**Executive Summary of the**

**2014 SDG&E Measurement and Evaluation**

**Load Impact Reports**

**April 1st, 2015**

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# SDG&E’s 2014 Load Impact Executive Summary Background

In Decision (D.) 08-04-050 the Commission required the investor owned utilities (IOUs) - San Diego Gas & Electric Company (SDG&E), Southern California Edison (SCE) and Pacific Gas and Electric (PG&E) to perform annual studies of its demand response (DR) activities in accordance with the load impact protocols and to file the load impact reports by April 1st each year. The load impact protocols require the preparation of a voluminous amount of tables that resulted in the load impact reports being too large to be filed in hard copy.  On April 6th 2009 the investor owned utilities (IOUs) filed a petition to modify D.08-41-050.  The petition asked for two things:  1) the removal of the requirement to file the load impact reports in their entirety and 2) to provide the reports to the energy division of the CPUC.  On April 8th 2010 D.10-04-006 granted the utilities requests, which meant that they were not required to file the load impact reports in their entirety.  This new decision also directed the utilities to file an executive summary of the load impact reports.

SDG&E submits this executive summary in accordance with D.10-04-006. This report contains a summary of the ex-post and ex-ante load impacts of the SDG&E Capacity Bidding Program (CBP), Critical Peak Pricing Default (CPP-D), Base Interruptible Program (BIP), Demand Bidding Program (DBP), Summer Saver program, Residential Peak Time Rebate Program and Small Commercial Technology deployment program (SCTD), Permanent Load Shifting program (PLS), Non-Residential SPP Rates, and Commercial Thermostat Program. This report includes a summary of the ex-ante forecasts for these new demand response activities. The summary ex-ante tables that include the 12-year forecast (from 2014 through 2025) for the 1 in 2 individual program scenario, the 1 in 2 portfolio scenario, the 1 in 10 individual program scenario, and the 1 in 10 portfolio scenario are provided in a separate document named Appendix A. The ex-ante starts in 2014 for the purpose of ex-post and ex-ante comparison.

Note that all ex-ante summaries in this report are average results for the current RA hours of 1pm-6pm in the summer (Apr-Oct) and 4pm-9pm all other months. The RA hours may change in future years as more renewable generation comes online but this report uses current RA hours.

# Summary of SDG&E’s Capacity Bidding Program Report

## CBP Program Description

CBP program provides monthly capacity payments ($/kW) to participants based on the nominated kW load, the specific operating month, and the program notice option Day Ahead (DA) or Day Of (DO). The program has two options Capacity Bidding Program day-ahead (CBP DA) and Capacity Bidding Program day-of (CBP DO). Customers may also choose a maximum event length of 4 hour, 6 hour, or 8 hours. CBP events may be called on non-holiday weekdays in the months of May through October, between the hours of 11 a.m. and 7 p.m., with a maximum of forty-four event hours per month. Customers enrolled in CBP may participate in another DR program, so long as it is an energy-payment program and does not have the same advanced notification (*i.e.*, day-ahead or day-of). SDG&E plans two changes in CBP beginning in 2015. The current day-of CBP products required the customer to be notified by 9 a.m. In 2015 a 30-minute notice option will be added to the DO product. In addition, CBP will be open to small customers of less than 20 kW in size.

## CBP Ex-Post Evaluation Methodology

The primary evaluation method used in the ex-post portion of this study involved customer-level regression analysis applied to hourly load data to estimate hourly load impacts for each customer account that was nominated and called for an event. The regression equations model hourly load as a function of a set of variables designed to control for factors affecting consumers’ hourly demand levels, such as:

* *Seasonal and hourly time patterns* (e.g., month, day-of-week, and hour, plus various hour/day-type interactions to allow hourly load patterns to vary by day-type);
* *Weather*, including hour-specific weather coefficients;
* *Event variables*. Indicator variables are included to account for each hour of each event day, for all DR programs in which the service account participates, which allows estimation of aggregator program load impacts for all hours across each event day, for each service account.

The models use the level of hourly demand (kW) as the dependent variable and a separate equation is estimated for each service account that was nominated and called for at least one event in 2014. As a result, the estimated coefficients on the event day/hour variables are direct estimates of the ex-post load impacts, and their standard errors indicate the precision of the estimates. For example, an hour15 event coefficient of -100 on a particular event day implies that the service account reduced load by 100 kWh during hour 15 of that event day relative to what its usage in that hour would have been otherwise, under the observed day-type and weather conditions on that day. Weekends and holidays were excluded from the estimation database because aggregator events may be called only on non-holiday weekdays.

### Regression Model

The model shown below characterizes the nature of the regression equations, which were estimated separately for each service account. Table 2–1 describes the terms included in the equation.



Table2-1: Descriptions of Terms included in the *Ex-Post* Regression Equation

|  |  |
| --- | --- |
| Variable Name / Term | Variable / Term Description |
| *Qt,d* | The demand in hour *t*, on day *d* for a customer nominated to the aggregator program prior to the last event date |
| The various b’s | The estimated parameters |
| *hi,t* | An indicator variable for hour *i* (*i.e.*, hi,t = 1 if *i*=*t*, and 0 otherwise |
| AGGt,d | An indicator variable for aggregator program event days |
| Weathert,d | The weather variables selected in our model screening process |
| E | The number of event days that occurred during the program year |
| MornLoadd | The average of day *d*’s load in hours 1 through 10 |
| OtherEvtd | Equals one on event days of other demand response programs in which the customer is enrolled |
| MONd | An indicator variable for Mondays |
| FRId | An indicator variable for Fridays |
| SUMMERd | An indicator variable for the summer pricing season[[1]](#footnote-1) |
| DTYPEi,d | A series of indicator variables for each day of the week |
| MONTHi,d | A series of indicator variables for each month |
| *et,d* | The error term. |
| et | The error term. |

The OtherEvt variables help the model explain load changes that occur on event days in cases in which aggregator service accounts are dually enrolled in other DR programs. (In the absence of these variables, any load reductions that occur on such days may be falsely attributed to other included variables, such as weather condition or day-type variables.) The “morning load” variables are included in the same spirit as the day-of adjustment to the 10-in-10 baseline settlement method. That is, those variables help adjust the reference loads (or the loads that would have been observed in the absence of an event) for factors that affect pre-event usage, but are not accounted for by the other included variables.

The model allows for the hourly load profile to differ by: day of week, with separate profiles for Monday, Tuesday through Thursday, and Friday; and by pricing season (i.e., summer versus non-summer), in order to account for customer load changes in response to seasonal differences in peak energy prices and/or demand charges.

Separate models were estimated for each customer. The load impacts were aggregated across service accounts as appropriate to arrive at program-level load impacts, as well as load impacts by industry group and local capacity area (LCA).

### Development of Uncertainty-Adjusted Load Impacts

In addition to producing point estimates of the ex-post load impacts, this section includes the *uncertainty-adjusted* program impacts for each event, which show the uncertainty around the estimated impacts, as required by the Protocols. These methods use the estimated load-impact parameter values and the associated variances to derive scenarios of hourly load impacts.

## CBP Ex-Post Load Impact Estimates

Table 2-2 shows average event-hour estimated *reference load*, *observed load*, *load impacts* and *percentage load impacts* for the DA and DO notice and associated product types, for each of SDG&E’s CBP events, and for averages across the respective typical events. The average event-hour DA load impact for the typical event was 9.9 MW, while DO load impacts averaged 5 MW for the 1-4 Hour product, and 3.8 MW for the 2-6 Hour product. Average percentage load impacts were 25 percent for the DA product, and 15 to 18 percent for the two DO product types.

## CBP Ex-Ante Evaluation Methodology

Table 2-2: Average Event-Hour Load Impacts by Event – SDG&E CBP

This section describes the methods used to develop the relevant groups of customers, to develop reference loads for the relevant customer types and event day-types, and to develop load impacts for a typical event day.

### 2.4.1 Development of Reference Loads and Load Impacts

Reference loads and load impacts for the above customer groups were developed in the following series of steps:

1. Define data sources;
2. Estimate ex-ante regressions and simulate reference loads by service account and scenario;
3. Calculate percentage load impacts from ex-post results;
4. Apply percentage load impacts to the reference loads; and
5. Scale the reference loads using enrollment forecasts.

Each of these steps is described below.

*Define data sources:* The reference loads are developed using data for customers enrolled and nominated during the 2014 program year. The percentage load impacts are developed using the estimated ex-post load impacts for the same customers, using event-specific data for program years 2012, 2013 and 2014.

*Simulate reference loads:* In order to develop reference loads, we first re-estimate regression equations for each nominated customer account, using load and weather data for the current program year. The resulting estimates are used to simulate reference loads for each service account under the various scenarios required by the Protocols (e.g., the typical event day under 1-in-2 weather conditions).

The ex-ante models exclude the morning-usage variables. While these variables are useful for improving accuracy in estimating ex-post load impacts for particular events, they complicate the use of the equations for ex-ante simulation, because they would essentially require a separate simulation of the level of the morning load variable. The second difference between the ex-post and ex-ante models is that the ex-ante models use CDH60 as the weather variables in place of the weather variables used in the ex-post regressions. The primary reason for this is that ex-ante weather days were selected based on current-day temperatures, not factoring in lagged values or humidity. Therefore, we determined that including a weather variable that is based on only current-day temperature is the most consistent way of reflecting the alternative 1-in-2 and 1-in-10 weather conditions.

Once these models are estimated, we simulate 24-hour load profiles for each customer account, for each required scenario. The typical event day was assumed to occur in August. Most of the differences across scenarios can be attributed to varying weather conditions. The definitions of the two sets of 1-in-2 and 1-in-10 weather conditions for each utility have been newly developed for this program year.

*Calculate forecast percentage load impacts:* The percentage load impacts were based on the ex-post load impacts for each event during the 2012, 2013 and 2014 program years. Specifically, we examine only customers enrolled and nominated in PY2014, but include available data from the 2012 and 2013 program years for those customers that were also nominated in those years. This method allows us to base the ex-ante load impacts on a larger sample of events than just the current year, which should improve the reliability and consistency of the load impacts across forecasts.

For each service account, we calculate the average and standard deviation of the load impacts across the available event days for four categories of hours: event hours; hours immediately adjacent to events; hours prior to; and hours following the adjacent hours (*i.e*., morning and late evening). These values of load impacts for categories of hours are applied to the simulated reference loads to produce each customer’s hourly load impact forecast values.

For any given sub-group of customers (e.g., CBP day-of customers greater than or equal to 200 kW in size, in the Greater Bay Area), we sum the observed loads, hourly load impacts and their variances across the applicable service accounts for reporting purposes.

We calculate percentage load impacts by the four hour types in order to “standardize” the load impacts for application to the ex-ante forecast event window (1:00 to 6:00 p.m. in April through October). That is, it allows us to control for the fact that the historical (i.e., ex-post) event hours can differ across programs, customers, and event days, and generally differ from the ex-ante event window. The use of the load impacts by hour-type allows us to simulate load impacts as though all customers (within a program and notice level) are called for the same event window.

The uncertainty-adjusted load impacts (i.e., the 10th, 30th, 50th, 70th, and 90th percentile scenarios of load impacts) are based on the variability of each customer’s response across event days. That is, we calculate the standard deviation of each customer’s percentage load impact across the available event days. The square of the standard deviation (i.e., the variance) is added across customers within each required subgroup. Each uncertainty-adjusted scenario is then calculated under the assumption that the load impacts are normally distributed with a mean equal to the total estimated load impact and a variance based on the variability of load impacts across event days.

*Apply percentage load impacts to reference loads for each event scenario:* In this step, the percentage load impacts are applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts.

*Apply forecast enrollments to produce program-level load impacts:* The enrollments are then used to scale up the per-customer reference loads and load impacts for each required scenario and customer subgroup.

## CBP Ex-Ante Load Impact Estimates

The enrollment forecast provided by SDG&E for the purpose of this report anticipates that the number of nominated customer service accounts for CBP DA will remain steady at 159, while CBP DO will increase somewhat through the summer of 2015, from 239 in May, to 284 in October, and then remain constant over the forecast period.

Table 2-3 compares DA and DO (separately for DO 1-4 and 2-6) load impacts for an August peak day in 1-in-2 and 1-in-10 weather years, under the utility-peak and CAISO-peak scenarios. Average event-hour load impacts vary slightly across scenarios in expected ways, and are 11.9 MW for DA and 9.78 MW for DO in the 1-in-2 utility-peak weather scenario.

Table 2-3: Average Event-Hour Load Impacts for an August Peak Day in 1-in-2 and 1-in-10 Weather Years (2015 – 2025) – SDG&E CBP DA and DO



## CBP Comparisons of Ex-Post and Ex-Ante Results

In response to the request to improve the transparency of the linkage between ex-post and ex-ante results, this section compares three set of estimated load impacts.

### Ex-post load impacts from the current and previous studies

Table 2-4 compares estimated ex-post load impacts for the average of the typical CBP events in the current and two previous program years, by notice type, along with this year’s ex-ante forecast for 2015.

The number of customers nominated in CBP DA has increased steadily over the past three years. Customers nominated in CBP DO have declined over the same years. Forecast numbers of customers for 2015 are expected to remain approximately at the 2014 level for DA, and to increase somewhat for DO from the numbers in 2014. Aggregate estimated ex-post load impacts for both notice types have remained fairly level, except for a dip in 2012 for DA. Forecast load impacts for 2015 are up modestly for both DA and DO from the 2014 ex-post results. The forecasts are based on the ex-post performance for up to the last three program years for service accounts enrolled and nominated in 2014, and not dropping out of the program before the end of the summer.

Table2-4: *Ex-Post* Load Impacts for PY2012 through 2014, and *Ex-Ante* for 2015 –   
*SDG&E CBP*



### Previous versus current ex-ante

Table 2-5 compares the CBP ex-ante forecasts for program-year 2015 that were produced as part of this 2014 evaluation and the previous evaluation. In both cases, the forecast represents the August peak day in the utility-peak 1-in-2 weather scenario. There is no difference between the program- and portfolio-level impacts.

The projected aggregate load reductions for the CBP DA option increase from 9.5 MW to 11.9 MW between the two studies, which is consistent with the larger number of nominated service accounts and an increase in the projected percent load impacts (which is in turn based on the performance of the service accounts remaining in the program at the end of program-year 2014. For CBP DO, the projected aggregate load impact matches the previous forecast quite closely (9.8 MW in the current study compared to 10.2 MW in the previous study).

Table 2-5: Ex-Ante Load Impacts for 2015 from PY 2013 and PY 2014 Studies, SDG&E



### Current ex-post compared to previous ex-ante

Table 2-6 compares current PY2014 ex-post load impacts to values for 2014 from the PY2013 ex-ante forecast. Current-year numbers of nominated service accounts were higher than expected for CBP DA and lower than expected for CBP DO, compared to the forecast for 2014 in the PY2013 forecast. Average customer size, as reflected in the reference loads, is somewhat smaller than anticipated for DA, and slightly larger for DO, while percentage load impacts are similar.

For DA, the aggregate estimated load impact (9.9 MW) was slightly higher than the forecast value (9.5 MW). For DO, the aggregate load impact of 8.8 MW is down somewhat from the forecast value, which is consistent with the smaller number of nominated service accounts than forecast.

Table 2-6: Current Ex-Post and PY2013 Ex-Ante Load Impacts for 2014, SDG&E



# Summary of SDG&E’s Critical Peak Pricing Default Report

## CPP Rate Description

Critical Peak Pricing is an electric rate in which the utility charges a higher price for consumption of electricity during peak hours on selected days, referred to as critical peak days or event days. The higher price during peak hours on critical event days is designed to encourage reductions in demand and reflects the fact that electric demand during those hours drives a substantial portion of electric infrastructure costs. The CPPD schedule is the default commodity rate for customers currently receiving bundled utility service whose maximum demand is equal to or exceeds or is expected to equal or exceed 20 kW for twelve consecutive months. At SDG&E, customers are locked into the CPP rate for a full year if they do not opt out prior to going on the default rate; events for the SDG&E CPP-D rate last from 11am-6pm and can be called on any day of the year.

All customers have the ability to hedge part or all of their demand against higher CPP prices, a feature known as a capacity reservation (CR). The capacity reservation option, which is a type of insurance contract in which a customer pays a fee (paid per kW) to set a level of demand below which it will be charged the non-CPP, TOU price during event periods. The company charges $6.33 per kW per month, year-round, for this option and the default level for customers is 50% of a customer’s maximum on-peak demand from the prior summer. Default CRLs are set to zero for those customers with no SDG&E summer usage history.

In addition, the program offers customers CPP bill protection during their default year, which ensures that the customer does not pay more for the energy commodity under CPP than they would have under the otherwise applicable tariff (OAT).

## CPP-D Ex-Post Evaluation Methodology

Ex post evaluation is designed to estimate demand reductions on event days when higher CPP prices are in effect. Ex post impacts reflect the enrollment mix, weather, dispatch strategy and program rules in effect at the time of each event and, as a result, may not reflect the full demand reduction capability of a resource.

To calculate load reductions for demand response programs, customers’ load patterns in the absence of higher event-day prices—the reference load—must be estimated. Reference loads can be estimated using pre-enrollment data, by observing differences in behavior during event and non-event days (i.e., a within-subjects design), by using an external control group (a between-subjects design) or through a combination of the above. Load impacts are estimated for 2014 using a combination of customer specific regressions and difference-in-differences.

The subsections that follow describe the work to select a matching model and the subsequent control group selection.

### Proxy Day Selection

Proxy event days are selected by matching historical events to non-event days based on system loads, temperature conditions, month and day of week. CPP event days tend to differ from typical days. System loads are typically higher, the days are hotter and they are more likely to fall on specific weekdays. Most event days were matched to similar non-event days; however, comparable non-event days are not available for some of the days with the most extreme weather.

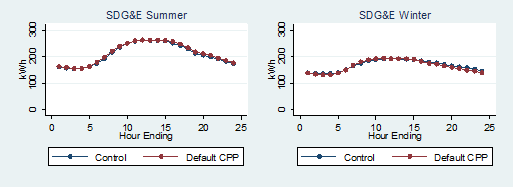
### Matching Model Selection

Propensity score matching using a probit model was used to select valid control groups for each utility and relevant customer segment. This method is a standard approach for identifying statistical look-alikes from a pool of control group candidates and is typically used to address self-selection based on observable differences between CPP participants and non-participants.

### Control group selection

The control group was selected from customers who were not on CPP rates, but were on the otherwise applicable TOU tariff. The best performing probit model and caliper were used to select customers from the control pool. The majority of CPP customers were successfully matched i.e. 93% for SDG&E. Customers who were not matched were moved to the individual customer regression group. Some control group customers were selected more than once – that is, if customer A was the best match for both customer B and customer C, it was chosen twice. Figure 3-1 shows load for the matched treatment and control customers on the average proxy event day. The loads match closely, particularly during event hours.

Figure 3-: Comparison of Matched Treatment and Control Group Load on Average Proxy Event Day



### Difference-in-difference Estimation

Using the matched control groups, 2014 ex post CPP load impacts were estimated for the majority of customers with the difference-in-differences approach.

The difference-in-differences regression makes full use of non-event and event day data available for CPP and control group customers. It takes into account whether peak load patterns changed for CPP customers and whether load patterns changed for customers who did not experience CPP prices. It also accounts for differences between CPP participants and the control group observed during non-event days.

The regression analysis employed a simple model that relies on no explanatory variables other than customer fixed effects and time effects. This model does not rely on modeling the relationship between customers’ electricity usage and other factors such as weather; it is informed by control group customers that experience the event day weather but do not experience the CPP event day prices.

Separate models are estimated for each hour. The analysis dataset consisted of the event-like days and actual event days for CPP customers and their matched control group customers. The dependent variable was the hourly consumption over the course of each hour. Nexant elected to use a treatment model rather than a price elasticity model for two reasons. First, for any hour there are only two price points, or at most three, which is insufficient for fitting price elasticity curves. Second, it avoids assumptions such as constant price elasticity inherent in demand models. The model is expressed by the below equations:

|  |  |
| --- | --- |
| Avg. Event Equation: |  |
| Individual Event Equation: |  |

|  |  |
| --- | --- |
| Variable | Definition |
| *i, t, n* | Indicate observations for each individual *i*, date *t* and event number *n*, where the number of events varies by utility and is denoted *max* |
| *a* | The model constant |
| *b* | Pre-existing difference between treatment and control customers |
| *c* | The difference between event and non-event days common to both CPP participants and control group members[[2]](#footnote-2) |
| *d* | The net difference between CPP and control group customers during event days – this parameter represents the difference-in-differences |
| *u* | Time effects for each date that control for unobserved factors that are common to all treatment and control customers but unique to the time period |
| *v* | Customer fixed effects that control for unobserved factors that are time-invariant and unique to each customer; fixed effects do not control for fixed characteristics such as air conditioning that interact with time varying factors like weather |
| *Ε* | The error for each individual customer and time period |
| *Treatment* | A binary indicator or whether or not the customer is part of the treatment (CPP) or control group |
| *Event* | A binary indicator of whether an event occurred that day – impacts are only observed if the customer is on CPP (*Treatment* = 1) and it was an event day |

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

### Individual Customers Regressions

This type of analysis consists of applying regression models to the hourly load data for each individual customer. The estimated coefficients vary for each customer, as does the amount of data used for each customer. The fact that each customer has its own parameters automatically accounts for variables that are constant for each customer, such as industry and geographic location.

Customer specific regressions were only used for customers who an adequate control group match could not be found.

For each customer, we:

* Analyzed hot weekdays from 2014. To the extent possible, the regressions for each customer excluded cooler days, which typically do not provide much information about behavior under event conditions. For example, if the lowest event day maximum temperature a customer experienced was 100°F, only days that exceed 85% of 100°F (or 85°F) were included.
* Estimated 10 different regression models and used them to predict out-of-sample for event-like days where, in fact, CPP events were not called. This allowed us to identify the regression model that produced the most accurate results for each customer. The 10 models vary in how weather variables were defined, if at all, and in the inclusion of monthly or seasonal variables.

Selected the most accurate model specification and used it to estimate demand reductions during actual event days.

## CPP-D Ex-Post Load Impacts Estimates

This section summarizes the ex post load impact evaluation for customers on SDG&E’s CPP tariff. SDG&E called six CPP events in 2014. The first event occurred on February 7 and the last was held on September 17. On average, there were 1,142 accounts enrolled on SDG&E’s tariff in 2014. There was some minor variation in enrollment during the course of the summer largely due to typical customer churn, with the highest enrollment at 1,143 participants and the lowest enrollment at 1,141. The average 2014 CPP customer enrollment of 1,142 represents a 7.3% increase from 2013 enrollment, which was 1,064 customers.

Table 3-1 shows the ex post load impact estimates for each event day and for the average event in 2014. The participant-weighted average temperature during the event period ranged from a low of 60.4°F to a high of 93.8°F. Percent impacts ranged from 7.1% to 11.7%, average impacts ranged from 12.8 kW to 29.5 kW and aggregate impacts ranged from 14.6 MW to 33.7 MW. On the average event day, the average participant reduced peak period load by 8.8%, or 22.3 kW. In aggregate, SDG&E’s CPP customers reduced load by 25.4 MW on average across the four events in 2014.

Table 3-1: Default CPP Ex-Post Load Impact Estimates by Event Day

SDG&E 2014 CPP Events (11 AM to 6 PM)

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Event Date** | **Day of Week** | **Accounts** | **Avg. Customer Reference Load** | **Avg. Customer Load w/ DR** | **Impact** | **Aggregate Impact** | **% Reduction** | **Avg. Temp.** | **Daily Maximum Temp.** |
| **(kW)** | **(kW)** | **(kW)** | **(MW)** | **%** | **°F** | **°F** |
| 2/7/2014 | Fri | 1,141 | 181.8 | 169.0 | 12.8 | 14.6 | 7.1% | 60.4 | 64.0 |
| 5/15/2014 | Thu | 1,142 | 242.8 | 221.5 | 21.3 | 24.3 | 8.8% | 93.8 | 101.5 |
| 7/31/2014 | Thu | 1,143 | 252.6 | 223.1 | 29.5 | 33.7 | 11.7% | 79.9 | 88.8 |
| 9/15/2014 | Mon | 1,143 | 282.1 | 259.0 | 23.0 | 26.3 | 8.2% | 87.2 | 97.3 |
| 9/16/2014 | Tue | 1,142 | 285.8 | 263.5 | 22.4 | 25.5 | 7.8% | 91.3 | 101.6 |
| 9/17/2014 | Wed | 1,141 | 281.4 | 256.8 | 24.6 | 28.1 | 8.7% | 83.7 | 96.3 |
| **Avg. Event** | | **1,142** | **254.4** | **232.2** | **22.3** | **25.4** | **8.8%** | **82.7** | **96.4** |

## CPP-D Ex-Ante Load Impacts Methodology

Ex ante impacts are designed to reflect demand reduction capabilities under a standard set of peak hours, 1 to 6 PM for the summer season, under both 1-in-2 and 1-in-10 weather conditions.

The process to estimate ex ante load impacts differed for large C&I customers (peak demands above 200 kW) and small/medium customers (peak demands between 20 and 200 kW). For large customers, the ex ante estimation process began by re-estimating ex post load impacts from 2013 and 2014 for customers enrolled in both years with data for all events (persistent customers), using the same estimation model. Then modeled reference loads for 1-in-2 and 1-in-10 weather conditions. Reference loads are estimated separately for the large and small/medium C&I customer classes. For the large C&I customer class, hourly default CPP customer load, by LCA, is modeled as a function of temperature and month. Temperature is represented by daily average of the first 17 hours (mean17), which is used to capture heat buildup in the daylight hours.

## CPP-D Ex-Ante Load Impacts Estimates

The ex ante impact estimates for SDG&E are based on ex post load impacts of CPP events that occurred in 2013 and 2014. In total, load impact estimates for up to 10 events were used as input to the ex ante model. All load impact estimates presented here are incremental to the effects of the underlying TOU rates.

This section presents the ex ante load impact projections separately for medium and large customers projected to receive service under SDG&E’s default CPP tariff. Load reduction capability is summarized for each segment under annual system peak day conditions for a 1-in-2 and a 1-in-10 weather year for selected years (e.g., 2015, 2016, and 2025).

### Large C&I Ex-Ante Impacts

The ex ante load impact estimates are based on a regression model that relates impacts to weather conditions using the ex post impacts and weather to estimate model coefficients. The model is based on ex post data from both 2013 and 2014.

The ex ante percent load reductions for large C&I customers are based on the 2013 and 2014 ex post results for large, persistent customers, which are those that have participated in all events over the past two years. By removing variation in the customer mix from the analysis, we are better able to identify the underlying relationship between temperature and percent impacts. Table 9-1 shows the ex post load impact estimates for each event day and for the average event day in 2013 and 2014 for large, persistent customers. The participant-weighted average temperature during the event period ranged from a low of 61.3°F to a high of 93.4°F. Percent impacts ranged from 6.0% to 10.6%; average impacts ranged from 11.8 kW to 27.3 kW; and aggregate impacts ranged from 12.0 MW to 27.8 MW.

