Executive Summary of the 2017 SDG&E Measurement and Evaluation Load Impact Reports

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SDGE

A Sempra Energy utility℠

Contents

1 Background

San Diego Gas & Electric (SDG&E) presents this Executive Summary for its Demand Response (DR) activities for program year 2017 in accordance with (D.) 08-4-050. In Decision (D.) 08-04-050 the California Public Utility Commission (Commission) required the Investor Owned Utilities (IOUs) - San Diego Gas & Electric Company (SDG&E), Southern California Edison (SCE) and Pacific Gas and Electric (PG&E) to perform annual studies of their DR activities in accordance with the load impact protocols[1] and to file the load impact reports by April 1st each year. The load impact protocols require the preparation of a voluminous number of tables that resulted in the load impact reports being too large to be filed in hard copy. On April 6th, 2009 the investor owned utilities (IOUs) filed a petition to modify D.08-41-050. The petition asked for two things: 1) the removal of the requirement to file the load impact reports in their entirety and 2) to provide the reports to the energy division of the Commission. On April 8th, 2010, D.10-04-006 granted the utilities requests, which meant that they were not required to file the load impact reports in their entirety and to provide the Commission's Energy Division (ED). The 2010 decision also directed the utilities to file an executive summary of the load impact reports.

This Executive Summary provides all relevant information regarding the load impact evaluations. Program descriptions, program options, *ex post* load impact methodology, program year 2017 event results, updated weather, *ex ante* methodology and *ex ante* load impacts. Much of the information presented in the executive summary are excerpts taken from the individual load impact reports.

In 2016 and 2017 SDG&E filed two separate applications that would affect SDG&E's future DR activities: the General Rate Case Phase 2 (GRCP2) application and the 2018-2022 DR application. Both applications received decisions during the second half of 2017 that will have impacts on future SDG&E demand response activities.

In the first filing, the GRCP2 application SDG&E proposed to change the trigger for its day ahead dynamic rates, to align the triggers, to change the hours during which Critical Peak Pricing (CPP) events could be called from the period 11am-6pm to the period 2pm-6pm, and to sunset SDG&E's Peak Time Rebate (PTR) program at the end of 2018. In August 2017 Decision -17-08-030 provided approval and directed SDG&E to file an advice letter by December 1, 2017 for implementation of these changes for the 2018 program year.

The second filing made on January 17, 2017 was the 2018-2022 Demand Response Program Application. In this application SDG&E proposed modifications to its existing DR programs and proposed two new DR pilots. Among those modifications were requests to improve the Capacity

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[1] On April 24, 2008 D.08-04-050 adopted the protocols used in estimation of demand response load impacts.

Bidding Program (CBP) by reducing the number of products offered and simplifying the program. On December 13, 2017 the CPUC issued Decision17-12-003 that provided approval of SDG&E's DR program application, and directed approval among other things directed the Permanent Load Shifting (PLS) program to be suspended after 2018. Additionally, SDG&E was directed to file Advice Letters for the modifications to its CBP program.

These recent decisions will impact SDG&E's DR programs going forward, as PLS and PTR will be discontinued at the end of 2018. For that reason, there are no *ex ante* load impacts for after 2018 for PTR, and although there is an *ex ante* forecast for PLS that goes out until 2028 it contains no new projects after 2018.

This report contains a summary of the *ex post* and *ex ante* load impacts of the SDG&E's Demand Response activities and includes the following programs and dynamic rates:

- Capacity Bidding Program (CBP);
- Critical Peak Pricing Default (CPP-D);
- Base Interruptible Program (BIP);
- Summer Saver program;
- Peak Time Rebate Program;
- Small Commercial Technology Deployment (SCTD) Residential Program;
- Permanent Load Shifting program (PLS);
- Default Small Commercial CPP;
- Commercial Thermostats Program;
- Voluntary Residential CPP

Ex ante forecasts for all of SDG&E's demand response activities are provided in Appendix A. Starting in program year 2014, SDG&E was directed to include weather scenarios for load impacts that were coincident with the CAISO system peak.[2] All *ex ante* load impact summaries are averaged over the current Resource Adequacy (RA) hours of 1pm to 6pm for the months of April through October and 4pm to 9pm all other months.

It should be noted that several of SDG&E's DR programs and dynamic rates typically are not called at the same time as the RA hours. For example, CPP events in 2017 were called during the period 11am to 6pm. The relevant load impacts for RA purposes would be those from 1pm to 6pm. SDG&E expects that the RA hours will change in future years as more renewable generation comes online, however this report uses the current RA hours in the eleven-year *ex*

[2] . In October of 2014 SDG&E received a letter from the Director the CPUC's Energy Division. The letter informed the IOUs that they needed to include ex ante forecasts that are to be used for RA should be with respect to the CAISO's system peak.

ante forecast (from 2017 through 2028). It should also be noted that *ex post* weather conditions are typically not the same as the 1 in 2, or 1 in 10 weather scenarios used in the *ex ante* tables.

Located in Appendix A, the *ex ante* tables contain both SDG&E and CAISO load impacts. The tables include the following:

- 1 in 2 weather scenario for individual programs
- 1 in 2 weather scenario for the portfolio,
- 1 in 10 weather scenario for individual programs, and
- 1 in 10 weather scenario for the portfolio

2 Summary of SDG&E's Capacity Bidding Program Report[3]

2.1 CBP Program Description

CBP program provides monthly capacity payments ($/kW) to participants based on the nominated kW load, the specific operating month, and the program notice option Day Ahead (DA) or Day Of (DO). The program has two options Capacity Bidding Program Day-Ahead (CBP DA) and Capacity Bidding Program Day-Of (CBP DO). Customers may also choose a maximum event length of 4, 6 or 8[4] hours in duration. CBP events may be called on non-holiday weekdays in the months of May through October, between the hours of 11 a.m. and 7 p.m., with maximum event hours per month of 24 in May, June and October; 32 in July and September or 44 in August. Customers enrolled in CBP may participate in another DR program, so long as it is an energy-payment program and does not have the same advanced notification (*i.e.*, day-ahead or day-of). SDG&E added a 30-minute notice option to the DO product in 2015. The Utility may call an event: When the utility expects the dispatch of electric supply resource with implied heat rates of 15,000 BTU/kWh or greater and a price of $75/MWh for Day-Ahead or 15,000 BTU/kWh and a price of $140/MWh for Day-Of. Whenever the California Independent System Operator has issued an alert or warning notice, the California Independent System Operator shall be entitled to request that the utility, at its discretion, call a program event pursuant to this Schedule.

As previously discussed the IOUs filed applications for their 2018-2022 demand response portfolios as directed by D.16-09-056. On December 13, 2017 SDG&E received the final decision for its 2018-2022 DR application. The Decision directed SDG&E to file an Advice

[3] The 2017 CBP statewide load impact study was conducted by Applied Energy Group. This section of the Executive Summary contains excerpts from the following evaluation: Parameter, K. AEG. (2018). "2017 Statewide Load Impact Evaluation of California Aggregator Demand Response Programs: *Ex post* and Ex ante Load Impacts"
[4] SDG&E has not received nominations for the eight-hour event duration product.

Letter seeking changes to its CBP program[5]. SDG&E requested to modify its Capacity Bidding Program in the following ways:

1) reduce the number of products offered from nine products to four;
2) extend the hours events may be called to 9:00 p.m.;
3) offer the option of event duration to be called from two hours up to four hours;
4) offer the option of two hours of availability during either 11:00 a.m. to 7:00 p.m. or 1:00 p.m. to 9:00 p.m.;
5) simplify the trigger, basing it only on price, rather than price and a heat rate, per AL3157-E, propose price triggers of $100/MWh for Day-Ahead; $95/MWh for Day-Of 11-7; $110/MWh for Day-Of 1-9 product;
6) update incentives

2017 CBP Products

Product / Notification Time	Event Duration Limit	Hours	Triggers
Day-Ahead / by 3:00 pm day prior to event	1-4 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $75/MWh
Day-Ahead / by 3:00 pm day prior to event	2-6 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $75/MWh
Day-Ahead / by 3:00 pm day prior to event	4-8 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $75/MWh
Day-Of – 30 min.	1-4 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of – 30 min.	2-6 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of – 30 min.	4-8 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of / two hours prior to event	1-4 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of / two hours prior to event	2-6 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of / two hours prior to event	4-8 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $140/MWh

2018 CBP Products

Product / Notification Time	Event Duration Limit	Hours	Triggers *NOTE: subject to change due to AL3157-E*
Day-Ahead 11am-7pm	2-4 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $75/MWh
Day-Ahead 1pm-9pm	2-4 hours	1:00 p.m. – 9:00 p.m.	15,000 Btu/kWh heat rate AND $75/MWh
Day-Of 11am-7pm	2-4 hours	11:00 a.m. – 7:00 p.m.	15,000 Btu/kWh heat rate AND $140/MWh
Day-Of 1pm-9pm	2-4 hours	1:00 p.m. – 9:00 p.m.	15,000 Btu/kWh heat rate AND $140/MWh

[5] As of the date of this filing there has been no approval of AL3190-E or AL 3157-E. Both Advice letters asked for modifications to SDG&E's CBP triggers and trigger prices.

2.2 CBP Ex post Evaluation Methodology

The PY2017 *ex post* analysis was designed specifically to meet each of the following goals:

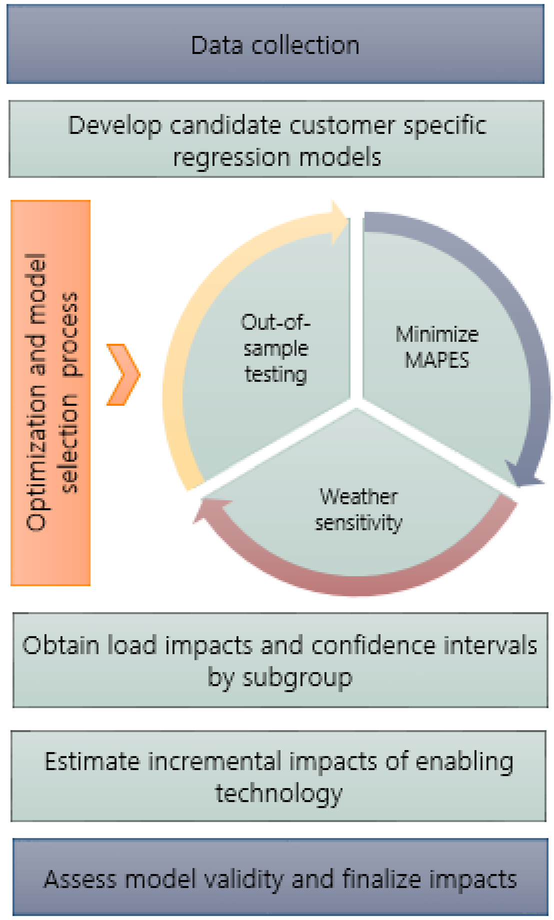
- To develop hourly and daily load impact estimates for each event in the 2017 program year.
- To provide these estimates by various segments: IOU, program, LCA, industry group, Automated Demand Response (AutoDR) and Technology A? (TA) &Technology Incentives (TI) participation, and notification type.
- To estimate the distribution of load impacts by customer segment for the average event.

The consultant Applied Energy Group (AEG)used customer-specific regressions to estimate the load impact for each customer on each event day. Given the goals of the project and the potential differences across service territories, customer-specific regressions offered the most flexible, consistent, and appropriate solution for several reasons:

- The individual customer impacts can simply be added together to estimate impacts at any level including, but not limited to, utility, program, aggregator, Local Capacity Area (LCA), North American Industry Classification System (NAICS), or notification type.
- They can be easily used to control for variation in load due to weather conditions, geography, and time-related variables (day of week, month, hour, etc.).
- Because impacts are estimated for each customer separately, they also control for unobservable customer-specific effects that are more difficult to account for in aggregate regression models.
- Commercial and industrial customers often vary significantly from one another in load shape, weather response, and overall size. Customer-specific regressions allow us to capture differences between customers; therefore, they are better able to model changes in energy usage than an aggregated model.
- Because the events are called only on isolated days over the course of the program year, and on all other days the participants and non-participants face similar TOU rates, the data conforms nicely to what researchers often call a repeated-measures design. This simply means that all participants are subjected to the treatment at the same time, repeatedly over the course of the study. In this case, the control can be defined as an absence of the treatment, or the non-event days.

It is not practical to develop models individually for thousands of participants, therefore AEG used a candidate model optimization process to select the best model for each participant. Figure 2-1 illustrates a high-level overview of the approach AEG used to develop *ex post* impacts. The subsections that follow describe the process in more detail.

Figure 2-1 *Ex post* Analysis Approach



2.2.1 Develop Candidate Customer-Specific Regression Models

Table 2-1 presents the different explanatory variables used to create candidate models for the CBP.

Table 2-1: Explanatory Variables Included in Candidate Regression Models

Variable Name	Variable Description
	Baseline Variables
$Weather_{i,d}$	Weather related variables including average daily temperature, multiple cooling degree hour (CDH) terms with base values of 75, 70, and 65 depending on service territory, and lagged versions of various weather-related variables
$Month_{i,d}$	A series of indicator variables for each month
$DayOfWeek_{i,d}$	A series of indicator variables for each day of the week
$Year_{i,d}$	An indicator for the year 2017[6]
$OtherEvt_{i,d}$	Equals one on event days of other demand response programs in which the customer is enrolled
$MornLoad_{i,d}$	The average of each day's load in hours 5 a.m. through 10 a.m.
	Impact Variables
$P_{i,d}$	An indicator variable for aggregator program event days
$P * Month_{i,d}$	An indicator variable for aggregator program event days interacted with the month
$P * Year_{i,d}$	An indicator variable for aggregator program event days interacted with the year 2017
$P{*}NonTypEvent_{i,d}$	An indicator variable for aggregator program event days interacted with an indicator for non-typical event windows (outside of HE 16-19)

AEG used the different variables presented above to create sets of candidate models that represent a wide variety of customers and their impacts. Each IOU has customized sets of candidate models, but in general, the candidate models fit into two basic categories:

- Weather-sensitive models that include weather effects and calendar effects. These models are less likely to require a morning load adjustment since much of the day-to-day variation in load is captured by weather terms.
- Non-weather sensitive models include the morning load adjustment and calendar effects.

