REPORT

Nexant

2015 Load Impact Evaluation of San Diego Gas and Electric Company's Commercial Thermostat Program

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Prepared for
San Diego Gas & Electric Company

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1 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. More than half of these customers will be defaulted onto Critical Peak Pricing (CPP) by April of 2016 In 2015, the thermostats were activated on residential Peak Time Rebate (PTR) event days.

The objectives of the SDG&E 2015 commercial thermostat program load impact evaluation are to:

- Estimate hourly ex post load reductions on 2015 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 2015–2026 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).

SDG&E called four events during summer 2015 during which 1,243 commercial customers and 1,079 commercially managed residential units were enrolled. As of February 2016, over 12,000 PCTs have been rolled out to roughly 1,250 commercial customers and 1,080 commercially managed residential units. Enrollment has grown substantially since summer 2014, but increased only slight since summer 2015.

1.1 Ex Post Load Impact Summary

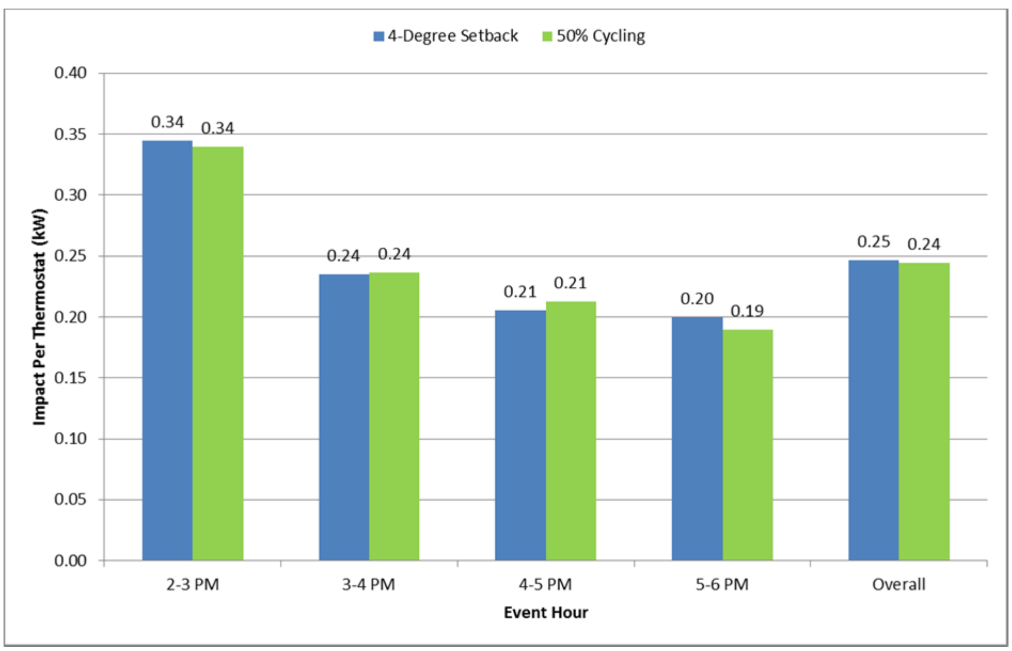
Table 1-1 summarizes the average load reduction provided by commercial customers across the four hour event window from 2 to 6 PM. As shown, the average percent reduction ranged from a low of 4% on August 28 to a high of 8% on September 11. An average reduction of 6% was obtained across the four event days. The average load reduction per thermostat ranged from a low of 0.16 kW to a high of 0.33 kW. Aggregate load reductions ranged from 1.77 MW to 3.74 MW. Aggregate load reductions for the four events averaged 3.09 MW per event.

Table 1-1: 2015 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)	Avg. Thermostat Impact (kW)	Mean17 (F)
Aug 28, 2015	1,243	11,292	37.1	1.4	3.8%	1.8	0.16	82.2
Sep 9, 2015	1,243	11,292	40.9	2.5	6.2%	3.1	0.28	86.5
Sep 10, 2015	1,243	11,292	41.4	3.0	7.2%	3.7	0.33	85.2
Sep 11, 2015	1,243	11,292	39.2	3.0	7.7%	3.7	0.33	82.6
Average Event	**1,243**	**11,292**	**39.7**	**2.5**	**6.3%**	**3.1**	**0.27**	**84.1**

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 the same rate as the 4-degree set-back during the events. As shown in Figure 1-1, the per-thermostat impacts for 50% cycling customers decreased from 0.34 kW in the first event hour to 0.19 kW in the last event hour. For 4-degree setback customers, the per-thermostat impacts also started at 0.34 kW and dropped to the statistically indistinguishable 0.20 kW. This finding is generally consistent with the 2014 finding that 50% cycling is not a superior strategy.

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



1.2 Ex Ante Load Impact Summary

Currently, there are nearly 2,526 customers enrolled. This number is expected to increase to 2,689 customers in August 2016, 2,891 customers in August 2017, and remain constant at

