

2014 Load Impact Evaluation of San Diego Gas and Electric Company's Commercial Thermostat Program

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# Executive Summary

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

The objectives of the SDG&E 2014 commercial thermostat program load impact evaluation are to:

* Estimate hourly ex post load reductions on 2014 event days (aggregate, per-customer, and per-device levels);
* Estimate ex post load reductions by cycling strategy, and by other customer segments of interest; and

Forecast 2014–2025 thermostat program ex ante load impacts for a 1-in-2 and 1-in-10 weather year by month (aggregate, per-customer level, and per-device levels).

These estimates are incremental to any conservation effect of the thermostats. Estimates of the conservation effect of the thermostats will be provided in an addendum to this report.

As of February 2015, over 9,350 PCTs have been rolled out to roughly 1,200 commercial customers. Enrollment has grown substantially since summer 2014. Across the four events called during summer 2014, enrollment averaged 341 customers and roughly 3,100 thermostats. During the first event, on July 31, 2014, there were 274 enrolled participants; and during the final three events, on September 15, 16, and 17, enrollment equaled 363 participants.

## Ex Post load Impact Summary

Table 1-1 summarizes the average load reduction provided by commercial customers across the four-hour event window from 2 to 6 PM. As shown, the average percent reduction ranged from a low of 4% on September 15and 16 to a high of 8% on July 31. An average reduction of 5% was obtained across the four event days. The average load reduction per thermostat ranged from a low of 0.18 kW to a high of 0.30 kW. Aggregate load reductions ranged from 0.59 MW to 0.77 MW. Aggregate load reductions for the four events averaged 0.68 MW per event.

Table 1-1: 2014 Commercial Thermostat Ex Post Load Impact Estimates (2 to 6 PM)  
(kW per Customer, Aggregate MW, and kW per Thermostat)

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

A common concern about temperature setback strategies is that they result in impacts that decline throughout the event window, given that indoor temperatures will gradually rise to the higher temperature set point. Instead, the results from this study suggest that the impacts for the 50% cycling strategy went down at a faster rate during the events. As shown in Figure 1-1, the per-thermostat impacts for 50% cycling customers decreased from 0.22 kW in the first event hour to 0.05 kW in the last event hour, which was a 77% decline. For 4-degree setback customers, the per-thermostat impacts started higher (at 0.35 kW), but also decreased. However, the percent drop was much lower (43%), and in the final hour of the event, 4-degree setback customers delivered an impact of 0.2 kW per thermostat, which was almost as high as the per-thermostat impacts for 50% cycling customers in the first event hour. Nonetheless, these findings should be inspected more thoroughly as the program expands and more events are called to see if the result still holds.

Figure 1-1: Hourly Per-thermostat Impacts for the Average Event by Cycling Strategy

## Ex Ante load Impact Summary

Currently, there are nearly 1,200 customers enrolled in the commercial thermostat program. This number is expected to gradually increase to 2,013 customers by the end of 2016. From 2017 through 2025, enrollment is expected to remain constant at 2,013 customers. Table 1-2 summarizes the 2017-2025 ex ante load impact estimates by weather year and day type for summer months. The third and sixth columns in the table show the average hourly ex ante load impact per thermostat (kW) over the event period from 2 to 6 PM for each type of weather, followed by the per-customer impact (kW) and the aggregate impact (MW). The first set of rows corresponds to 1-in-2 year weather conditions while the second set covers 1-in-10 year weather conditions. The highest impacts consistently occur on September peak days under both SDG&E and CAISO weather conditions, with aggregate impacts of 5.3 MW in a 1-in-10 year and around 4 MW in a 1-in-2 year.