2.2.2 Optimization Process

After developing a set of candidate models, a single "best" model was selected for each customer. The final model was selected to minimize error and bias through a series of out-of-sample tests and MAPE (mean absolute percentage error) and MPE (mean percentage error) comparisons.

[6] Because a large number of events were called in 2016, which was also a relatively mild year, we included data from 2014 and 2015 to ensure that we would have enough event-like days. Therefore, we also included a "year" indictor variable in the models.

Below are examples of two final models, one for a weather sensitive customer and one for a non-weather sensitive customer. For both types of models, the model specification is identical for each hour of the day.

Simple weather sensitive example:

$$kwh_{i,d} = \alpha_{i,d} + Month_{i,d} + Weather_{i,d} + P_{i,d} + (P_{i,d} * Weather_{i,d}) + \varepsilon_{it} \quad (2.1)$$

where:

$kwh_{i,d}$ is the customer's consumption in hour i, on day d.

$\alpha_{i,d}$ is the intercept.

$\varepsilon_{i,d}$ is the error for participant in hour i on day d.

and, all other terms are defined in above.

Simple non-weather sensitive example:

$$kwh_{i,d} = \alpha_{i,d} + MornLoad_{i,d} + DayofWeek_{i,d} + P_{i,d} + \varepsilon_{it} \quad (2.2)$$

where:

$kwh_{i,d}$ is the customer's consumption in hour i, on day d.

$\alpha_{i,d}$ is the intercept.

$\varepsilon_{i,d}$ is the error for participant in hour i on day d.

and, all other terms are defined in above.

After the "best" model was selected for each customer, AEG calculated the customer-specific impact as follows:

- AEG obtained the actual and predicted load on each hour and day based on the best model specification for each customer.
- AEG used the estimated coefficients and the baseline portion of the model to predict what this customer would have used on each day and hour if there had been no events. We call this prediction the reference load.
- AEG calculated the difference between the reference load (the estimate based on the baseline variables) and the predicted load (the estimate based on the baseline + impacts variables) on each event day. This difference represents our estimated load impact.
- In order to show the actual observed load (and avoid confusion associated with the predicted load) we re-estimated the reference load as the sum of the observed load and the load impact.

2.2.3 Obtain Load Impacts and Confidence Intervals by Subgroup

Because we estimated an impact for each customer, the model results are easily aggregated to represent impacts for each of the required subpopulations of participants for each of the three IOUs. In some cases, AEG needed to apply average per-customer impacts as a proxy for the "actual" impacts realized by one or more customers on a given event day because part of their data was invalid and, therefore, omitted during the data validation process. In these cases, we determined the aggregate impact for a particular grouping based on the per-customer average of the customers with valid data in the grouping and the total nominated accounts associated with that grouping for the given event.

It is important to note that the per-customer average may be different depending on the group or subgroup because of the different types and sizes of customers in the grouping. Therefore, during events where average per-customer data was used as a proxy for one or more customers, the sum of the individual subgroup totals for the event may not exactly add up to the total for the larger groupings or populations of customers. Consider the following hypothetical example:

- Subgroup #1 in Product A:
  - ✓ 24 nominated customers
  - ✓ 23 with sufficient valid data to estimate impacts
  - ✓ Aggregate impact for 23 customers = 2,300 kW
  - ✓ Average per-customer impact for the subgroup would be calculated with the aggregated data for the 23 customers: 2,300 kW / 23 customers = 100 kW per customer
  - ✓ Aggregate impact for all 24 nominated customers: 100 kW/customer x 24 customers = 2,400 kW

- Subgroup #2 in Product A:
  - ✓ 76 nominated customers, all with sufficient valid data to estimate impacts
  - ✓ Aggregate impact for 76 customers: 6,460 kW
  - ✓ Average per-customer impact: 6,460 kW / 76 customers = 85 kW per customer

- Total for Product A:
  - ✓ 100 nominated customers
  - ✓ 99 with sufficient valid data to estimate impacts
  - ✓ Aggregate impact for 99 customers = 2,300 kW + 6,460 kW = 8,760 kW
  - ✓ Average per-customer impact for the subgroup would be calculated with the aggregated data for the 99 customers: 8,760 kW / 99 customers = 88.48 kW per customer
  - ✓ Aggregate for all 100 nominated customers: 88.48 kW/customer x 100 customers = 8,848 kW

- Sum of Subgroup #1 plus Subgroup #2 = 2,400 kW + 6,460 kW= 8,860 kW, which does not equal the Total for Product A of 8,848 kW.

2.3 CBP Ex post Load Impact Estimates

Table 2-2 presents a summary of the 2017 events for SDG&E's CBP program by product. Over the course of the program year, the DO 1-4 hour and DO 2-6 hour participants experienced 9 event days, the DA 1-4 hour participants experienced 20 events, and the DA 2-6 hour participants experienced 12 events. Events were called with various event windows. An average event is defined as one called during hours-ending 16-19.

Table 2-2: Number of Accounts nominated by event – *SDG&E CBP*

Date	Day of Week	Event Hours (HE)	# Accounts DO 1-4 Hour	# Accounts DO 2-6 Hour	# Accounts DA 1-4 Hour	# Accounts DA 2-6 Hour
Avg. Event	**-**	**16-19**	**170**	**4**	**41**	**62**
6/20/2017	Tuesday	16-19	-	-	6	60
6/21/2017	Wednesday	16-19	-	-	6	60
6/22/2017	Thursday	16-19	-	-	6	60
7/7/2017	Friday	16-19	-	-	6	65
8/1/2017	Tuesday	16-19	170	4	69	-
8/2/2017	Wednesday	16-19	170	4	69	-
8/3/2017	Thursday	16-19	-	-	69	-
8/22/2017	Tuesday	16-19	-	-	69	-
8/28/2017	Monday	17-19 16-19	170 -	4 -	- 69	- -
8/29/2017	Tuesday	16-19	-	-	69	-
8/30/2017	Wednesday	18-19 16-19	170 -	4 -	- 69	- -
8/31/2017	Thursday	16-19	170	4	69	-
9/1/2017	Friday	16-19	174	4	4	65
9/11/2017	Monday	18-19	-	-	4	65
10/16/2017	Monday	18-19	-	-	4	65
10/17/2017	Tuesday	18-19	-	-	4	65
10/23/2017	Monday	18-19 17-19	169 -	4 -	- 4	- 65
10/24/2017	Tuesday	16-19	169	4	4	65
10/25/2017	Wednesday	18-19	169	4	4	65
10/27/2017	Friday	18-19	-	-	4	65

Table 2-3 through table 2-6 show the average event-hour impacts for the CBP DO 1-4 hour and 2-6 hour products and the DA 1-4 hour product. Impacts are included for each event at the average per-customer level and in aggregate. The tables include results for the average event day.

Table 2-3: SDG&E CBP Day-Of Product (1-4 Hour): Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Avg. Event	**170**	**4.6**	**147.2**	**18.5**	**25.0**	**3.1**	**13%**	**85**
8/1/2017	170	4.6	141.6	19.0	24.1	3.2	13%	79
8/2/2017	170	4.6	144.2	19.0	24.5	3.2	13%	83
8/28/2017	170	4.6	138.0	14.3	23.5	2.4	10%	78
8/30/2017	170	4.6	152.7	21.7	26.0	3.7	14%	82
8/31/2017	170	4.6	148.4	19.1	25.2	3.2	13%	84
9/1/2017	174	4.9	149.7	17.2	26.0	3.0	11%	88
10/23/2017	169	4.6	148.3	21.6	25.1	3.6	15%	88
10/24/2017	169	4.6	151.4	18.2	25.6	3.1	12%	93
10/25/2017	169	4.6	146.7	21.6	24.8	3.6	15%	80

Table 2-4: SDG&E CBP Day-Of Product (2-6 Hour): Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Avg. Event	**4**	**0.2**	**20.3**	**13.4**	**0.1**	**0.1**	**66%**	**89**
8/1/2017	4	0.1	43.2	12.0	0.2	<0.1	28%	82
8/2/2017	4	0.1	12.4	12.0	<0.1	<0.1	97%	87
8/28/2017	4	0.1	25.1	24.6	0.1	0.1	98%	81
8/30/2017	4	0.1	39.5	39.2	0.2	0.2	99%	87
8/31/2017	4	0.1	12.2	12.0	<0.1	<0.1	99%	90
9/1/2017	4	0.2	16.7	14.4	0.1	0.1	87%	92
10/23/2017	4	0.2	39.4	39.2	0.2	0.2	99%	89
10/24/2017	4	0.2	16.9	16.4	0.1	0.1	97%	94
10/25/2017	4	0.2	39.4	39.2	0.2	0.2	99%	82

Table 2-5: SDG&E CBP Day-Ahead (1-4 Hour): Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Avg. Event	**41**	**0.1**	**268.0**	**11.5**	**11.0**	**0.5**	**4%**	**77**
6/20/2017	6	0.1	623.6	32.9	3.7	0.2	5%	72
6/21/2017	6	0.1	610.5	32.9	3.7	0.2	5%	71
6/22/2017	6	0.1	587.7	32.9	3.5	0.2	6%	69
7/7/2017	6	0.1	650.9	31.2	3.9	0.2	5%	76
8/1/2017	69	0.3	234.4	9.5	16.2	0.7	4%	76
8/2/2017	69	0.3	239.9	9.5	16.6	0.7	4%	80
8/3/2017	69	0.3	257.3	9.7	17.8	0.7	4%	75
8/22/2017	69	0.3	222.3	9.5	15.3	0.7	4%	73
8/28/2017	69	0.3	238.7	9.5	16.5	0.7	4%	76
8/29/2017	69	0.3	232.3	9.5	16.0	0.7	4%	78
8/30/2017	69	0.3	245.6	9.5	16.9	0.7	4%	81
8/31/2017	69	0.3	249.6	9.5	17.2	0.7	4%	79
9/1/2017	4	0.1	844.6	90.0	3.4	0.4	11%	84
9/11/2017	4	0.1	783.9	47.8	3.1	0.2	6%	77
10/16/2017	4	<0.1	693.3	47.8	2.8	0.2	7%	84
10/17/2017	4	<0.1	705.6	47.8	2.8	0.2	7%	77
10/23/2017	4	<0.1	778.2	39.8	3.1	0.2	5%	87
10/24/2017	4	<0.1	845.5	56.1	3.4	0.2	7%	91
10/25/2017	4	<0.1	790.4	47.8	3.2	0.2	6%	79
10/27/2017	4	<0.1	762.0	47.8	3.0	0.2	6%	71

Table 2-6: SDG&E CBP Day-Ahead (2-6 Hour): Impacts by Event

Event	# of Accts	Nominated Capacity (MW)	Per Customer Impact (kW)		Aggregate Impact (MW)		% Impact	Temp (˚F)
			Reference Load	Impact	Reference Load	Impact		
Avg. Event	**62**	**0.2**	**203.6**	**7.6**	**12.6**	**0.5**	**4%**	**77**
6/20/2017	60	0.2	206.5	7.5	12.4	0.5	4%	72
6/21/2017	60	0.2	201.9	7.5	12.1	0.5	4%	71
6/22/2017	60	0.2	189.5	7.5	11.4	0.5	4%	69
7/7/2017	65	0.2	191.5	0.7	12.4	<0.1	0%	76
9/1/2017	65	0.2	209.6	12.0	13.6	0.8	6%	84
9/11/2017	65	0.2	180.6	5.6	11.7	0.4	3%	77
10/16/2017	65	0.2	164.3	5.6	10.7	0.4	3%	84
10/17/2017	65	0.2	166.5	5.6	10.8	0.4	3%	77
10/23/2017	65	0.2	183.2	3.7	11.9	0.2	2%	87
10/24/2017	65	0.2	212.0	9.8	13.8	0.6	5%	91
10/25/2017	65	0.2	175.5	5.6	11.4	0.4	3%	79
10/27/2017	65	0.2	160.1	5.6	10.4	0.4	4%	71

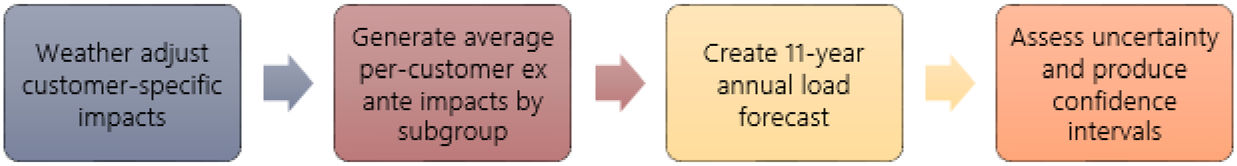
2.4 CBP Ex ante Evaluation Methodology

The main goal of the *ex ante* analysis is to produce an annual 11-year forecast of the load impacts expected from the CBP program. AEG developed the *ex ante* forecasts using the following general steps:

- AEG first provided the IOUs with the appropriate weather-adjusted, per-customer impacts for each subgroup.
- The IOUs used the per-customer impacts, along with contractual MW agreements and adjustments based on historical load reduction performance and/or the latest development of the program, to determine the enrollment forecasts.
- AEG then used the enrollment forecasts and the per-customer *ex ante* impacts to develop the 11-year annual load impact forecasts for the participant populations and subgroups.

Figure 2-2 provides an overview of the *ex ante* analysis approach which includes four basic steps after assembling the required data: 1) prediction of weather-adjusted impacts for each customer; 2) generation of per-customer average impacts by subgroup; 3) creation of annual load impact forecasts over the next 11 years; and 4) an assessment of uncertainty and the development of confidence intervals.