2,951 from 2018 through 2026. Table 1-2 summarizes the 2018-2026 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 1 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 4.1 MW in a 1-in-10 year and roughly 3.0 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 (1-6 PM)			CAISO Mean Hourly Impacts (1-6 PM)		
		Per Thermostat (kW)	Per Customer (kW)	Aggregate (MW)	Per Thermostat (kW)	Per Customer (kW)	Aggregate (MW)
1-in-2	Typical Event Day	0.15	0.8	2.4	0.15	0.9	2.6
	January Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	February Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	March Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	April Monthly Peak	0.06	0.3	1.0	0.04	0.2	0.7
	May Monthly Peak	0.09	0.5	1.5	0.05	0.3	0.8
	June Monthly Peak	0.09	0.5	1.5	0.10	0.6	1.7
	July Monthly Peak	0.14	0.8	2.3	0.13	0.8	2.2
	August Monthly Peak	0.18	1.0	2.9	0.19	1.1	3.2
	September Monthly Peak	0.18	1.0	3.0	0.19	1.1	3.2
	October Monthly Peak	0.13	0.7	2.1	0.09	0.5	1.6
	November Monthly Peak	0.04	0.2	0.7	0.03	0.2	0.5
	December Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
1-in-10	Typical Event Day	0.21	1.2	3.5	0.19	1.1	3.2
	January Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	February Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	March Monthly Peak	0.05	0.3	0.8	0.07	0.4	1.2
	April Monthly Peak	0.17	1.0	2.8	0.16	0.9	2.7
	May Monthly Peak	0.19	1.1	3.1	0.15	0.9	2.5
	June Monthly Peak	0.15	0.9	2.6	0.15	0.9	2.5
	July Monthly Peak	0.21	1.2	3.6	0.16	0.9	2.7
	August Monthly Peak	0.22	1.3	3.7	0.20	1.1	3.3
	September Monthly Peak	0.24	1.4	4.1	0.25	1.4	4.1
	October Monthly Peak	0.19	1.1	3.2	0.17	1.0	2.9
	November Monthly Peak	0.15	0.8	2.4	0.11	0.6	1.8
	December Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0

2 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. Over half of these customers will be defaulted onto Critical Peak Pricing (CPP) within by April of 2016. In 2015, the thermostats were activated on residential Peak Time Rebate (PTR) event days.

The objectives of the SDG&E 2015 commercial thermostat program load impact evaluation are to:

- Estimate hourly ex post load reductions on 2015 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 2015–2026 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).

As of February 2016, over 12,000 PCTs have been rolled out to roughly 2,500 customers. Enrollment has grown substantially since summer 2014, but remained relatively constant since summer 2015. 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 roughly 10% of the thermostats in the program. These customers have been segmented for a separate analysis accordingly.

2.1 Report Organization

The remainder of this report proceeds as follows. Section 3 summarizes the ex post methods and validation process. Section 4 provides the 2015 ex post results for all customers and for various segments of the commercial thermostat population. It also compares the results with load impact estimates from 2014. Section 5 focuses on the ex ante evaluation, including the methodology and results. Finally, the report concludes with recommendations for future evaluations.

3 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 because it eliminates the problem of model misspecification.[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.

3.1 Matched Control Group Methodology – Commercial

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 group was 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 best 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 and climate zone. It was based on a single variable that characterized usage in the middle of the day on hot non-event days in August and September. The usage variable in the propensity score model was the average demand from 2 PM to 6 PM on each of six hot non-event days.[2] These days were chosen because they were the only days with temperatures that closely reflected those on event days. Fourteen candidate propensity score models were tested and the final model using a six-fold cross-validation process, iteratively using one of the hot non-event days as the test

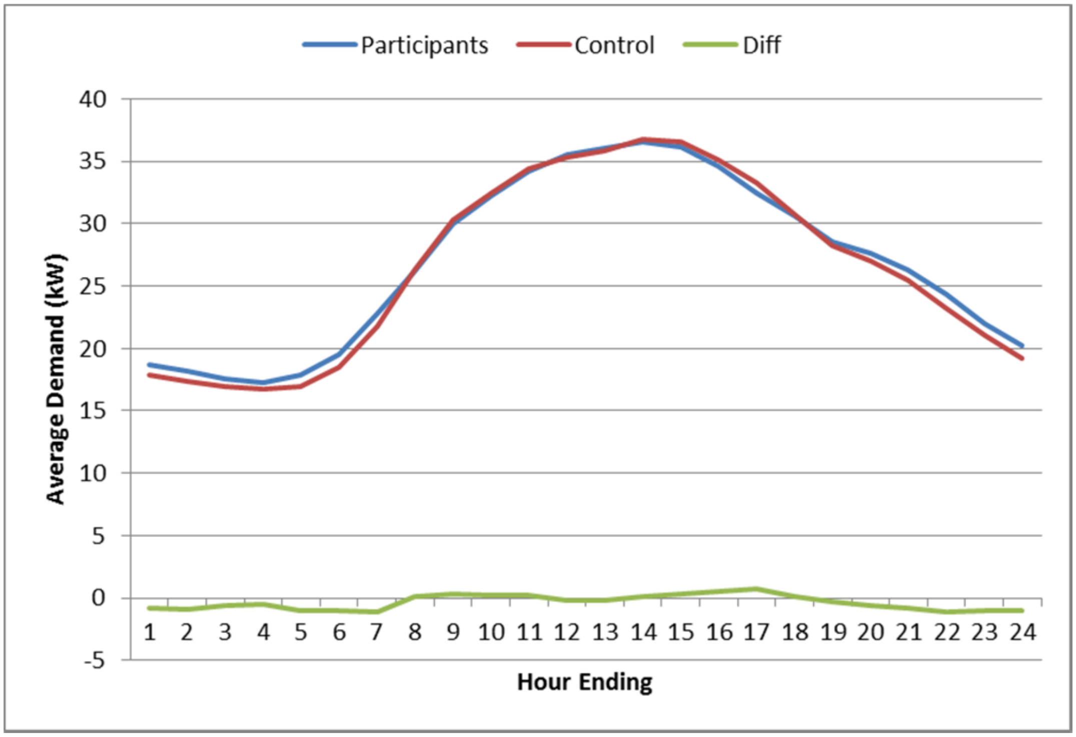
[1] For a comparison of results using various research methods, including RCT/RED designs, statistical matching and within-subjects regression analysis, see the interim report on Sacramento Municipal Utility District's Smart Pricing Options pilot: https://www.smartgrid.gov/sites/default/files/MASTER_SMUD%20CBS%20Interim%20Evaluation_Final_SUBMITTED%20TO%20TAG%2020131023.pdf

[2] The days were August 4, August 17, August 18, September 14, September 22, and September 28.

data and the other five days as the training data. The simple model described above was chosen because it resulted in the closet match between participants and control customer average demand. 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. The average difference between participants and their matched control hovers around zero and is relatively small—particularly during event hours.