Table 3-2: Default CPP Ex Post Load Impact Estimates for

Persistent Customers by Event Day

SDG&E 2013, 2014 CPP Events (11 AM-6 PM)

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Event Date** | **Day of Week** | **Accounts** | **Avg. Customer Reference Load** | **Avg. Customer Load w/ DR** | **Impact** | **Aggregate Impact** | **% Reduction** | **Avg. Event Temp.** | **Daily Max. Temp.** |
| (kW) | (kW) | (kW) | (MW) | (%) | (°F) | (°F) |
| 8/29/2013 | Thu | 1,020 | 260.6 | 244.9 | 15.7 | 16.0 | 6.0% | 84.0 | 88.1 |
| 9/4/2013 | Wed | 1,020 | 278.9 | 253.5 | 25.4 | 26.0 | 9.1% | 83.5 | 87.7 |
| 9/5/2013 | Thu | 1,020 | 277.5 | 251.9 | 25.6 | 26.1 | 9.2% | 83.6 | 86.6 |
| 9/6/2013 | Fri | 1,020 | 275.4 | 249.2 | 26.3 | 26.8 | 9.5% | 84.8 | 91.1 |
| 2/7/2014 | Fri | 1,020 | 185.1 | 173.3 | 11.8 | 12.0 | 6.4% | 61.3 | 62.9 |
| 5/15/2014 | Thu | 1,020 | 251.8 | 228.0 | 23.8 | 24.3 | 9.5% | 93.4 | 98.0 |
| 7/31/2014 | Thu | 1,020 | 256.5 | 229.3 | 27.3 | 27.8 | 10.6% | 79.2 | 82.9 |
| 9/15/2014 | Mon | 1,020 | 291.3 | 266.6 | 24.6 | 25.1 | 8.5% | 86.2 | 91.3 |
| 9/16/2014 | Tue | 1,020 | 294.8 | 271.0 | 23.9 | 24.3 | 8.1% | 91.0 | 95.6 |
| 9/17/2014 | Wed | 1,020 | 287.0 | 263.7 | 23.3 | 23.8 | 8.1% | 82.7 | 92.1 |

Table 3-3 shows SDG&E’s enrollment projections for large C&I CPP customers through 2025. Overall, 1,142 large customers were enrolled in default CPP in 2014. The forecasted year-to-year change in enrollment is minimal and simply reflects the expected growth of SDG&E’s large customer population. Years 2017 through 2024 are omitted as enrollment in these years follows a similar trend to that which occurs throughout 2015 and 2016.

Table 3-3: SDG&E Enrollment Projections for Large C&I CPP Customers  
by Forecast Year and Month

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | **Jan.** | **Feb.** | **Mar.** | **Apr.** | **May** | **Jun.** | **Jul.** | **Aug.** | **Sep.** | **Oct.** | **Nov.** | **Dec.** |
| 2015 | 1,251 | 1,251 | 1,252 | 1,252 | 1,252 | 1,253 | 1,253 | 1,253 | 1,254 | 1,254 | 1,254 | 1,255 |
| 2016 | 1,256 | 1,258 | 1,259 | 1,261 | 1,262 | 1,264 | 1,265 | 1,267 | 1,268 | 1,270 | 1,272 | 1,273 |
| 2025 | 1,396 | 1,397 | 1,398 | 1,400 | 1,401 | 1,402 | 1,404 | 1,405 | 1,406 | 1,408 | 1,409 | 1,410 |

#### Annual System Peak Day Impacts

Table 3-4 summarizes the aggregate load impact estimates for large customers on SDG&E’s CPP tariff for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios based on both SDG&E and CAISO weather scenarios. The table shows the average load reduction across the 11 AM to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on normal, SDG&E-specific 1-in-2 year weather conditions, load reductions grow from roughly 25 MW to 28 MW between 2015 and 2025. Impacts based on 1-in-10 year SDG&E weather conditions equal roughly 27 MW in 2015 and grow to 30 MW by 2025. These estimates equal roughly 8% of the aggregate reference load for large C&I customers. Impacts estimates based on CAISO weather 1-in-2 year weather conditions are roughly 2% larger than the estimates based on SDG&E weather. The CAISO 1-in-10 year weather values produce a load reduction that is about 5% less than the 1-in-10 year SDG&E estimates.

Table 3-4: Default CPP Ex Ante Load Impact Estimates by Weather   
Scenario for Large C&I  
SDG&E August System Peak Day (11 AM to 6 PM)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Type** | **Weather Year** | **Year** | **Enrolled Accounts** | **Aggregate Reference Load** | **Aggregate Estimated Load w/ DR** | **Aggregate Load Impact** | **% Load Reduction** | **Weighted Temp.** |
| **(MW 1-6 PM)** | **(MW 1-6 PM)** | **(MW 1-6 PM)** | **(%)** | **(°F)** |
| SDG&E | 1-in-10 | 2015 | 1,253 | 322.6 | 295.2 | 27.4 | 8.5% | 86.6 |
| 2016 | 1,267 | 326.0 | 298.4 | 27.6 | 8.5% | 86.6 |
| 2025 | 1,405 | 361.2 | 330.9 | 30.4 | 8.4% | 86.6 |
| 1-in-2 | 2015 | 1,253 | 308.6 | 283.4 | 25.2 | 8.2% | 81.0 |
| 2016 | 1,267 | 311.9 | 286.5 | 25.4 | 8.2% | 81.0 |
| 2025 | 1,405 | 345.5 | 317.6 | 27.9 | 8.1% | 81.0 |
| CAISO | 1-in-10 | 2015 | 1,253 | 314.5 | 288.4 | 26.1 | 8.3% | 83.6 |
| 2016 | 1,267 | 317.9 | 291.5 | 26.4 | 8.3% | 83.6 |
| 2025 | 1,405 | 352.2 | 323.2 | 29.0 | 8.2% | 83.6 |
| 1-in-2 | 2015 | 1,253 | 312.4 | 286.6 | 25.8 | 8.3% | 83.6 |
| 2016 | 1,267 | 315.8 | 289.7 | 26.0 | 8.2% | 83.6 |
| 2025 | 1,405 | 349.8 | 321.2 | 28.6 | 8.2% | 83.6 |

#### Ex Ante Load Impact Uncertainty

Table 3-5 summarizes the statistical uncertainty in the ex ante annual system peak load impact estimates for large C&I customers. The ex ante impacts and the uncertainty reported in Table 3-5 do not reflect uncertainty in the CPP enrollment forecast. They do, however, reflect the challenge of accurately estimating small percentage demand reductions for individual event days. The uncertainty is relatively broad. For example, in 2015, the projected load impacts for August 1-in-2 year, SDG&E weather, are 25.2±7.0z MW, with 80% confidence. But in percentage terms, the uncertainty seems smaller, 8.2%±2.3%, with 80% confidence. For this program in particular, small differences in the estimated percent demand reductions can appear to be large changes in the estimated MW reductions, if the uncertainty is not considered.

Table 3-5: Default CPP Ex Ante Load Impact Estimates by Weather Scenario for Large C&I with Uncertainty

SDG&E August System Peak Day (11 AM - 6 PM)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Type** | **Weather Year** | **Year** | **Expected Aggregate Load Impact** | **Impact Uncertainty** | | | | |
| **(MW 1-6 PM)** | **10th** | **30th** | **50th** | **70th** | **90th** |
| SDG&E | 1-in-10 | 2015 | 27.4 | 20.2 | 24.4 | 27.4 | 30.3 | 34.6 |
| 2016 | 27.6 | 20.4 | 24.7 | 27.6 | 30.6 | 34.9 |
| 2025 | 30.4 | 22.4 | 27.1 | 30.4 | 33.6 | 38.3 |
| 1-in-2 | 2015 | 25.2 | 18.2 | 22.3 | 25.2 | 28.0 | 32.2 |
| 2016 | 25.4 | 18.4 | 22.5 | 25.4 | 28.3 | 32.5 |
| 2025 | 27.9 | 20.2 | 24.8 | 27.9 | 31.1 | 35.6 |
| CAISO | 1-in-10 | 2015 | 26.1 | 19.1 | 23.2 | 26.1 | 29.0 | 33.2 |
| 2016 | 26.4 | 19.3 | 23.5 | 26.4 | 29.3 | 33.5 |
| 2025 | 29.0 | 21.2 | 25.8 | 29.0 | 32.1 | 36.8 |
| 1-in-2 | 2015 | 25.8 | 18.8 | 22.9 | 25.8 | 28.7 | 32.8 |
| 2016 | 26.0 | 19.0 | 23.1 | 26.0 | 28.9 | 33.1 |
| 2025 | 28.6 | 20.8 | 25.4 | 28.6 | 31.8 | 36.4 |

#### Comparison of 2013 and 2014 Ex Ante Estimates

Table 3-6 compares the ex ante estimates produced for the 2013 evaluation to those presented earlier in this report. Because ex ante impacts take into account changes in utility enrollment forecasts, program design and customer mix as well as additional experience, the forecasts are adjusted each year. In general, forecasts a year out are more reliable while forecasts further into the future are less certain. The largest changes observed in Table 9-5 are in the percentage load impact estimates and in the forecasted enrollments. The net effect is that this year’s forecast for 2015 is 25.2 MW, which is 35% higher than last year’s forecast of 18.8 due primarily to an increased enrollment forecast and higher percentage load impact estimates from this evaluation.

Table 3-6: Comparison of Ex Ante Estimates to Prior Year Estimates

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Year** | **Year** | **Accounts** | | **Reference Loads (MW)** | | **Percent Reductions** | | **Aggregate Impacts (MW)** | |
| **2013 Estimates** | **2014 Estimates** | **2014 Estimates** | **2014 Estimates** | **2013 Estimates** | **2014 Estimates** | **2013 Estimates** | **2014 Estimates** |
| 1-in-10 | 2015 | 1,164 | 1,253 | 274.3 | 257.4 | 6.7% | 8.5% | 21.4 | 27.4 |
| 2016 | 1,193 | 1,267 | 274.3 | 257.4 | 6.7% | 8.5% | 22.0 | 27.6 |
| 2024 | 1,318 | 1,389 | 274.3 | 257.1 | 6.7% | 8.4% | 24.3 | 30.0 |
| 1-in-2 | 2015 | 1,164 | 1,253 | 261.1 | 246.2 | 6.2% | 8.2% | 18.8 | 25.2 |
| 2016 | 1,193 | 1,267 | 261.1 | 246.2 | 6.2% | 8.2% | 19.2 | 25.4 |
| 2024 | 1,318 | 1,389 | 261.1 | 245.9 | 6.2% | 8.1% | 21.2 | 27.6 |

### Relationship between Ex Post and Ex Ante Estimates

Table 3-7 summarizes the key factors that lead to differences between ex post and ex ante estimates for CPP and the expected influence that these factors have on the relationship between ex post and ex ante impacts. Given that the CPP load impacts are sensitive to variation in weather, even small changes in mean17 between ex post and ex ante weather conditions can produce relatively large differences in load impacts. For the typical event day, ex ante impacts are significantly lower when based on SDG&E ex ante weather and also lower than the ex post values when based on CAISO weather conditions. This change decreases the ex ante impacts by roughly 10% for the typical event day under 1-in-2 SDG&E weather conditions, as compared to the average 2014 event day. Changes in enrollment between the values used for ex post estimation and the 2015 enrollment values increase impact estimates by about 10%. Finally, the fact that the ex ante model is based on ex post impacts from both 2013 and 2014 for persistent customers, which exhibit a stronger relationship with temperature, will result in slightly higher ex ante load impacts at higher temperature values than ex post impacts at similar values.

Table 3-7: Summary of Factors Underlying Differences between Ex Post and Ex Ante Impacts for the Default CPP Customers for the Ex Ante Typical Event Day

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex Post | Ex Ante | Expected Impact |
| Weather | Default CPP customers:  58 < event day mean17 < 84  Average event day mean17 = 78 | Program specific mean17 for 1-in-2 typical event day = 72.5 and 73.2 for SDG&E and CAISO weather, respectively.  Program specific mean17 for 1-in-10 typical event day = 77.5 and 76.0 for SDG&E and CAISO weather, respectively | Ex ante estimates are sensitive to variation in mean17 – impacts will be lower based on both SDG&E weather and CAISO weather. |
| Enrollment | Enrollment remained fairly constant over the 2014 summer | 2015 enrollment is forecast to be about 10% higher | Ex ante estimates will be about 10% higher than ex post |
| Methodology | 2014 impacts based on combination of matched control groups and individual customer regressions | Impacts: regression of ex post percent impacts against mean17 for each hour using two years’ worth of ex post impacts for persistent customers  Reference Load: regression of kW against mean17 and date variables for each hour using default cpp population | Pooled impacts from 2013 and 2014 for persistent customers exhibit a stronger temperature relationship than those for all customers. Impacts will be higher at higher temperatures and lower or similar at lower temperatures.  Reference load of the ex ante population is similar to that of the ex post population. |

Table 3-8 shows how aggregate load impacts change for large default CPP customers as a result of differences in the factors underlying ex post and ex ante estimates. The third column uses the 2014 ex post impacts shown in Table 8-1 and the projected enrollment for August of 2015 to produce a scaled-up ex post impact estimate. This leads to an average increase in load reductions of about 10%. The next column shows what the ex ante model would produce using the same August 2015 enrollment figures and the ex post weather conditions for each event day. The ex ante model predicts load reductions fairly accurately on average, but estimates tend to be higher on individual days, with the exception of the July 31 event. As discussed above, this is the result of estimating ex ante impacts using percent impacts from the persistent population’s 2013 and 2014 ex post values. The final four columns show how aggregate load reductions vary with the different ex ante weather scenarios. The impacts are similar across SDG&E and CAISO weather scenarios.

Table 3-8: Differences in Large C&I Ex Post and Ex Ante Impacts Due to Key Factors

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **Mean 17** | **Enrollment-adjusted Ex Post Impact** | **Ex Post Impact with Ex Ante Enrollment** | **Ex Ante Model Ex Post Weather** | **CAISO 1-in-2** | **SDG&E 1-in-2** | **CAISO 1-in-10** | **SDG&E 1-in-10** |
| **(F)** | **(MW)** | **(MW)** | **(MW)** | **(MW)** | **(MW)** | **(MW)** | **(MW)** |
| 2/7/2014 | 57.5 | 14.6 | 16.1 | 17.6 | 24.8 | 24.8 | 25.0 | 25.0 |
| 5/15/2014 | 83.9 | 24.3 | 26.7 | 31.6 |
| 7/31/2014 | 75.4 | 33.7 | 37.0 | 26.1 |
| 9/15/2014 | 81.4 | 26.3 | 28.9 | 29.8 |
| 9/16/2014 | 84.1 | 25.5 | 28.0 | 31.7 |
| 9/17/2014 | 83.1 | 28.1 | 30.8 | 31.0 |
| Avg. | 77.6 | 25.4 | 27.9 | 28.0 |

### Medium C&I Ex-Ante Impacts

Overall, there is greater uncertainty regarding medium C&I customer impacts under default CPP. To date, default CPP has been implemented on a very limited basis for medium customers and those medium C&I customers who are on the rate are generally not representative of the medium C&I sector as a whole. While some medium customers volunteered onto CPP rates, their mix and demand reductions are not representative of the current and future medium default customer population. The few pilots that tested time varying pricing for small and medium businesses did not do so for default rates, but rather included only customers who volunteered into the pilots. Among such pilots is PG&E’s EEP for small and medium CPP customers. In brief, the empirical data on medium customer response is limited.

Previous studies of residential customers have shown that customers who enroll on an opt-in basis tend to be more engaged and deliver significantly larger percent reductions than those who enroll on a default basis.[[3]](#footnote-3) Nexant therefore used the PG&E EPP CPP percent reductions as an upper bound for the expected response of defaulted small and medium customers, and adjusted the overall percent reduction downward. This yielded percent reductions of 2.5%. The reference loads were developed by using a sample of interval data for customers that are eligible to be defaulted in March 2016. We simply applied the percent reductions to the reference loads, with an awareness factor that increased from 0.7 in 2016 to 0.9 in 2018 onwards.

Table 3-9 presents SDG&E's enrollment projections for medium C&I customers through 2025. In March 2016, medium C&I customers with at least 24 months of experience on a TOU rate will be defaulted onto CPP, leading to the increase in enrollment. Of the customers who were already defaulted in March 2016, 7,670 medium C&I customers are projected to remain on CPP in March 2018. The enrollment is expected to increase slowly thereafter as a result of growth in accounts.

Table 3-9: SDG&E Enrollment Projections for Medium C&I CPP Customers

by Forecast Year and Month

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Year | Jan. | Feb. | Mar. | Apr. | May | Jun. | Jul. | Aug. | Sep. | Oct. | Nov. | Dec. |
| 2016 | 0 | 0 | 9,572 | 9,589 | 9,606 | 9,623 | 9,639 | 8,914 | 8,929 | 8,944 | 8,961 | 8,976 |
| 2017 | 9,160 | 9,173 | 8,412 | 8,424 | 8,437 | 8,449 | 8,461 | 8,050 | 8,062 | 8,073 | 8,085 | 8,097 |
| 2018 | 8,106 | 8,115 | 7,662 | 7,670 | 7,679 | 7,687 | 7,695 | 7,704 | 7,712 | 7,721 | 7,729 | 7,738 |
| 2025 | 8,499 | 8,510 | 8,521 | 8,532 | 8,543 | 8,555 | 8,566 | 8,577 | 8,588 | 8,599 | 8,610 | 8,621 |

### Monthly System Peak Day Impacts

Table 3-10 summarizes the aggregate load impact estimates for large customers on SDG&E’s CPP tariff for each forecast year under both 1-in-2 and 1-in-10 year weather scenarios based on both SDG&E and CAISO weather scenarios. The table shows the average load reduction across the 11 AM to 6 PM event period for an August monthly system peak day.

Looking first at the aggregate load impacts based on normal, SDG&E-specific 1-in-2 year weather conditions, load reductions will grow from roughly 25 MW to 28 MW between 2015 and 2025. Impacts based on 1-in-10 year SDG&E weather conditions equal roughly 27 MW in 2015 and will grow to 30 MW by 2025. These estimates equal roughly 8% of the aggregate reference load for large C&I customers. Impacts estimates based on CAISO weather 1-in-2 year weather conditions are roughly 2% larger than the estimates based on SDG&E weather. The CAISO 1-in-10 year weather values produce a load reduction that is about 5% less than the 1-in-10 year SDG&E estimates.

Table 3-10: Default CPP Ex Ante Load Impact Estimates by Weather   
Scenario for Large C&I  
SDG&E August System Peak Day (11 AM to 6 PM)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Type** | **Weather Year** | **Year** | **Enrolled Accounts** | **Aggregate Reference Load** | **Aggregate Estimated Load w/ DR** | **Aggregate Load Impact** | **% Load Reduction** | **Weighted Temp.** |
| **(MW 1–6 PM)** | **(MW 1–6 PM)** | **(MW 1–6 PM)** | **(%)** | **(°F)** |
| SDG&E | 1-in-10 | 2015 | 1,253 | 322.6 | 295.2 | 27.4 | 8.5% | 86.6 |
| 2016 | 1,267 | 326.0 | 298.4 | 27.6 | 8.5% | 86.6 |
| 2025 | 1,405 | 361.2 | 330.9 | 30.4 | 8.4% | 86.6 |
| 1-in-2 | 2015 | 1,253 | 308.6 | 283.4 | 25.2 | 8.2% | 81.0 |
| 2016 | 1,267 | 311.9 | 286.5 | 25.4 | 8.2% | 81.0 |
| 2025 | 1,405 | 345.5 | 317.6 | 27.9 | 8.1% | 81.0 |
| CAISO | 1-in-10 | 2015 | 1,253 | 314.5 | 288.4 | 26.1 | 8.3% | 83.6 |
| 2016 | 1,267 | 317.9 | 291.5 | 26.4 | 8.3% | 83.6 |
| 2025 | 1,405 | 352.2 | 323.2 | 29.0 | 8.2% | 83.6 |
| 1-in-2 | 2015 | 1,253 | 312.4 | 286.6 | 25.8 | 8.3% | 83.6 |
| 2016 | 1,267 | 315.8 | 289.7 | 26.0 | 8.2% | 83.6 |
| 2025 | 1,405 | 349.8 | 321.2 | 28.6 | 8.2% | 83.6 |

# Summary of SDG&E’s Base Interruptible Program Report

## BIP Program Description

SDG&E BIP is a voluntary program that offers participants a monthly capacity bill credit in exchange for committing to reduce their demand to a contracted firm service level (FSL) on short notice during emergency situations. Non-residential customers who can commit to curtail 15% of monthly peak demand with a minimum load reduction of 100 kW are eligible for the program. Customers in BIP are notified no later than 30 minutes before the event. Incentive payments are $12 per kW during May through October and $2 per KW during all other months. Curtailment events for an individual BIP customer are limited to a single 4-hour event per day, no more than 10 events per month and no more than 120 event hours per calendar year. A curtailment event may be called under BIP at any time during the year.

In 2012 SDG&E implemented a program change to how the FSL is calculated for the BIP program. Beginning in 2012, if a customer does not reduce its load below the FSL during an event the FSL is raised to the amount of energy the customer used during the event. Since the monthly capacity payment is equal to the average monthly on-peak energy use load minus the firm service level, raising the FSL lowers the future capacity payments for customers who did not perform during the event. This program change successfully encouraged free-riders to opt out of the program in both 2012 and 2013 because it greatly reduces the potential for a free-rider to earn capacity payments during months with no events.

## BIP Ex-Post Evaluation Methodology

We estimated ex post hourly load impacts using regression equations applied to customer-level hourly load data. The regression equation models hourly load as a function of a set of variables designed to control for factors affecting consumers’ hourly demand levels, such as:

• Seasonal and hourly time patterns (e.g., year, month, day-of-week, and hour, plus various hour/day-type interactions);

• Weather, including hour-specific weather coefficients;

• Event variables. A series of dummy variables was included to account for each hour of each event day, allowing us to estimate the load impacts for all hours across the event days.

The models use the level of hourly demand (kW) as the dependent variable and a separate equation is estimated for each enrolled customer. As a result, the coefficients on the event day/hour variables are direct estimates of the ex post load impacts. For example, a BIP hour 15 event coefficient of -100 would mean that the customer reduced load by 100 kWh during hour 15 of that event day relative to its normal usage in that hour. Weekends and holidays were excluded from the estimation database

The model shown below was separately estimated for each enrolled customer. Table 4.1 describes the terms included in the equation.



Table 4.1: Descriptions of Terms included in the Ex Post Regression Equation

|  |  |
| --- | --- |
| **Variable Name / Term** | **Variable / Term Description** |
| *Qt* | the demand in hour *t* for a customer enrolled in BIP prior to the last event date |
| The various *b*’s | the estimated parameters |
| *hi,t* | a dummy variable for hour *i* |
| *BIPt* | an indicator variable for program event days |
| *Weathert* | the weather variables selected using our model screening process |
| *E* | the number of event days that occurred during the program year |
| *MornLoadt* | a variable equal to the average of the day’s load in hours 1 through 10 |
| *OtherEvtDRt* | equals one on the event days of other demand response programs in which the customer is enrolled |
| *MONt* | a dummy variable for Monday |
| *FRIt* | a dummy variable for Friday |
| *SUMMERt* | a dummy variable for the summer pricing season[[4]](#footnote-4) |
| *DTYPEi,t* | a series of dummy variables for each day of the week |
| *MONTHi,t* | a series of dummy variables for each month |
| *et* | the error term. |

The *OtherEvt* variables help the model explain load changes that occur on event days for programs in which the BIP customers are dually enrolled. (In the absence of these variables, any load reductions that occur on such days may be falsely attributed to other included variables, such as weather condition or day type variables.) The “morning load” variables are included in the same spirit as the day-of adjustment to the 10-in-10 baseline settlement method used in some DR programs (e.g., Demand Bidding Program, or DBP). That is, those variables help adjust the reference loads (or the loads that would have been observed in the absence of an event) for factors that affect pre-event usage, but are not accounted for by the other included variables.

The model allows for the hourly load profile to differ by: day of week, with separate profiles for Monday, Tuesday through Thursday, and Friday; and by pricing season (i.e., summer versus non-summer), in order to account for potential customer load changes in response to seasonal changes in rates.

Separate models were estimated for each customer. The load impacts were aggregated across customer accounts as appropriate to arrive at program-level load impacts, as well as load impacts by industry group and local capacity area (LCA).

A parallel set of non-summer models was estimated for each customer. The structure matches the model described above, with appropriate modifications made to the month indicators, summer variables, and weather variables.

## BIP Ex-Ante Evaluation Methodology

The DR Load Impact Evaluation Protocols require that hourly load impact forecasts for event-based DR resources must be reported at the program level and by LCA for the following scenarios:

* For a typical event day in each year; and
* For the monthly system peak load day in each month for which the resource is available;

under both:

* 1-in-2 weather conditions for both utility-specific and CAISO-coincident load conditions, and
* 1-in-10 weather conditions for both utility-specific and CAISO-coincident load conditions;

at both:

* the program level (*i.e.*, in which only the program in question is called), and
* the portfolio level (*i.e.*, in which all demand response programs are called).

Reference loads and load impacts for all of the above factors were developed in the following series of steps:

1. Define data sources;
2. Estimate ex ante regressions and simulate reference loads by service account and scenario;
3. Calculate historical FSL achievement rates from ex post results;
4. Apply achievement rates to the reference loads; and
5. Scale the reference loads using enrollment forecasts.

Each of these steps is described below.

1. *Define data sources*

The reference loads are developed using data for customers enrolled in BIP during the 2014 program year. The load impacts are developed using the historical FSL achievement rates based on the estimated ex post load impacts for the same customers.

For each service account, we determine the appropriate size group and LCA. Although BIP customers may be dually enrolled in some other DR programs, the BIP obligation takes precedence on event days, so *program-specific* scenarios (in which each DR program is assumed to be called in isolation) are identical to *portfolio-level* scenarios (in which all DR programs are assumed to have been called) for this program.

1. *Simulate reference loads*

In order to develop reference loads, we first re-estimated regression equations for each enrolled customer account using data for the current program year. The resulting estimates were used to simulate reference loads for each service account under the various scenarios required by the Protocols (*e.g.*, the typical event day in a utility-specific 1-in-2 weather year).

For the summer months, the re-estimated regression equations were similar in design to the ex post load impact equations described in Section 3.2, differing in two ways. First, the ex ante models excluded the morning-usage variables. While these variables are useful for improving accuracy in estimating ex post load impacts for particular events, they complicate the use of the equations in ex ante simulation. That is, they would require a separate simulation of the level of the morning load. The second difference between the ex post and ex ante models is that the ex ante models do not use weather variables using information from prior days.[[5]](#footnote-5) The primary reason for this is that the ex ante weather days were not selected based on weather from the prior day, restricting the use of lagged weather variables to construct the ex ante scenarios.

Because BIP events may be called in any month of the year, we estimated separate regression models to allow us to simulate non-summer reference loads. The non-summer model is shown below. This model is estimated separately from the summer ex ante model. It only differs from the summer model in two ways: it includes different weather variables; and the month dummies relate to a different set of months. Table 4.5 describes the terms included in the equation.



Table 4.5: Descriptions of Terms included in the Ex Ante Regression Equation

|  |  |
| --- | --- |
| **Variable Name** | **Variable Description** |
| *Qt* | the demand in hour *t* for a customer enrolled in BIP prior to the last event date |
| The various *b*’s | the estimated parameters |
| *hi,t* | a dummy variable for hour *i* |
| *BIPt* | an indicator variable for program event days |
| *OtherEvtDRt* | equals one on the event days of other demand response programs in which the customer is enrolled |
| *Weathert* | the weather variables selected using our model screening process |
| *MONt* | a dummy variable for Monday |
| *FRIt* | a dummy variable for Friday |
| *DTYPEi,t* | a series of dummy variables for each day of the week |
| *MONTHi,t* | a series of dummy variables for each month |
| *et* | the error term. |

1. *Calculate forecast load impacts*

Each service account’s achievement rate is defined as the estimated load impact divided by the difference between the reference load and the FSL. A result of 100 percent implies that the customer dropped its load exactly to its FSL. Values greater than 100 percent imply event-day loads lower than the FSL, and values less than 100 percent imply event-day loads higher than the FSL. The achievement rates are based on the estimates for the most recent observed event day.