Table 1-2: 2017-2025 Ex Ante Load Impact Estimates by Weather Year and Day Type   
(kW per Customer, Aggregate MW, and kW per Thermostat)

| Weather Year | Day Type | SDG&E Mean Hourly Impacts (2-6 PM) | | | CAISO Mean Hourly Impacts (2-6 PM) | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Per Thermostat | Per Customer | Aggregate | Per Thermostat | Per Customer | Aggregate |
| (kW) | (kW) | (MW) | (kW) | (kW) | (MW) |
| 1-in-2 | Typical Event Day | 0.15 | 1.49 | 2.99 | 0.16 | 1.58 | 3.17 |
| May Monthly Peak | 0.10 | 0.95 | 1.92 | 0.06 | 0.56 | 1.12 |
| June Monthly Peak | 0.09 | 0.91 | 1.83 | 0.10 | 1.00 | 2.02 |
| July Monthly Peak | 0.15 | 1.48 | 2.98 | 0.13 | 1.32 | 2.67 |
| August Monthly Peak | 0.17 | 1.69 | 3.41 | 0.20 | 1.94 | 3.90 |
| September Monthly Peak | 0.19 | 1.86 | 3.74 | 0.21 | 2.04 | 4.11 |
| October Monthly Peak | 0.13 | 1.30 | 2.62 | 0.09 | 0.86 | 1.73 |
| 1-in-10 | Typical Event Day | 0.22 | 2.19 | 4.40 | 0.20 | 1.97 | 3.96 |
| May Monthly Peak | 0.19 | 1.93 | 3.88 | 0.16 | 1.59 | 3.20 |
| June Monthly Peak | 0.16 | 1.63 | 3.29 | 0.16 | 1.56 | 3.14 |
| July Monthly Peak | 0.22 | 2.19 | 4.41 | 0.17 | 1.64 | 3.31 |
| August Monthly Peak | 0.23 | 2.28 | 4.58 | 0.20 | 2.02 | 4.06 |
| September Monthly Peak | 0.27 | 2.64 | 5.32 | 0.27 | 2.65 | 5.33 |
| October Monthly Peak | 0.20 | 1.98 | 3.98 | 0.17 | 1.72 | 3.47 |

# Introduction

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

The objectives of the SDG&E 2014 commercial thermostat program load impact evaluation are to:

* Estimate hourly ex post load reductions on 2014 event days (aggregate, per-customer, and per-device levels);
* Estimate ex post load reductions by cycling strategy, and by other customer segments of interest; and

Forecast 2014–2025 thermostat program ex ante load impacts for a 1-in-2 and 1-in-10 weather year by month (aggregate, per-customer level, and per-device levels).

These estimates are incremental to any conservation effect of the thermostats. Estimates of the conservation effect of the thermostats will be provided in an addendum to this report.

As of February 2015, over 9,350 PCTs have been rolled out to roughly 1,200 commercial customers. Enrollment has grown substantially since summer 2014. Across the four events called during summer 2014, enrollment averaged 341 customers and roughly 3,100 thermostats. During the first event, on July 31, 2014, there were 274 enrolled participants; and during the final three events, on September 15, 16, and 17, enrollment equaled 363 participants. A few participants are considered residential customers in SDG&E’s records, even though these customers are part of a commercial DR program. These residential premises are located in commercially-managed facilities. This small, unique group accounts for less than 5% of the thermostats in the program. These customers have been segmented for a separate analysis accordingly.

## Report Organization

The remainder of this report proceeds as follows. Section 3 summarizes the ex post methods and validation process. Section 4 provides the 2014 ex post results for all customers and for various segments of the commercial thermostat population. Section 5 focuses on the ex ante evaluation, including the methodology and results. Finally, the report concludes with recommendations for future evaluations.

# Ex Post Methods and Validation

The fundamental problem for estimating load impacts is developing an estimate of the reference load. The reference load is an estimate of what load would have been in the absence of the thermostat control that is in effect for participants. For this evaluation, the focus is on what load would have been on days in which thermostat control was dispatched. The methods used in the commercial thermostat program evaluation rely on the selection of a control group using statistical matching and individual customer regressions, as explained in Sections 3.1 and 3.2, respectively.

The matched control group method used for most of this analysis is superior to a within-subjects analysis (individual customer regressions approach) when there is a large population of non-participating customers to use as a pool for matching and because it eliminates the problem of model misspecification.[[1]](#footnote-1) Any reference load model based on loads observed at non-event times requires the modeler to make assumptions about the relationships between load, time, and temperature. If this assumed function does not reflect the true relationships between load, time, and temperature, then the model can produce incorrect results. In contrast, the matched control group automatically deals with this problem by assuming that the customers who behave similarly to participants during non-event periods would also behave similarly during event periods. This eliminates the need to specify load as a function of weather.

