,726 | 1,840 |
| 2028 | 1,368 | 1,637 | 1,288 | 1,624 | 1,471 | 1,732 | 1,631 | 1,831 | 1,806 | 2,025 | 1,698 | 1,809 |
| CAISO Specific | 2018 | 931 | 1,335 | 953 | 1,423 | 1,621 | 1,763 | 1,934 | 1,984 | 2,211 | 2,196 | 1,676 | 1,959 |
| 2019 | 1,321 | 1,864 | 1,386 | 1,933 | 1,621 | 1,763 | 1,934 | 1,984 | 2,211 | 2,196 | 1,676 | 1,959 |
| 2020 | 1,321 | 1,864 | 1,386 | 1,933 | 1,621 | 1,763 | 1,934 | 1,984 | 2,211 | 2,196 | 1,676 | 1,959 |
| 2021 | 1,315 | 1,855 | 1,380 | 1,921 | 1,611 | 1,751 | 1,920 | 1,971 | 2,196 | 2,180 | 1,668 | 1,947 |
| 2022 | 1,305 | 1,841 | 1,370 | 1,903 | 1,596 | 1,735 | 1,900 | 1,951 | 2,174 | 2,157 | 1,655 | 1,930 |
| 2023 | 1,282 | 1,809 | 1,345 | 1,868 | 1,564 | 1,702 | 1,863 | 1,914 | 2,133 | 2,114 | 1,626 | 1,895 |
| 2024 | 1,259 | 1,778 | 1,320 | 1,834 | 1,533 | 1,670 | 1,826 | 1,877 | 2,093 | 2,072 | 1,599 | 1,860 |
| 2025 | 1,237 | 1,747 | 1,297 | 1,800 | 1,502 | 1,638 | 1,791 | 1,841 | 2,054 | 2,031 | 1,571 | 1,827 |
| 2026 | 1,215 | 1,718 | 1,273 | 1,768 | 1,472 | 1,608 | 1,757 | 1,807 | 2,016 | 1,991 | 1,545 | 1,794 |
| 2027 | 1,194 | 1,689 | 1,251 | 1,736 | 1,444 | 1,578 | 1,723 | 1,773 | 1,978 | 1,952 | 1,519 | 1,762 |
| 2028 | 1,173 | 1,660 | 1,228 | 1,705 | 1,415 | 1,549 | 1,690 | 1,739 | 1,942 | 1,914 | 1,494 | 1,731 |

### Relationship between Ex Post and Ex Ante Estimates

Table 6‑21 compares the current ex post results from the 2017 program year evaluation with last year’s 2016 program year ex ante forecast for 2017. This comparison shows how similar or different the forecast was from what actually took place. Most of the differences observed between the 2017 forecast and the 2017 ex post evaluation are due to the differences in evaluation methodology. For the ex post evaluation, Nexant was not able to evaluate the full load impact for one of the customers due to a lack of available data. The unavailable data accounts for a large amount of the difference observed between the ex post and ex ante estimates. Additionally, ex ante estimates were based off of premise-level data and building simulations for identified projects, and so there was a large amount of uncertainty around the actual load shift that would be observed in 2017, as discussed further below.

Table ‑: Comparison of 2017 Ex Post to Prior Year Ex Ante Estimates   
(June Average Weekday – Utility Specific)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Analysis** | **Accounts** | **Reference Loads (MW)** | **Percent Reductions** | **Aggregate Impacts (MW)** |
| 2017 Ex Post | 3 | 1.89 | 48% | 0.90 |
| 2017 Ex Ante 1-in-2 | 3 | 1.85 | 91% | 1.69 |
| 2017 Ex Ante 1-in-10 | 3 | 1.94 | 90% | 1.75 |

Table 6‑22 provides an analysis of how the current ex ante results differ from the current ex post results. Four key factors contribute to the differences between the ex post and the ex ante forecast. The weather and event window provide small differences. However, the enrollment and methodology are interrelated and provide more significant differences. Technically, the enrollment forecast is a function of the methodology for forecasting program growth based on anticipated utilization of available budgets. Given PLS is a growing program with low enrollment rates, yet a large impact per customer, very small changes to the enrollment forecast can have a large influence on program MW. In 2018, two more customers are expected to enroll in the program. After that point, there is expected to be significant departure from the ex post results observed this year. The other factor related to the methodology is the specific analysis method used for the estimation of load impacts. In 2017 ex post data was available for the three operational customers; however, no such data exists for the projects projected to come online in the future. To address this, generalizable building simulation models and assumptions about the number and size of future projects are necessary. This is meant to represent the best estimate from program staff, but also involves a significant amount of uncertainty.