From these customer-level forecasts of reference loads and load impacts, we form results for any given sub-group of customers (e.g., customers over 200 kW in size in the Greater Bay Area), by summing the reference loads and load impacts across the relevant customers.

Because the forecast event window (1:00 to 6:00 p.m. in April through October; and 4:00 to 9:00 p.m. in all other months) differs from the historical event window (which can vary across event days), we needed to adjust the historical load impacts for use in the ex ante study. Load impacts are assumed to be zero until the hour prior to the beginning of the event, at which time we apply historical load impacts to the forecast window to best represent the pattern of customer response given the limitations of the observed events. We develop forecast load impacts through the end of the event day because customers load reductions often persist well after the end of the event hours.

The uncertainty-adjusted load impacts (i.e., the 10th, 30th, 50th, 70th, and 90th percentile scenarios of load impacts) are based on the standard errors associated with the estimated load impacts from the event day used to determine the customer’s event-day achievement rate. The square of these standard errors (i.e., the variance) is added across customers within each required subgroup. Each uncertainty-adjusted scenario is then calculated under the assumption that the load impacts are normally distributed with a mean equal to the total estimated load impact and a variance based on the standard errors in the estimated load impacts.

1. *Apply achievement rates to reference loads for each event scenario*.

In this step, the customer-specific achievement rates are applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts.

1. *Apply forecast enrollments to produce program-level load impacts*.

SDG&E’s enrollment forecast assumes that the number of customers remains constant (at PY2014 levels) throughout the forecast period.

## BIP Comparison of Previous versus current ex post

Table 4-7 compares ex post load impacts between PY2013 and PY2014. Seven service accounts were enrolled in each year. The PY2013 load impacts are based on the September 5, 2013 event (four hours in duration), while the PY2014 load impacts are based on the May 16, 2014 event (four hours in duration). The total reference load and load impact was somewhat lower in PY2013, though the percentage load impact was similar in the two years.

Table 4.7: Comparison of Average Event-day Ex Post Impacts (in MW) in PY 2013 and PY2014, *SDG&E*

|  |  |  |  |
| --- | --- | --- | --- |
| **Level** | **Outcome** | **PY2013** | **PY2014** |
| **Total** | # SAIDs | 7 | 7 |
| Reference (MW) | 3.2 | 4.0 |
| Load Impact (MW) | 1.7 | 2.0 |
| **Per SAID** | Reference (kW) | 450 | 575 |
| Load Impact (kW) | 236 | 288 |
| % Load Impact | 52.4% | 50.1% |

## BIP Comparison of previous versus current ex ante

In this sub-section, we compare the ex ante forecast prepared following PY 2013 (the “previous study”) to the ex ante forecast contained in this study (the “current study”). Table 6.12 presents this comparison for the ex ante forecasts of the utility-specific 1-in-2 August peak day. Reference loads, load impacts, and percentage load impacts are all slightly lower in the current ex ante forecast. These likely reflect differences in customer usage levels across PY2013 and PY2014. The relationship between event-day loads and the FSL is similar across the two years, in that the program load is above the FSL early in the event window but below the FSL for the latter portion of the event.

Table 4.8: Comparison of Ex Ante Impacts from PY 2013 and PY 2014 Studies, *SDG&E*

|  |  |  |  |
| --- | --- | --- | --- |
| **Level** | **Outcome** | **Previous Study 2015** | **Current Study 2015** |
| **Total** | # SAIDs | 7 | 7 |
| Reference (MW) | 3.4 | 3.2 |
| Load Impact (MW) | 1.8 | 1.4 |
| **Per SAID** | Reference (kW) | 484 | 458 |
| Load Impact (kW) | 262 | 205 |
| % Load Impact | 54.1% | 44.8% |

## BIP Comparison of previous ex ante versus current ex post

Table 4.9 compares the ex ante forecast prepared following PY2013 to the PY2014 ex post load impact estimates contained in this report. The ex ante load impacts are based on the typical event day in a utility-specific 1-in-2 weather year. The ex post load impacts are based on the May 16, 2014 event day. The ex post reference loads and load impacts are somewhat higher than the ex ante forecast, though the percentage load impacts are quite similar.

Table 4.9: Comparison of Previous Ex Ante and Current Ex Post Impacts, *SDG&E*

|  |  |  |  |
| --- | --- | --- | --- |
| **Level** | **Outcome** | **Ex Ante for TED in PY2014, following PY2013 Study** | **Ex Post Average Event Day, PY2014** |
| **Total** | # SAIDs | 7 | 7 |
| Reference (MW) | 3.4 | 4.0 |
| Load Impact (MW) | 1.8 | 2.0 |
| **Per SAID** | Reference (kW) | 484 | 575 |
| Load Impact (kW) | 262 | 288 |
| % Load Impact | 54.1% | 50.1% |

## BIP Comparison of current ex post versus current ex ante

Table 4.10 describes the factors that differ between the ex post and ex ante load impacts for SDG&E. The ex ante forecast is based on the ex post achievement (i.e., observed loads) relative to the FSL during event hours. So in that way, the ex post and ex ante load impacts match. The key difference in the level (MW) and percentage load impacts is that the historical event occurred earlier in the day when program loads are high relative to the loads during the 1:00 to 4:00 p.m. ex ante event window. Therefore, the level of the ex ante load impacts is lower than the ex post load impacts.

Enrollments are not a factor because the customers enrolled during PY2014 are carried forward into the ex ante forecast. Weather is not a factor because the program reference load is not very weather sensitive.

Table 4.10: SDG&E BIP Ex Post versus Ex Ante Factors, Typical Event Day

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex Post | Ex Ante | Expected Impact |
| Weather | 89.1 degrees Fahrenheit during HE 12-15 on the May 16th event day | 80.0 degrees Fahrenheit during HE 14-18 on utility-specific 1-in-2 typical event day | Program load is not very weather sensitive, so a small effect. |
| Event window | HE 12-15 | HE 14-18 in Apr-Oct. | Reference loads are higher earlier in the day, so the load impacts are higher in ex post even though the event-day loads relative to FSL are set to be the same. |
| % of resource dispatched | All | All | None |
| Enrollment | 7 service accounts | 7 service accounts | None. We assume that enrollment does not change in the forecast period. |
| Methodology | SAID-specific regressions using own within-subject analysis. | Reference loads are simulated from SAID-specific regressions. | Small differences between simulated ex ante and estimated ex post reference loads |

Table 4.11 shows a comparison of ex post and ex ante load impacts. The average reference loads and load impacts are calculated across the relevant event hours. This table illustrates the explanation above: that reference loads were higher during the earlier event window on the May 16th event day, causing the ex post load impacts to be higher than the forecast load impacts.

Table 4.11: Comparison of Ex Post and Ex Ante Load Impacts, SDG&E

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Date** | **Event Hours** | **Reference**  **(MW)** | **Load Impact**  **(MW)** | **Temp.** | **% LI** |
| 5/16/2014 | HE 12-14 | 4.0 | 2.0 | 89.6 | 50.1% |
| Ex Ante TED 1-in-2 | HE 14-18 | 3.2 | 1.4 | 80.0 | 44.8% |

# Summary of SDG&E’s Demand Bidding Program Report

## DBP Program Description

SDG&E has two DBP programs described below:

Schedule DBP-DA: Schedule DBP-DA provides day-ahead notice of event days. The DBP-DA incentive is $0.40 per kWh for customers who purchase commodity from the utility (bundled customers).

Schedule DBP-DO: Demand/energy bidding program offers incentives to nonresidential customers for reducing energy consumption and demand during a specific Demand Bidding Event. This program is applicable to customers who are capable of providing at least a 5 MW load reduction based on the customer’s specific baseline. The DBP-DA Incentive is $0.50 per kWh for customers who purchase commodity from the Utility (bundled customers).

Schedule DBP-DO and DBP-DA programs are available year-round and there is no limit to the number of Demand Bidding Events per month or per year. A customer may not participate simultaneously in DBP-DA or DBP-DO and any other Demand Response rate or program.

## DBP Ex-Post Evaluation Methodology

Ex-post hourly load impacts were estimated using regression equations applied to customer-level hourly load data. The regression equation models hourly load as a function of a set of variables designed to control for factors affecting consumers’ hourly demand levels, such as:

* Seasonal and hourly time patterns (*e.g.*, year, month, day-of-week, and hour, plus various hour/day-type interactions);
* Weather, including hour-specific weather coefficients;
* Event variables. A series of dummy variables was included to account for each hour of each event day, allowing us to estimate the load impacts for all hours across the event days.

The models use the level of hourly demand (kW) as the dependent variable and a separate equation is estimated for each enrolled customer. As a result, the coefficients on the event day/hour variables are direct estimates of the *ex-post* load impacts. For example, a DBP hour 15 event coefficient of -100 would mean that the customer reduced load by 100 kWh during hour 15 of that event day relative to its normal usage in that hour. Weekends and holidays were excluded from the estimation database.[[6]](#footnote-6)

### Regression Model

The model shown below was separately estimated for each enrolled customer. The table 5-1 describes the terms included in the equation.



Table 5-1: Descriptions of Terms included in the Ex-post Regression Equation

|  |  |
| --- | --- |
| **Variable Name / Term** | **Variable / Term Description** |
| *Qt* | the demand in hour *t* for a customer enrolled in DBP prior to the last event date |
| The various *b*’s | the estimated parameters |
| *hi,t* | a dummy variable for hour *i* |
| *DBPt* | an indicator variable for program event days |
| *Weathert* | the weather variables selected using our model screening process |
| *E* | the number of event days that occurred during the program year |
| *MornLoadt* | a variable equal to the average of the day’s load in hours 1 through 10 |
| *OtherEvtDRt* | equals one on the event days of other demand response programs in which the customer is enrolled |
| *MONt* | a dummy variable for Monday |
| *FRIt* | a dummy variable for Friday |
| *SUMMERt* | a dummy variable for the summer pricing season[[7]](#footnote-7) |
| *DTYPEi,t* | a series of dummy variables for each day of the week |
| *MONTHi,t* | a series of dummy variables for each month |
| *et* | the error term. |

The OtherEvt variables help the model explain load changes that occur on event days for programs in which the DBP customers are dually enrolled. (In the absence of these variables, any load reductions that occur on such days may be falsely attributed to other included variables, such as weather condition or day-type variables.) The “morning load” variables are included in the same spirit as the day-of adjustment to the 10-in-10 baseline settlement method. That is, those variables help adjust the reference loads (or the loads that would have been observed in the absence of an event) for factors that affect pre-event usage, but are not accounted for by the other included variables.

The model allows for the hourly load profile to differ by: day of week, with separate profiles for Monday, Tuesday through Thursday, and Friday; and by pricing season (i.e., summer versus winter), in order to account for potential customer load changes in response to seasonal changes in rates.

Separate models were estimated for each customer. The load impacts were aggregated across customer accounts as appropriate to arrive at program-level load impacts, as well as load impacts by industry group and local capacity area (LCA).

### Development of Uncertainty-Adjusted Load Impacts

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. In the case of ex-post load impacts, the parameters that constitute the load impact estimates are not estimated with certainty. We base the uncertainty-adjusted load impacts on the variances associated with the estimated load impact coefficients.

Specifically, we added the variances of the estimated load impacts across the customers who submit a bid for the event in question. These aggregations were performed at either the program level, by industry group, or by LCA, as appropriate. The uncertainty-adjusted scenarios were then simulated under the assumption that each hour’s load impact is normally distributed with the mean equal to the sum of the estimated load impacts and the standard deviation equal to the square root of the sum of the variances of the errors around the estimates of the load impacts. Results for the 10th, 30th, 70th, and 90th percentile scenarios are generated from these distributions.

## DBP Ex-Ante Evaluation Methodology

Reference loads and load impacts for all of the above factors were developed in the following series of steps:

1. *Define data sources*

The reference loads are developed using data for customers enrolled in the DBP during the 2014 program year. The percentage load impacts are developed using the estimated *ex-post* load impacts for the same customers, using data for 2013 and 2014.

For each service account, we determine the appropriate size group, LCA, and dual enrollment status. Service accounts that are dually enrolled in the BIP or an aggregator program (e.g., the Aggregated Managed Portfolio or Capacity Bidding Program) will have their reference loads and load impacts counted in the *program-specific* scenarios (in which each DR program is assumed to be called in isolation), but not in the *portfolio-level* scenarios (in which all DR programs are assumed to have been called).

1. *Simulate reference loads*

In order to develop reference loads, we first re-estimated regression equations for each enrolled service account using data for the current program year. The resulting estimates were used to simulate reference loads for each service account under the various scenarios required by the Protocols (*e.g.*, the typical event day in a utility-specific 1-in-2 weather year).

For the summer months, the re-estimated regression equations were similar in design to the *ex-post* load impact equations. First, the *ex-ante* models excluded the morning-usage variables. While these variables are useful for improving accuracy in estimating *ex-post* load impacts for particular events, they complicate the use of the equations in *ex-ante* simulation. That is, they would require a separate simulation of the level of the morning load. The second difference between the *ex-post* and *ex-ante* models is that the *ex-ante* models use CDH60 as the weather variables in place of the lagged CDH variables used in the *ex-post* regressions. The primary reason for this is that the *ex-ante* weather days were not selected based on weather from the prior day, restricting the use of lagged weather variables to construct the *ex-ante* scenarios.

Because DBP events may be called in any month of the year, we estimated separate regression models to allow us to simulate non-summer reference loads. The non-summer model is shown below. This model is estimated separately from the summer *ex-ante* model. It only differs from the summer model in two ways: it includes *HDHt* variables, where the summer model does not; and the month dummies relate to a different set of months.



Table 5.4: Descriptions of Terms included in the *Ex-ante* Regression Equation

|  |  |
| --- | --- |
| **Variable Name** | **Variable Description** |
| *Qt* | the demand in hour *t* for a customer enrolled in DBP prior to the last event date |
| The various *b*’s | the estimated parameters |
| *hi,t* | a dummy variable for hour *i* |
| *DBPt* | an indicator variable for program event days |
| *OtherEvtDRt* | equals one on the event days of other demand response programs in which the customer is enrolled |
| *CDHt* | cooling degree hours |
| *HDHt* | heating degree hours[[8]](#footnote-8) |
| *MONt* | a dummy variable for Monday |
| *FRIt* | a dummy variable for Friday |
| *DTYPEi,t* | a series of dummy variables for each day of the week |
| *MONTHi,t* | a series of dummy variables for each month |
| *et* | the error term. |

Once these models were estimated, we simulated 24-hour load profiles for each required scenario. The typical event day was assumed to occur in August. Much of the differences across scenarios can be attributed to varying weather conditions.

1. *Calculate forecast percentage load impacts*

SDG&E used only 2013 and 2014, as the program did not exist in 2012. Specifically, we examined only customers enrolled in PY2014, but included load impact estimates from the previous two program years for the PY 2014 program participants that also participated in the program in 2013. This method allowed us to base the *ex-ante* load impacts on a larger sample of events, which helps improve the reliability and consistency of the load impacts across forecasts.

For each service account, we collect the hourly *ex-post* load impact estimates and observed loads for every event available for PY13 and PY14. Within each service account, we then calculated the average hourly load impact and observed load profile, as well as the variance of the each hour’s load impact across the event days. The average load impacts and their associated variances are converted to percentages by dividing them into the customer’s average *ex-post* reference load for the corresponding hour. These percentages are applied to the customer’s *ex-ante* (forecast) reference load for each required scenario (e.g., the August peak month day during a utility-specific 1-in-2 weather year).

1. *Apply percentage load impacts to reference loads for each event scenario.*

In this step, the percentage load impacts were applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts.

1. *Apply forecast enrollments to produce program-level load impacts.*

SDG&E assumes that current enrollments persist through the end of the analysis period. The enrollments are then used to scale up the reference loads and load impacts for each required scenario and customer subgroup.

|  |
| --- |
|  |

The total load impact for the DBP-DA customer (the eight service accounts in PY2013 and PY2013 are all from the same customer) dropped substantially in PY2014. It is not clear why customer performance deteriorated across program years. In contrast, the DBP-DO customer increased the level of its load impacts slightly across program years, but by less than the increase in its reference load, such that the percentage load impact fell.

# Summary of SDG&E’s Summer Saver Report

## Summer Saver Program Description

SDG&E’s Summer Saver program is a demand response resource based on CAC load control. It is implemented through an agreement between SDG&E and Alternative Energy Resources (AER), a subsidiary of Comverge, Inc.,[[9]](#footnote-9) and is expected to continue to be implemented at SDG&E through 2016.

The Summer Saver program is available to both residential and nonresidential customers, where eligible nonresidential customers are subject to a demand limit. Only those nonresidential customers with average monthly peak demand up to a maximum of 100 kW over a 12-month period may participate. Summer Saver events may only be called during the months of May through October. Events must run for at least 2 hours and no more than 4 hours and cannot be called for more than 40 hours per month or 120 hours per year. Load control events can occur on weekends but not on holidays and cannot be called more than three-days in any calendar week. These rules apply to both residential and nonresidential customers alike.

Summer Saver is classified as a day-of demand response program. The program does not notify participating customers when an event is called. SDG&E may call an event whenever the utility’s electric system supply portfolio reaches resource dispatch equivalence of 15,000 Btu/kWh heat rate or as utility system conditions warrant. A Summer Saver event may also be triggered by extreme system conditions, such as special alerts issued by the California Independent System Operator, SDG&E system emergencies related to grid operations, conditions of high forecasted California spot market prices, or for testing or evaluation purposes.

There are two enrollment options for both residential and nonresidential participants. Residential customers can choose to have their CAC units cycled 50% or 100% of the time during an event. The incentive paid for each option varies; the 50% cycling option pays $11.50 per ton per year of CAC capacity and the 100% cycling option pays $38 per ton per year. A residential customer with a four-ton CAC unit would be paid the following on an annual basis under each option:

* $46 for 50% cycling; or

$152 for 100% cycling.

Nonresidential customers have the option of choosing 30% or 50% cycling. The incentive payment for 30% cycling is $9 per ton per year and $15 per ton per year for the 50% cycling option. A nonresidential customer with a nine-ton CAC unit would be paid the following on an annual basis under each option:

* $45 for 30% cycling; or

$75 for 50% cycling.

## Summer Saver Ex-post Methodology

An Randomized Control Trial (RCT) is an experimental research approach where customers are randomly assigned to treatment and control conditions so that the only difference between the two groups, other than random chance, is the existence of the treatment condition. In this context, for each of the five non-May events this year, roughly half of the 1,512 customers in the residential sample and half of the 1,475 customers in the nonresidential sample had their CAC unit cycled while the remaining customers served as the control group. The group that received the event signal alternated from event to event. This design has significant advantages in providing fast, reliable impact estimates if sample sizes are large enough.

Ex post event impacts for each cycling option were estimated for each hour of each event by taking the average load in the group that received the event and subtracting it from the average adjusted load of the group that did not receive the event. The adjustment was based on the ratio of usage between the treatment and control groups for the hour prior to the event start. This adjustment is referred to as a “same-day adjustment” and is an effective way of accounting for small differences in load that can arise between randomly assigned treatment and control groups. Such an adjustment is appropriate in this setting because the vast majority of customers were not notified of Summer Saver events prior to the events’ initiation. Since Summer Saver is a day-of demand response program, the notification occurs within hours of the actual event.

Hourly impact estimates for the residential and nonresidential Summer Saver population were calculated by taking a weighted average of the impact estimates for each cycling option, with weights determined by the number of tons enrolled on each cycling option. Similar weighting was done to calculate cycle percentage level impacts. For cycle percentage level impacts, weights were determined by the number of tons enrolled in each climate zone. Impacts for the average event day were calculated from treatment and control group load shapes averaged across the three events that lasted from 2 to 6 PM.

## Summer Saver Ex-Post Load Impact Estimates

This section contains the ex-post load impact estimates for program year 2014. Residential estimates are provided first, followed by nonresidential estimates.

### Summer Saver Residential Ex-Post Load Impact Estimates

Summer Saver program events were triggered eight times in 2014 and each event lasted four hours. The hours covered by each event varied, but three of the eight events lasted from 2 to 6 PM. Two events were called late in the day, from 4 to 8 PM. Table 4-1 presents ex post load impacts for the residential program segment for 2014 and 2013, for comparison. Aggregate load impacts ranged from a low of 6.0 MW on May 16, 2014 to a high of 19.5 MW on September 16, 2014. The three events that occurred from 2 to 6 PM produced, on average, 11.2 MW of load reduction. These load impacts represent some of the lowest estimated load impacts in recent years. Two factors may explain these low impacts. First, there were three events called in the month of May during a Santa Ana weather event in the San Diego region. These three events are the first time that Summer Saver has been dispatched in the month of May. Such early events may reflect reduced air conditioning load due to the fact that many HVAC systems were not set to cooling mode yet. Second, the Summer Saver events called in 2014 were called during historically cool weather conditions—on average, the temperatures observed during the event hours are the lowest observed since 2010.

Table 6-1: Summer Saver Residential Ex Post Load Impact Estimates

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Year** | **Date** | **Impact** | | | **Avg. Temperature During Event (°F)** |
| **Per CAC Unit (kW)** | **Per Premise (kW)** | **Aggregate (MW)** |
| 2013 | 8/28/2013 | 0.48 | 0.52 | 12 | 84 |
| 8/29/2013 | 0.46 | 0.51 | 12 | 88 |
| 8/30/2013 | 0.68 | 0.78 | 18 | 91 |
| 9/3/2013 | 0.58 | 0.65 | 15 | 88 |
| 9/5/2013 | 0.57 | 0.63 | 14 | 89 |
| 9/6/2013 | 0.84 | 0.90 | 21 | 92 |
| Average\* | 0.66 | 0.74 | 17 | 90 |
| 2014 | 5/14/2014 | 0.26 | 0.31 | 6.9 | 85 |
| 5/15/2014 | 0.41 | 0.49 | 10.9 | 87 |
| 5/16/2014 | 0.22 | 0.27 | 6.0 | 93 |
| 7/29/2014 | 0.45 | 0.54 | 12.2 | 80 |
| 8/27/2014 | 0.23 | 0.27 | 6.1 | 85 |
| 9/15/2014 | 0.68 | 0.81 | 18.2 | 88 |
| 9/16/2014 | 0.73 | 0.87 | 19.5 | 89 |
| 9/17/2014 | 0.53 | 0.64 | 14.3 | 83 |
| Average\*\* | 0.42 | 0.50 | 11.2 | 85 |
| \*Reflects the average 1–5 PM 2013 Summer Saver event | | | | | |
| \*\*Reflects the average 2–6 PM 2014 Summer Saver event | | | | | |

Table 6-2 shows the estimated load impacts for residential participants on each event day segmented by cycling option. On a per premise basis, load impacts for 100% cycling range from a high of 1.05 kW to a low of 0.43 kW. Load impacts for 50% cycling range from 0.85 kW to 0.11 kW per premise. Across the three days with the same event times, load impacts for 100% cycling are 35% higher than for 50% cycling, despite the fact that the cycling percentage differs by a factor of two. This is primarily due to the fact that average reference load for customers taking the 50% cycling option is about 40% higher than for those taking the 100% option. Put another way, customers that use their CAC units more are less likely to take the 100% cycling options.

In the case of two event days, July 29, 2014 and September 15, 2014, reference loads for 100% cycling customers are in fact much higher, which is also when load impacts for 100% cycling are actually lower than 50% cycling,. While the differences between the estimated load impacts for 50% and 100% cycling are not statistically significant, on both of these days, reference loads for customers on the 50% cycling option are about 60% higher than for customers on the 100% option. Similar outcomes have been observed in prior evaluations of the Summer Saver program, but given the relatively small sample sizes at the cycling option level of aggregation, this result may just be due to random fluctuation. There may also have been slightly different weather patterns for the two groups that caused the larger reference load increase for the 50% cycling customers on these days (100% cycling customers are more highly concentrated in the moderate coastal climate zone than are 50% cycling customers, so there are small differences in average weather for the two groups).

Table 6-2: Summer Saver Residential Average (kW per Premise) and Aggregate (MW) Load Impacts by Cycling Option

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Event Date** | **Average Load Impact per Premise (kW)** | | **Aggregate Load Impact (MW)** | |
| **100%** | **50%** | **100%** | **50%** |
| 5/14/2014 | 0.45 | 0.19 | 4.8 | 2.2 |
| 5/15/2014 | 0.58 | 0.41 | 6.1 | 4.8 |
| 5/16/2014 | 0.43 | 0.12 | 4.5 | 1.5 |
| 7/29/2014 | 0.56 | 0.54 | 5.9 | 6.3 |
| 8/27/2014 | 0.44 | 0.11 | 4.6 | 1.3 |
| 9/15/2014 | 0.80 | 0.85 | 8.5 | 10.0 |
| 9/16/2014 | 1.05 | 0.69 | 11.2 | 8.1 |
| 9/17/2014 | 0.68 | 0.63 | 7.3 | 7.4 |
| Average\* | 0.58 | 0.43 | 6.2 | 5.0 |
| \*Reflects the average 2-6 PM 2014 Summer Saver event | | | |  |

### Summer Saver Nonresidential Ex-Post Load Impact Estimates

Table 6-3 presents ex post load impact estimates for nonresidential customers for each 2014 event day and on average across the three Summer Saver events in 2014 with common event hours from 2 to 6 PM, in addition to the 2013 ex post load impacts for comparison. Nonresidential customers represent 17% of total Summer Saver participants and 31% of enrolled CAC tonnage. Nonresidential aggregate impacts varied from a low of 0.5 MW on July 29 to a high of 4.0 MW on September 16. While both nonresidential and residential load impacts peaked on the same day, nonresidential and residential load impacts were at their lowest in 2014 on different days. Nonresidential load impacts were extremely low on July 29, but not unprecedentedly so. The average temperature observed on this day for nonresidential customers during the event was 78°F, which is the lowest observed average event temperature since the same average event temperature was observed during an event in 2012. Per premise load impacts for this event (on September 13, 2012) were estimated at 0.13 kW, similar to the 0.10 kW per premise estimated for July 29, 2014. Like the residential program segment, the nonresidential segment saw relatively low load impacts for the first event day during the May Santa Ana weather event, but unlike the residential segment, the nonresidential segment returned to the typical range of load impacts for nonresidential participants on hot summer days.

Table 6-3: Summer Saver Nonresidential Ex Post Load Impact Estimates

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | | **Date** | **Impact** | | | **Avg. Temperature During Event (°F)** | |
| **Per CAC Unit (kW)** | **Per Premise (kW)** | **Aggregate (MW)** |
| 2013 | | 8/28/2013 | 0.20 | 0.50 | 2 | 82 | |
| 8/29/2013 | 0.28 | 0.69 | 3 | 87 | |
| 8/30/2013 | 0.34 | 0.83 | 4 | 90 | |
| 9/3/2013 | 0.34 | 0.84 | 4 | 85 | |
| 9/5/2013 | 0.34 | 0.83 | 4 | 86 | |
| 9/6/2013 | 0.38 | 0.94 | 4 | 90 | |
| Average\* | 0.35 | 0.86 | 4 | 88 | |
| 2014 | | 5/14/2014 | 0.16 | 0.37 | 1.7 | 85 | |
| 5/15/2014 | 0.25 | 0.60 | 2.8 | 86 | |
| 5/16/2014 | 0.33 | 0.79 | 3.7 | 91 | |
| 7/29/2014 | 0.04 | 0.10 | 0.5 | 78 | |
| 8/27/2014 | 0.31 | 0.74 | 3.5 | 84 | |
| 9/15/2014 | 0.24 | 0.56 | 2.6 | 86 | |
| 9/16/2014 | 0.36 | 0.85 | 4.0 | 89 | |
| 9/17/2014 | 0.32 | 0.76 | 3.5 | 82 | |
| Average\*\* | 0.29 | 0.69 | 3.2 | 84 | |
| \*Reflects the average 1–5 PM 2013 Summer Saver event | | | | | |
| \*\*Reflects the average 2–6 PM 2014 Summer Saver event | | | | | |

In 2014, the overall difference between load impacts per CAC unit is not as large, and no clear directional difference in load impacts is observed between residential and nonresidential 50% cycling, as shown in Table 6-4 below.