Figure 2-2 *Ex ante* Analysis Approach



2.4.1 Weather-Adjusted Impacts for Each Customer

The first step in the *ex ante* analysis is to use the customer-specific regression models to predict weather-adjusted per-customer average impacts for each IOU and for each of the appropriate subgroups (LCA, size, and industry segment). This produces a set of impacts under each of the different monthly peak day weather conditions: 1 in 2 CAISO peak; 1 in 10 CAISO peak; 1 in 2 IOU peak; and 1 in 10 IOU peak. To do this, the following steps were completed:

- For each customer, AEG began with the coefficients estimated in the customer-specific regression models developed for the *ex post* analysis.

- Then, AEG replaced the actual weather, from the program year, with the 1 in 2 and 1 in 10 weather data, based on the actual calendars for each year, to predict a customer's load for each of these scenarios on each day assuming no events are called. The result is a weather-adjusted monthly peak day reference load for each customer for each weather year.

- Next, AEG predicted the weather-adjusted event day load by again applying the coefficients from the *ex post* models to both the 1 in 2 and 1 in 10 weather data; however, this time we assumed that events were called on each monthly peak day by changing the event-indicator variables from zero to one. AEG also assumed that all events occurred during the Resource Adequacy window, which is between hour-ending 14 and hour-ending 18. As part of the *ex ante* forecast development for SDG&E, the predicted impacts were applied under August weather conditions to each month so that the per-customer impacts would not vary by month in a given forecast year. The assumption is not unreasonable, as the load impacts should be a function of the monthly nomination, which is not weather-dependent within a given month. Aggregators target delivery at the nominated level, with little incentive to deliberately over-deliver the load reduction even under extreme weather.

- AEG then calculated the load impact for each of the participants by subtracting the weather-adjusted event-day load from the weather-adjusted reference load.

2.4.2 Generation of Per-Customer Average Impacts by Subgroup

Once weather-adjusted impacts have been predicted for each customer for each of the desired event day types, it becomes a relatively simple exercise to average the individual impacts and generate per-customer average impacts by subgroup. For example, the average impact for a particular LCA is the average of the impacts predicted for each customer in that LCA. At this stage, AEG also worked with the IOUs to determine the best way to account for dual participation between programs to ensure that they are not double-counted in the forecast.

2.4.3 Creation of 11-Year Annual Load Impact Forecasts

AEG provided the IOUs with the per-customer average *ex ante* impacts by year and subgroup. SDGE used the per-customer impacts—along with contractual MW adjusted by historical performance relative to the aggregator’s MW nomination and/or anticipated program changes—to determine the enrollment forecasts. AEG used the enrollment forecasts and set of per-customer average *ex ante* impacts to create the annual forecast of load impacts over the next 11 years.

2.5 CBP Ex ante Load Impact Estimates

For the CBP DA and DO products, the enrollment forecast assumes the customer enrollment will increase by 3% per year starting in 2019 through 2022 due to the CBP program improvements proposed by SDG&E in the application for 2018-2022. In addition, SDG&E forecasts that the customer enrollment in the CBP DO program will increase by another 7% per year starting in 2019 through 2022 due to growth in the Technical Incentives (TI) program. Therefore, total DO enrollment is expected to increase by 10% per year (3% + 7%) starting in 2019 through 2022, due to program improvements and growth in TI. The enrollment forecasts for the DA and DO products after 2022 and through 2027 show a flat trend at the 2022 values.

The *ex ante* load impact forecast follows the 2017-2027 enrollment forecast trends for the DA and DO products. In addition, the impacts are expected to remain constant during the months of May through October.

Table 2-7 summarizes the average event-hour load impact forecasts for the DA and DO products on an August peak day in 2018. The table includes impact forecasts under the 1-in-2 and 1-in-10 weather scenarios and for the utility peak and the CAISO peak.

Table 2-7: SDG&E CBP: Average Event-Hour *Ex ante* Impacts for an August Peak Day, 2018

		Per Customer Impact (kW)				Aggregate Impact (MW)			
		Utility Peak		CAISO Peak		Utility Peak		CAISO Peak	
Notice	Accts	1 in 2	1 in 10	1 in 2	1 in 10	1 in 2	1 in 10	1 in 2	1 in 10
Total DA	69	9.8	9.8	9.8	9.8	0.7	0.7	0.7	0.7
Total DO	171	18.5	18.5	18.4	18.5	3.2	3.2	3.1	3.2

2.6 CBP Comparisons of Ex post and Ex ante Results

In response to the request to improve the transparency of the linkage between *ex post* and *ex ante* results, the following two sections compare the estimated load impacts.

2.6.1 *Ex post* load impacts from the current and previous studies

Table 2-7 summarizes the CBP DA and DO average event-hour *ex post* load impact results for the past five years for an average event day. The table includes the number of participating accounts, the average event-hour reference loads, and average event temperature. Both per-customer and aggregate results are presented.

Table 2-7: SDG&E CBP: Previous and Current *Ex post*, Average Event Day

			Per Customer (kW)		Aggregate (MW)			
	Ex post Year	Accounts	Reference Load	Load Impact	Reference Load	Load Impact	% Impact	Event Temp (˚F)
DA	2012	78	320.3	81.6	25.0	6.4	25%	83
	2013	142	304.8	75.9	43.2	10.8	25%	88
	2014	163	247.0	60.6	40.4	9.9	25%	87
	2015[7]	122	148.0	64.1	18.1	7.8	43%	80
	2016	69	276.3	51.4	19.1	3.5	19%	79
	2017	68	241.1	9.9	16.4	0.7	4%	77
DO	2012	321	229.7	30.5	73.7	9.8	13%	86
	2013	260	234.5	40.2	61.1	10.5	17%	87
	2014	237	228.5	37.0	54.1	8.8	16%	87
	2015	223	208.4	25.6	46.4	5.7	12%	82
	2016	200	189.9	24.0	38.0	4.8	13%	84
	2017	174	144.3	18.4	25.1	3.2	13%	85

[7] In 2015, there was a change to the CBP trigger that resulted in many more events being called. The average event temperature dropped significantly, as well as the number of customers on the program starting in 2016.

2.6.2 Previous and Current *Ex ante* and *Ex post*

Table 2-8: compares the current year's analysis with the previous year's analysis of CBP *ex post* and *ex ante* average event-hour impacts. To make the comparison as consistent as possible, the *ex post* and *ex ante* results represent events on monthly system peak days in August, unless otherwise noted.[8] In addition, the *ex ante* results reflect the utility peak 1 in 2 weather scenario.

Table 2-8: SDG&E CBP: Previous and Current *Ex ante* and *Ex post*, August Peak Day

	Model	Year	Day	Accts	Per Customer (kW) Ref. Load	Per Customer (kW) Impact	Aggregate (MW) Ref. Load	Aggregate (MW) Impact	% Impact	Event Temp (˚F)
DA	Current	*Ex post* 2017	Aug 2	69	239.9	9.5	16.6	0.7	4%	80
DA	Current	*Ex ante* 2018	Aug Peak	69	248.9	9.8	17.2	0.7	4%	80
DA	Previous	*Ex post* 2016	Aug 16	72	309.2	93.9	22.3	6.8	30%	78
DA	Previous	*Ex ante* 2017	Aug Peak	70	264.2	12.1	18.5	0.8	5%	83
DA	Previous	*Ex ante* 2018	Aug Peak	70	264.2	12.1	18.5	0.8	5%	83
DO	Current	*Ex post* 2017	Aug 31	174	145.2	18.9	25.3	3.3	13%	84
DO	Current	*Ex ante* 2018	Aug Peak	171	141.3	18.5	24.2	3.2	13%	84
DO	Previous	*Ex post* 2016	Aug 15	200	198.6	22.2	39.7	4.4	11%	83
DO	Previous	*Ex ante* 2017	Aug Peak	199	180.6	25.5	35.9	5.1	14%	85
DO	Previous	*Ex ante* 2018	Aug Peak	199	180.6	25.5	35.9	5.1	14%	85

Table 2-8: shows the following trends for the CBP DA and DO products:

- ***Current Ex post Compared with Previous Ex ante:*** For DA, the current *ex post* results show similar aggregate impacts (0.7 MW) as the previous *ex ante* projections for PY2017 (0.8 MW). For DO, the current aggregate *ex post* impacts (3.3 MW) are lower than the previous *ex ante* projections for PY2017 (5.1 MW) due to lower enrollment and lower per-customer impacts realized in 2017 than previously expected

- ***Current Ex ante Compared with Previous Ex ante:*** The current PY2018 aggregate *ex ante* impacts for DA (0.7 MW) are similar to previous *ex ante* impacts for PY2018 (0.8 MW). The current *ex ante* analysis for DO projects lower impacts in PY2018 (3.2 MW) than did the previous *ex ante* analysis (5.1 MW) due to lower expected per-customer impacts and lower enrollment.

- ***Current Ex ante Compared with Current Ex post:*** For DA, the current *ex ante* estimates for PY2018 show comparable aggregate impacts (0.7 MW) to the current *ex post* estimates for PY2017 (0.7 MW). For DO, the current *ex ante* estimates for PY2018 (3.2

[8] Though the *ex ante* impacts are labeled as an August peak day, the *ex ante* results are identical for each monthly system peak day, May through October, because of the way the SDG&E ex ante impacts were modeled.

MW) show fairly comparable aggregate impacts to the current *ex post* estimates for PY2017 (3.3 MW), although the *ex ante* impacts are projected to be slightly smaller.

3 Summary of SDG&E's Critical Peak Pricing Default Report[9]

3.1 CPP Rate Description

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

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

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

Large C&I customers were defaulted onto CPP, starting in 2008. SDG&E began to default its Small and Medium Business (SMB) customers between November 2015 and April 2016. By April of 2016 over 140,000 SMB customers were defaulted onto CPP. This report covers

[9] The CPP statewide load impact evaluation was conducted by Christensen Associates. This section of the Executive Summary contains excerpts from the following evaluation: Lott, C, Crowley, N., Hansen, D. & Clark, M. Christensen Associates (2018). "2017 Statewide Load Impact Evaluation of Non-Residential Critical Peak Pricing (CPP) Rates"

SDG&E's medium and large customers which are customers 20 kW and larger. A separate CPP study was conducted for SDG&E's small business and agricultural customers.[10]

In 2009, the California Public Utilities Commission (CPUC) issued rate design guidance for dynamic pricing tariffs such as CPP (CPUC decision (D.) 10-02-032). The decision standardized several key elements of dynamic pricing rate design for California IOUs:

- The default tariff for large and medium C&I customers must be a dynamic pricing tariff;[11]
- Default rates must include a high price during peak periods on a limited number of critical event days and TOU rates on nonevent days;
- The opt-out tariff for all nonresidential default customers should be a time varying rate—in other words, there should no longer be a flat rate option for nonresidential customers once the default schedule is completed;
- The critical peak price should represent the cost of capacity required to meet peak energy needs plus the marginal cost of energy—in essence, all capacity value should be allocated to peak period hours on critical event days; and
- Utilities should offer first year bill protection to customers defaulted onto dynamic rates.

The decision also served to standardize other aspects of rate design affecting nonresidential customers, including components of the default process and a schedule for each utility's implementation of dynamic pricing across all customer classes.

SDG&E has developed CPP tariffs that adhere to the principles and direction provided by D.10-02-032 described below:

- SDG&E was the first to default customers onto a CPP tariff, on May 1, 2008.
- SDG&E defaulted customers whose maximum demand exceeded 200 kW for the prior 12 consecutive months.
- At SDG&E, customers are locked into the CPP rate for a full year if they do not opt out prior to going on the default rate.
- For SDG&E, both the CPP event period hours and TOU summer peak period hours are from 11 AM to 6 PM. Off-peak prices apply on the weekends at all three IOUs, unless a CPP event is called on a weekday;
- SDG&E can call CPP events throughout the calendar year and on any day of the week.

[10] See Section 9 for SPP Rates.
[11] Customers with loads of 200kW or greater were defaulted onto CPP. SDG&E considers its medium sized customers to be >20 kW and less than 500 kW. Therefore, some medium customers were included in the 2008 CPP default rollout.

- SDG&E notify customers by 3 PM the day before.
- SDG&E offers customers the ability to hedge part or all of their demand against higher CPP prices, a feature known as a capacity reservation level (CRL).
- SDG&E offers customers CPP bill protection during their default year, which ensures that the customer does not pay more for the energy commodity under CPP than they would have under the otherwise applicable tariff (OAT). The bill comparison is sent to customers at the end of their first year on the rate. If the bill comparison shows that the customer paid more under CPP than they would have if they were subject to the OAT, then the customer's account is credited the difference.

SDG&E triggers CPP event days using their own protocols, which depend on forecasted conditions for their individual transmission and distribution system. Due to the climatic diversity in California, system load patterns across utilities are not always coincident, particularly between Northern and Southern California. SDG&E system peak occurred on September 1st, 2017. Another key difference in *ex post* results is event duration. SDG&E uses a longer event window, 11 AM to 6 PM.

Table 3-1 provides examples of the default CPP and opt-out TOU rates. There are a number of different CPP rates which vary with customer size and service voltage level. These various CPP rates also change over time due to periodic rate changes. SDG&E defines summer as May through September.

Table 3-1: Example Summer Default CPP Rates at SDG&E[12]

Season	TOU/CPP Component	Type of Charge/Credit	Period	Rate SDG&E AL-TOU
Summer	TOU Component	Energy Charges (per kWh)	On-peak	$0.13
			Semi-peak	$0.12
			Off-peak	$0.09
		Demand Charges (per kW)	On-peak	$21.13
			Semi-peak	$0.00
			Maximum	$24.51
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.28
			On-peak	$0.13
			Semi-peak	$0.12
			Off-peak	$0.09
		Demand Charges (per kW)	On-peak	$10.25
			Semi-peak	$0.00
			Maximum	$24.51
		Capacity Reservation Charge (per kW per month)	Summer	$6.14

[12] Tables 3-1 and 3-2 do not include all CPP rates at each utility, and the rates shown are presented for illustrative purposes only. Rates may vary over the course of the program year, by customer size and service voltage level. The rates shown are for customers at the secondary service voltage level. AL-TOU applies to all SDG&E customers whose monthly maximum demand equals, exceeds, or is expected to equal or exceed 20 kW. This example the SDG&E rate was effective March 1, 2017.

