**Executive Summary of the**

**2012 SDG&E Measurement and Evaluation**

**Load Impact Reports**

**April 1st, 2013**

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# SDG&E’s 2012 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), Critical Peak Pricing Emergency (CPP-E), Base Interruptible Program (BIP), Demand Bidding Program (DBP), Summer Saver program, the residential and small commercial Peak Time Rebate Program (PTR), small commercial technology deployment program (SCTD), and the Permanent Load Shifting program (PLS).[[1]](#footnote-1) This report includes a summary of the ex-ante forecasts for these new demand response activities. The summary ex-ante tables that include the 10-year forecast 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.

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

This report documents the results of an ex post and ex ante load impact evaluation of the Capacity Bidding Program (CBP) of San Diego Gas & Electric (SDG&E), for Program Year 2012. 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. The program is available from May through October and events may be called any time between 11 am and 7 pm. Results for the day-ahead and day-of options were forecasted separately. In this program aggregators contract with commercial and industrial customers to act on their behalf with respect to all aspects of the DR program. This includes receiving notices from the utility, arranging for load reductions on event days, receiving incentive payments, and paying penalties to the utility. Each aggregator forms a “portfolio” of individual customer accounts such that their aggregated load participates in the DR programs.

## CBP Ex-Post Results

There were 78 meters that were nominated in the CBP DA program and 321 meters that were nominated in the CBP DO program during 2012. The table below shows the accounts nominated, percentage load reduction, average customer and aggregate load impact, the temperature, and the nominated load reduction.

****Estimated Ex Post Load Impacts by Event Day  
2012 SDG&E CBP Events****



## CBP evaluation methodology

## 2.3.1 Overview

The primary evaluation method used in the ex post portion of this study involved customer-level regression analysis[[2]](#footnote-2) applied to hourly load data to estimate hourly load impacts. 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. 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 nominated customer. 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, a CBP hour-15 event coefficient of -100 would imply 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.[[3]](#footnote-3)

### 2.3.2 Regression Model

The model shown below was separately estimated for each nominated customer. The table below describes the terms included in the equation.



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 |
| 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 the day’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 | a dummy variable for Monday |
| FRIt | a dummy variable for Friday |
| SUMMERt | a dummy variable for the summer pricing season[[4]](#footnote-4) |
| DTYPEi,t | a series of dummy variables for each day of the week |
| MONTHi,t | a series of dummy variables for each month |
| et | The error term. |

The OtherEvt variables help the model explain load changes that occur on event days 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 price changes.

The model specification shown above has the level of load in a particular hour as the dependent variable.

## CBP Ex-Ante Analysis

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 2010 and 2012.

*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. Therefore, we determined that this method is the most consistent way of reflecting the 1-in-2 and 1-in-10 weather conditions.

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. 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 2010 and 2012 program years. Specifically, we examined only customers enrolled in PY2012, but included available data from the 2010 program year for customers that were also enrolled in that year. This method allowed us to base the ex ante load impacts on a larger sample of events, 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 PY10 and PY12. Within service account, we calculate the average and standard deviation of the load impact across the event days for three hour types: event hours, hours adjacent to events, and all other hours. These values are applied to the simulated reference loads to develop each customer’s hourly load impact forecast.

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 percentages by the three 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 this (i.e., the variance) is added across customers within each required subgroup. Each uncertainty-adjusted scenario was 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.

SDG&E anticipates that nominations and load impacts for CBP DA and DO will remain constant over the forecast period, as shown in table below. Nominations are 81 customer accounts for DA and 381 for DO. Average hourly load impacts are 7.7 MW for DA and 10.4 MW for DO, representing 30 percent and 13 percent of the reference load respectively.

Customer Nominations and Ex Ante Load Impacts for August in a 1-in-2 Weather Year ­ *SDG&E CBP DA and DO*



The table below compares DA and DO load impacts for an August peak day in 1-in-2 and 1-in-10 weather years. There is very little difference between the 1-in-2 and the 1-in-10 load impact estimates because the reference loads were not very weather sensitive.

Average Hourly Load Impacts for an August Peak Day in 1-in-2 and 1-in-10 Weather Years (2013 – 2023) – *SDG&E CBP DA and DO*



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

## CPP-D Rate Description

This report documents the results of a load impact evaluation for program-year 2012 of the SDG&E CPP-D rate. The primary goals of the evaluation were to estimate the hourly ex-post load impacts achieved on each event day and to provide ex-ante forecasts of the load impacts expected to be achieved by CPP-D for 2013-2023. SDG&E implemented CPP-D in 2008 with an “opt-out” provision and bill protection, and began transitioning previous volunteers onto the new default rate.

SDG&E’s default CPP takes on different values for different rate classes. The default CPP rate is a commodity-only rate and customers pay all non-commodity charges according to their otherwise applicable tariff. Customers on SDG&E’s default CPP are allowed to pay a monthly capacity reservation charge (CRC) that limits the amount of their load that is exposed to CPP prices on event days. In addition, customers receive a bill protection guarantee for the first year, during which their bill under default CPP is guaranteed not to exceed what it would have been had they opted out to the new otherwise applicable tariff. Events for the SDG&E CPP-D rate last from 11am-6pm and can be called on any day of the year.

## CPP-D Ex-Post Results

This section summarizes the ex post load impact evaluation for customers on SDG&E’s CPP tariff. SDG&E called seven CPP events in 2012, two of which occurred on Saturdays. The first event occurred on August 9 and the last was held on October 2. On average, there were 1,117 accounts enrolled on SDG&E’s tariff in 2012. There was some variation in enrollment during the course of the summer largely due to typical customer churn, with the highest enrollment at 1,138 participants and the lowest enrollment at 1,103. The participant-weighted average temperature during the event period was 80**°**F for the weekday events and 87**°**F for the weekend event.

The table below shows the estimated ex post load impacts for each event day and for average weekday and weekend events in 2012. The participant-weighted average temperature during the event period ranged from a low of 76°F to a high of 95°F. Percent impacts range from 5.4% to 8.4%, average impacts range from 12.7 kW to 23.5 kW and aggregate impacts range from 14.5 MW to 25.9 MW. On the average weekday event day, the average participant reduced peak period load by 6.0%, or 16.2 kW. In aggregate, SDG&E’s CPP customers reduced load by 18.1 MW on average across the seven weekday events in 2012. On the average weekend event, the average participant reduced load by 6.3%, or 13.9 kW, and the aggregate impact averaged 15.8 MW. As expected for a group of large C&I customers, weekend reference load is lower than weekday reference load. Notably, despite the lower weekend reference load, SDG&E’s CPP customers produced similar percent load reductions on average for weekdays and weekends.

Estimated Ex Post Load Impacts by Event Day  
2012 SDG&E CPP Events

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Event Date | Day of Week | Accounts | Avg. Customer Reference Load (kW) | Avg. Customer Load w/ DR (kW) | Impact (kW) | Aggregate Impact (MW) | Reduction % | Avg. Temp. °F | Daily Maximum Temp. °F |
| 8/9/2012 | Thur | 1,103 | 263.4 | 249.0 | 14.4 | 15.9 | 5.5% | 79.8 | 81.5 |
| 8/11/2012 | Sat | 1,135 | 217.3 | 201.0 | 16.2 | 18.4 | 7.5% | 82.1 | 84.1 |
| 8/14/2012 | Tue | 1,103 | 278.0 | 254.6 | 23.5 | 25.9 | 8.4% | 80.9 | 83.2 |
| 8/21/2012 | Tue | 1,135 | 262.0 | 246.8 | 15.2 | 17.2 | 5.8% | 75.7 | 78.3 |
| 8/30/2012 | Thur | 1,135 | 270.7 | 255.0 | 15.7 | 17.8 | 5.8% | 80.6 | 82.7 |
| 9/15/2012 | Sat | 1,138 | 226.9 | 214.2 | 12.7 | 14.5 | 5.6% | 95.1 | 100.0 |
| 10/2/2012 | Tue | 1,109 | 273.8 | 259.0 | 14.9 | 16.5 | 5.4% | 84.5 | 90.5 |
| **Avg. Weekday Event** | | **1,117** | **269.1** | **252.9** | **16.2** | **18.1** | **6.0%** | **80.4** | **82.9** |
| **Avg. Weekend Event** | | **1,137** | **221.5** | **207.6** | **13.9** | **15.8** | **6.3%** | **87.1** | **90.3** |

## 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. For example, if a resource is weather-sensitive and delivers larger demand reductions on hotter days, ex post events under cooler weather conditions understate the resource’s capability.

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.

2012 load impacts were estimated using two methods:

* Difference-in-differences panel regressions – this method makes use of both an external control group and non-event day data; and

Individual customer regressions – this approach relies on electricity usage patterns for individual customers on non-event days to estimate the reference load for event days. Individual customer regressions are used primarily for comparative purposes in the ex post estimation setting, but as the primary estimation method in the ex ante setting.

Although the estimated load impacts for the average event day are quite similar for both approaches for all three utilities, the primary ex post impacts reported here rely on the difference-in-differences panel regressions. The difference-in-differences approach produces more accurate results for individual CPP days when tested side-by-side with individual customer regressions. In other words, the difference-in-differences method produces individual event day results that are less noisy, but the average impacts across all days are quite similar for the two methods.

In addition to improved accuracy and precision, there are other reasons to use the difference-in-differences method. A control group provides information about how program participants would have used electricity if they were not exposed to CPP event prices and notification. The control groups developed for the 2012 evaluation are nearly identical to CPP participants across observable characteristics and mirror their usage during hot non-event days. Moreover, the difference-in-differences method makes use of both hot non-event days and a control group.

In addition, the difference-in-differences calculation is simpler, transparent and does not require predicting out of sample using models that may suffer from specification error. The difference-in-differences method still works when events are called on nearly all hot days, whereas individual customer regressions have lower accuracy when most or all hot days are event days.

## 3.4 CPP-D Ex Ante Load Impacts

This section presents ex ante load impact estimates for SDG&E's non-residential CPP tariff. These estimates are based on the ex post estimates for 2012 developed using the difference-in-differences approach. Typically, a multi-year analysis is preferable as it helps better define variation in performance across events and the relationship between demand reductions and weather. However, a multi-year analysis with a control group was not representative because only 50% of current CPP customers were both matched and had complete multi-year history of participation on default CPP. In addition, SDG&E experienced cooler weather and called few weekday events in 2010 and 2011 and as a result the loss of information by developing ex ante estimates based on 2012 ex post results alone was minimal. While individual regressions are flexible and can be customized to analyze the event history unique to each customer, they produced inaccurate ex ante impacts for SDG&E: the estimates were too high at hotter temperatures and too low for cooler temperatures.

Two primary steps were required to produce SDG&E’s ex ante estimates. First, reference loads were estimated based on the weather observed in 1-in-2 and 1-in-10 weather year conditions for each month. Next, we applied the average percent demand reduction, by industry, observed in 2012. The averages were used because the 2012 ex post percent reductions using the difference-in-differences method showed little weather sensitivity. In other words, reference loads varied based on temperature and industry mix, while the percent demand reductions were constant across temperature but varied by industry.

The remainder of this section separately presents the ex ante load impact projections for medium and large customers projected to receive service under SDG&E’s default CPP tariff. For simplicity, all current participants are referred to as large, although some currently do not meet the official definition. Load reduction capability is summarized for each segment under annual system peak day conditions for a 1-in-2 and a 1-in-10 weather year for the 2012 to 2023 period. This section presents program level impacts – that is, demand reduction capability is not adjusted for dual enrollment of CPP participants in other DR programs.

## Large C&I Ex Ante Impacts

Overall, 1,144 large customers were enrolled in default CPP in 2012. In total, 76% of current participants have been enrolled on default CPP since 2008 and have experienced 17 weekday events since enrolling.

The table below shows SDG&E’s enrollment projections for large customers through 2023. The forecasted year-to-year change in enrollment is minimal and simply reflects the expected growth of SDG&E’s large customer population.