## Matched Control Group Methodology – Commercial

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

The fundamental idea behind the matching process is to find customers who were not subject to events that have similar characteristics to those who were subject to events. The control groups were selected using a propensity score match to find customers who had demand patterns most similar to participants. In this procedure, a probit model is used to estimate a score for each customer based on a set of observable variables that are assumed to affect the decision to participate in the commercial thermostat program. A probit model is a regression model designed to estimate probabilities—in this case, the probability that a customer would choose to participate. The score can be interpreted two different ways. First, the propensity score can be thought of as a summary variable that includes all the relevant information in the observable variables about whether a customer would choose to participate. Each participant is matched with a non-participant that has the closest propensity score. The second way to think of the propensity score is as the probability that a customer will participate based on the included independent variables. Thinking of it this way, each customer in the control group is matched to a participant with a similar probability of participating given the observed variables.

The match was performed for commercial customers within each 2-digit NAICS, climate zone, and month. It was based on a set of variables that characterize usage in the middle of the day on two hot non-event days in the same month as the events. The set of usage variables in the propensity score model were the average usage from 10 AM to 6 PM on each of the two hot non-event days.[[2]](#footnote-2) These days were chosen because they were the only days with temperatures that closely reflected those on event days. Many matching models were tested and the final model was chosen because it resulted in the closet match between participants and control customer average usage during event hours on hot, non-event days (discussed below). A match was found for each participant, but the same control customer could be matched to multiple participants, meaning that a control customer could be represented more than once in the control group.

Figure 3-1 shows average hourly usage for participants and matched control customers on hot, non-event days. Though there are differences between average participant and control group demand, we ran a *t* test for these differences and found that they are not statistically significant in the aggregate.

Figure 3-1: Average Usage per Customer on Hot, Non-event Days for   
Commercial Thermostat Customers and the Control Group



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

Equation 3-1: Specification of Difference-in-Differences Reference Load

Table 3-2: Variables Used for Difference-in-differences Calculation

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

Figure 3-2 illustrates the change in usage from hot non-event days to event days for participants and control group customers. As in Figure 3-1, the control group load on hot, non-event days is higher than participant load, but the increase in usage from hot non-event days to event days is larger for participants than for non-participants. The primary assumption behind the difference-in-differences method is that any factor that could impact load and changes from non-event days to event days affects participants and control group customers equally. Since there is little evidence that participants are changing their behavior in the hours before events, an additional adjustment was made to correct for pre-event load patterns. This additional adjustment controlled for the higher level of weather sensitivity among participants, relative to the matched control group.

Figure 3-2: Average Usage per Customer on Hot, Non-event Days and Event Days for  
Participants and Control Group Customers



The adjustment factor is calculated using average load in pre-event period from 9 AM to 2 PM. Once the adjustment is calculated, it is applied to the reference load to get an adjusted reference load for the hours from 10 AM to 7 PM, in order to correct for the difference in weather sensitivities. These hours were chosen for the adjustment because they are the hours with the most variable load, during which participants are more sensitive to the differences in weather between the event days and hot non-event days. Though this adjustment is a small part of overall load, it is important for calculating the true impact since the impacts are also a small part of the overall load, especially for commercial premises that have many other end uses. Equation 3-2 summarizes the adjustment calculation and Table 3-3 provides the definitions for variables in the equation.

Equation 3-2: Specification of Adjusted Reference Load

Table 3-3: Variables Used for Adjustment Calculation

| Variable | Description |
| --- | --- |
| *adjref* | Adjusted reference load (kW) |
| *ref* | Unadjusted reference load (kW) |
| *kW* | Average demand from 9 AM to 2PM |
| *p* | Indicates whether a customer is a participant (p=1) or a control group member (p=0) |
| *e* | Indicates whether a given day was an event (e=1) or not (e=0) |
| *i* | Indexes the participants along with their matched control customer |
| *d* | Indexes the event days and their corresponding average proxy day, September proxies for September events, July proxies for July events |
| *h* | Indexes the hour |

Figure 3-3 illustrates the differences between the actual load for the control group and the reference load predicted by the model. The blue line shows the participant usage and the red line shows the unadjusted control group usage. The green line shows the unadjusted reference load, which clearly under predicts impacts, due to the difference in weather sensitivities between the participant group and the control group. Finally, the orange line shows the adjusted reference load, which matches nearly exactly with the participant group load for all hours leading up to the event. After the adjustment, impact estimates are calculated by subtracting average hourly usage on each event day for the adjusted reference load from average hourly participant usage on each event day.