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



Once the control group was matched and validated, load impacts were estimated using a triple differences methodology, which combines a difference-in-differences regression and a same-day (weather sensitivity) adjustment.[3] 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 and then adjusts for differences in weather sensitivity within the treatment and control groups. This calculation controls for residual differences in load between the groups that are not eliminated through the matching

3 For more on the triple differences regression methodology, see Imbens and Wooldridge (2009), "Recent Developments in the Econometrics of Program Evaluation" and Chetty et. al. (2009), "Salience and Taxation: Theory and Evidence."

process, thus reducing bias. Equation 3-1 summarizes the triple differences calculation and Table 3-2 provides the definitions for variables in the equation.[4]

Equation 3-1: Specification of Triple Differences Regression

$$kW_{i,t,h} = a * treat_i * eday_t * eperiod_h + \sum_{cust=1}^{customers} b_{cust} * customer_{cust\ i} + \sum_{hr=1}^{hours} c_{hr} * hour_{hr\ h}$$

$$+ \sum_{date=1}^{days} d_{date} * day_{date\ t} + e * eday_t * eperiod_h + f * treat_i * eperiod_h$$

$$+g * treat_i * eday_t + u_{ith}$$

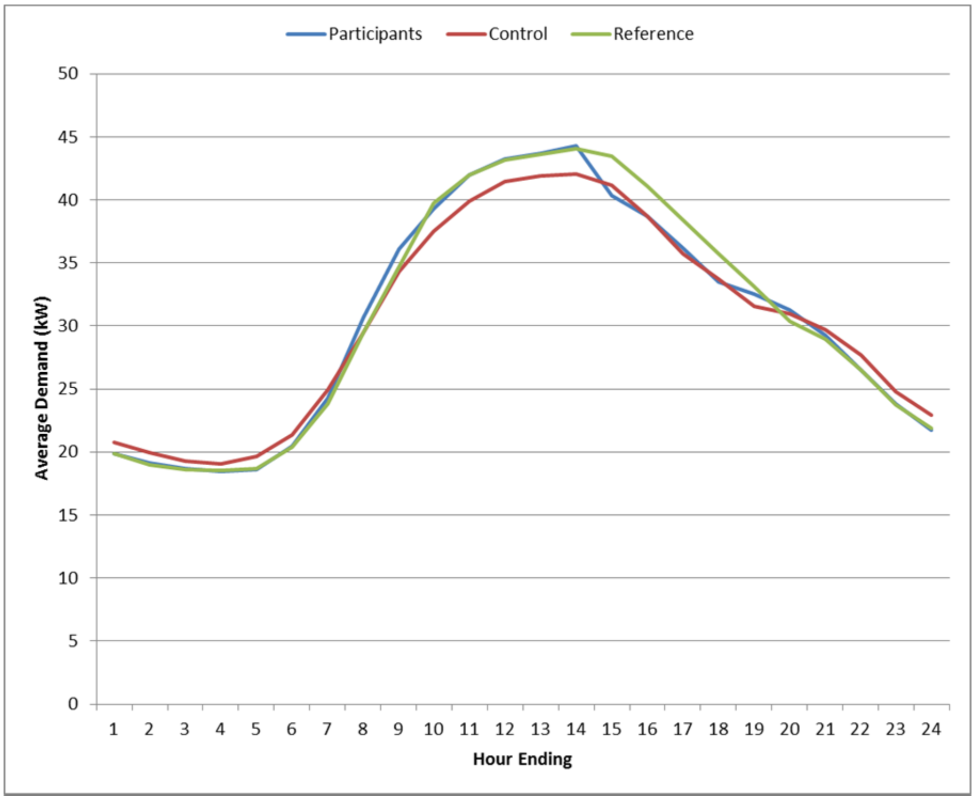
Table 3-2: Variables Used for Triple Differences Calculation

Variable	Description
kW	Average demand
treat	Indicates whether a customer is a participant (treat=1) or a control group member (treat =0)
eday	Indicates whether a given day was an event (eday=1) or not (eday=0)
eperiod	Indicates whether a given hour was an event hour (eperiod=1) or not (eperiod=0)
customer	A set of indicator variables that equal one if cust=i
hour	A set of indicator variables that equal one if hr=h
day	A set of indicator variables that equal one if date=t
a	Estimated effect of the treatment
b, c, d	Estimated fixed effects
e, f, g	Estimated parameters
i	Indexes customers
t	Indexes the days
h	Indexes hours

[4] A standard difference-in-differences model is used to estimate impacts before 10 AM and after 7 PM. The data used in the triple differences model is restricted to hours ending at 10 AM through 2 PM as well as each event hour for which an impact is being estimated.

Figure 3-2 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 reference load, which matches nearly exactly with the participant group load for all hours leading up to the event, taking into account factors fixed through time, time-dependent factors observed by all customers, and weather sensitivity. The impact estimates are calculated by subtracting average hourly usage on each event day for the reference load from average hourly participant usage on each event day.

Figure 3-2: Example of Control Group Usage Adjustment; Average Event Day



3.2 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 10% of the thermostats in the program, so this within-subjects approach was used instead. The regression model used is specified in Equation 3-2, and the variable definitions are provided in Table 3-3. 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 3-2: Model Specification for Individual Customer Regressions

$$kwh_{it} = a + b * mean17_{i,t} + c * mean17_{i,t}^{2} + e_{i,t}$$

Table 3-3: 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
mean17	The mean temperature from midnight until 5 PM
e	The error term

4 2015 Ex Post Load Impacts

This section summarizes the ex post load impact estimates for commercial thermostat program participants for the 2015 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; and
- 50% cycling and 4-degree setback.

