**Executive Summary of the**

**2013 SDG&E Measurement and Evaluation**

**Load Impact Reports**

**April 1st, 2014**

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# SDG&E’s 2013 Load Impact Executive Summary

In Decision (D.) 08-04-050 the Commission required San Diego Gas & Electric Company (SDG&E) to perform annual studies of its demand response (DR) activities using the load impact protocols and to file the entire load impact reports by April 1st each year. The load impact protocols require the preparation of numerous tables and as a result the load impact reports were too large to be filed in hard copy. The electric investor-owned utilities filed a petition to modify the D.08-41-050 on April 6th 2009 to request the requirement to file the load impact reports in their entirety be removed and replaced with a requirement to provide the reports to the energy division of the CPUC. On April 8th 2010 D.10-04-006 granted the utilities permission not to file the entire load impact reports, but 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, Opt-in Peak Time Rebate Program (PTR) and Non-Alert Peak Time Rebate Program (PTR), small commercial technology deployment program (SCTD), and the Permanent Load Shifting program (PLS). 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 2013 through 2024) 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 2013 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 twenty-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).

## 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.*, year, month, day-of-week, and hour, plus various hour/day-type interactions);
* *Weather*, including hour-specific weather coefficients;
* *Event variables*. Indicator variables are included to account for each hour of each event day, which allows us to estimate load impacts for all hours across each event day, for each customer.

The models use the level of hourly demand (kW) as the dependent variable and a separate equation is estimated for each customer that is nominated and called for at least one event. 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 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 because aggregator events may be called only on weekdays.

### Regression Model

The model shown below characterizes the nature of the regressions equations that were separately estimated for each customer. The 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 | The demand in hour t 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* |
| AGGt | 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 day *t*’s load in hours 1 through 10 |
| OtherEvtt | Equals one in the event hours of other demand response programs in which the customer is enrolled |
| MONt | An indicator variable for Monday |
| FRIt | An indicator variable for Friday |
| SUMMERt | An indicator variable for the summer pricing season[[1]](#footnote-1) |
| DTYPEi,t | A series of indicator variables for each day of the week |
| MONTHi,t | A series of indicator variables for each month |
| et | The error term. |

The OtherEvt variables help the model explain load changes that occur on event days in cases in which aggregator 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 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 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

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

The 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 each of the respective typical events. The average event-hour DA load impact was 10.8 MW, while DO load impacts averaged 6 MW for the 1-4 Hour product, and 4.5 MW for the 2-6 Hour product. Average percentage load impacts were 25 percent for the DA product, and 16 to 19 percent for the two DO product types.

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



## CBP Ex-Ante Evaluation Methodology

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 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 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 during the 2012 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 2011, 2012 and 2013.

*Simulate reference loads:* In order to develop reference loads, we first re-estimated regression equations as described below, 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 1-in-2 weather year).

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 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 1-in-2 and 1-in-10 weather conditions.

Once these models were estimated, 24-hour load profiles were simulated 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 1-in-2 and 1-in-10 weather years, developed following PY2009, are the same as those used to develop ex-ante load forecasts in previous studies.

*Calculate forecast percentage load impacts:* The percentage load impacts were based on the ex-post load impacts for each event during the 2011, 2012, and 2013 program years. Specifically, we examined only customers enrolled and nominated in PY2013, but included available data from the 2011 and 2012 program years for customers that were also enrolled in those years. This method allowed 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 collect the hourly ex-post load impact estimates and observed loads for every event available from PY2011, PY2012, and PY2013. For each service account, we calculate the average and standard deviation of the load impacts across the available event days for four hour types: event hours, hours adjacent to events, hours prior to, and hours following the adjacent hours (i.e., morning and late evening). These values are applied to the simulated reference loads to develop each customer’s hourly load impact forecast values.

For any given sub-group of customers, 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 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 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.

*Apply forecast enrollments to produce program-level load impacts:* The enrollments are used to scale up the 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 nominations and load impacts for CBP DA and DO will remain constant over the forecast period, at levels as of the end of the summer of 2013. Forecast nominations are 145 customer accounts for DA and 275 for DO. The table 2-3 compares DA and DO load impacts for an August peak day in 1-in-2 and 1-in-10 weather years. Average event-hour load impacts are 9.7 MW for DA and 10.5 MW for DO in 1-in-2 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 (2014 – 2024) – *SDG&E CBP DA and DO*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Day-Ahead** | | **Day-Of** | |
| **Year** | **1-in-2** | **1-in-10** | **1-in-2** | **1-in-10** |
| 2014 - 2024 | 9.5 | 9.5 | 10.2 | 10.3 |

## 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.

### Previous and current ex-post, and forecast for 2014

The table 2-4 summarizes the number of nominated customer accounts and average event-hour reference loads and estimated ex-post load impacts for the average of the typical CBP events (i.e., events in which all aggregators were called) in the current and two previous program years, by notice type. Also shown is the ex-ante forecast for 2014.

The number of customers nominated in CBP DA has increased over the past three years, particularly in 2013. After holding steady for the first two years, customers nominated in CBP DO declined somewhat in 2013. Forecast nominations for 2014 (and 2015) are expected to increase somewhat for both notice types. Despite the increase in the numbers of customers nominated, 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 are down slightly for both DA and DO in 2014 compared to the 2013 ex-post results, reflecting the use of ex-post percentage load impacts for prior years for customers who were nominated in those years.

Table2-4: Ex-Post Load Impacts for PY2011 through 2013, and 2014 *Ex-Ante* –   
*SDG&E CBP*



### Previous versus current ex-ante

The table 2-5 compares the CBP *ex-ante* forecasts for 2015 produced as part of this 2013 evaluation and the previous evaluation. In both cases, the forecast represents the 1-in-2 August peak day. There is no difference between the program- and portfolio-level impacts. Between PY2012 and PY2013 there was an increase in expected DA nominations and a reduction in expected DO nominations. Both forecasts assumed that future customer nominations would match those at the end of the given *ex-post* year. Projected percent load impacts, which are based on current and prior years of *ex-post* results for customers nominated in the current year, are somewhat smaller for DA in the current study than last year’s study, and are somewhat higher for DO. Both differences result from different mixes of customers who were nominated in the years of the two studies.

The projected aggregate load reduction for the CBP DA option increased from 7.7 MW to 9.5 MW between the two studies. This change is largely explained by two factors. One is that the number of customers nominated in 2013 exceeded the forecast. More important, however, is the return to higher performance of two large customer accounts that comprise much of the aggregate load impact, as described in a footnote above. The projected aggregate load reduction for the CBP DO option is nearly identical (10.4 MW versus 10.2 MW) between the forecast years. In this case, the number of customers nominated in 2013 was below the previous forecast, but this was offset by an increase in the ex-post percentage load reductions in 2013.

Table 2-5: Ex-Ante Load Impacts for 2015 from PY 2012 and PY 2013 Studies, *SDG&E*



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

The table 2-6 compares current *ex-post* nominations and load impacts to values for 2013 from the PY2012 *ex-ante* forecast. Current-year nominations were higher than expected for CBP DA and lower than expected for CBP DO, compared to the forecast for 2013 in the PY2012 forecast. Average customer size, as reflected in the reference loads, is similar in the forecast and observed cases for both notice types.

For DA, the aggregate estimated load impact (10.8 MW) was higher than the forecast value (7.7 MW), reflecting a somewhat lower percent load impact, but a larger number of customers than in the forecast. For DO, the aggregate load impact of 10.5 is essentially same as the forecast value, but was produced by a smaller number of customers with a somewhat higher percentage load impact than forecast.

Table 2-6: Comparison of Current *Ex-Post* and Previous *Ex-Ante* Load Impacts, SD*G&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 event day higher 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 2013 using a combination of customer specific regressions and differences-in-differences.

The subsections that follow describe the work to select a control group for the weather-sensitive industries, differences-in-differences estimation, and to model load for non-weather sensitive industries using individual regressions.

### Control group selection

Propensity score matching was used to select valid control groups for each utility and relevant customer segment. The three weather-sensitive industries for which a control group was selected are Institutional/Government, Offices, Hotels, Finance, Services and Retail Stores. This method is a standard approach for identifying statistical look-alikes from a pool of control group candidates and it explicitly addresses self-selection onto CPP tariffs based on observable differences between CPP participants and non-participants. The control group was selected from customers who were not on CPP rates but were on the otherwise applicable TOU tariff. With propensity score matching, customer characteristics are weighted based on the degree to which they predict program participation and are used to produce a propensity score. For each CPP customer, the control group candidate with the closest propensity score was selected.

### Difference-in-difference Estimation

Using the matched control groups, 2013 ex-post CPP load impacts were estimated for the three weather-sensitive industry segments 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. We elected to use a treatment model rather than a price elasticity model for two reasons. First, for any hour there are only have two price points, or at most three, which is insufficient for fitting price elasticity curves.[[2]](#footnote-2) 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[[3]](#footnote-3) |
| *c* | The difference between event and non-event days common to both CPP participants and control group members[[4]](#footnote-4) |
| *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 industrial customers, which are generally less weather sensitive than commercial buildings. As a result, their behavior during cooler non-event days is similar to load patterns absent dispatch on hotter days.

For each customer, we:

* Analyzed hot weekdays from multiple years. Up to four years of data were included per customers; less data was available for newer accounts. To the extent possible, the regressions for each customer avoided cooler days, which typically do not provide much information about behavior under event conditions.
* Estimated 10 different regression models and used them 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 four CPP events in 2013. The first event occurred on August 29 and the last was held on September 6. On average, there were 1,063 accounts enrolled on SDG&E’s tariff in 2013. There was some variation in enrollment during the course of the summer largely due to typical customer churn, with the highest enrollment at 1,064 participants and the lowest enrollment at 1,060.

Table 3-1 shows the ex-post load impact estimates for each event day and for the average event in 2013. The participant-weighted average temperature during the event period ranged from a low of 84.4°F to a high of 86.3°F. Percent impacts range from 6.0% to 7.4%, average impacts range from 16.2 kW to 20.5 kW and aggregate impacts range from 17.2 MW to 21.8 MW. On the average event day, the average participant reduced peak period load by 6.9%, or 18.4 kW. In aggregate, SDG&E’s CPP customers reduced load by 19.6 MW on average across the four events in 2013.

Table 3-1: Default CPP Ex-post Load Impact Estimates by Event Day  
SDG&E 2013 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. Temp.** | **Daily Maximum Temp.** |
| (kW) | (kW) | (kW) | (MW) | (%) | (°F) | (°F) |
| 8/29/2013 | Thur. | 1,064 | 267.4 | 248.7 | 18.7 | 19.9 | 7.0% | 84.9 | 90.3 |
| 9/4/2013 | Wed. | 1,064 | 276.6 | 256.1 | 20.5 | 21.8 | 7.4% | 84.9 | 90.8 |
| 9/5/2013 | Thur. | 1,064 | 270.7 | 254.5 | 16.2 | 17.2 | 6.0% | 84.4 | 88.8 |
| 9/6/2013 | Fri. | 1,060 | 269.8 | 251.5 | 18.3 | 19.4 | 6.8% | 86.3 | 93.2 |
| **Avg. Event** | | **1,063** | **267.4** | **249.0** | **18.4** | **19.6** | **6.9%** | **85.1** | **89.9** |

## CPP-D Ex-Ante Load Impacts Methodology

Ex-ante impact are designed to reflect demand reduction capability under a standard set peak hours, 1-6 PM for summer, and 1-in-2 and 1-in-10 weather conditions.

The process to estimate ex-ante load impacts begins with modeling reference load for 1-in-2 and 1-in-10 weather conditions. Reference load is estimated separately for the large and 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. For the medium C&I customer class, hourly load for a representative sample of medium C&I customers is modeled by industry group and LCA as a function of temperature and month. In both cases, separate hourly models are estimated for the winter and summer season. Once these models are estimated, we can predict reference load for each month of the year under both 1-in-2 and 1-in-10 weather conditions.

The next step in ex-ante estimation is modeling the relationship of ex-post load impacts to temperature conditions. Load impacts from 2012 and 2013 are modeled as a function of temperature, in the case of large C&I, for each LCA and in the case of medium C&I, by industry. Given that the large C&I default CPP population has been subject to CPP for so many years, projecting ex-post load impacts into the future is fairly simple since the load impacts by LCA are representative of the large C&I default CPP population in each LCA. This, however, is not the case for medium C&I. The industry distribution of medium C&I customers across LCAs is different from that of large C&I CPP customers, necessitating estimating the relationship of load impacts to temperature by industry so that the estimates can be properly weighted by industry to accurately represent the industry mix in each LCA.

## CPP-D Ex-Ante Load Impacts Estimates

The main purpose of ex-ante load impact estimates is to reflect the load reduction capability of a demand response resource under a standard set of conditions that align with system planning. The ex-ante impact estimates for SDG&E are based on ex-post load impacts of CPP events that occurred in 2012 and 2013. In total, load impact estimates for up to nine events were used as input to the ex-ante model. 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.

### Large C&I Ex-Ante Impacts

Overall, 1,063 large customers were enrolled in default CPP in 2013. [[5]](#footnote-5) Table 3-2 shows SDG&E’s enrollment projections for large customers through 2024. The forecasted year-to-year change in enrollment is minimal and simply reflects the expected growth of SDG&E’s large customer population.

Table 3-2: 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.** |
| 2013 | 1,063 | 1,063 | 1,063 | 1,063 | 1,063 | 1,063 | 1,063 | 1,063 | 1,063 | 1,063 | 1,063 | 1,063 |
| 2014 | 1,146 | 1,146 | 1,146 | 1,146 | 1,146 | 1,146 | 1,146 | 1,146 | 1,146 | 1,146 | 1,146 | 1,146 |
| 2015 | 1,148 | 1,151 | 1,153 | 1,155 | 1,158 | 1,160 | 1,162 | 1,164 | 1,167 | 1,169 | 1,171 | 1,174 |
| 2016 | 1,176 | 1,179 | 1,181 | 1,183 | 1,186 | 1,188 | 1,190 | 1,193 | 1,195 | 1,197 | 1,200 | 1,202 |
| 2017 | 1,203 | 1,205 | 1,206 | 1,207 | 1,208 | 1,210 | 1,211 | 1,212 | 1,213 | 1,214 | 1,216 | 1,217 |
| 2018 | 1,218 | 1,219 | 1,220 | 1,222 | 1,223 | 1,224 | 1,225 | 1,227 | 1,228 | 1,229 | 1,230 | 1,231 |
| 2019 | 1,233 | 1,234 | 1,235 | 1,236 | 1,238 | 1,239 | 1,240 | 1,241 | 1,243 | 1,244 | 1,245 | 1,246 |
| 2020 | 1,248 | 1,249 | 1,250 | 1,251 | 1,253 | 1,254 | 1,255 | 1,256 | 1,258 | 1,259 | 1,260 | 1,261 |
| 2021 | 1,263 | 1,264 | 1,265 | 1,266 | 1,268 | 1,269 | 1,270 | 1,272 | 1,273 | 1,274 | 1,275 | 1,277 |
| 2022 | 1,278 | 1,279 | 1,280 | 1,282 | 1,283 | 1,284 | 1,286 | 1,287 | 1,288 | 1,289 | 1,291 | 1,292 |
| 2023 | 1,293 | 1,295 | 1,296 | 1,297 | 1,298 | 1,300 | 1,301 | 1,302 | 1,304 | 1,305 | 1,306 | 1,308 |
| 2024 | 1,309 | 1,310 | 1,312 | 1,313 | 1,314 | 1,315 | 1,317 | 1,318 | 1,319 | 1,321 | 1,322 | 1,323 |

Table 3-3 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 weather year scenarios. The table shows the average load reduction across the 11 AM to 6 PM event period for an August monthly system peak day. The results do not reflect adjustments for dual enrollment on other DR programs.

The differences in demand reductions from year to year are minimal and are the direct result of expected growth of SDG&E’s large customer population. The aggregate 1-in-2 weather year demand reductions forecasted for August 2014, 21.1 MW, grows to 24.3 MW by 2024 due to SDG&E’s expected large C&I customer growth. The percent demand reduction does not change across forecast years because the industry mix is expected to remain stable. The aggregate load impact does vary by weather year, however, because it reflects higher reference loads under 1-in-10 and 1-in-2 weather year conditions in addition to moderately higher load impacts under hotter weather. For example, under 1-in-2 weather conditions the 2014 ex-ante estimate is for 18.5 MW but under 1-in-1o weather the forecast is for 21.1 MW.

The portfolio-adjusted load impacts exclude customers dually-enrolled in BIP or aggregator programs, which are among the most responsive participants. Under 1-in-10 weather conditions the 2014 ex-ante estimate is 17.5 MW and under 1-in-2 weather conditions it is 15.3.

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

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

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Weather Year | Year | Enrolled Accounts | Avg. Reference Load | Avg. Estimated Load w/ DR | Avg. Load Impact | % Load Reduction | Weighted Temp. |
| (MW) | (MW) | (MW) | (%) | (°F) |
| 1-in-10 August System Peak Day | 2013 | 1,063 | 291.6 | 272.0 | 19.6 | 6.7% | 84.4 |
| 2014 | 1,146 | 314.3 | 293.2 | 21.1 | 6.7% | 84.4 |
| 2015 | 1,164 | 319.4 | 298.0 | 21.4 | 6.7% | 84.4 |
| 2016 | 1,193 | 327.1 | 305.2 | 22.0 | 6.7% | 84.4 |
| 2017 | 1,212 | 332.4 | 310.1 | 22.3 | 6.7% | 84.4 |
| 2018 | 1,227 | 336.4 | 313.8 | 22.6 | 6.7% | 84.4 |
| 2019 | 1,241 | 340.5 | 317.6 | 22.9 | 6.7% | 84.4 |
| 2020 | 1,256 | 344.6 | 321.5 | 23.1 | 6.7% | 84.4 |
| 2021 | 1,272 | 348.7 | 325.3 | 23.4 | 6.7% | 84.4 |
| 2022 | 1,287 | 353.0 | 329.3 | 23.7 | 6.7% | 84.4 |
| 2023 | 1,302 | 357.2 | 333.2 | 24.0 | 6.7% | 84.4 |
| 2024 | 1,318 | 361.5 | 337.3 | 24.3 | 6.7% | 84.4 |
| 1-in-2 August System Peak Day | 2013 | 1,063 | 277.5 | 260.4 | 17.1 | 6.2% | 82.0 |
| 2014 | 1,146 | 299.2 | 280.8 | 18.5 | 6.2% | 82.0 |
| 2015 | 1,164 | 304.0 | 285.3 | 18.8 | 6.2% | 82.0 |
| 2016 | 1,193 | 311.4 | 292.2 | 19.2 | 6.2% | 82.0 |
| 2017 | 1,212 | 316.4 | 296.9 | 19.5 | 6.2% | 82.0 |
| 2018 | 1,227 | 320.2 | 300.5 | 19.8 | 6.2% | 82.0 |
| 2019 | 1,241 | 324.1 | 304.1 | 20.0 | 6.2% | 82.0 |
| 2020 | 1,256 | 328.0 | 307.8 | 20.2 | 6.2% | 82.0 |
| 2021 | 1,272 | 332.0 | 311.5 | 20.5 | 6.2% | 82.0 |
| 2022 | 1,287 | 336.0 | 315.3 | 20.7 | 6.2% | 82.0 |
| 2023 | 1,302 | 340.0 | 319.1 | 21.0 | 6.2% | 82.0 |
| 2024 | 1,318 | 344.1 | 322.9 | 21.2 | 6.2% | 82.0 |

#### Comparison of Ex-Post to Ex-Ante Estimates for Large C&I

Table 3-4 compares the ex-ante estimates produced for the 2012 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 3-4 are in the percentage load impact estimates and in the forecasted enrollments. The net effect is that this year’s forecast for 2014 is 18.5 MW, which is 9% higher than last year’s forecast of 16.9 due primarily to an increased enrollment forecast and higher percentage load impact estimates from this evaluation.