Figure 3-3: Example of Control Group Usage Adjustment;   
Average Event Day



## Individual Customer Regression Methodology – Residential

For the small group of customers that are considered residential premises in SDG&E’s records, even though they are located on commercially-managed properties, individual customer regressions were used to estimate load impacts. It would have been time-consuming and very difficult (if not impossible) to find an appropriate control group for this small, unique group that accounts for less than 5% of the thermostats in the program, so this within-subjects approach was used instead. The regression model used is specified in Equation 3-3, and the variable definitions are provided in Table 3-4. The customers for whom we used the individual customer regression methodology are very difficult to accurately model because data on when the units are and are not occupied is not available. We validated many models using the same hot non-event days we used to construct the matched control groups, and chose this as the best performing model.

Equation 3-3: Model Specification for Individual Customer Regressions

Table 3-4: Variables Used for Individual Customer Regressions

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

# 2014 Ex Post Load Impacts

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

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

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

SDG&E called four events during summer 2014. During the first event, on July 31, 2014, there were 274 enrolled participants; and during the final three events, on September 15, 16, and 17, enrollment equaled 363 participants. The next two sections summarize the results for commercial customers. The final section shows the average event impacts for the small number of residential customers that are located on commercially-managed properties.

## Average Event Impacts – Commercial

Figure 4-1 shows the hourly load impacts for the average commercial customer across the four event days. The number of enrolled customers, 343, is the average number of enrolled commercial customers across the four event days. The average impact per customer for all events across the 4-hour event window was nearly 2 kW, or 5.1% of the whole building load. The percentage load reduction was relatively constant across the hours, with only a slight decline throughout the event. However, the kW impact declined throughout the event due to the decrease in the reference load, which is typical for commercial load from 2 to 6 PM. The reference load decreased from a high of 43 kW in the first event hour to a low of 34 kW in the final event hour. In the evening hours following the end of the event, there was a slight increase in electricity consumption relative to the reference load.

Figure 4-1: Commercial Thermostat Program Load Impact (kW) per Hour for the Average 2014 Event Day   
(Average Commercial Participant) 

Table 4-1 summarizes the average load reduction provided by commercial customers across the four-hour event window from 2 to 6 PM. As shown, the average percent reduction ranged from a low of 4% on September 15and 16 to a high of 8% on July 31. An average reduction of 5% was obtained across the four event days. The average load reduction per thermostat ranged from a low of 0.18 kW to a high of 0.30 kW. Aggregate load reductions ranged from 0.59 MW to 0.77 MW. Aggregate load reductions for the four events averaged 0.68 MW per event.

Table 4-1: 2014 Commercial Thermostat Ex Post Load Impact Estimates (2 to 6 PM)  
(kW per Customer, Aggregate MW, and kW per Thermostat)

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

## Load Impacts for Specific Customer Segments - Commercial

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

### Load Impacts by Climate Zone

SDG&E’s service territory has limited climatic diversity, but the variation in temperature and AC use has a real impact on many customers’ loads on summer days when the ocean breeze cools off the coast and leaves customers further inland hot. Participants in the commercial thermostat program as of the 2014 summer come from one of two climate zones – Coastal and Inland. Table 4-2 shows the average hourly load impacts for these two climate zones. These estimates are based on the same methodology involving statistically matched control groups as was used to develop the program level load impacts. The Inland climate zone is hotter, has higher AC usage, and accordingly produced higher load impacts per thermostat. The per-thermostat impact is 20% higher in the Inland climate zone than in the Coastal climate zone. The sample sizes for the 2014 commercial thermostat ex post analysis were fairly small, so this difference in per-thermostat impacts was not statistically significant. Given that the program has grown substantially since summer 2014, future load impacts may produce a statistically significant difference in per-thermostat impacts by climate zone.