SDG&E Enrollment Projections for Large CPP Customers   
by Forecast Year and Month

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Forecast Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| 2013 | 0 | 0 | 0 | 1,143 | 1,079 | 1,080 | 1,083 | 1,083 | 1,084 | 1,085 | 1,086 | 1,086 |
| 2014 | 1,090 | 1,091 | 1,091 | 1,092 | 1,095 | 1,096 | 1,096 | 1,097 | 1,100 | 1,102 | 1,103 | 1,104 |
| 2015 | 1,104 | 1,107 | 1,107 | 1,109 | 1,110 | 1,110 | 1,113 | 1,114 | 1,114 | 1,117 | 1,117 | 1,118 |
| 2016 | 1,119 | 1,120 | 1,122 | 1,123 | 1,124 | 1,126 | 1,127 | 1,128 | 1,129 | 1,131 | 1,132 | 1,133 |
| 2017 | 1,135 | 1,136 | 1,137 | 1,138 | 1,140 | 1,141 | 1,142 | 1,144 | 1,145 | 1,146 | 1,148 | 1,149 |
| 2018 | 1,150 | 1,152 | 1,153 | 1,154 | 1,155 | 1,157 | 1,158 | 1,159 | 1,161 | 1,162 | 1,163 | 1,165 |
| 2019 | 1,166 | 1,167 | 1,169 | 1,170 | 1,171 | 1,173 | 1,174 | 1,175 | 1,177 | 1,178 | 1,179 | 1,181 |
| 2020 | 1,182 | 1,184 | 1,185 | 1,186 | 1,188 | 1,189 | 1,190 | 1,192 | 1,193 | 1,194 | 1,196 | 1,197 |
| 2021 | 1,198 | 1,200 | 1,201 | 1,203 | 1,204 | 1,205 | 1,207 | 1,208 | 1,209 | 1,211 | 1,212 | 1,214 |
| 2022 | 1,215 | 1,216 | 1,218 | 1,219 | 1,221 | 1,222 | 1,223 | 1,225 | 1,226 | 1,228 | 1,229 | 1,230 |
| 2023 | 1,232 | 1,233 | 1,235 | 1,236 | 1,237 | 1,239 | 1,240 | 1,242 | 1,243 | 1,244 | 1,246 | 1,247 |
| 2023 | 1,232 | 1,233 | 1,235 | 1,236 | 1,237 | 1,239 | 1,240 | 1,242 | 1,243 | 1,244 | 1,246 | 1,247 |

The table below 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. As mentioned earlier, the results do not reflect adjustments for dual enrollment on other DR programs.

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 2013, 16.7 MW, do not differ substantially from the 2023 forecast, 19.2 MW. On a percentage basis, the demand reductions are identical to those observed in 2012 for the average event, 5.9%, for all forecast years and weather year conditions. The percent demand reduction does not change across forecast years because the industry mix is expected to remain stable. It does not change across weather years because percent demand reductions did not vary with weather for ex post events. The aggregate impact does vary, however, because it reflects higher reference loads under 1-in-10 and 1-in-2 weather year conditions. The differences are minimal. For example, the 2013 1-in-2 weather year impact is forecasted to be 16.7 MW versus 17.2 MW for 1-in-10 weather year conditions.

The portfolio-adjusted load impacts exclude customers dually enrolled in BIP or aggregator programs, which are among the most responsive participants. However, the difference between program and portfolio adjusted impacts for SDG&E is very small, less than 0.1 MWs, due to the small number of dually enrolled customers. In 2012, only 6 of SDG&E’s 1,144 default CPP participants were dually enrolled.

SDG&E August Peak Day CPP Program Load Impacts for Large Customers   
(Hourly Average Reduction in MW Over Event Day Period – 1 PM to 6 PM)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Weather Year | Year | Enrolled Accts (Forecast) | Avg. Reference Load  MW  11 AM–6 PM | Avg. Estimated Load w DR  MW  11 AM–6 PM | Avg. Load impact  MW  11 AM–6 PM | % Load Reduction  MW  11 AM–6 PM | Weighted Temp  MW  11 AM–6 PM |
| 1-in-10 August System Peak Day | 2012 | — | — | — | — | 5.9% | 84.4 |
| 2013 | 1,083 | 291.8 | 274.6 | 17.2 |
| 2014 | 1,097 | 295.5 | 278.1 | 17.4 |
| 2015 | 1,114 | 300.0 | 282.3 | 17.7 |
| 2016 | 1,128 | 303.9 | 286.0 | 17.9 |
| 2017 | 1,144 | 308.1 | 289.9 | 18.1 |
| 2018 | 1,159 | 312.3 | 293.9 | 18.4 |
| 2019 | 1,175 | 316.6 | 298.0 | 18.6 |
| 2020 | 1,192 | 321.0 | 302.1 | 18.9 |
| 2021 | 1,208 | 325.4 | 306.2 | 19.2 |
| 2022 | 1,225 | 329.9 | 310.4 | 19.4 |
| 2023 | 1,242 | 334.4 | 314.7 | 19.7 |
| 1-in-2 August System Peak Day | 2012 | — | — | — | — | 5.9% | 82.0 |
| 2013 | 1,083 | 282.2 | 265.5 | 16.7 |
| 2014 | 1,097 | 285.7 | 268.8 | 16.9 |
| 2015 | 1,114 | 290.1 | 272.9 | 17.2 |
| 2016 | 1,128 | 293.8 | 276.4 | 17.4 |
| 2017 | 1,144 | 297.9 | 280.3 | 17.6 |
| 2018 | 1,159 | 302.0 | 284.1 | 17.9 |
| 2019 | 1,175 | 306.1 | 288.0 | 18.1 |
| 2020 | 1,192 | 310.4 | 292.0 | 18.4 |
| 2021 | 1,208 | 314.6 | 296.0 | 18.6 |
| 2022 | 1,225 | 319.0 | 300.1 | 18.9 |
| 2023 | 1,242 | 323.4 | 304.2 | 19.1 |

## 

## Medium C&I Ex Ante Impacts

For SDG&E, there is more data available on how much load reduction medium customers provide during default CPP events than there is for other utilities. In addition, SDG&E’s expected retention rates for default CPP are better understood than for the other utilities. Medium customers are on the same rate, AL-TOU, as large ones. In addition, SDG&E defaulted roughly 600 medium customer accounts onto CPP between 2008 and 2012, and approximately 400 remained on the rate.

Although SDG&E has more information about medium customer price responsiveness for default CPP, overall, there remains a high degree of uncertainty for both enrollment and demand reductions. The medium customers that were defaulted early are not representative of the general medium C&I population. Medium customers defaulted onto CPP were among the largest medium sized customers and had a disproportionate number of schools. To obtain a larger and more diverse sample of customers for the medium customer price-responsiveness analysis, customers with average annual hourly demand below 200 kW were also included along with medium customers.[[5]](#footnote-5) In other words, customers that are slightly above the large customer threshold were used as a proxy for medium customers. As with large customers, the ex ante impacts were developed solely using 2012 events analyzed using difference-in-differences.

The table below compares the industry mix of the estimating sample to the industry mix expected to remain on default CPP. It also summarizes the percent demand reductions, by industry, for the estimating sample. The ex ante impacts adjust for differences in industry mix between the estimating sample and medium customers.

SDG&E Industry Distribution for Estimating Sample and Medium Population

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Industry | Medium Proxy Accts | % | Medium Population | % | % Demand Reductions  (Medium Proxy Accts) |
|
| Agriculture, Mining & Construction 2 | — | — | 390 | 3.4% | — |
| Manufacturing | 97 | 12.8% | 832 | 7.2% | 9.3% |
| Wholesale & Transport | 113 | 14.9% | 733 | 6.3% | 15.9% |
| Retail Stores | 65 | 8.6% | 1,905 | 16.5% | 11.4% |
| Offices, Hotels, Finance, Services | 188 | 24.8% | 5,334 | 46.1% | 2.8% |
| Schools | 204 | 26.9% | 604 | 5.2% | 1.6% |
| Institutional/Government | 92 | 12.1% | 1,781 | 15.4% | 3.9% |
| 2 Control group matches could not be found for agricultural pumps because nearly all of them opted to remain on CPP or enrolled in other DR programs. | | | | | |
|

The medium customer ex ante impacts includes two additional adjustments. The impacts were adjusted down to reflect expected lower awareness rates among the medium population relative to large 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%. Put differently, depending on the year, the impacts are 70% to 90% of those observed among default CPP participants that are closest to medium customers.

The table below shows SDG&E's enrollment projections for medium customers through 2023. All SDG&E’s medium customers are expected to be defaulted onto CPP in 2014. SDG&E forecasted retention rates to vary by industry in a similar manner as they varied for large 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 2016-2023 reflects the expected growth of SDG&E’s medium customer population.

SDG&E’s Enrollment Projections for Medium   
CPP Customers by Forecast Year and Month

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Forecast 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 | 8,678 | 8,688 | 8,697 | 8,707 | 8,717 | 8,727 | 8,737 | 8,747 |
| 2015 | 8,757 | 8,767 | 8,777 | 8,787 | 7,095 | 7,103 | 7,111 | 7,119 | 7,128 | 7,136 | 7,144 | 7,152 |
| 2016 | 7,160 | 7,168 | 7,176 | 7,185 | 6,752 | 6,760 | 6,768 | 6,775 | 6,783 | 6,791 | 6,799 | 6,806 |
| 2017 | 6,814 | 6,818 | 6,822 | 6,830 | 6,837 | 6,845 | 6,853 | 6,861 | 6,869 | 6,877 | 6,884 | 6,892 |
| 2018 | 6,900 | 6,908 | 6,916 | 6,924 | 6,932 | 6,940 | 6,947 | 6,955 | 6,963 | 6,971 | 6,979 | 6,987 |
| 2019 | 6,995 | 7,003 | 7,019 | 7,027 | 7,035 | 7,043 | 7,051 | 7,059 | 7,067 | 7,075 | 7,083 | 7,092 |
| 2020 | 7,100 | 7,108 | 7,116 | 7,124 | 7,132 | 7,140 | 7,148 | 7,157 | 7,165 | 7,173 | 7,181 | 7,189 |
| 2021 | 7,197 | 7,206 | 7,214 | 7,222 | 7,230 | 7,239 | 7,247 | 7,255 | 7,263 | 7,272 | 7,280 | 7,288 |
| 2022 | 7,297 | 7,305 | 7,313 | 7,322 | 7,330 | 7,338 | 7,347 | 7,355 | 7,363 | 7,372 | 7,380 | 7,389 |
| 2023 | 7,397 | 7,406 | 7,414 | 7,422 | 7,431 | 7,439 | 7,448 | 7,456 | 7,465 | 7,473 | 7,482 | 7,490 |