SDG&E called four events during summer 2015 during which 1,243 commercial customers and 1,079 commercially managed residential units were enrolled. The next two sections summarize the results for commercial customers. The final section shows the average event impacts for the small number of residential thermostats that are located on commercially-managed properties.

4.1 Average Event Impacts – Commercial

Figure 4-1 shows the hourly load impacts for the average commercial customer across the four event days. The average impact per customer for all events across the four hour event window was 2.49 kW, or 6.3% 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 36 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.

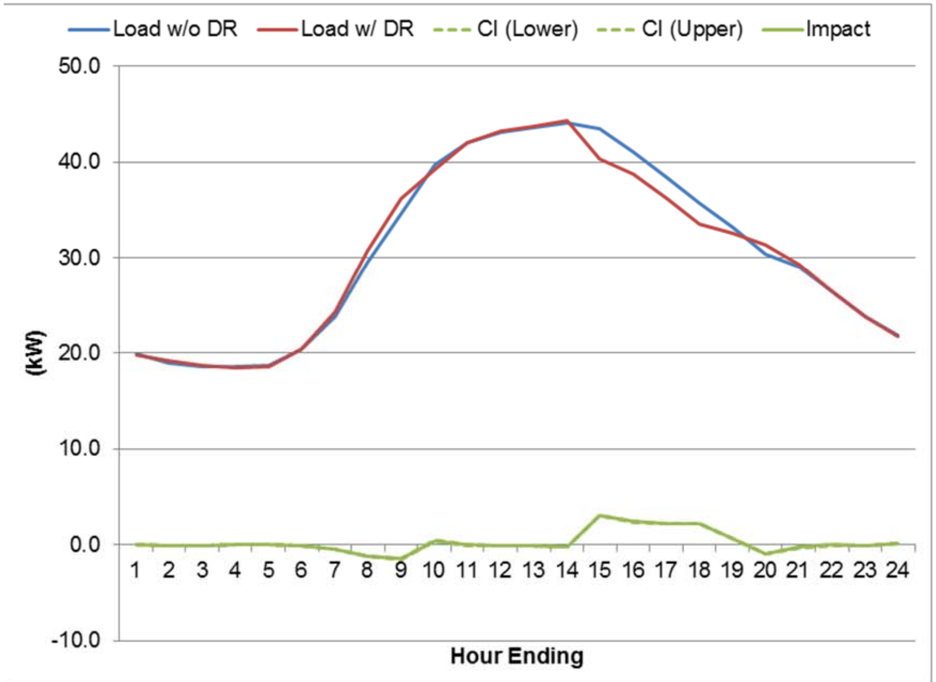
Figure 4-1: Commercial Thermostat Program Load Impact (kW) per Hour for the Average 2015 Event Day (Average Commercial Participant)

TABLE 1: Menu options

Customer Segment	All Commercial
Date	Average Event Day
Result Type	Average Customer
Average Thermostats	9.1
Enrolled Customers	1,243

TABLE 2: Event Day Information

Event Start	2 PM
Event End	6 PM
Average Temp. for Event Window	92
Mean17	84
Load Reduction for Event Window	2.49
% Load Reduction for Event Window	6.3%



Hour Ending	Load w/o DR (kW)	Load w/ DR (kW)	Impact (kW)	Impact (%)	Avg. Temp (°F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1	19.90	19.84	0.06	0%	79	0.05	0.05	0.06	0.06	0.07
2	19.01	19.15	-0.14	-1%	79	-0.15	-0.15	-0.14	-0.14	-0.13
3	18.63	18.68	-0.05	0%	77	-0.07	-0.06	-0.05	-0.05	-0.04
4	18.55	18.49	0.06	0%	77	0.05	0.06	0.06	0.07	0.08
5	18.69	18.62	0.07	0%	77	0.05	0.06	0.07	0.07	0.08
6	20.37	20.46	-0.09	0%	77	-0.10	-0.09	-0.09	-0.08	-0.07
7	23.85	24.30	-0.46	-2%	76	-0.47	-0.46	-0.46	-0.45	-0.44
8	29.51	30.69	-1.18	-4%	78	-1.20	-1.18	-1.18	-1.17	-1.16
9	34.66	36.14	-1.48	-4%	82	-1.50	-1.49	-1.48	-1.47	-1.46
10	39.73	39.28	0.45	1%	85	0.44	0.44	0.45	0.45	0.46
11	41.97	42.00	-0.03	0%	88	-0.04	-0.04	-0.03	-0.03	-0.03
12	43.15	43.25	-0.10	0%	92	-0.11	-0.11	-0.10	-0.10	-0.10
13	43.63	43.68	-0.05	0%	93	-0.06	-0.05	-0.05	-0.05	-0.05
14	44.05	44.31	-0.26	-1%	93	-0.27	-0.26	-0.26	-0.26	-0.25
15	43.44	40.33	3.11	7%	93	3.09	3.10	3.11	3.11	3.12
16	41.10	38.70	2.40	6%	91	2.38	2.39	2.40	2.40	2.41
17	38.42	36.18	2.24	6%	92	2.22	2.23	2.24	2.25	2.26
18	35.69	33.49	2.21	6%	91	2.19	2.20	2.21	2.22	2.23
19	33.16	32.51	0.65	2%	89	0.63	0.64	0.65	0.66	0.67
20	30.38	31.30	-0.92	-3%	87	-0.94	-0.92	-0.92	-0.91	-0.90
21	28.97	29.24	-0.26	-1%	86	-0.28	-0.27	-0.26	-0.26	-0.24
22	26.51	26.53	-0.03	0%	83	-0.05	-0.03	-0.03	-0.02	-0.01
23	23.76	23.85	-0.09	0%	81	-0.11	-0.10	-0.09	-0.08	-0.07
24	21.92	21.73	0.18	1%	80	0.17	0.18	0.18	0.19	0.20
Avg Hour in Event Window	39.66	37.17	2.49	6%	92					

Table 4-1 summarizes the average load reduction for each event day 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 August 28 to a high of 8% on September 11. An average reduction of 6% was obtained across the four event days. The average load reduction per thermostat ranged from a low of 0.16 kW to a high of 0.33 kW. Aggregate load reductions ranged from 1.8 MW to 3.7 MW. Aggregate load reductions for the four events averaged 3.1 MW per event. The average per-thermostat and per-customer load reductions are slightly higher than the estimates calculated for the 2014 program year, which were 0.22 kW and 2.0 kW, respectively. The aggregate impacts also increased, largely as a function of the much greater number of participants.