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

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

### Load Impacts by Industry

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

Table 4-3 shows the average load reduction by industry. Some industries are left out of the table altogether due to insufficient sample sizes. Given the sample size, the most reliable estimate for any industry breakout is that for Offices, Hotels, Finance, and Services. The per-thermostat impact for this industry was 0.13 kW, nearly 41% lower than the estimate for the average commercial customer (0.22 kW per thermostat). The average event-day temperature for participants in this industry was nearly the same as the average event-day temperature for the average commercial customer, indicating that the higher impact per thermostat among these customer was most likely not due to weather conditions. Since there are relatively few customers in the other industries, it is difficult to assess why this industry underperformed other industries and whether it will continue to in the future. It is, instead, just a sign that there may be other industries that can be targeted to achieve greater per-thermostat savings.

Table 4‑3: 2014 Commercial Thermostat Average Hourly Load Reduction   
for Event Period (2 to 6 PM) by Industry   
(kW per Customer, Aggregate MW, and kW per Thermostat)

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

### Load Impacts by Cycling Strategy

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

Table 4‑4: 2014 Commercial Thermostat Average Hourly Load Reduction   
for Event Period (2 to 6 PM) by Cycling Strategy   
(kW per Customer, Aggregate MW, and kW per Thermostat)

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

A common concern about temperature setback strategies is that they result in impacts that decline throughout the event window, given that indoor temperatures will gradually rise to the higher temperature set point. Instead, the results from this study suggest that the impacts for the 50% cycling strategy went down at a faster rate during the events. As shown in Figure 4-2, the per-thermostat impacts for 50% cycling customers decreased from 0.22 kW in the first event hour to 0.05 kW in the last event hour, which was a 77% decline. For 4-degree setback customers, the per-thermostat impacts started higher (at 0.35 kW), but also decreased. However, the percent drop was much lower (43%), and in the final hour of the event, 4-degree setback customers delivered an impact of 0.2 kW per thermostat, which was almost as high as the per-thermostat impacts for 50% cycling customers in the first event hour. Nonetheless, just as the overall differences may have been partly due to pre-existing differences in the customer mix, these findings should be taken as provisional and inspected more thoroughly as the program expands and more events are called to see if the result still holds.

Figure 4-2: Hourly Per-thermostat Impacts for the Average Event by Cycling Strategy

### Load Impacts by Source

The commercial thermostat customers came from one of two different internal sources within SDG&E – Demand Response and Direct Install. Table 4-5 shows the average hourly load reduction by source. Many more commercial customers were signed up through Demand Response (262) than through Direct Install (78), and many more thermostats were signed up through Demand Response (2,849) than Direct Install (232). Nonetheless, the two customer groups provided very similar per-thermostat response.

Table 4‑5: 2014 Commercial Thermostat Average Hourly Load Reduction   
for Event Period (2 to 6 PM) by Source within SDG&E  
(kW per Customer, Aggregate MW, and kW per Thermostat)

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

## Average Event Impacts – Residential

As discussed above, a few participants are considered residential customers in SDG&E’s records, even though these customers are part of a commercial DR program. These residential premises are located in commercially-managed facilities. This small, unique group accounts for less than 5% of the thermostats in the program. Figure 4-3 shows the hourly load impacts for the average residential customer across the four event days. The number of enrolled customers, 193, is the average number of enrolled commercial customers across the four event days. The average impact per customer for all events across the 4-hour event window was 0.13 kW, or 6.7% of the reference load.

Figure 4-3: Load Impact (kW) per Hour for the Average 2014 Event Day   
(Average Residential Participant) 

# Ex Ante Methodology and Results

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

The methodology used to estimate ex ante impacts is summarized in Section 5.1. Then, Section 5.2 summarizes the ex ante weather conditions that underlie the impact estimates, which are new this year and are estimated under two sets of assumptions, one based on SDG&E-specific operating conditions and the other based on CAISO operating conditions. Estimated impacts are presented in Section 5.3 and a comparison of ex post and ex ante estimates is presented in Section 5.4.

## Ex Ante Estimation Methodology

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

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

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

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

Equation 5-1: Reference Load Ex Ante Regression Model Specification

Table 5-1: Description of Ex Ante Reference Load Regression Variables

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

Equation 5-2: Summer Saver Load Impact Ex Ante Regression Model Specification

Table 5-2: Description of Ex Ante Reference Load Regression Variables

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

Figure 5-1 shows the results of the reference load regression at hour ending 4 PM. The blue circles show the average ex post reference load and the *mean17* for a given day. The red dots correspond to the predicted values. The difference between the predicted and actual values is in green. As shown in the figures, the model error is a very small percentage of the overall load.