The table below 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 9-6: Program Annual Peak Day Load Impacts for Medium SDG&E CPP Customers   
(Hourly Average Reduction in MW Over Event Day Period 11 AM to 6 PM)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Weather Year** | **Year** | **Enrolled Accts (Forecast)** | **Avg. Reference Load** | **Avg. Estimated Load w DR** | **Avg. Load impact** | **% Load Reduction** | **Weighted Temp** |
| **MW**  **11 am ­̶ 6 pm** | **MW**  **11 am ­̶ 6 pm** | **MW**  **11 am ­̶ 6 pm** | **MW**  **11 am ­̶ 6 pm** | **MW**  **11 am ­̶ 6 pm** |
| 1-in-10 August System Peak Day | 2013 | - | - | - | - | - | - |
| 2014 | 8,707 | 478.5 | 460.3 | 18.2 | 3.8% | 84.4 |
| 2015 | 7,119 | 388.9 | 371.4 | 17.4 | 4.5% | 84.4 |
| 2016 | 6,775 | 370.1 | 351.4 | 18.7 | 5.0% | 84.4 |
| 2017 | 6,861 | 374.8 | 355.8 | 18.9 | 5.0% | 84.4 |
| 2018 | 6,955 | 379.9 | 360.8 | 19.2 | 5.0% | 84.4 |
| 2019 | 7,059 | 385.6 | 366.1 | 19.5 | 5.0% | 84.4 |
| 2020 | 7,157 | 390.9 | 371.2 | 19.7 | 5.0% | 84.4 |
| 2021 | 7,255 | 396.3 | 376.3 | 20.0 | 5.0% | 84.4 |
| 2022 | 7,355 | 401.7 | 381.5 | 20.3 | 5.0% | 84.4 |
| 2023 | 7,456 | 407.3 | 386.7 | 20.5 | 5.0% | 84.4 |
| 1-in-2 August System Peak Day | 2013 | - | - | - | - | - | - |
| 2014 | 8,707 | 460.5 | 442.8 | 17.6 | 3.8% | 81.9 |
| 2015 | 7,119 | 374.3 | 357.4 | 16.9 | 4.5% | 81.9 |
| 2016 | 6,775 | 356.3 | 338.2 | 18.1 | 5.1% | 81.9 |
| 2017 | 6,861 | 360.8 | 342.4 | 18.3 | 5.1% | 81.9 |
| 2018 | 6,955 | 365.7 | 347.2 | 18.6 | 5.1% | 81.9 |
| 2019 | 7,059 | 371.2 | 352.3 | 18.8 | 5.1% | 81.9 |
| 2020 | 7,157 | 376.3 | 357.2 | 19.1 | 5.1% | 81.9 |
| 2021 | 7,255 | 381.5 | 362.1 | 19.4 | 5.1% | 81.9 |
| 2022 | 7,355 | 386.7 | 367.1 | 19.6 | 5.1% | 81.9 |
| 2023 | 7,456 | 392.1 | 372.2 | 19.9 | 5.1% | 81.9 |

There is a noticeable drop in enrollment between 2014 and 2015, from 8,707 to 7,119 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 2015, 17.6 MW, are very similar to the 2014 forecast, 17.9 MW. The estimated impacts do not decrease substantially for two reasons. First, 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.

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

## 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.

## BIP Evaluation Methodology

This section discusses the methodology that was used to develop ex post load impact estimates for BIP. For demand response resources that have numerous events, regression analysis can be used to estimate the typical (absolute or percentage) load reduction associated with events as a function of event-day conditions (e.g., weather, day-of-week, etc.). These regression models can then be used to predict either ex ante or ex post impacts as a function of the conditions that occurred on those historical days or that are expected to occur on future days on which program events are most likely to be called.

With DR resources for which there is little event history like BIP, this regression-based method cannot be used to predict load reductions because there is not enough empirical event data for estimating the impact coefficients. However, for ex ante load impact estimation purposes, regression analysis can be used to predict the reference load (i.e., the load that would occur in the absence of a program event), and the expected load reductions from those customers given their FSL. For ex post load impact estimation purposes, regression analysis can be used to predict the reference load for the historical event day; the actual metered load for that day can be subtracted from the reference load to estimate the load impact.

For ex ante analysis, the estimated load reduction for BIP is 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 load is estimated using the regression model discussed below. 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. Although the number of events is too small to be used in a regression to predict the load with DR, it can be used to adjust load relative to the FSL. By subtracting the estimated load with DR from the reference load, the ex ante load impact can be estimated.

The regression models used to predict reference loads were developed with the primary goal of accurately predicting the average customer load given time-of-day, day-of-week, month and temperature. Given that all BIP customers are on TOU rates, rate-period variables were also included in the model specification. The estimated models were based on one year of hourly load data for each customer. Individual regressions with all 24 hours included were run for each customer.

The dependent variable in the regression model was the kW load in each hourly interval for each participant. The regression model contained hundreds of 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 when the underlying TOU rates changed during the day and season were also included to capture the change in load due to price variation. The regression model is as follows:

Variable Descriptions

| Variable | Description |
| --- | --- |
| kWt | hourly BIP customer load at time t |
| A | estimated constant term |
| B through M­ij | estimated parameters |
| SummerOnt, SummerMidt, SummerOfft and WinterMidt | binary variables that indicate which TOU rate block is in effect for each hour |
| Houri | 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 |
| DayTypej | series of binary variables representing five different day types (Mon, Tues-Thurs, Fri, Sat, Sunday/Holiday) |
| Monthj | series of binary variables for each month |
| TotalCDHt | total number of cooling degree hours (base 70) per day |
| TotalCDHsqrt | total number of cooling degree hours per day squared |
| TotalHDHt | total number of heating degree hours (base 70) per day |
| TotalHDHsqrt | total number of heating degree hours squared |
| Other\_Eventdayt | binary variable for event days from other DR programs |
| BIP\_Eventdayj | binary variable representing each BIP event day;[[6]](#footnote-6) |
| et | error term |

Load was significantly lower in recent years for many BIP customers due to changes in overall economic conditions. If these conditions were not accounted for in the model, there would be a downward bias in the forecasted reference load for the ex ante analysis, assuming that economic growth rebounds from recent years.

SDG&E BIP load is assumed to remain the same. With so few customers in the program, it is difficult to determine whether a customer experienced a decline in load due to the economic downturn or had a permanent change in their business practices.

## BIP Ex Post Results

SDG&E called a BIP event on September 14 that lasted from 1 PM to 5 PM for all customers. All customers received 30-minute notice of the event. In total, 11 customers participated in the event.

The table below shows the average load impact per customer for all customers. The 11 event participants span across 5 different industry categories[[7]](#footnote-7) and there are 3 of fewer customers within each category, so impacts for specific industries are excluded due to confidentiality.

Average Customer Load Impact for September 14, 2012 SDG&E Event

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Customer Category** | **Number of Customers** | **Ref. Load (kW)** | **Load with DR (kW)** | **Load Reduction (kW)** | **Average FSL (kW)** | **Performance (%)** |
| All Customers | 11 | 267.7 | 191.5 | 76.2 | 42.9 | 33.9 |

The table below shows the aggregate impacts. Customers provided a 28.5% load reduction, which is well short of the 84% load reduction that participants needed in order to reduce usage to the FSL.

Aggregate Load Impact for September 14, 2012 SDG&E Event

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Customer Category** | **Number of Customers** | **Ref. Load (MW)** | **Load with DR (MW)** | **Load Reduction (MW)** | **% Load Reduction** | **FSL (MW)** | **Performance (%)** |
| All Customers | 11 | 2.95 | 2.11 | 0.84 | 28.5 | 0.47 | 33.9 |

## 4.4 BIP Ex Ante Load Impact Estimates

For SDG&E’s over/under performance analysis, data for the 2012 BIP event was used. Data for multiple years was not pooled together, as in SCE’s and PG&E’s over/under performance analysis. No new customers joined or left the program since the 2012 event. Therefore, SDG&E’s over/under performance analysis is based on data for the 11 customers who experienced the 2012 BIP event

Figure 6-3 shows the aggregate load impacts for the 2012 SDG&E BIP event for customers that are still enrolled in the program. Considering that all of the BIP customers were in Option A, curtailment was required from 1 PM to 5 PM. Among the 11 customers that are still enrolled in the program, the aggregate hourly impact during the event period was 0.8 MW and performance was 33.9%. Considering that these customers are identical to the current program, the 33.9% performance value is what was used for the ex ante analysis.

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 | 2013 | 2014 | 2015-2023 |
| 1-in-2 | Typical Event Day | 1-6 PM | 0.80 | 0.80 | 0.80 |
| January Peak | 4-9 PM | 0.54 | 0.54 | 0.54 |
| February Peak | 4-9 PM | 0.54 | 0.54 | 0.54 |
| March Peak | 4-9 PM | 0.58 | 0.58 | 0.58 |
| April Peak | 1-6 PM | 0.96 | 0.96 | 0.96 |
| May Peak | 1-6 PM | 1.04 | 1.04 | 1.04 |
| June Peak | 1-6 PM | 0.97 | 0.97 | 0.97 |
| July Peak | 1-6 PM | 1.06 | 1.06 | 1.06 |
| August Peak | 1-6 PM | 0.81 | 0.81 | 0.81 |
| September Peak | 1-6 PM | 0.90 | 0.90 | 0.90 |
| October Peak | 1-6 PM | 0.72 | 0.72 | 0.72 |
| November Peak | 4-9 PM | 0.60 | 0.60 | 0.60 |
| December Peak | 4-9 PM | 0.59 | 0.59 | 0.59 |
| 1-in-10 | Typical Event Day | 1-6 PM | 0.79 | 0.79 | 0.79 |
| January Peak | 4-9 PM | 0.54 | 0.54 | 0.54 |
| February Peak | 4-9 PM | 0.59 | 0.59 | 0.59 |
| March Peak | 4-9 PM | 0.67 | 0.67 | 0.67 |
| April Peak | 1-6 PM | 0.95 | 0.95 | 0.95 |
| May Peak | 1-6 PM | 1.05 | 1.05 | 1.05 |
| June Peak | 1-6 PM | 0.99 | 0.99 | 0.99 |
| July Peak | 1-6 PM | 1.06 | 1.06 | 1.06 |
| August Peak | 1-6 PM | 0.79 | 0.79 | 0.79 |
| September Peak | 1-6 PM | 0.87 | 0.87 | 0.87 |
| October Peak | 1-6 PM | 0.71 | 0.71 | 0.71 |
| November Peak | 4-9 PM | 0.55 | 0.55 | 0.55 |
| December Peak | 4-9 PM | 0.54 | 0.54 | 0.54 |

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

## Program Description

SDG&E’s 2012 DBP program is limited to customers capable of providing at least 5 MW load reductions during event hours. The baseline is calculating as the usage during the immediately preceding “similar day” prior to the event.[[8]](#footnote-8) The customer is paid $0.50 per kWh below the program baseline. Customers must reduce load by a minimum of 50 percent of their bid amount to qualify for a credit, and they are paid for load reductions up to 150 percent of their bid amount.

## DBP Ex Post Evaluation Methodology

### Overview

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

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

Weather, including hour-specific weather coefficients;

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

The models use the level of hourly demand (kW) as the dependent variable and a separate equation is estimated for each enrolled customer. As a result, the coefficients on the event day/hour variables are direct estimates of the ex post load impacts. For example, a 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.[[9]](#footnote-9)

### Description of method

The model shown below was separately estimated for each enrolled customer. Table 3.1 describes the terms included in the equation.



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 |
| *OtherEvtt* | 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[[10]](#footnote-10) |
| *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.

The model specification shown above has the level of load in a particular hour as the dependent variable. As part of our model validation process, we tested models in which the dependent variable is the difference between the current hour’s load and the load during the same hour on the previous day. We refer to these as models of “differences,” in which these differences are calculated for all of the variables included in the model. Therefore, instead of estimating the equation using Qt as the dependent variable (as in the levels model), the model is estimated using dQt, which is calculated from hourly data as follows:



Every explanatory variable in the estimating equation is transformed in the same fashion and the model is estimated using the differenced data.

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).

## DBP Ex Post Load Impacts

The table below summarizes average hourly reference loads and load impacts at the program level for each of SDG&E’s three DBP events. Across all events, the average hourly load impact was 5.1 MW. The load impacts showed little variation across event days, ranging from 4.6 to 5.4 MW. On average, the load impacts were 50.4 percent of the total reference load.

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 | 8/14/2012 | Tuesday | 9.0 | 3.9 | 5.1 | 57.1% |
| 2 | 9/14/2012 | Friday | 10.6 | 5.2 | 5.4 | 51.4% |
| 3 | 10/2/2012 | Tuesday | 10.5 | 5.9 | 4.6 | 43.7% |
| **Average** | | | **10.0** | **5.0** | **5.1** | **50.4%** |
| **Std. Dev.** | | |  |  | **0.4** | **4.3%** |

The table below compares the bid quantities to the estimated load impacts for each event. The customer bid 5 MW for each event, which was closely matched by the average estimated 5.1 MW load impact. The average bid realization rate (estimated load impacts as a percentage of bid amounts) across all event hours was 101.1 percent.