Table ‑: Summary of Factors Underlying Differences between 2017 Ex Post and 2018 Ex Ante Impacts   
(June Average Weekday – Utility Specific)

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex Post | Ex Ante | Expected Impact |
| Weather | Average weekday Mean17 = 68  Note: Mean17 is the average temperature between midnight and 5pm (hour ending 17). This metric helps to account for heat buildup during the day, which can affect cooling load. | Program specific Mean17 for 1-in-2 average weekday = 64 and 63 for SDG&E and CAISO weather, respectively  Program specific mean17 for 1-in-10 average weekday = 67 and 66 for SDG&E and CAISO weather, respectively | Ex ante estimates are sensitive to temperature– impacts will be lower based on 1-in-2 SDG&E weather and more similar based on 1-in-10 PG&E weather and CAISO weather |
| Event window | Program hours from 11 AM to 6 PM | Resource adequacy window is from 1 to 6 PM | In some cases average ex ante impacts will be lower because in many cases the impacts are largest in the 12-1 PM hour that isn’t included |
| Enrollment | Three customers | 2018+ includes additional identified customers | Ex ante estimates will start to increase significantly in 2018+ as the program is projected to grow |
| Methodology | 2017 impacts based on partial operational data for one customer and premise-level data for the other two customers | 2018+ combines impacts based on operational data and building simulations for identified and unidentified customers | 2018+ rely on a variety of assumptions and a different approach. Results are not directly comparable |

### Comparison of 2016 and 2017 Ex Ante Estimates

Figure 6-7 compares the ex ante load impact estimates from this evaluation to those from last year’s PLS program evaluation, for the September 1-in-10 monthly system peak day. In last year’s evaluation, there were no additional identified projects other than the projects evaluated in the 2017 ex post. However, there were several unidentified projects expected to come online through 2024. This year, two additional identified projects are expected to come online in 2018, but there are no additional unidentified projects since the program has been cancelled. Therefore, last year’s predictions are much higher compared to this year after 2018 because of the additional unidentified customers that were expected to come online.

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

# Recommendations

The PLS program is now closed and will not accept any new applications in the future. Additionally, this is the last year that the impacts of the program will be evaluated. As such, Nexant does not have any further recommendations for the program moving forward.

1. Customer Regression Models for Ex Post Analysis
   1. PG&E

Site 1

Table A-1: Description of Regression Model Variables

| Variable | Definition |
| --- | --- |
| kWt | Average hourly demand (kW) for each time period |
| A | Estimated constant term |
| Bij through Di | Regression model parameters |
| Houri | 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 |
| DOWj | Series of binary variables representing weekdays (Mon-Fri); weekends and holidays are excluded from the model |
| Monthj | Series of binary variables for each month designed to reflect seasonality in loads |
| Mean17t | Mean17—the average temperature between midnight to 5 PM |
| et | Error term |

* 1. SCE

Site 1

Customer Regression Model:

Site 2

Customer Regression Model:

Site 3

Customer Regression Model:

Table A-2: Description of Regression Model Variables

| Variable | Definition |
| --- | --- |
| kWt | Average hourly demand (kW) for each time period |
| A | Estimated constant term |
| Bij through Ji | Regression model parameters |
| Houri | 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 |
| DOWj | Series of binary variables representing weekdays (Mon-Fri); weekends and holidays are excluded from the model. Energy use immediately before or after a weekend may be different compared to load in the middle of the week |
| Monthj | Series of binary variables for each month designed to reflect seasonality in loads |
| CDDt | 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 |
| CDDsqrt | The square of Cooling Degree Day |
| CDHt | Cooling Degree Hour—the max of zero and the hourly temperature value less a base value of 60°F |
| CDHsqrt | The square of Cooling Degree Hour |
| OvernightCDHt | The average cooling degree hour between the hours of 12:00 am and 9:00 am |
| Summert | Binary variable reflecting the summer months of July through October |
| PLSt | Binary variable reflecting when the TES system is operational |
| et | Error term |

* 1. SDG&E

Site 1

No Regression Model

Site 2

Customer Regression Model:

Site 3

Customer Regression Model:

Table A-3: Description of Regression Model Variables

| Variable | Definition |
| --- | --- |
| kWt | Average hourly demand (kW) for each time period |
| A | Estimated constant term |
| Bij through Gi | Regression model parameters |
| Houri | 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 |
| DOWj | Series of binary variables representing weekdays (Mon-Fri); weekends and holidays are excluded from the model. Energy use immediately before or after a weekend may be different compared to load in the middle of the week |
| Monthj | Series of binary variables for each month designed to reflect seasonality in loads |
| CDHt | Cooling Degree Hour—the max of zero and the hourly temperature value less a base value of 60°F |
| OvernightCDHt | The average cooling degree hour between the hours of 12:00 am and 9:00 am |
| Summert | Binary variable reflecting the summer months of July through October |
| PLSt | Binary variable reflecting when the TES system is operational |
| et | Error term |

1. Methodology for Developing Ex Ante Conversion Factors

As described in Section 1.1, the PLS program kW load shift amount for incentive calculations for identified 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.

* 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).[[31]](#footnote-32) 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.

* + 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 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.[[32]](#footnote-33) This was due to the need for a generalizable solution, rather than focusing on the outputs from a specific model that didn’t align with an actual project. 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[[33]](#footnote-34)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 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. | | | | | | | | | | | | | |

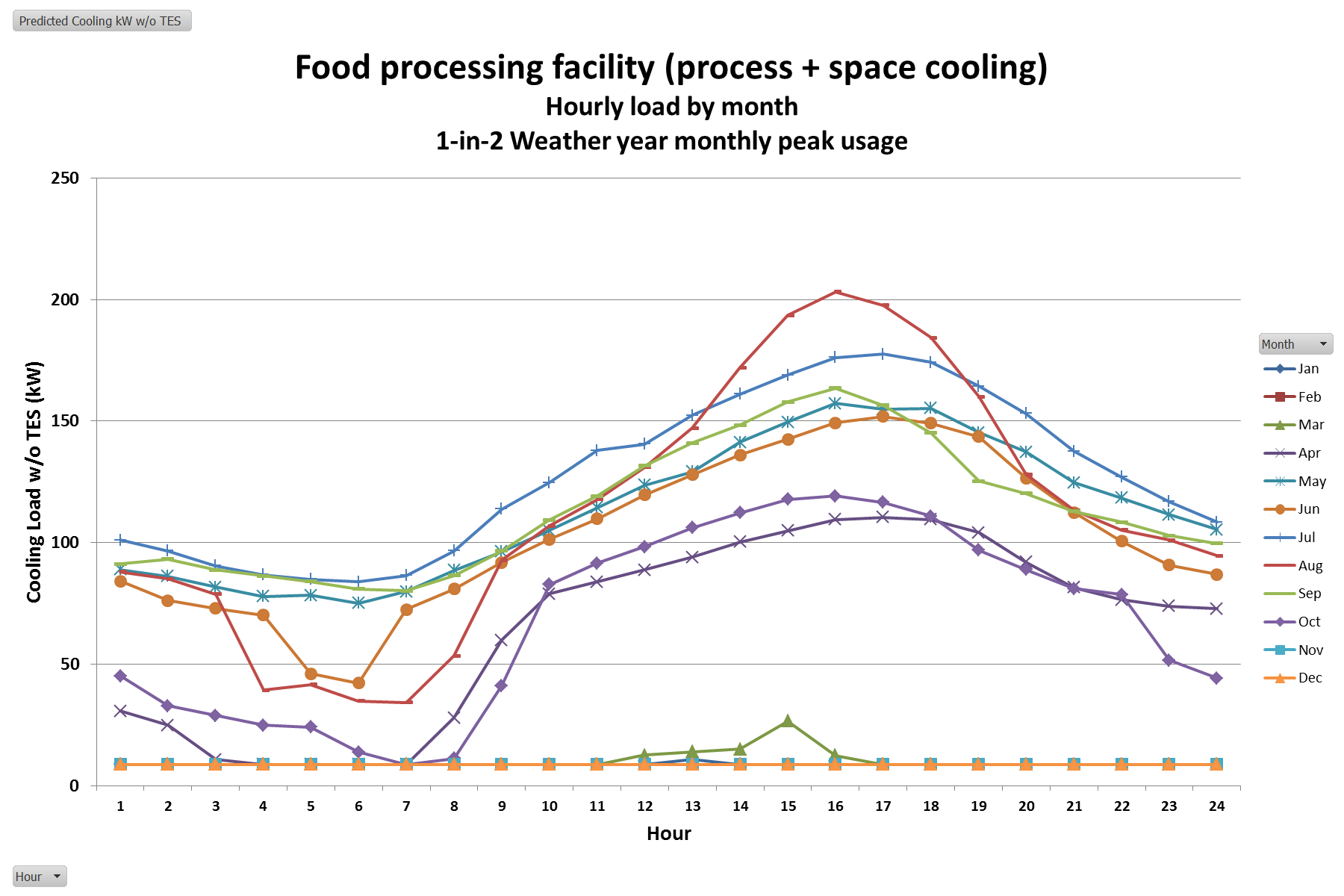
Table A-2: Characteristics of Buildings in Table A-1[[34]](#footnote-35)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 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 |