Table 3-4: Comparison of Ex-ante Estimates to Prior Year Estimates

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Weather Year | Year | 2012 Reference Load | 2013 Reference Load | 2012 Percent Load Impact | 2013 Percent Load Impact | 2012 Accounts | 2013 Accounts | 2012 Load Impact (MW) | 2013 Load Impact (MW) |
| 1-in-10 | 2014 | 269.4 | 274.3 | 5.9% | 6.7% | 1,097 | 1,146 | 17.4 | 21.1 |
| 1-in-10 | 2015 | 269.4 | 274.3 | 5.9% | 6.7% | 1,114 | 1,164 | 17.7 | 21.4 |
| 1-in-10 | 2016 | 269.4 | 274.3 | 5.9% | 6.7% | 1,128 | 1,193 | 17.9 | 22.0 |
| 1-in-10 | 2017 | 269.4 | 274.3 | 5.9% | 6.7% | 1,144 | 1,212 | 18.1 | 22.3 |
| 1-in-10 | 2018 | 269.4 | 274.3 | 5.9% | 6.7% | 1,159 | 1,227 | 18.4 | 22.6 |
| 1-in-10 | 2019 | 269.4 | 274.3 | 5.9% | 6.7% | 1,175 | 1,241 | 18.6 | 22.9 |
| 1-in-10 | 2020 | 269.4 | 274.3 | 5.9% | 6.7% | 1,192 | 1,256 | 18.9 | 23.1 |
| 1-in-10 | 2021 | 269.4 | 274.3 | 5.9% | 6.7% | 1,208 | 1,272 | 19.2 | 23.4 |
| 1-in-10 | 2022 | 269.4 | 274.3 | 5.9% | 6.7% | 1,225 | 1,287 | 19.4 | 23.7 |
| 1-in-10 | 2023 | 269.4 | 274.3 | 5.9% | 6.7% | 1,242 | 1,302 | 19.7 | 24.0 |
| 1-in-2 | 2014 | 260.5 | 261.1 | 5.9% | 6.2% | 1,097 | 1,146 | 16.9 | 18.5 |
| 1-in-2 | 2015 | 260.5 | 261.1 | 5.9% | 6.2% | 1,114 | 1,164 | 17.2 | 18.8 |
| 1-in-2 | 2016 | 260.5 | 261.1 | 5.9% | 6.2% | 1,128 | 1,193 | 17.4 | 19.2 |
| 1-in-2 | 2017 | 260.5 | 261.1 | 5.9% | 6.2% | 1,144 | 1,212 | 17.6 | 19.5 |
| 1-in-2 | 2018 | 260.5 | 261.1 | 5.9% | 6.2% | 1,159 | 1,227 | 17.9 | 19.8 |
| 1-in-2 | 2019 | 260.5 | 261.1 | 5.9% | 6.2% | 1,175 | 1,241 | 18.1 | 20.0 |
| 1-in-2 | 2020 | 260.5 | 261.1 | 5.9% | 6.2% | 1,192 | 1,256 | 18.4 | 20.2 |
| 1-in-2 | 2021 | 260.5 | 261.1 | 5.9% | 6.2% | 1,208 | 1,272 | 18.6 | 20.5 |
| 1-in-2 | 2022 | 260.5 | 261.1 | 5.9% | 6.2% | 1,225 | 1,287 | 18.9 | 20.7 |
| 1-in-2 | 2023 | 260.5 | 261.1 | 5.9% | 6.2% | 1,242 | 1,302 | 19.1 | 21.0 |

### Medium C&I Ex-Ante Impacts

SDG&E defaulted roughly 600 medium C&I customer accounts onto CPP between 2008 and 2012. Approximately 400 of those defaulted medium C&I customers remained on the rate.

Although SDG&E has more information about medium C&I customer price responsiveness for default CPP, overall, there remains a high degree of uncertainty for both enrollment and demand reductions. The medium C&IO customers that were defaulted early are not representative of the general medium C&I population. Medium C&I customers defaulted onto CPP were among the largest medium sized customers and included a disproportionate number of schools. To obtain a larger and more diverse sample of customers for the medium customer price-responsiveness analysis.

The medium customer ex-ante impacts include an additional adjustment. The impacts were adjusted down to reflect expected lower awareness rates among the medium C&I population relative to large C&I customers. While large customers have an assigned account representative, many medium customers do not. As a result, some customers may not be aware they were defaulted onto CPP or understand the rate. The ex-ante impacts assume that awareness is low (relative to large customers) immediately after the default, 70%, and gradually increases to 90%. Depending on the year, the impacts are 70% to 90% of those observed among default CPP participants that are closest to medium customers.

Table 3-6 shows SDG&E's enrollment projections for medium C&I customers through 2024. All SDG&E’s medium C&I customers are expected to be defaulted onto CPP in 2015. SDG&E forecasts retention rates to vary by industry in manner similar to how they vary for large C&I customers. Notice that enrollment decreases immediately after the initial default year and increases thereafter. This pattern reflects the fact that some customers who try out default CPP during the initial bill protection period opt-out once they have experienced the rate. Enrollment growth from 2016–2024 reflects the expected growth of SDG&E’s medium customer population.

Table 3-6: SDG&E Enrollment Projections for Medium C&I CPP Customers

CPP Customers by Forecast Year and Month

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | **Jan.** | **Feb.** | **Mar.** | **Apr.** | **May** | **Jun.** | **Jul.** | **Aug.** | **Sep.** | **Oct.** | **Nov.** | **Dec.** |
| 2013 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2014 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2015 | 0 | 0 | 0 | 0 | 8,974 | 8,991 | 9,008 | 9,025 | 9,042 | 9,060 | 9,077 | 9,094 |
| 2016 | 7,289 | 7,303 | 7,317 | 7,331 | 7,345 | 7,359 | 7,373 | 7,387 | 7,401 | 7,415 | 7,429 | 7,443 |
| 2017 | 6,566 | 6,577 | 6,588 | 6,598 | 6,609 | 6,619 | 6,630 | 6,640 | 6,651 | 6,662 | 6,672 | 6,683 |
| 2018 | 6,691 | 6,699 | 6,707 | 6,715 | 6,723 | 6,731 | 6,739 | 6,747 | 6,756 | 6,764 | 6,772 | 6,780 |
| 2019 | 6,789 | 6,799 | 6,808 | 6,818 | 6,827 | 6,837 | 6,847 | 6,856 | 6,866 | 6,875 | 6,885 | 6,895 |
| 2020 | 6,904 | 6,914 | 6,924 | 6,933 | 6,943 | 6,953 | 6,962 | 6,972 | 6,982 | 6,992 | 7,002 | 7,011 |
| 2021 | 7,021 | 7,031 | 7,041 | 7,051 | 7,061 | 7,070 | 7,080 | 7,090 | 7,100 | 7,110 | 7,120 | 7,130 |
| 2022 | 7,140 | 7,150 | 7,160 | 7,170 | 7,180 | 7,190 | 7,200 | 7,210 | 7,220 | 7,231 | 7,241 | 7,251 |
| 2023 | 7,261 | 7,271 | 7,281 | 7,291 | 7,302 | 7,312 | 7,322 | 7,332 | 7,343 | 7,353 | 7,363 | 7,374 |
| 2024 | 7,384 | 7,394 | 7,405 | 7,415 | 7,425 | 7,436 | 7,446 | 7,457 | 7,467 | 7,477 | 7,488 | 7,498 |

Table 3-7 summarizes the aggregate load impact estimates for medium customers on SDG&E’s CPP tariff for each forecast year under both 1-in-2 and 1-in-10 weather year scenarios. The table shows the average load reduction across the 11 AM to 6 PM event period for an August monthly system peak day.

Table 3-7: Default CPP Ex-ante Load Impact Estimates by Weather Scenario for Medium C&I  
SDG&E August System Peak Day (11 AM - 6 PM)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Weather Year | Year | Enrolled Accounts | Avg. Reference Load | Avg. Estimated Load w/ DR | Avg. Load Impact | % Load Reduction | Weighted Temp. |
| (11 AM - 6 PM MW) | (11 AM - 6 PM MW) | (11 AM - 6 PM MW) | (%) | (°F) |
| 1-in-10 August System Peak Day | 2013 | 0 | - | - | - | - | - |
| 2014 | 0 | - | - | - | - | - |
| 2015 | 9,025 | 448.6 | 428.4 | 20.1 | 4.5% | 84.3 |
| 2016 | 7,387 | 365.0 | 345.6 | 19.3 | 5.3% | 84.3 |
| 2017 | 6,640 | 327.2 | 307.5 | 19.7 | 6.0% | 84.3 |
| 2018 | 6,747 | 332.5 | 312.5 | 20.0 | 6.0% | 84.3 |
| 2019 | 6,856 | 337.8 | 317.5 | 20.3 | 6.0% | 84.3 |
| 2020 | 6,972 | 343.5 | 323.0 | 20.6 | 6.0% | 84.3 |
| 2021 | 7,090 | 349.4 | 328.5 | 20.9 | 6.0% | 84.3 |
| 2022 | 7,210 | 355.3 | 334.1 | 21.2 | 6.0% | 84.3 |
| 2023 | 7,332 | 361.3 | 339.8 | 21.5 | 5.9% | 84.3 |
| 2024 | 7,457 | 367.4 | 345.6 | 21.8 | 5.9% | 84.3 |
| 1-in-2 August System Peak Day | 2013 | 0 | - | - | - | - | - |
| 2014 | 0 | - | - | - | - | - |
| 2015 | 9,025 | 428.7 | 410.9 | 17.8 | 4.2% | 81.9 |
| 2016 | 7,387 | 348.9 | 331.9 | 17.0 | 4.9% | 81.9 |
| 2017 | 6,640 | 312.9 | 295.5 | 17.3 | 5.5% | 81.9 |
| 2018 | 6,747 | 317.9 | 300.3 | 17.6 | 5.5% | 81.9 |
| 2019 | 6,856 | 323.0 | 305.2 | 17.8 | 5.5% | 81.9 |
| 2020 | 6,972 | 328.5 | 310.4 | 18.1 | 5.5% | 81.9 |
| 2021 | 7,090 | 334.1 | 315.7 | 18.4 | 5.5% | 81.9 |
| 2022 | 7,210 | 339.7 | 321.1 | 18.6 | 5.5% | 81.9 |
| 2023 | 7,332 | 345.5 | 326.5 | 18.9 | 5.5% | 81.9 |
| 2024 | 7,457 | 351.3 | 332.1 | 19.2 | 5.5% | 81.9 |

There is a noticeable drop in enrollment between 2015 and 2016, from 9,025 to 7,387 customers, which reflects some customers opting out after testing default CPP during the bill protection period. The drop in enrollment is not accompanied by a corresponding decrease in forecasted impacts. In fact, the demand reductions under 1-in-2 weather conditions for 2016, 17.0 MW, are very similar to the 2015 forecast, 17.8 MW. The estimated impacts do not decrease substantially for a simple reason. Customers that were not aware or did not fully understand the CPP rates are expected to opt-out. Almost by definition, customers that are not aware or understand the rate do not reduce demand. In other words, while enrollments decrease, the decrease is among customers that are not price responsive. The more price-responsive customers are expected to remain on the rate and have a higher awareness of the CPP rate. The forecasted demand reduction capability also increases in 2017, since customers who on the rate then are assumed to have higher awareness rate. This pattern is similar to what has happened with large customers defaulted onto CPP. Overall enrollments have dropped, as customers who initially tried it opted out, but aggregate reductions have not decreased much and in some cases have increased.

#### Comparison of Ex-Post to Ex-Ante Estimates for Medium C&I

Table 3-8 below presents information to show the drivers of the change in aggregate load impacts between the 2012 load impact evaluation and the 2013 load impact evaluation. The net effect of higher percentage load impacts, slightly lower reference load and slightly lower forecasted enrollment is 6% lower load impacts in 2016 under 1-in-2 weather conditions – 17.0 MW as estimated in this evaluation compared to 18.1 MW estimated in the 2012 load impact evaluation.

Table 3-8: Comparison of 2012 SDG&E Medium C&I Ex-Ante Load Impacts to 2013 Ex-Ante Load Impacts

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Year** | **Year** | **2012 Reference Load** | **2013 Reference Load** | **2012 Percent Load Impact** | **2013 Percent Load Impact** | **2012 Accounts** | **2013 Accounts** | **2012 Load Impact (MW)** | **2013 Load Impact (MW)** |
| 1-in-10 | 2014 | - | - | - | - | 0 | 0 | - | - |
| 1-in-10 | 2015 | 54.6 | 49.7 | 4.5% | 4.5% | 7,119 | 9,025 | 17.4 | 20.1 |
| 1-in-10 | 2016 | 54.6 | 49.4 | 5.0% | 5.3% | 6,775 | 7,387 | 18.7 | 19.3 |
| 1-in-10 | 2017 | 54.6 | 49.3 | 5.0% | 6.0% | 6,861 | 6,640 | 18.9 | 19.7 |
| 1-in-10 | 2018 | 54.6 | 49.3 | 5.0% | 6.0% | 6,955 | 6,747 | 19.2 | 20.0 |
| 1-in-10 | 2019 | 54.6 | 49.3 | 5.0% | 6.0% | 7,059 | 6,856 | 19.5 | 20.3 |
| 1-in-10 | 2020 | 54.6 | 49.3 | 5.0% | 6.0% | 7,157 | 6,972 | 19.7 | 20.6 |
| 1-in-10 | 2021 | 54.6 | 49.3 | 5.0% | 6.0% | 7,255 | 7,090 | 20.0 | 20.9 |
| 1-in-10 | 2022 | 54.6 | 49.3 | 5.0% | 6.0% | 7,355 | 7,210 | 20.3 | 21.2 |
| 1-in-10 | 2023 | 54.6 | 49.3 | 5.0% | 5.9% | 7,456 | 7,332 | 20.5 | 21.5 |
| 1-in-2 | 2014 | - | - | - | - | 0 | 0 | - | - |
| 1-in-2 | 2015 | 52.6 | 47.5 | 4.5% | 4.2% | 7,119 | 9,025 | 16.9 | 17.8 |
| 1-in-2 | 2016 | 52.6 | 47.2 | 5.1% | 4.9% | 6,775 | 7,387 | 18.1 | 17.0 |
| 1-in-2 | 2017 | 52.6 | 47.1 | 5.1% | 5.5% | 6,861 | 6,640 | 18.3 | 17.3 |
| 1-in-2 | 2018 | 52.6 | 47.1 | 5.1% | 5.5% | 6,955 | 6,747 | 18.6 | 17.6 |
| 1-in-2 | 2019 | 52.6 | 47.1 | 5.1% | 5.5% | 7,059 | 6,856 | 18.8 | 17.8 |
| 1-in-2 | 2020 | 52.6 | 47.1 | 5.1% | 5.5% | 7,157 | 6,972 | 19.1 | 18.1 |
| 1-in-2 | 2021 | 52.6 | 47.1 | 5.1% | 5.5% | 7,255 | 7,090 | 19.4 | 18.4 |
| 1-in-2 | 2022 | 52.6 | 47.1 | 5.1% | 5.5% | 7,355 | 7,210 | 19.6 | 18.6 |
| 1-in-2 | 2023 | 52.6 | 47.1 | 5.1% | 5.5% | 7,456 | 7,332 | 19.9 | 18.9 |

# 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. Previously, there was an option B with a 3-hour notification lead time, but it is no longer offered. 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-Ante and Ex-Post Evaluation Methodology

This section discusses the methodology that was used to develop ex-post and ex-ante load impact estimates for BIP. Reference loads are calculated using regression analysis on customer usage on days that are similar to, but not actual, event days. The observed loads are then subtracted from the reference loads to calculate ex-post impacts. In ex-ante analysis, historical weather data is used to determine the weather patterns of a typical BIP event day. The same models used in the ex-post analysis are then run on these typical BIP event days to determine ex-ante reference loads. However, in ex-ante analysis, there are no observed loads to compare to the reference loads. In order to calculate ex-ante impacts, impacts are calculated as a function of:

* Forecasted load in the absence of a DR event (i.e., the reference load);
* The participant’s FSL; and

Over/under performance relative to the FSL.

The reference loads are estimated using the regression models presented in Figure 4-1. Over/under performance, which is a measure of how well customers perform during BIP events relative to the FSL, is determined for each industry using historical event data. The number of events is too small to be used in a regression to predict the load with DR. Instead, impacts were estimated using average historical performance by industry, relative to FSL.

The regression models used to predict reference loads were chosen based on bias and accuracy metrics. The estimated models were based on one year of hourly load data for each customer, using all 24 hours for each individual’s regression. The regression model was used to predict the kW load for each hour separately for each participant. The regression models were based on many variables, consisting largely of shape and trend variables (and interaction terms) designed to track variation in load across days of the week and hours of the day. Weather variables were tested and had significant impacts for certain customers. Binary variables representing season were also included to capture the change in load due to seasonal. The regression model is as follows:

**Figure 4-1: Reference Load Model – SDG&E**



**Table 4-1: Variable Descriptions**

| Variable | Description |
| --- | --- |
|  | hourly BIP customer load at time t |
|  | estimated constant term |
|  | estimated parameters |
|  | cooling degree days (base 60) |
|  | cooling degree hours (base 70) |
|  | total cooling degree hours (base 70) per day |
|  | total number of heating degree hours (base 70) per day |
|  | total cooling degree hours (base 70) per day squared |
|  | total number of heating degree hours (base 70) per day squared |
|  | series of binary variables representing five different day types (Mon, Tues-Thurs, Fri, Sat, Sunday/Holiday) |
|  | series of binary variables for each month |
|  | series of binary variables for each hour, which is interacted with all of the remaining variables because each has an impact that varies by hour |
|  | indicates if the data is from the 2013 dataset that ranges from October 2012 – September 2013 |
| , | binary variable representing each program event day if customer is also enrolled in that program |
|  | binary variables that indicate if month is between May and October for each hour |
|  | binary variables that indicate which TOU rate block is in effect for each hour |
|  | error term |

## BIP Ex-Post Load Impact Estimates

SDG&E called a BIP event on September 5 that lasted from 1 PM to 5 PM for all customers. All customers received 30-minute notice of the event. In total, seven customers participated in the event.