Table 4-1: 2015 Commercial Thermostat Ex Post Load Impact Estimates (2 to 6 PM) by Event Day (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)	Avg. Thermostat Impact (kW)	Mean17 (F)
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4.2 Load Impacts for Specific Customer Segments—Commercial

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

4.2.1 Load Impacts by Climate Zone

SDG&E's service territory is not large, 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 2015 summer come from one of two climactic regions—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 produced higher load impacts per thermostat in 2014. Despite this, the Inland climate zone produced slightly lower impacts per-thermostat this year. The per-thermostat impact is 15% higher in the Coastal climate zone than in the Inland climate zone. However, the differences in per-thermostat impacts are not statistically significant. Importantly, though, this suggests that using climate zone to target commercial customers for demand response from smart thermostats may not likely provide additional benefits.

Table 4-2: 2015 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)	Avg. Thermostat Impact (kW)	Mean17 (F)
Coastal	671	5,066	39.2	2.2	5.7%	1.5	0.30	82.3
Inland	572	6,226	40.3	2.8	6.9%	1.6	0.26	86.3
Both	**1,243**	**11,292**	**39.7**	**2.5**	**6.3%**	**3.1**	**0.27**	**84.1**

4.2.2 Load Impacts by Industry

The participants in the commercial thermostat program come from a number of different industries. During 2015 events, Offices, Hotels, Finance, and Services accounted for nearly half of all of the participating commercial customers, as they did in 2014, and a slightly higher percentage of the total number of thermostats. Schools made up 11% of the total participating customers, but had 20% of the installed thermostats. Retail stores made up 7% of the participating customers, while having nearly 2% 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, Finance, Restaurants, and Services. The per-thermostat impact for this industry was 0.34 kW, nearly 26% higher than the estimate for the average commercial customer (0.27 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 customers was most likely not due to weather conditions. This finding runs counter to the findings from the 2014 load impact analysis, which estimated that Offices, Hotels, Finance, and Services thermostats resulted in a 41% lower impact per thermostat than the average customer. Instead, Hotels appear to be responsible for bringing down the industry average with a nearly non-existent load impact per thermostat. Since there are relatively few customers in the Hotels or Retail industries, it is difficult to assess why these industries performed so differently from other industries and whether it will continue to in the future. It is, instead, a suggestion that retail may be a good target in the future, and hotels should not be pursued for further installs.

Table 4-3: 2015 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)	Avg. Thermostat Impact (kW)	Mean17 (F)
Hotels	75	3,176	148.0	1.0	0.7%	0.1	0.02	83.9
Institutional/Government	247	2,225	33.6	2.3	7.0%	0.6	0.26	84.3
Offices, Finance, Restaurants, Services	545	2,646	24.7	1.7	6.8%	0.9	0.34	84.0
Retail Stores	84	267	23.4	1.5	6.2%	0.1	0.46	83.9
Schools	140	2,215	58.8	5.4	9.1%	0.8	0.34	85.1
All Industries	**1,243**	**11,292**	**39.7**	**2.5**	**6.3%**	**3.1**	**0.27**	**84.1**

4.2.3 Load Impacts by Cycling Strategy

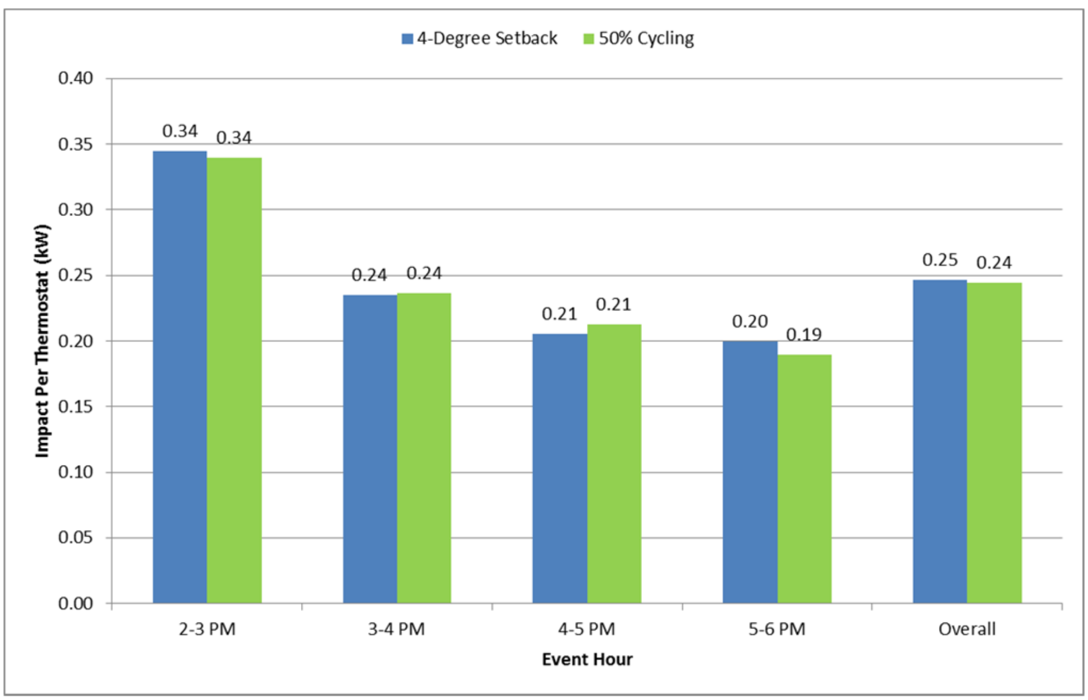
Nearly all commercial thermostat program participants are on one of two cycling strategies—a 4-degree setback or 50% cycling. The number of thermostats is split almost evenly into the two groups. This segmentation allows for a comparison between the two cycling strategies. Table 4-4 shows the average load reduction by cycling strategy. The average event-day temperature for participants assigned to each of the two strategies was nearly the same; the load reduction in per-thermostat terms is nearly the same for both customer groups. This runs counter to the finding in the 2014 load impact analysis, which suggested that the 4-degree setback was out-performing the 50% cycling strategy. A small number of idiosyncratic customers was assigned to an alternative cycling strategy and have been left out of this comparison.