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 | 8/14/2012 | Tuesday | 5.0 | 5.1 | 103.0% |
| 2 | 9/14/2012 | Friday | 5.0 | 5.4 | 108.8% |
| 3 | 10/2/2012 | Tuesday | 5.0 | 4.6 | 91.7% |
| **Average** | | | **5.0** | **5.1** | **101.1%** |

## 5.4 DBP Ex Ante Evaluation Methodology

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. 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.

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 below describes the terms included in the equation.



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[[11]](#footnote-11) |
| *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.

## 5.5 DBP Ex Ante Load Impacts

SDG&E has requested that its DBP be extended through 2014. It expects that its enrollment will continue to consist of one customer. The table below presents the DBP Aggregate Load Impacts forecast from 2012 thru 2023.

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **SDG&E DBP Program Aggregate Load Impacts (MW)** | | | | | | | | | | | | |
| **(Portfolio, Weather 1in2)** | | | | | | | | | | | | |
| **Year** | **JAN** | **FEB** | **MAR** | **APR** | **MAY** | **JUN** | **JUL** | **AUG** | **SEP** | **OCT** | **NOV** | **DEC** |
| 2012 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2013 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2014 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2015 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2016 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2017 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2018 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2019 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2020 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2021 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2022 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |
| 2023 | 1.71 | 1.13 | 2.45 | 4.58 | 3.36 | 3.17 | 3.72 | 4.60 | 5.54 | 4.97 | 2.96 | 1.07 |

# Summary of SDG&E’s Summer Saver Report

## Summer Saver Program Description

San Diego Gas & Electric Company’s (SDG&E) Summer Saver program is a demand response resource based on air conditioning load control. It is implemented through an agreement between SDG&E and Alternate Energy Resources, formerly known as Comverge, and is currently scheduled to continue through 2016.

The Summer Saver program is available to residential customers and commercial facilities that use up to a maximum of 100 kW on average during a 12-month period. For both residential and commercial customers enrolled in the program, events may be called between May 1 and October 31. Summer Saver is classified as a day-of demand response program and does not notify participating customers when an event is being called. A Summer Saver event may be triggered the day of an event if warranted by temperature and system load conditions. Events may be called at any time between 12pm and 8pm and have a maximum length of 4 hours.

There are four enrollment options each for residential and commercial customers. Residential customers can choose to be cycled 50% or 100% of the time during an event and can have cycling occur only on weekdays or on both weekdays and weekends. The incentive paid for each option varies; the 50% cycling option pays $11.50/ton of CAC capacity and the 100% cycling option pays $46/ton. The 7-day option pays an extra $10 compared to the weekday-only option. Thus, a residential customer with a 4-ton CAC (which is close to the average) would be paid the following under each option:

$46 for the summer for the weekday, 50% cycling option;

$56 for the 7-day, 50% cycling option;

$184 for the weekday only, 100% cycling option; or

$194 for the 7-day, 100% cycling option.

Commercial customers have an option of choosing 30% or 50% cycling, on weekdays only or for seven days a week. The incentive payment equals $9/ton for the 30% cycling option and $15/ton for the 50% cycling option. As for residential customers, the incremental payment for the 7-day a week option compared with the weekday-only option is $10. The average commercial participant has roughly nine enrolled tons of CAC (although some participants have significantly more). As such, the incentive payment for the average commercial customer under each enrollment option is as follows:

$81 for the summer for the weekday, 30% cycling option;

$91 for the 7-day, 30% cycling option;

$135 for the weekday only, 50% cycling option; or

$145 for the 7-day, 50% cycling option.

## Residential Customer Ex Post Methodology

The methods used in the residential portion of the Summer Saver evaluation differ from those used in prior years. Because smart meter data was available for a large sample of residential Summer Saver customers, the evaluation was based on a randomized experiment.

For each of the eight events during summer 2012, roughly half of the 1,379 customers in the residential sample received an event signal while the rest of the customers served as the control group. The group that received the event signal was alternated from event to event. Sample sizes of about 700 customers in each group eliminated the need for more complex regression methods, as were used in previous evaluations. 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 are 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 in the group that did not receive the event. The adjustment is based on the ratio of usage between the treatment and control groups for the five hours prior to the event start. For example, if the average usage in the treatment group during the five hours preceding an event is 1.2 kW, and the average usage in the control group is 1.3 kW, the ratio would be equal to 0.92 (1.2/1.3=0.92) and the control group load for the entire day would be multiplied by 0.92 to more closely match treatment group load. Impact estimates for the entire Summer Saver residential sample for each hour of each event are 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 are calculated from unadjusted treatment and control group load shapes averaged across the six weekday events that contained the common hours of 2 to 4 PM.

## Commercial Customer Ex Post Methodology

The methods used in the commercial portion of the Summer Saver evaluation also differ from those used in prior years, as well as from the methods used for the residential evaluation this year. The commercial customer sample was limited to 393 customers, meaning that there were roughly 200 customers in the control and treatment groups on a given 2012 event day. Due to these small sample sizes and the inherent variability in commercial customer smart meter loads, the results produced using the residential ex post methodology were not plausible. It was instead necessary to use the control and treatment group data in a panel model that also incorporates information from hot non-event days.

A panel model approach to modeling event impacts is different than individual customer regressions in that data from all of the customers is used in a single regression model. Each hour of each event is included as the set of treatment variables in a model of kW usage that controls for temperature effects. Data from non-event days was included in the model estimation; however, this data was limited to the hours during which Summer Saver events occurred and days with maximum temperature equal to or above 80°F. Customer-level fixed effects were used to control for time-consistent characteristics at the customer level and the standard errors from the regression were corrected to account for correlation of observations from the same customer. Models were run separately by cycling option and for weekday and weekend events. A slightly different model that included each applicable event day, but modeled an average hourly effect from the common hours of 2 to 4 PM was used for estimation of average event impacts. In each case, the models included the full panel of data, that is, models were not run separately by hour.

The table below defines the variables in the regression models. The regression specification for estimating the weekday and weekend events is shown first, followed by the similar, but slightly different specification for modeling the average event.

|  |  |
| --- | --- |
|  |  |
|  | (2) |

Description of AC Load Regression Variables

| Variable | Description |
| --- | --- |
|  | Estimated parameter coefficients, indicate the estimated coefficient for event day, d, at time interval, t |
|  | Estimated parameter coefficients, indicate the estimated coefficient for a time interval, t |
|  | Estimated parameter coefficients |
|  | Indicator variables representing whether or not a Summer Saver event occurred for customer, i, on event day, d, at time interval, t |
|  | Indicator variable representing whether or not a Summer Saver event occurred for customer, i, during the hour from 2 to 3 PM |
|  | Indicator variable representing whether or not a Summer Saver event occurred for customer, i, during the hour from 3 to 4 PM |
|  | Average of the first 17 hourly temperature readings from each day, specific to each customer, i, with a value for each time interval, t, corresponding to the daily value |
|  | Error term for each customer, i, for each time interval, t |
|  | Indicator variable for each customer, i, captures customer-level fixed effects |

The estimated event coefficients for each event day and hour were taken as the commercial ex post impacts and the standard errors were used to construct confidence intervals. In the final step, reference loads for each event day and for the average event day were estimated to which the impacts were applied. This was to complete the requirement of a load shape in the Excel-based load impact tables.

## Summer Saver Ex Post Load Impact Estimates

The table below shows the load impacts per CAC unit and in aggregate by cycling option for residential and commercial customers. The average impact per unit is higher for the more intensive cycling options.

|  |  |  |
| --- | --- | --- |
| \*reflects the average 2-hour event from 2-4 PM, omitting the Aug. 10 and Sept. 15 events. |  |  |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Date | Impact | | | Temperature During Event |
| Per CAC Unit (kW) | Per Premise (kW) | Aggregate (MW) |
| 8-Aug-12 | 0.37 | 0.51 | 14 | 86 |
| 10-Aug-12 | 0.50 | 0.67 | 19 | 82 |
| 13-Aug-12 | 0.57 | 0.78 | 21 | 88 |
| 17-Aug-12 | 0.62 | 0.82 | 23 | 87 |
| 13-Sep-12 | 0.33 | 0.46 | 13 | 80 |
| 14-Sep-12 | 0.60 | 0.81 | 23 | 99 |
| 15-Sep-12 | 1.07 | 1.35 | 9 | 95 |
| 1-Oct-12 | 0.49 | 0.65 | 18 | 86 |
| Average\* | 0.52 | 0.70 | 19 | 88 |

It is also important to note the significant differences in usage between cycling options that mask the difference in load impacts between cycling options, particularly for residential customers. Residential customers enrolled on 50% cycling used about 2.5 kW across the hours of 2 to 4 PM on the average event day, while residential customers enrolled on 100% cycling used roughly 2 kW during the same time period. Scaling the 100% cycling results to the 50% cycling loads, the impact for the average event for customers on 100% cycling would be about 0.90 kW. The difference in usage for commercial customers on 30% cycling and 50% cycling during this same time period is about 5%, with customers on the 30% cycling option using slightly more. This does not have a material impact on the results by cycling option for commercial customers.

## Summer Saver Ex Ante Impact Estimation Methodology

Calculating the ex ante load impacts is a multi-step process, but is driven by a straightforward approach to modeling load impacts. In short, load impacts from the previous three years are modeled as a function of temperature and the parameters are used in a regression model to predict load impacts under ex ante weather conditions.

Ex ante load impacts are developed by using the available ex post data. For both residential and commercial customers, load impacts during the overlapping event hours from 2010, 2011 and 2012 from 2 to 4 PM are modeled as a function of the average temperature for the first 17 hours of each event day. Per ton load impacts are used so that load impacts are scalable to ex ante scenarios where the tonnage and number of devices per premise may be different. The models are run separately by customer type (residential or commercial) and cycling strategy and the parameters from the models are used to predict load impacts under 1-in-2 and 1-in-10 ex ante weather conditions. The final regression only includes one explanatory variable because more complicated models were not found to perform better in cross-validation. The model that was used to predict average ex post impacts was:

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

The models described above were used to estimate load impacts based on ex ante event conditions and enrollment projections for the years 2013 through 2023. Enrollment is not expected to change in the future, so the tables in this section represent predictions for the whole period 2013 through 2023. The data represents weather under 1-in-2 and 1-in-10 year conditions for each monthly system peak day.[[12]](#footnote-12) The ex ante event window is from 1 to 6 PM, which is the CPUC resource adequacy window.

The tables below summarize the average and aggregate load impact estimates for residential and commercial customers, respectively. Aggregate impacts are based on steady enrollment levels equal to those as of fall 2012. Load impact estimates are presented for the average AC unit and for each customer segment as a whole.

For a typical event with 1-in-2 year weather conditions, the average impact per AC unit is 0.43 kW for residential customers. The 1-in-10 year typical event day estimate is 19% higher at 0.51 kW. The aggregate program load reduction potential for residential customers is 12 MW for a typical event day under 1-in-2 year weather conditions and 14 MW under 1-in-10 year weather conditions. September ex ante conditions is much hotter than typical conditions. The residential program is estimated to provide an average impact of 20 MW over a 5-hour event on a 1-in-10 September event day.

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 impact estimates. The May and June 1-in-2 impacts for residential customers are only about 25% and 31% of the September estimate, respectively, which is the highest of any month in 1-in-2 year weather conditions. For residential customers, the May and June 1-in-10 year estimates are more than 2.5 times the 1-in-2 year estimates, which is a result of the 1-in-10 temperatures being much warmer than the 1-in-2 temperatures for May and June.

Commercial customers are estimated to provide lower per CAC unit impacts than residential customers. Due to the smaller number of commercial installations in the program, aggregate impacts for the commercial segment are much smaller than for residential customers. The commercial program is expected to provide the highest impact under 1-in-10 conditions in September, when its expected impact is 6 MW.