The table 4-2 shows the average load impact per customer for all SDG&E BIP participants. The seven event participants span four industry categories, with three or fewer customers within each category. Impacts for specific industries are excluded from this report to protect the confidentiality of the participants’ identities.

Table 4-2: Aggregate Load Impact for September 5, 2013 SDG&E Event

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Customer Category** | **Number of Customers** | **Hour Ending** | **Ref. Load (MW)** | **Load with DR (MW)** | **Load Reduction (MW)** | **Aggregate FSL (MW)** | **Performance (%)** |
| All Customers | 7 | 14 | 4.1 | 1.8 | 2.4 | 1.5 | 90 |
| 15 | 3.1 | 1.4 | 1.7 | 1.5 | 109 |
| 16 | 2.8 | 1.4 | 1.3 | 1.5 | 107 |
| 17 | 2.6 | 1.4 | 1.2 | 1.5 | 114 |
| **Avg.** | **3.2** | **1.5** | **1.7** | **1.5** | **102** |

## BIP Ex-Ante Load Impact Estimates

The table 4-3 presents the aggregate on-peak ex-ante load impact estimates for each day type by weather year and forecast year. In accordance with the revised Resource Adequacy hours, the peak period is defined as 1 PM to 6 PM for the typical event day occurring on April through October monthly peak days and 4 PM to 9 PM for the November through March monthly peak days. Aggregate impacts fluctuate throughout the year as a result of the change in peak period timing. Aggregate load impacts for the 1-in-10 weather year vary from 0.1 MW to 0.4 MW in November through March, and 0.4 MW to 2.0 MW in April through October.

Table 4-3: SDG&E BIP Aggregate On-peak Load Impacts (MW)  
for each Day Type by Weather Year and Forecast Year

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Weather Year | Day Type | Peak Period | 2014 | 2015 | 2016-2024 |
| 1-in-2 | Typical Event Day | 1-6 PM | 1.8 | 1.8 | 1.8 |
| January Peak | 4-9 PM | 0.1 | 0.1 | 0.1 |
| February Peak | 4-9 PM | 0.2 | 0.2 | 0.2 |
| March Peak | 4-9 PM | 0.3 | 0.3 | 0.3 |
| April Peak | 1-6 PM | 0.9 | 0.9 | 0.9 |
| May Peak | 1-6 PM | 1.1 | 1.1 | 1.1 |
| June Peak | 1-6 PM | 1.1 | 1.1 | 1.1 |
| July Peak | 1-6 PM | 1.0 | 1.0 | 1.0 |
| August Peak | 1-6 PM | 1.8 | 1.8 | 1.8 |
| September Peak | 1-6 PM | 1.3 | 1.3 | 1.3 |
| October Peak | 1-6 PM | 0.6 | 0.6 | 0.6 |
| November Peak | 4-9 PM | 0.4 | 0.4 | 0.4 |
| December Peak | 4-9 PM | 0.1 | 0.1 | 0.1 |
| 1-in-10 | Typical Event Day | 1-6 PM | 1.9 | 1.9 | 1.9 |
| January Peak | 4-9 PM | 0.1 | 0.1 | 0.1 |
| February Peak | 4-9 PM | 0.2 | 0.2 | 0.2 |
| March Peak | 4-9 PM | 0.3 | 0.3 | 0.3 |
| April Peak | 1-6 PM | 1.2 | 1.2 | 1.2 |
| May Peak | 1-6 PM | 1.1 | 1.1 | 1.1 |
| June Peak | 1-6 PM | 1.1 | 1.1 | 1.1 |
| July Peak | 1-6 PM | 1.1 | 1.1 | 1.1 |
| August Peak | 1-6 PM | 2.0 | 2.0 | 2.0 |
| September Peak | 1-6 PM | 1.3 | 1.3 | 1.3 |
| October Peak | 1-6 PM | 0.4 | 0.4 | 0.4 |
| November Peak | 4-9 PM | 0.4 | 0.4 | 0.4 |
| December Peak | 4-9 PM | 0.1 | 0.1 | 0.1 |

## BIP Comparison of Ex-Post to Ex-Ante Estimates

Table 4-4 shows the ex-post and ex-ante results from this load impact evaluation side by side. Aggregate ex-ante results are smaller than those seen ex-post by 42% even though SDG&E’s BIP program is projected to have the same number of customers and higher FSLs in 2014. This remarkable outcome is due to one important factor: weather. The total CDH during the September 5 event was roughly 28% higher than the July monthly peak in 1-in-2 and 1-in-10 weather conditions. This causes a large increase in estimated customer reference loads. If customers are expected to have the same performance on a smaller reference load, they need to reduce their electricity usage by much less, therefore resulting in smaller aggregate load reductions.

Table 4-4: Ex-ante Estimates vs. Ex-post Estimates from the 2013 Evaluation

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Result Type | Weather Year / Date | Number of Customers | FSL (kW) | Reference Load (kW) | Performance (%) | Agg. Load Reduction (MW) | Total CDH |
| Ex-Ante (2014) | 1-in-2, July Monthly Peak | 7 | 224.0 | 364.5 | 97 | 1 | 161 |
| Ex-Ante (2014) | 1-in-10, July Monthly Peak | 7 | 224.0 | 379.8 | 100 | 1 | 182 |
| Ex-Post (2013) | 9/5/2013 | 7 | 218.4 | 450.3 | 102 | 2 | 225 |

Figure 4-2 and Table 4-5 present the differences between ex-ante load impact estimates from the 2013 and 2012 BIP load impact evaluations. Both the 2012 and 2013 load impact evaluations assume no load growth for participating customers in addition to no enrollment growth. But a key difference is in the number of customers – the 2013 load impact evaluation assumes 36% fewer customers than in 2012. The FSL projected for the forecast horizon is also very different in the 2013 load impact evaluation: the 2012 ex-ante FSL for the average customer was 42.9 kW while the 2013 ex-ante FSL is 224 kW. Reference load is also far higher for the average customer while FSL performance has also dramatically increased to 101% in the 2013 evaluation from 34% in the 2012 evaluation. Despite the 36% drop in enrollment, in this 2013 evaluation, aggregate load impacts are forecast to be more than double the magnitude of load impacts forecast in 2012. The increased performance in 2013 is also likely due to SDG&E’s efforts to encourage free-riders to exit the 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 FSL, raising the FSL lowers future capacity payments to customers who did not perform during the event.

Figure 4-2: Ex-ante Aggregate Impacts for a 1-in-2 Weather Year, August Monthly Peak Day by Evaluation Year and Forecast Year



Table 4-5: Ex-ante 1-in-2 Weather Year, August Monthly Peak Day Estimations for Forecast Year 2023 by Evaluation Year

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Evaluation Year | Number of Customers | FSL (kW) | Reference Load  (kW) | Performance (%) | Agg. Load Reduction (MW) |
| 2013 | 7 | 224 | 477.7 | 101 | 1.8 |
| 2012 | 11 | 42.9 | 259.5 | 34 | 0.8 |

# 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 is restricted to non-residential customers and provides day-ahead notice of event days. This program is applicable to customers who are capable of providing at least a 3 MW load reduction based on the customer’s specific baseline. 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 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).

### 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-Post Load Impacts Estimates

The table 5-2 summarizes average hourly reference loads and load impacts at the program level for each of SDG&E’s three DBP events. The last row of the table contains the average outcome across the two day-of notice events. The DO customer averaged a 4.5 MW, or 39.4 percent load impact across its two events. The second event (September 5) had a substantially higher load impact than the first event. The DA customer reduced load by an average of 5.7 MW (14.2 percent) during its sole event.

Table 5-2: Average Hourly Load Impacts by Event, *SDG&E*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Event** | **Date** | **Day of Week** | **Estimated Reference Load (MW)** | **Observed Load (MW)** | **Estimated Load Impact (MW)** | **% LI** |
| 1 (DO) | 8/30/2013 | Friday | 9.9 | 7.0 | 2.9 | 29.4% |
| 2 (DO) | 9/5/2013 | Thursday | 12.7 | 6.7 | 6.0 | 47.1% |
| 3 (DA) | 9/6/2013 | Friday | 40.5 | 34.7 | 5.7 | 14.2% |
| **Average DO Event** | | | **11.3** | **6.9** | **4.5** | **39.4%** |

The table 5-3 compares the bid quantities to the estimated load impacts for each event. The DO customer bid 5 MW for each event and averaged 4.5 MW of response across the two days for an average bid realization rate of 89 percent. The DA customer bid 3.1 MW but reduced load by 5.7 MW, which amounts to a 185 percent bid realization rate.

Table 5-3: Average Hourly Bid Realization Rates by Event*, SDG&E*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Event** | **Date** | **Day of Week** | **Average Bid Quantity (MW)** | **Estimated Load Impact (MW)** | **LI as % of Bid Amount** |
| 1 (DO) | 8/30/2013 | Friday | 5.0 | 2.9 | 58% |
| 2 (DO) | 9/5/2013 | Thursday | 5.0 | 6.0 | 120% |
| 3 (DA) | 9/6/2013 | Friday | 3.1 | 5.7 | 185% |
| **Average DO Event** | | | **5.0** | **4.5** | **89%** |

## DBP Ex-Ante Evaluation Methodology

For SDG&E, we use usage data and load impacts from PY2013 only. 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 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 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 use CDH60 as the weather variables in place of the THI variables used in the ex-post regressions and we remove the lagged weather variables. The primary reason for this is that the historical data used in the ex-ante scenarios do not contain complete data on relative humidity, such that we would need to fill in missing data in order to use THI in our simulations. In addition, 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 three ways: it includes *HDHt* variables, where the summer model does not; the month dummies relate to a different set of months; and the event variables are removed (because no event days occurred during the regression timeframe). The table 5-4 describes the terms included in the equation.



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* |
| *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.

## DBP Ex-Ante Load Impacts Estimates

SDG&E has requested that its DBP be extended through 2014. Tables 5-5 and 5-6 present the DBP-DA and DBP-DO Aggregate Load Impacts forecast from 2013 thru 2024.

|  |
| --- |
| **Tale 5-5: DBP-DA Program Aggregate Load Impacts (MW)** |
| **(Portfolio, Weather 1in2)**   |  |  |  |  |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | **Year** | **JAN** | **FEB** | **MAR** | **APR** | **MAY** | **JUN** | **JUL** | **AUG** | **SEP** | **OCT** | **NOV** | **DEC** | | 2013 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2014 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2015 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2016 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2017 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2018 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2019 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2020 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2021 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2022 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2023 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 | | 2024 | 5.01 | 3.08 | 3.75 | 6.13 | 5.21 | 6.11 | 5.91 | 5.98 | 5.82 | 5.63 | 5.54 | 4.98 |   **Tale 5-6: DBP-DO Program Aggregate Load Impacts (MW)**  **(Portfolio, Weather 1in2)**   |  |  |  |  |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | **Year** | **JAN** | **FEB** | **MAR** | **APR** | **MAY** | **JUN** | **JUL** | **AUG** | **SEP** | **OCT** | **NOV** | **DEC** | | 2013 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2014 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2015 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2016 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2017 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2018 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2019 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2020 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2021 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2022 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2023 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 | | 2024 | 1.14 | 1.42 | 0.84 | 2.76 | 2.06 | 1.80 | 2.75 | 2.80 | 3.82 | 3.05 | 2.75 | 1.24 |  DBP 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, the section below compares three set of estimated load impacts.

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

Table 5-7 only includes results for DBP-DA. Note that this variant of DBP differed somewhat in PY2012 and did not exist prior to that program year. The DBP-DO is not included in the table because it did not exist prior to PY2013.

Table 5-7: Comparison of Average Event-day Ex-post Impacts (in MW)

PY 2012- PY 2013

|  |  |  |  |
| --- | --- | --- | --- |
| **Level** | **Outcome** | **PY2012** | **PY2013** |
|
| **Total** | Reference (MW) | 10 | 40 |
| Load Impact (MW) | 5 | 6 |
| **Per SAID** | Reference (kW) | 10,027 | 5,058 |
| Load Impact (kW) | 5,057 | 719 |
| % Load Impact | 50% | 14.20% |

The total load impact did not change substantially across program years, but the total reference load increased by a factor of four. This reduces the percentage load impact from 50 percent to 14 percent. Note that we do not use PY2012 result in our ex-ante forecast because we do not believe it is sufficiently comparable to PY2013.

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

In this sub-section, we compare the ex-ante forecast prepared following PY 2012 (the “previous study”) to the ex-ante forecast contained in this study (the “current study”). Table 5-8 presents this comparison for the DBP-DA 2014 ex-ante forecasts of the 1-in-2 August peak day. In this case, there is no difference between the program- and portfolio-level impacts. We do not include DBP-DO because the program did not exist prior to PY2013.

Table 5-8: Comparison of Ex-ante Impacts from PY 2012 and PY 2013 Studies

|  |  |  |  |
| --- | --- | --- | --- |
| **Level** | **Outcome** | **Program Level** | |
|  | **Current 2014** |
| **Previous 2014** |
|  |
| **Total** | Reference (MW) | 9.2 | 42 |
| Load Impact (MW) | 4.7 | 6 |
| **Per SAID** | Reference (kW) | 9,225 | 5,252 |
| Load Impact (kW) | 4,670 | 747 |
| % Load Impact | 50.60% | 14.20% |

Both forecasts assumed that future enrollments would match current enrollments. Because seven service accounts were added to the program in PY2013, the resulting ex-ante forecast is quite different.

### Previous ex-ante versus current ex-post

Although there has been an increase in the number of accounts enrolled, there are still less than 15 accounts enrolled in DBP-DO. We found an average DBP-DO load impact of 4.5 MW during PY2013, compared to an average ex-ante load impact of 4.7 MW from the 1-in-2 typical event day forecast following PY2012. Though these values are close to one another, it is difficult to assess the accuracy of the forecast because of the added service accounts.

DBP-DA did not exist in PY2012, so no ex-ante forecast was prepared for that program.

### Current ex-post and ex-ante load impacts

The table 5-9 describes the factors that differ between the ex-post and ex-ante load impacts for SDG&E’s DBP-DA customers. We note that the ex-post and ex-ante load impacts nearly match, so there is essentially no difference to explain. In both cases, we find a percentage load impact of 14.2 percent with only a 0.1 MW difference in the level of load impacts (5.7 MW for the ex-post event and 5.8 MW for the September 2014 1-in-2 peak day).

Table 5-9: DBP-DA Ex-Post versus Ex-Ante Factors

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex-post | Ex-ante | Expected Impact |
| Weather | 84.0 degrees Fahrenheit during HE 14-17 on the sole event day | 84.8 degrees Fahrenheit during HE 14-17 on 1-in-2 Sep. peak day | Little difference in temperature, so a small effect. |
| Event window | HE 14-17 | HE 14-18 in Apr-Oct;  HE 17-21 in Nov-Mar. | Minimal in summer; non-summer load impacts are speculative as we have not observed events in those months. |
| % of resource dispatched | All | All | None |
| Enrollment | Less than 15 service accounts | Less than 15 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 |

The table 5-10 compares ex-post and ex-ante load impacts for SDG&E’s DBP-DO program. The average reference loads and load impacts are calculated across the relevant event hours. The ex-ante load impacts are taken from the 2014 1-in-2 September peak day. Notice that the reference load, load impact, and percentage load impact are somewhat lower in the ex-ante forecast than in the average ex-post event day, though the differences are (arguably) not large.

Tale 5-10: DBP-DO Comparison of Ex-post and Ex-ante Load Impacts

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Date** | **Event Hours** | **Reference**  **(MW)** | **Load Impact**  **(MW)** | **Temp.** | **% LI** |
| 8/30/2013 | HE 13-16 | 9.9 | 2.9 | 87.3 | 29.4% |
| 9/5/2013 | HE 14-17 | 12.7 | 6.0 | 82.0 | 47.1% |
| Avg. Ex-post |  | 11.3 | 4.4 | 84.6 | 39.3% |
| Ex-ante Sep. 1-in-2 | HE 14-18 | 10.1 | 3.8 | 84.6 | 37.9% |

The table 5-11 contains descriptions of the potential sources of differences between the ex-post and ex-ante load impacts for CBP-DO. There are two primary sources. First, the percentage load impacts for the ex-ante scenarios will not exactly match the average ex-post percentage load impact because we need to adapt the varying ex-post event windows to a different ex-ante event window. Therefore, while the ex-ante percentage load impact is based on the ex-post load findings, the values do not exactly match.

The second primary source of differences between the ex-post and ex-ante load impacts is that the customer’s load level can vary dramatically across days. Since we simulate ex-ante references loads based on “typical” usage patterns, the simulated reference load may differ from the observed load (or estimated reference load) for any one historical day.

Table 5-11: DBP-DO Ex-Post versus Ex-Ante Factors

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | Ex-post | Ex-ante | Expected Impact |
| Weather | 84.7 degrees Fahrenheit during HE 14-16 on average event day | 84.3 degrees Fahrenheit during HE 14-16 on 1-in-2 Sep. peak day | Little difference in temperature, so no effect |
| Event window | HE 13-16 and HE 14-17. | HE 14-18 in Apr-Oct;  HE 17-21 in Nov-Mar. | Minimal in summer. There is not a perfect match of percentage load impacts because we need to conform varying ex-post event windows to a different ex-ante window. Non-summer load impacts are speculative as we have not observed events in those months. |
| % of resource dispatched | All | All | None |
| Enrollment | Less than 15 service accounts | Less than 15 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. | Because customer load can vary considerably across days, simulated ex-ante reference loads can differ from ex-post reference loads for specific event days. |

# 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:

* $81 for 30% cycling; or

$135 for 50% cycling.

## Summer Saver Residential Customer Ex-post Methodology

The residential ex-post impact estimates were developed using an experimental treatment and control group that was randomly picked from the Summer Saver population. Nonresidential ex-post impact estimates were developed using a control group selected from non-Summer Saver customers using statistical matching based on usage and load shape factors. Each method is described further below.

### Summer Saver Residential Customer Ex-Post Methodology

The residential customer ex-post methodology involved a relatively large-scale experiment design known as a randomized control trial (RCT). With an RCT experiment, 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 six events during summer 2013, roughly half of the 1,489 customers in the residential sample received an event signal while the remaining customers served as the control group. The group that received the event signal was alternated from event to event. Sample sizes of about 740 customers in each group eliminated the need for more complex regression methods. 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 customers were not notified of Summer Saver events prior to the events’ initiation. Impact estimates for the entire Summer Saver residential sample for each hour of each event were calculated by taking a weighted average of the impact estimates for each cycling option, with weights determined by the number of customers enrolled on each cycling option. Impacts for the average event day were calculated from unadjusted treatment and control group load shapes averaged across the four events that lasted from 1 to 5 PM.

### Summer Saver Nonresidential Customer Ex-Post Methodology

Propensity score matching was used to develop a control group comprised of non-Summer Saver customers with observable characteristics similar to nonresidential Summer Saver customers.