Table 3-2: Example Winter Default CPP Rates at SDG&E

Season	TOU/CPP Component	Type of Charge/Credit	Period	Rate SDG&E AL-TOU
Winter	TOU Component	Energy Charges (per kWh)	On-peak	$0.12
			Semi-peak	$0.10
			Off-peak	$0.08
		Demand Charges (per kW)	On-peak	$7.57
			Semi-peak	$0.00
			Maximum	$24.51
	CPP Component	Energy Charges and Credits (per kWh)	CPP Event Adder	$1.28
			On-peak	$0.12
			Semi-peak	$0.10
			Off-peak	$0.08
		Demand Charges (per kW)	On-peak	$7.57
			Semi-peak	$0.00
			Maximum	$24.51
		Capacity Reservation Charge (per kW per month)	Winter	$6.14

3.2 CPP-D Ex post Evaluation Methodology

The primary goals of the evaluation include:

1. Estimate hourly *ex post* load impacts of the CPP rates for each of the Joint Utilities in 2017;
2. Estimate *ex post* load impacts for 2017 for each of the utilities' Technical Assistance and Technology Incentives (TA/TI) and Automated Demand Response (AutoDR) programs for those customers enrolled in those programs.

3.2.1 Data

Analysis that addresses each of the load impact objectives listed in Section 3.2 requires the following types of data:

- Customer information for the CPP customers and potential control-group customers (e.g., industry group, weather station, LCA, size group);
- Billing-based interval load data on event days and event-like non-event days (i.e., hourly loads for each treatment and potential control group customers);

- Weather data (i.e., hourly temperatures and other variables for the relevant time period, by weather station);
- Program event data (i.e., dates and hours of CPP events and any programs in which CPP customers are dually enrolled).

3.2.2 Analysis Methods

Load impacts are estimated from panel models estimated separately for each hour of the day and customer sub-group, with the model taking the following form:

$$kW_{c,d} = \beta_0 + \Sigma_{Evts(i)} (\beta_{1,i} \text{ x } CPP_{c,d} \text{ x } Evt_{i,d}) + C_c + D_d + \varepsilon_{c,d}$$

The variables and coefficients in the equation are described in the following table:

Table 3.3: Panel Model Terms

Symbol	Description
$kW_{c,d}$	Load during a given hour for customer *c* on day *d*
$CPP_{c,d}$	Variable indicating whether customer *c* is a CPP (1) or Control (0) customer
$Evt_{i,d}$	Variable indicating that day *d* is the i^{th} event day (1) or not (0)
β_0	Estimated constant coefficient
$\beta_{1,i}$	Estimated load impact for event *i*
C_c	Customer fixed effects
D_d	Date fixed effects
$\varepsilon_{c,d}$	Error term (correlated at the customer level)

The model includes date and customer fixed effects to account for factors that commonly affect all customers over time such as weather and time-invariant customer characteristics (such as establishment size). In addition, the model can include additional variables, including indicators for other program events in which treatment customers are dually enrolled; weather variables such as the mean temperature across the first 17 hours of the day[13]; and a "morning load" variable, which is the average usage during the first 10 hours the day.[14] The $\beta_{1,i}$ coefficients represent the estimated load impacts for each hour of every event day. This model is estimated separately for each hour of the day using only event and event-like non-event days, and is estimated for all required sub-groups.

[13] The inclusion of weather variables may improve the effectiveness of the date fixed effects, particularly in models that include customers in different weather regions (*e.g.*, models by size and industry group that include customers in all LCAs).

[14] The morning load variable can help the model identify days on which the customer is operating (*e.g.*, a manufacturing customer in production vs. not in production) or open for business (*e.g.*, for commercial customers).

Estimating distributions of load impacts for different customer segments

The distribution of load impacts across different subgroups of customers is explored by performing load impact analyses at the subgroup level (*e.g.*, load impacts for AutoDR and TA/TI participants, by LCA, or industry group).

Calculating uncertainty-adjusted load impacts

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. Thus, in addition to producing point estimates of the *ex post* load impacts, we produce *uncertainty-adjusted* program impacts for each event, which show the uncertainty around the estimated impacts, as required by the Protocols. These methods use the estimated load-impact parameter values and the associated variances to derive scenarios of hourly load impacts. We also report the uncertainty associated with the average event hour, both on an event-specific basis and for the typical event day, which are based on the standard errors from regression models that aggregate the corresponding load impacts (*e.g.*, by estimating a single average event-hour load impact).

Validity assessment

To assess the validity of the control-group matching processes, we compare the characteristics and non-event-day load profiles of the matched control-group and treatment customers. In addition, we perform various consistency checks of the panel model estimated load impacts compared to: 1) simple difference-in-differences calculations (*i.e.*, from means of data rather than regression analyses), 2) program-level day matching comparisons (*i.e.*, by comparing event-day program loads to event-like non-event day program loads), and 3) estimates from prior evaluations.

3.3 CPP-D Ex post Load Impacts Estimates

This section documents the findings from the *ex post* load impact analysis for SDG&E. The primary load impact results include estimates of average event-hour load impacts, in aggregate and per-customer, for the typical event day as well as for each individual event. Results for all hours for the typical event day are also illustrated in figures and presented in data tables.

3.3.1 CPP Large Customers

This section summarizes results for all large SDG&E customers, defined as customers with maximum demand over 200 kW. The presented results include: the average event-hour load impact by event day; the hourly load impact for the average event day; and load impacts by industry group.

Table 3.4 summarizes enrollments, average event-hour load impacts, and reference loads for each event day and the average event. The enrollments remain the same for the three consecutive event days. Estimated load reductions averaged for 14.1 kWh/hour/customer across weekday event days, which amounts to a 4.3 percent load reduction.

Table 3.4: Average Event-Hour Load Impacts by Event, *SDG&E Large*

Event Date	# Enrolled	Aggregate (MWh/hour)		Per-Customer (kWh/hour)		% Load Impact	Ave. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
8/31/2017	1,281	416.2	19.2	324.9	15.0	4.6%	88.8
9/1/2017	1,281	413.4	16.8	322.7	13.1	4.1%	95.0
9/2/2017*	1,281	310.0	8.9	242.0	7.0	2.9%	94.3
Typical Event Day	**1,281**	**414.8**	**18.0**	**323.8**	**14.1**	**4.3%**	**91.9**

*9/2/2017 was a Saturday and is not included in the average of the typical event day calculation

3.3.2 CPP Medium Customers

This section summarizes results for SDG&E's medium-sized CPP customers (defined as customers with maximum demand between 20 and 199.99 kW), excluding those dually enrolled in SCTD. The presented results include: the average event-hour load impact by event day; the hourly load impact for the average event day; and load impacts by industry group for the average event hour.

Table 3.5 summarizes enrollments, average event-hour load impacts, and reference loads for each event day and the average event. Enrollments increased by one for the weekend event. The typical event day exhibits a load impact of 1 MWh/hour for the two weekday events, although this amounts to only 0.2% of the reference load (and as the previous figure indicated, is not statistically significant). Our estimates indicate an increase in usage for the weekend event of 5.9 MWh/hour (1.6% of reference load).

Table 3.5: Average Event-Hour Load Impacts by Event, *SDG&E Medium*

Event Date	# Enrolled	Aggregate (MWh/hour)		Per-Customer (kWh/hour)		% Load Impact	Ave. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
8/31/2017	11,808	450.2	1.4	38.1	0.1	0.3%	88.1
9/1/2017	11,808	459.7	0.7	38.9	0.1	0.1%	94.6
9/2/2017*	11,809	367.4	-5.9	31.1	-0.5	-1.6%	93.7
Typical Event Day	**11,808**	**455.0**	**1.0**	**38.5**	**0.1**	**0.2%**	**91.4**

*9/2/2017 was a Saturday and is not included in the average of the typical event day calculation

3.4 CPP-D Ex ante Evaluation Methodology

Ex ante load impacts represent forecasts of load impacts that are expected to occur when program events are called in future years under standardized weather conditions.

Estimating *ex ante* load impacts requires three key pieces of information:

1. An enrollment forecast for relevant components of the program, which consists of forecasts of the number of customers by required type of customer;
2. Reference loads by customer type;
3. A forecast of load impacts per customer, again by relevant customer type, where the load impact forecast also varies with weather conditions (if applicable), as determined in the *ex post* evaluation.

Ex ante load impacts are developed for the following subgroups of customers:

1. Size group;
2. LCA;
3. Busbar (by November 1, 2018); and
4. Program vs. portfolio load impacts based on dual enrollment status.

The load impacts are also provided for the years 2018 through 2028,[15] for a number of day types, and weather scenarios, including the following:

- Estimates are provided for a typical event day under the four scenarios defined by both utility-specific and CAISO peaking conditions in both 1-in-2 (normal) and 1-in-10 (extreme) scenarios; and
- The monthly system peak load day of each month, again under the above four scenarios.

SDG&E provided the enrollment forecasts and *ex ante* weather conditions for each required scenario. The per-customer reference loads are simulated based on regression models designed to reflect customer load patterns on non-event days during summer and non-summer months, accounting for weather and seasonal usage patterns. The reference load regression models require 8760 load profile data (as opposed to the *ex post* regression models, which include only event and event-like days), which we requested for either all CPP customers or a representative sample of treatment customers (where the number of customers is high, such as PG&E's small customers). Reference loads are simulated using the appropriate weather scenario data (*i.e.*, the 1-in-2 and 1-in-10 weather-year conditions to be provided by the utilities) and month.

The *per-customer load impacts* are derived from an analysis of the current and previous *ex post* load impact evaluations, with a focus on the effect, if any, of weather on the estimated load

[15] SDG&E's forecast begins in 2017.

impacts. The resulting per-customer load impacts are then applied to the appropriate reference loads to develop the forecast load impacts and (by extension) event-day reference load profiles. CPP load impacts must be forecast for both winter and summer months. Because we don't observe winter event days, we assume that winter percentage load impacts are equal to the summer percentage load impacts.

In practice, the *ex ante* percentage load impacts are based on regressions of the group-level percentage load impact as a function of a constant term and a weekend indicator variable, as follows (where *evt* indexes event days and h indexes hours):

$$PctImpact_{evt,h} = a + b \text{ x } Weekend_{evt,h} + \mathrm{e}_{evt,h}$$

Separate models are estimated by customer group and hour of the day. The estimated constant term (a) is average weekday percentage load impact for the modeled customer group and hour of the day. The standard error of the constant is the basis for the uncertainty-adjusted load impacts.

3.5 CPP-D Ex ante Load Impacts Estimates

This section provides the *ex ante* CPP load impact forecasts based on an enrollment forecast provided by SDG&E. Results are presented by size group. First, the enrollment forecast provided by SDG&E is summarized in figures on an annual basis. Second, results for all hours for the typical event day in 2022 are illustrated in figures to convey the shape of *ex ante* reference loads and compare *ex ante* results with *ex post* results. Finally, forecasted *ex ante* load impacts are summarized in figures by month and forecast year. Detailed results for each hour, weather scenario, month, and forecast year are available in electronic form in Protocol table generators provided along with this report.

Per-customer load impacts are derived from current *ex post* load impacts. The *ex post* percentage load impacts for the two weekday events, August 31st and September 1st, are applied to the *ex ante* reference loads to produce *ex ante* load impacts that vary by weather scenario and month.[16] Beginning on December 1, 2017, SDG&E changed its CPP event hours, reducing the seven-hour event window of 11 a.m. to 6 p.m. (HE 12 to 18) to a four-hour event widow of 2 to 6 p.m. (HE 15 to 18). In order to apply *ex post* load impacts that correspond to the updated CPP event hours, we first categorize each hour of the day with respect to the old and updated CPP event hours. Table 3.6 summarizes our categorization of each hour, with the *ex post* column representing the old event hours and the *ex ante* column representing the new CPP event

[16] The *ex post* percentage load impacts for the weekday events are used because the small sample size of events reduces the variation that can be used to identify an adequate relationship between load impacts and weather.

window. The *ex post* reference loads and load impacts are averaged over these periods to obtain percentage load impacts, which are then applied to *ex ante* reference loads during the corresponding categorized period to calculate the *ex ante* load impacts. For example, the percentage load impact for the hour before the event in *ex post* (HE 11) is applied the *ex ante* reference load for the hour before the event in *ex ante* (HE 14).

Table 3.6: SDG&E Hourly Categorization of Periods Relating to Change in CPP Event Window

<table>
<tr><th>Hour</th><th>Ex post</th><th>Ex ante</th></tr>
<tr><td>1</td><td rowspan="10">beginning of event day</td><td rowspan="13">beginning of event day</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td></tr>
<tr><td>6</td></tr>
<tr><td>7</td></tr>
<tr><td>8</td></tr>
<tr><td>9</td></tr>
<tr><td>10</td></tr>
<tr><td>11</td><td>pre-event hour</td></tr>
<tr><td>12</td><td rowspan="2">beginning of event</td></tr>
<tr><td>13</td></tr>
<tr><td>14</td><td rowspan="3">middle of event</td><td>pre-event hour</td></tr>
<tr><td>15</td><td>beginning of event</td></tr>
<tr><td>16</td><td rowspan="2">middle of event</td></tr>
<tr><td>17</td><td rowspan="2">end of event</td></tr>
<tr><td>18</td><td>end of event</td></tr>
<tr><td>19</td><td>hour-ending 19</td><td>hour-ending 19</td></tr>
<tr><td>20</td><td>hour-ending 20</td><td>hour-ending 20</td></tr>
<tr><td>21</td><td>hour-ending 21</td><td>hour-ending 21</td></tr>
<tr><td>22</td><td>hour-ending 22</td><td>hour-ending 22</td></tr>
<tr><td>23</td><td>hour-ending 23</td><td>hour-ending 23</td></tr>
<tr><td>24</td><td>hour-ending 24</td><td>hour-ending 24</td></tr>
</table>

3.5.1 Large C&I *Ex ante* Impacts

Figure 3.1 summarizes SDG&E's enrollment forecast for large customers. The enrollments exclude any customers dually enrolled in SCTD. SDG&E anticipates an average increase in large customers of about 2% per year after 2018.