Table 4-4: 2015 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)	Avg. Thermostat Impact (kW)	Mean17 (F)
4-Degree Setback	475	5,264	44.4	2.7	6.2%	1.3	0.25	84.0
50% Cycling	729	5,807	36.3	1.9	5.4%	1.4	0.24	84.2
Overall	**1,243**	**11,292**	**39.7**	**2.5**	**6.3%**	**3.1**	**0.27**	**84.1**

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. The results from this study suggest that the impacts for both strategies resulted in a nearly identical pattern of demand response. As shown in Figure 4-2, the per-thermostat impacts for 50% cycling customers decreased from 0.34 kW in the first event hour to 0.19 kW in the last event hour, which is a 44% decline. For 4-degree setback customers, the per-thermostat impacts started at 0.34 kW and decreased by nearly the same amount (41%).

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



4.3 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 roughly 10% of the thermostats in the program. Figure 4-3 shows the hourly load impacts for the average residential customer across the four event days. Table 4-5 shows the average event-window impact across days. The number of enrolled customers, 1,079, is the average number of enrolled commercial customers across the four event days. The average impact per customer for all events across the four hour event window was 0.11 kW, or 7.9% of the reference load.

Table 4-5: 2015 Commercial Thermostat Ex Post Load Impact Estimates (2 to 6 PM) by Event Day, Residential Customers (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)	Avg. Thermostat Impact (kW)	Mean17 (F)
Aug 28, 2015	1,079	1,130	1.36	0.03	2.2%	0.03	0.03	80.9
Sep 9, 2015	1,079	1,130	1.37	0.12	8.5%	0.13	0.11	85.1
Sep 10, 2015	1,079	1,130	1.32	0.15	11.7%	0.17	0.15	84.4
Sep 11, 2015	1,079	1,130	1.33	0.12	9.2%	0.13	0.12	81.6
Average Event	**1,079**	**1,130**	**1.34**	**0.11**	**7.9%**	**0.11**	**0.10**	**83.0**

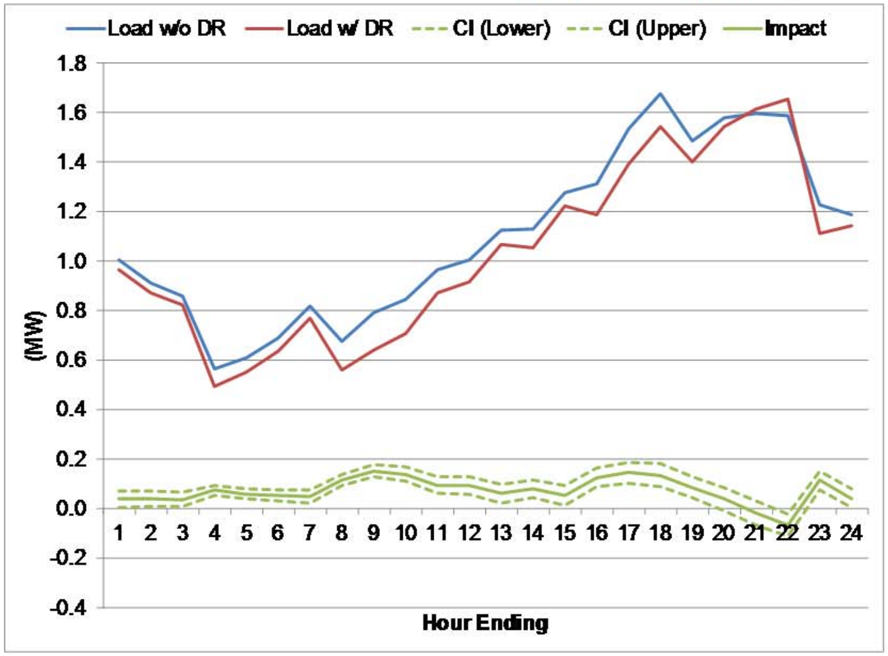
Figure 4-3: Load Impact (kW) per Hour for the Average 2014 Event Day (Average Residential Participant)

TABLE 1: Menu options

Customer Segment	Residential
Date	Average Event Day
Result Type	Aggregate
Average Thermostats	1.0
Enrolled Customers	1,079

TABLE 2: Event Day Information

Event Start	2 PM
Event End	6 PM
Average Temp. for Event Window	90
Mean17	83
Load Reduction for Event Window	0.11
% Load Reduction for Event Window	7.9%