The matched control group method used for this analysis is superior to a within-subjects analysis because there is a large population of non-Summer Saver customers to use as a pool for matching and because it eliminates the problem of model misspecification.[[10]](#footnote-10) Any reference load model based on loads observed at non-event times requires the modeler to make assumptions about the relationships between load, time and temperature. If this assumed function does not reflect the true relationships between load, time and temperature, then the model can produce incorrect results. Accurately estimating such a model is particularly difficult when there are relatively few non-event days with similar characteristics to event days. This is often the case in SDG&E’s service territory where the number of hot days each summer is small and events are called on the hottest days. The matched control group methodology eliminates the need to model such relationships by assuming that customers who behave similarly to nonresidential Summer Saver customers during non-event periods would also behave similarly during event periods. This eliminates the need to specify load as a function of weather.

The control group was selected using a propensity score match to find non-Summer Saver customers who had similar load shapes and characteristics as the nonresidential Summer Saver participants. In this procedure, a probit model was used to estimate a score for each customer based on a set of observable variables such as load shape, percent of usage that occurs on peak and average usage. A probit model is a regression model designed to estimate probabilities – in this case, the probability that a customer would behave like a specific Summer Saver customer. The propensity score can be thought of as a summary variable that includes all the relevant information on the observable variables about a Summer Saver customer’s daily load. Each customer in the treatment population is matched with a customer in the non-Summer Saver population with the closest propensity score.

With the matched control group in hand, ex-post event impacts for each nonresidential 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, exactly like the residential load impacts were calculated. The adjustment is based on the ratio of usage between the treatment and control groups for the hour prior to the event start.

## Summer Saver Ex-Post Load Impact Estimates

This section contains the ex-post load impact estimates for program year 2013. Residential estimates are provided first, followed by nonresidential estimates.

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

Six Summer Saver events were called in 2013 and each one lasted four hours. Four of the six events were from 1 to 5 PM, with the remaining two going from 2 to 6 PM and 3 to 7 PM. For the four events with common hours, the average aggregate demand reduction for residential customers equaled 16.8 MW. The average reduction per household equaled 0.74 kW. Residential impacts ranged from a low of 11.8 MW on August 29 to a high of 20.6 MW on September 6.

Table 6-1: Summer Saver Residential Ex-post Impact Estimates

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Date** | **Event Timing** | **Impact** | | | **Temperature During Event (°F)** |
| **Per CAC Unit (kW)** | **Per Premise (kW)** | **Aggregate (MW)** |
| 8/28/2013 | 3 to 7 PM | 0.48 | 0.52 | 12.0 | 84 |
| 8/29/2013 | 2 to 6 PM | 0.46 | 0.51 | 11.8 | 88 |
| 8/30/2013 | 1 to 5 PM | 0.68 | 0.78 | 17.8 | 91 |
| 9/3/2013 | 1 to 5 PM | 0.58 | 0.65 | 14.8 | 88 |
| 9/5/2013 | 1 to 5 PM | 0.57 | 0.63 | 14.5 | 89 |
| 9/6/2013 | 1 to 5 PM | 0.84 | 0.9 | 20.6 | 92 |
| Average\* | 1 to 5 PM | 0.66 | 0.74 | 16.8 | 90 |
| \*Average for the four event days with common hours from 1 to 5 PM | | | | | |

Table 6-2 shows the estimated load impacts for residential participants on each event day segmented by cycling option. Overall, the average impact for the four event days with a common set of hours (the last four days in the table) differs by roughly 15% across the two cycling options even though the cycling percentage differs by a factor of 2. This is primarily due to the fact that the average reference load for customers on the 50% cycling option is much higher than for those on the 100% cycling option. It can also be noted that the differences between the two cycling options varies significantly across event days, with large differences on some days and virtually none on others. On September 6, the impact for the 100% cycling group is slightly less than for the 50% cycling option, although this difference is definitely not statistically significant. A close look at this particular day shows that the reference load for the 50% cycling group is almost 50% higher than for the 100% cycling group.

Table 6-2: Residential Average (per CAC unit) and Aggregate Load Impacts by Cycling Option

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Event Date | Average Impact per CAC Unit (kW) | | Aggregate Impact (MW) | |
| 100% | 50% | 100% | 50% |
| 8/28/2013 | 0.67 | 0.29 | 8.2 | 3.6 |
| 8/29/2013 | 0.49 | 0.44 | 5.9 | 5.9 |
| 8/30/2013 | 0.81 | 0.56 | 10.6 | 7.0 |
| 9/3/2013 | 0.62 | 0.53 | 8.0 | 6.7 |
| 9/5/2013 | 0.61 | 0.53 | 7.6 | 6.8 |
| 9/6/2013 | 0.83 | 0.85 | 10.3 | 10.3 |
| Average\* | 0.71 | 0.61 | 9.1 | 7.6 |

\*Average for the four event days with common hours from 1 to 5 PM

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

Table 6-3 shows ex-post load impact estimates for nonresidential customers for each 2013 event day and for the average across the four days with common event hours from 1 to 5 PM. Nonresidential customers constitute roughly 17% of total participants and about 30% of enrolled CAC tonnage. Average impacts per customer for the four days with common hours equaled 0.35 kW per CAC unit and 0.86 kW per premise. Aggregate impacts varied from a low of about 2.3 MW on August 28 to a high of roughly 4.4 MW on September 6.

Table 6-3: Nonresidential Ex-post Load Impact Estimates

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Date | **Event Timing** | Impact | | | Temperature During Event (°F) |
| Per CAC Unit (kW) | Per Premise (kW) | Aggregate (MW) |
| 28-Aug-13 | 3 to 7 PM | 0.20 | 0.50 | 2.3 | 82 |
| 29-Aug-13 | 2 to 6 PM | 0.28 | 0.69 | 3.2 | 87 |
| 30-Aug-13 | 1 to 5 PM | 0.34 | 0.83 | 3.9 | 90 |
| 3-Sep-13 | 1 to 5 PM | 0.34 | 0.84 | 3.9 | 85 |
| 5-Sep-13 | 1 to 5 PM | 0.34 | 0.83 | 3.9 | 86 |
| 6-Sep-13 | 1 to 5 PM | 0.38 | 0.94 | 4.4 | 90 |
| Average\* | 1 to 5 PM | 0.35 | 0.86 | 4.0 | 88 |

\*Average for the four event days with common hours from 1 to 5 PM

Table 6-4 shows the average ex-post load impacts for nonresidential participants by cycling strategy. Comparing the load impacts for residential 50% cycling participants in Table 6-2 with those for nonresidential 50% cycling participants in Table 6-3, shows that the nonresidential impacts are about one third less per CAC unit even under the same cycling option. The same comparison based on impact per ton of air conditioning shows that nonresidential impacts per ton are almost 45% lower than residential impacts based on 50% cycling for both customer segments. There are several possible explanations for the lower impacts for nonresidential customers. One is that nonresidential buildings may have excess cooling capacity compared with residential buildings, which would lead to lower duty cycles and lower impacts for the same cycling option. Another possibility is that not all air conditioners on nonresidential buildings are enrolled in the program so that when enrolled units are cycled, other units work harder to make up for the drop in cooling. A third possibility is that there are differential communication success rates for nonresidential control devices compared with residential devices. It is likely that some combination of all three of these factors, or perhaps others, explains this observed difference in load impacts across customers segments.

Table 6-4: Nonresidential Average (per CAC unit) and Aggregate Load Impacts by Cycling Option

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Average Impact per CAC Unit (kW) | | Aggregate Impact (MW) | |
| Event Date | 50% | 30% | 50% | 30% |
| 8/28/2013 | 0.22 | 0.16 | 1.8 | 0.6 |
| 8/29/2013 | 0.32 | 0.19 | 2.6 | 0.7 |
| 8/30/2013 | 0.35 | 0.30 | 2.9 | 1.0 |
| 9/3/2013 | 0.35 | 0.32 | 2.8 | 1.1 |
| 9/5/2013 | 0.39 | 0.24 | 3.1 | 0.8 |
| 9/6/2013 | 0.44 | 0.28 | 3.5 | 0.9 |
| Average\* | 0.38 | 0.28 | 3.1 | 1.0 |

## 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 2013. Only the hours from 2 to 4 PM were used for the analysis because these hours were common across the greatest number of ex-post event days. The average load reduction across these hours was modeled as a function of the average temperature for the first 17-hours (mean17) of each event day. 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 4 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

Tables 6-6 and 6-7 summarize the average and aggregate load impact estimates per CAC unit for residential and nonresidential customers, respectively. For a typical event day with 1-in-2 year weather conditions, the impact per CAC unit is 0.46 kW for residential customers. The 1-in-10 year typical event day estimate is 20% higher at 0.55 kW. The aggregate program load reduction potential for residential customers is 13.0 MW for a typical event day under 1-in-2 year weather conditions and 15.7 MW under 1-in-10 year weather conditions. September ex-ante conditions are much hotter than typical conditions. The residential program is estimated to provide an average impact of 22.6 MW over the 5-hour event window from 1 to 6 PM on a 1-in-10 September peak day and 17.6 MW on the system peak day under 1-in-2 year weather conditions.

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 22% 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 more than 2.5 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.

Due to the smaller number of nonresidential installations in the program, aggregate impacts for the nonresidential segment are much smaller than for residential customers. The nonresidential program is expected to provide the highest impact under 1-in-10 year conditions in September, when its expected impact is 4.8 MW.

Table 6-6: Summer Saver Residential Ex-ante Impact Estimates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Day Type | Per CAC Unit Impact (kW) | | Aggregate Impact (MW) | |
| Weather Year | | Weather Year | |
| 1-in-10 | 1-in-2 | 1-in-10 | 1-in-2 |
| Typical Event Day | 0.55 | 0.46 | 15.7 | 13.0 |
| May Monthly Peak | 0.40 | 0.13 | 11.3 | 3.6 |
| June Monthly Peak | 0.53 | 0.14 | 15.0 | 4.0 |
| July Monthly Peak | 0.54 | 0.47 | 15.4 | 13.2 |
| August Monthly Peak | 0.57 | 0.44 | 16.2 | 12.6 |
| September Monthly Peak | 0.80 | 0.62 | 22.6 | 17.6 |
| October Monthly Peak | 0.42 | 0.31 | 11.9 | 8.8 |

Table 6-7: Summer Saver Nonresidential Ex-ante Impact Estimates

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Day Type | Per CAC Unit Impact (kW) | | Aggregate Impact (MW) | |
| Weather Year | | Weather Year | |
| 1-in-10 | 1-in-2 | 1-in-10 | 1-in-2 |
| Typical Event Day | 0.32 | 0.28 | 3.7 | 3.2 |
| May Monthly Peak | 0.26 | 0.15 | 3.0 | 1.8 |
| June Monthly Peak | 0.30 | 0.16 | 3.5 | 1.8 |
| July Monthly Peak | 0.30 | 0.29 | 3.5 | 3.3 |
| August Monthly Peak | 0.32 | 0.27 | 3.7 | 3.2 |
| September Monthly Peak | 0.41 | 0.35 | 4.8 | 4.0 |
| October Monthly Peak | 0.27 | 0.22 | 3.1 | 2.5 |

## 

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

Ex-post and ex-ante load impacts may differ for a variety of reasons, including differences in weather conditions, the number of customers dispatched, the timing and length of the event window, and other factors. Tables 6-8 and 6-9 and Figure 6-1 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 6-8 pertains to residential customers in the 50% cycling option and Table 6-9 pertains to 100% cycling participants. The figure graphs the average values at the bottom of each table.

The event window and mean17 values vary across ex-post event days but the percent of the resource dispatched (Column D) is constant at 97%. Column E shows the aggregate impacts for the percent of the program dispatched, whereas Column F represents what the load reduction would have been under historical weather conditions and event window timing and length if all customers had been dispatched.

Columns G through J incorporate the influence of ex-ante assumptions about weather and the event window as well as differences in the methodology used to estimate ex-post and ex-ante impacts. Column G uses the ex-ante model to predict what the impacts would have been under ex-post weather conditions and event duration and timing. This reflects the influence of the change in methodology from the RCT-based ex-post estimates to the regression-based ex-ante estimates. For 50% cycling, the regression model over predicts the ex-post values by about 13% (from 6.9 MW to 7.8 MW as seen in columns F and G in Table 6-8). The regression model for 100% cycling under predicts the ex-post values by about 1% (from 8.7 MW to 8.6 MW as seen in columns F and G in Table 6-9). Column H shows the effect of changing from the actual event window to the standardized resource adequacy window (from 1 to 6 PM). This did not change impacts much for either cycling option. The last two columns, I and J, show the impact of changing from ex-post weather conditions to 1-in-2 and 1-in-10 year weather conditions. Shifting from ex-post to ex-ante 1-in-2 year weather for a typical event day decreased aggregate impacts by about 20% for both cycling options and shifting to 1-in-10 year weather conditions decreased the impacts by nearly 5% compared with ex-post conditions. As previously discussed, the ex-ante numbers are lower because mean17 for the typical event day under 1-in-2 and 1-in-10 year weather conditions equals about 77°F and 79°F, respectively. Both of these temperatures are lower than the average mean17 for 2013, which equaled 80.1°F.

**Table 6-8: Differences in Ex-Post and Ex-Ante Load Impacts Due to Key Factors for 50% Cycling Participants – Residential Customers**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2013 Ex-post Aggregate Estimates** | | | | | **Aggregate Estimates Based on Ex-ante Model Standardized Event Window** | | | |
| **Event Window** | **Mean17 (**°F) | **% of Resources Dispatched** | **Aggregate Reduction (MW)** | **Aggregate Reduction if All Participants are Controlled (MW)** | **Historical Window & Weather (MW)** | **Historical Weather & Standardized Event Window (MW)** | **1-in-2 Year Weather, Forecast Enrollment (MW)** | **1-in-10 Year Weather, Forecast Enrollment (MW)** |
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** |
| 28-Aug-13 | 3-7 pm | 78.0 | 97% | 3.6 | 3.8 | 6.3 | 6.8 | 6.3 | 7.5 |
| 29-Aug-13 | 2-6 pm | 78.1 | 97% | 5.9 | 6.1 | 7.1 | 6.9 |
| 30-Aug-13 | 1-5 pm | 83.0 | 97% | 7.0 | 7.2 | 9.3 | 9.2 |
| 3-Sep-13 | 1-5 pm | 79.0 | 97% | 6.7 | 6.9 | 7.4 | 7.3 |
| 5-Sep-13 | 1-5 pm | 80.8 | 97% | 6.8 | 7.0 | 8.2 | 8.2 |
| 6-Sep-13 | 1-5 pm | 81.8 | 97% | 10.3 | 10.6 | 8.7 | 8.6 |
| **Average** | | **80.1** | **97%** | **6.7** | **6.9** | **7.8** | **7.8** |

**Table 6-9: Differences in Ex-Post and Ex-Ante Load Impacts Due to Key Factors for 100% Cycling Participants – Residential Customers**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | | **2013 Ex-post Aggregate Estimates** | | | | | **Aggregate Estimates Based on Ex-ante Model Standardized Event Window** | | | |
| **Event Window** | **Mean17 (**°F) | **% of Resources Dispatched** | **Aggregate Reduction (MW)** | **Aggregate Reduction if All Participants are Controlled (MW)** | **Historical Window & Weather (MW)** | **Historical Weather & Standardized Event Window (MW)** | **1-in-2 Year Weather, Forecast Enrollment (MW)** | **1-in-10 Year Weather, Forecast Enrollment (MW)** |
| **A** | **B** | | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** |
| 28-Aug-13 | 3-7 pm | | 77.3 | 97% | 8.2 | 8.5 | 7.6 | 7.2 | 6.7 | 8.2 |
| 29-Aug-13 | 2-6 pm | | 77.6 | 97% | 5.9 | 6.1 | 7.9 | 7.4 |
| 30-Aug-13 | 1-5 pm | | 82.8 | 97% | 10.6 | 11.0 | 10.4 | 10.4 |
| 3-Sep-13 | 1-5 pm | | 78.5 | 97% | 8.0 | 8.3 | 7.9 | 7.9 |
| 5-Sep-13 | 1-5 pm | | 80.0 | 97% | 7.6 | 7.9 | 8.7 | 8.8 |
| 6-Sep-13 | 1-5 pm | | 81.2 | 97% | 10.3 | 10.7 | 9.4 | 9.5 |
| **Average** | | | **79.6** | **97%** | **8.5** | **8.7** | **8.6** | **8.5** |

To better understand the possible reason for the difference in ex-post and ex-ante estimates based on the ex-ante model using ex-post weather and event conditions (columns F and G in Tables 6-8 and 6-9), we replicated those tables while constraining the impact values to the two hours from 2 to 4 PM. These are the hours used in the regression model that is the basis for the ex-ante forecasts because they were most common across all ex-post event days. Tables 6-10 and 6-11 show the relationship between ex-post and ex-ante estimates using just the hours from 2 to 4 PM. A comparison of columns F and G in Table 6-10 shows that ex-post and ex-ante estimates match almost perfectly for 50% cycling participants but now the ex-ante model under predicts by about 8% using ex-post weather for the 100% cycling group as seen in Table 6-11.

**Table 6-10: Differences Ex-post and Ex-ante Impacts for 50% Cycling Customers Using Only the Hours from 2 to 4 PM – Residential Customers**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2013 Ex-post Aggregate Estimates** | | | | | **Aggregate Estimates Based on the Ex-ante Model** | | | |
| **Analysis Window** | **Mean17 (**°F) | **% of Resources Dispatched** | **Aggregate Reduction (MW)** | **Aggregate Reduction if All Participants are Controlled (MW)** | **Historical Window & Weather (MW)** | **Historical Weather & Standardized Event Window (MW)** | **1-in-2 Year Weather, Forecast Enrollment (MW)** | **1-in-10 Year Weather, Forecast Enrollment (MW)** |
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** |
| 28-Aug-13 | 2-4 pm | 78.0 | 97% | 5.8 | 6.0 | 7.0 | 6.8 | 6.3 | 7.5 |
| 29-Aug-13 | 2-4 pm | 78.1 | 97% | 3.7 | 3.8 | 7.1 | 6.9 |
| 30-Aug-13 | 2-4 pm | 83.0 | 97% | 9.0 | 9.3 | 9.5 | 9.2 |
| 3-Sep-13 | 2-4 pm | 79.0 | 97% | 7.7 | 7.9 | 7.5 | 7.3 |
| 5-Sep-13 | 2-4 pm | 80.8 | 97% | 8.0 | 8.2 | 8.4 | 8.2 |
| 6-Sep-13 | 2-4 pm | 81.8 | 97% | 12.3 | 12.7 | 8.9 | 8.6 |
| **Average** | | **80.1** | **97%** | **7.8** | **8.0** | **8.1** | **7.8** |

**Table 6-11: Differences in Ex-post and Ex-ante Impacts for 100% Cycling Customers Using Only the Hours from 2 to 4 PM – Residential Customers**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2013 Ex-post Aggregate Estimates** | | | | | **Aggregate Estimates Based on the Ex-ante Model** | | | |
| **Analysis Window** | **Mean17 (**°F) | **% of Resources Dispatched** | **Aggregate Reduction (MW)** | **Aggregate Reduction if All Participants are Controlled (MW)** | **Historical Window & Weather (MW)** | **Historical Weather & Standardized Event Window (MW)** | **1-in-2 Year Weather, Forecast Enrollment (MW)** | **1-in-10 Year Weather, Forecast Enrollment (MW)** |
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** |
| 28-Aug-13 | 2-4 pm | 77.3 | 97% | 6.2 | 6.4 | 7.1 | 7.2 | 6.7 | 8.2 |
| 29-Aug-13 | 2-4 pm | 77.6 | 97% | 5.2 | 5.3 | 7.3 | 7.4 |
| 30-Aug-13 | 2-4 pm | 82.8 | 97% | 10.7 | 11.1 | 10.3 | 10.4 |
| 3-Sep-13 | 2-4 pm | 78.5 | 97% | 9.4 | 9.7 | 7.8 | 7.9 |
| 5-Sep-13 | 2-4 pm | 80.0 | 97% | 9.0 | 9.2 | 8.7 | 8.8 |
| 6-Sep-13 | 2-4 pm | 81.2 | 97% | 12.4 | 12.8 | 9.4 | 9.5 |
| **Average** | | **79.6** | **97%** | **8.8** | **9.1** | **8.4** | **8.5** |

Going from Column F to G in Tables 6-12 and 6-13, again reflects the influence of the change in methodology from the RCT-based ex-post estimates to the regression-based ex-ante estimates. For 30% cycling, the regression model over predicts the ex-post values by about 7% (from 0.9 MW to 1.0 MW in Table 6-12). The regression model for 50% cycling under predicts the ex-post values by about 6% (from 2.9 MW to 2.7 MW in Table 6-13). The last two columns, I and J, show the impact of changing from ex-post weather conditions to 1-in-2 and 1-in-10 year weather conditions. Shifting from ex-post to ex-ante 1-in-2 year weather decreased aggregate impacts by about 9% for 30% cycling and 14% for 50% cycling. Shifting to 1-in-10 year weather conditions decreased the impacts by about 1% compared with ex-post conditions. As discussed previously, these ex-ante numbers are lower because mean17 is lower under ex-ante weather on a typical event day than under 2013 weather conditions. The 1-in-10 year conditions show impacts that are 9% higher than 1-in-2 year conditions for 30% cycling and nearly 15% higher for 50% cycling.