Table 6-4: Comparison of Residential and Nonresidential Summer Saver 50% Cycling Load Impacts

|  |  |  |
| --- | --- | --- |
| Event Date | Average Load Impact per CAC Unit (kW) | |
| Residential 50% | Nonresidential 50% |
| 5/14/2014 | 0.16 | 0.22 |
| 5/15/2014 | 0.35 | 0.33 |
| 5/16/2014 | 0.11 | 0.37 |
| 7/29/2014 | 0.46 | 0.05 |
| 8/27/2014 | 0.10 | 0.37 |
| 9/15/2014 | 0.73 | 0.28 |
| 9/16/2014 | 0.59 | 0.32 |
| 9/17/2014 | 0.53 | 0.44 |
| Average\* | 0.37 | 0.35 |

## Summer Saver Ex-Ante Impact Estimation Methodology

Ex ante load impacts were developed by using the available ex post data. For both residential and nonresidential customers, load impacts for a common set of hours across all ex post events from 2010 through 2014 were used in the estimation database for developing the ex ante model. Only the hours from 2 to 5 PM were used for the analysis because these hours were common across the greatest number of ex post event days. Certain prior Summer Saver event days were not used in the ex ante regression analysis because of atypical circumstances surrounding the event. September 8 and 9, 2011 were excluded as they were associated with a regional system outage. September 15, 2012 was excluded because it is a Saturday. August 10, 2012 was excluded because the event only had one hour during the period 2 to 5 PM, and the May 2014 events were excluded because of the unusually high temperatures, attributable to Santa Ana wind conditions and fires, recorded during those events which were coupled with unusually low load impacts.

The average load reduction from 2 to 5 PM was modeled as a function of the average temperature for the first 17 hours of each event day, midnight to 5 PM, (mean17). This 17-hour average was used to capture the impact of heat buildup leading up to and including the event hours. Per ton load impacts were used so that the load impacts would be scalable to ex ante scenarios where the tonnage and number of devices per premise may be different. The models were run separately by customer type (residential and nonresidential) and cycling strategy. The estimated parameters from the models were used to predict load impacts under 1-in-2 and 1-in-10 year ex ante weather conditions. The final regressions only included one explanatory variable because more complicated models were not found to perform better in cross-validations done in previous Summer Saver evaluations. The model that was used to predict average ex post impacts was:

Table 6‑5: Ex Ante Regression Variables

| Variable | Description |
| --- | --- |
| *Impactd* | Average per ton ex post load impact for each event day from 2 to 5 PM |
|  | Estimated constant |
|  | Estimated parameter coefficient |
|  | Average temperature over the 17 hours prior to the start of the event for each event day |
|  | The error term for each day *d* |

## Summer Saver Ex-Ante Load Impact Estimates

Enrollment in the Summer Saver program is not expected to change over the forecast horizon so the tables in this section represent predictions for the entire eleven-year period from 2015 to 2025. The Protocols 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 two years (1-in-2 conditions) and extreme conditions are those that would be expected to occur once every ten years (1-in-10 conditions). 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: the first set reflects operating conditions for each IOU and the second reflects operating conditions for the CAISO system.

The extent to which utility-specific ex ante weather conditions differ from CAISO ex ante weather conditions largely depends on the correlation between individual utility and CAISO peak loads. Based on CAISO and SDG&E system peak loads for the top 25 CAISO system load days each year from 2006 to 2013, the correlation coefficient for SDG&E is 0.56, indicating that there are many days on which the CAISO system loads are high while SDG&E loads are more modest. This correlation for SDG&E tends to be weakest when CAISO loads have been below 46,000 MW. CAISO loads often reach 43,000 MW when loads in the Los Angeles area are extreme but San Diego loads are moderate (or vice-versa). However, whenever CAISO loads have exceeded 45,000 MW, loads typically have been high across all three IOU’s.

Table 6-6 shows the Summer Saver enrollment-weighted average temperature from midnight to 5 PM (mean17) for the typical event day and the monthly system peak day under the four sets of weather conditions for which load impacts are estimated. The differences in mean17 values based on SDG&E peak conditions and CAISO peak conditions and based on normal and extreme weather can be quite large. There are also large differences across months. As seen later, even small differences in the value of mean17 can have large impacts on aggregate load impacts.

**Table 6-6: Summer Saver Enrollment-weighted Ex Ante Weather Values (mean17)**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Customer Type | Cycle | Day Type | CAISO-based Weather (°F) | | SDG&E-based Weather (°F) | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| Nonresidential | 30% | Typical Event Day | 74 | 77 | 73 | 78 |
| May Peak Day | 65 | 74 | 68 | 77 |
| June Peak Day | 69 | 74 | 68 | 74 |
| July Peak Day | 72 | 74 | 73 | 79 |
| August Peak Day | 77 | 77 | 75 | 79 |
| September Peak Day | 77 | 82 | 76 | 82 |
| October Peak Day | 68 | 75 | 71 | 77 |
| 50% | Typical Event Day | 73 | 76 | 73 | 78 |
| May Peak Day | 65 | 73 | 68 | 76 |
| June Peak Day | 69 | 73 | 68 | 73 |
| July Peak Day | 72 | 74 | 72 | 78 |
| August Peak Day | 76 | 77 | 75 | 79 |
| September Peak Day | 77 | 81 | 75 | 81 |
| October Peak Day | 68 | 75 | 71 | 76 |
| Residential | 50% | Typical Event Day | 74 | 78 | 74 | 79 |
| May Peak Day | 65 | 74 | 69 | 77 |
| June Peak Day | 69 | 74 | 69 | 75 |
| July Peak Day | 72 | 75 | 73 | 80 |
| August Peak Day | 77 | 78 | 75 | 80 |
| September Peak Day | 78 | 83 | 77 | 83 |
| October Peak Day | 68 | 76 | 72 | 78 |
| 100% | Typical Event Day | 74 | 77 | 73 | 79 |
| May Peak Day | 65 | 74 | 69 | 77 |
| June Peak Day | 69 | 74 | 68 | 74 |
| July Peak Day | 72 | 75 | 73 | 79 |
| August Peak Day | 77 | 78 | 75 | 80 |
| September Peak Day | 78 | 83 | 76 | 83 |
| October Peak Day | 68 | 75 | 72 | 77 |

While Summer Saver events can be called any time between noon and 8 PM, ex ante load impacts reported here represent the average load impact across the hours from 1 to 6 PM, reflecting the peak period as defined by the CPUC for determining resource adequacy requirements.

Tables 6-7 and 6-8 summarize the average and aggregate load impact estimates per premise under SDG&E-specific peaking conditions and CAISO peaking conditions, respectively. For a typical event day with 1-in-2 year, SDG&E-specific weather conditions, the impact per premise is 0.41 kW for residential customers. The 1-in-10 year typical event day estimate is 56% higher at 0.64 kW. Under 1-in-2 CAISO peak conditions, the typical event day residential load impact per premise is 0.44 kW; for the 1-in-10 scenario, it is 0.56 kW, or 27% higher. These large differences are driven by the larger differences in mean17, which vary by 5 or 6 degrees across some of the above conditions. A difference of 5 degrees on average over 17 hours represents a very large difference in temperature conditions and air conditioning requirements.

Nonresidential Summer Saver load impacts for the typical event day are 0.57 kW per premise under 1-in-2 SDG&E-specific peak conditions, and 0.77 kW for 1-in-10. Under CAISO peak conditions, nonresidential typical event day load impacts are 0.59 kW per premise for 1-in-2 and 0.71 kW per premise for 1-in-10 weather. The 1-in-2 to 1-in-10 increase in load impacts is 35% for SDG&E-specific peak conditions and 20% for CAISO peak conditions.

The aggregate program load reduction potential for residential customers is 9.4 MW for a typical event day under SDG&E-specific 1-in-2 year weather conditions and 14.6 MW under SDG&E-specific 1-in-10 year weather conditions. Residential aggregate load impacts for 1-in-2 CAISO peaking conditions are 10.0 MW and 13.0 MW for the 1-in-10 weather scenario. For SDG&E peaking conditions, nonresidential aggregate program load reduction potential is 2.7 MW under the 1-in-2 scenario and 3.7 MW under the 1-in-10 scenario for the typical event day. For CAISO peaking conditions, the nonresidential typical event day load impacts for 1-in-2 and 1-in-10 conditions are similar: 2.8 MW and 3.4 MW, respectively.

### Comparison of Ex-Ante results by Month

September ex ante conditions are much hotter than typical event day conditions. The residential program is estimated to provide an average impact of 17.9 MW over the 5-hour event window from 1 to 6 PM on a 1-in-10 September monthly system peak day and 12.1 MW on the September monthly system peak day under 1-in-2 year weather conditions for SDG&E-specific peaking conditions. Under CAISO peak conditions, residential aggregate load reduction on a September monthly system peak day is 13.5 MW for 1-in-2 and 18.1 MW for 1-in-10.

There is significant variation in load impacts across months and weather conditions. Based on 1-in-2 year weather, the low temperatures in May and June typically experienced in San Diego result in small average and aggregate load impacts. The May and June 1-in-2 year impacts for residential customers are only about 40% of the September estimate, which is the highest of any month under 1-in-2 year weather conditions. For residential customers, the May and June 1-in-10 year estimates are 1.5 times greater than the 1-in-2 year estimates as a result of the 1-in-10 year temperatures being much warmer than the 1-in-2 year temperatures for May and June.

For the residential segment of Summer Saver, the May 2014 ex post load impacts are quite a bit larger than the 1-in-2 ex ante load impacts for May, attributable to the fact that the Santa Ana weather event created temperature conditions far from the norm for San Diego in May. The two midsummer events’ ex post load impacts on average similar to 1-in-2 typical event day load impacts, while the three September events’ ex post load impacts are closer to the 1-in-10 September monthly peak day ex ante estimate than the 1-in-2.

The nonresidential segment’s ex post reflects the same general relationship with the ex ante load impacts: The May 2014 events’ ex post load impacts far exceed the May 1-in-2 ex ante estimate, most likely due to the Santa Anas. The midsummer events are on average lower than even the 1-in-2 ex ante estimate for the typical event day, and this outcome is strongly influenced by the very low load impacts observed on July 29, 2014 – one of the coolest Summer Saver events in recent years. The September 2014 events’ load impacts are generally in between the 1-in-2 and 1-in-10 ex ante load impacts.

On a per premise basis, the nonresidential segment provides more load impacts than residential customers. But in aggregate, the residential segment provides far more MW of load reduction due the much greater numbers of residential participants than non-participants.

Table 6-7: Summer Saver Ex Ante Load Impact Estimates by CAISO and SDG&E-specific Weather and Day Type (1 to 6 PM, 1-in-10 Conditions)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Customer Type** | **Day Type** | **Per Premise Impact (kW)** | | **Aggregate Impact (MW)** | |
| **CAISO** | **SDGE** | **CAISO** | **SDGE** |
| Residential | Typical Event Day | 0.56 | 0.64 | 13.0 | 14.6 |
| May Monthly Peak | 0.44 | 0.55 | 10.0 | 12.7 |
| June Monthly Peak | 0.43 | 0.45 | 9.9 | 10.4 |
| July Monthly Peak | 0.46 | 0.64 | 10.5 | 14.8 |
| August Monthly Peak | 0.58 | 0.67 | 13.4 | 15.4 |
| September Monthly Peak | 0.79 | 0.78 | 18.1 | 17.9 |
| October Monthly Peak | 0.49 | 0.57 | 11.3 | 13.1 |
| Non-Residential | Typical Event Day | 0.71 | 0.77 | 3.4 | 3.7 |
| May Monthly Peak | 0.58 | 0.70 | 2.8 | 3.4 |
| June Monthly Peak | 0.59 | 0.60 | 2.8 | 2.9 |
| July Monthly Peak | 0.61 | 0.79 | 2.9 | 3.8 |
| August Monthly Peak | 0.73 | 0.82 | 3.5 | 3.9 |
| September Monthly Peak | 0.91 | 0.89 | 4.3 | 4.3 |
| October Monthly Peak | 0.65 | 0.71 | 3.1 | 3.4 |

Table 6-8: Summer Saver Ex Ante Load Impact Estimates by CAISO and SDG&E-specific Weather and Day Type (1 to 6 PM, 1-in-2 Conditions)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Customer Type** | **Day Type** | **Per Premise Impact (kW)** | | **Aggregate Impact (MW)** | |
| **CAISO** | **SDGE** | **CAISO** | **SDGE** |
| Residential | Typical Event Day | 0.44 | 0.41 | 10.0 | 9.4 |
| May Monthly Peak | 0.09 | 0.22 | 2.0 | 5.1 |
| June Monthly Peak | 0.24 | 0.21 | 5.6 | 4.9 |
| July Monthly Peak | 0.36 | 0.40 | 8.2 | 9.2 |
| August Monthly Peak | 0.56 | 0.48 | 12.8 | 11.2 |
| September Monthly Peak | 0.59 | 0.53 | 13.5 | 12.1 |
| October Monthly Peak | 0.20 | 0.34 | 4.7 | 7.9 |
| Non-Residential | Typical Event Day | 0.59 | 0.57 | 2.8 | 2.7 |
| May Monthly Peak | 0.25 | 0.38 | 1.2 | 1.8 |
| June Monthly Peak | 0.41 | 0.39 | 2.0 | 1.9 |
| July Monthly Peak | 0.53 | 0.55 | 2.5 | 2.6 |
| August Monthly Peak | 0.71 | 0.66 | 3.4 | 3.2 |
| September Monthly Peak | 0.73 | 0.67 | 3.5 | 3.2 |
| October Monthly Peak | 0.39 | 0.50 | 1.9 | 2.4 |

## Relationship between Ex-Post and Ex-Ante Estimates

Table 6-9 presents enrollment-weighted, mean17 temperatures for the new CAISO and SDG&E-weather and for the old ex ante weather file (which was SDGE-based only). As seen, the old and new SDG&E-based weather differs in some important ways. First, for the average event day, while the 1-in-10 weather is relatively unchanged, the new SDG&E based 1-in-2 weather is 3 degrees cooler than the old SDG&E-based weather. For the September monthly system peak day, both 1-in-2 and 1-in10 weather year conditions showing as lower in the new weather file with the largest decreases occurring in the case of the 1-in-2 weather year. For September 1-in-10 weather, which is the month and weather year combination with the highest potential for Summer Saver load impacts, per premise load impacts would be 0.89 kW for the residential segment under the old weather conditions. Under the new weather conditions, the same estimate is 0.78 kW. A similar effect for the nonresidential segment is also present: 1.02 kW per premise with the old weather and 0.89 kW per premise with the new weather.

Table 6-9: Comparison of Summer Saver Enrollment-weighted Temperatures (mean17) across Weather Scenarios

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Customer Type | Cycle | Day Type | **CAISO-based Weather** | | **SDG&E-based Weather** | | **Old Weather** | |
| **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** |
| Nonresidential | 30% | Typical Event Day | 74 | 77 | 73 | 78 | 76 | 79 |
| May Peak Day | 65 | 74 | 68 | 77 | 68 | 75 |
| June Peak Day | 69 | 74 | 68 | 74 | 68 | 76 |
| July Peak Day | 72 | 74 | 73 | 79 | 77 | 78 |
| August Peak Day | 77 | 77 | 75 | 79 | 76 | 79 |
| September Peak Day | 77 | 82 | 76 | 82 | 81 | 85 |
| October Peak Day | 68 | 75 | 71 | 77 | 73 | 76 |
| 50% | Typical Event Day | 73 | 76 | 73 | 78 | 76 | 78 |
| May Peak Day | 65 | 73 | 68 | 76 | 67 | 75 |
| June Peak Day | 69 | 73 | 68 | 73 | 68 | 76 |
| July Peak Day | 72 | 74 | 72 | 78 | 77 | 77 |
| August Peak Day | 76 | 77 | 75 | 79 | 76 | 78 |
| September Peak Day | 77 | 81 | 75 | 81 | 81 | 84 |
| October Peak Day | 68 | 75 | 71 | 76 | 72 | 76 |
| Residential | 50% | Typical Event Day | 74 | 78 | 74 | 79 | 77 | 80 |
| May Peak Day | 65 | 74 | 69 | 77 | 68 | 76 |
| June Peak Day | 69 | 74 | 69 | 75 | 68 | 77 |
| July Peak Day | 72 | 75 | 73 | 80 | 77 | 80 |
| August Peak Day | 77 | 78 | 75 | 80 | 77 | 79 |
| September Peak Day | 78 | 83 | 77 | 83 | 82 | 86 |
| October Peak Day | 68 | 76 | 72 | 78 | 74 | 77 |
| 100% | Typical Event Day | 74 | 77 | 73 | 79 | 76 | 79 |
| May Peak Day | 65 | 74 | 69 | 77 | 68 | 76 |
| June Peak Day | 69 | 74 | 68 | 74 | 68 | 77 |
| July Peak Day | 72 | 75 | 73 | 79 | 77 | 79 |
| August Peak Day | 77 | 78 | 75 | 80 | 77 | 79 |
| September Peak Day | 78 | 83 | 76 | 83 | 82 | 85 |
| October Peak Day | 68 | 75 | 72 | 77 | 74 | 77 |

. Tables 6-10 and 6-11 show how aggregate load impacts for residential participants change as a result of differences in the factors underlying ex post and ex ante estimates. Table 6-12 pertains to residential customers in the 50% cycling option and Table 6-13 pertains to 100% cycling participants.

Columns A through D describe the particular circumstances of each 2014 Summer Saver load control event. Each event is denoted by its date, shown in Column A. Column B shows the time of the event window, and column C shows the temperature for each event day, as measured by mean17 (the enrollment-weighted temperature averaged across the hours midnight to 5 PM). Column C reflects the temperatures of this report and in the ex post table generators.

Column D reflects the mean17 temperature for each event using only two weather stations, San Diego International Airport (KSAN) and Miramar Marine Corps Air Station (KNKX). This is the first difference between the ex post and ex ante load impacts: ex ante load impacts are estimated using weather conditions determined by only these two weather stations; so the first step in the comparison process is to translate the ex post temperatures using seven weather stations to ex post temperatures based on two weather stations. Column F then presents the load impacts that the ex ante model predicts for the ex post event window (Column B) and for the ex post weather conditions (Column E). Column G makes a final adjustment to the predicted load impacts shown in Column F by recalculating the predicted load impacts for the ex ante event window, which is always 1 to 6 PM.

Columns H and I compare Column G with the ex ante load impact estimate given the SDG&E-specific ex ante weather conditions for 1-in-2 and 1-in-10 year system peaking scenarios. Columns H and I are divided into three rows, orange, blue, and purple. The orange rows represent the May monthly system peak day ex ante estimates, which is appropriate to use to compare with the values in Column G for the May events. The blue rows show the typical event day ex ante estimates, which are most representative of the July and August events. Finally the purple rows show the September monthly peak day ex ante estimates, for comparison with the September event load impacts shown in Column G.

Columns J through K, like Columns H and I, show ex ante load impacts for 1-in-2 and 1-in-10 year conditions, but for CAISO peaking conditions

**Table 6-10: Differences in Ex Post and Ex Ante Load Impacts Due to Key Factors  
Residential 50% Cycling**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2014 Ex Post** | | | | **2014 Ex Ante Model** | | | | | |
| **Event Window** | **Mean17 (**°F ) | **Ex Post Aggregate Impact (MW)** | **Mean17 using KSAN KNKX Only (°F)** | **Ex Ante Impact with Ex Post Event Window and Weather (MW)** | **Ex Ante Impact (1PM-6PM) using Ex Post Weather (MW)** | **Ex Ante Impact SDG&E 1-in-2 (MW)** | **Ex Ante Impact SDG&E 1-in-10 (MW)** | **Ex Ante Impact CAISO 1-in-2 (MW)** | **Ex Ante Impact CAISO 1-in-10 (MW)** |
|
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** | **K** |
| 5/14/2014 | 4-8 pm | 82 | 2.2 | 82 | 9 | 8.6 | 3.0  (69°F) | 6.6  (77°F) | 1.6  (65°F) | 5.3  (74°F) |
| 5/15/2014 | 4-8 pm | 84 | 4.8 | 86 | 10.5 | 10.1 |
| 5/16/2014 | 12-4 pm | 82 | 1.5 | 83 | 8.7 | 8.9 |
| 7/29/2014 | 3-7 pm | 80 | 6.3 | 78 | 7.3 | 6.9 | 5.0  (74°F) | 7.5  (79°F) | 5.3  (74°F) | 6.7  (78°F) |
| 8/27/2014 | 2-6 pm | 79 | 1.3 | 79 | 7.5 | 7.2 |
| 9/15/2014 | 2-6 pm | 84 | 10 | 82 | 9 | 8.7 | 6.3  (77°F) | 9.1  (83°F) | 7.0  (78°F) | 9.1  (83°F) |
| 9/16/2014 | 3-7 pm | 86 | 8.1 | 86 | 10.7 | 10.1 |
| 9/17/2014 | 2-6 pm | 86 | 7.4 | 84 | 9.6 | 9.2 |

**Table 6-11: Differences in Ex Post and Ex Ante Impacts Due to Key Factors**

**Residential 100% Cycling**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2014 Ex Post** | | | | **2014 Ex Ante Model** | | | | | |
| **Event Window** | **Mean17 (**°F ) | **Ex-Post Aggregate Impact (MW)** | **Mean17 using KSAN KNKX Only (°F)** | **Ex Ante Impact with Ex Post Event Window and Weather (MW)** | **Ex-Ante Impact (1PM-6PM) using Ex Post Weather (MW)** | **Ex Ante Impact SDG&E 1-in-2 (MW)** | **Ex Ante Impact SDG&E 1-in-10 (MW)** | **Ex Ante Impact CAISO**  **1-in-2 (MW)** | **Ex Ante Impact CAISO**  **1-in-10 (MW)** |
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** | **K** |
| 5/14/2014 | 4-8 pm | 82 | 4.8 | 82 | 9.9 | 8.6 | 2.0  (69°F) | 6.1  (77°F) | 0.3  (65°F) | 4.7  (74°F) |
| 5/15/2014 | 4-8 pm | 84 | 6.1 | 85 | 11.8 | 10.3 |
| 5/16/2014 | 12-4 pm | 82 | 4.5 | 83 | 8.1 | 8.9 |
| 7/29/2014 | 3-7 pm | 79 | 5.9 | 78 | 7.4 | 6.6 | 4.3  (73°F) | 7.1 (79°F) | 4.7  (74°F) | 6.3  (77°F) |
| 8/27/2014 | 2-6 pm | 79 | 4.6 | 79 | 7.4 | 6.9 |
| 9/15/2014 | 2-6 pm | 83 | 8.5 | 82 | 9.3 | 8.7 | 5.8  (76°F) | 8.9  (83°F) | 6.5  (78°F) | 9.0  (83°F) |
| 9/16/2014 | 3-7 pm | 85 | 11.2 | 85 | 11.6 | 10.3 |
| 9/17/2014 | 2-6 pm | 85 | 7.3 | 83 | 9.8 | 9.2 |

**Table 6-12: Differences in Ex Post and Ex Ante Impacts Due to Key Factors**

**Nonresidential 30% Cycling**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2014 Ex Post** | | | | **2014 Ex Ante Model** | | | | | |
| **Event Window** | **Mean17 (**°F ) | **Ex-Post Aggregate Impact (MW)** | **Mean17 using KSAN KNKX Only (°F)** | **Ex Ante Impact with Ex Post Event Window and Weather (MW)** | **Ex-Ante Impact (1PM-6PM) using Ex Post Weather (MW)** | **Ex Ante Impact SDG&E 1-in-2 (MW)** | **Ex Ante Impact SDG&E 1-in-10 (MW)** | **Ex Ante Impact CAISO**  **1-in-2 (MW)** | **Ex Ante Impact CAISO**  **1-in-10 (MW)** |
|
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** | **K** |
| 5/14/2014 | 4-8 pm | 82 | 0.1 | 82 | 0.9 | 1 | 0.7  (69°F) | 0.9 (77°F) | 0.6  (65°F) | 0.8  (74°F) |
| 5/15/2014 | 4-8 pm | 84 | 0.4 | 85 | 1 | 1.1 |
| 5/16/2014 | 12-4 pm | 81 | 0.9 | 82 | 1.1 | 1 |
| 7/29/2014 | 3-7 pm | 79 | 0.1 | 78 | 0.9 | 0.9 | 0.8  (74°F) | 0.9 (79°F) | 0.8  (74°F) | 0.9  (78°F) |
| 8/27/2014 | 2-6 pm | 78 | 0.7 | 78 | 0.9 | 0.9 |
| 9/15/2014 | 2-6 pm | 82 | 0.6 | 82 | 1 | 1 | 0.9  (77°F) | 1.0 (83°F) | 0.9  (78°F) | 1.0  (83°F) |
| 9/16/2014 | 3-7 pm | 85 | 1.5 | 85 | 1 | 1.1 |
| 9/17/2014 | 2-6 pm | 84 | 0.3 | 83 | 1 | 1 |

**Table 6-13: Differences in Ex Post and Ex Ante Impacts Due to Key Factors**

**Nonresidential 50% Cycling**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2014 Ex Post** | | | | **2014 Ex Ante Model** | | | | | |
| **Event Window** | **Mean17 (**°F ) | **Ex Post Aggregate Impact (MW)** | **Mean17 using KSAN KNKX Only (°F)** | **Ex Ante Impact with Ex Post Event Window and Weather (MW)** | **Ex Ante Impact (1PM-6PM) using Ex Post Weather (MW)** | **Ex Ante Impact SDG&E 1-in-2 (MW)** | **Ex Ante Impact SDG&E 1-in-10 (MW)** | **Ex Ante Impact CAISO**  **1-in-2 (MW)** | **Ex Ante Impact CAISO**  **1-in-10 (MW)** |
|
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** | **K** |
| 5/14/2014 | 4-8 pm | 82 | 1.6 | 82 | 3.1 | 3.3 | 1.1  (69°F) | 2.5 (77°F) | 0.6  (65°F) | 2.0  (74°F) |
| 5/15/2014 | 4-8 pm | 84 | 2.4 | 85 | 3.5 | 3.9 |
| 5/16/2014 | 12-4 pm | 81 | 2.8 | 82 | 3.5 | 3.3 |
| 7/29/2014 | 3-7 pm | 78 | 0.4 | 78 | 2.6 | 2.7 | 1.9  (73°F) | 2.7 (79°F) | 2.0  (74°F) | 2.5  (77°F) |
| 8/27/2014 | 2-6 pm | 78 | 2.8 | 78 | 2.7 | 2.7 |
| 9/15/2014 | 2-6 pm | 82 | 2.1 | 81 | 3.3 | 3.3 | 2.3  (76°F) | 3.2 (83°F) | 2.5  (78°F) | 3.3 (83°F) |
| 9/16/2014 | 3-7 pm | 84 | 2.4 | 85 | 3.7 | 3.8 |
| 9/17/2014 | 2-6 pm | 83 | 3.3 | 82 | 3.4 | 3.4 |

# Opt-in Peak Time Rebate Program (PTR) and Small Customer Technology Deployment (SCTD) Program

## 7.1 Opt-in PTR Program Description

The program provides customers with notification on a day-ahead basis that a PTR event will occur on the following day. In emergency situations, a PTR event can be called on a day-of basis to help address an emergency, but day-of events are not the primary design or intended use of the program. PTR is a two-level incentive program, providing a basic incentive level ($0.75/kWh) to customers that reduce energy use through manual means and a premium incentive ($1.25/kWh) to customers that reduce energy use through automated demand response (DR) enabling technologies. The PTR bill credit is calculated based on their event day reduction in electric usage below their established customer-specific reference level (CRL). The program is marketed under the name Reduce Your Use (RYU) and is an opt-in program for residential customers. CPUC Decision D-13-07-003 directed SDG&E to require residential customers to enroll in PTR to receive a bill credit beginning in 2014. Prior to 2014, the PTR program was a default program for all SDG&E residential customers with an opt-in component whereby customers could receive notification of events.