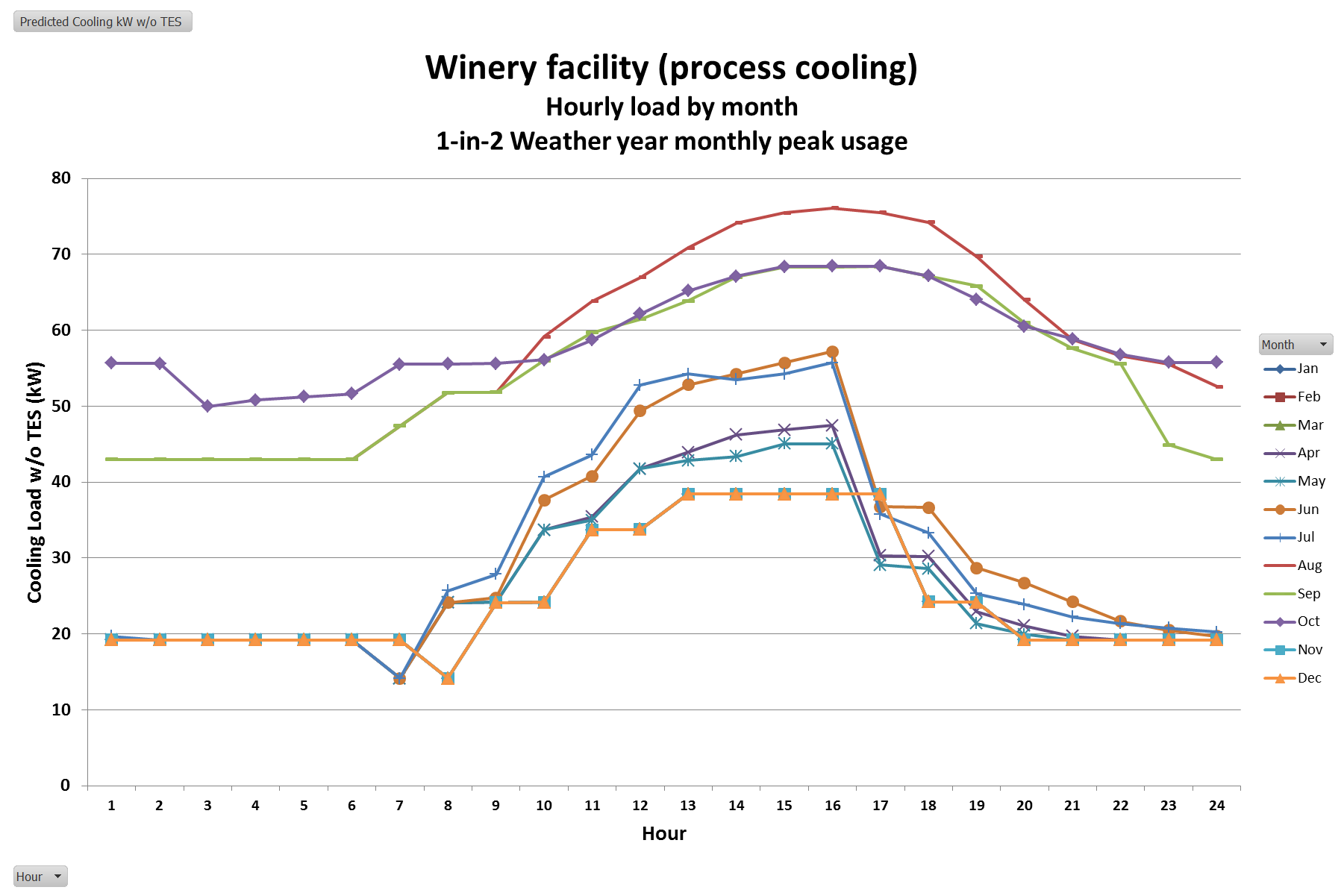
* + 1. Treatment of Space and Process Cooling Installations

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.