**Table 6-12: 30% Cycling Ex-ante Regression Model and 2010-2013 Impacts from 2-4 PM –**

**Non Residential Customers**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2013 Ex-post Aggregate Estimates** | | | | | **Aggregate Estimates Based on the Ex-ante Model** | | | |
| **Event Window** | **Mean17 (**°F) | **% of Resources Dispatched** | **Aggregate Reduction (MW)** | **Aggregate Reduction if All Participants are Controlled (MW)** | **Historical Window & Weather (MW)** | **Historical Weather & Standardized Event Window (MW)** | **1-in-2 Year Weather, Forecast Enrollment (MW)** | **1-in-10 Year Weather, Forecast Enrollment (MW)** |
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** |
| 28-Aug-13 | 3-7 pm | 76.5 | 93% | 0.6 | 0.6 | 0.7 | 0.9 | 0.9 | 1.0 |
| 29-Aug-13 | 2-6 pm | 77.5 | 93% | 0.7 | 0.7 | 0.9 | 0.9 |
| 30-Aug-13 | 1-5 pm | 82.5 | 93% | 1.0 | 1.1 | 1.1 | 1.1 |
| 3-Sep-13 | 1-5 pm | 77.8 | 93% | 1.1 | 1.2 | 1.0 | 0.9 |
| 5-Sep-13 | 1-5 pm | 79.0 | 93% | 0.8 | 0.9 | 1.0 | 1.0 |
| 6-Sep-13 | 1-5 pm | 80.8 | 93% | 0.9 | 1.0 | 1.1 | 1.0 |
| **Average** | | **79.6** | **93%** | **0.9** | **0.9** | **1.0** | **1.0** |

**Table 6-13: 50% Cycling Ex-ante Regression Model and 2010-2013 Impacts from 2-4 PM –**

**Non Residential Customers**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Date** | **2013 Ex-post Aggregate Estimates** | | | | | **Aggregate Estimates Based on the Ex-ante Model** | | | |
| **Event Window** | **Mean17 (**°F) | **% of Resources Dispatched** | **Aggregate Reduction (MW)** | **Aggregate Reduction if All Participants are Controlled (MW)** | **Historical Window & Weather (MW)** | **Historical Weather & Standardized Event Window (MW)** | **1-in-2 Year Weather, Forecast Enrollment (MW)** | **1-in-10 Year Weather, Forecast Enrollment (MW)** |
| **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** |
| 28-Aug-13 | 3-7 pm | 75.9 | 97% | 1.8 | 1.8 | 1.8 | 2.3 | 2.3 | 2.7 |
| 29-Aug-13 | 2-6 pm | 76.9 | 97% | 2.6 | 2.7 | 2.5 | 2.5 |
| 30-Aug-13 | 1-5 pm | 82.1 | 97% | 2.9 | 2.9 | 3.4 | 3.2 |
| 3-Sep-13 | 1-5 pm | 77.4 | 97% | 2.8 | 2.9 | 2.7 | 2.5 |
| 5-Sep-13 | 1-5 pm | 78.5 | 97% | 3.1 | 3.2 | 2.8 | 2.7 |
| 6-Sep-13 | 1-5 pm | 80.1 | 97% | 3.5 | 3.6 | 3.1 | 2.9 |
| **Average** | | **78.5** | **97%** | **2.8** | **2.9** | **2.7** | **2.7** |

# Opt-in Peak Time Rebate Program

## 7.1 Opt-in PTR Program Description

PTR offers bill credits for reduced energy use between 11 AM and 6 PM on PTR event days. In 2013, any customer with a working smart meter was eligible for the PTR bill credit. Starting in 2014, only customers who opt in to receive event alerts via text or email one day in advance of an event will be eligible for PTR rebates. Therefore, the scope of this evaluation is restricted to residential opt-in PTR customers, which includes customers that will receive a programmable communicating thermostat (PCT) through the Small Customer Technology Deployment (SCTD) program. There was only one PTR event in 2013, which occurred on August 31, 2013. At the time, there were 57,586 customers enrolled in PTR event notification. Currently, there are roughly 55,000 opt-in PTR customers, but the program is expected to grow to over 73,000 participants by the end of August 2014.

7.2 Opt-in PTR Ex-Post Evaluation Methodology

Reference loads for the opt-in PTR impact estimates were calculated using a matched control group drawn from the non-alert PTR population, a group that has not provided load impacts in the past (and did not show response for the 2013 event either). The control group is designed to ensure that the load on event days is an accurate estimate of what load would have been among opt-in alert customers on the PTR event day had there been no event.

The control group was selected using a propensity score match to find non-alert customers who had similar load shapes to the opt-in PTR customers. In this procedure, a probit model was used to estimate a score for each customer based on a set of observable variables that are assumed to affect the decision to opt into PTR alerts, such as average daily use and hourly use. A probit model is a regression model designed to estimate probabilities – in this case, the probability that a customer would opt in or enroll. The propensity score can be thought of as a summary variable that includes all the relevant information in the observable variables about whether a customer would opt into PTR alerts. Each customer in the treatment population was matched with a customer in the non-alert population with the closest propensity score.

After the control groups for opt-in alert customers were matched and validated, load impacts were estimated using a difference-in-differences methodology. Nexant calculated the estimated impacts as the difference in average loads between opt-in PTR and control customers on the August 31 event day, with the slight difference between the two groups on the chosen event-like days removed. This calculation controls for residual differences in load between the groups that are not eliminated through the matching process, thus reducing bias.

7.3 Opt-in PTR Ex-Post Load Impact Estimates

SDG&E called one PTR event in 2013, on Saturday, August 31. The table 7-1 presents the average and aggregate PTR ex-post load impact estimates by climate, usage level, enrollment year, and notification type. As measured by the percent load reduction, customers who enrolled in 2013 and customers who receive both notification types had the highest performance, with 14% and 12% load reductions, respectively. In terms of aggregate MW of load reduction, customers with high usage levels (top half of electricity users) delivered the greatest aggregate reductions (5.98 MW, relative to 0.67 MW among the same number of low usage customers). Opt-in PTR customers in the inland climate zone delivered a 7.8% load reduction. In addition to delivering a larger percent reduction than coastal customers (who deliver a 6.4% load reduction), reference loads were higher in the hotter inland areas, which led to a load impact that was double that of coastal customers.

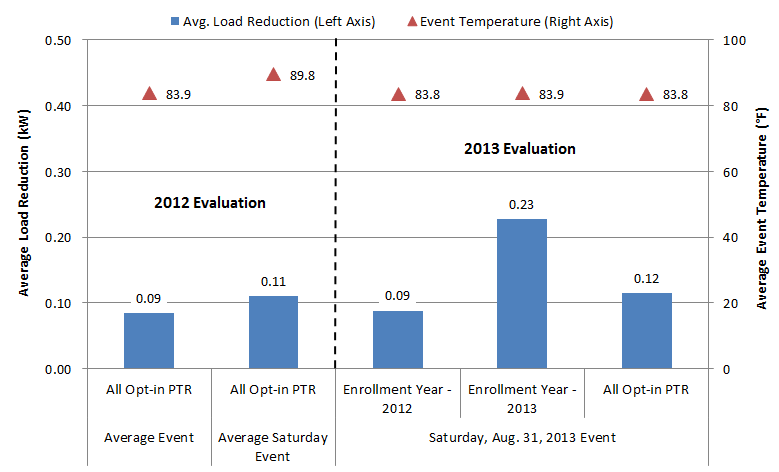
Table 7-1: Opt-in PTR Ex-post Load Impact Estimates by Customer Category  
August 31, 2013 (11 AM to 6 PM)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Customer Category** | **Number of Customers** | **Avg. Reference Load (kW)** | **Avg. Load with DR (kW)** | **Avg. Load Reduction (kW)** | **% Load Reduction** | **Aggregate Load Reduction (MW)** | **Heat Buildup (Avg. °F, 12 AM to 5 PM)** |
| Climate Zone - Coastal | 32,128 | 1.31 | 1.23 | 0.08 | 6.4% | 2.7 | 79.5 |
| Climate Zone - Inland | 25,458 | 2.00 | 1.85 | 0.16 | 7.8% | 4.0 | 80.6 |
| Non-Summer Saver | 54,149 | 1.59 | 1.47 | 0.11 | 7.2% | 6.2 | 79.9 |
| Summer Saver | 3,437 | 2.07 | 1.93 | 0.14 | 6.9% | 0.5 | 80.5 |
| Non-CARE | 45,382 | 1.67 | 1.54 | 0.12 | 7.3% | 5.5 | 80.0 |
| CARE | 12,204 | 1.43 | 1.34 | 0.09 | 6.6% | 1.2 | 80.0 |
| Usage Level - High | 28,571 | 2.60 | 2.38 | 0.22 | 8.4% | 6.2 | 80.2 |
| Usage Level - Low | 29,015 | 0.65 | 0.63 | 0.01 | 2.1% | 0.4 | 79.8 |
| Enrollment Year - 2012 | 46,404 | 1.62 | 1.53 | 0.09 | 5.5% | 4.1 | 80.0 |
| Enrollment Year - 2013 | 11,182 | 1.60 | 1.37 | 0.23 | 14.3% | 2.5 | 80.0 |
| Notification Type - Email | 33,995 | 1.52 | 1.44 | 0.09 | 5.7% | 2.9 | 80.0 |
| Notification Type - Text | 9,340 | 1.67 | 1.56 | 0.11 | 6.4% | 1.0 | 80.0 |
| Notification Type - Both | 14,251 | 1.81 | 1.61 | 0.19 | 10.7% | 2.7 | 80.0 |
| **All Customers** | **57,586** | **1.62** | **1.50** | **0.12** | **7.2%** | **6.7** | **80.0** |

7.4 Opt-in PTR Comparison of 2012 and 2013 Ex-post Load impact Estimates

Figure 7-1 provides a comparison of the ex-post load impact estimates that were reported in the 2012 opt-in PTR evaluation to those reported in this evaluation. The 2012 PTR evaluation found that opt-in alert customers provided a 0.09 kW load reduction (6.6%) on average across seven event days. For the two Saturday events in 2012, opt-in PTR customers delivered an average load reduction of 0.11 kW (6.7%). The 2013 evaluation found that opt-in PTR customers provided a 0.12 kW load reduction (7.2%) on the August 31 event. However, customers that enrolled in 2012 provided a relatively low reduction of 0.09 kW, which is equal to the average event estimate from the 2012 evaluation, but slightly lower than the average Saturday event in 2012. While it seems most appropriate to compare the Saturday estimates, the two Saturdays in 2012 featured an average event temperature of 89.8 °F, which is significantly higher than temperatures during 2013 event hours (83.8 °F). Therefore, it is not surprising that the Saturday ex-post load impact estimates are slightly lower in 2013 for customers that have participated in PTR since 2012. However, after incorporating the relatively high impacts from customers that enrolled in 2013, the August 31 load impact estimate increased by nearly 33% (from 0.09 kW to 0.12 kW). As a result, the 2013 ex-post load impact estimates are higher because the 2013 enrollees provided relatively large load impacts, albeit for a single event. It will be important to observe if their performance remains strong in 2014.

Figure 7-1: Comparison of 2012 and 2013 Ex-post Load Impact Estimates



7.5 Opt-in PTR Ex-Ante Load Impact Methodology

The modeling steps consist of the following:

* First, groups of opt-in PTR customers were identified who were representative of the population at the end of 2013 and who experienced all the 2012 and 2013 opt-in PTR events. Propensity score matching was used to find these groups;
* Next, ex-post estimates were developed for these customers for 2012 and 2013 using matched control groups of non-alert customers for each year;
* Then an ex-ante regression model was developed to explain average ex-post impacts from 11 AM to 6 PM as a function of temperatures that day. This model was not estimated separately for each hour; rather, a single average value from 11 AM to 6 PM was used as the dependent variable. The data from both climate zones was pooled. Pooling increases the range of temperatures included in the estimating sample, thus reducing the need to extrapolate outside of the historical conditions to estimate impacts for 1-in-10 year weather conditions, which represent temperatures within many climate zones that are not often experienced during the ex-post period. The model was used to predict average impacts from 11 AM to 6 PM for the set of ex-ante weather conditions;
* The ex-ante impact estimates were then converted to hourly impacts from 11 AM to midnight (including post-event period) using a scaling factor based on the average ratio between impacts at different hours. The scaling factor was calculated by comparing average impacts from the entire event period to average impacts for each event hour and post-event hour based on ex-post results; and

Next, hourly whole-house reference loads were predicted for each set of ex-ante weather conditions based on loads observed in 2013. These reference loads are needed to comply with the load impact protocols, but are not necessary for ex-ante load impact estimation, as impacts are estimated directly from ex-post impact values. Reference load shapes were estimated by running a simple regression model on 2013 participant load by climate zone. The regression model related hourly usage to temperature, month and day of week.

For opt-in PTR-only customers, the final model specification takes as its dependent variable the ex-post impact for each event, averaged over the entire event period. The independent variable is the average temperature from midnight to 5 PM on the event day. The final specification was:

Table 7-2: Description of Opt-in PTR Ex-ante Load Regression Variables

|  |  |
| --- | --- |
| Variable | Description |
| *Impact (kW)* | Per customer ex-post load impact for each event day, averaged over the event period |
| *a* | Estimated constant |
| *b* | Estimated parameter coefficient |
| *mean17* | Average temperature from 12 AM to 5 PM |
| *Ɛ* | The error term, assumed to be a mean zero and uncorrelated with any of the independent variables |

7.6 Opt-in PTR Ex-Ante Load Impact Estimates

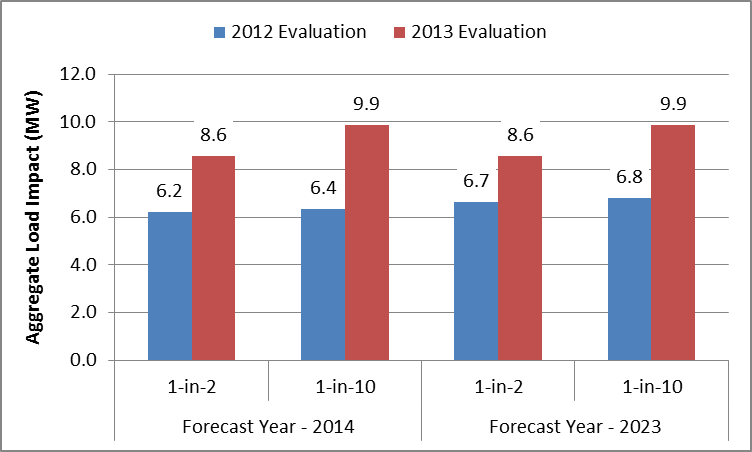
The reference load and estimated load with DR for the average opt-in PTR customer on a typical event day based on 1-in-2 and 1-in-10 weather year conditions for the year 2015. Impacts are reported for 2015 because it is the year in which enrollment growth reaches a steady state. For a 1-in-2 typical event day, the estimated load impact for the average participant is 0.12 kW from 1 PM to 6 PM. For a 1-in-10 typical event day, the estimated load impact for the average participant is slightly higher, at 0.13 kW. The load impact is around 9% of the reference load under both weather conditions.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Type of Results** | Average Customer |  |  |  | **Type of Results** | Average Customer |  |  |
| **Weather Year** | 1-in-10 |  |  |  | **Weather Year** | 1-in-2 |  |  |
| **Forecast Year** | 2015 |  |  |  | **Forecast Year** | 2015 |  |  |
| **Day Type** | Typical Event Day |  |  |  | **Day Type** | Typical Event Day |  |  |
| **Avg. 1-6 PM Impact(kW)** | 0.13 |  |  |  | **Avg. 1-6 PM Impact(kW)** | 0.12 |  |  |
| **Hour Ending** | **Reference Load (kW)** | **Load Impact (kW)** | **%Load Reduction** |  | **Hour Ending** | **Reference Load (kW)** | **Load Impact (kW)** | **%Load Reduction** |
|  |
| 12 | 1.0 | 0.08 | 8.1% |  | 12 | 0.9 | 0.08 | 8.1% |
| 13 | 1.2 | 0.11 | 9.8% |  | 13 | 1.0 | 0.10 | 9.9% |
| 14 | 1.3 | 0.13 | 10.2% |  | 14 | 1.1 | 0.12 | 10.4% |
| 15 | 1.4 | 0.14 | 9.9% |  | 15 | 1.2 | 0.12 | 10.2% |
| 16 | 1.5 | 0.13 | 9.0% |  | 16 | 1.3 | 0.12 | 9.4% |
| 17 | 1.6 | 0.14 | 9.1% |  | 17 | 1.4 | 0.13 | 9.5% |
| 18 | 1.7 | 0.13 | 7.6% |  | 18 | 1.4 | 0.11 | 7.9% |

7.7 Comparison of 2012 and 2013 Ex-Ante Estimates

The opt-in PTR ex-ante impacts calculated in 2013 (this year’s evaluation) are significantly higher than the estimates provided in 2012 (last year’s evaluation). Figure 7-2 compares the two forecasts for the August system peak day by weather year in 2014 and 2023. The 2014 and 2023 August opt-in PTR load impacts are equal in this year’s evaluation because enrollment is assumed to remain flat once it reaches around 73,000 customers as of August 2014. Last year’s enrollment forecast also projected around 73,000 customers as of August 2014, but enrollment was assumed to increase by about 1% per year through 2023, resulting in proportional percentage increase in aggregate impacts. Nonetheless, the 2013 evaluation produces aggregate load impacts that are 29% to 55% higher for the August system peak day throughout the overlapping forecast period. This increase is primarily attributed to the relatively high performance of the 2013 opt-in PTR enrollees who comprise 24% of current participants.