## ***SCTD Program Description***

The program provides demand response enabling technology to residential customers. In 2014 the enabling technology was offered free of charge and customers received bill credits through the PTR program. The enabling technology offered in 2014 was the Ecobee Smart Si thermostat These thermostats are signaled by SDG&E through Wi-Fi. Two cycling strategies were being tested. The first strategy is a four degree thermostat setback and the other is a 50% AC cycling strategy. Customer were randomly assigned to one of the two strategies. Although PTR events are seven hours long SCTD participant’s thermostats were curtailed for 4 hours, typically from 2 p.m. – 6 p.m.

Since PTR is now opt-in a customer must enroll to receive a bill credit. Not all SCTD customers enrolled themselves in PTR. If the customers did not enroll in PTR their thermostat was curtailed but they did not receive a bill credit.

SDG&E also offers an air-conditioning cycling program called Summer Saver. Residential customers are either enrolled on a 50% cycling option or a 100% cycling option. Some of these customers are also enrolled in PTR and receive the higher bill credit of $1.25. The Summer Saver program is run by a third party aggregator and the contract expires after summer of 2016. This evaluation will be used to compare the SCTD participants with the 50% cycling option to those Summer Saver participants with 50% cycling.

## ***Summary of 2014 PTR and SCTD Events***

The table 7.1 presents the summary of 2014 PTR and SCTD Events.

**Table 7.1 Summary of 2014 PTR and SCTD Events**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Date | PTR | | | | SCTD | | | |
| **Total Active Participants** | **Modeled Active Participants\*** | **Start Time** | **End Time** | **Total Active Participants** | **Modeled Active Participants\*** | **Start Time** | **End Time** |
| February 7th, 2014 | 36,894 | 33,103 | 11 a.m. | 6 p.m. | - | - | - | - |
| May 14th, 2014 | 39,974 | 34,713 | 11 a.m. | 6 p.m. | - | - | - | - |
| May 15th, 2014 | 40,076 | 34,826 | 11 a.m. | 6 p.m. | - | - | - | - |
| July 31st, 2014 | 56,002 | 48,923 | 11 a.m. | 6 p.m. | 1,285 | 558 | 2 p.m. | 6 p.m. |
| September 15th, 2014 | 67,189 | 57,643 | 11 a.m. | 6 p.m. | 2,455 | 1,028 | 2 p.m. | 6 p.m. |
| September 16th, 2014 | 67,189 | 58,140 | 11 a.m. | 6 p.m. | 2,495 | 2,043 | 2 p.m. | 6 p.m. |
| September 17th, 2014 | 67,189 | 58,139 | 11 a.m. | 6 p.m. | 2,554 | 2,091 | 2 p.m. | 6 p.m. |

\* Participants included in the analysis that were not excluded due to data attrition

## ***Opt-in PTR Ex-Post Evaluation Methodology***

To estimate ex post load impacts for the PTR opt-in and SCTD programs was developed regression-based models using a difference in differences (DiD) format, comparing participant and reference aggregate hourly residential loads. The reference loads for these models were calculated from matched control groups selected from SDG&E’s population of non-program participants. The methods for the matching and ex post estimations are described in detail below.

### Control Group Selection

Control groups were used to measure impacts from the PTR and SCTD programs due to the following conditions: a) few events, with the potential of these events being the hottest days during the summer, b) some events occurring during non-cooling months and/or months where hot weather is not typical, c) small average impacts relative to the overall size of the average participant load during the events, and d) a large population from which to develop a matched control group. To develop control groups for this evaluation was used a Stratified Propensity Score Matching (SPSM) method.

### Pre-Matching Stratification and Design

Prior to generating propensity scores, the participant sites were stratified to control for variables that may observationally influence participation. Strata were defined using a combination of climate zone (coastal and inland) and annual usage group (small, medium, large). Net Energy Metering (NEM) customers were placed into their own respective strata, as there were too few premises to include as an additional stratification variable. In total, this provided seven different strata from which to develop control groups. Using these, the SPSM methodology used a logistic regression (logit) model to estimate the probability of participation within each stratum. The matching routine paired each participant with a non-participant that had the most similar estimated probability of participation.

The control group selection was based on a two-stage approach. In the first stage, PSM was used to identify an initial set of five control group candidate premises for every participant based on variables calculated using 2013 monthly billing data. After requesting the hourly interval data for these candidate premises, a second stage of PSM selected the final control group using variables developed from interval data. Second-stage matching was done separately for all PTR participants, as well as for the other various participant groups, namely, NEM, SCTD, Summer Saver, Low Income, and Summer Tier.

After experimenting with various combinations, the final set of variables chosen for the first stage’s logit model included: monthly kWh usage, average monthly kWh, correlation coefficients between monthly CDD65 and kWh usage for summer and winter months, coefficient of variation of kWh usage, ratio of average monthly usage between summer and winter months, ratio of summer kWh usage to total CDD65, and a dummy variable for Low Income customers. The second stage of matching saw the inclusion of hourly kWh usage during the event hours for summer and hot days, as well as monthly event hour kWh usage.

### Propensity Score Matching Results

One of the key methods of assessing the effectiveness of the PSM is to conduct t-tests on the independent variables used in the logistic regression for the groups both before and after matching. If the matching is successful, the participant and control groups should not be statistically significantly different for these variables. The results of the t-tests for both stages of the PTR participant PSM matching show that none of the PSM variables had a statistically significant difference after selecting the control premise candidates. A final assessment of the efficacy of the PSM is a graphical comparison of the annual load profiles of the participant premises with the control premises before and after matching.

### PTR Ex Post Estimation

A number of different combinations of specifications were tested in developing the aggregate *ex post* model. The final model specifications used for the analysis included variables for hour, day of the week, month, cooling degree hours (CDH65), and event indicators. Additionally, because enrollment increased during the summer, the model included a binary variable to indicate whether a participant was “active,” meaning that they had opted in to the program by the date in question. This means that for periods prior to enrollment, some participants were effectively part of the control group.

Expressed symbolically, the model is as follows:

Where

|  |  |
| --- | --- |
|  | Is the kWh in hour t |
|  | Is the intercept |
|  | Is the set coefficient for day of week (DOW) d |
|  | Is the set of coefficient for month m |
|  | Is the set of coefficients for hour h |
|  | Is the set of coefficients for the interaction of hour h and DOW d |
|  | Is the set of coefficients for the interaction of hour h and month m |
|  | Is the coefficient for cooling degree hours (CDH) |
|  | Is the set of coefficients for CDH interacted with hour h |
|  | Is the set of coefficients for the interaction of CDH with event days |
|  | Is the set of coefficients for interaction of CDH with hour h and event days for inactive participants |
|  | Is the set of coefficients for interaction of CDH with hour h and event days for active participants |
|  | Is the error |

The program impacts were based on the interaction of four variables: the event day flag, the active participant flag, the hour, and the cooling degree hours (CDH). The interaction with CDH served two purposes. First, it allowed for the estimation of savings for individual events, since temperatures were obviously not the same. Second, it allows for the use of the results to develop ex ante impacts. The remainder of the variables allowed controlling for weather and other periodic factors that determine aggregate customer loads.

### SCTD Ex Post Estimation

The model used to estimate savings for the SCTD participants was nearly identical to that applied to the PTR opt-in alert customers. Using the population of SCTD participants and its associated matched control group, *ex post* impacts were estimated in an analogous fashion to the PTR groups. Each set of estimated impacts were grouped by SCTD cycling strategy (4 degree setback or 50% cycling) as well as overall.

## **PTR and SCTD Ex-Post Results**

This section presents the *ex post* load impact estimates by customer category.

Table 7‑2: PTR Ex Post Load Impact Estimates by Customer Category –

Average 2014 Event (11 a.m. to 6 p.m.)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Customer Category | Mean Active Partic-ipants | Mean Reference Load (kW) | Mean Observed Load (kW) | Mean Impact (kW) | % Load Reduction | Aggregate Load Reduction (MW) | Mean °F |
| All | 56,270 | 1.52 | 1.42 | 0.11 | 6.9% | 5.92 | 88.0 |
| Large | 24,200 | 2.41 | 2.20 | 0.21 | 8.7% | 5.10 | 88.3 |
| Medium | 19,765 | 1.07 | 1.01 | 0.06 | 5.6% | 1.20 | 87.9 |
| Small | 11,435 | 0.45 | 0.45 | 0.00 | 1.1% | 0.05 | 87.5 |
| Coastal | 30,599 | 1.38 | 1.29 | 0.10 | 7.0% | 2.95 | 86.5 |
| Inland | 24,801 | 1.70 | 1.58 | 0.12 | 6.8% | 2.88 | 89.8 |
| No SCTD | 54,757 | 1.51 | 1.41 | 0.11 | 7.2% | 5.95 | 88.0 |
| No Load Control (SCTD or Summer Saver) | 51,855 | 1.50 | 1.40 | 0.10 | 6.7% | 5.14 | 88.0 |
| Summer Saver – 50% Cycling | 871 | 2.29 | 2.11 | 0.18 | 7.3% | 0.16 | 87.3 |
| Summer Saver – 100% Cycling | 2,028 | 2.02 | 1.43 | 0.59 | 28.1% | 1.20 | 87.0 |
| Low Income | 16,199 | 1.35 | 1.31 | 0.04 | 2.8% | 0.60 | 87.8 |
| Non-Low Income | 35,656 | 1.55 | 1.44 | 0.11 | 7.1% | 3.85 | 88.1 |
| Enroll. Year – 2012 | 24,224 | 1.53 | 1.40 | 0.13 | 8.4% | 3.08 | 88.5 |
| Enroll. Year – 2013 | 8,086 | 1.51 | 1.39 | 0.12 | 8.0% | 0.96 | 88.5 |
| Enroll. Year – 2014 | 19,545 | 1.47 | 1.40 | 0.07 | 4.5% | 1.30 | 87.0 |
| Notification – Email | 35,765 | 1.52 | 1.41 | 0.10 | 7.0% | 3.74 | 88.0 |
| Notification – Text | 8,049 | 1.40 | 1.34 | 0.06 | 4.4% | 0.49 | 88.0 |
| Notification – Both | 7,251 | 1.54 | 1.41 | 0.13 | 8.7% | 0.96 | 88.1 |
| Summer Billing Tier 1 | 20,499 | 1.45 | 1.35 | 0.10 | 6.8% | 2.01 | 87.7 |
| Summer Billing Tier 2 | 4,673 | 1.42 | 1.35 | 0.07 | 5.0% | 0.32 | 87.5 |
| Summer Billing Tier 3 | 9,391 | 1.49 | 1.38 | 0.10 | 7.0% | 0.97 | 87.8 |
| Summer Billing Tier 4 | 8,700 | 1.53 | 1.47 | 0.06 | 4.1% | 0.53 | 88.3 |
| Summer Billing Tier 5 | 8,542 | 1.64 | 1.51 | 0.12 | 7.6% | 1.05 | 88.6 |
| Net Energy Metered | 2,864 | 0.57 | 0.14 | 0.43 | -21.3%[[10]](#footnote-10) | 1.23 | 88.4 |

Table 7‑3: SCTD Ex Post Load Impact Estimates by Customer Category –

Average 2014 Event (2 p.m. to 6 p.m.)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Customer Category | Mean Active Partic-ipants | Mean Reference Load (kW) | Mean Observed Load (kW) | Mean Impact (kW) | % Load Reduction | Aggregate Load Reduction (MW) | Mean °F |
| All | 1,887 | 2.70 | 2.09 | 0.61 | 22.9% | 1.16 | 87.0 |
| 4 Degree Setback | 923 | 2.58 | 1.93 | 0.65 | 25.6% | 0.60 | 86.2 |
| 50% Cycling | 964 | 2.80 | 2.21 | 0.58 | 20.9% | 0.56 | 87.7 |
| PTR | 1,162 | 2.66 | 2.00 | 0.66 | 24.9% | 0.77 | 87.1 |
| PTR – 4 Deg. Setback | 556 | 2.55 | 1.83 | 0.72 | 28.3% | 0.40 | 86.1 |
| PTR – 50% Cycling | 606 | 2.76 | 2.14 | 0.62 | 22.5% | 0.37 | 87.8 |
| SCTD Only | 725 | 2.76 | 2.22 | 0.55 | 20.0% | 0.40 | 87.0 |
| SCTD Only – 4 Degree Setback | 366 | 2.64 | 2.07 | 0.57 | 21.8% | 0.21 | 86.3 |
| SCTD Only – 50% Cycling | 359 | 2.87 | 2.34 | 0.53 | 18.6% | 0.19 | 87.5 |

7.6 Ex-Ante Load Impact Methodology

Ex ante impacts for the PTR program for four participant segments (Opt-In PTR-Only, PTR Dually Enrolled in Summer Saver, PTR Dually Enrolled in SCTD, and SCTD-Only) were estimated by combining the regression model results from the ex post impacts with two other sources of data. The first data source was a 20-year forecast of enrollment for four separate participant segments. The second data source was two separate versions of weather scenarios containing hourly weather for different types of weather years and day types for each month of the year. The results presented in this section use the weather conditions based on SDG&E estimates.

The ex ante estimation process was relatively straightforward, involving two main steps. The first step required taking the model parameters from the *ex post* regression model and combining them with the weather scenarios to calculate per participant average reference loads, observed loads, and load impacts. Because the impacts were based on variables that were interacted with temperature variables, they can be applied to the weather data from the various year and day types to generated estimated savings for those scenarios. The standard errors from the impact variable parameters from the ex post model were used to calculate the uncertainty estimates. The second step was to combine estimated per-participant impacts for the different weather scenarios and multiply them by the forecast of enrolled participants to generate the total program impacts. SDG&E forecasts that the PTR, Summer Saver, and SCTD programs will continue to grow. By the end of 2016, the PTR program is expected to grow to over 73,000 participants (including dual enrollments in the other programs), while the SCTD program is expected to grow to over 8,000 participants. These projections are then expected to remain constant throughout the remainder of the ex ante forecast period.

While this process was straightforward, there were some nuances to the data that call for additional discussion. First, the enrollment forecasts were based on total participants by participant segment, whereas the weather scenarios and estimated impacts have more detailed information. Consequently, the alignment of these data sources called for making certain assumptions about the allocation of program participants. Total participants from the forecast were allocated to climate zones and, for the SCTD and Summer Saver groups, to the cycling strategies based on the relative shares as of the last event day from 2014. Additionally, since the weather scenarios were provided by climate zone, an average weather scenario was created using an average where the same participant shares were used as weights. Note that this weighting was program segment specific. For example, the overall weather for the SCTD 100% cycling participants was based on the shares by climate zone for that particular group. The shares used for the allocation of the enrollment forecast are presented in Table 7-4.

Table 7-4: Shares for Allocation of Enrollment Forecast

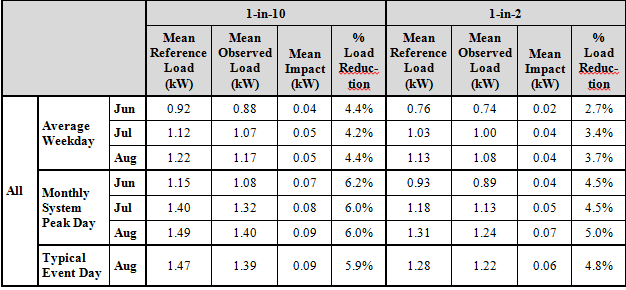
| **Participant Segment** | | **Coastal** | **Inland** | **All** |
| --- | --- | --- | --- | --- |
| **PTR-Only** | **All** | 56% | 44% | 100% |
| **PTR Dually Enrolled in Summer Saver** | **100% Cycle** | 32% | 38% | 70% |
| **50% Cycle** | 12% | 18% | 30% |
| **All** | 44% | 56% | 100% |
| **PTR Dually Enrolled in SCTD** | **4 Degree Setback** | 22% | 26% | 48% |
| **50% Cycle** | 24% | 28% | 52% |
| **All** | 46% | 54% | 100% |
| **SCTD-Only** | **4 Degree Setback** | 23% | 27% | 50% |
| **50% Cycle** | 22% | 27% | 50% |
| **All** | 45% | 55% | 100% |

7.7 Ex-Ante Load Impact Estimates

### **7.7.1 PTR Only**

Table 7-5 shows the ex ante load impact estimates for the average PTR-only customer on an average weekday, monthly system peak day, and a typical event day based on 1-in-2 and 1-in-10 weather year conditions for 2016. The average weekday and monthly system peak days are presented for June, July, and August, while the typical event day is presented for the month of August. For a 1-in-2 typical event day, the estimated load reduction for the average participant is 0.06 kW during event hours. The average estimated aggregate load reduction under this scenario is 3.91 MW. For a 1-in-10 typical event day, the estimated load reduction is higher, at 0.09 kW. The average estimated aggregate reduction is 5.60 MW. These estimates represent approximately 4.8% and 5.9% of the reference load, respectively for each weather scenario.

Table 7-5: Ex Ante Hourly Load Impact Results – PTR-Only

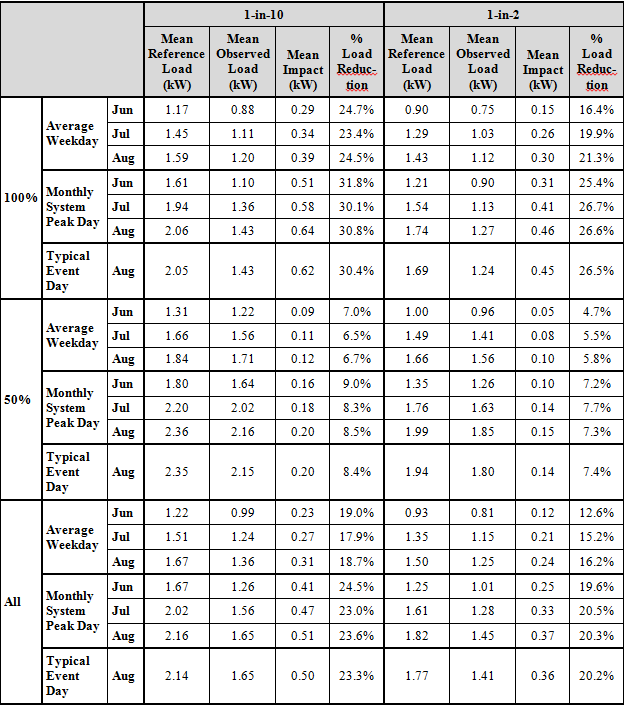


### **7.7.2 PTR Dually Enrolled in Summer Saver**

Table 7-6 shows the ex ante load impact estimates for the average PTR customer dually enrolled in Summer Saver for the various combinations of day types and weather scenarios for 2016. For a 1-in-2 typical event day, the estimated load reduction for the average participant is 0.36 kW during event hours. For a 1-in-10 typical event day, the estimated load reduction is higher, at 0.50 kW. These estimates are much higher than the PTR-only group due to the additional effects of automatic cycling of ACs during events. The average estimated aggregate load reductions are 1.62 MW (20.2%) and 2.25 MW (23.3%), respectively.

The 100% cycling group has an estimated load reduction during event hours of 0.45 kW under the 1-in-2 scenario, representing a 26.5% reduction from the reference load. Under the 1-in-10 conditions, this group has an estimated event hour load reduction of 0.62 kW, or 30.4%. The 50% cycling group has much lower estimated load reductions of 0.14 kW (7.4%) and 0.20 kW (8.4%) for the 1-in-2 and 1-in-10 scenarios, respectively. These estimates are less than a third of the 100% cycling group.

Table 7-6: Ex Ante Hourly Load Impact Results – PTR Dually Enrolled in Summer Saver

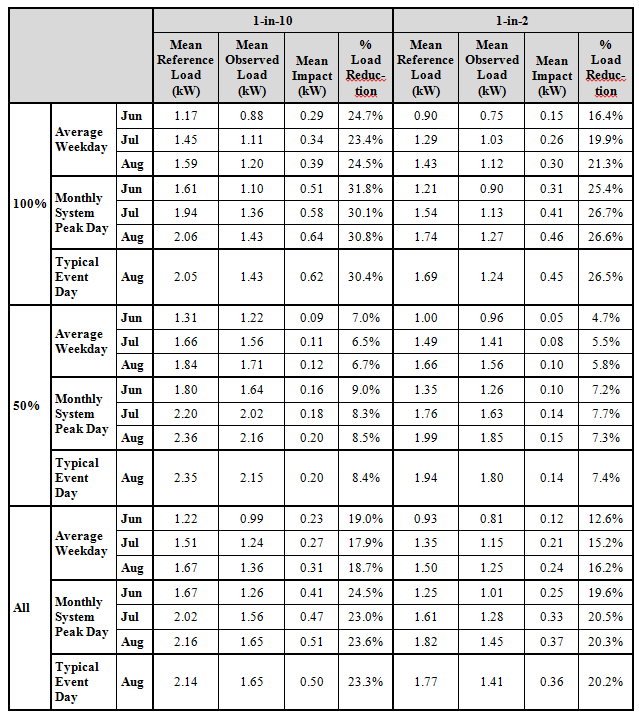


### **7.7.3 PTR Dually Enrolled in Summer Saver**

Table 7-7 shows the *ex ante* load impact estimates for the average PTR customer dually enrolled in Summer Saver for the various combinations of day types and weather scenarios for 2016. For a 1-in-2 typical event day, the estimated load reduction for the average participant is 0.36 kW during event hours. For a 1-in-10 typical event day, the estimated load reduction is higher, at 0.50 kW. These estimates are much higher than the PTR-only group due to the additional effects of automatic cycling of ACs during events. The average estimated aggregate load reductions are 1.62 MW (20.2%) and 2.25 MW (23.3%), respectively.

The 100% cycling group has an estimated load reduction during event hours of 0.45 kW under the 1-in-2 scenario, representing a 26.5% reduction from the reference load. Under the 1-in-10 conditions, this group has an estimated event hour load reduction of 0.62 kW, or 30.4%. The 50% cycling group has much lower estimated load reductions of 0.14 kW (7.4%) and 0.20 kW (8.4%) for the 1-in-2 and 1-in-10 scenarios, respectively. These estimates are less than a third of the 100% cycling group.

**Table 7-7: Ex Ante Hourly Load Impact Results – PTR Dually Enrolled in Summer Saver**

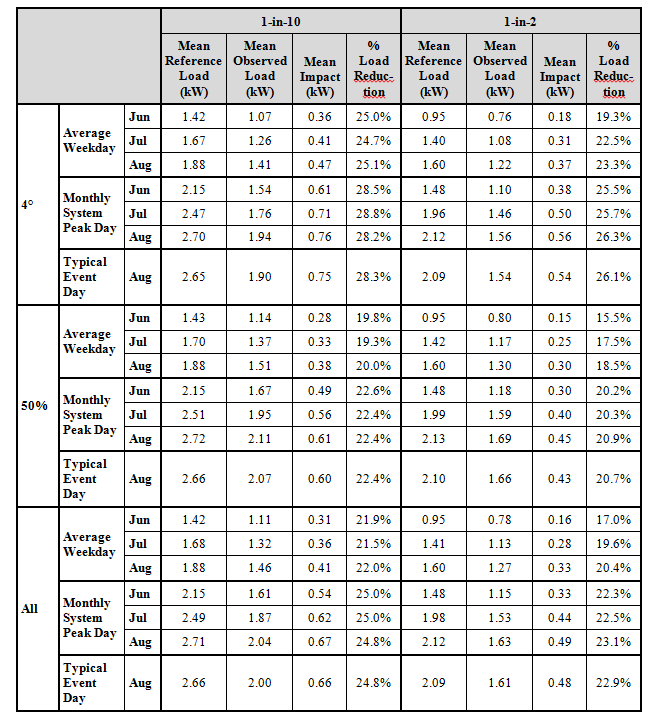


### **7.7.4 PTR Dually Enrolled in SCTD**

Table 7-8 shows the *ex ante* load impact estimates for the average PTR customer dually enrolled in SCTD for the various combinations of day types and weather scenarios for 2016. For a 1-in-2 typical event day, the estimated load reduction for the average dual PTR-SCTD participant is 0.48 kW during SCTD event hours. For a 1-in-10 typical event day, the estimated load reduction is 0.66 kW. These estimates represent the highest average event hour reductions of all of the groups, showing the combination of the demand response effects of the PTR notifications and SCTD thermostats. The average estimated aggregate load reductions are 2.26 MW (22.9%) and 3.12 MW (24.8%), respectively.

The 4 degree setback has a higher load reduction estimate than the 50% cycling group. The former has an average event hour load reduction estimate of 0.54/0.75 kW, while the latter has an average estimate of 0.43/0.60 kW. The percentage load reductions for the 4 degree setback group are 26.1%/28.3%, while the percentage load reductions for the 50% cycling group are 20.7%/22.4%.

**Table 7-8: Ex Ante Hourly Load Impact Results – PTR Dually Enrolled in SCTD**

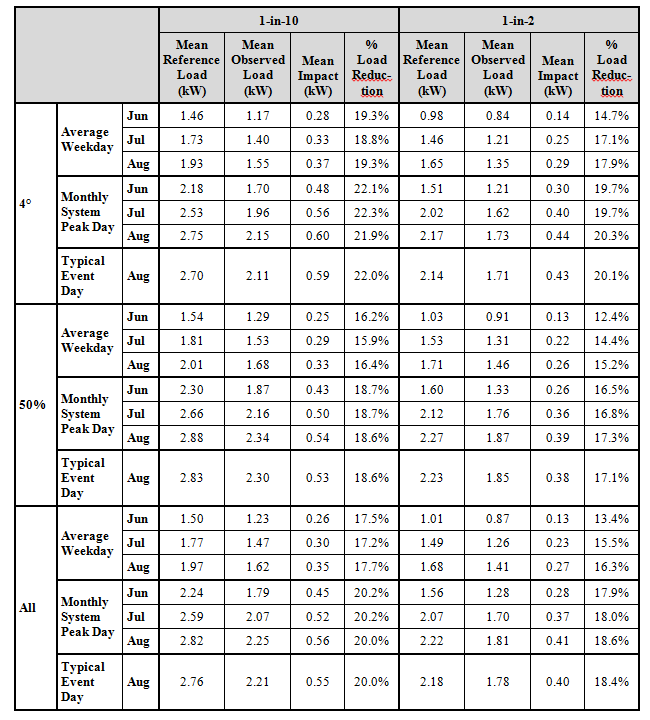


### **7.7.5 SCTD Only**

Table 7-9 show the *ex ante* load impact estimates for the average customer only enrolled in the SCTD program for the various combinations of day types and weather scenarios for 2016. For a 1-in-2 typical event day, the estimated load reduction for the average SCTD-only participant is 0.40 kW during SCTD event hours (2 p.m.-6 p.m.). For a 1-in-10 typical event day, the estimated load reduction is 0.55 kW. The average estimated aggregate load reductions are 1.30 MW (18.4%) and 1.79 MW (20.0%), respectively. As the enrollment in the SCTD programs continues to grow, these aggregate estimates will increase.