Figure 3.1: CPP Enrollments, *SDG&E Large*

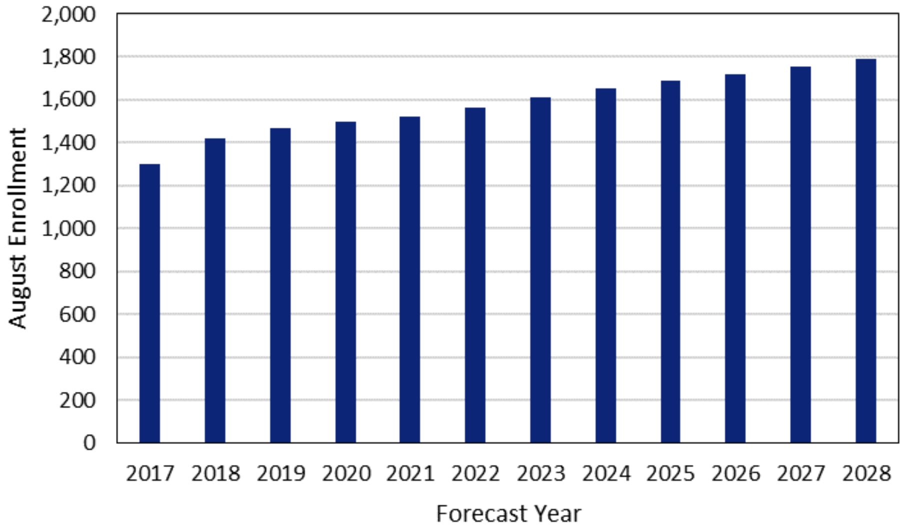
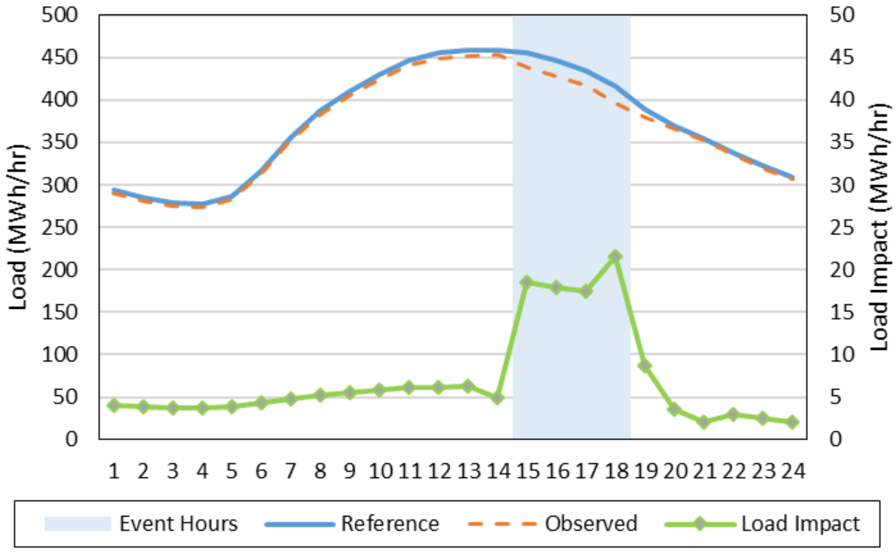


Figure 3.2 illustrates the aggregate reference loads, observed loads, and load impacts for large customers on the typical event day in August in 2022 for the SDG&E 1-in-2 weather scenario. The shape of the *ex ante* loads and load impacts is similar to the *ex post* results in **Error! Reference source not found.**, while the magnitudes are slightly larger because of the larger reference loads. The duration of the event-hours has also been reduced by three hours (from 11:00 a.m. to 6:00 p.m. in *ex post* to 2:00 p.m. to 6:00 p.m. in *ex ante*). The forecast predicts an average load impact of 18.9 MWh/hour for large customers on the typical event day in 2022 for the SDG&E 1-in-2 weather scenario, which is a 4.3 percent reduction in reference loads.

Figure 3.2: Aggregate Hourly Loads and Load Impacts in 2022 for *SDG&E 1-in-2 Typical Event Day, SDG&E Large*



3.5.1.1 CPP Large - Relationship between *Ex post* and *Ex ante* Estimates

In a continuing effort to clarify the relationships between *ex post* and *ex ante* results, this section compares several sets of estimated load impacts for CPP, including the following:

- *Ex post* load impacts from the current and previous studies;
- *Ex ante* load impacts from the current and previous studies;
- Current *ex post* and previous *ex ante* load impacts; and
- Current *ex post* and *ex ante* load impacts.

The term "current" refers to the present study, which includes *ex post* and *ex ante* results for PY2017. The term "previous" refers to findings in reports for PY2016.

Previous vs. Current Ex post

Table 3.7 shows the average event-hour reference loads and load impacts for the average event day during the current and previous program years. The number of enrolled customer decreased slightly from 1,299 in PY2016 to 1,281 in PY2017; however, all customer dually enrolled in CPP and SCTD are completely removed from the PY2017 analysis. The average per-customer reference load is larger in the PY2017 study, even with the average event-hour temperature being cooler. The PY2017 study exhibits a higher percentage load impact of 4.3 percent compared to 2.0 percent in PY2016.

Table 3.7: Current vs. Previous *Ex post* Load Impacts for the Average Event, *SDG&E Large*

Level	Outcome	PY2016	PY2017
Total	# SAIDs	1,299	1,281
	Reference (MW)	363	415
	Load Impact (MW)	7.3	18.0
	Avg. Temp.	97.8	91.9
Per SAID	Reference (kW)	279	324
	Load Impact (kW)	5.6	14.1
	% Load Impact	2.0%	4.3%

Previous versus current ex ante

In this sub-section, a comparison is made with the *ex ante* forecast prepared following PY2016 (the "previous study") to the *ex ante* forecast contained in this study (the "current study"). Table3.8 reports the average event-hour load impacts for the August 2018 peak day under utility-specific 1-in-2 weather conditions. The total forecast load impact is higher in the current study, primarily due to the higher percentage load impact.

Table 3.8: Previous vs. Current *Ex ante* Load Impacts, *Utility 1-in-2 August 2018 Peak Day, SDG&E Large*

Level	Outcome	Previous Study	Current Study
Total	# SAIDs	1,437	1,422
	Reference (MW)	383	430
	Load Impact (MW)	8.8	18.5
	Avg. Temp.	84.6	86.2
Per SAID	Reference (kW)	267	302
	Load Impact (kW)	6.1	13.0
	% Load Impact	2.3%	4.3%

Previous ex ante versus current ex post

Table 3.93.9 provides a comparison of the *ex ante* forecast of 2017 load impacts prepared following PY2016 and the PY2017 load impacts estimated as part of this study. The *ex ante* forecast shown in the table represents the August peak day during a utility-specific 1-in-2 weather year. The *ex post* load impacts are based on the average event day. While the number of customers in 2017 was below forecast levels, the average per-customer reference load was higher than forecast (324 kWh/hour to 267 kWh/hour). The percentage load impact was also higher than expected (4.3 percent vs. 2.3 percent).

Table 3.9: Comparison of Previous *Ex ante* and Current *Ex post* Impacts, *SDG&E Large*

Level	Outcome	*Ex ante* for 2017 August Peak Day from PY2016 Study	*Ex post* for Average Event Day from PY2017 Study
Total	# SAIDs	1,425	1,281
	Reference (MW)	380	415
	Load Impact (MW)	8.7	18.0
	Avg. Temp.	84.6	91.9
Per SAID	Reference (kW)	267	324
	Load Impact (kW)	6.1	14.1
	% Load Impact	2.3%	4.3%

Current ex post versus current ex ante

Table3.10 compares the *ex post* and *ex ante* load impacts from this study. The *ex ante* load impacts in the table represent the 2018 August peak day with utility-specific 1-in-2 weather conditions. The percentage load impact is equivalent between the current *ex post* and *ex ante* analysis by design. The enrollment number is higher in the *ex ante* study which contributes to the higher aggregate reference load and load impact. The per-customer load impact level is slightly lower in the *ex ante* study due to the cooler August 2018 peak day temperature.

Table 3.10: Comparison of Current *Ex post* and *Ex ante* Load Impacts, *SDG&E Large*

Level	Outcome	*Ex post* for Average Event Day from PY2017 Study	*Ex ante* for 2018 August Peak Day from PY2017 Study
Total	# SAIDs	1,281	1,422
	Reference (MW)	415	430
	Load Impact (MW)	18.0	18.5
	Avg. Temp.	91.9	86.2
Per SAID	Reference (kW)	324	302
	Load Impact (kW)	14.1	13.0
	% Load Impact	4.3%	4.3%

Table 3.113.11 documents the various potential sources of differences between the *ex post* and *ex ante* load impacts.

Table 3.11: Comparison of *Ex post* and *Ex ante* Factors

Factor	*Ex post*	*Ex ante*	Expected Impact
Weather	Average event-hour temperature of 91.9 °F during the average event day.	Average event-hour temperature of 86.2 °F during the SDG&E 1-in-2 August peak day.	Lower *ex ante* temperatures result in smaller reference load and load impacts.
Event window	Hours-ending 12 through 18.	Hours-ending 15 through 18.	The shorter event window during the later period corresponds with higher average event hour temperatures and reference loads.
% of resource dispatched	100%	100%	None. All customers are assumed to be called in both cases.
Enrollment	1,281 service accounts.	1,422 service accounts.	Higher *ex ante* enrollment leads to higher aggregate reference loads and load impacts (*ceteris paribus)*.
Methodology	Panel models by industry group with customer and date fixed effects and a matched control-group of non-participants.	Simulated reference loads using average program loads for large customers. Then applied percentage load impacts derived from the *ex post* analysis, excluding the weekend event day.	The method is not expected to consistently produce differences between the *ex post* and *ex ante* impacts.

3.5.2 Medium C&I *Ex ante* Impacts

Figure 3.3. summarizes SDG&E's enrollment forecast for medium customers. The enrollments exclude any customers dually enrolled in SCTD. SDG&E anticipates an average decrease in medium customers of 1% per year after 2018.

Figure 3.3: CPP Enrollments, *SDG&E Medium*

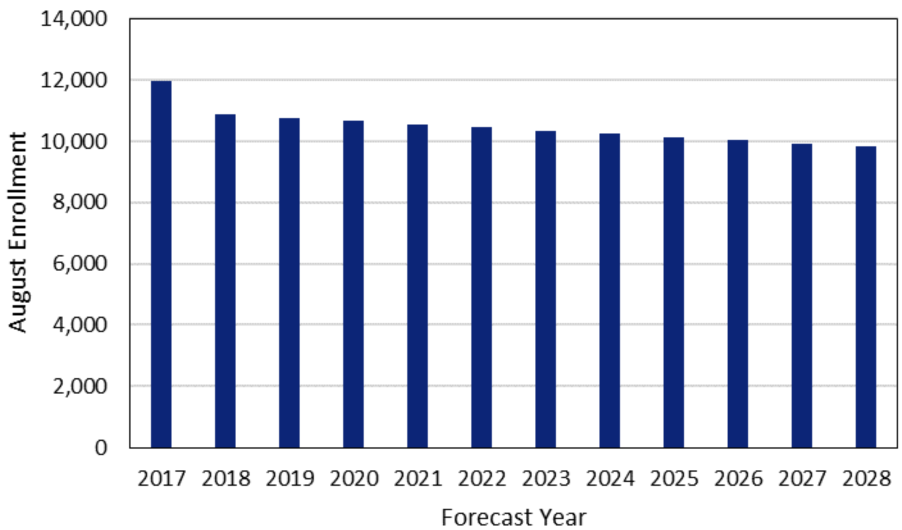
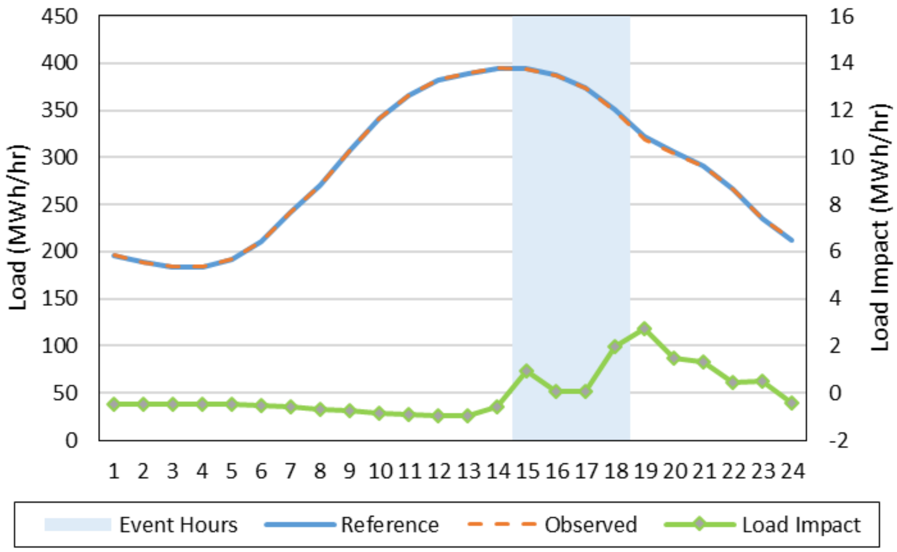


Figure 3.4 illustrates the aggregate reference loads, observed loads, and load impacts for medium customers on the typical event day in August in 2022 for the SDG&E 1-in-2 weather scenario. The shape of the *ex ante* loads and load impacts is similar to the *ex post* results in **Error! Reference source not found.**, while the magnitudes are smaller because of the decrease in enrollments. Additionally, the duration of the event-hours has been reduced by three hours (from 11:00 a.m. to 6:00 p.m. in *ex post* to 2:00 p.m. to 6:00 p.m. in *ex ante*). The forecast predicts an average load impact of 0.8 MWh/hour, or 0.2 percent of the reference load.