Figure 5-1: Actual and Predicted Commercial Thermostat Customer Load  
versus *Mean17* for 3 to 4 PM



As a validation of the ex ante impact model, Table 5-3 shows the results of the ex ante impact modeling for the four event days at hour ending 4 PM, as compared to the estimates in the ex post analysis. The July 31 event had the largest per-customer impact, while it was the coldest day. Since, in general, higher impacts on hotter days are expected, and that is consistent with the findings in the Summer Saver analysis, the impacts for July 31 are underestimated with the ex ante methodology. The estimates are closest for the September 17 event, which was a day like many of the summer monthly peaking conditions.

Table 5-3: Ex Post and Ex Ante Impact Validation for Event Days at Hour Ending 4 PM

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

## Estimating Ex Ante Weather Conditions

The CPUC Load Impact Protocols[[3]](#footnote-3) require that ex ante load impacts be estimated assuming weather conditions associated with both normal and extreme utility operating conditions. Normal conditions are defined as those that would be expected to occur once every 2 years (1-in-2 conditions) and extreme conditions are those that would be expected to occur once every 10 years (1-in-10 conditions). Since 2008, the IOUs have based the ex ante weather conditions on system operating conditions specific to each individual utility. However, ex ante weather conditions could alternatively reflect 1-in-2 and 1-in-10 year operating conditions for the California Independent System Operator (CAISO) rather than the operating conditions for each IOU. While the protocols are silent on this issue, a letter from the CPUC Energy Division to the IOUs dated October 21, 2014 directed the utilities to provide impact estimates under two sets of operating conditions starting with the April 1, 2015 filings: one reflecting operating conditions for each IOU and one reflecting operating conditions for the CAISO system.

In order to meet this new requirement, California’s IOUs contracted with Nexant to develop ex ante weather conditions based on the peaking conditions for each utility and for the CAISO system. The previous ex ante weather conditions for each utility were developed in 2009 and were updated this year along with the development of the new CAISO based conditions. Both sets of estimates used a common methodology, which is documented in a report delivered to the IOUs.[[4]](#footnote-4)

Table 5-4 shows the value for *mean17* for the typical event day and the monthly system peak day under the four sets of weather for which load impacts are estimated. As seen, there are small differences in weather conditions based on SDG&E peak conditions and CAISO peak conditions, for normal and extreme weather. The CAISO-based conditions on the typical event day are slightly higher in a 1-in-2 weather year and lower in a 1-in-10 weather year. For the September peak day under 1-in-10 weather conditions, the *mean17* value is the same (83.9 °F).

Table 5-4: Ex Ante Weather Values (*mean17*, °F)

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

## Ex Ante Load Impact Results

Section 5.1 summarized the methodology used to develop ex ante impact estimates for the average customer, under ex ante weather conditions. Aggregate ex ante estimates combine these average estimates with projections of program enrollment provided by SDG&E. Per-thermostat ex ante estimates also combine the average customer estimates with projections of the average number of thermostats, which is expected to remain around 9 thermostats per customer. Table 5-5 summarizes the projected commercial thermostat enrollment by month and year from 2015 through 2025. Currently, there are nearly 1,200 customers enrolled. This number is expected to gradually increase to 2,013 customers by the end of 2016. From 2017 through 2025, enrollment is expected to remain constant at 2,013 customers.

Table 5-5: Projected 2015-2025 Commercial Thermostat Enrollment  
Total Number of Customers Enrolled

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

Table 5-6 summarizes the 2017-2025 ex ante load impact estimates by weather year and day type. The third and sixth columns in the table show the average hourly ex ante load impact per thermostat (kW) over the event period from 2 to 6 PM for each type of weather, followed by the per-customer impact (kW) and the aggregate impact (MW). The first set of rows corresponds to 1-in-2 year weather conditions while the second set covers 1-in-10 year weather conditions. The highest impacts consistently occur on September peak days under both SDG&E and CAISO weather conditions, with aggregate impacts of 5.3 MW in a 1-in-10 year and around 4 MW in a 1-in-2 year.