For the SCTD-only customers, the 4 degree setback group has an average event hour load reduction estimate that is slightly higher than the 50% cycling group. The former has an average event hour load reduction estimate of 0.43/0.59 kW, while the latter has an average estimate of 0.38/0.53 kW. The aggregate load reduction estimate for the 4 degree setback group is 0.69/0.95 MW (20.1%/22.0%). The aggregate load reduction estimate for the 50% cycling group is 0.62/0.85 MW (17.1%/18.6%).

**Table 7-9: Ex Ante Hourly Load Impact Results – SCTD Only**



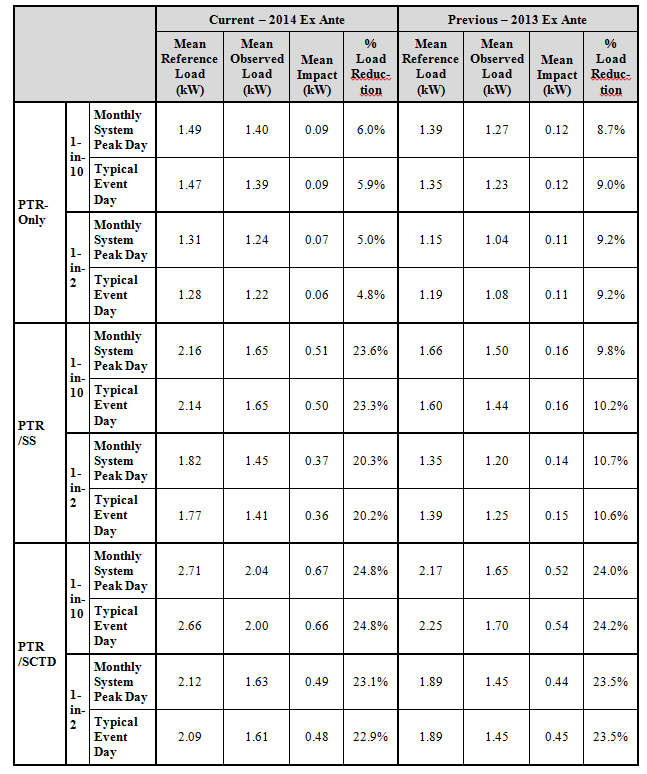
7.8 Comparison of 2013 and 2014 Ex Ante Estimates

Table 7-10 shows the comparisons between the *ex ante* estimates in the current evaluation and those reported in the previous evaluation for the forecast year 2015. The current *ex ante* estimates are slightly lower for the PTR-only group – the current estimates are 0.06 kW for a 1-in-2 event day and 0.09 kW for a 1-in-10 event day, while the previous estimates are 0.11 kW and 0.12 kW, respectively. This is largely a function of a lower forecasted temperature between the two evaluation cycles – the current average temperature forecast is 80°F during event hours under the 1-in-2 scenario, whereas the previous analysis had a forecasted average temperature of 84°F. The percentage load reductions are also lower, from approximately 9% in the previous analysis to approximately 6% in the current analysis.

The estimates for the group dually enrolled in Summer Saver are substantially higher in the current evaluation. This is mainly a result of the fact that the model for the previous analysis was adapted from the opt-in PTR-only group due to small sample size and few historical events. The current analysis was able to capture the effects of the dual enrollment and thus delivers impact estimates of 0.36 kW (20.2%) and 0.50 kW (23.3%) for 1-in-2 and 1-in-10 conditions on typical event days. The previous analysis had estimates of 0.15 kW (10.6%) and 0.16 kW (10.2%), which are more akin to the PTR-only numbers.

The estimates for the SCTD participants in the current analysis are slightly higher than in the previous analysis. The previous analysis found estimates of 0.45 kW on 1-in-2 event days and 0.54 kW on 1-in-10 event days. The current analysis projects 0.48 kW on 1-in-2 event days and 0.66 kW on 1-in-10 event days. The percentage load reduction estimates under the previous analysis were around 24%, while the current estimates are essentially the same, between 22.9% and 24.8%.

**Table 7-10: Comparison of 2013 and 2014 Ex Ante Estimates – Forecast Year 2015**



## **Relationship between Ex Post and Ex Ante Estimates**

Table 7-11 shows comparisons between the *ex ante* and *ex post* estimates from this evaluation. For all of the groups, it seems that the weather in 2014 was particularly hot, and thus the results are more aligned with 1-in-10 weather conditions.

For the overall PTR-only group, both the *ex post* and 1-in-10 *ex ante* show average event hour load reductions of 0.09 kW, around 6% of the reference load. The predicted 1-in-10 average event hour load reductions for the overall PTR-Summer Saver dually enrolled group (0.50 kW, or 23.3%) are slightly higher than the *ex post* impacts (0.47 kW, or 22.4%). The same relationship exists for the 50% and 100% cycling sub-groups. For the dually enrolled PTR-SCTD group, the *ex post* and 1-in-10 *ex ante* estimates are essentially identical, at 0.66 kW, approximately 25% of the reference load. The estimates for the load control sub-groups are also similar. The 4 degree setback group’s 1-in-10 *ex ante* estimate 0.03 kW higher than the *ex post* estimate, while the 50% cycling group’s is 0.02 kW lower. As with the other groups, the SCTD-only *ex post* estimates are very similar to the 1-in-10 *ex ante* estimates. The overall event hour load reduction estimate is 0.55 kW in both cases, representing about 20% of the reference load. The 50% cycling sub-group also has the same estimates, with averages of 0.53 kW, approximately 18.5% of the reference load. The 4 degree setback has a slightly higher 1-in-10 estimate, with 0.59 kW, compared to the *ex post* estimate of 0.57 kW.

Table 7-11: Comparison of Ex Ante and Ex Post Estimates

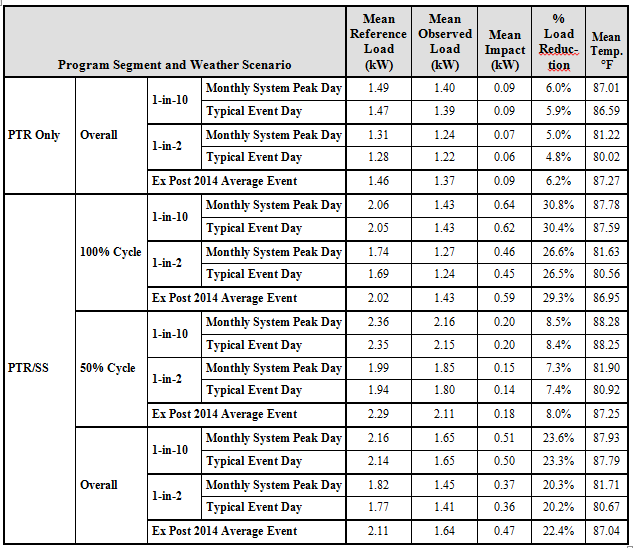
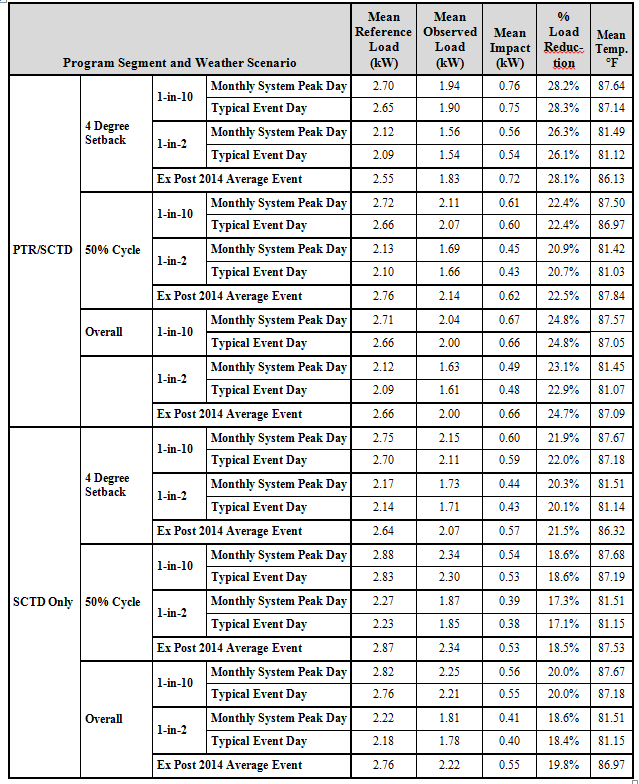


Table 7-11 (Cont’d): Comparison of Ex Ante and Ex Post Estimates



# Permanent Load Shifting

## PLS Program Overview

The PLS program provides a one-time incentive payment ($875/kW) to customers who install qualifying PLS technology on chilled water cooling units (which differ substantially from typical central air conditioning units). Incentives will be determined based on the designed peak load shift capability of the system and the installation must undergo a feasibility study by a qualified engineer. The load shift is typically accomplished completely through substituting overnight chiller load for daytime chiller load. All customers are eligible for the program, including residential, commercial, industrial, agricultural, direct access and Community Choice Aggregation customers.

In order to qualify for the PLS program incentive payment, customers must go through the program application 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 application
2. IOU approves application and sets aside incentive funds
3. Customer submits feasibility study
4. IOU reviews feasibility study
5. IOU conducts pre-installation inspection
6. IOU and customer sign agreement
7. Customer installs PLS system
8. IOU conducts post-installation inspection
9. Customer receives PLS program incentive

After a customer submits an application and the utility approves the application, customers participating in the program must provide, in advance of installation, an engineering feasibility study. This study will include an estimated cooling profile. Energy models will be used to determine a customer's cooling load profile over a year (8,760 hours). To accomplish this, building simulation models will be used to determine hourly cooling needs over the course of a year, based on building specifications, regional temperatures, occupancy and other inputs. Both retrofit and new construction customers will be subjected to the energy modeling process, unless utility approved cooling usage data is available.

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

The incentive payments are intended to offset the cost of installation and thereby make the system more attractive financially. Under the program rules, the incentive cannot exceed 50% of the installation cost for a given customer, and the incentive for a given site cannot exceed $1.5M. Customers’ incentives will be determined as the least of (1) the incentive reservation amount calculated from the system design, (2) 50% of the actual final installed project cost or (3) $1.5M. In addition, customers will be required to be on a time-of-use (TOU) rate for the first five years after installation.

Customers are required to run the PLS system during all weekday peak periods during summer months (May1 –October 31) from 11am through 6pm. PLS program participants may also shift load during non-summer months, in case cooling is needed during those months. For process cooling installations, cooling may be needed year round.

## PLS Ex-Ante Methodology

The PLS program evaluation used two different methodologies for estimating ex-ante load impacts for unidentified projects and identified projects.

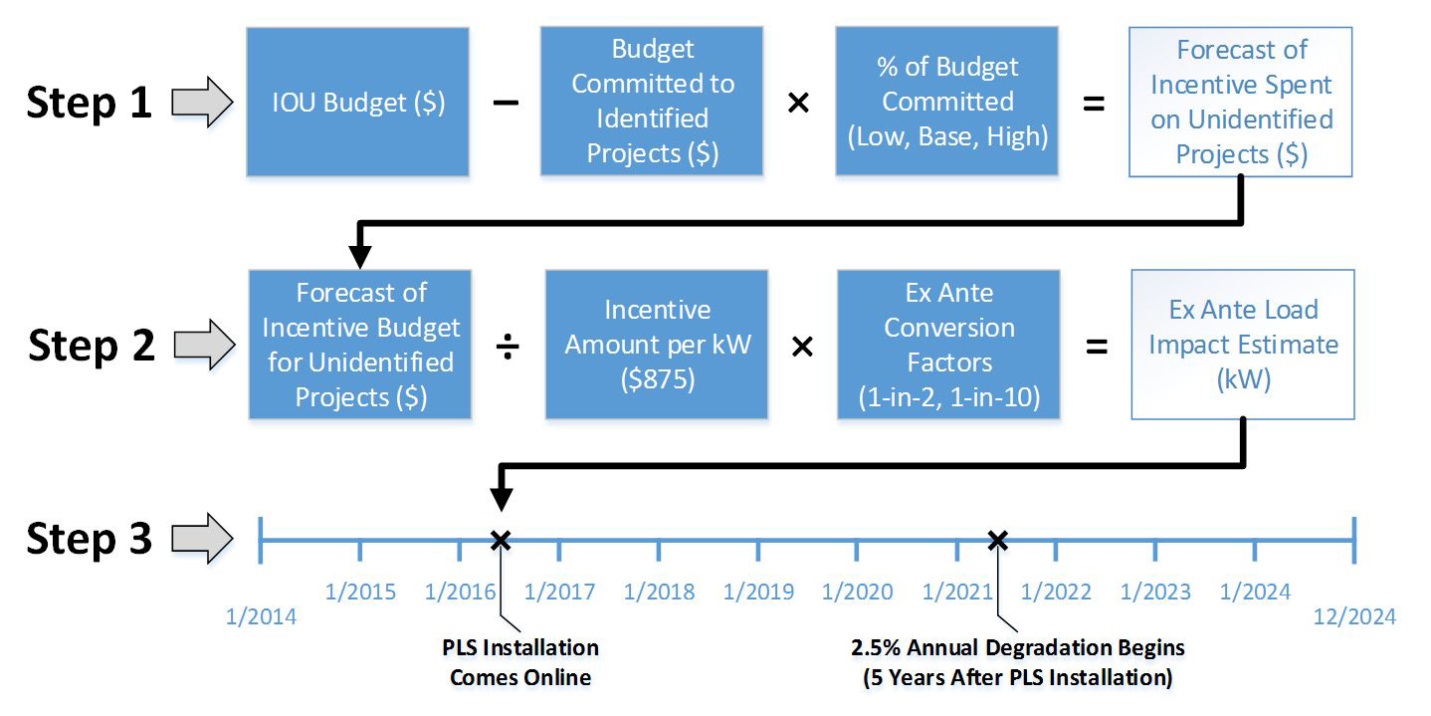
*Unidentified projects:* In addition to customers who have already submitted application it is expected that new customer will apply as well (unidentified projects). Load impacts for unidentified projects are based on assumptions developed with the utility PLS program managers and EM&V staff. The main uncertainty is the number and size of projects that will be included in the program, a range of scenarios was generated for each IOU in order to capture the uncertainty related to market adoption of PLS technologies.

Figure 8-1 summarizes the methodology for estimating ex-ante load impacts for unidentified PLS projects. The three steps for estimating ex-ante load impacts for unidentified projects are:

* **Step 1** involves forecasting the amount of incentive dollars that will be spent on unidentified projects for each IOU. The first key input for this calculation is the total PLS budget for each IOU. The budget that has been committed to identified projects was subtracted from the total incentive budget amount. Then, the remaining budget for unidentified projects was multiplied by the percentage of each IOU’s budget that will be committed to projects by the end of 2016, under the low, base case and high scenarios. This produced the forecast of incentives available to be spent on unidentified projects.
* **Step 2** converted the incentive dollar forecast into the ex ante load impact estimates. To do this, the forecast of incentive dollars spent on unidentified projects was divided by the incentive amount per kW load shift ($875/kW). This kW load shift amount represents the peak load shift[[11]](#footnote-11) 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 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 address the new requirement for reporting results for the CAISO system peak in addition to the IOU system peak.

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

Figure 8-1: Methodology for Estimating Ex-ante Load Impacts of Unidentified PLS Projects



The ex ante conversion factors were used to convert the load shift under the incentive payment, maximum cooling load and weather conditions to the load shift that can be expected under the various ex ante temperature scenarios. The ex ante temperature scenarios include the monthly system peak days and average weekdays under 1-in-2 year and 1-in-10 year weather conditions for the utility specific and CAISO peak. Essentially, the conversion factors facilitate the estimation of the PLS-TES load impacts under a variety of different weather conditions with ease and efficiency. The analysis shows that relative usage values across different weather conditions are basically insensitive to building characteristics, and the ratio for a given ex ante condition hardly changes as the building characteristics vary substantially. This relationship is a critical factor in the evaluation, and the current conversion factor approach would need to be modified if this weren’t the case.

It is important to note that these conversion factors were developed with building simulation models of space cooling installations. Some of the applications that have been received thus far also include process cooling installations, which have load profiles that frequently differ from the typical space cooling profile. Unfortunately, the process cooling installations do not make good candidates for generalized modeling because they are highly customized by industry and location; in addition, while space cooling loads exhibit significant seasonality due to temperature variation, process cooling loads may vary seasonally by temperature and changes in the underlying production process. 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 for both space cooling and process cooling installations.

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

* Peak load shift of typical unidentified projects;
* Number of projects of each size; and

Expected project installation and verification timeline (the time between when an application is received and when the installation and verification are completed).

These assumptions are IOU-specific and were informed by the current applications for identified projects. The PY2014 evaluation refined these assumptions based on the most recent information on budget, program enrollment, the current status of identified projects and the recently revised and adopted Statewide PLS Program Handbook (September 2014).

Finally, because local weather conditions influence the load shift that is actually experienced, the ex ante load impacts are dependent on the specific geographic region in which an installation is located. As such, it was necessary to allocate the unidentified projects to LCAs within each utility’s service area. SDG&E has only a single LCA, so no population weighting was necessary. Considering that the utilities have received applications from customers that are located in LCAs that are not usually associated with having high cooling load, the expectation regarding where these PLS-TES installations will be located is unclear. Essentially, with process cooling being eligible for PLS program incentives, the program is viable in many different climates, as the current applications have shown.

*Identified projects:* Identified projects include those for which customers have completed an application or a feasibility study. 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. SDG&E decided to use building simulation modeling, the ex ante conversion factors were used to convert the expected load shift from the application/feasibility study to ex ante weather conditions. This methodology is nearly identical to Step 2 and Step 3 in the methodology used for unidentified projects discussed in Section 10.2, except that the incentive amount was taken from the latest available information for that project (the application or feasibility study). In addition, considering that the location and installation date were provided in the application for identified projects, the forecast for SDG&E 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

Tables 8-1 shows 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 SDG&E, the CAISO weather is slightly warmer under 1-in-2 year weather and slightly cooler under 1-in-10 year conditions.

Table 8-1:  SDG&E Enrollment Weighted Ex Ante Weather Values (mean17)

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

## PLS Ex-Ante Load Estimates

This section provides the ex ante impact estimates for peak period (1 to 6 PM) conditions for the program operational months of May through October. In accordance with the Resource Adequacy window, the peak period is defined as 1 to 6 PM, even though PLS program participants are required to shift load from 11 AM to 6 PM (for SDG&E).

Table 8-2 provides the ex ante load impact estimates for 2015–2025 monthly system peak days in May through October for SDG&E-specific and CAISO 1-in-2 and 1-in-10 year weather conditions for the base scenario. SDG&E’s service territory only has one LCA so the results are not divided geographically. The difference between utility specific and CAISO peaks tend to vary by month. Impacts range from the CAISO-specific, September 1-in-2 monthly peak day in 2018 being 17% greater than the utility specific comparable peak at 3.5 MW and 2.9 MW respectively; to the utility specific July 1-in-10 monthly peak day in 2018 being 24% greater than the CAISO specific comparable peak at 3.6 MW and 2.9 MW respectively. Year over year, the difference between the utility specific peak and the CAISO peak appears to remain fairly constant. For example, the utility specific August 1-in-10 monthly peak load impact is typically around 4% higher than the comparable CAISO specific impact.

Table 8-2: SDG&E Ex Ante Load Impact Estimates (1 to 6 PM)   
on Monthly Peak Days for April-October 2015-2025 (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 | 2015 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2016 | 1,567 | 1,787 | 1,628 | 1,761 | 1,621 | 2,063 | 1,781 | 1,970 | 1,693 | 2,102 | 1,804 | 1,841 |
| 2017 | 2,200 | 2,509 | 2,286 | 2,473 | 2,277 | 2,897 | 2,501 | 2,766 | 2,377 | 2,952 | 2,533 | 2,585 |
| 2018 | 2,707 | 3,087 | 2,812 | 3,043 | 2,801 | 3,564 | 3,077 | 3,403 | 2,924 | 3,632 | 3,116 | 3,180 |
| 2019 | 2,707 | 3,087 | 2,812 | 3,043 | 2,801 | 3,564 | 3,077 | 3,403 | 2,924 | 3,632 | 3,116 | 3,180 |
| 2020 | 2,707 | 3,087 | 2,812 | 3,043 | 2,801 | 3,564 | 3,077 | 3,403 | 2,924 | 3,632 | 3,116 | 3,180 |
| 2021 | 2,667 | 3,042 | 2,771 | 2,998 | 2,761 | 3,512 | 3,032 | 3,354 | 2,882 | 3,579 | 3,071 | 3,134 |
| 2022 | 2,629 | 2,998 | 2,731 | 2,956 | 2,722 | 3,461 | 2,988 | 3,305 | 2,841 | 3,527 | 3,027 | 3,090 |
| 2023 | 2,563 | 2,923 | 2,663 | 2,882 | 2,654 | 3,373 | 2,913 | 3,223 | 2,770 | 3,438 | 2,952 | 3,013 |
| 2024 | 2,499 | 2,850 | 2,596 | 2,809 | 2,589 | 3,288 | 2,839 | 3,142 | 2,701 | 3,352 | 2,878 | 2,937 |
| 2025 | 2,437 | 2,778 | 2,531 | 2,739 | 2,525 | 3,205 | 2,768 | 3,063 | 2,633 | 3,267 | 2,807 | 2,864 |
| CAISO Specific | 2015 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2016 | 1,372 | 1,859 | 1,525 | 1,794 | 1,741 | 1,666 | 1,822 | 1,899 | 2,036 | 2,076 | 1,637 | 1,837 |
| 2017 | 1,927 | 2,611 | 2,141 | 2,519 | 2,446 | 2,340 | 2,558 | 2,666 | 2,860 | 2,916 | 2,299 | 2,579 |
| 2018 | 2,371 | 3,212 | 2,635 | 3,099 | 3,009 | 2,879 | 3,148 | 3,280 | 3,518 | 3,587 | 2,829 | 3,173 |
| 2019 | 2,371 | 3,212 | 2,635 | 3,099 | 3,009 | 2,879 | 3,148 | 3,280 | 3,518 | 3,587 | 2,829 | 3,173 |
| 2020 | 2,371 | 3,212 | 2,635 | 3,099 | 3,009 | 2,879 | 3,148 | 3,280 | 3,518 | 3,587 | 2,829 | 3,173 |
| 2021 | 2,336 | 3,166 | 2,597 | 3,054 | 2,966 | 2,837 | 3,102 | 3,233 | 3,467 | 3,535 | 2,788 | 3,127 |
| 2022 | 2,303 | 3,121 | 2,559 | 3,010 | 2,924 | 2,797 | 3,058 | 3,186 | 3,417 | 3,483 | 2,749 | 3,082 |
| 2023 | 2,245 | 3,043 | 2,496 | 2,935 | 2,851 | 2,727 | 2,981 | 3,106 | 3,331 | 3,394 | 2,680 | 3,004 |
| 2024 | 2,188 | 2,966 | 2,433 | 2,861 | 2,780 | 2,659 | 2,907 | 3,028 | 3,247 | 3,307 | 2,614 | 2,928 |
| 2025 | 2,133 | 2,892 | 2,373 | 2,789 | 2,712 | 2,593 | 2,834 | 2,952 | 3,165 | 3,223 | 2,549 | 2,854 |

# Non-Residential SPP Rates

## Non-Residential SPP Rates Overview

SDG&E’s Smart Pricing Program (SPP) was originally proposed in 2010 and provides a dynamic pricing option to virtually all of its estimated 1.2 million residential, 116,000 small commercial (i.e., customers with maximum demand less than 20 kW), and 3,400 agricultural customers.[[12]](#footnote-12) Implementation of time varying rates is a significant shift for SDG&E’s customers and provides an incentive for reducing consumption during peak periods as well as an opportunity for customers to save on monthly bills by adjusting their behavior.

The SPP pricing plans include both time of use (TOU) and critical peak pricing (CPP) rate components with different enrollment strategies (mandatory, default, and opt-in) for small commercial and agricultural customers. Table 9-1 summarizes these enrollment policies and the dates of availability for each customer class. For the purpose of consistent terminology, any rate that has both TOU and CPP components will be referred to as a “TOU-CPP” rate. Since customers have a choice about which rate to enroll in, all rates are technically voluntary, however TOU is mandatory in the sense that all rate options have a TOU component. Small commercial customers will be defaulted onto the TOU-CPP rate (with opt-out to TOU) starting in November 2015. Agricultural customers will be defaulted onto TOU starting in November 2015 and will be able to opt-out to the TOU-CPP rate. The defaulting of small commercial and agricultural customers will gradually occur from November 2015 through April 2016.

Table 9-1: SPP Rates and Availability

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Customer Segment | Rate | Enrollment Policy | Start Date | Current Enrollment |
| Small Commercial\* | TOU | Opt-in from non-time varying rate | February 1, 2015 | 1,028 |
| TOU-CPP | Opt-in from non-time varying rate | February 1, 2015 | 1,132 |
| TOU-CPP | Default | November 2015 | n/a |
| TOU | Customers may opt out of TOU-CPP onto TOU | November 2015 | n/a |
| Agricultural\* | TOU | Opt-in from non-time varying rate | February 1, 2015 | 3 |
| TOU-CPP | Opt-in from non-time varying rate | February 1, 2015 | 0 |
| TOU | Default | November 2015 | n/a |
| TOU-CPP | Opt-in from default TOU | November 2015 | n/a |

Note: Starting in November 2015, flat rates will no longer be available for small commercial and agricultural customers.

SDG&E has applied to change the rate periods and prices charged for each SPP tariff. A summary of the approved and proposed rates in the summer period is provided in Table 9-2. The proposed rate is different in two important ways. First, although the TOU peak period is the same length as the approved rate, it runs from 2 to 9 PM rather than from 11 AM to 6 PM. Second, the CPP period for the proposed TOU-CPP rate only runs from 2 to 6 PM and no longer perfectly aligns with the TOU peak period. As a result, on CPP days, the proposed tariff actually has four rate periods rather than three. A decision from the CPUC regarding the proposed rates is not expected until April 2015 and as a consequence, this report contains estimates only for the approved prices and rate windows. An analysis of the proposed rates will be completed as an addendum to this report.

**Table 9-2: Structure of Approved and Proposed SPP Rate Options   
for the Summer Period**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Rate Option | Day Type | Midnight to  6 AM | 6 to 11 AM | 11 AM to 2 PM | 2 to 6 PM | 6 to 9 PM | 9 PM to Midnight |
| Approved | Weekday | SOP | SP | P/CP | P/CP | SP | SOP |
| Weekend | SOP | SOP | SOP | SOP | SOP | SOP |
| Proposed | Weekday | SOP | SP | SP | P/CP | P | SOP |
| Weekend | SOP | SP | SP | SP | SP | SP |

## Non-Residential SPP Rates Ex-Post Evaluation Methodology

Load impacts for the opt-in TOU and TOU-CPP rates offered to selected SDG&E small commercial customers were estimated using cluster analysis, propensity score matching methods, and difference-in-differences estimation. This section provides a detailed description of the implementation of each of these components.

### Cluster Analysis

Marketing of the SPP rates to small commercial customers was not random, but rather targeted customers who were most likely to benefit from being on one of the two SPP rates. Given this marketing strategy, the subset of customers who enrolled in the rates was expected to consist of structural winners who are not representative of the entire SDG&E small commercial customer population. Because of the marketing strategy, it was important to understand the uniqueness of the enrolled TOU and TOU-CPP customers in terms of both demographics and consumption patterns. This initial analysis was conducted using simple descriptive statistics of customer characteristics and k-means cluster analysis of load data.