Figure 3.4: Aggregate Hourly Loads and Load Impacts in 2022 for
SDG&E 1-in-2 Typical Event Day, SDG&E Medium



3.5.2.1 CPP Medium - Relationship between *Ex post* and *Ex ante* Estimates

Previous vs. Current Ex post

Table3.12 shows the average event-hour reference loads and load impacts for the average event day during the current and previous program years. The average per-customer reference loads are similar between years, even though the average event-hour temperature decreased. The percentage load impact is directionally different between PY2016 and PY2017. However, the load impacts are not statistically significant in either study.

Table 3.12: Current vs. Previous *Ex post* Load Impacts for the Average Event,
SDG&E Medium

Level	Outcome	PY2016	PY2017
Total	# SAIDs	11,002	11,808
	Reference (MW)	438	455
	Load Impact (MW)	-3.0	1.0
	Avg. Temp.	97.5	91.4
Per SAID	Reference (kW)	40	39
	Load Impact (kW)	-0.3	0.1
	% Load Impact	-0.7%	0.2%

Previous versus current ex ante

In this sub-section, a comparison is made with the *ex ante* forecast prepared following PY2016 (the "previous study") to the *ex ante* forecast contained in this study (the "current study"). Table 3.133.13 reports the average event-hour load impacts for the August 2018 peak day under utility-specific 1-in-2 weather conditions. The total forecast load impact is lower in the current study (0.8 MWh/hour vs 2.7 MWh/hour), due to a combination of lower forecast enrollment and a lower percentage load impact. Note that the different temperatures between the previous and current studies occurs from having different compositions of customers at varying weather stations.

Table 3.13: Previous vs. Current *Ex ante* Load Impacts, *Utility 1-in-2 August 2018 Peak Day, SDG&E Medium*

Level	Outcome	Previous Study	Current Study
Total	# SAIDs	11,221	10,879
	Reference (MW)	444	399
	Load Impact (MW)	2.7	0.8
	Avg. Temp.	84.7	86.1
Per SAID	Reference (kW)	40	37
	Load Impact (kW)	0.2	0.1
	% Load Impact	0.6%	0.2%

Previous ex ante versus current ex post

Table3.14 provides a comparison of the *ex ante* forecast of 2017 load impacts prepared following PY2016 and the PY2017 load impacts estimated as part of this study. The *ex ante* forecast shown in the table represents the August peak day during a utility-specific 1-in-2 weather year. The *ex post* load impacts are based on the average event day. The forecast load impact was higher than the *ex post* load impact (2.7 MWh/hour vs. 1.0 MWh/hour) because of a lower-than-forecast percentage load impact. The reduction in the total load impact was mitigated by higher-than-forecast enrollments.

Table 3.14: Comparison of Previous *Ex ante* and Current *Ex post* Impacts, *SDG&E Medium*

Level	Outcome	*Ex ante* for 2017 August Peak Day from PY2016 Study	*Ex post* for Average Event Day from PY2017 Study
Total	# SAIDs	11,320	11,808
	Reference (MW)	448	455
	Load Impact (MW)	2.7	1.0
	Avg. Temp.	84.7	91.4
Per SAID	Reference (kW)	40	39
	Load Impact (kW)	0.2	0.1
	% Load Impact	0.6%	0.2%

Current ex post versus current ex ante

Table3.15 compares the *ex post* and *ex ante* load impacts from this study. The *ex ante* load impacts in the table represent the 2018 August peak day with utility-specific 1-in-2 weather conditions. The percentage load impact is equivalent between the current *ex post* and *ex ante* analysis by design. *Ex ante* enrollment is somewhat lower than *ex post* enrollment, which results in lower total reference loads and load impacts. The per-customer reference load is slightly lower in the *ex ante* study because of the cooler 86-degree temperature.

Table 3.15: Comparison of Current *Ex post* and *Ex ante* Load Impacts, *SDG&E Medium*

Level	Outcome	*Ex post* for Average Event Day from PY2017 Study	*Ex ante* for 2018 August Peak Day from PY2017 Study
Total	# SAIDs	11,808	10,879
	Reference (MW)	455	399
	Load Impact (MW)	1.0	0.8
	Avg. Temp.	91.4	86.1
Per SAID	Reference (kW)	39	37
	Load Impact (kW)	0.1	0.1
	% Load Impact	0.2%	0.2%

Table3.16 documents the various potential sources of differences between the *ex post* and *ex ante* load impacts.

Table 3.16: Comparison of *Ex post* and *Ex ante* Factors

Factor	*Ex post*	*Ex ante*	Expected Impact
Weather	Average event-hour temperature of 91.4 °F during the average event day.	Average event-hour temperature of 86.1 °F during the SDG&E 1-in-2 August peak day.	Lower *ex ante* temperatures result in smaller reference load and load impacts.
Event window	Hours-ending 12 through 18.	Hours-ending 15 through 18.	The shorter event window during the later period corresponds with higher average event hour temperatures and reference loads.
% of resource dispatched	100%	100%	None. All customers are assumed to be called in both cases.
Enrollment	11,808 service accounts.	10,879 service accounts.	Lower *ex ante* enrollment leads to lower aggregate reference loads and load impacts (*ceteris paribus)*.
Methodology	Panel models by industry group with customer and date fixed effects and a matched control-group of non-participants.	Simulated reference loads using average program loads for medium customers. Then applied percentage load impacts derived from the *ex post* analysis, excluding the weekend event day.	The method is not expected to consistently produce differences between the *ex post* and *ex ante* impacts.

4 Summary of SDG&E's Base Interruptible Program (BIP) Report[17]

4.1 BIP Program Description

SDG&E's BIP is a voluntary program that offers participants a monthly capacity bill credit in exchange for committing to reduce their demand to a contracted Firm Service Level (FSL) on short notice during emergency situations. Non-residential customers who can commit to curtail 15 percent of monthly peak demand with a minimum load reduction of 100 kW are eligible for

[17] The BIP statewide load impact evaluation was conducted by Christensen Associates. This section of the Executive Summary contains excerpts from the following evaluation: Crowley, N., Hansen, D. & Clark, M. Christensen Associates (2018). "2017 Load Impact Evaluation of California Statewide Base Interruptible Programs (BIP) for Non-Residential Customers: *Ex post* and Ex ante Report"

the program. Customers were notified no later than 20 minutes before the event. Monthly incentive payments are $12 per kW during May through October and $2 per kW during all other months. Currently, the monthly incentive payments are $10.80 per kW during May through October and $1.80 per kW during all other months. Curtailment events for an individual BIP customer are limited to a single 4-hour event per day, no more than 10 events per month and no more than 120 event hours per calendar year. A curtailment event may be called under BIP at any time during the year.

Participation in SDG&E's program has been historically low, consistent with the California Public Utilities Commission ("Commission" or "CPUC") direction to focus marketing efforts on price responsive programs.[18] There were no participants in 2006, three participants in 2007, five participants in 2008, 20 in 2009, 19 customers in 2010, 21 customers in 2011, 11 in 2012, seven participants in 2013 and 2014, five participants in 2015, seven participants in 2016, and six in 2017.

4.2 BIP Ex post Evaluation Methodology

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

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

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

A variety of weather variables were tested in an attempt to determine which set best explains usage on event-like non-event days. Each customer was first classified according to whether it is

[18] Previously SDG&E offered a BIP option B which required that participating customer be notified at least three hours before the event but SDG&E discontinued this option in 2012.

weather-sensitive. We then selected specifications by customer group, defined by industry group and weather sensitivity (i.e., sixteen groups, with eight industry groups for each of the non-weather-sensitive customers and weather-sensitive customers).

4.2.1 Regression Model

The following is a general form of the model that was separately estimated for each enrolled BIP customer. The specific form of the model varied across utilities and customer groups, as shown in Appendix A. Table 3.1 below describes the terms included in this equation for the observed demand in a given hour *h* and date *d*:

$$
\begin{aligned}
Q_t = & \sum_{i=1}^{24}(b_i^h \times h_{i,t}) + \sum_{Evt=1}^{E}\sum_{i=1}^{24}(b_{i,Evt}^{BIP} \times h_{i,t} \times BIP_t) + \sum_{DR}\sum_{i=1}^{24}(b_i^{DR} \times h_{i,t} \times OtherEvt_{i,t}^{DR}) \\
& + \sum_{i=1}^{24}(b_i^{Weather} \times h_{i,t} \times Weather_t) + \sum_{i=1}^{24}(b_i^{MornLoad} \times h_{i,t} \times MornLoad_{i,t}) \\
& + \sum_{j=2}^{5}(b_j^{DTYPE} \times DTYPE_{j,t}) + \sum_{i=2}^{24}(b_i^{MON} \times h_{i,t} \times MON_t) + \sum_{i=2}^{24}(b_i^{FRI} \times h_{i,t} \times FRI_t) \\
& + \sum_{i=6}^{10}(b_i^{MONTH} \times MONTH_{i,t}) + \sum_{i=2}^{24}(b_i^{SUMMER} \times h_{i,t} \times SUMMER_t) + e_t
\end{aligned}
$$

Table 4.1: Descriptions of Variables included in the *Ex post* Regression Equation

Variable Name	Variable Description
Q_t	the demand in hour *t* for a BIP customer
The various *b*'s	the estimated parameters
$h_{i,t}$	an indicator variable for hour *i*, equal to one when *t* corresponds to hour *i* of a given day
BIP_t	an indicator variable for program event days
E	the number of program event days that occurred during the program year
$OtherEvt_{i,t}^{DR}$	an indicator variable for event day *DR* of other demand response programs in which the customer is enrolled (e.g. *DR* = CPP Event 1, CPP Event 2, ...)
$Weather_t$	the weather variables selected using our model screening process
$MornLoad_t$	a variable equal to the average of the day's load in hours 1 through 10 (may be excluded via model screening)
$DTYPE_{j,t}$	a series of indicator variables for each day of the week
MON_t, FRI_t,	indicator variables for Monday and Friday
$MONTH_{j,t}$	a series of indicator variables for each month (model screening may include separate hourly profiles by month)
$SUMMER_t$	an indicator variable for the summer pricing season[19]
e_t	the error term

[19] The summer pricing season is June through September for SCE, June through October for SDG&E, and May through October for PG&E.

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

The model allows for the hourly load profile to differ by time periods, which can vary across specifications selected for each customer group. The time-based patterns reflect day of week, with separate profiles for Monday, Tuesday through Thursday, and Friday; month of year; and pricing season (i.e., summer versus winter), to account for potential customer load changes in response to seasonal changes in rates.

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

A parallel set of winter models was estimated for each customer, which were used to simulate *ex ante* reference loads for those months. The structure matches the model described above, with the appropriate month indicators substituted in. A separate model selection process was conducted for the winter models.

4.2.2 Development of Uncertainty-Adjusted Load Impacts

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

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

In order to develop the uncertainty-adjusted load impacts associated with the average event hour (i.e., the bottom rows in the tables produced by the *ex post* table generator), an additional set of customer-specific regression models were estimated in which each event day's average event-hour load impact is estimated using a single variable (rather than the hour-specific variables used in the primary model described above). The standard error associated with these event-specific coefficients serves as the basis of the average event-hour uncertainty-adjusted load impacts for each *ex post* event day. The standard errors are used to develop the uncertainty-adjusted scenarios in the same manner as the hour-specific standard errors in the primary model.

4.3 BIP Ex post Load Impact Estimates

Average event-hour reference loads and load impacts for SDG&E single event (August 31, 2017) are summarized in Table 4.2. The average load impact over the four-hour event was 2.5MW

Table 4.2: Average Event-hour Load Impacts, *SDG&E*

Event	Date	Day of Week	Estimated Reference Load (MW)	Observed Load (MW)	Estimated Load Impact (MW)	% LI
1	8/31/2017	Thursday	3.6	1.0	2.5	71.1%

Table 4.3 compares the average observed load to the FSL on the event day. The observed load was below the FSL throughout the event.

Table 4.3: Average Event-hour Observed Loads and FSLs, *SDG&E*

Event	Date	Day of Week	Observed Load (MW)	Firm Service Level (MW)	Estimated LI / LI at FSL
1	8/31/2017	Thursday	1.0	1.2	108%

4.4 BIP Ex ante Evaluation Methodology

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

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

under both:

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

at both:

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

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

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

Each of these steps is described below.

1. <u>*Define data sources*</u>

The reference loads are developed using data for customers enrolled in BIP at the start of the 2018 program year. The load impacts are developed using the historical FSL achievement rates of customers remaining enrolled at the start of the 2018 program year, based on their estimated *ex post* load impacts during program year 2017.

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

2. <u>*Simulate reference loads*</u>

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

For the summer months, the re-estimated regression equations were similar in design to the *ex post* load impact equations described in Section 3.2, differing in two ways. First, the *ex ante* models excluded the morning-usage variables. While these variables are useful for improving accuracy in estimating *ex post* load impacts for particular events, they complicate the use of the equations in *ex ante* simulation. That is, they would require a separate simulation of the level of the morning load. The second difference between the *ex post* and *ex ante* models is that the *ex* *ante* models do not use weather variables using information from prior days.[20] The primary reason for this is that the *ex ante* weather days were not selected based on weather from the prior day, restricting the use of lagged weather variables to construct the *ex ante* scenarios.