Table 5-6: 2017-2025 Ex Ante Load Impact Estimates by Weather Year and Day Type   
(kW per Customer, Aggregate MW, and kW per Thermostat)

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

## Relationship Between Ex Post and Ex Ante Estimates

The ex post estimates presented in Section 4 and the ex ante estimates presented above differ for a number of reasons, including differences in weather, enrollment, and estimation methodology. This section discusses the impact of each of these factors on the difference between ex post and ex ante impact estimates.

Table 5-7 summarizes the key factors that lead to differences between ex post and ex ante estimates for the commercial thermostat program and the expected influence that these factors have on the relationship between ex post and ex ante impacts. Given that the load impacts are quite sensitive to variation in weather, even small changes in *mean*17 between ex post actual and ex ante weather conditions can produce relatively large differences in load impacts. Changes in enrollment between the values used for ex post estimation and the 2015 enrollment values are expected to more than double impact estimates as the program has grown substantially since the last event in September.

Table 5-7: Summary of Factors Underlying Differences Between Ex Post and Ex Ante Impacts   
for the Commercial Thermostat Program for the Ex Ante Typical Event Day

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

Table 5-8 shows how aggregate load impacts change as a result of differences in the factors underlying ex post and ex ante estimates. The third column reproduces the ex post values from Table 4-1. The next column grosses these estimates up by the difference in ex post and ex ante enrollment in August 2016. As expected, this produces a nearly five-times increase in the impacts. The next column shows what the ex ante model would produce using the same 2016 August enrollment figures and the ex post weather conditions for each event day. As discussed above, the ex ante model over predicts load reductions for September and under predicts for July. This is due to the unexpected high impact on the relatively cool July 31 event day, and the relatively limited number of events available to determine whether the observed trend of higher impacts on cooler day was spurious, or was due to a real trend. One other potential explanation for this difference is the change in the population from the July event to the September events. The final four columns show how aggregate load reductions vary with the different ex ante weather scenarios. The SDG&E 1-in-10 conditions are most similar to the 2014 SDG&E ex post weather conditions on average across all event days, although for any given ex post day, the weather conditions can differ significantly. Using the SDG&E 1-in-10 year conditions decreases the average impacts by about 2% compared with ex post weather.

Table 5-8: Differences in Ex Post and Ex Ante Impacts Due to Key Factors

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

# Recommendations

A common concern about temperature setback strategies is that they result in impacts that decline throughout the event window, given that indoor temperatures will gradually rise to the higher temperature set point. Instead, the results from this study suggest that the impacts for the 50% cycling strategy were lower overall and also went down at a faster rate during the events. In the *final hour* of the event, 4-degree setback customers delivered an impact of 0.2 kW per thermostat, which was almost as high as the per-thermostat impacts for 50% cycling customers in the *first event hour*. Considering that this difference in effectiveness of the cycling strategies may be partly due to pre-existing differences in the customer mix, Nexant recommends that SDG&E continue to see if this result still holds as the program expands and more events are called. In addition, Nexant recommends that SDG&E consider alternating cycling strategies from event to event, which would allow for a comparison of how the same customers respond to both 50% cycling and the 4-degree setback.

1. For a comparison of results using various research methods, including RCT/RED designs, statistical matching and within-subjects regression analysis, see the interim report on Sacramento Municipal Utility District’s Smart Pricing Options pilot: <https://www.smartgrid.gov/sites/default/files/MASTER_SMUD%20CBS%20Interim%20Evaluation_Final_SUBMITTED%20TO%20TAG%2020131023.pdf> [↑](#footnote-ref-1)
2. The days were July 24th and July 30th to estimate impacts for the one July event day, and September 8th, and September 9th to estimate impacts for the three consecutive September event days. Several alternative sets of days were tested and validated, including sets of up to 10 days, but we ultimately found that only including two recent days that were most similar to the event days was the most accurate approach. [↑](#footnote-ref-2)
3. See CPUC Rulemaking (R.) 07-01-041 Decision (D.) 08-04-050, “Adopting Protocols for Estimating Demand Response Load Impacts” and Attachment A, “Protocols.” [↑](#footnote-ref-3)
4. See *Statewide Demand Response Ex Ante Weather Conditions*. Nexant, Inc. January 30, 2015. [↑](#footnote-ref-4)