K-means cluster analysis is an algorithm-based approach to identifying a discrete number of similar subgroups within a larger sample of data. The algorithm defines subgroups using centroids in Cartesian space and assigns customers to a cluster based on the proximity to that cluster’s centroid. The best location for the cluster centroids are then determined using an iterative process that consists of the following steps:

* Move the cluster centroids;
* Assign each customer to the nearest cluster; and then

Calculate the sum of the distances between each customer and their assigned centroid.

These steps are repeated as long as the sum of distances can be reduced by moving the centroids. When the sum of distances can no longer be reduced, the optimal cluster assignments have been reached.

### Selection of Matched Control Groups

Despite the clear threat to external validity, internally valid impact estimates for the opt-in SPP rates can be attained using a control group identified by propensity score matching techniques that pair SPP customers with non-SPP customers from the same industry and with a similar load shape. Matching was based on pre-enrollment consumption data and six different models were tested for use:



(where t= HE 17 through HE 22)



(where t= HE 17 through HE 22)

In the equations listed above, the dependent variable is a binary variable representing whether or not customer *i* opted in to an SPP rate.[[13]](#footnote-13) Explanatory variables include average daily consumption (*avgdailykwh*), the ratio of peak-to-offpeak consumption for summer months (*avg\_peakratio*), consumption in individual hours (*hourlykwh*), the percentage of electricity consumed during individual hours (*percentofdailykwh*), and the share of total electricity consumed during different rate periods (*avg\_peakshare* and *avg\_shouldershare[[14]](#footnote-14)*). The pool of possible control customers consisted of a random sample of approximately 20,000 SDG&E small commercial customers and each treatment-control pair was restricted to be in the same industry as identified by the first two digits of their NAICS codes.

The 6 matching models were estimated using pre-treatment data from the summer of 2013 (June–October) and were evaluated on the basis of differences in consumption between treatment and each matched control group for a pre-determined holdout period (May 2013). Two statistics were calculated to represent the performance of each model during the holdout period:

* Average Percent Error =

Absolute Sum of Errors =

For both APE and ASE, the kWh terms represent the average daily peak usage for a customer (i.e., total kWh between 11 AM and 6 PM). Better performing models have relatively lower values of APE and ASE, indicating that the consumption of the matched control group is similar to the consumption of the enrolled SPP group. These error calculations for the TOU treatment group are presented in Table 9-3.

Table 9-3: Propensity Score Matching Model Assessment for TOU Treatment Cohort

| Statistic | Model | Overall | Information | Public Administration | Other |
| --- | --- | --- | --- | --- | --- |
| APE | 1 | 6.7% | -9.9% | 37.2% | 9.9% |
| 2 | -4.1% | -20.7% | 42.3% | -4.8% |
| 3 | -1.2% | 3.5% | 13.3% | -11.0% |
| 4 | -15.4% | -0.9% | -36.3% | -9.9% |
| 5 | -2.6% | -20.1% | 42.7% | -2.0% |
| 6 | -11.5% | -15.9% | 21.2% | -20.0% |
| ASE | 1 | 4,304 | 950 | 875 | 2,479 |
| 2 | 4,777 | 1,331 | 1,107 | 2,339 |
| 3 | 5,091 | 1,016 | 1,625 | 2,450 |
| 4 | 6,001 | 957 | 2,231 | 2,812 |
| 5 | 4,665 | 1,262 | 997 | 2,405 |
| 6 | 4,949 | 1,123 | 1,126 | 2,700 |

The metrics in Table 9-3 show that model performance varies significantly both within and across different industries. For this reason, the best performing models for each industry[[15]](#footnote-15) were used to select the matched control group for each analysis: Model 4 for Information, Model 3 for Public Administration and Model 2 for Other Industries.

### Difference-in-differences Estimation

After identifying matched control groups for each treatment cohort (TOU and TOU-CPP), impact estimates were obtained using difference-in-differences. This approach uses comparisons of the control and treatment groups both before and after implementation of the rate to identify the load impacts.

Using difference-in-differences means that the matched control group does not need to perfectly match the treatment group in the pre-treatment period. This is because any differences that may be due to unobservable factors that could not be included in the matching model will be netted out by the differencing. This feature, however, is not a cure-all and therefore it is still desirable for pre-treatment consumption for the treatment and matched control groups to be as similar as possible.

Difference-in-differences estimation can be implemented using either simple means or a panel regression with fixed effects and time effects. For robustness, both methods were used in this evaluation, but the estimates from the regression model are reported due to their increased precision. The increased precision is achieved by including variables that explain energy use, such as temperature and day-of-week effects, which filter background noise (variation) and allow the signal (the response to TOU rates) to be more easily detected. Separate regression equations were estimated for each hour to produce load impact estimates for all hours of the day. The dependent variable in the regression equation is hourly electricity use and only non-holiday weekdays were included in the analysis. The full panel model specification is presented as Equation 1:

| Variable | Definition |
| --- | --- |
| *i, t* | Indicate observations for each individual (i) and date (t). |
|  | The model constant. |
|  | The change in electricity use due to the treatment. This change is only experienced by the treatment group after TOU is implemented. The parameter represents the difference-in-differences. |
|  | The difference pre and post TOU implementation period unrelated to treatment. |
|  | Change in electricity use due to weather (Avg. temperature during first 17 hours of  the day). |
|  | Change in electricity use due to month. |
|  | Customer fixed effects, which control for unobserved factors that are time invariant and unique to each customer. They do not control for fixed characteristics such as air conditioning that interact with time varying factors like weather. |
|  | The idiosyncratic (white-noise) error for each individual customer and time period. |
|  | A binary indicator of whether or not the customer is part of the treatment or control group. |
|  | A binary indicator of whether the time period occurs before (0) or after (1) implementation of TOU. |
|  | Average temperature during first 17 hours of the day. |
|  | Set of dummy variables for each summer month. |

## Non-Residential SPP Rates Ex-Post Load Impact Estimates

This section present the results of the ex post impact evaluation for each SPP rate along with interpretations of the estimates.

### TOU

Estimates of the peak period load impacts on average summer weekdays for the TOU rate are shown in Table 9-4 for each industry. None of the impacts were found to be statistically significant at even the 90% confidence level and some point estimates were negative (i.e., load increases[[16]](#footnote-16)).

Table 9-4: Peak Period Load Impacts for TOU Customers

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Industry | Month | Reference Load (kW) | Impact (kW) | Std. Error of Impact | %  Reduction | Aggregate Impact (kW) |
| Information (Treatment N=173) | July | 1.41 | 0.13 | 0.52 | 9% | 22 |
| August | 1.39 | 0.17 | 0.46 | 12% | 30 |
| September | 1.45 | 0.14 | 0.58 | 10% | 25 |
| October | 1.39 | 0.11 | 0.53 | 8% | 19 |
| **Avg. Summer** | **1.41** | **0.14** | **0.52** | **10%** | **24** |
| Public  Administration (Treatment N=191) | July | 0.86 | 0.06 | 0.26 | 7% | 11 |
| August | 0.86 | 0.06 | 0.29 | 7% | 12 |
| September | 0.90 | 0.02 | 0.35 | 2% | 3 |
| October | 0.77 | 0.04 | 0.34 | 5% | 7 |
| **Avg. Summer** | **0.85** | **0.05** | **0.31** | **5%** | **8** |
| Other (Treatment N=89) | July | 3.84 | -0.12 | 0.84 | -3% | -11 |
| August | 3.84 | -0.01 | 0.91 | 0% | -1 |
| September | 3.80 | -0.09 | 1.05 | -3% | -8 |
| October | 3.47 | -0.28 | 0.97 | -8% | -25 |
| **Avg. Summer** | **3.74** | **-0.13** | **0.95** | **-4%** | **-11** |
| All Customers (Treatment N=453) | July | 1.66 | 0.05 | 0.28 | 3% | 23 |
| August | 1.65 | 0.09 | 0.28 | 6% | 41 |
| September | 1.68 | 0.04 | 0.34 | 3% | 19 |
| October | 1.54 | 0.00 | 0.31 | 0% | 2 |
| **Avg. Summer** | **1.63** | **0.05** | **0.30** | **3%** | **21** |

\* = Significant at 90% confidence, \*\* = Significant at 95% confidence

It is important to note that the lack of statistical significance does not mean that small customers in general do not respond to time-varying price signals. The lack of statistical significance may be due to a combination of small sample sizes, unique load shapes that prove difficult to match, and diverse customers within each industry that increase the amount of noise in the average load shape. The robustness of the ex post results was tested by using different models to identify the matched control groups for the analysis. Using different models did not have any material effect on the results—that is, in all cases, impact estimates turned out to be small and statistically insignificant.

### TOU-CPP

Due to the nature of the TOU-CPP rate, there are two separate analyses to be considered: one for non-event weekdays and a second for event days. The non-event day analysis is identical to the TOU analysis since TOU and TOU-CPP rates are equivalent on those days. For event days, several modifications to the analysis must be made. The simplest of these is that the post-treatment days of interest for the TOU-CPP rate are each of the two CPP event days called during the summer of 2014 (September 15 and September 16). Because CPP events are typically called on days that are particularly hot, it is also important to identify “event-like” days in the pre-treatment period and remove all other days in the pre-treatment period from the analysis dataset. The four hottest days in September 2013 were chosen as “event-like” days and a comparison of these days with other hot September days in 2014 (including the CPP days) is shown in Table 9-5. Although the “event-like” days are not quite as hot as the actual events, they will suffice as a pre-treatment period in the difference-in-differences estimation.

Table 9-5: Ten Hottest September Days in 2013 and 2014 by Mean17[[17]](#footnote-17)

|  |  |  |  |
| --- | --- | --- | --- |
| Rank | | Date | Mean17 |
| 1 | | 16-Sep-14 | 83.4 |
| 2 | | 17-Sep-14 | 83.4 |
| 3 | | 15-Sep-14 | 81.7 |
| 4 | | 6-Sep-13 | 80.1 |
| 5 | | 8-Sep-14 | 79.9 |
| 6 | | 4-Sep-13 | 79.7 |
| 7 | | 5-Sep-13 | 79.3 |
| 8 | | 3-Sep-13 | 78.1 |
| 9 | | 9-Sep-14 | 77.9 |
| 10 | | 12-Sep-14 | 77.0 |
|  | CPP event days | | |
|  | Pre-treatment “event-like” days | | |

Load impacts for TOU-CPP customers on non-event days are presented in Table 9-6. The results are very similar to those for TOU customers, with impacts generally being small in absolute terms and statistically indistinguishable from zero. Although percent impacts appear large, this is entirely due to relatively small loads during the peak period. Estimated standard errors are substantially larger than the absolute impacts, indicating that the estimates are very noisy and should not be interpreted with a high degree of confidence.

Table 9-6: Peak Period Load Impacts for TOU-CPP Customers on   
Non-event Summer Weekdays

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Industry | Month | Reference Load (kW) | Avg. Impact (kW) | Std. Error of Impact | % Reduction | Aggregate Impact (kW) |
| Public Administration (Treatment N=190) | August | 0.52 | -0.07 | 0.21 | -14% | -14 |
| September | 0.53 | -0.05 | 0.43 | -10% | -10 |
| October | 0.50 | -0.07 | 0.25 | -14% | -13 |
| **Avg. Summer** | **0.52** | **-0.06** | **0.30** | **-13%** | **-12** |
| Other (Treatment N=102) | August | 1.71 | 0.31 | 0.97 | 18% | 31 |
| September | 1.73 | 0.35 | 0.94 | 20% | 35 |
| October | 1.60 | 0.31 | 1.04 | 19% | 31 |
| **Avg. Summer** | **1.68** | **0.32** | **0.98** | **19%** | **32** |
| All Customers (Treatment N=292) | August | 0.94 | 0.06 | 0.37 | 6% | 17 |
| September | 0.95 | 0.09 | 0.43 | 9% | 26 |
| October | 0.88 | 0.06 | 0.40 | 7% | 17 |
| **Avg. Summer** | **0.92** | **0.07** | **0.40** | **7%** | **20** |

\* = Significant at 90% confidence, \*\* = Significant at 95% confidence

Peak period impacts for the two CPP event days are presented in Table 9-7. Estimates are again very noisy and do not show any statistically significant impacts for individual industries or all customers taken as a whole. Based on these results, combined with those in Table 11-6, there is no evidence of any load reductions that can be attributed to the SPP rates. Given the strategic targeting of structural winners and the unique subset of customers who chose to enroll, these results should not be interpreted as what might happen if these rates were offered to the broader population as either opt-in or default tariffs.

**Table 9-7: Peak Period Load Impacts for TOU-CPP Customers on Event Days**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Industry | Event | Reference Load | Impact (kW) | Std. Error of Impact | % Reduction | Aggregate Impact (kW) |
| Public Administration (Treatment N=190) | 15-Sept | 0.57 | 0.05 | 0.54 | 8% | 9 |
| 16-Sept | 0.61 | -0.02 | 0.50 | -4% | -4 |
| **Average** | **0.59** | **0.01** | **0.38** | **2%** | **2** |
| Other  (Treatment N=102) | 15-Sept | 1.97 | -0.35 | 1.35 | -18% | -36 |
| 16-Sept | 2.06 | -0.36 | 1.34 | -17% | -36 |
| **Average** | **2.02** | **-0.35** | **1.28** | **-17%** | **-36** |
|  | 15-Sept | 1.06 | -0.10 | 0.59 | -9% | -28 |
| All Industries (Treatment N = 292) | 16-Sept | 1.12 | -0.14 | 0.57 | -12% | -40 |
|  | **Average** | **1.09** | **-0.12** | **0.51** | **-11%** | **-34** |

\* = Significant at 90% confidence, \*\* = Significant at 95% confidence

## Non-Residential SPP Rates Ex-Ante Evaluation Methodology

As mentioned earlier in this report, the CPUC Load Impact Protocols[[18]](#footnote-18) 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).

### Reference Loads

Reference loads provide a baseline level of consumption for customers representing what their electricity usage would be in the future if they did not switch to an SPP rate, but rather remained on their current rate (i.e., they are an estimate of counterfactual consumption). Reference loads can be compared to the predicted loads for customers after they transition to SPP rates to assess the effect of the new rates.

Since nearly all small commercial customers in SDG&E’s service territory are currently on a non-time-varying rate, there is ample data that can be used to model reference loads. The best approach for this modeling (in the absence of holding back a control group) is to develop a regression model that predicts electricity consumption as a function of weather conditions, month, day of week, hour of day, and other variables that influence usage. To develop the best possible model, 10 specifications were tested and the one that most accurately predicted loads during an out-of-sample test was selected as the final model. This model is shown as Equation 2:

|  |  |
| --- | --- |
|  |  |
| Variable | Definition | |
| *h, i, d* | Indicate observations for each hour (h), industry (i) and day (d). | |
|  | The model constant. | |
|  | Cooling degree days on day d, defined as max(0, Avg. daily temp – 60). | |
|  | A binary indicator of whether the day of the observation is a weekday (0=weekend, 1=weekday). | |
|  | Set of dummy variables for each month of the year. | |
|  | Error term (assumed to be mean zero and independent of all other regressors). | |

The reference load model was estimated separately for each small commercial industry type for each hour of the day and includes terms for a weekday dummy variable interacted with cooling degree days, the same weekday dummy interacted with cooling degree days squared, the weekday dummy by itself, and a set of dummy variables for the months of the year. This specification captures changes in weather conditions as well as seasonal variation in electricity usage and was used to estimate reference loads for every combination of industry, day type (weekday or weekend), month, and set of weather conditions. Estimated reference loads for the average small commercial customer throughout the year are presented in Table 9-8.

The values in the table represent average load during the peak period for monthly peak days under each set of weather conditions. The highest reference loads during the peak period for this group of customers occur in September for each of the weather scenarios. During the summer months, the CAISO and SDG&E based reference loads (and underlying weather) are quite similar under 1-in-2 year conditions. For 1-in-10 year conditions, the SDG&E based weather conditions are typically a bit higher than the CAISO based conditions.

**Table 9-8: Estimated Reference Loads for Small Commercial Customer**

**under Ex Ante Weather Conditions**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Month | Reference Loads (kW) | | | |
| CAISO | | SDG&E | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| January | 1.70 | 1.70 | 1.70 | 1.70 |
| February | 1.71 | 1.71 | 1.71 | 1.71 |
| March | 1.70 | 2.01 | 1.70 | 1.92 |
| April | 1.86 | 2.27 | 1.94 | 2.36 |
| May | 1.93 | 2.37 | 2.10 | 2.47 |
| June | 2.20 | 2.44 | 2.20 | 2.45 |
| July | 2.44 | 2.52 | 2.44 | 2.70 |
| August | 2.66 | 2.69 | 2.61 | 2.80 |
| September | 2.71 | 2.92 | 2.68 | 2.90 |
| October | 2.20 | 2.47 | 2.30 | 2.56 |
| November | 1.81 | 2.09 | 1.85 | 2.21 |
| December | 1.67 | 1.67 | 1.67 | 1.67 |

## Non-Residential SPP Rates Ex-Ante Load Impact Estimates

This section presents the results of the ex ante impact evaluation for each class of SDG&E customer that will transition to the SPP rates.

### Small Commercial Customers (Approved Rate Windows)

Peak period load impact estimates attributable to the TOU component of the SPP rates on a July system peak day (SDG&E weather conditions) are presented in Table 11-9 for each industry. Percent impacts range from -6% for Manufacturing (load increase) to 9% for Agriculture, Mining & Construction. The forecasted aggregate impact for all small commercial customers is about 11 MW under 1-in-2 conditions and approximately 9% higher (11 MW) under 1-in-10 conditions.

Table 9-9: Ex Ante TOU Load Impacts for Small Commercial Customers   
on September Monthly System Peak Day (SDG&E Weather Conditions)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Industry | SDG&E 1-in-2 | | | SDG&E 1-in-10 | | | % Impact |
| Ref Load (kW) | Avg. Impact per Customer (kW) | Aggregate Impact (MW) | Ref Load (kW) | Avg. Impact per Customer (kW) | Aggregate Impact (MW) |
| Agriculture, Mining & Construction | 2.14 | 0.19 | 1.49 | 2.36 | 0.21 | 1.64 | 8.8% |
| Manufacturing | 2.48 | -0.15 | -1.39 | 2.66 | -0.16 | -1.50 | -6.0% |
| Wholesale, Transport & Other Utilities | 2.61 | 0.15 | 1.06 | 2.83 | 0.16 | 1.14 | 5.7% |
| Retail Stores | 3.63 | 0.04 | 0.50 | 3.91 | 0.04 | 0.54 | 1.1% |
| Offices, Hotels, Finance, Services | 2.87 | 0.09 | 5.09 | 3.11 | 0.10 | 5.51 | 3.2% |
| Schools | 3.24 | 0.11 | 0.27 | 3.54 | 0.12 | 0.30 | 3.4% |
| Institutional/Government | 2.03 | 0.15 | 3.93 | 2.18 | 0.16 | 4.23 | 7.5% |
| **All Small Commercial** | **2.68** | **0.09** | **10.95** | **2.90** | **0.10** | **11.87** | **3.4%** |

Aggregate impacts for each month of the year are presented in Table 9-10. The impacts range from a low of about 8 MW in May to a high of almost 13 MW in November. It should be noted that impacts are approximately 30–40% larger in the winter compared to the summer, which is a direct consequence of basing the ex ante estimates on the results from PG&E.

Table 9-10: Aggregate Ex Ante TOU Load Impacts for Small Commercial Customers on   
Monthly System Peak Days

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Month | Load Impact (MW) | | | |
| CAISO | | SDG&E | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| January | 12.15 | 12.15 | 12.15 | 12.15 |
| February | 12.21 | 12.21 | 12.21 | 12.21 |
| March | 12.12 | 14.26 | 12.11 | 13.67 |
| April | 13.19 | 16.16 | 13.76 | 16.81 |
| May | 7.96 | 9.83 | 8.69 | 10.23 |
| June | 9.09 | 10.12 | 9.09 | 10.15 |
| July | 10.02 | 10.40 | 10.06 | 11.14 |
| August | 10.97 | 11.09 | 10.75 | 11.53 |
| September | 11.10 | 11.96 | 10.95 | 11.87 |
| October | 8.92 | 10.07 | 9.36 | 10.43 |
| November | 12.84 | 14.84 | 13.16 | 15.70 |
| December | 11.91 | 11.92 | 11.92 | 11.92 |

The empirical evidence available for estimating the incremental impact of CPP prices on event days is extremely limited and so these impacts are conservatively assumed to be zero.

### Agricultural Customers (Approved Rate Windows)

Peak period load impact estimates attributable to the TOU component of the SPP rates on a July system peak day for agricultural customers are presented in Table 9-11 by industry. The agricultural customer segment was separated into two distinct industries—agricultural pumping and water districts. The majority of customers fall into the agricultural pumping category and this industry is responsible for nearly the entire forecasted load reductions associated with the TOU rate. Overall, SDG&E’s agricultural customers are expected to reduce their peak period usage by about 1.10 MW in response to the TOU portion of the SPP rates.

Table 9-11: Ex Ante TOU Load Impacts for Agricultural Customers on July Monthly System Peak Day (SDG&E Weather Conditions)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Industry | SDG&E 1-in-2 | | | SDG&E 1-in-10 | | | % Load Reduction |
| Ref Load (kW) | Avg. Impact per Customer (kW) | Aggregate Impact (MW) | Ref Load (kW) | Avg. Impact per Customer (kW) | Aggregate Impact (MW) |
| Agriculture Pumping | 2.46 | 0.47 | 1.05 | 2.49 | 0.47 | 1.06 | 19.1% |
| Water Districts | 2.55 | 0.14 | 0.05 | 2.71 | 0.15 | 0.06 | 5.7% |
| All Agriculture | 2.47 | 0.42 | 1.10 | 2.52 | 0.43 | 1.12 | 17.0% |

Impacts for agricultural customers by month are shown in Table 9-12. Unlike the results for small commercial customers, impacts for agricultural customers are largest in the summer and smaller in the winter due to the seasonal nature of the growing season and pumping activities. The results are also fairly consistent across each set of ex ante weather conditions, with impacts ranging from a low of around 0.45 MW in December to a high of approximately 1.10 MW in July.

Table 9-12: Aggregate Ex Ante TOU Load Impacts for Agricultural Customers on   
Monthly System Peak Days

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Month | Load Impact (MW) | | | |
| CAISO | | SDG&E | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| January | 0.53 | 0.53 | 0.53 | 0.53 |
| February | 0.45 | 0.45 | 0.45 | 0.45 |
| March | 0.43 | 0.50 | 0.43 | 0.49 |
| April | 0.57 | 0.63 | 0.58 | 0.64 |
| May | 1.00 | 1.10 | 1.06 | 1.11 |
| June | 1.06 | 1.11 | 1.06 | 1.11 |
| July | 1.10 | 1.11 | 1.10 | 1.12 |
| August | 1.06 | 1.06 | 1.05 | 1.06 |
| September | 1.08 | 1.06 | 1.08 | 1.07 |
| October | 0.97 | 1.01 | 0.99 | 1.02 |
| November | 0.50 | 0.56 | 0.52 | 0.57 |
| December | 0.45 | 0.45 | 0.45 | 0.45 |

As with small commercial customers, the incremental impact of the CPP component of the SPP rates is assumed to be zero for agricultural customers.

# Commercial Thermostats

## Commercial Thermostats Overview

SDG&E’s commercial thermostat program provides commercial customers with programmable communicating thermostats (PCTs). On event days, customers are subject to two different AC cycling strategies—50% cycling and a 4-degree temperature setback. Customers receive the PCTs for free, but do not currently receive an incentive payment, and are able to override the signal or opt out of DR events. Most of these customers will be defaulted onto Critical Peak Pricing (CPP) within a year. For now, the thermostats are activated on residential Peak Time Rebate (PTR) event days.

## Commercial Thermostats Overview

The methods used in the commercial thermostat program evaluation rely on the selection of a control group using statistical matching and individual customer regressions.

### Matched Control Group Methodology – Commercial

The primary source of reference loads, and hence impact estimates, is a number of matched control groups. These control groups are assembled from among the non-participant population. The methods used to assemble the groups are designed to ensure that the control group load on event days is an accurate estimate of what load would have been among participants on event days had they not participated.

The fundamental idea behind the matching process is to find customers who were not subject to events that have similar characteristics to those who were subject to events. The control groups were selected using a propensity score match to find customers who had demand patterns most similar to participants. In this procedure, a probit model is used to estimate a score for each customer based on a set of observable variables that are assumed to affect the decision to participate in the commercial thermostat program. A probit model is a regression model designed to estimate probabilities—in this case, the probability that a customer would choose to participate.

Once the control groups were matched and validated, load impacts were estimated using a difference-in-differences methodology. This methodology calculates the estimated impacts as the difference in average loads between participants and control customers on event days minus the difference between the two groups on hot, non-event days. This calculation controls for residual differences in load between the groups that are not eliminated through the matching process, thus reducing bias. Equation 10-1 summarizes the difference-in-differences calculation and Table 3-2 provides the definitions for variables in the equation.

Equation 10-1: Specification of Difference-in-Differences Reference Load

Table 10-1: Variables Used for Difference-in-differences Calculation

| Variable | Description |
| --- | --- |
| *ref* | Reference load (kW) |
| *kW* | Average demand |
| *p* | Indicates whether a customer is a participant (p=1) or a control group member (p=0) |
| *e* | Indicates whether a given day was an event (e=1) or not (e=0) |
| *i* | Indexes the participants along with their matched control customer |
| *d* | Indexes the event days and their corresponding average proxy day, September proxies for September events, July proxies for July events |
| *h* | Indexes the hour |

### Individual Customer Regression Methodology – Residential

For the small group of customers that are considered residential premises in SDG&E’s records, even though they are located on commercially-managed properties, individual customer regressions were used to estimate load impacts. It would have been time-consuming and very difficult (if not impossible) to find an appropriate control group for this small, unique group that accounts for less than 5% of the thermostats in the program, so this within-subjects approach was used instead. The regression model used is specified in Equation 10-2, and the variable definitions are provided in Table 10-2. The customers for whom we used the individual customer regression methodology are very difficult to accurately model because data on when the units are and are not occupied is not available. We validated many models using the same hot non-event days we used to construct the matched control groups, and chose this as the best performing model.

Equation 10-2: Model Specification for Individual Customer Regressions

Table 10-2: Variables Used for Individual Customer Regressions

| Variable | Description |
| --- | --- |
| *A* | a is an estimated constant |
| *b, c, and d* | b, c, and d are estimated parameters |
| *year2014* | year2014 is a dummy variable indicating whether the year was 2013 or 2014 |
| *mean17* | The mean temperature from midnight until 5 PM |
|  | The error term |

## Commercial Thermostats Ex Post

This section summarizes the ex post load impact estimates for commercial thermostat program participants for the 2014 program year. In keeping with the requirements for ex post load impact evaluations, results are presented for each hour of each event day for the average customer and for all customers enrolled at the time of each event. In addition to meeting the basic load impact protocol requirements, detailed analysis has been conducted to understand how commercial load impacts vary across a number of factors, including:

* Climate zone;
* Industry;
* 50% cycling and 4-degree setback; and

Direct Install vs. Demand Response (two SDG&E groups that recruited participants).

SDG&E called four events during summer 2014. During the first event, on July 31, 2014, there were 274 enrolled participants; and during the final three events, on September 15, 16, and 17, enrollment equaled 363 participants.