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 | 0.51 | 0.43 | 14 | 12 |
| May Monthly Peak | 0.38 | 0.15 | 11 | 4 |
| June Monthly Peak | 0.49 | 0.17 | 13 | 5 |
| July Monthly Peak | 0.50 | 0.44 | 14 | 12 |
| August Monthly Peak | 0.52 | 0.42 | 14 | 12 |
| September Monthly Peak | 0.71 | 0.56 | 20 | 16 |
| October Monthly Peak | 0.40 | 0.30 | 11 | 8 |

Summer Saver Commercial 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 | 0.36 | 0.30 | 4 | 4 |
| May Monthly Peak | 0.28 | 0.12 | 3 | 1 |
| June Monthly Peak | 0.33 | 0.13 | 4 | 2 |
| July Monthly Peak | 0.34 | 0.31 | 4 | 4 |
| August Monthly Peak | 0.36 | 0.30 | 4 | 3 |
| September Monthly Peak | 0.49 | 0.40 | 6 | 5 |
| October Monthly Peak | 0.29 | 0.22 | 3 | 3 |

# Peak Time Rebate Program

# 7.1 Program Description

In 2012, all SDG&E residential customers were automatically enrolled in PTR. SDG&E arranged for day-ahead public announcements (e.g., through radio and TV news, and weather features) of PTR events (which are also referred to as “Reduce Your Use” days), and all customers have the opportunity to earn bill credits for usage reductions during event hours. Customers are also encouraged to sign up to receive electronic notification, or alerts, of events through email or text messages (or both).

In addition a group of customers located in the City of San Diego enrolled in the San Diego Energy Challenge (SDEC). The SDEC is a separate effort within the PTR (Reduce Your Use) program that involves a competition among middle schools in the San Diego Unified School District, in which schools earn entries into a sweepstakes for every percentage point of their school population that signs up.

7.2 Ex-Post AnalysisThe evaluation approach involved first designing and selecting samples of customers from two populations of SDG&E residential customers – the approximately 41,000 customers who opted to receive electronic notification, or alerts of PTR events, and the approximately one million non-Summer Saver customers, other than SDEC and alert customers, who did not receive electronic event notification. Customer-level regression equations were then estimated using hourly load data for all of approximately 4,600 SDEC participants, 650 customers with installed In-Home Display (IHD) or Programmable Communicating Thermostat (PCT) devices, and samples of 17,000 opt-in alert customers, and 35,000 customers in the remaining population. These regressions resulted in estimates of hourly load impacts for each analyzed customer, for each of the seven PTR events called in 2012. Results from the estimated equations were then tabulated and summarized for the various requested categories of customers.

The primary overall finding from this study is that, on average, only customers who opted to receive electronic notifications, or alerts, of PTR events reduced their electricity usage during PTR event hours. They did so by relatively small but statistically significant amounts of 0.064 to 0.070 kWh per hour, or 5.0 to 8.5 percent of their reference load.[[13]](#footnote-13) These opt-in alert customers include about 850 of the SDEC customers (the remaining SDEC customers received default email notifications through the program) and 41,000 customers from the general population.[[14]](#footnote-14) Approximately 650 customers with IHD devices also reduced usage in comparable amounts. However, the average customer in the remaining population of more than 1 million customers did not reduce usage by any significant amount.

Table ES–1 summarizes PTR usage impact results for the average event for each of the major relevant SDG&E customer sub-groups, differentiated by climate zone. The first three rows in each panel show usage impacts for: 1) SDEC participants; 2) those customers opting to receive PTR alerts; and 3) those customers with IHD/PCT devices. Overall, those three groups reduced usage on average during PTR events by 2.2, 5.0, and 2.7 percent respectively, relative to their reference loads. The PTR usage impacts for the 2,917 Summer Saver participants who opted to receive PTR alerts are shown in the last line of the “All” results, since those results were not reported by climate zone.

The remaining population of non-opt-in alert customers is divided approximately evenly between those who registered for My Account and those that did not. Little difference was found between these groups, and the average estimated load impacts for both imply usage increases during PTR events. These estimates are not statistically significant, and likely reflect event-day responses to weather conditions or other factors that are not fully explained by the regression equations.



## PTR Ex-Post evaluation methodology

This section discusses technical issues that need to be addressed in the ex post evaluation portion of this study, including sample design and methods for estimating ex post load impacts. Methods for developing the ex ante forecasts are described in Section 7. Sample design was based on customer and usage data provided by SDG&E, and was guided by targeted levels of precision in estimating load impacts. Our approach for conducting the ex post impact evaluation involves exploration and testing of regression-based methods for estimating load impacts for event-based demand response programs. These methods apply regression analysis to hourly load data for populations and samples of participating customers in various groups of interest. Customers’ loads on non-event days are used as controls for their use on event days (i.e., “participant-only” approach). The analysis controls for factors other than PTR events that influence customers’ load profiles, including hour of day, day of week, and weather conditions, and also includes hourly variables that indicate event days. The coefficients on the event variables allow direct estimation of hourly PTR load impacts for each event day.

## Sample Design

The key factors that guided the sample design were the number of characteristics by which the sample should be stratified (e.g., climate zone and customer size), as well as possible separate treatment of certain key population groups (e.g., enrollment in SDEC and presence of IHD), and the required sample sizes. Discussions with SDG&E staff at the PI meeting and subsequently led to the following overall sample design framework:

Summer Saver participants were excluded from the target population and their PTR load response will be estimated in a separate evaluation.

The SDEC participants (approximately 4,600) were treated as a separate “certainty” sample due to their relatively small number and strong interest by SDG&E in load impact results for that group.

The IHD participants (approximately 600) were also treated as a separate “certainty” sample.

The Alert group (about 48,000) was removed from the remaining population and over-sampled to achieve a designed 95/5 degree of confidence and precision.

Net-metering customers with solar installations were also held out of the target population and analyzed separately.

The remaining eligible target population of approximately a million customers was sampled at a rate designed to obtain 90/10 precision at the climate zone level. The sample was stratified by climate zone (Coastal and Inland) and size (small, medium, and high-use customers, based on summer average daily usage). Information on usage variability by climate zone and size obtained from the 2011 PTR pilot, along with population counts from the target population were combined to allocate the sample to strata using Neyman allocation methods.

A control group of SCE customers may be selected in a separate sample design undertaken in conjunction with an impact evaluation of SCE’s PTR program.

The remaining sub-groups of interest (CARE/low-income customers, My Account customers, and Orange County customers) were to be evaluated using the relevant customers of those types that were drawn into the analysis samples or subgroups.

Sample size requirements are generally related to two primary factors: 1) the variability in usage across customers, and 2) the expected size of the event-day usage reductions that need to be estimated. We worked closely with SDG&E staff on the sample design and selection of customers. As described above, CA Energy Consulting designed separate samples of Alert customers and customers in the remaining eligible population, and SDG&E selected customers at random according to the design parameters (i.e., sample sizes and sample strata). The sample sizes and comparable target populations were summarized in Section 2.3.

Level of Analysis

The relatively large number of customer types for which PTR load impact results have been requested suggested that the most straightforward approach to the evaluation would be to use customer-level regression analysis, which allows results for customers to be aggregated into any relevant category.

In a preliminary analysis of SDEC customers, we conducted initial tests of the performance of various possible regression specifications using data for the average customer in four subgroups of participants, differentiated by climate zone (Coastal and Inland) and type of event notification (“Requested PTR Alert” and “SDEC Alert Only”). The regression testing focused on the selection of the most effective set of weather variables. We applied the selected models to data for the average customer in each group to produce preliminary estimates of PTR load impacts by group and event.

Similar testing was conducted for the Alert and “Remaining population” groups, as described in Appendix A. The selected regression models were applied to customer-level data for the customers in each of the certainty subgroups and the samples.

## Estimating Ex post Load Impacts

The model presented below represents the “base” ex post load impact model that was used to estimate hourly impacts for each event day, for the individual customer accounts, 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). The base model is:



The variables are explained in the table below.

|  |  |
| --- | --- |
| **Variable Name / Term** | **Variable / Term Description** |
| *Qt* | the customer’s demand in hour *t* |
| ** and the various **’s | the estimated parameters |
| *hi,t* | a dummy variable for hour *i* |
| *DRt* | an indicator variable for program event days |
| *Wtht* | weather conditions during hour *t* (*e.g.*, measured by CDD, CDH, or THI) |
| *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 |
| *DTi,t* | a dummy variable for day type *i* |
| *MONTHi,t* | a series of dummy variables for each month |
| *SEPi,t* | a dummy variable for the month of September |
| *et* | the error term. |

The first term in the equation that contains the double summation signs is the component of the equation that allows estimation of hourly load impacts (the bEvti coefficients). It does so via the hourly indicator variables hi,t interacted with the event variables (indicated by DRt). 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 day-type indicators with the hourly indicators is designed to account for potentially different hourly load profiles on different days of the workweek and weekends.

We allow for a different hourly profile during the month of September to account for changes in usage patterns that may occur when summer ends and children return to school. The “morning load” variable is used in the same spirit as the optional day-of adjustment to the 10-in-10 baseline method currently used in some DR programs (e.g., Demand Bidding Program). That is, it is intended to adjust the reference load (i.e., the regression-based estimate of the loads that are expected to occur on a given day, including the load that would have occurred on event days if the events had not been called) for unobservable exogenous factors that cause loads to vary from day to day.[[15]](#footnote-15) Finally, the models were estimated using Newey-West standard errors that account for autocorrelation of one hour.

We have tested a variety of specifications to determine the regression model that performs best according to several performance and validity tests. As noted above, these tests are conducted using average-customer data (e.g., by climate zone) rather than at the individual customer level. The model variations and the performance statistics are reported in an appendix.

## PTR Ex-Ante Forecast

This section describes the *ex ante* load impact requirements, methods used, assumptions made, and the resulting load impact forecasts.

## Ex ante Load Impact Requirements

The DR Load Impact Evaluation Protocols require that hourly load impact forecasts for event-based DR resources must be reported at the program level and by Local Capacity Area (LCA)[[16]](#footnote-16) for the following scenarios:

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

under both:

* 1-in-2 weather-year conditions, and
* 1-in-10 weather-year conditions.

at both:

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

The program-level load impacts include load impacts from customers dually enrolled in PTR and Summer Saver. The portfolio-level load impacts exclude customers enrolled in the Summer Saver program.

## Description of Methods

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

### Development of Reference Loads and Load Impacts

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

1. Define data sources
2. Estimate *ex ante* regressions and simulate reference loads by customer group and scenario
3. Calculate percentage load impacts by customer group
4. Apply percentage load impacts to the reference loads
5. Scale the reference loads using enrollment forecasts

Each of these steps is described below.

*Define data sources*

In the *ex ante* forecast, we consider only opt-in alert customers. The majority of these customers are represented by the sample of approximately 17,000 customers. Some additional opt-in alert customers are contained in the sub-set of SDEC customers. These are merged in with the larger sample of customers to represent all opt-in alert PTR customers.

The percentage load impacts that are applied to the reference loads to create hourly load impacts are based upon the *ex post* load impacts from the 2012 *ex post* evaluation. Because the *ex ante* forecast includes non-summer months (*i.e.*, because PTR events may be called in any month of the year) but we do not observe any events during those months, we use information from the Statewide Pricing Pilot (SPP) to adjust the summer load impacts to the conditions in the non-summer months.[[17]](#footnote-17)

*Simulate reference loads*

In order to develop reference loads, we first re-estimated regression equations for the average customer in each cell defined by climate zone, size, and whether the customer was in SDEC. Separate equations were estimated for the summer months of May through October, and for the remaining non-summer months. These equations were then used to simulate reference loads by customer type 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 described in Section 3.3, 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 CDH65 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. Therefore, we determined that this method is the most consistent way of reflecting the 1-in-2 and 1-in-10 weather conditions in the reference loads.

Because PTR 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). Table 6–1 describes the terms included in the equation.