Because BIP events may be called in any month of the year, we estimated separate regression models to allow us to simulate winter reference loads. The winter model is shown below. This model is estimated separately from the summer *ex ante* model. It only differs from the summer model in two ways: it includes different weather variables; and the month dummies relate to a different set of months. Table 5.1 describes the terms included in the equation.

$$\begin{aligned} Q_t \; = & \sum_{i=1}^{24}(b_i^h \times h_{i,t}) + \sum_{Evt=1}^{E}\sum_{i=1}^{24}(b_{i,Evt}^{BIP} \times h_{i,t} \times BIP_t) + \sum_{DR}\sum_{i=1}^{24}(b_i^{DR} \times h_{i,t} \times OtherEvt_{i,t}^{DR}) \\ & + \sum_{i=1}^{24}(b_i^{Weather} \times h_{i,t} \times Weather_t) + \sum_{j=2}^{5}(b_j^{DTYPE} \times DTYPE_{j,t}) \\ & + \sum_{i=2}^{24}(b_i^{MON} \times h_{i,t} \times MON_t) + \sum_{i=2}^{24}(b_i^{FRI} \times h_{i,t} \times FRI_t) \\ & + \sum_{j=2-4,11-12}(b_j^{MONTH} \times MONTH_{j,t}) + e_t \end{aligned}$$

Table 4.4: Descriptions of Terms included in the *Ex ante* Regression Equation

Variable Name	Variable Description
Q_t	the demand in hour *t* for a customer enrolled in BIP prior to the last event date
The various *b*'s	the estimated parameters
$h_{i,t}$	an indicator variable for hour *i*, equal to one when *t* corresponds to hour *i* of a given day
BIP_t	an indicator variable for program event days
E	the number of program event days that occurred during the program year
$OtherEvt_{i,t}^{DR}$	an indicator variable for event day *DR* of other demand response programs in which the customer is enrolled (e.g. *DR* = DBP Event 1, DBP Event 2, ...)
$Weather_t$	the weather variables selected using our model screening process
$DTYPE_{j,t}$	a series of indicator variables for each day of the week
MON_t, FRI_t,	indicator variables for Monday and Friday
$MONTH_{j,t}$	a series of indicator variables for each month
e_t	the error term

Similar to the *ex post* analysis, a variety of weather variables were tested and included in the above regression equation to determine the best specification for explaining usage on event-like non-event days. Each specification is tested separately by customer group, defined by industry group and weather sensitivity. Once these models were estimated, 24-hour load profiles were

[20] In particular, where CDH60 and CDH60_MA24, the 24-hour moving average of CDH60, are used together for summer *ex post* regressions, only CDH60 is used for the *ex ante* models. Similarly, where CDH60_MA3, the three-hour moving average, is used for *ex post* regressions, CDH60 is used for the *ex ante* analysis. See Appendix A for weather variable details.

simulated for each required scenario. The typical event day was assumed to occur in August. In 2014, two sets of 1-in-2 and 1-in-10 weather years were introduced in the load impact analyses. The sets are differentiated according to whether they correspond to utility-specific conditions or CAISO-coincident conditions. The weather conditions used in prior evaluations corresponded to the utility-specific scenarios.

3. *<u>Calculate forecast load impacts</u>*

Each service account's FSL achievement rate is defined as the estimated load impact divided by the difference between the reference load and the FSL. A result of 100 percent implies that the customer dropped its load exactly to its FSL. Values greater than 100 percent imply event-day loads lower than the FSL, and values less than 100 percent imply event-day loads higher than the FSL.[21]

The achievement rates are based on the estimates for the most recent observed event day. In consultation with the utilities, we determined that using a longer time period (e.g., three years of *ex post* load impacts) was not appropriate for this program. Specifically, as customers experience events, they are re-tested if they fail to meet their obligation (i.e., reduce load to the FSL). If they continue to fail, their FSL is increased to the point at which the customer is expected to be able to comply. Therefore, the most recent load impact estimates should provide a good indication of customer performance going forward. In addition, some program design changes make older load impacts less relevant as predictors of future performance. For example, an increased excess energy charge for non-compliance (and a higher excess energy charge for failing to comply during re-test events) may make more recent performance rates higher than performance rates in the more distant past.

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

Because the forecast event window (1:00 to 6:00 p.m. in April through October; and 4:00 to 9:00 p.m. in all other months) differs from the historical event window (which can vary across utilities and event days), an adjustment was made to the historical load impacts for use in the *ex ante* study. Load impacts are assumed to be zero until the hour prior to the beginning of the event, at which time the customer's historical FSL performance rate is applied to the forecast window to best represent the pattern of customer response given the limitations of the observed events. Forecast load impacts are developed through the end of the event day because customers load reductions often persist well after the end of the event hours.

[21] It is not possible to calculate an achievement rate for customers with reference loads below their FSLs throughout an event period—the event effectively has no effect on them.

The uncertainty-adjusted load impacts (i.e., the 10th, 30th, 50th, 70th, and 90th percentile scenarios of load impacts) are based on the standard errors associated with the estimated load impacts from the event day used to determine the customer's event-day achievement rate, scaled to account for the difference between observed and forecast enrollments. The square of these standard errors (i.e., the variance) is added across customers within each required subgroup. Each uncertainty-adjusted scenario is then calculated under the assumption that the load impacts are normally distributed with a mean equal to the total estimated load impact and a variance based on the standard errors in the estimated load impacts. The uncertainty-adjusted load impacts for the average event hour are based on the same event-hour standard errors used in the *ex post* study.

4. Apply achievement rates to reference loads for each event scenario.

In this step, the customer-specific FSL achievement rates are applied to the reference loads for each scenario to produce all of the required estimated event-day loads and load impacts. For customers for which an achievement rate cannot be calculated, either because their reference loads were below their FSLs, the average achievement rate among all customers is used. The FSL achievement rate is assumed to be 100% for newly enrolled customers, as well as for customers that change their FSL in the beginning of 2018.

5. Apply forecast enrollments to produce program-level load impacts.

SDG&E forecasts BIP enrollments to increase by one in each year until 2022, at which time enrollment is forecast to remain constant at eleven service accounts through 2028.

4.5 BIP Ex ante Load Impacts Estimates

Figure 4.1 shows the load impact forecast for an August 2018 event day in a utility-specific 1-in-2 weather year. The average hourly load impact from 1:00 to 6:00 p.m. is forecast to be 1.3 MW, which represents 52.7 percent of the enrolled reference load. The average event-hour program load of 1.1 MW is lower than the program-level FSL of 1.4 MW. Customers over-perform throughout all event hours, consistent with our *ex post* estimates for the August 31, 2017 event day that serves as the basis for the *ex ante* load impacts.

Figure 4.1: SDG&E Hourly Event Day Load Impacts for the August 2018 Event Day in a Utility-Specific 1-in-2 Weather Year

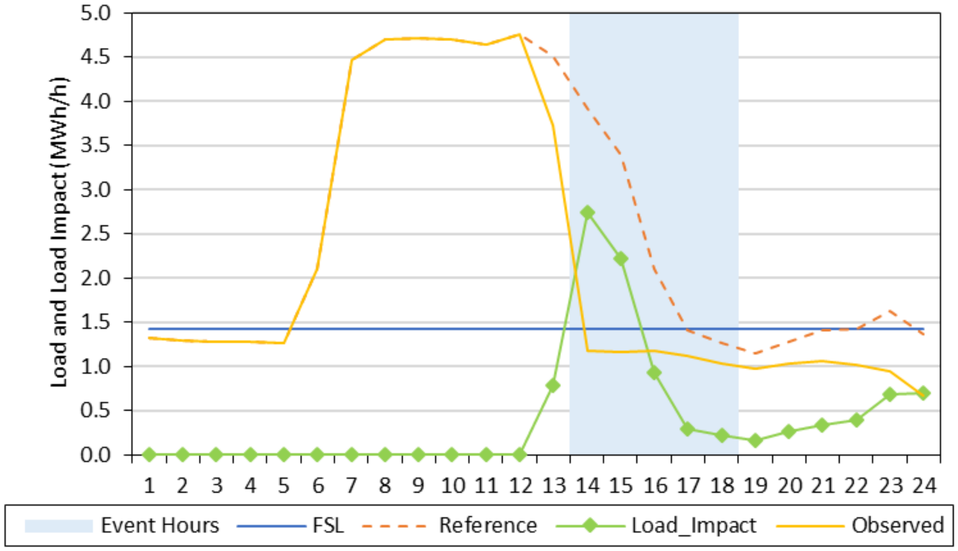
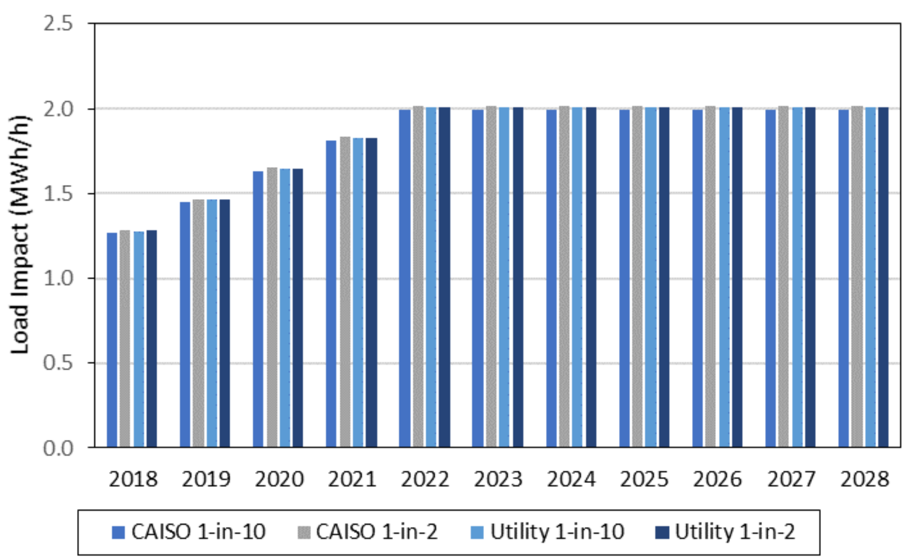


Figure 4.2 illustrates 2018 to 2028 August load impact for each forecast scenario, differentiated by 1-in-2 versus 1-in-10 weather conditions under both utility-specific and CAISO-coincident peak conditions. The enrollment forecast slightly increases until 2022 and then remains constant. These load impacts are consistent with the increases in enrollments and the load impacts found in the *ex post* analysis.

Figure 4.2: Average August *Ex ante* Load Impacts by Scenario, 2018-2028, *SDG&E*



4.6 BIP Comparison of current Ex post versus Ex ante

4.6.1 Previous versus current *ex post*

Table 4.5 compares *ex post* load impacts between PY2016 and PY2017. The PY2016 load impacts are based on the September 26, 2016 event with event hours-ending 14 through 17, while the PY2017 load impacts are based on the single August 31, 2017 event with event hours-ending 12 through 15. Enrollment has dropped from seven to six, yet loads have increased slightly. The increase in reference loads occurs because the earlier event hours in PY2017 correspond to a period of higher loads for the enrolled customers.

Table 4.5: Comparison of *Ex post* Impacts in PY2016 and PY2017, *SDG&E*

Level	Outcome	*Ex post* PY2016	*Ex post* PY2017
Total	# SAIDs	7	6
	Reference (MWh/h)	2.6	3.6
	Load Impact (MWh/h)	1.5	2.5
Per SAID	Reference (kWh/h)	371.4	596.5
	Load Impact (kWh/h)	221.0	423.8
	% Load Impact	59.5%	71.1%

4.6.2 Previous versus current *Ex ante*

In this sub-section, the *ex ante* forecast prepared is compared following PY2016 (the "previous study") to the *ex ante* forecast contained in this study (the "current study"). Table 4.6 presents this comparison for the *ex ante* forecasts of the utility-specific 1-in-2 August typical event day. Reference loads and load impacts significantly lower in the current study.

Table 4.6: Comparison of *Ex ante* Impacts from PY2016 and PY2017 Studies, *SDG&E*

Level	Outcome	*Ex ante* 2018 Typical Event Day, *Previous Study*	*Ex ante* 2018 Typical Event Day, *Current Study*
Total	# SAIDs	8	7
	Reference (MWh/h)	9.2	2.4
	Load Impact (MWh/h)	6.1	1.3
	FSL (MWh/h)	3.2	1.4
Per SAID	Reference (kWh/h)	1,153.6	340.7
	Load Impact (kWh/h)	765.6	178.8
	% Load Impact	66.4%	52.5%

4.6.3 Previous *ex ante* versus current *ex post*

Table 4.7 compares the *ex ante* forecast prepared following PY2016 to the PY2017 *ex post* load impact estimates contained in this report for the August 31, 2017 event day. The *ex ante* load impacts are based on the typical event day in a utility-specific 1-in-2 weather year. The differences in reference loads and load impacts occur because of the different event hours represented. For example, the average reference load for the current *ex post* analysis over the previous study *ex ante* period (HE 14-18) is 2 MW, which is equivalent to the previous study.

Table 4.7: Comparison of Previous *Ex ante* and Current *Ex post* Impacts, *SDG&E*

Level	Outcome	*Ex ante* 2017 Typical Event Day, Previous Study	*Ex post* *PY2017*
Total	# SAIDs	6	6
	Reference (MW)	2.0	3.6
	Load Impact (MW)	0.7	2.5
Per SAID	Reference (kW)	327.5	596.5
	Load Impact (kW)	122.5	423.8
	% Load Impact	37.4%	71.1%

4.6.4 Current *ex post* versus current *ex ante*

Table 4.8 shows a comparison of *ex post* and *ex ante* load impacts. Enrollment increases, but the aggregate load impact is nonetheless forecast to be lower in the forecast period.

Table 4.8: Comparison of Current *Ex post* and Current *Ex ante* Impacts, *SDG&E*

Level	Outcome	*Ex post* PY2017	*Ex ante* 2018 Typical Event Day, Current Study
Total	# SAIDs	6	7
	Reference (MW)	3.6	2.4
	Load Impact (MW)	2.5	1.3
	FSL (MW)	1.2	1.4
Per SAID	Reference (kW)	596.5	340.7
	Load Impact (kW)	423.8	178.8
	% Load Impact	71.1%	52.5%

Table 4.9 below describes the factors that differ between the *ex post* and *ex ante* load impacts for SDG&E.