Table 10-3 summarizes the average load reduction provided by commercial customers across the four-hour event window from 2 to 6 PM. As shown, the average percent reduction ranged from a low of 4% on September 15and 16 to a high of 8% on July 31. An average reduction of 5% was obtained across the four event days. The average load reduction per thermostat ranged from a low of 0.18 kW to a high of 0.30 kW. Aggregate load reductions ranged from 0.59 MW to 0.77 MW. Aggregate load reductions for the four events averaged 0.68 MW per event.

Table 10-3: 2014 Commercial Thermostat Ex Post Load Impact Estimates (2 to 6 PM)  
(kW per Customer, Aggregate MW, and kW per Thermostat)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **Enrolled Participants** | **Total Number of Thermostats** | **Avg. Reference Load (kW)** | **Avg. Load Reduction (kW)** | **Percent Load Reduction (%)** | **Aggregate Load Reduction (MW)** | **Average Thermostat Impact (kW)** | **Mean17 (°F)** |
| July 31, 2014 | 274 | 2,556 | 33.92 | 2.82 | 8% | 0.77 | 0.30 | 75 |
| Sept. 15, 2014 | 363 | 3,254 | 40.51 | 1.61 | 4% | 0.59 | 0.18 | 80 |
| Sept. 16, 2014 | 363 | 3,254 | 41.68 | 1.62 | 4% | 0.59 | 0.18 | 83 |
| Sept. 17, 2014 | 363 | 3,254 | 40.37 | 1.90 | 5% | 0.69 | 0.21 | 82 |
| **Average Event** | **341** | **3,085** | **39.12** | **1.99** | **5%** | **0.68** | **0.22** | **80** |

## Load Impacts for Specific Customer Segments - Commercial

This subsection examines how commercial customer load impacts vary by climate zone, industry, cycling strategy, and participant source. The segment-specific results are based on the same treatment-control group methodology that was used to produce the commercial customer impacts summarized above.

### Load Impacts by Climate Zone

SDG&E’s service territory has limited climatic diversity, but the variation in temperature and AC use has a real impact on many customers’ loads on summer days when the ocean breeze cools off the coast and leaves customers further inland hot. Participants in the commercial thermostat program as of the 2014 summer come from one of two climate zones – Coastal and Inland. Table 10-4 shows the average hourly load impacts for these two climate zones. These estimates are based on the same methodology involving statistically matched control groups as was used to develop the program level load impacts. The Inland climate zone is hotter, has higher AC usage, and accordingly produced higher load impacts per thermostat. The per-thermostat impact is 20% higher in the Inland climate zone than in the Coastal climate zone. The sample sizes for the 2014 commercial thermostat ex post analysis were fairly small, so this difference in per-thermostat impacts was not statistically significant. Given that the program has grown substantially since summer 2014, future load impacts may produce a statistically significant difference in per-thermostat impacts by climate zone.

Table 10-4: 2014 Commercial Thermostat Average Hourly Load Reduction   
for Event Period (2 to 6 PM) by Climate Zone   
(kW per Customer, Aggregate MW, and kW per Thermostat)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Climate Zone** | **Enrolled Participants** | **Total Number of Thermostats** | **Avg. Reference Load (kW)** | **Avg. Load Reduction (kW)** | **Percent Load Reduction (%)** | **Aggregate Load Reduction (MW)** | **Average Thermostat Impact (kW)** | **Mean17 (°F)** |
| Coastal | 192 | 1,675 | 42.28 | 1.74 | 4% | 0.33 | 0.20 | 79 |
| Inland | 149 | 1,411 | 35.06 | 2.31 | 7% | 0.34 | 0.24 | 81 |
| **Both** | **341** | **3,085** | **39.12** | **1.99** | **5%** | **0.68** | **0.22** | **80** |

### Load Impacts by Industry

The participants in the commercial thermostat program come from a number of different industries. During 2014 events, Offices, Hotels, Finance, and Services accounted for nearly half of all of the participating commercial customers and a slightly higher percentage of the total number of thermostats. Schools made up 12% of the total participating customers, but had 21% of the installed thermostats. Retail stores made up 8.5% of the participating customers, while having under 3% of the thermostats.

Table 10-5 shows the average load reduction by industry. Some industries are left out of the table altogether due to insufficient sample sizes. Given the sample size, the most reliable estimate for any industry breakout is that for Offices, Hotels, Finance, and Services. The per-thermostat impact for this industry was 0.13 kW, nearly 41% lower than the estimate for the average commercial customer (0.22 kW per thermostat). The average event-day temperature for participants in this industry was nearly the same as the average event-day temperature for the average commercial customer, indicating that the higher impact per thermostat among these customer was most likely not due to weather conditions. Since there are relatively few customers in the other industries, it is difficult to assess why this industry underperformed other industries and whether it will continue to in the future. It is, instead, just a sign that there may be other industries that can be targeted to achieve greater per-thermostat savings.

**Table 10-5: 2014 Commercial Thermostat Average Hourly Load Reduction   
for Event Period (2 to 6 PM) by Industry   
(kW per Customer, Aggregate MW, and kW per Thermostat)**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Industry** | **Enrolled Participants** | **Total Number of Thermostats** | **Avg. Reference Load (kW)** | **Avg. Load Reduction (kW)** | **Percent Load Reduction (%)** | **Aggregate Load Reduction (MW)** | **Average Thermostat Impact (kW)** | **Mean17 (°F)** |
| Institutional/Government | 82 | 691 | 31.30 | 2.16 | 7% | 0.18 | 0.26 | 80 |
| Offices, Hotels, Finance, Services | 165 | 1,549 | 42.81 | 1.25 | 3% | 0.21 | 0.13 | 80 |
| Retail Stores | 29 | 84 | 27.00 | 3.09 | 11% | 0.09 | 1.06 | 80 |
| Schools | 41 | 641 | 63.16 | 4.19 | 7% | 0.17 | 0.26 | 79 |
| **All Industries** | **341** | **3,085** | **39.12** | **1.99** | **5%** | **0.68** | **0.22** | **80** |

### Load Impacts by Cycling Strategy

Commercial thermostat program participants are on one of two cycling strategies – a 4-degree setback or 50% cycling. These customers are split almost evenly into the two groups. This segmentation allows for a comparison between the two cycling strategies. Table 10-6 shows the average load reduction by cycling strategy. The average event-day temperature for participants assigned to each of the two strategies were nearly the same, yet the load reduction in aggregate, per-thermostat, and per-customer terms were all considerably higher among the 4-degree setback customers. Since there were large and statistically significant differences in peak demand on non-event days for these two groups, it is difficult to assess whether this effect will continue to hold in the future, but it suggests that the 4-degree setback may be a better approach going forward.

Table 10-6: 2014 Commercial Thermostat Average Hourly Load Reduction   
for Event Period (2 to 6 PM) by Cycling Strategy   
(kW per Customer, Aggregate MW, and kW per Thermostat)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Strategy** | **Enrolled Participants** | **Total Number of Thermostats** | **Avg. Reference Load (kW)** | **Avg. Load Reduction (kW)** | **Percent Load Reduction (%)** | **Aggregate Load Reduction (MW)** | **Average Thermostat Impact (kW)** | **Mean17 (°F)** |
| 4-Degree Setback | 173 | 1,855 | 46.51 | 2.74 | 6% | 0.47 | 0.25 | 80 |
| 50% Cycling | 163 | 1,193 | 30.87 | 1.21 | 4% | 0.20 | 0.17 | 80 |
| **Overall** | **341** | **3,085** | **39.12** | **1.99** | **5%** | **0.68** | **0.22** | **80** |

### Load Impacts by Source

The commercial thermostat customers came from one of two different internal sources within SDG&E – Demand Response and Direct Install. Table 10-7 shows the average hourly load reduction by source. Many more commercial customers were signed up through Demand Response (262) than through Direct Install (78), and many more thermostats were signed up through Demand Response (2,849) than Direct Install (232). Nonetheless, the two customer groups provided very similar per-thermostat response.

Table 10-7: 2014 Commercial Thermostat Average Hourly Load Reduction   
for Event Period (2 to 6 PM) by Source within SDG&E  
(kW per Customer, Aggregate MW, and kW per Thermostat)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Source** | **Enrolled Participants** | **Total Number of Thermostats** | **Avg. Reference Load (kW)** | **Avg. Load Reduction (kW)** | **Percent Load Reduction (%)** | **Aggregate Load Reduction (MW)** | **Average Thermostat Impact (kW)** | **Mean17 (°F)** |
| Demand Response | 262 | 2,849 | 46.76 | 2.37 | 5% | 0.62 | 0.22 | 80 |
| Direct Install | 78 | 232 | 14.01 | 0.69 | 5% | 0.05 | 0.23 | 80 |
| **Both** | **341** | **3,085** | **39.12** | **1.99** | **5%** | **0.68** | **0.22** | **80** |

## Ex Ante Methodology and Results

This section summarizes the modeling approach and results associated with ex ante impact estimation for the commercial thermostat program. Ex ante impacts are intended to represent what the commercial thermostat program can deliver under a standardized set of weather and event conditions given changes in enrollment over the forecast horizon. The weather used for ex ante load impact estimation is meant to reflect conditions on high demand days when there is a high likelihood that events will be called under normal (1-in-2 year) and extreme (1-in-10 year) weather.

## Ex Ante Estimation Methodology

At a high level, ex ante impact estimates were developed using the following multi-step process:

* First, ex post estimates were developed using the matching methodology described in Section 3, with the key output being the 2014 average event day per-thermostat impact (0.22 kW);
* Second, regression models were estimated that relate hourly usage to weather for customers that are currently enrolled in the commercial thermostat program. This model was fit using one data point for each customer segment, hour and day;
* Third, a regression model was estimated that related the ex post impacts for 50% cycling customers in the Summer Saver program to average temperatures from midnight to 5 PM (referred to as mean17) on the event day. Ex ante weather conditions were used as input to the regression model to predict Summer Saver impacts for each hour for monthly system peak days and for the typical event day; and

Fourth, the ratio of impact to weather observed in the Summer Saver program was applied to the 2014 average event day per-thermostat impact for the commercial thermostat program (from Step 1).

The final model specifications used for the reference loads and Summer Saver impact-temperature relationship are shown below. The reference load specification was chosen based on its performance in estimating reference loads in the 2014 Critical Peak Pricing program ex ante evaluation. The impact model matches the model used in the 2014 Summer Saver evaluation to maintain consistency.

Equation 10-3: Reference Load Ex Ante Regression Model Specification

Table 10-8: Description of Ex Ante Reference Load Regression Variables

|  |  |
| --- | --- |
| Variable | Description |
| *kW* | Per customer ex post reference load for each event day |
| *a* | Estimated constant |
| *b and c* | Estimated parameters describing the relationship between temperature and demand |
| *d* | Estimated parameters describing the average difference in load for that weekday from Monday |
| *m* | Estimated parameters describing the average difference in load for that month from January |
| *mean17* | Average temperature from midnight to 5 PM |
| *mean172* | Average temperature from midnight to 5 PM, squared |
| *DOW* | Dummy variable for each weekday (Monday not included) |
| *Month* | Dummy variable for each month (January not included) |
| *Ɛ* | The error term, assumed to be a mean zero and uncorrelated with any of the independent variables |
| *d* | Indexes event days within a given segment |
| *day* | Indexes weekday |
| *month* | Indexes month |

Equation 10-4: Summer Saver Load Impact Ex Ante Regression Model Specification

Table 10-9: Description of Ex Ante Reference Load Regression Variables

|  |  |
| --- | --- |
| Variable | Description |
| *impact* | Per customer ex post load impact (kW) for each event day |
| *a* | Estimated constant |
| *b* | Estimated parameter describing the relationship between temperature and demand |
| *mean17* | Average temperature from midnight to 5 PM |
| *Ɛ* | The error term, assumed to be a mean zero and uncorrelated with any of the independent variables |

Table 10-10 shows the results of the ex ante impact modeling for the four event days at hour ending 4 PM, as compared to the estimates in the ex post analysis. The July 31 event had the largest per-customer impact, while it was the coldest day. Since, in general, higher impacts on hotter days are expected, and that is consistent with the findings in the Summer Saver analysis, the impacts for July 31 are underestimated with the ex ante methodology. The estimates are closest for the September 17 event, which was a day like many of the summer monthly peaking conditions.

Table 10-10: Ex Post and Ex Ante Impact Validation for Event Days at Hour Ending 4 PM

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Date | Ex Post Impact (kW) | Ex Ante Impact (kW) | Difference (kW) | Mean17 |
|
| July 31, 2014 | 2.81 | 1.52 | -1.29 | 74.6 |
| Sept. 15, 2014 | 1.32 | 2.02 | 0.70 | 80.0 |
| Sept. 16, 2014 | 1.88 | 2.33 | 0.45 | 82.9 |
| Sept. 17, 2014 | 2.12 | 2.23 | 0.12 | 81.9 |

## Estimating Ex Ante Weather Conditions

The CPUC Load Impact Protocols[[19]](#footnote-19) 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 the ex ante weather conditions 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 this year along with the development of the new CAISO based conditions. Both sets of estimates used a common methodology, which is documented in a report delivered to the IOUs.[[20]](#footnote-20) .

Table 10-11 shows the value for mean17 for the typical event day and the monthly system peak day under the four sets of weather for which load impacts are estimated. As seen, there are small differences in weather conditions based on SDG&E peak conditions and CAISO peak conditions, for normal and extreme weather. The CAISO-based conditions on the typical event day are slightly higher in a 1-in-2 weather year and lower in a 1-in-10 weather year. For the September peak day under 1-in-10 weather conditions, the mean17 value is the same (83.9 °F).

Table 10-11: Ex Ante Weather Values (*mean17*, °F)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Day Type | SDG&E Based Weather (°F) | | CAISO Based Weather (°F) | |
| 1-in-2 | 1-in-10 | 1-in-2 | 1-in-10 |
| Typical Event Day | 73.8 | 79.9 | 74.6 | 78.0 |
| January Peak Day | 51.0 | 47.7 | 50.7 | 46.0 |
| February Peak Day | 51.2 | 52.5 | 53.8 | 53.6 |
| March Peak Day | 55.7 | 64.4 | 53.0 | 66.3 |
| April Peak Day | 65.9 | 76.0 | 64.6 | 75.1 |
| May Peak Day | 69.1 | 77.6 | 65.6 | 74.7 |
| June Peak Day | 68.7 | 75.1 | 69.5 | 74.4 |
| July Peak Day | 73.7 | 79.9 | 72.3 | 75.1 |
| August Peak Day | 75.6 | 80.7 | 77.7 | 78.4 |
| September Peak Day | 77.0 | 83.9 | 78.6 | 83.9 |
| October Peak Day | 72.1 | 78.1 | 68.3 | 75.9 |
| November Peak Day | 64.6 | 73.4 | 63.0 | 70.0 |
| December Peak Day | 54.8 | 49.6 | 55.7 | 49.6 |

## Ex Ante Load Impact Results

Aggregate ex ante estimates combine these average estimates with projections of program enrollment provided by SDG&E. Per-thermostat ex ante estimates also combine the average customer estimates with projections of the average number of thermostats, which is expected to remain around 9 thermostats per customer. Table 10-12 summarizes the projected commercial thermostat enrollment by month and year from 2015 through 2025. Currently, there are nearly 1,200 customers enrolled. This number is expected to gradually increase to 2,013 customers by the end of 2016. From 2017 through 2025, enrollment is expected to remain constant at 2,013 customers.

Table 10-12: Projected 2015-2025 Commercial Thermostat Enrollment  
Total Number of Customers Enrolled

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | **Jan** | **Feb** | **Mar** | **Apr** | **May** | **Jun** | **Jul** | **Aug** | **Sept** | **Oct** | **Nov** | **Dec** |
| 2015 | 1,193 | 1,193 | 1,245 | 1,297 | 1,349 | 1,401 | 1,453 | 1,505 | 1,557 | 1,609 | 1,661 | 1,713 |
| 2016 | 1,738 | 1,763 | 1,788 | 1,813 | 1,838 | 1,863 | 1,888 | 1,913 | 1,938 | 1,963 | 1,988 | 2,013 |
| 2017-2025 | 2,013 | 2,013 | 2,013 | 2,013 | 2,013 | 2,013 | 2,013 | 2,013 | 2,013 | 2,013 | 2,013 | 2,013 |

Table 10-13 summarizes the 2017-2025 ex ante load impact estimates by weather year and day type. The third and sixth columns in the table show the average hourly ex ante load impact per thermostat (kW) over the event period from 2 to 6 PM for each type of weather, followed by the per-customer impact (kW) and the aggregate impact (MW). The first set of rows corresponds to 1-in-2 year weather conditions while the second set covers 1-in-10 year weather conditions. The highest impacts consistently occur on September peak days under both SDG&E and CAISO weather conditions, with aggregate impacts of 5.3 MW in a 1-in-10 year and around 4 MW in a 1-in-2 year.

Table 10-13: 2017-2025 Ex Ante Load Impact Estimates by Weather Year and Day Type   
(kW per Customer, Aggregate MW, and kW per Thermostat)

| Weather Year | Day Type | SDG&E Mean Hourly Impacts (2-6 PM) | | | CAISO Mean Hourly Impacts (2-6 PM) | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Per Thermostat | Per Customer | Aggregate | Per Thermostat | Per Customer | Aggregate |
| (kW) | (kW) | (MW) | (kW) | (kW) | (MW) |
| 1-in-2 | Typical Event Day | 0.15 | 1.49 | 2.99 | 0.16 | 1.58 | 3.17 |
| January Monthly Peak | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| February Monthly Peak | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| March Monthly Peak | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| April Monthly Peak | 0.06 | 0.59 | 1.19 | 0.04 | 0.45 | 0.90 |
| May Monthly Peak | 0.10 | 0.95 | 1.92 | 0.06 | 0.56 | 1.12 |
| June Monthly Peak | 0.09 | 0.91 | 1.83 | 0.10 | 1.00 | 2.02 |
| July Monthly Peak | 0.15 | 1.48 | 2.98 | 0.13 | 1.32 | 2.67 |
| August Monthly Peak | 0.17 | 1.69 | 3.41 | 0.20 | 1.94 | 3.90 |
| September Monthly Peak | 0.19 | 1.86 | 3.74 | 0.21 | 2.04 | 4.11 |
| October Monthly Peak | 0.13 | 1.30 | 2.62 | 0.09 | 0.86 | 1.73 |
| November Monthly Peak | 0.04 | 0.44 | 0.89 | 0.03 | 0.26 | 0.53 |
| December Monthly Peak | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 1-in-10 | Typical Event Day | 0.22 | 2.19 | 4.40 | 0.20 | 1.97 | 3.96 |
| January Monthly Peak | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| February Monthly Peak | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| March Monthly Peak | 0.04 | 0.42 | 0.85 | 0.06 | 0.63 | 1.27 |
| April Monthly Peak | 0.18 | 1.74 | 3.50 | 0.17 | 1.64 | 3.31 |
| May Monthly Peak | 0.19 | 1.93 | 3.88 | 0.16 | 1.59 | 3.20 |
| June Monthly Peak | 0.16 | 1.63 | 3.29 | 0.16 | 1.56 | 3.14 |
| July Monthly Peak | 0.22 | 2.19 | 4.41 | 0.17 | 1.64 | 3.31 |
| August Monthly Peak | 0.23 | 2.28 | 4.58 | 0.20 | 2.02 | 4.06 |
| September Monthly Peak | 0.27 | 2.64 | 5.32 | 0.27 | 2.65 | 5.33 |
| October Monthly Peak | 0.20 | 1.98 | 3.98 | 0.17 | 1.72 | 3.47 |
| November Monthly Peak | 0.15 | 1.45 | 2.92 | 0.11 | 1.05 | 2.12 |
| December Monthly Peak | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

## Relationship Between Ex Post and Ex Ante Estimates

This section discusses the impact of each of these factors on the difference between ex post and ex ante impact estimates.

Table 10-14 summarizes the key factors that lead to differences between ex post and ex ante estimates for the commercial thermostat program and the expected influence that these factors have on the relationship between ex post and ex ante impacts. Given that the load impacts are quite sensitive to variation in weather, even small changes in mean17 between ex post actual and ex ante weather conditions can produce relatively large differences in load impacts. Changes in enrollment between the values used for ex post estimation and the 2015 enrollment values are expected to more than double impact estimates as the program has grown substantially since the last event in September.

Table 10-14: Summary of Factors Underlying Differences Between Ex Post and Ex Ante Impacts   
for the Commercial Thermostat Program for the Ex Ante Typical Event Day

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex Post | Ex Ante | Expected Impact |
| Weather | 75< event day mean17 < 83  Average event day mean17 = 80 | Mean17 for 1-in-2 typical event day = 73.8 and 74.6 for SDG&E and CAISO weather, respectively | Ex ante estimates are highly sensitive to variation in mean17 – ex ante weather is generally cooler than the observed weather for 2014, so ex ante should generally be lower than ex post, all else equal |
| Mean17 for 1-in-10 typical event day = 79.9 and 78.0 for PG&E and CAISO weather, respectively |
| Enrollment | Enrollment grew by nearly 50% from the first to second event | 2017-2015 enrollment is forecast to be more than five times higher than September 2014 enrollment | Ex ante estimates will grow to be more than five-times higher than ex post |
| Methodology | Impacts are largely based on matched control groups and adjustments based on differences in pre-event hours and weather sensitivity | Regression of ex post reference loads against mean17 for each hour and a weather-based adjustment estimated from Summer Saver weather-sensitivity | Impacts will vary differently with weather, given that Summer Saver is a larger, more established program that shows a strong relationship between weather and impacts, whereas the commercial thermostat temperature-impact relationship has few data points (4 event days) |

Table 10-15 shows how aggregate load impacts change as a result of differences in the factors underlying ex post and ex ante estimates. The third column reproduces the ex post values from Table 4-1. The next column grosses these estimates up by the difference in ex post and ex ante enrollment in August 2016. As expected, this produces a nearly five-times increase in the impacts. The next column shows what the ex ante model would produce using the same 2016 August enrollment figures and the ex post weather conditions for each event day. As discussed above, the ex ante model over predicts load reductions for September and under predicts for July. This is due to the unexpected high impact on the relatively cool July 31 event day, and the relatively limited number of events available to determine whether the observed trend of higher impacts on cooler day was spurious, or was due to a real trend. One other potential explanation for this difference is the change in the population from the July event to the September events. The final four columns show how aggregate load reductions vary with the different ex ante weather scenarios. The SDG&E 1-in-10 conditions are most similar to the 2014 SDG&E ex post weather conditions on average across all event days, although for any given ex post day, the weather conditions can differ significantly. Using the SDG&E 1-in-10 year conditions decreases the average impacts by about 2% compared with ex post weather.

Table 10-15: Differences in Ex Post and Ex Ante Impacts Due to Key Factors

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Date | Mean17 | Ex Post Impact | Ex Post Impact with August 2016 Ex Ante Enrollment | Ex Ante Model Ex Post Weather and Event Window | CAISO 1-in-2 | SDG&E 1-in-2 | CAISO  1-in-10 | SDG&E 1-in-10 |
| (°F) | (MW) | (MW) | (MW) | (MW) | (MW) | (MW) | (MW) |
| 7/31/2014 | 75 | 0.77 | 5.40 | 2.91 | 3.02 | 2.84 | 3.76 | 4.18 |
| 9/15/2014 | 80 | 0.59 | 3.09 | 3.87 |
| 9/16/2014 | 83 | 0.59 | 3.11 | 4.46 |
| 9/17/2014 | 82 | 0.69 | 3.63 | 4.46 |
| Average | 80 | 0.68 | 3.80 | 4.27 |

1. The summer pricing season is July through September for SCE, May through September for SDG&E, and May through October for PG&E. This variable is designed to account for the effect of the strong summer peak TOU prices that are in effect during this period for most customers at each of the three utilities. Since the summer pricing season for PG&E overlaps exactly with the months included in the regression analysis, no Summer variable is included in the regressions for PG&E [↑](#footnote-ref-1)
2. In practice, this term is absorbed by the time effects, but it is useful for representing the model logic. [↑](#footnote-ref-2)
3. Interim report on Sacramento Municipal Utility District’s Smart Pricing Options pilot: <https://www.smartgrid.gov/sites/default/files/MASTER_SMUD%20CBS%20Interim%20Evaluation_Final_SUBMITTED%20TO%20TAG%2020131023.pdf> [↑](#footnote-ref-3)
4. The summer pricing season is June through September for SCE, May through September for SDG&E, and May through October for PG&E. [↑](#footnote-ref-4)
5. In particular, whereas CDH60 and CDH60\_MA24 are used for summer ex post regressions, only CDH60 is used for the ex ante models. See Appendix A for weather variable details. [↑](#footnote-ref-5)
6. Including weekends and holidays would require the addition of variables to capture the fact that load levels and patterns on weekends and holidays can differ greatly from those of non-holiday weekdays. Because event days do not occur on weekends or holidays, the exclusion of these data does not affect the model’s ability to estimate *ex-post* load impacts. [↑](#footnote-ref-6)
7. The summer pricing season is June through September for SCE, May through September for SDG&E, and May through October for PG&E. [↑](#footnote-ref-7)
8. Heating degree hours (HDH) was defined as MAX[0, 50 – TMP], where TMP is the hourly temperature expressed in degrees Fahrenheit. Customer-specific HDH values are calculated using data from the most appropriate weather station. [↑](#footnote-ref-8)
9. SDG&E’s contract with Comverge, Inc. was amended in 2007 to reflect that the agreement is thereafter recognized to be between a subsidiary of Comverge Inc., AER, and SDG&E. In remainder of this document, the company is referred to as Comverge. [↑](#footnote-ref-9)
10. The data modeled for NEM households represented the net of grid energy used minus PV generation returned to the grid. The negative load reduction in this case reflects an increase in the amount of excess PV generation returned to the grid. [↑](#footnote-ref-10)
11. This peak load shift value is the amount of demand shifting that each utility expects to pay incentives for. This means that these are expected output from the model used in the engineering feasibility study for each site. Although we do not know with certainty what conditions the engineers performing the study used to represent peak yearly conditions, the new building simulation models were calibrated such that the 1-in-10 peak day conditions for the hottest month in each LCA represented the maximum cooling load conditions. Because the models creating the conversion factors used the weather from the hottest 1-in-10 peak day to set the maximum cooling load, and consequently the maximum peak load shift, the hottest 1-in-10 peak weather day can also be used as a proxy for weather conditions under which the incentive would be calculated. See Appendix A for additional discussion. [↑](#footnote-ref-11)
12. See Application A.10-07-009 for original proposal - http://www.sdge.com/node/476 [↑](#footnote-ref-12)
13. Matching was performed separately for TOU and TOU-CPP customers. [↑](#footnote-ref-13)
14. In Equation 6, *avg\_pm\_shouldershare* is the average share of daily electricity consumed during the afternoon shoulder period. [↑](#footnote-ref-14)
15. In some cases (such as Information) the best performing model is quite clear. In situations where there is more ambiguity, we chose the model with the lowest APE. Sensitivity analysis of the final results was performed using different models and showed that the matching model used did not lead to any meaningful changes to the results. [↑](#footnote-ref-15)
16. Though negative impacts seem counterintuitive at first sight, load increases in response to the TOU rate may be a rational response since all customers were structural winners. For these customers, the switch to the TOU rate represented a reduction in their average price of electricity based on their historical consumption pattern. [↑](#footnote-ref-16)
17. Mean17 is the average temperature from midnight to 5 PM. [↑](#footnote-ref-17)
18. 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-18)
19. 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-19)
20. See *Statewide Demand Response Ex Ante Weather Conditions*. Nexant, Inc. January 30, 2015. [↑](#footnote-ref-20)