**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.

* + 1. 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.

* 1. 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 LCA 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.

* 1. 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.

* 1. 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)**



2. Methodology to Estimate Chiller kW Based on   
   Chiller Amperage

There were several data management issues that needed to be resolved in order to conduct the ex post analysis using operational data. The data were collected for a three month pre-TES installation period spanning July to September 2015. The customer installed the TES system sometime in May 2016, and post-installation data span May through October 2016, with some missing data between September and October.[[35]](#footnote-36) In addition to the missing data, the customer initially captured the chiller component of cooling system load as a current measurement (unit of amps) instead of electricity demand (kW). The customer was later able to provide the corresponding chiller kW data for May through July; however, the remaining chiller data for August to October was recorded in amps. Nexant used the three month period with overlapping chiller kW and amps data to estimate a relationship between current and electricity demand and used this relationship to convert the amperage data to kW for August to October. While there are known equations to directly convert from amps to kW, the observed values for the system’s power factor and additional voltage information were unavailable, thus necessitating the need to develop an estimation model. The power factor is a ratio of the real power that is used to do the work and the apparent power that is supplied to the circuit, and is a value that varies with the proportion of the chiller’s capacity that is being used.

Figure B-1 shows a plot of the relationship between the observed current (amps) and electric load (kW) values from the period with overlapping data. The relationship appears roughly linear; however, the relationship between kW and amps is proportional to a series of constants, the power factor, and the voltage. Thus, depending on the proportion of total chiller capacity being used, there is a range of observable electricity demand.

Figure B‑: Observed Chiller kW vs Observed Chiller Current (amps) –

May–July 2016





Given the approximately linear relationship, Nexant tested two models to estimate chiller kW based on recorded current:

* **Model 1**—Use a linear relationship between current and kW and directly predict kW from the observed amperage data.

**Model 2**—Predict power factor based on the proportion of total capacity used during a given interval. We were able to roughly calculate this value based on the engineering specifications for the chillers provided by the engineering firm that was collecting and managing the data. The specifications indicated a maximum current capacity of 570 amps, so the proportional capacity was calculated as the ratio of the observed current and the maximum current. The other inputs to calculating power factor include the ratio of observed kW to amps, several constants, and voltage.[[36]](#footnote-37)

Nexant used each model to predict chiller kW using the observed amperage and compared the results to the actually observed kW. Figures B-2 through B-7 show the comparison of the actual values to model predictions for the average weekday in each month with overlapping amperage and kW data.

Figure B‑: Comparison of Actual vs. Predicted kW   
for the May Average Weekday – Model 1



Figure B‑: Comparison of Actual vs. Predicted kW   
for the June Average Weekday – Model 1



Figure B‑: Comparison of Actual vs. Predicted kW   
for the July Average Weekday – Model 1



Figure B‑: Comparison of Actual vs. Predicted kW   
for the May Average Weekday – Model 2



Figure B‑: Comparison of Actual vs. Predicted kW   
for the June Average Weekday – Model 2



Figure B‑: Comparison of Actual vs. Predicted kW   
for the July Average Weekday – Model 2



The figures above show that both models predict chiller kW quite well, on average. To select the final model, we developed accuracy metrics, similar to those used in the ex post and ex ante model selections, to compare the performance of each model during the operational load shifting hours of noon to 6 PM. 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 model. Overall, Model 1, the direct estimation of chiller kW from observed amperage, performed slightly better than Model 2, and on average, underestimates chiller kW by 2.2 kW during the operational load shifting hours of noon to 6 PM.