Table 8–1: Descriptions of Terms included in the *Ex ante* Regression Equation

|  |  |
| --- | --- |
| **Variable Name** | **Variable Description** |
| *Qt* | the demand in hour *t* for the modeled customer group |
| The various *b*’s | the estimated parameters |
| *hi,t* | a dummy variable for hour *i* |
| *CDHt* | cooling degree hours |
| *HDHt* | heating degree hours[[18]](#footnote-18) |
| *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. The definitions of the 1-in-2 and 1-in-10 weather years were provided by SDG&E.

*Calculate forecast percentage load impacts*

The *ex ante* percentage load impacts are based on the estimated ex load impacts from the 2012 program year. That is, we calculate the average hourly percentage load impacts across the event days. To account for the effect of changing weather conditions and seasons on customer price responsiveness, we varied the hourly percentage load impacts from the *ex post* typical event day using the estimated elasticity of substitution equations from the SPP. In those equations, the elasticity of substitution varies with the weather conditions (the difference between peak and off-peak cooling degree hours), the central air conditioning saturation rate, and season (summer, winter, and “inner” winter).

Using these SPP equations, we simulated the elasticity of substitution for the *ex post* typical event day using the conditions averaged across the PY2012 event days. We then performed the same calculation for each of the Protocol scenarios. The hourly percentage load impacts for each Protocol scenario were then calculated as the *ex post* typical event day percentage load impacts multiplied by the ratio of the SPP elasticity of substitution for the Protocol day divided by the value for the PY2012 typical event day.

The uncertainty-adjusted scenarios of load impacts were developed using the variability of the percentage load impacts across the event days. Specifically, we calculated the standard deviation of the percentage load impacts for each hour of the typical event day. These values were adjusted using the SPP-based elasticity ratios described above.

Finally, the percentage load impacts are shifted to account for the event windows required by the Protocols, which are 1:00 to 6:00 p.m. from April through October and 4:00 to 9:00 p.m. in all other months. The event window is reduced from the historical window of seven hours to the forecast window of five hours as follows: the 2nd and 3rd hours of the historical window are averaged together to form the 2nd hour of the forecast window; and the 4th and 5th hours of the historical window are averaged together to form the 3rd hour of the forecast window. To account for the timing of the window, the load impacts are shifted back two hours (for April through October) to four hours (for all other months), with zero load impact values inserted at the beginning of the day.

Table 8-2 PTR Enrollment Forecast

|  |  |
| --- | --- |
| **Year** | **August Opt-in Alert Enrollment** |
| 2013 | 63,221 |
| 2014 | 73,221 |
| 2015 | 73,807 |
| 2016 | 74,675 |
| 2017 | 75,522 |
| 2018 | 76,355 |
| 2019 | 77,183 |
| 2020 | 78,003 |
| 2021 | 78,826 |
| 2022 | 79,658 |
| 2023 | 80,499 |

**Table 8-3 PTR Ex-Ante Forecast**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **PTR Ex-Ante Forecast 1 in 2 Weather Year** | | | | | | | | | | | | |
| **Year** | **JAN** | **FEB** | **MAR** | **APR** | **MAY** | **JUN** | **JUL** | **AUG** | **SEP** | **OCT** | **NOV** | **DEC** |
| 2012 | 0.8 | 0.9 | 0.7 | 1.9 | 1.7 | 1.4 | 2.3 | 2.5 | 2.9 | 2.6 | 0.6 | 1.0 |
| 2013 | 0.9 | 0.9 | 0.7 | 2.0 | 2.1 | 1.9 | 3.3 | 3.8 | 4.3 | 3.9 | 0.9 | 1.4 |
| 2014 | 1.2 | 1.3 | 1.0 | 2.9 | 2.7 | 2.3 | 4.0 | 4.4 | 5.0 | 4.5 | 1.0 | 1.7 |
| 2015 | 1.4 | 1.5 | 1.2 | 3.4 | 2.9 | 2.5 | 4.1 | 4.4 | 5.0 | 4.5 | 1.1 | 1.7 |
| 2016 | 1.5 | 1.5 | 1.2 | 3.4 | 2.9 | 2.5 | 4.2 | 4.5 | 5.1 | 4.6 | 1.1 | 1.7 |
| 2017 | 1.5 | 1.5 | 1.2 | 3.4 | 3.0 | 2.5 | 4.2 | 4.5 | 5.1 | 4.6 | 1.1 | 1.7 |
| 2018 | 1.5 | 1.5 | 1.2 | 3.5 | 3.0 | 2.6 | 4.2 | 4.6 | 5.2 | 4.7 | 1.1 | 1.7 |
| 2019 | 1.5 | 1.6 | 1.2 | 3.5 | 3.0 | 2.6 | 4.3 | 4.6 | 5.2 | 4.7 | 1.1 | 1.8 |
| 2020 | 1.5 | 1.6 | 1.3 | 3.6 | 3.1 | 2.6 | 4.3 | 4.7 | 5.3 | 4.8 | 1.1 | 1.8 |
| 2021 | 1.5 | 1.6 | 1.3 | 3.6 | 3.1 | 2.6 | 4.4 | 4.7 | 5.3 | 4.8 | 1.1 | 1.8 |
| 2022 | 1.6 | 1.6 | 1.3 | 3.6 | 3.1 | 2.7 | 4.4 | 4.8 | 5.4 | 4.9 | 1.1 | 1.8 |
| 2023 | 1.6 | 1.6 | 1.3 | 3.7 | 3.2 | 2.7 | 4.5 | 4.8 | 5.5 | 4.9 | 1.1 | 1.8 |

# Small Commercial PTR Program

## Program Description

The SDG&E small commercial PTR program was authorized by the CPUC in resolution E-4502 issued May 29th 2012 due to the fact that both Unit 2 and Unit 3 of SONGS were not operating last summer. Approximately 112,199 small commercial premises were automatically enrolled in the PTR program in July of 2012. In addition, a subset of approximately 341 customers requested to be notified by e-mail or text alert when PTR events occur. The program was scheduled to end on December 31st 2012 and SDG&E is not currently seeking to continue the program past that date.

The PTR program provides small commercial customers the opportunity to earn a bill credit for lowering their consumption during events. For those that receive notification, the program provides customers with day-ahead notification of an event. In emergency situations, an event can be called on a day-of basis, but day-of events are not the primary design or intended use of the program. There is no maximum number of PTR events that can be called, but the incentive payments were designed assuming that an average of nine events would be called each year

The PTR rate is a two-level incentive program, providing a basic incentive level ($0.75/kWh) to customers that reduce energy use through manual means and an additional incentive ($1.25/kWh) to customers that reduce energy use through automated enabling technologies. In 2012 the only customers who were eligible for the enabling technology credit were those enrolled in the Summer Saver program.[[19]](#footnote-19) The incentive is paid to customers through a bill credit that is calculated based on each customer’s event day reduction in electric usage below their established customer-specific reference level (CRL).[[20]](#footnote-20)

After being defaulted onto the rate, customers were provided with a PTR education kit including information on the program, how they can earn a rebate on event days and the benefit of enrolling for event notifications. The intent of the information is to assist customers in achieving the bill credit. The education kit encouraged customers to sign up for day-ahead electronic notifications of event days through e-mail and/or text. The kit also includes information on how to access information about their consumption history, CRL, event performance, and rebate calculation through web presentment, e-mail, and on their energy bill.

## Ex-Post Methodology

### Sample Design

Because there are 107,918 small commercial PTR participants being considered in this evaluation and performing analysis on a population of that size is prohibitive, we used a large sample of participants for the analysis. SDG&E created a new Dynamic Load Profiling (DLP) sample for the small commercial class in summer of 2011. The sample consists of approximately 8,500 customers and was designed using typical stratified random sampling techniques to represent the small commercial population. We decided to use the DLP sample for our analysis of the small commercial PTR program for several reasons:

* The DLP sample customers were distributed relatively proportionally across the subgroups of interest.
* Because the DLP sample customers were part of a load research sample they had more thoroughly validated and complete interval data, especially during the pre-treatment period.
* Using the DLP sample eliminated the need to select a new random stratified sample and submit an interval data request for that sample within the limited time available for this analysis.

### Data Validation

We used a variety of methods to validate the interval data supplied by SDG&E which are consistent with methods of data validation we use in similar evaluation work. We obtained access to interval data (up to 24 months, depending on the installation date of the meter) for each sample participant a total of 8,575 customers[[21]](#footnote-21). We also obtained the VEE codes that indicate if a particular interval was estimated. Consistent with SDG&E’s internal procedures, we first eliminated any estimated data. Because the sample is being used to create the Daily Load Profiles, the data undergoes additional VEE procedures at SDG&E, therefore we expected the data to be high quality and require very little editing or exclusions. This was confirmed when the data was screened for excessive zeros and erroneous values in order to identify participants with problematic data that needed to be excluded from the analysis. We did not eliminate any participants based on these secondary screens.

### Regression Approach

Due to the challenges identified above, isolating and estimating *ex-post* impacts for the small commercial PTR program was difficult, and in most cases our estimates were insignificant and assumed to be zero. However, during this evaluation we used several different methods to attempt to isolate impacts in specific subgroups and to confirm and validate the statistically insignificant results.

A regression based approach was used to estimate the hourly impacts for each of the three subgroups on each event day, however nearly all of those estimates were insignificant. In addition, it is likely that the very few significant estimates we were able to obtain, were merely are result of random variation, rather than a result of actions being taken by customers, a very common phenomenon when making may estimates. Therefore, we also included both a load shape analysis, which is similar to a baseline analysis, and a matched control group analysis for the Opt-in Alert customers. We included the matched control group analysis for the Opt-in customers only because both the regression results and the load shape analysis indicated that those customers might be taking some actions.

We used hourly regression models for each subgroup of interest (Non-Notified, My Account, and Opt-in Alerts) to estimate the effect of a PTR event on customers’ loads. Because the PTR events are called only on isolated days over the course of the program year, and on all other days the participants and non-participants face the same rate, the data conforms nicely to what researchers often call a repeated measures design. This simply means that all participants are subjected to the treatment at the same time, repeatedly over the course of the study. In this case the control can be defined as an absence of the treatment, which includes all non-PTR days. In addition we can use pre-treatment data, prior to participation in the PTR program to isolate any differences that result from the program on non-PTR days and to better isolate the effects of weather and other seasonal variables on usage.

First, we defined the treatment and pre-treatment periods. We defined the treatment period as beginning July 1, 2012 when customers were first defaulted onto the rate, and ending on October 31, 2012. The pre-treatment period will be defined as the 12 months prior to the treatment period, beginning July 1, 2011. We include pre-treatment data so that we can better estimate the effect of the program under a variety of weather conditions and day types.

After establishing a pre and post-treatment period, we evaluated various modeling frameworks for estimating the effect of a PTR event on the participants. In general, the data we used to analyze the participants included both a customer-specific component and a time component. This type of data is generally referred to as panel data and can be modeled in several different ways; however, it is important to recognize that panel data has some inherent issues. When estimating panel data, the variance of the error term is not constant due to correlation within and across individuals. Thus, the Ordinary Least Squares (OLS) is still consistent, but not optimal. For the estimation method we considered employing three different panel estimators: first-differencing (FD), fixed effects (FE), and random effects (RE). A crucial condition of FE and FD is that the independent variables in the model must have variation across each customer. When a full set of customer-specific dummy variables are included, as in our case, the estimation of time-constant variables such as location cannot be included in the model.

The FE estimator assumes that the error term is uncorrelated with the independent variables across all time periods for the time-variant portion of the error term () but allows the time constant portion of the error term ( to be correlated with the explanatory variables in any time period since it will be purged from the equation during estimation. For a large number of observations, and a small number of time periods the choice to use FD or FE lies in the relative efficiency of the estimators determined by the serial correlation in (). When no serial correlation is present, FE is more efficient than FD. Random effects has the additional assumption that is uncorrelated with the explanatory variables across all time periods (a very unlikely case).

Ultimately we decided to use the fixed-effect model with robust errors, which is a common approach for a repeated measures with pre-treatment and post-treatment design using panel data in the industry.[[22]](#footnote-22) A somewhat simplified version of the hourly model specification used to estimate the effects of PTR events for each subgroup is presented in Equation 1 below.