Hour Ending	Load w/o DR	Load w/ DR	Impact	Impact	Avg. Temp	Uncertainty Adjusted Impact - Percentiles				
	(MW)	(MW)	(MW)	(%)	(°F)	10th	30th	50th	70th	90th
1	1.00	0.96	0.04	4%	79	0.01	0.02	0.04	0.05	0.07
2	0.91	0.87	0.04	4%	78	0.01	0.03	0.04	0.05	0.07
3	0.86	0.82	0.04	4%	77	0.01	0.03	0.04	0.05	0.06
4	0.57	0.49	0.07	13%	77	0.05	0.06	0.07	0.08	0.09
5	0.61	0.55	0.06	10%	77	0.04	0.05	0.06	0.07	0.08
6	0.69	0.64	0.05	7%	77	0.03	0.04	0.05	0.06	0.07
7	0.82	0.77	0.05	6%	77	0.02	0.04	0.05	0.06	0.08
8	0.67	0.56	0.11	17%	78	0.09	0.11	0.11	0.12	0.13
9	0.79	0.64	0.15	19%	81	0.13	0.14	0.15	0.16	0.18
10	0.84	0.71	0.14	16%	83	0.11	0.13	0.14	0.15	0.17
11	0.96	0.87	0.09	10%	86	0.06	0.08	0.09	0.11	0.13
12	1.00	0.91	0.09	9%	89	0.06	0.08	0.09	0.11	0.13
13	1.12	1.07	0.06	5%	90	0.02	0.04	0.06	0.07	0.10
14	1.13	1.05	0.08	7%	91	0.04	0.06	0.08	0.09	0.11
15	1.28	1.22	0.05	4%	91	0.01	0.04	0.05	0.07	0.09
16	1.31	1.19	0.13	10%	89	0.09	0.11	0.13	0.14	0.16
17	1.54	1.39	0.14	9%	90	0.10	0.13	0.14	0.16	0.19
18	1.67	1.54	0.13	8%	89	0.09	0.12	0.13	0.15	0.18
19	1.49	1.40	0.08	6%	87	0.04	0.07	0.08	0.10	0.13
20	1.58	1.54	0.04	2%	86	-0.01	0.02	0.04	0.06	0.08
21	1.60	1.61	-0.02	-1%	85	-0.07	-0.04	-0.02	0.00	0.03
22	1.59	1.66	-0.07	-4%	83	-0.11	-0.09	-0.07	-0.05	-0.02
23	1.23	1.11	0.11	9%	80	0.07	0.10	0.11	0.13	0.15
24	1.18	1.14	0.04	3%	80	0.00	0.03	0.04	0.06	0.08
Avg Hour in Event Window	1.45	1.34	0.11	8%	90					

5 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. Section 5.2 summarizes the ex ante weather conditions that underlie the impact estimates, which 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.

5.1 Ex Ante Estimation Methodology

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

1. Ex post estimates were developed using the matching methodology described in Section 3, with the key output being the 2015 average event day per-thermostat impact (0.27 kW);
2. 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;
3. 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
4. The ratio of impact to weather observed in the Summer Saver program was applied to the 2015 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 impact model matches the model used in the Summer Saver evaluation to maintain consistency.

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

$$kW_t = a + b \cdot mean17_t + c \cdot mean17_t^2 + \sum_{day=Tuesday}^{Friday} d_{day} \cdot DOW_{t,day} + \sum_{month=February}^{December} m_{month} \cdot Month_{t,month} + \varepsilon_t$$

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
$mean17^2$	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)
ε	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

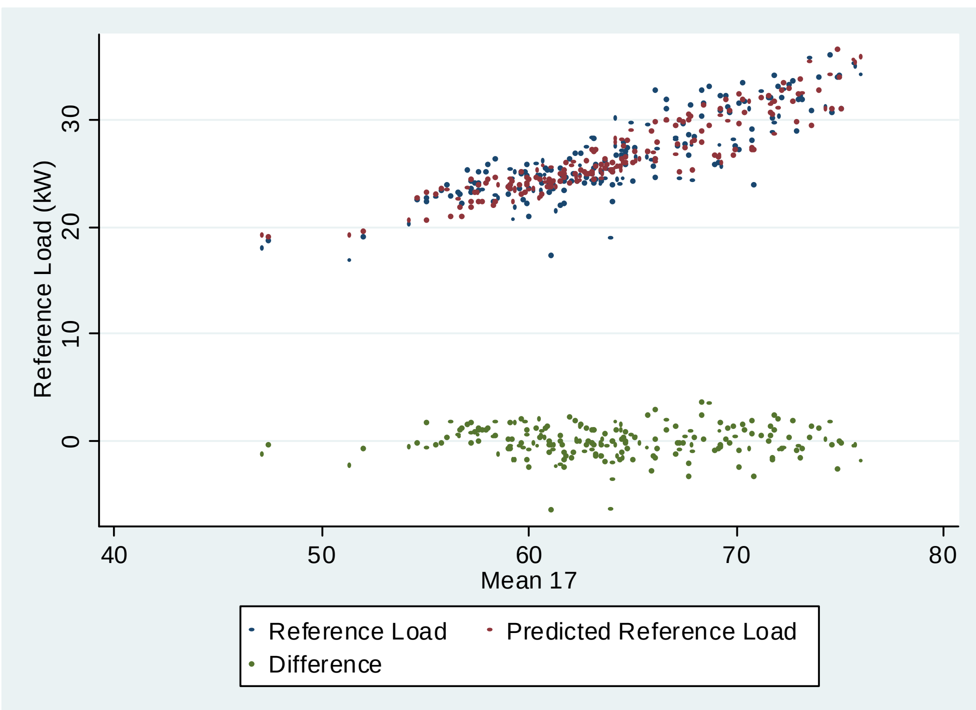
$$impact_t = a + b \cdot mean17_t + \varepsilon_t$$

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
ε	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 ex post impacts estimated in the 2014 and 2015 analyses do not show an obvious relationship with weather. 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 September 10 and 11 are underestimated with the ex ante methodology.