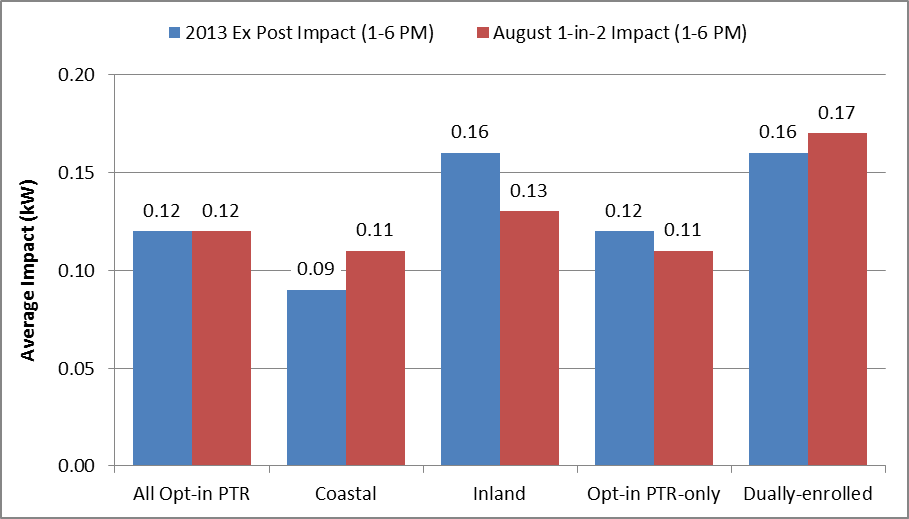
Figure 7-2: Comparison of 2012 and 2013 Estimates of Opt-in PTR Aggregate Load Impact (MW) for an August System Peak Day by Weather Year in 2014 and 2023



7.8 Relationship between Ex-Post and Ex-ante Estimates

Figure 7-3 provides a comparison of the ex-post and ex-ante estimates from the 2013 evaluation. The 2013 event in the ex-post analysis is most comparable to a 1-in-2 August peak day in the ex-ante analysis. In addition, considering that the ex-ante estimates are summarized in the 1-6 PM time period, this comparison focuses on the same time period in the ex-post estimates. In general, the per-customer ex-post impacts are very similar to the ex-ante impacts in magnitude and show similar trends by type of participant (opt-in PTR-only or dually-enrolled). By region, the impacts do not match as closely, but some differences are expected given that regional temperatures for the August 31 event day do not match exactly with temperatures for the 1-in-2 August peak day. The ex-ante impact are aggregated up from the regional level, so even if the average temperature for all participants is similar, underlying variation in regional temperatures can lead to some differences in estimates.

Figure 7-3: Comparison of Ex-post and Ex-Ante Estimates of  
Opt-in PTR Average Load Impact (kW) in August (1-6 PM)



# Non-Alert Peak Time Rebate Program

## Non-Alert PTR Program Description

SDG&E’s PTR program is a default program for eligible residential customers who have received a Smart Meter. Eligible customers can receive bill credits for usage reductions below a baseline level during the event window from 11 a.m. to 6 p.m. This section focuses on the population of residential customers who did not request electronic notification of PTR events (i.e., they are classified as “non-Alert”) prior to the summer of 2013 or participate in the Summer Saver air conditioner cycling program, or related technology programs.

## Non-Alert PTR Evaluation Methodology

This section discusses the sample design and analysis approach for SDG&E’s residential customers who are not covered by the separate SDG&E PTR and Summer Saver evaluation projects.

### Sample design

A stratified random sample of the target population was designed, with stratification by climate zone and usage category (e.g., low, medium, and high summer average daily usage). SDG&E selected customers at random from the target population of non-alert, non-technology customers within those strata. Hourly load data were then requested for the selected sample customers.

### Analysis approach

The basic analysis approach involved exploration and testing of traditional methods for estimating load impacts for event-based demand response programs using participants’ own load data for the period in which events were called. A regression analysis was applied to hourly load data for June through September 2013 for the selected sample. The analysis controls for factors other than PTR event occurrence that influence customers’ load profiles, including hour of day, day of week, month, and weather, and also includes hourly variables indicating the one event day. The coefficients on the hourly event variables allow direct estimation of hourly PTR load impacts for each customer.

The data used in the analysis were restricted to weekend days from June through September, for which temperatures in hour-ending 15 exceeded the average for those day types.[[11]](#footnote-11) Additionally, was excluded two late-September weekend days which met the hour 15 temperature criterion, but which had uncharacteristically low loads. This low usage could be due to a shift in cooling behavior following a week of relatively mild weather where customers may have turned off air conditioning systems. Weather effects are represented by the three- and 24-hour moving averages of cooling degree hours calculated using a 60-degree threshold.[[12]](#footnote-12)

The model presented below represents the “base” *ex-post* load impact model that we have used in previous evaluations to estimate hourly impacts for individual customer accounts, or for a relevant group of customers, for each event day, while controlling for factors such as weather conditions and regular daily and monthly usage patterns (*i.e.*, accounting for differences in load levels across hours of the day, days of the week, and months of the year). We then describe a range of variations that we explored to ensure that we selected the most appropriate model for estimating PTR load impacts.

The base model is shown below, with each term described in table 8-1.



Table 8-1: Variable descriptions

|  |  |
| --- | --- |
| **Variable Name / Term** | **Variable / Term Description** |
| *Qt* | the hourly usage in time period *t* for a particular customer |
| The various *b*’s | the estimated parameters |
| *hi,t* | an indicator variable for hour *i* |
| *PTRt* | an indicator variable for PTR event days |
| *Wtht* | the weather conditions during hour *t*[[13]](#footnote-13) |
| *Sundayj,t* | indicator variables for Sunday |
| *MONTHi,t* | a series of indicator variables for each month |
| *et* | the error term |

The first term is the component of the equation that allows estimation of *hourly load impacts* (the *bi,Evt* coefficients) for the PTR event day. It does so via the hourly indicator variables *hi,t* interacted with the event variables (indicated by *PTRt*). The remaining terms in the equation are designed to control for weather and other periodic factors (*e.g*., hours, days, and months) that determine customers’ loads. The interaction of the Sunday day type indicator with the hourly indicators is designed to account for potentially different hourly load profiles on Sundays relative to Saturdays.

## Non-Alert PTR Ex-Post Load Impact Estimates

The table 8-2 summarizes the average event-hour estimated reference loads and load impacts for the Coastal and Inland climate zones, and all customers combined, for both the average customer and in aggregate. The bottom-line result is that the average non-alert customers in the inland climate zones reduced usage by an estimated average of about 3 percent during the PTR event window. This implies aggregate minimum load impacts of about 5 MW for the Inland region maximum load impacts of 50 MWs, with the average load impact of 27 MW. The coastal climate zone estimates are not significantly different from zero. However, both estimates are subject to a fairly wide range of uncertainty, based on the variability and lack of precision of the individual hourly estimates.

Table 8-2: Average Event-Hour Loads and Load Impacts – by Climate Zone



# Small Customer Technology Deployment (SCTD) Program

## SCTD Program Description

Small Customer Technology Deployment is a new demand response program which provides enabling technology to residential customers at no cost in order to automate load reduction on demand response event days. In 2014 and 2015, SDG&E plans to deploy over 10,000 PCTs through the SCTD program. These PCTs will be activated through Wi-Fi and/or zigbee (when possible) communications on PTR event days. Half of SCTD PCTs will feature a 4-degree temperature setback and the other half will have 50% cycling curtailment strategy. SDG&E plans to curtail load in 4-hour increments on PTR event days. Although SDG&E has the flexibility to during any 4-hour period between 11 AM and 6 PM, it is expected that most of the time curtailment will occur from 2 PM to 6 PM. SDG&E plans to market the SCTD program to 190,000 targeted customers with usage patterns that indicate that they have an air conditioner and use it during peak periods

## SCTD Ex-Ante Load Impact Methodology

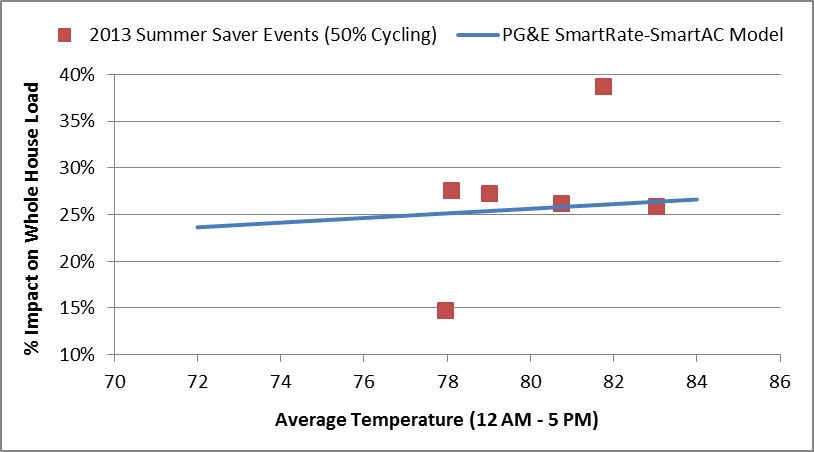
To develop the hourly reference loads in the ex-ante analysis, Nexant analyzed the 2013 aggregate hourly interval usage data for these 190,000 customers, using a simple regression model that relates hourly usage to temperature, month and day of week (same model that was used to develop reference loads for the opt-in PTR customers). At this point, it not known which of the 190,000 customers will enroll, so the aggregate data for all customers that will receive SCTD marketing was analyzed. This produced the hourly whole-house reference loads for each set of ex-ante weather conditions.

To develop the impact estimates, the ex-ante evaluation incorporated information from PG&E’s SmartRate program. The SmartRate program was most applicable because it has dually-enrolled (SmartAC) customers whose air conditioners are cycled at 50% during SmartRate events. Therefore, this source of information was most relevant to opt-in PTR customers that will have air conditioning usage curtailed during PTR events, as part of the SCTD program. Nonetheless, given that the event window is flexible, impacts are estimated for the 5-hour summer resource adequacy window of 1 PM to 6 PM. Impacts for November through April are assumed to be zero, considering that air conditioning load is expected to be negligible during those months.

The impact model focused on the percent impacts of dually-enrolled customers during SmartRate events. The model described here is nearly identical to the opt-in PTR-only impact model, except the dependent variable in the model is the percent impact instead of kW impact. Figure 9-1 summarizes the impact model that was used for SCTD customers. The blue line represents the linear relationship between *Mean17* (midnight to 5 PM average temperature) and the percent impact on whole house load when SmartAC switches are activated during SmartRate events. That linear model is used to estimate SCTD percent impacts under ex-ante weather conditions. The red squares represent the 2013 Summer Saver ex-post load impact estimates for customers on 50% cycling, which align relatively closely with the PG&E percent impacts. These Summer Saver estimates do not factor into the SCTD impact model. They are simply meant to provide additional indication of what can be expected from controlling air conditioning loads in San Diego, which further supports that using the SmartRate-SmartAC model is reasonable, considering that the two sources of information closely align.

Figure 9-1: Impact Model for SCTD Customers

(2013 Summer Saver Results are provided as a Comparison)



The next step was to multiply the percent impact estimate from the SCTD impact model by the average reference load from 1 PM to 6 PM. This produced the average impact estimate. As in the opt-in PTR analysis, the ex-ante impact estimates were then converted to hourly impacts from 1 PM to midnight (including post-event period) using a scaling factor based on the average ratio between impacts at different hours. In this case, the ratios were based on the experience of SDG&E’s dually-enrolled customers, considering that both sets of customers have air conditioning.

## SCTD Ex-Ante Load Impact Estimates

The reference load and estimated load with DR for the average SCTD customer on a typical event day based on 1-in-2 and 1-in-10 weather year conditions for the year 2015. The 2015 was the year in which SCTD enrollment growth reaches a steady state. For a 1-in-2 typical event day, the estimated load impact for the average SCTD participant is 0.45 kW from 1 PM to 6 PM. For a 1-in-10 typical event day, the estimated load impact for the average participant is 22% higher, at 0.55 kW, which is primarily due to the higher reference load under 1-in-10 conditions. The load impact is around 25% of the reference load under both weather conditions.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Type of Results** | Average Customer |  |  |  | **Type of Results** | Average Customer |  |  |
| **Weather Year** | 1-in-10 |  |  |  | **Weather Year** | 1-in-2 |  |  |
| **Forecast Year** | 2015 |  |  |  | **Forecast Year** | 2015 |  |  |
| **Day Type** | Typical Event Day |  |  |  | **Day Type** | Typical Event Day |  |  |
| **Avg. 1-6 PM Impact(kW)** | 0.55 |  |  |  | **Avg. 1-6 PM Impact(kW)** | 0.45 |  |  |
| **Hour Ending** | **Reference Load (kW)** | **Load Impact (kW)** | **%Load Reduction** |  | **Hour Ending** | **Reference Load (kW)** | **Load Impact (kW)** | **%Load Reduction** |
|  |
| 12 | 1.5 | 0.00 | 0.0% |  | 12 | 1.3 | 0.00 | 0.0% |
| 13 | 1.7 | 0.00 | 0.0% |  | 13 | 1.5 | 0.00 | 0.0% |
| 14 | 1.9 | 0.57 | 30.1% |  | 14 | 1.6 | 0.47 | 29.3% |
| 15 | 2.0 | 0.67 | 32.6% |  | 15 | 1.7 | 0.55 | 31.7% |
| 16 | 2.2 | 0.60 | 26.9% |  | 16 | 1.9 | 0.49 | 26.1% |
| 17 | 2.3 | 0.48 | 20.3% |  | 17 | 2.0 | 0.39 | 19.7% |
| 18 | 2.4 | 0.43 | 18.3% |  | 18 | 2.0 | 0.36 | 17.8% |

# 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:* 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 10-1 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 total budget amount is 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.[[14]](#footnote-14) Finally, the budget that has been committed to identified projects is subtracted from that expected budget spend, which produces the forecast of incentives to be spent on unidentified projects.
* **Step 2** converts the incentive dollar forecast into the ex-ante load impact estimates. To do this, the forecast of incentive dollars spent on unidentified projects is divided by the incentive amount per kW load shift ($875/kW). Per the program design, this kW load shift amount represents the peak load shift that can be expected under ASHRAE 2% weather conditions. The kW load shift is multiplied by the ex-ante conversion factors, which convert the load shift under ASHRAE 2% weather conditions to the ex-ante load impact estimates for monthly system peak days and average weekdays under 1-in-2 and 1-in-10 weather conditions (as per the California DR Load Impact Protocols). These conversion factors vary from 0.5 to 2 from June through September, so they do not change the initial kW load shift by more than 50%.
* **Step 3** is to forecast when each expected PLS installation will 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 12 to 24 months, so projects do not come online until 2015 or later. Five years after each forecasted PLS installation, the ex-ante impacts begin to degrade at a rate of 2.5% per year. Over time, the load shifting capacity of the PLS technologies is expected to degrade as the system ages. This assumption was made in consultation with program managers, and it is consistent with last year’s evaluation.

It is important to note that these conversion factors were developed under the assumption that PLS would primarily involve space cooling installations. We have assumed that the unidentified projects only include space cooling installations, for the sake of simplicity and in the absence of any further information.

Figure 10-1: Methodology for Estimating Ex-ante Load Impacts of Unidentified PLS Projects



*Identified projects:* include those for which the customer has either completed a feasibility study or submitted a complete application. Applications are submitted by potential PLS participants to initiate their enrollment in the program. Each application includes an initial estimate of the proposed PLS installation’s peak load shifting capacity. SDG&E received one application, and that customer has submitted a feasibility study. All of these projects are similar in size, with an expectation to deliver around 1 MW of load shift or less for each one.

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 was nearly identical to Step 2 and Step 3 in the methodology used for unidentified projects, 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 are provided in the application for identified projects, the forecast for identified projects incorporates this information by having the project come online on the expected installation date and by assigning the ex-ante load impacts for that project to the customer’s LCA.

## PLS Ex-Ante Load Impact Estimates

The table 10-1 provides the ex-ante load impact estimates for 2015-2024 monthly system peak days in April through October, under 1-in-2 and 1-in-10 weather conditions for the base scenario. SDG&E’s service territory only has one LCA, so the results are not divided geographically. In the base scenario, one SDG&E unidentified project comes online in 2015 and another comes online in 2016 along with the identified project that comes online at that time. As such, the 2015 aggregate impacts are attributed to the first unidentified project, and from 2016 onwards, all three projects are included in the forecast. The table also shows the expected trajectory of load impacts through 2024. As a result of the assumed 2.5% annual degradation in load impacts after year five of each installation, the aggregate load reduction under August 1-in-10 weather conditions decreases from around 2.2 MW in 2018 to 1.9 MW in 2024.

Table 10-1: SDG&E Ex-ante Load Impact Estimates (1-6 PM) on Monthly Peak Days for April-October 2015-2024 (kW) – Base Scenario

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Forecast Year** | **April** | | **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** | **1-in-2** | **1-in-10** |
| 2015 | 472 | 675 | 378 | 693 | 392 | 399 | 574 | 626 | 518 | 654 | 612 | 759 | 644 | 745 |
| 2016 | 1,562 | 2,233 | 1,250 | 2,291 | 1,296 | 1,319 | 1,898 | 2,071 | 1,713 | 2,164 | 2,025 | 2,511 | 2,129 | 2,465 |
| 2017 | 1,562 | 2,233 | 1,250 | 2,291 | 1,296 | 1,319 | 1,898 | 2,071 | 1,713 | 2,164 | 2,025 | 2,511 | 2,129 | 2,465 |
| 2018 | 1,562 | 2,233 | 1,250 | 2,291 | 1,296 | 1,319 | 1,898 | 2,071 | 1,713 | 2,164 | 2,025 | 2,511 | 2,129 | 2,465 |
| 2019 | 1,523 | 2,177 | 1,218 | 2,234 | 1,264 | 1,286 | 1,850 | 2,020 | 1,670 | 2,110 | 1,974 | 2,448 | 2,076 | 2,403 |
| 2020 | 1,485 | 2,123 | 1,188 | 2,178 | 1,232 | 1,254 | 1,804 | 1,969 | 1,628 | 2,057 | 1,925 | 2,387 | 2,024 | 2,343 |
| 2021 | 1,448 | 2,070 | 1,158 | 2,124 | 1,201 | 1,223 | 1,759 | 1,920 | 1,587 | 2,006 | 1,877 | 2,327 | 1,973 | 2,284 |
| 2022 | 1,412 | 2,018 | 1,129 | 2,070 | 1,171 | 1,192 | 1,715 | 1,872 | 1,548 | 1,955 | 1,830 | 2,269 | 1,924 | 2,227 |
| 2023 | 1,376 | 1,968 | 1,101 | 2,019 | 1,142 | 1,162 | 1,672 | 1,825 | 1,509 | 1,907 | 1,784 | 2,212 | 1,876 | 2,172 |
| 2024 | 1,342 | 1,919 | 1,074 | 1,968 | 1,113 | 1,133 | 1,630 | 1,779 | 1,471 | 1,859 | 1,740 | 2,157 | 1,829 | 2,117 |

# Temperatures

The ex-ante forecast temperatures for each month were calculated using weather data from 2003-2011. The temperature on the date of the monthly system peak day for each year for the SDG&E Miramar weather station was taken. Then for each month the date of the median temperature was selected for the 1 in 2 temperature scenario and the date of the second highest temperature was selected for the 1 in 10 temperature date. For example, for the month of May SDG&E took the temperatures on the monthly system peak day for May 2003-May2011. The median of these values was selected and that date was used for the 1 in 2 weather. Each month however can have their 1 in 2 date come from a different year because there are no years in which every month is 1 in 2. For example, one year might have a very hot May but an average July.