(1)

Where:

= the consumption in hour *j* of customer *i* on day *t.*

= a fixed effect for each customer *i*

= a vector of seasonal indicator variables i.e. month, year, and day of week

= a variable capturing the effect of temperatures above 70 degrees in hour *j*

= a variable capturing the effect of temperatures above 70 degrees in the on-peak period

= a dummy variable that indicates the treatment period

= a dummy variable indicating that day *t* was a PTR event day

= an interaction capturing weather related differences in response to a PTR event

is the error for participant *i* in hour(j) on day *t*

We estimated the model above for each subgroup individually rather than estimating one population level model to limit the complexity of the model by eliminating the interaction terms necessary to distinguish the impacts between each group. In addition we also estimated both a weekday and weekend version of this model in order to estimate the impact of weekend PTR events.

The model specified above allows us to estimate the average impact for each PTR event based on the average temperature during the on-peak period. The impact at a given temperature can be estimated for participants using Equation 2 below.

(2)

Where:

= the effect of a PTR event on usage in hour *j*

= the incremental effect of a PTR event on usage for each CDH during the on-peak period in hour *j*

There are two ways to estimate the impacts of PTR using the model. We can estimate the impact using the parameter estimates as described above, or we can use the model to estimate a baseline, defined as what the customer would have used in the absence of the PTR event, and compare that with what the customer actually used. We believe that the impact estimates using the model will be more consistent. While comparing actual usage to a baseline is appealing in concept, it adds all the error from the model on a particular day into the impact. While this should not systematically bias the estimates, since the errors should be unbiased, it adds variability to the impact estimate. Using the model parameters excludes that error from the impact estimate, so should provide more stable impact estimates.

In this case, we experimented with many different model specifications; however we were unable to estimate consistently statistically significant impacts for any of the subgroups using the model.[[23]](#footnote-23) Therefore it was important to validate the accuracy of the model to ensure that modeling error was not preventing us from capturing the impacts of a PTR event.

When we look at the average precision across all of the hot non-event days the predicted load is within 2.11% of the actual load. The model is generally underestimating the actual load on hot days, which is what we would expect considering that in general, models are most accurate at the mean and least accurate at the extremes. This tendency to underestimate the load would make it difficult for the model to detect very small changes in usage in response to PTR events. So while this level of precision should allow us to pick up changes in usage resulting from a PTR event that are in the 5% range, very small changes in usage are likely to be lost in the model variation and will be very hard to detect.

## Ex-Post Results

After completing three separate analyses of ex-post impacts for the small commercial PTR program, the evaluation resulted in an official estimate of zero impact on an average PTR event day for all three groups. Within the Opt-in Alerts subgroup both the regression analysis and matched control group analysis suggested to presence of small impacts, however the impact across days could not be estimated due to a lack of statistical significance. On individual event days within the Opt-in Alerts group, there are three very small but statistically significant impacts; these impacts are at most 50 kW for the entire group, or about 0.14 kW per customer. Table E-3 shows the impact estimates based on the hourly regression models for each program subgroup, on each event day. The zeros with asterisks in the Opt-in Alert group represent positive impact estimates that were not significant at the 90% level.

Table E- Summary of Program Impacts Across Groups

|  |  |  |  |
| --- | --- | --- | --- |
| **Event Day** | **Average Impact (MW)**  **Non-Notified** | **Average Impact (MW)**  **My Account** | **Average Impact (MW)**  **Opt-In Alerts** |
| 20-Jul-12 | 0 | 0 | 0\* |
| 9-Aug-12 | 0 | 0 | 0.04 |
| 10-Aug-12 | 0 | 0 | 0.05 |
| 11-Aug-12 | 0 | 0 | 0 |
| 14-Aug-12 | 0 | 0 | 0.05 |
| 21-Aug-12 | 0 | 0 | 0\* |
| 15-Sep-12 | 0 | 0 | 0 |
| Average PTR Day | 0 | 0 | 0\* |

The following were identified as key findings during the SmartHours 2012 impact evaluation:

* Based on the results of the regression analysis and the load shape analysis, we can conclude that the Non-Notified participants are not responding to PTR events.
* Again, based on the results of the regression analysis and the load shape analysis, we can conclude that the My Account participants are not responding to PTR events, and may actually be using more on PTR days.
* The analysis for the Opt-in Alert customers was somewhat inconclusive. Based on the regression analysis, some of the PTR events show small reductions in usage, around 3%. However, the matched control group analysis did not show any statistically significant reductions in usage during PTR event days. While our official estimate of savings for the group is zero, the mixed results indicate that one could logically conclude that some participants are likely to be taking action on some days; however the overall effect of such actions is small falling between 1% and 3%.
* Many industry studies have found small commercial customers to be much less price responsive than residential customers on dynamic pricing rates, and they are typically the least targeted for DR programs. Given this information, it is not surprising that we were unable to detect any impacts in this group of customers.

The PCT ex-ante forecast used the weather station for coastal customers and the SDG&E Miramar weather station for inland customers. The weighted average temperatures for the August peak day in a 1 in 2 weather year and a 1 in 10 weather year are shown in Table 9-4 below.

# Small Customer Technology Deployment (SCTD) Program

## Program Description

SDG&E’s Small Customer Technology Deployment (SCTD) Program will offer

DR enabling technologies at no cost to SDG&E residential customers enrolled in PTR or the residential peak shift at home rate. At present, SDG&E plans to deploy meter connected programmable communicating thermostats (PCT) that can be controlled by SDG&E and other enabling technologies are under consideration. SDG&E plans to market the program through contractor driven energy efficiency programs such as the Energy Upgrade CA - Whole House program (EUC-WHP), MIDI, HVAC tune up and the energy savings assistance program. In addition SDG&E plans to market the program directly to high usage customers who have been identified as having significant air-conditioning useage based on their Smart Meter data. SCTD customers receive a PCT at no cost and will earn an incentive of $1.25 for reducing their energy usage during PTR events.

## Forecast Methodology

The goal for this analysis is to use data from a sample of customers known to have air-conditioning to predict load impacts for the proposed PCT load control program. The analysis consists of the following steps:

1. Develop an econometric model of AC load to predict AC usage for ex ante weather conditions;
2. Develop a reasonable assumption for the incremental impact of PCT load control on top of a PTR rate;
3. Apply the assumed load impacts to the calculated reference loads on ex ante weather days for the group of customers selected by the targeting strategy.

SDG&E has maintained an air-conditioner load-research sample (AC LRS) containing 371 customers that is representative of the SDG&E AC-owning residential population. The AC LRS is used as a proxy for the entire AC-owning SDG&E population. For the AC LRS sample, both AC-usage data at an hourly level and whole-building usage data at an hourly level for all of 2009 and through September 2010 were available for analysis. Having both a set of data to use for simulated customer targeting and actual AC loads for the same customers was necessary to perform the analysis. Otherwise there would be no way to predict AC usage levels for the targeted group.

Each customer has a different usage pattern over time, and each customer’s usage is likely to respond differently to changes in weather. This led us to estimate separate regressions for each AC unit in the sample, but using a common regression model in each case. For all AC units, the factors used to estimate usage patterns are weather variables interacted with time indicators. These allow the model to take into account different reactions to weather conditions at different times of day, times of the week and times of year. For example, a residential customer’s energy usage might respond strongly to high temperatures on a Saturday afternoon when they are at home, while it might not respond at all on a Wednesday afternoon when they are at work.The subscript t indicates the particular value at hour t within the whole dataset. Only non-holiday weekdays were modeled. Table 1-1 defines the variables and describes the effects they seek to identify. The regression specification was:

Table 9-1  
Description of AC Load Regression Variables

|  |  |
| --- | --- |
| Variable | Description |
|  | Estimated constant |
|  | Estimated parameter coefficients |
|  | Indicator variables representing the hours of the day, designed to estimate the effect of daily schedule on usage behavior and event impacts |
|  | Indicator variables for summer versus non-summer, designed to pick up seasonal effects |
|  | Indicator variables for weekend days |
|  | Weighted average of the past 6 hours of cooling degree hours using a base of 70. Weights decrease 10% each hour so that most recent temperatures have the highest weight |
|  | The error term, assumed to be mean zero and uncorrelated with any of the independent variables |

Table 1-2 shows the SDG&E enrollment forecast for 2013-2014. Since the program has not been approved for 2015 and beyond enrollment is held constant after 2014. Table 1-3 shows the reference loads. The load impacts were obtained from the reference loads by multiplying them by the expected incremental load impact from the thermostats. The total expected load impact was taken from the 2007 SDG&E smart thermostat pilot which was 38% of air-conditioning load. The percentage load impact of PTR opt-in alert customers was 5% of the whole house load which SDG&E estimates to be 11% of air-conditioning load. Therefore the incremental percentage load impact of the PCT program used is 27% of the reference AC load.

**Table 9-2 SCTD Enrollment Forecast**

|  |  |  |
| --- | --- | --- |
| **Year** | **Month** | **Customers** |
| 2013 | 1 | 0 |
| 2013 | 2 | 0 |
| 2013 | 3 | 0 |
| 2013 | 4 | 0 |
| 2013 | 5 | 0 |
| 2013 | 6 | 0 |
| 2013 | 7 | 211 |
| 2013 | 8 | 422 |
| 2013 | 9 | 633 |
| 2013 | 10 | 844 |
| 2013 | 11 | 1055 |
| 2013 | 12 | 1266 |
| 2014 | 1 | 1477 |
| 2014 | 2 | 1688 |
| 2014 | 3 | 1899 |
| 2014 | 4 | 2110 |
| 2014 | 5 | 2321 |
| 2014 | 6 | 2532 |
| 2014 | 7 | 2743 |
| 2014 | 8 | 2954 |
| 2014 | 9 | 3165 |
| 2014 | 10 | 3376 |
| 2014 | 11 | 3587 |
| 2014 | 12 | 3798 |

Table 9-3   
Air-Conditioning Reference Loads

(Average Customer, Monthly Peak Days)

|  | Average reference loads (kW) | |
| --- | --- | --- |
| 1-in-2 | 1-in-10 |
| May | 1.36 | 1.90 |
| June | 0.74 | 1.47 |
| July | 1.39 | 1.70 |
| August | 1.60 | 1.82 |
| September | 1.87 | 1.99 |
| October | 1.84 | 1.90 |

Table 9-4  
Aggregate Load Impacts (MW)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Small Customer Technology Deployment forecast 1 in 2 Weather Year (MW)** | | | | | | | | | | | | | | |
| **Program** | **Year** | **Weather** | **Jan** | **Feb** | **Mar** | **Apr** | **May** | **Jun** | **Jul** | **Aug** | **Sep** | **Oct** | **Nov** | **Dec** |
| SCTD | 2013 | 1in 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0 | 0 |
| SCTD | 2014 | 1in 2 | 0 | 0 | 0 | 0 | 0.9 | 0.9 | 1 | 1.3 | 1.6 | 1.7 | 0 | 0 |

# Permanent Load Shifting

## PLS Program Overview

As it is currently proposed, the PLS program will provide a one-time incentive payment 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 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 usage data is available.

The incentive 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 adopted for both full and partial storage systems. The proposed incentive levels for the program are $875/kW for PG&E and SCE and $475/kW for SDG&E.

The incentive payments are intended to offset the cost of installation and thereby make the system more attractive financially. Under the proposed rules, the incentive cannot exceed 50% of the installation cost for a given customer, and the incentive for a given site cannot exceed 10% of a given utility’s incentive budget. Customer’s incentive will be determined as the lesser of the incentive reservation amount calculated from the system design or 50% of the actual final installed project cost. In addition, customers will be required to be on a time-of-use (TOU) rate for the first five years after installation. The TOU structure dovetails well with the goals of the PLS program and customers are likely to save money by being on TOU if they have PLS equipment installed.