1. CPUC Resolution E-4586 issued on May 9, 2013. [↑](#footnote-ref-2)
2. The SDG&E peak impact is from June, when all three sites had data available. [↑](#footnote-ref-3)
3. CPUC Resolution E-4586 issued on May 9, 2013. [↑](#footnote-ref-4)
4. CPUC D.14-05-025 issued on May 19, 2014. [↑](#footnote-ref-5)
5. This amount is the remaining funds from the 2015–2016 bridge year budgets. [↑](#footnote-ref-6)
6. CPUC D.08-04-050 issued on April 28, 2008 with Attachment A. [↑](#footnote-ref-7)
7. 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. [↑](#footnote-ref-8)
8. 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. [↑](#footnote-ref-9)
9. 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. [↑](#footnote-ref-10)
10. The post-installation data was inadvertently overwritten by the customer’s data logger. The issue has now been identified and resolved. [↑](#footnote-ref-11)
11. Classified as in military, defense, or government related. [↑](#footnote-ref-12)
12. Other tests may have been conducted. These days were included in the test data from SDG&E and showed full depletion of the ice. [↑](#footnote-ref-13)
13. Overnight cooling degree hour (CDH) is the average of CDH values from midnight to 8 AM, where CDH is the max of zero and the hourly temperature value less a base value of 60°F. [↑](#footnote-ref-14)
14. CDD is the max of zero and the mean temperature of the day of the hourly observation less a base value of 60°F. [↑](#footnote-ref-15)
15. The model specification is provided in Section 2.1. [↑](#footnote-ref-16)
16. Mean17 is a variable that helps to capture overnight heat buildup and is often used for load modeling. [↑](#footnote-ref-17)
17. The operational data did not include the actual system peak days in October; however, there were enough data to construct average weekday impacts for all months. [↑](#footnote-ref-18)
18. See *2015 Load Impact Evaluation of the California Statewide Permanent Load Shifting Program.* Nexant, Inc. April 1, 2016. [↑](#footnote-ref-19)
19. LCA is the CAISO-defined term that represents each transmission-constrained load pocket in the California IOU service territories. [↑](#footnote-ref-20)
20. Due to a lack of available data for one of SDG&E’s installations, Nexant used the methodology used for identified projects rather than the methods detailed below. [↑](#footnote-ref-21)
21. One of SDG&E’s installations did provide operational data rather than premise-level data. However, since the operational data monitored cooling load rather than the variables traditionally provided for operational data the data was treated as if it were premise-level data in the modeling process. [↑](#footnote-ref-22)
22. See CPUC Rulemaking (R.) 07-01-041 Decision (D.) 08-04-050, “Adopting Protocols for Estimating Demand Response Load Impacts” and Attachment A, “Protocols.” [↑](#footnote-ref-23)
23. See *Statewide Demand Response Ex Ante Weather Conditions*. Nexant, Inc. January 30, 2015. [↑](#footnote-ref-24)
24. 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. [↑](#footnote-ref-25)
25. Although the RA summer months include April, PLS customers are only required to shift load from May through October. Thus, there are insufficient data to provide April ex ante estimates, and the impacts are assumed to be zero, similar to in winter months. [↑](#footnote-ref-26)
26. Due to the confidentiality concerns described in Section 1, these load impact tables are not available publicly. [↑](#footnote-ref-27)
27. 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. [↑](#footnote-ref-28)
28. May and October are not reported since they are not included in SCE’s program months, and so the PLS system is not necessarily in use during those months. [↑](#footnote-ref-29)
29. See the ex ante weather description in Section 4.4 of the *2015 Load Impact Evaluation of the California Statewide Permanent Load Shifting Program.* Nexant, Inc. April 1, 2016 [↑](#footnote-ref-30)
30. May and October Results are not included because they are not a part of SCE’s program months. [↑](#footnote-ref-31)
31. eQUEST, <<http://www.doe2.com/equest/>> [↑](#footnote-ref-32)
32. The direct outputs were validation for reasonableness, but not directly used for load impact estimation. [↑](#footnote-ref-33)
33. This table and the associated conversion factors are from the PY2013 evaluation, and provided for comparative purposes in this appendix only. [↑](#footnote-ref-34)
34. This table and the associated conversion factors are from the PY2013 evaluation, and provided for comparative purposes in this appendix only. [↑](#footnote-ref-35)
35. The customer had an out dated server on site, which did not have sufficient memory to store all of the required operational data, resulting in missing data. The server is scheduled to be replaced in March 2017. [↑](#footnote-ref-36)
36. The voltage varies with the proportion of chiller capacity. Because this data were unavailable, Nexant used the maximum voltage of 600 V from the chiller engineering specifications for the analysis. [↑](#footnote-ref-37)