SDG&E uses 9 weather stations in its evaluations so the weather date that corresponded to the median Miramar weather was used to pull the weather for the other 9 stations. This method ensures that the weather for all 9 stations come from the same date. If we allowed different dates for different weather stations that could overestimate the temperature. Each evaluation uses a weighted average temperature based on where customers are located. So for a program like summer saver that was marketed to Inland customers more customers will assigned to Inland weather stations whereas there are more commercial customers on the coast than inland so the commercial evaluations will have more customers associated to the costal weather stations. The Miramar temperatures used for the 1 in 2 and 1 in 10 scenarios are below.

**Table 11-1 Monthly Peak Temperatures 1 in 2**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Month | WEATHER\_STATION\_ID | Hour | WEATHER\_STATION\_NAME | TEMP\_FAHR |
| 1 | KNKX | 0 | Miramar | 51 |
| 1 | KNKX | 1 | Miramar | 50 |
| 1 | KNKX | 2 | Miramar | 47 |
| 1 | KNKX | 3 | Miramar | 46 |
| 1 | KNKX | 4 | Miramar | 45 |
| 1 | KNKX | 5 | Miramar | 45 |
| 1 | KNKX | 6 | Miramar | 44 |
| 1 | KNKX | 7 | Miramar | 45 |
| 1 | KNKX | 8 | Miramar | 50 |
| 1 | KNKX | 9 | Miramar | 53 |
| 1 | KNKX | 10 | Miramar | 54 |
| 1 | KNKX | 11 | Miramar | 59 |
| 1 | KNKX | 12 | Miramar | 61 |
| 1 | KNKX | 13 | Miramar | 61 |
| 1 | KNKX | 14 | Miramar | 60 |
| 1 | KNKX | 15 | Miramar | 59 |
| 1 | KNKX | 16 | Miramar | 58 |
| 1 | KNKX | 17 | Miramar | 54 |
| 1 | KNKX | 18 | Miramar | 54 |
| 1 | KNKX | 19 | Miramar | 52 |
| 1 | KNKX | 20 | Miramar | 49 |
| 1 | KNKX | 21 | Miramar | 47 |
| 1 | KNKX | 22 | Miramar | 47 |
| 1 | KNKX | 23 | Miramar | 47 |
| 2 | KNKX | 0 | Miramar | 53 |
| 2 | KNKX | 1 | Miramar | 51 |
| 2 | KNKX | 2 | Miramar | 51 |
| 2 | KNKX | 3 | Miramar | 50 |
| 2 | KNKX | 4 | Miramar | 49 |
| 2 | KNKX | 5 | Miramar | 49 |
| 2 | KNKX | 6 | Miramar | 51 |
| 2 | KNKX | 7 | Miramar | 51 |
| 2 | KNKX | 8 | Miramar | 50 |
| 2 | KNKX | 9 | Miramar | 49 |
| 2 | KNKX | 10 | Miramar | 52 |
| 2 | KNKX | 11 | Miramar | 54 |
| 2 | KNKX | 12 | Miramar | 54 |
| 2 | KNKX | 13 | Miramar | 51 |
| 2 | KNKX | 14 | Miramar | 53 |
| 2 | KNKX | 15 | Miramar | 53 |
| 2 | KNKX | 16 | Miramar | 51 |
| 2 | KNKX | 17 | Miramar | 51 |
| 2 | KNKX | 18 | Miramar | 50 |
| 2 | KNKX | 19 | Miramar | 50 |
| 2 | KNKX | 20 | Miramar | 50 |
| 2 | KNKX | 21 | Miramar | 50 |
| 2 | KNKX | 22 | Miramar | 51 |
| 2 | KNKX | 23 | Miramar | 51 |
| 3 | KNKX | 0 | Miramar | 50 |
| 3 | KNKX | 1 | Miramar | 50 |
| 3 | KNKX | 2 | Miramar | 50 |
| 3 | KNKX | 3 | Miramar | 51 |
| 3 | KNKX | 4 | Miramar | 51 |
| 3 | KNKX | 5 | Miramar | 51 |
| 3 | KNKX | 6 | Miramar | 53 |
| 3 | KNKX | 7 | Miramar | 54 |
| 3 | KNKX | 8 | Miramar | 57 |
| 3 | KNKX | 9 | Miramar | 59 |
| 3 | KNKX | 10 | Miramar | 62 |
| 3 | KNKX | 11 | Miramar | 57 |
| 3 | KNKX | 12 | Miramar | 61 |
| 3 | KNKX | 13 | Miramar | 63 |
| 3 | KNKX | 14 | Miramar | 62 |
| 3 | KNKX | 15 | Miramar | 60 |
| 3 | KNKX | 16 | Miramar | 59 |
| 3 | KNKX | 17 | Miramar | 58 |
| 3 | KNKX | 18 | Miramar | 56 |
| 3 | KNKX | 19 | Miramar | 55 |
| 3 | KNKX | 20 | Miramar | 54 |
| 3 | KNKX | 21 | Miramar | 55 |
| 3 | KNKX | 22 | Miramar | 55 |
| 3 | KNKX | 23 | Miramar | 55 |
| 4 | KNKX | 0 | Miramar | 51 |
| 4 | KNKX | 1 | Miramar | 52 |
| 4 | KNKX | 2 | Miramar | 51 |
| 4 | KNKX | 3 | Miramar | 50 |
| 4 | KNKX | 4 | Miramar | 50 |
| 4 | KNKX | 5 | Miramar | 50 |
| 4 | KNKX | 6 | Miramar | 52 |
| 4 | KNKX | 7 | Miramar | 62 |
| 4 | KNKX | 8 | Miramar | 67 |
| 4 | KNKX | 9 | Miramar | 71 |
| 4 | KNKX | 10 | Miramar | 72 |
| 4 | KNKX | 11 | Miramar | 76 |
| 4 | KNKX | 12 | Miramar | 79 |
| 4 | KNKX | 13 | Miramar | 81 |
| 4 | KNKX | 14 | Miramar | 84 |
| 4 | KNKX | 15 | Miramar | 86 |
| 4 | KNKX | 16 | Miramar | 77 |
| 4 | KNKX | 17 | Miramar | 69 |
| 4 | KNKX | 18 | Miramar | 66 |
| 4 | KNKX | 19 | Miramar | 58 |
| 4 | KNKX | 20 | Miramar | 56 |
| 4 | KNKX | 21 | Miramar | 55 |
| 4 | KNKX | 22 | Miramar | 55 |
| 4 | KNKX | 23 | Miramar | 52 |
| 5 | KNKX | 0 | Miramar | 56 |
| 5 | KNKX | 1 | Miramar | 56 |
| 5 | KNKX | 2 | Miramar | 55 |
| 5 | KNKX | 3 | Miramar | 54 |
| 5 | KNKX | 4 | Miramar | 55 |
| 5 | KNKX | 5 | Miramar | 53 |
| 5 | KNKX | 6 | Miramar | 61 |
| 5 | KNKX | 7 | Miramar | 65 |
| 5 | KNKX | 8 | Miramar | 70 |
| 5 | KNKX | 9 | Miramar | 75 |
| 5 | KNKX | 10 | Miramar | 79 |
| 5 | KNKX | 11 | Miramar | 79 |
| 5 | KNKX | 12 | Miramar | 79 |
| 5 | KNKX | 13 | Miramar | 78 |
| 5 | KNKX | 14 | Miramar | 77 |
| 5 | KNKX | 15 | Miramar | 79 |
| 5 | KNKX | 16 | Miramar | 79 |
| 5 | KNKX | 17 | Miramar | 77 |
| 5 | KNKX | 18 | Miramar | 75 |
| 5 | KNKX | 19 | Miramar | 67 |
| 5 | KNKX | 20 | Miramar | 64 |
| 5 | KNKX | 21 | Miramar | 62 |
| 5 | KNKX | 22 | Miramar | 60 |
| 5 | KNKX | 23 | Miramar | 58 |
| 6 | KNKX | 0 | Miramar | 63 |
| 6 | KNKX | 1 | Miramar | 61 |
| 6 | KNKX | 2 | Miramar | 62 |
| 6 | KNKX | 3 | Miramar | 62 |
| 6 | KNKX | 4 | Miramar | 62 |
| 6 | KNKX | 5 | Miramar | 62 |
| 6 | KNKX | 6 | Miramar | 62 |
| 6 | KNKX | 7 | Miramar | 63 |
| 6 | KNKX | 8 | Miramar | 65 |
| 6 | KNKX | 9 | Miramar | 68 |
| 6 | KNKX | 10 | Miramar | 73 |
| 6 | KNKX | 11 | Miramar | 75 |
| 6 | KNKX | 12 | Miramar | 76 |
| 6 | KNKX | 13 | Miramar | 76 |
| 6 | KNKX | 14 | Miramar | 74 |
| 6 | KNKX | 15 | Miramar | 74 |
| 6 | KNKX | 16 | Miramar | 73 |
| 6 | KNKX | 17 | Miramar | 71 |
| 6 | KNKX | 18 | Miramar | 68 |
| 6 | KNKX | 19 | Miramar | 66 |
| 6 | KNKX | 20 | Miramar | 64 |
| 6 | KNKX | 21 | Miramar | 64 |
| 6 | KNKX | 22 | Miramar | 63 |
| 6 | KNKX | 23 | Miramar | 63 |
| 7 | KNKX | 0 | Miramar | 70 |
| 7 | KNKX | 1 | Miramar | 71 |
| 7 | KNKX | 2 | Miramar | 69 |
| 7 | KNKX | 3 | Miramar | 69 |
| 7 | KNKX | 4 | Miramar | 69 |
| 7 | KNKX | 5 | Miramar | 68 |
| 7 | KNKX | 6 | Miramar | 70 |
| 7 | KNKX | 7 | Miramar | 73 |
| 7 | KNKX | 8 | Miramar | 77 |
| 7 | KNKX | 9 | Miramar | 82 |
| 7 | KNKX | 10 | Miramar | 83 |
| 7 | KNKX | 11 | Miramar | 87 |
| 7 | KNKX | 12 | Miramar | 88 |
| 7 | KNKX | 13 | Miramar | 87 |
| 7 | KNKX | 14 | Miramar | 85 |
| 7 | KNKX | 15 | Miramar | 87 |
| 7 | KNKX | 16 | Miramar | 86 |
| 7 | KNKX | 17 | Miramar | 83 |
| 7 | KNKX | 18 | Miramar | 78 |
| 7 | KNKX | 19 | Miramar | 74 |
| 7 | KNKX | 20 | Miramar | 73 |
| 7 | KNKX | 21 | Miramar | 71 |
| 7 | KNKX | 22 | Miramar | 71 |
| 7 | KNKX | 23 | Miramar | 68 |
| 8 | KNKX | 0 | Miramar | 69 |
| 8 | KNKX | 1 | Miramar | 68 |
| 8 | KNKX | 2 | Miramar | 68 |
| 8 | KNKX | 3 | Miramar | 66 |
| 8 | KNKX | 4 | Miramar | 66 |
| 8 | KNKX | 5 | Miramar | 66 |
| 8 | KNKX | 6 | Miramar | 67 |
| 8 | KNKX | 7 | Miramar | 70 |
| 8 | KNKX | 8 | Miramar | 77 |
| 8 | KNKX | 9 | Miramar | 82 |
| 8 | KNKX | 10 | Miramar | 84 |
| 8 | KNKX | 11 | Miramar | 86 |
| 8 | KNKX | 12 | Miramar | 87 |
| 8 | KNKX | 13 | Miramar | 89 |
| 8 | KNKX | 14 | Miramar | 90 |
| 8 | KNKX | 15 | Miramar | 89 |
| 8 | KNKX | 16 | Miramar | 86 |
| 8 | KNKX | 17 | Miramar | 81 |
| 8 | KNKX | 18 | Miramar | 76 |
| 8 | KNKX | 19 | Miramar | 72 |
| 8 | KNKX | 20 | Miramar | 72 |
| 8 | KNKX | 21 | Miramar | 68 |
| 8 | KNKX | 22 | Miramar | 68 |
| 8 | KNKX | 23 | Miramar | 67 |
| 9 | KNKX | 0 | Miramar | 72 |
| 9 | KNKX | 1 | Miramar | 72 |
| 9 | KNKX | 2 | Miramar | 71 |
| 9 | KNKX | 3 | Miramar | 73 |
| 9 | KNKX | 4 | Miramar | 71 |
| 9 | KNKX | 5 | Miramar | 73 |
| 9 | KNKX | 6 | Miramar | 72 |
| 9 | KNKX | 7 | Miramar | 78 |
| 9 | KNKX | 8 | Miramar | 83 |
| 9 | KNKX | 9 | Miramar | 90 |
| 9 | KNKX | 10 | Miramar | 94 |
| 9 | KNKX | 11 | Miramar | 94 |
| 9 | KNKX | 12 | Miramar | 91 |
| 9 | KNKX | 13 | Miramar | 91 |
| 9 | KNKX | 14 | Miramar | 91 |
| 9 | KNKX | 15 | Miramar | 91 |
| 9 | KNKX | 16 | Miramar | 91 |
| 9 | KNKX | 17 | Miramar | 88 |
| 9 | KNKX | 18 | Miramar | 82 |
| 9 | KNKX | 19 | Miramar | 77 |
| 9 | KNKX | 20 | Miramar | 75 |
| 9 | KNKX | 21 | Miramar | 76 |
| 9 | KNKX | 22 | Miramar | 73 |
| 9 | KNKX | 23 | Miramar | 71 |
| 10 | KNKX | 0 | Miramar | 60 |
| 10 | KNKX | 1 | Miramar | 60 |
| 10 | KNKX | 2 | Miramar | 58 |
| 10 | KNKX | 3 | Miramar | 60 |
| 10 | KNKX | 4 | Miramar | 59 |
| 10 | KNKX | 5 | Miramar | 60 |
| 10 | KNKX | 6 | Miramar | 61 |
| 10 | KNKX | 7 | Miramar | 66 |
| 10 | KNKX | 8 | Miramar | 75 |
| 10 | KNKX | 9 | Miramar | 85 |
| 10 | KNKX | 10 | Miramar | 88 |
| 10 | KNKX | 11 | Miramar | 89 |
| 10 | KNKX | 12 | Miramar | 91 |
| 10 | KNKX | 13 | Miramar | 92 |
| 10 | KNKX | 14 | Miramar | 91 |
| 10 | KNKX | 15 | Miramar | 91 |
| 10 | KNKX | 16 | Miramar | 87 |
| 10 | KNKX | 17 | Miramar | 83 |
| 10 | KNKX | 18 | Miramar | 74 |
| 10 | KNKX | 19 | Miramar | 70 |
| 10 | KNKX | 20 | Miramar | 68 |
| 10 | KNKX | 21 | Miramar | 67 |
| 10 | KNKX | 22 | Miramar | 63 |
| 10 | KNKX | 23 | Miramar | 62 |
| 11 | KNKX | 0 | Miramar | 60 |
| 11 | KNKX | 1 | Miramar | 59 |
| 11 | KNKX | 2 | Miramar | 58 |
| 11 | KNKX | 3 | Miramar | 59 |
| 11 | KNKX | 4 | Miramar | 61 |
| 11 | KNKX | 5 | Miramar | 58 |
| 11 | KNKX | 6 | Miramar | 55 |
| 11 | KNKX | 7 | Miramar | 63 |
| 11 | KNKX | 8 | Miramar | 75 |
| 11 | KNKX | 9 | Miramar | 83 |
| 11 | KNKX | 10 | Miramar | 84 |
| 11 | KNKX | 11 | Miramar | 86 |
| 11 | KNKX | 12 | Miramar | 88 |
| 11 | KNKX | 13 | Miramar | 88 |
| 11 | KNKX | 14 | Miramar | 85 |
| 11 | KNKX | 15 | Miramar | 84 |
| 11 | KNKX | 16 | Miramar | 80 |
| 11 | KNKX | 17 | Miramar | 71 |
| 11 | KNKX | 18 | Miramar | 64 |
| 11 | KNKX | 19 | Miramar | 59 |
| 11 | KNKX | 20 | Miramar | 60 |
| 11 | KNKX | 21 | Miramar | 58 |
| 11 | KNKX | 22 | Miramar | 58 |
| 11 | KNKX | 23 | Miramar | 57 |
| 12 | KNKX | 0 | Miramar | 50 |
| 12 | KNKX | 1 | Miramar | 50 |
| 12 | KNKX | 2 | Miramar | 49 |
| 12 | KNKX | 3 | Miramar | 49 |
| 12 | KNKX | 4 | Miramar | 49 |
| 12 | KNKX | 5 | Miramar | 49 |
| 12 | KNKX | 6 | Miramar | 48 |
| 12 | KNKX | 7 | Miramar | 49 |
| 12 | KNKX | 8 | Miramar | 49 |
| 12 | KNKX | 9 | Miramar | 50 |
| 12 | KNKX | 10 | Miramar | 51 |
| 12 | KNKX | 11 | Miramar | 50 |
| 12 | KNKX | 12 | Miramar | 50 |
| 12 | KNKX | 13 | Miramar | 51 |
| 12 | KNKX | 14 | Miramar | 51 |
| 12 | KNKX | 15 | Miramar | 52 |
| 12 | KNKX | 16 | Miramar | 52 |
| 12 | KNKX | 17 | Miramar | 51 |
| 12 | KNKX | 18 | Miramar | 50 |
| 12 | KNKX | 19 | Miramar | 50 |
| 12 | KNKX | 20 | Miramar | 50 |
| 12 | KNKX | 21 | Miramar | 50 |
| 12 | KNKX | 22 | Miramar | 50 |
| 12 | KNKX | 23 | Miramar | 50 |