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

Date	Ex Post Impact (kW/Customer)	Ex Ante Impact (kW/Customer)	Difference (kW)	Mean17
Aug 28, 2015	1.5	2.2	0.7	82.2
Sept 9, 2015	2.3	2.6	0.4	86.5
Sept 10, 2015	3.0	2.5	-0.5	85.2
Sept 11, 2015	2.8	2.2	-0.5	82.6

5.2 Estimating Ex Ante Weather Conditions

The CPUC Load Impact Protocols[5] 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 in 2015 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.[6]

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.

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[5] See CPUC Rulemaking (R.) 07-01-041 Decision (D.) 08-04-050, "Adopting Protocols for Estimating Demand Response Load Impacts" and Attachment A, "Protocols."

[6] See *Statewide Demand Response Ex Ante Weather Conditions*. Nexant, Inc. January 30, 2015.

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	72.4	77.2	73.0	75.7
January Peak Day	52.6	49.1	52.4	47.5
February Peak Day	53.9	54.2	55.0	55.2
March Peak Day	56.4	64.8	55.0	66.6
April Peak Day	65.6	74.3	64.2	73.9
May Peak Day	67.6	75.7	64.4	72.7
June Peak Day	68.1	73.0	68.6	72.8
July Peak Day	71.7	77.7	71.5	73.5
August Peak Day	74.9	78.4	75.8	76.4
September Peak Day	74.9	79.8	76.1	80.3
October Peak Day	70.7	75.8	68.3	74.6
November Peak Day	64.1	72.5	63.0	69.6
December Peak Day	55.5	51.1	56.9	51.1

5.3 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. Currently, there are nearly 2,526 customers enrolled. This number is expected to increase to 2,689 customers in August 2016, 2,891 customers in August 2017, and remain constant at 2,951 from 2018 through 2026.

Table 5-5 summarizes the 2018-2026 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 1 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 4.1 MW in a 1-in-10 year and around 3.0 MW in a 1-in-2 year.

Table 5-5: 2018-2026 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 (1-6 PM)			CAISO Mean Hourly Impacts (1-6 PM)		
		Per Thermostat (kW)	Per Customer (kW)	Aggregate (MW)	Per Thermostat (kW)	Per Customer (kW)	Aggregate (MW)
1-in-2	Typical Event Day	0.15	0.8	2.4	0.15	0.9	2.6
	January Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	February Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	March Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	April Monthly Peak	0.06	0.3	1.0	0.04	0.2	0.7
	May Monthly Peak	0.09	0.5	1.5	0.05	0.3	0.8
	June Monthly Peak	0.09	0.5	1.5	0.10	0.6	1.7
	July Monthly Peak	0.14	0.8	2.3	0.13	0.8	2.2
	August Monthly Peak	0.18	1.0	2.9	0.19	1.1	3.2
	September Monthly Peak	0.18	1.0	3.0	0.19	1.1	3.2
	October Monthly Peak	0.13	0.7	2.1	0.09	0.5	1.6
	November Monthly Peak	0.04	0.2	0.7	0.03	0.2	0.5
	December Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
1-in-10	Typical Event Day	0.21	1.2	3.5	0.19	1.1	3.2
	January Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	February Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0
	March Monthly Peak	0.05	0.3	0.8	0.07	0.4	1.2
	April Monthly Peak	0.17	1.0	2.8	0.16	0.9	2.7
	May Monthly Peak	0.19	1.1	3.1	0.15	0.9	2.5
	June Monthly Peak	0.15	0.9	2.6	0.15	0.9	2.5
	July Monthly Peak	0.21	1.2	3.6	0.16	0.9	2.7
	August Monthly Peak	0.22	1.3	3.7	0.20	1.1	3.3
	September Monthly Peak	0.24	1.4	4.1	0.25	1.4	4.1
	October Monthly Peak	0.19	1.1	3.2	0.17	1.0	2.9
	November Monthly Peak	0.15	0.8	2.4	0.11	0.6	1.8
	December Monthly Peak	0.00	0.0	0.0	0.00	0.0	0.0

5.4 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 5-6 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 2016 enrollment values are expected to increase the aggregate impacts by roughly 6% given the continued projected growth of the program.

Table 5-6: 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	82 < event day mean17 < 86 Average event day mean17 = 84	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 cooler than the observed weather for 2015, 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 increased by many multiples between 2014 and 2015 events	Enrollment is forecast to steadily increase until 2018, at which point the program will remain stable at 117% of 2015 enrollment.	Ex ante estimates will increase to be roughly 17% than greater 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 (eight event days over two years)

Table 5-7 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 small increase in the impacts. The next column shows what the ex ante model would produce using the same 2016 August enrollment figures, the ex post event window (2-6 PM), and the ex post weather conditions for each event day. As discussed above, the ex ante model over predicts for the August day and under predicts for the last two September days. This is due to the unexpected high impact on the relatively cool September days, 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. The final four columns show how aggregate load reductions vary with the different ex ante weather scenarios for the average hour between 2 PM and 6 PM. The SDG&E 1-in-10 conditions are most similar to the 2015 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. Notably, even the coldest event, August 28, is considerably warmer that the SDG&E 1-in-10 weather with a mean17 of 77.2. Using the SDG&E 1-in-10 year conditions therefore decreases the average impacts by about 23% compared with ex post weather.

Table 5-7: 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)
28-Aug	82.2	1.8	2.1	3.4	2.0	1.9	2.4	2.7
9-Sep	86.5	3.1	3.7	4.0				
10-Sep	85.2	3.7	4.4	3.8				
11-Sep	82.6	3.7	4.5	3.4				
Average	84.1	3.1	3.7	3.7				

6 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 and 4-degree setback are nearly the same and follow the same pattern. 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.