Customers will be required to commit to running their system for five years after installation, and the utilities expect that the systems will have an expected life of about 20 years.

Customers are required to run the PLS system during all weekday peak periods during summer

## PLS Ex-Ante methodology

Our method begins with estimates of the enrollment for each utility from now until the end of 2014, including the number of sites, the designed peak shift and the geographic distribution of those sites. We have broken this forecast into two categories: sites expected to be installed prior to June 2014 and sites expected to be installed after that. For simplicity, we assume that sites installed after June 2014 will not be operational until the following summer. This simplifying assumption allows us to avoid the false precision of attempting to project site installations precisely at the monthly level. As it is, these projections should be understood to be highly approximate and the distinction between pre-June 2014 and post-June 2014 is mainly meant to illustrate that we expect some installations to take place during or after summer 2014, but prior to the end of the program cycle when the incentive budgets will no longer support new installations.

As a first step, we must know what the weather conditions were that were associated with the demand shift values in the table. The values in the table are forecasts of the amount of demand shifting that each utility expects to pay incentives for. This means that these are expected output from the model used in the engineering feasibility study for each site. Although we do not know with certainty what conditions the engineers performing the study will use to represent peak yearly conditions, based on discussions with PLS program managers and knowledgeable staff, we expect the engineers to use ASHRAE 2% weather conditions for the relevant geography of each site. These conditions are available in the ASHRAE Handbook[[24]](#footnote-24) and they are the conditions we assume underlie the values in Table 2-1.

One detail to note is that the ASHRAE conditions are not specified as 24-hour temperature profiles in the way that ex ante weather conditions are. Instead they are specified as a temperature threshold that would be expected to be exceeded in no more than 2% of hours in a given month. They do not correspond to any particular hours of the day. We therefore make the following assumption about how feasibility study engineers will calculate peak shift values for incentive payments: they will choose the hottest month among the ASHRAE conditions for the relevant geography and then assume that the 2% conditions represent the average temperature during the period 1-6 PM of the peak day which is then used to simulate cooling load.

The next step is to find peak shift values for ex ante weather conditions that are consistent with those in Table 2-1 for ASHRAE 2% weather conditions. We begin with the assumption that the shifted load in Table 2-1 represents the full chiller load of all sites under ASHRAE 2% conditions. An alternative possibility would be that the system is designed to shift only part of the chiller load under peak conditions. This distinction is referred to as full versus partial storage. If the partial storage alternative were true for some sites, then our ex ante impact estimates for cooler weather conditions might be understated because under our assumption, load shift automatically falls as temperature decreases. Under partial storage, the load shift might be constant over some range of ex ante weather conditions at the hotter end of the conditions. Because we begin with the designed peak shift as our main input, and because the designed peak shift takes place under conditions similar to the hottest ex ante conditions, our assumption is unlikely to have a significant effect on the accuracy of load impact estimates under the hottest weather conditions. Additionally, to the degree that it is inaccurate for cooler conditions, it will tend to understate load impacts under those conditions. With this assumption in place, we focus on determining chiller load in a building without worrying about the possibility that not all of it will be shifted.

To find cooling load values for ex ante weather conditions that are consistent with those in for ASHRAE 2% weather conditions, we use Lawrence Berkeley Lab’s Demand Response Quick Assessment Tool (DRQAT) interface with EnergyPlus building simulation software. This software allows us to predict total building cooling load for a chilled water system (including both chiller and fan) based on specified weather conditions, building size, number of stories, orientation (North, South, etc.), number of windows and location. Although we know all the relevant weather conditions that we wish to estimate loads for, we do not know the building characteristics because it is not known which customers will enroll. This model was used to determine how the predicted load impacts vary with weather.

Table 10-1 provides the ex ante impact estimates for peak day conditions during April-October.

The ex-ante forecasts in Table 10-1 focus on load impacts during the peak period. It is important to understand that these impacts represent load that is shifted, not eliminated. This is evident in the excel tables that accompany this report. In those tables, we assume that all avoided peak period load, plus an additional 5%, is consumed during the hours of 9 PM – 6 AM. PLS systems are required to use no more than 5% additional energy than the baseline system. Because not all cooling load comes during the peak period and we have only added 5% to the shifted peak period load, our assumption implies that the 5% limit will be binding for many, but not all sites.

**Table 10-1 PLS Ex-Ante Forecast**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | **April** | **May** | **June** | **July** | **August** | **September** | **October** |
| 2014 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2015 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2016 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2017 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2018 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2019 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2020 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2021 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2022 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |
| 2023 | 540 | 432 | 449 | 655 | 589 | 698 | 733 |

# Critical Peak Pricing Emergency

## Program Overview

Prior to defaulting large C&I customers to CPP-D in 2008, SDG&E offered a voluntary non-residential CPP tariff called Critical Peak Pricing – Emergency (CPP-E). Upon defaulting large customers to CPP-D, SDG&E did not close the legacy CPP-E tariff. However, due to dwindling customer participation, SDG&E proposed closing the rate in its application to the CPUC for 2012-2014 demand response programs and budgets. Later, in light of the protracted SONGS outage particularly affecting southern California, SDG&E later proposed in Advice Letter 2373-E to retain the CPP-E rate through December 31, 2012. The proposal to close CPP-E at the end of 2012 was approved.

## Ex-Post Results

Two CPP-E events were called in 2012, both on weekdays. While technically not a part of the CPP-D program at SDG&E, we present estimated 2012 load impacts for CPP-E customers in Table 6-6 for completeness. Due to the very small number of customers taking this rate, these load impacts were estimated using individual customer regressions.

Table 11-1: Estimated Ex Post Load Impacts by Event Day  
SDG&E 2012 CPP-E Events

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| CPP-E Event | Day of Week | Accounts | Avg. Customer Reference Load (kW) | Avg. Customer Load w/ DR (kW) | Impact (kW) | Aggregate Impact (MW) | Reduction % | Avg. Temp °F | Stat. significant? |
| 8/13/2012 | Mon | 5 | 377.5 | 143.9 | 233.6 | 1.2 | 61.9% | 80.7 | Yes |
| 9/14/2012 | Fri | 5 | 324.6 | 147.6 | 177.0 | 0.9 | 54.5% | 88.2 | Yes |
| Avg. Event | | 5 | 351.1 | 145.8 | 205.3 | 1.0 | 58.5% | 84.4 | Yes |

# Temperatures

The ex-ante forecast temperatures for each month were calculated using weather data from 2013-2011. 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 12-1 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 12-2 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 |
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| 4 | KNKX | 22 | Miramar | 52 |
| 4 | KNKX | 23 | Miramar | 52 |
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| 5 | KNKX | 6 | Miramar | 65 |
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| 5 | KNKX | 8 | Miramar | 81 |
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| 5 | KNKX | 11 | Miramar | 93 |
| 5 | KNKX | 12 | Miramar | 92 |
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| 5 | KNKX | 22 | Miramar | 63 |
| 5 | KNKX | 23 | Miramar | 61 |
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| 6 | KNKX | 12 | Miramar | 87 |
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| 6 | KNKX | 15 | Miramar | 88 |
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| 6 | KNKX | 17 | Miramar | 81 |
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| 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. CPP-E has ex-post results but no ex-ante forecast since it ended in December of 2012. Since SCTD is new it only has an ex-ante forecast and no ex-post results. [↑](#footnote-ref-1)
2. Strictly speaking a regression model was created for each meter however the methodology is commonly referred to as customer-level regression analysis. Throughout the CBP section a customer is defined as one meter. [↑](#footnote-ref-2)
3. 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-3)
4. This is May through September. [↑](#footnote-ref-4)
5. Customers are classified as small, medium and large based on maximum demand levels rather than average demand levels. The size categorization used is based on consumption. As a result, customers with average annual hourly demand of 200 kW include many customers that are classified as large, based on maximum demand levels. [↑](#footnote-ref-5)
6. [↑](#footnote-ref-6)
7. Agriculture, Mining & Construction, Manufacturing, Wholesale, Transport & Other Utilities, Retail Stores and Offices, Hotels, Finance & Services [↑](#footnote-ref-7)
8. “Similar days” exclude weekends, holidays, days when a customer was paid to reduce load, days when load reductions were requested, days when the customer was subject to a DR event, and days on which the customer experienced a rotating outage. [↑](#footnote-ref-8)
9. 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-9)
10. [↑](#footnote-ref-10)
11. 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-11)
12. The typical event day is an hourly average of the weather during the top 9 system load days in a 1-in-2 year and in a 1‑in‑10 year. [↑](#footnote-ref-12)
13. Close examination of customer-level results indicates that approximately 25 to 35 percent of the opt-in alert customers, differentiated by climate zone and size, reduced usage by consistent and statistically significant amounts on the order of 5 to 6 times the magnitude of the average opt-in alert customer. [↑](#footnote-ref-13)
14. Approximately 2,900 Summer Saver participants also opted to receive PTR alerts, and they reduced usage on average by 0.4 kW, or 23 percent, where these greater usage reductions are presumably due in part to their air conditioning usage capacity, which is larger than for non-SS customers. [↑](#footnote-ref-14)
15. The use of the morning load variable assumes that variations in the morning load are related to variations in reference loads later in the day; but that the changes in the morning load are not part of the customer’s response to the event itself (*e.g.*, pre-cooling). If customers do shift usage to morning hours, the presence of the morning variable could produce an upward bias in the load impact estimate. (That is, the reference load will be shifted too high under the assumption that exogenous factors have increased the customer’s reference load.) In our experience, there does not appear to be a significant amount of pre-cooling or other load shifting behavior, at least into hours 1 through 10 on event days, and the presence of the morning load variable has helped to estimate more reasonable load impacts in some difficult cases of highly variable loads. We will continue to examine event-day behavior for the 2012 program year to ensure that this remains the case, and remove the variable if we determine that it is not improving the load impact estimates. [↑](#footnote-ref-15)
16. SDG&E’s entire service area is considered to be one LCA. [↑](#footnote-ref-16)
17. The California SPP included a voluntary CPP rate for residential and small commercial customers, as well as a TOU rate, an information-only component, and a residential enabling technology component. Customers’ price response was modeled by a demand model for which an elasticity of substitution and overall elasticity were estimated. In this study, we used the relevant model for voluntary CPP. [↑](#footnote-ref-17)
18. Heating degree hours (HDH) was defined as MAX[0, 60 – TMP], where TMP is the hourly temperature expressed in degrees Fahrenheit. Customer-group-specific HDH values are calculated using data from the most appropriate weather station. In the non-summer model, CDH variables are also calculated with a threshold of 60 degrees Fahrenheit. [↑](#footnote-ref-18)
19. Load impacts for the summer saver program and the incremental impacts of summer saver over PTR were estimated in the Summer Saver evaluation. Therefore all Summer Saver customers were excluded from this analysis. [↑](#footnote-ref-19)
20. The CRL for a weekday event is defined as the total consumption for the event period averaged over the three highest days from within the immediately preceding five similar non-holiday weekdays prior to the event. The highest days are defined to be the days with the highest total consumption between 11 AM and 6 PM. The similar days will exclude weekends, holidays, other event days, and will exclude other demand response program event days for customers participating in multiple demand response programs. The CRL for a weekend or holiday event is defined as the total consumption during the PTR even period for the highest day from within the immediately preceding three (3) weekend days. [↑](#footnote-ref-20)
21. This total already excludes the Summer Saver, TOU, and Net Metering customers from the sample [↑](#footnote-ref-21)
22. Freeman Sullivan & Co., 2011 Statewide Non-Residential Critical peak Pricing Evaluation, June 1, 2012

    The Brattle Group, BG&E’s Smart Energy Pricing Pilot Summer 2008 Impact Evaluation, April 28 2009

    [↑](#footnote-ref-22)
23. See Chapter 3, Regression Results section, for a table that shows the number of statistically significant event related variables for each population subgroup. [↑](#footnote-ref-23)
24. ASHRAE® Handbook Online: 2009 Fundamentals. [↑](#footnote-ref-24)