**Table 11-2 Monthly Peak Temperatures 1 in 10**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Month | WEATHER\_STATION\_ID | Hour | WEATHER\_STATION\_NAME | TEMP\_FAHR |
| 1 | KNKX | 0 | Miramar | 33 |
| 1 | KNKX | 1 | Miramar | 32 |
| 1 | KNKX | 2 | Miramar | 30 |
| 1 | KNKX | 3 | Miramar | 30 |
| 1 | KNKX | 4 | Miramar | 31 |
| 1 | KNKX | 5 | Miramar | 33 |
| 1 | KNKX | 6 | Miramar | 35 |
| 1 | KNKX | 7 | Miramar | 33 |
| 1 | KNKX | 8 | Miramar | 47 |
| 1 | KNKX | 9 | Miramar | 50 |
| 1 | KNKX | 10 | Miramar | 55 |
| 1 | KNKX | 11 | Miramar | 58 |
| 1 | KNKX | 12 | Miramar | 60 |
| 1 | KNKX | 13 | Miramar | 61 |
| 1 | KNKX | 14 | Miramar | 60 |
| 1 | KNKX | 15 | Miramar | 56 |
| 1 | KNKX | 16 | Miramar | 55 |
| 1 | KNKX | 17 | Miramar | 52 |
| 1 | KNKX | 18 | Miramar | 51 |
| 1 | KNKX | 19 | Miramar | 49 |
| 1 | KNKX | 20 | Miramar | 45 |
| 1 | KNKX | 21 | Miramar | 40 |
| 1 | KNKX | 22 | Miramar | 47 |
| 1 | KNKX | 23 | Miramar | 46 |
| 2 | KNKX | 0 | Miramar | 43 |
| 2 | KNKX | 1 | Miramar | 41 |
| 2 | KNKX | 2 | Miramar | 44 |
| 2 | KNKX | 3 | Miramar | 42 |
| 2 | KNKX | 4 | Miramar | 43 |
| 2 | KNKX | 5 | Miramar | 40 |
| 2 | KNKX | 6 | Miramar | 40 |
| 2 | KNKX | 7 | Miramar | 40 |
| 2 | KNKX | 8 | Miramar | 48 |
| 2 | KNKX | 9 | Miramar | 52 |
| 2 | KNKX | 10 | Miramar | 54 |
| 2 | KNKX | 11 | Miramar | 56 |
| 2 | KNKX | 12 | Miramar | 56 |
| 2 | KNKX | 13 | Miramar | 57 |
| 2 | KNKX | 14 | Miramar | 57 |
| 2 | KNKX | 15 | Miramar | 52 |
| 2 | KNKX | 16 | Miramar | 54 |
| 2 | KNKX | 17 | Miramar | 50 |
| 2 | KNKX | 18 | Miramar | 50 |
| 2 | KNKX | 19 | Miramar | 49 |
| 2 | KNKX | 20 | Miramar | 45 |
| 2 | KNKX | 21 | Miramar | 43 |
| 2 | KNKX | 22 | Miramar | 42 |
| 2 | KNKX | 23 | Miramar | 42 |
| 3 | KNKX | 0 | Miramar | 46 |
| 3 | KNKX | 1 | Miramar | 45 |
| 3 | KNKX | 2 | Miramar | 47 |
| 3 | KNKX | 3 | Miramar | 47 |
| 3 | KNKX | 4 | Miramar | 48 |
| 3 | KNKX | 5 | Miramar | 48 |
| 3 | KNKX | 6 | Miramar | 48 |
| 3 | KNKX | 7 | Miramar | 49 |
| 3 | KNKX | 8 | Miramar | 52 |
| 3 | KNKX | 9 | Miramar | 54 |
| 3 | KNKX | 10 | Miramar | 54 |
| 3 | KNKX | 11 | Miramar | 55 |
| 3 | KNKX | 12 | Miramar | 59 |
| 3 | KNKX | 13 | Miramar | 58 |
| 3 | KNKX | 14 | Miramar | 57 |
| 3 | KNKX | 15 | Miramar | 57 |
| 3 | KNKX | 16 | Miramar | 54 |
| 3 | KNKX | 17 | Miramar | 54 |
| 3 | KNKX | 18 | Miramar | 52 |
| 3 | KNKX | 19 | Miramar | 52 |
| 3 | KNKX | 20 | Miramar | 52 |
| 3 | KNKX | 21 | Miramar | 52 |
| 3 | KNKX | 22 | Miramar | 52 |
| 3 | KNKX | 23 | Miramar | 52 |
| 4 | KNKX | 0 | Miramar | 54 |
| 4 | KNKX | 1 | Miramar | 54 |
| 4 | KNKX | 2 | Miramar | 53 |
| 4 | KNKX | 3 | Miramar | 52 |
| 4 | KNKX | 4 | Miramar | 53 |
| 4 | KNKX | 5 | Miramar | 50 |
| 4 | KNKX | 6 | Miramar | 48 |
| 4 | KNKX | 7 | Miramar | 50 |
| 4 | KNKX | 8 | Miramar | 55 |
| 4 | KNKX | 9 | Miramar | 54 |
| 4 | KNKX | 10 | Miramar | 57 |
| 4 | KNKX | 11 | Miramar | 51 |
| 4 | KNKX | 12 | Miramar | 56 |
| 4 | KNKX | 13 | Miramar | 59 |
| 4 | KNKX | 14 | Miramar | 57 |
| 4 | KNKX | 15 | Miramar | 59 |
| 4 | KNKX | 16 | Miramar | 58 |
| 4 | KNKX | 17 | Miramar | 55 |
| 4 | KNKX | 18 | Miramar | 53 |
| 4 | KNKX | 19 | Miramar | 52 |
| 4 | KNKX | 20 | Miramar | 53 |
| 4 | KNKX | 21 | Miramar | 53 |
| 4 | KNKX | 22 | Miramar | 52 |
| 4 | KNKX | 23 | Miramar | 52 |
| 5 | KNKX | 0 | Miramar | 62 |
| 5 | KNKX | 1 | Miramar | 63 |
| 5 | KNKX | 2 | Miramar | 60 |
| 5 | KNKX | 3 | Miramar | 61 |
| 5 | KNKX | 4 | Miramar | 59 |
| 5 | KNKX | 5 | Miramar | 58 |
| 5 | KNKX | 6 | Miramar | 65 |
| 5 | KNKX | 7 | Miramar | 76 |
| 5 | KNKX | 8 | Miramar | 81 |
| 5 | KNKX | 9 | Miramar | 85 |
| 5 | KNKX | 10 | Miramar | 90 |
| 5 | KNKX | 11 | Miramar | 93 |
| 5 | KNKX | 12 | Miramar | 92 |
| 5 | KNKX | 13 | Miramar | 91 |
| 5 | KNKX | 14 | Miramar | 89 |
| 5 | KNKX | 15 | Miramar | 87 |
| 5 | KNKX | 16 | Miramar | 84 |
| 5 | KNKX | 17 | Miramar | 83 |
| 5 | KNKX | 18 | Miramar | 82 |
| 5 | KNKX | 19 | Miramar | 73 |
| 5 | KNKX | 20 | Miramar | 66 |
| 5 | KNKX | 21 | Miramar | 64 |
| 5 | KNKX | 22 | Miramar | 63 |
| 5 | KNKX | 23 | Miramar | 61 |
| 6 | KNKX | 0 | Miramar | 67 |
| 6 | KNKX | 1 | Miramar | 66 |
| 6 | KNKX | 2 | Miramar | 68 |
| 6 | KNKX | 3 | Miramar | 65 |
| 6 | KNKX | 4 | Miramar | 65 |
| 6 | KNKX | 5 | Miramar | 65 |
| 6 | KNKX | 6 | Miramar | 70 |
| 6 | KNKX | 7 | Miramar | 75 |
| 6 | KNKX | 8 | Miramar | 80 |
| 6 | KNKX | 9 | Miramar | 84 |
| 6 | KNKX | 10 | Miramar | 85 |
| 6 | KNKX | 11 | Miramar | 86 |
| 6 | KNKX | 12 | Miramar | 87 |
| 6 | KNKX | 13 | Miramar | 88 |
| 6 | KNKX | 14 | Miramar | 88 |
| 6 | KNKX | 15 | Miramar | 88 |
| 6 | KNKX | 16 | Miramar | 86 |
| 6 | KNKX | 17 | Miramar | 81 |
| 6 | KNKX | 18 | Miramar | 78 |
| 6 | KNKX | 19 | Miramar | 76 |
| 6 | KNKX | 20 | Miramar | 72 |
| 6 | KNKX | 21 | Miramar | 70 |
| 6 | KNKX | 22 | Miramar | 68 |
| 6 | KNKX | 23 | Miramar | 67 |
| 7 | KNKX | 0 | Miramar | 71 |
| 7 | KNKX | 1 | Miramar | 70 |
| 7 | KNKX | 2 | Miramar | 70 |
| 7 | KNKX | 3 | Miramar | 69 |
| 7 | KNKX | 4 | Miramar | 68 |
| 7 | KNKX | 5 | Miramar | 68 |
| 7 | KNKX | 6 | Miramar | 71 |
| 7 | KNKX | 7 | Miramar | 77 |
| 7 | KNKX | 8 | Miramar | 82 |
| 7 | KNKX | 9 | Miramar | 89 |
| 7 | KNKX | 10 | Miramar | 92 |
| 7 | KNKX | 11 | Miramar | 93 |
| 7 | KNKX | 12 | Miramar | 95 |
| 7 | KNKX | 13 | Miramar | 95 |
| 7 | KNKX | 14 | Miramar | 96 |
| 7 | KNKX | 15 | Miramar | 89 |
| 7 | KNKX | 16 | Miramar | 83 |
| 7 | KNKX | 17 | Miramar | 80 |
| 7 | KNKX | 18 | Miramar | 77 |
| 7 | KNKX | 19 | Miramar | 76 |
| 7 | KNKX | 20 | Miramar | 75 |
| 7 | KNKX | 21 | Miramar | 71 |
| 7 | KNKX | 22 | Miramar | 72 |
| 7 | KNKX | 23 | Miramar | 69 |
| 8 | KNKX | 0 | Miramar | 72 |
| 8 | KNKX | 1 | Miramar | 72 |
| 8 | KNKX | 2 | Miramar | 71 |
| 8 | KNKX | 3 | Miramar | 71 |
| 8 | KNKX | 4 | Miramar | 71 |
| 8 | KNKX | 5 | Miramar | 71 |
| 8 | KNKX | 6 | Miramar | 70 |
| 8 | KNKX | 7 | Miramar | 73 |
| 8 | KNKX | 8 | Miramar | 77 |
| 8 | KNKX | 9 | Miramar | 85 |
| 8 | KNKX | 10 | Miramar | 88 |
| 8 | KNKX | 11 | Miramar | 92 |
| 8 | KNKX | 12 | Miramar | 88 |
| 8 | KNKX | 13 | Miramar | 87 |
| 8 | KNKX | 14 | Miramar | 87 |
| 8 | KNKX | 15 | Miramar | 88 |
| 8 | KNKX | 16 | Miramar | 87 |
| 8 | KNKX | 17 | Miramar | 85 |
| 8 | KNKX | 18 | Miramar | 84 |
| 8 | KNKX | 19 | Miramar | 78 |
| 8 | KNKX | 20 | Miramar | 77 |
| 8 | KNKX | 21 | Miramar | 77 |
| 8 | KNKX | 22 | Miramar | 74 |
| 8 | KNKX | 23 | Miramar | 73 |
| 9 | KNKX | 0 | Miramar | 77 |
| 9 | KNKX | 1 | Miramar | 76 |
| 9 | KNKX | 2 | Miramar | 76 |
| 9 | KNKX | 3 | Miramar | 75 |
| 9 | KNKX | 4 | Miramar | 74 |
| 9 | KNKX | 5 | Miramar | 73 |
| 9 | KNKX | 6 | Miramar | 76 |
| 9 | KNKX | 7 | Miramar | 82 |
| 9 | KNKX | 8 | Miramar | 87 |
| 9 | KNKX | 9 | Miramar | 93 |
| 9 | KNKX | 10 | Miramar | 99 |
| 9 | KNKX | 11 | Miramar | 103 |
| 9 | KNKX | 12 | Miramar | 98 |
| 9 | KNKX | 13 | Miramar | 96 |
| 9 | KNKX | 14 | Miramar | 95 |
| 9 | KNKX | 15 | Miramar | 96 |
| 9 | KNKX | 16 | Miramar | 95 |
| 9 | KNKX | 17 | Miramar | 90 |
| 9 | KNKX | 18 | Miramar | 88 |
| 9 | KNKX | 19 | Miramar | 82 |
| 9 | KNKX | 20 | Miramar | 80 |
| 9 | KNKX | 21 | Miramar | 79 |
| 9 | KNKX | 22 | Miramar | 77 |
| 9 | KNKX | 23 | Miramar | 75 |
| 10 | KNKX | 0 | Miramar | 59 |
| 10 | KNKX | 1 | Miramar | 59 |
| 10 | KNKX | 2 | Miramar | 61 |
| 10 | KNKX | 3 | Miramar | 62 |
| 10 | KNKX | 4 | Miramar | 63 |
| 10 | KNKX | 5 | Miramar | 57 |
| 10 | KNKX | 6 | Miramar | 66 |
| 10 | KNKX | 7 | Miramar | 72 |
| 10 | KNKX | 8 | Miramar | 83 |
| 10 | KNKX | 9 | Miramar | 89 |
| 10 | KNKX | 10 | Miramar | 90 |
| 10 | KNKX | 11 | Miramar | 92 |
| 10 | KNKX | 12 | Miramar | 94 |
| 10 | KNKX | 13 | Miramar | 96 |
| 10 | KNKX | 14 | Miramar | 94 |
| 10 | KNKX | 15 | Miramar | 93 |
| 10 | KNKX | 16 | Miramar | 91 |
| 10 | KNKX | 17 | Miramar | 87 |
| 10 | KNKX | 18 | Miramar | 83 |
| 10 | KNKX | 19 | Miramar | 76 |
| 10 | KNKX | 20 | Miramar | 71 |
| 10 | KNKX | 21 | Miramar | 69 |
| 10 | KNKX | 22 | Miramar | 69 |
| 10 | KNKX | 23 | Miramar | 68 |
| 11 | KNKX | 0 | Miramar | 39 |
| 11 | KNKX | 1 | Miramar | 39 |
| 11 | KNKX | 2 | Miramar | 40 |
| 11 | KNKX | 3 | Miramar | 39 |
| 11 | KNKX | 4 | Miramar | 35 |
| 11 | KNKX | 5 | Miramar | 37 |
| 11 | KNKX | 6 | Miramar | 39 |
| 11 | KNKX | 7 | Miramar | 39 |
| 11 | KNKX | 8 | Miramar | 46 |
| 11 | KNKX | 9 | Miramar | 51 |
| 11 | KNKX | 10 | Miramar | 56 |
| 11 | KNKX | 11 | Miramar | 58 |
| 11 | KNKX | 12 | Miramar | 59 |
| 11 | KNKX | 13 | Miramar | 59 |
| 11 | KNKX | 14 | Miramar | 59 |
| 11 | KNKX | 15 | Miramar | 58 |
| 11 | KNKX | 16 | Miramar | 56 |
| 11 | KNKX | 17 | Miramar | 53 |
| 11 | KNKX | 18 | Miramar | 50 |
| 11 | KNKX | 19 | Miramar | 50 |
| 11 | KNKX | 20 | Miramar | 46 |
| 11 | KNKX | 21 | Miramar | 43 |
| 11 | KNKX | 22 | Miramar | 45 |
| 11 | KNKX | 23 | Miramar | 41 |
| 12 | KNKX | 0 | Miramar | 43 |
| 12 | KNKX | 1 | Miramar | 42 |
| 12 | KNKX | 2 | Miramar | 41 |
| 12 | KNKX | 3 | Miramar | 40 |
| 12 | KNKX | 4 | Miramar | 41 |
| 12 | KNKX | 5 | Miramar | 40 |
| 12 | KNKX | 6 | Miramar | 40 |
| 12 | KNKX | 7 | Miramar | 40 |
| 12 | KNKX | 8 | Miramar | 45 |
| 12 | KNKX | 9 | Miramar | 48 |
| 12 | KNKX | 10 | Miramar | 54 |
| 12 | KNKX | 11 | Miramar | 56 |
| 12 | KNKX | 12 | Miramar | 56 |
| 12 | KNKX | 13 | Miramar | 56 |
| 12 | KNKX | 14 | Miramar | 57 |
| 12 | KNKX | 15 | Miramar | 58 |
| 12 | KNKX | 16 | Miramar | 57 |
| 12 | KNKX | 17 | Miramar | 52 |
| 12 | KNKX | 18 | Miramar | 50 |
| 12 | KNKX | 19 | Miramar | 50 |
| 12 | KNKX | 20 | Miramar | 47 |
| 12 | KNKX | 21 | Miramar | 45 |
| 12 | KNKX | 22 | Miramar | 44 |
| 12 | KNKX | 23 | Miramar | 43 |

1. The summer pricing season is May through October for SDG&E. [↑](#footnote-ref-1)
2. Given the limited number of price points per hour, price elasticities can be manually estimated based on the percent change in consumption and percent change in prices. [↑](#footnote-ref-2)
3. In practice, this term is absorbed by the fixed effects, but it is useful for representing the model logic. [↑](#footnote-ref-3)
4. In practice, this term is absorbed by the time effects, but it is useful for representing the model logic. [↑](#footnote-ref-4)
5. For ex-ante estimation, SDG&E split its existing default CPP population into medium and large customers. In contrast, ex-post impacts were reported for all default CPP customers. [↑](#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 May through October for SDG&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. For a comparison of results using various research methods, including RCT/RED designs, statistical matching and within-subjects regression analysis, see the 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-10)
11. Weekend days with more mild weather appeared to have a fundamentally different load profile that did not resemble the event-day load profile. Rather than enhance the regression model to properly account for these days, we opted to exclude them. This allowed us to use a simpler model structure and focus the analysis on the days that were most similar the PTR event day. [↑](#footnote-ref-11)
12. Many weather variables were tested and those used in the model were determined to provide the most accurate prediction of loads. See Appendix A for a description of how weather variables are selected. [↑](#footnote-ref-12)
13. For example, this could be cooling degree days, which are typically defined as MAX[0, (MaxT + MinT) / 2 – 65], where MaxT is the maximum daily temperature in degrees Fahrenheit, MinT is the minimum daily temperature, and 65 degrees is the reference temperature. In some recent evaluations we have replaced the CDD variable with cooling degree hours (CDH). As described in the text, in this study we propose to explore alternatives to the 65-degree reference temperature, as well as other weather variables. In all cases, customer-specific weather variables are calculated using data for the appropriate climate zone. [↑](#footnote-ref-13)
14. The percent budget commitment does not necessarily reflect the amount that will ultimately be spent, since some projects may drop from the PLS program prior to installation (for instance, if the feasibility study indicates that the project would not be cost-effective for the customer). To account for this, the forecast assumes a 10% drop off rate between projects committed and projects actually installed. This drop off rate was assumed to be the same probability for each project size and LCA within each IOU. [↑](#footnote-ref-14)