The *ex ante* forecast is based on the *ex post* FSL achievement (*i.e.*, observed loads) relative to the FSL during event hours. In terms of achievement relative to the FSL, the *ex post* and *ex ante* load impacts for the six continuing customers match by design. However, the forecast reference loads may differ from the *ex post* event-hour reference loads for various reasons. For instance, forecast reference loads are lower partly due to a difference in event windows, as the historical event was earlier than the *ex ante* event window (hours-ending 12 to 15 vs. 14 to 18, respectively). The later *ex ante* window includes hours with relatively low loads, which reduces the load impact because the FSL does not change across hours.

Table 4.9: SDG&E BIP *Ex post* versus *Ex ante* Factors, Typical Event Day

Factor	*Ex post*	*Ex ante*	Expected Impact
Weather	93.9 degrees Fahrenheit during HE 12 to 15 on the August 31st event day	86.4 degrees Fahrenheit during HE 14 to 18 on utility-specific 1-in-2 typical event day	Program load is not very weather sensitive, so a small effect.
Event window	HE 12 to 15	HE 14 to 18 in Apr-Oct.	Reference loads are substantially lower by 4 p.m. relative to earlier in the day, so the inclusion of hour-ending 17 and 18 tends to drag down the average *ex ante* reference loads and load impacts relative to *ex post*.
% of resource dispatched	All	All	None
Enrollment	6 service accounts	7 service accounts	Increase aggregate reference load and load impact. No increase in per-customer reference load or load impacts because results are scaled by enrollments.
Methodology	SAID-specific regressions using own within-subject analysis.	Reference loads are simulated from SAID-specific regressions.	Possible difference between simulated *ex ante* and estimated *ex post* reference loads. In this case, however, the aggregate differences are minimal.

5 Summary of the Summer Saver Program[22]

5.1 Summer Saver Program Description

San Diego Gas and Electric Company's (SDG&E) Summer Saver program is a demand response resource based on central air conditioner (CAC) load control that is implemented through an agreement between SDG&E and Comverge, Inc. The previously funded program

[22] The Summer Saver load impact evaluation was conducted by Nexant Inc. This section of the Executive Summary contains excerpts from the following evaluation: Potter, C. & Stansell, A., Nexant, Inc. (2018). "San Diego Gas and Electric Company Summer Saver 2017 Program Evaluation".

cycle ended in 2016; in January 2017, SDG&E filed its request to the CPUC for funding to cover the program years 2018 to 2022. The 2017 program year was funded through CPUC-authorized bridge funding. This report provides 2017 *ex post* load impact estimates and *ex ante* load impact estimates for an 11-year forecast horizon (2018–2028) as required by the California Public Utilities Commission (CPUC) Load Impact Protocols , even though the program may not continue in its current form in upcoming years.

The Summer Saver program is classified as a day-of demand response program and is available to both residential and commercial customers, where eligible commercial customers are subject to a demand limit; only those commercial customers with average monthly peak demand up to a maximum of 100 kW over a 12-month period may participate. Summer Saver events may only be called during the months of May through October. Under the current program, load control events may not run for more than 4.5 hours. Participants' air conditioners cannot be cycled for more than 4.5 hours in any event day and events cannot be triggered for more than 80 hours per year. Load control events can occur on weekends but not on holidays and cannot be called more than three days in any calendar week. These program rules apply to both residential and commercial customers alike.

In 2017, several changes occurred to the program design. First, the annual maximum of event hours was increased from 60 hours to 80 hours. A second change was how Summer Saver events are triggered. Previously, an event was triggered by system conditions, specifically when day-ahead forecasted system load reaches 4,000 MW. Under the new program design, event triggers vary by month. During the months of July, August, or September, a Summer Saver event can be triggered by any of the following criteria:

- Generator heat rates reaching or exceeding 19,000 Btu[23] /kWh;
- Imminent statewide or local emergencies, extreme conditions, and/or local distribution needs; or
- Upon the award of a bid into the California Independent System Operator (CAISO) wholesale market;

Summer Saver events may be called between noon and 9 PM, and each event may last 1 to 4.5 hours in duration. In previous years, a Summer Saver event could have been called between noon and 8 PM, and each event could last 2 to 4 hours.

There are two enrollment options for both residential and commercial participants. Residential customers can choose to have their CAC units cycled 50% or 100% of the time during an event. The incentive paid for each option varies; the 50% cycling option pays $10.35

[23] British thermal unit, defined as the amount of heat required to raise the temperature of one pound of water by one degree Fahrenheit.

per ton per year of CAC capacity and the 100% cycling option pays $27 per ton per year. A residential customer with a four-ton CAC unit would be paid the following in the form of an annual credit on their SDG&E bill:

$41.40 for 50% cycling; or
$108 for 100% cycling.

Commercial customers have the option of choosing 30% or 50% cycling. The incentive payment for 30% cycling is $4.50 per ton per year and $7.50 per ton per year for the 50% cycling option. A commercial customer with five tons of air conditioning would be paid the following in the form of an annual credit on their SDG&E bill:

$22.50 for 30% cycling; or
$37.50 for 50% cycling.

Enrollment in the Summer Saver program as of October 2017 is summarized in Table 5-1.

Table 5-1: Summer Saver Enrollment - October 2017

Customer Type	Cycling Option	Enrolled Customers	Enrolled Control Devices	Enrolled Tons
Commercial	30%	1,011	2,950	11,485
	50%	3,813	8,195	31,342
	Total	4,824	11,145	42,827
Residential	50%	9,820	11,421	39,917
	100%	5,839	7,211	26,273
	Total	15,659	18,632	66,190
Grand Total		**20,483**	**29,777**	**109,017**

5.2 Summer Saver Ex post Evaluation Methodology

The primary task in developing *ex post* load impacts is to estimate a reference load for each event. The reference load is a measure of what participant demand would have been in the absence of the CAC cycling during an event.

Two separate approaches were used for estimating the reference loads: a randomized controlled trial (RCT) design and a statistical matching design. Residential customer impacts were estimated using an RCT. The commercial customer impacts were estimated with a matching study. Under the randomized controlled trial, random samples of residential Summer

Saver customers were selected for each cycling strategy. During each event, half of the sample did not have their CAC units cycled so that these customers could be used to provide a reference load for those who did have their units cycled. Under the matching design, a matched control was selected for nearly all of the commercial Summer Saver program participants.

An RCT is an experimental research approach in which customers are randomly assigned to treatment and control conditions so that the only difference between the two groups, other than random chance, is the existence of the treatment condition. In this context, half of the roughly 3,200 customers in the residential sample had their CAC unit cycled while the remaining customers served as the control group. The group that received the event signal alternated from event to event. This design has significant advantages in providing fast, reliable impact estimates if sample sizes are large enough.

Consistent with the methodology used in the 2015 and 2016 evaluations, a matched control group was selected for the commercial program population—whereby one nonparticipant was selected as a match for each participant on each event. The entire SDG&E small and medium business (SMB) customer population was made available for the statistical matching analysis. Each matched customer was chosen because they most closely resembled their matched participant in terms of a dissimilarity statistic described in Equation 5-1. The dissimilarity statistic measures how similar each candidate for a match is to any given participant customer based on how well (or not) their energy usage characteristics match those of the participant on both the event day and other hot non-event days in 2017, called proxy days. The characteristics used in the dissimilarity statistic are:

- Average demand during the hours 3 to 7 PM on the average proxy day;
- Average demand from midnight to 10 AM on the event day; and
- Average demand from 10 AM to 3 PM on the event day[24].

Equation 5-1: Dissimilarity Statistic for Commercial Matching

$$\begin{aligned} Dissimilarity_i = (PeakProxy_i - PeakProxy_1)^2 + (EventMorn_i - EventMorn_1)^2 \\ + (EventMidday_i - EventMidday_1)^2 \end{aligned}$$

[24] All 2017 events began at 3 PM or later.

Variable	Definition
$PeakProxy$	Average demand across the 2017 proxy days during the hours 3 to 7 PM
$EventMorn$	Average demand on the event day from midnight to 10 AM
$EventMidday$	Average demand on the event day from 10 AM to 3 PM
1	Commercial Summer Saver participant to be matched
i	Indexes the pool of control customers

This dissimilarity statistic used was chosen as the optimal metric for matching among four alternately specified metrics and following an out-of-sample testing exercise with many propensity score matching models that suggested an alternative approach may perform better. The best metric was chosen based on pre-treatment balance measures.

Matches were chosen such that only customers in the same industry and climate zone would be matched to one another. Likewise NEM customers were only matched to other NEM customers, and customers taking the Critical Peak Pricing (CPP) electric rate or the time-of-use (TOU) electric rate were only matched to customers with the same electric rate. This approach minimizes the differences between participants and matched nonparticipants while allowing for good subgroup estimates.

The matching process simply proceeds, one Summer Saver participant at a time, by selecting the non-participant with the same industry, NEM, and pricing status and with the smallest dissimilarity statistic. A single non participant may be selected more than once as a matched control customer.

Ex post event impacts were estimated for a broad collection of program segments including customer class, cycling strategy, NEM status, climate zone, industry, size, and status of dual-enrollment in other pricing and demand response programs at SDG&E. Within each of these program segments, load impacts were estimated for each hour of each event day for both RCT and matching customers using two approaches.

The difference was calculated between the average demand for those customers who were cycled and those who were not (this simple difference in average hourly load as the “unadjusted” load impact).

However, since randomization and matching both can leave some residual differences between the treatment and control groups that is not due to the CAC cycling, also it was estimated what we refer to as the “adjusted” load impact that takes into account the small differences between the treatment and control group usage and thereby improves the accuracy and precision of the estimate. This adjusted estimate of load impacts is determined by a lagged dependent variable (LDV) regression model.

The regression, described in Equation 5-2, essentially uses variation among the group that was not cycled to figure out the relationship between demand before the event and on proxy days to the demand during the event window and afterward. The regression can then make a prediction for all of the cycled customers based on that simple model. This is very similar to how a ratio adjustment works. A ratio adjustment multiplies event window demand for the control group by the difference the cycled and control demand prior to the event. An LDV model with one variable does the same thing, but it allows the adjustment to account for differences between the cycled and control group on proxy days as well.[25]

Equation 5-2: LDV Model for Estimating Impacts

$$Demand_i = a + t * Cycled_i + b * Proxy_i + c * ProxyWindow_i + d * ProxyEve_i + e * EventMorn1_i + f * EventMorn2_i + g * EventMorn3_i + h * PreEvent_i + u_i$$

[25] Such an LDV model would be specified as

$$Demand_i = a_2 + t_2 * Cycled_i + h_2 * PreEvent_i + u_i$$

Variable	Definition
$Demand$	Average demand in the event hour being studied
$Cycled$	An indicator for whether customer i was cycled
$Proxy$	Average demand in the hour being studied on the average proxy day
$ProxyWindow$	Average demand in the event window on the average proxy day
$ProxyEve$	Average demand after the event window on the average proxy day
$EventMorn1$	Average demand from midnight to 7 AM on the event day
$EventMorn2$	Average demand from 7 AM to 10 AM on the event day
$EventMorn3$	Average demand from 10 AM to four hours before the event on the event day
$PreEvent$	Average demand during the four hours before the event
i	Indexes customers
t	Estimated impact
$a - h$	Estimated regression coefficients
u	Error term

For estimating treatment effects, as we are doing in this setting, the adjustments from the LDV only change the estimate of the treatment effect if the group that was cycled is different from the group that was not cycled on proxy days or in the hours leading up to the event. These differences should be relatively small for most of the important treatment effect estimates since the matching and RCT performed well. When that is true, the treatment effect estimates with and without the adjustment will look similar, but the confidence intervals will be much smaller for the adjusted version because the LDV model uses the data more efficiently.

Hourly impact estimates for the residential Summer Saver population were calculated by taking a weighted average of the impact estimates for each cycling option, with weights determined by the number of tons enrolled on each cycling option. Similar weighting was done to calculate cycle percentage level impacts. For cycle percentage level impacts, weights were determined by the number of tons enrolled in each climate zone. Impacts for the average event day were calculated from treatment and control group load shapes averaged across 8/2/2017, 8/3/2017, 8/28/2017, 8/31/2017, and 9/1/2017. These five events were all called from 4 to 8 PM.

5.3 Summer Saver Ex post Load Impact Estimates

5.3.1 Summer Saver Residential *Ex post* Load Impact Estimates

A total of 19 Summer Saver events were called in 2017 including two EM&V cold weather test events. Table 5-2 presents *ex post* load impacts for the residential program segment for program years 2017 and 2016, for comparison. The 2017 *ex post* load impacts do not include load impacts estimates for the two EM&V cold weather events, since the whole program was not dispatched on those days.

Aggregate residential load impacts ranged from a low of 0.46 MW on September 26, 2017 to a high of 9.8 MW on September 2, 2017. The temperatures on September were also the lowest across all the 2017 events. A temperature metric that captures overnight heat buildup – the average temperature from midnight to 5PM, denoted "mean17" – was only 69 °F on September 26th, indicating that cooling loads that day would likely be minimal. On the other hand, mean17 on September 2 (which should be noted was also the Saturday of Labor Day weekend in 2017) was 84 °F. It should be noted that there were three events that were called under similarly low temperature conditions, September 5, 26, and 28. All three of those events yielded de minimus load impacts. The two days with the highest load impacts were associated with the Labor Day weekend, Friday, September 1 and Saturday, September 2, both dispatched under similar temperature conditions. All 2017 Summer Saver residential impacts are statistically significant at the 90% confidence level.

Average Event Day load impacts are calculated in a way such that the events included in the average are the same with respect to duration of event and time of day. It would be misleading to calculate an average event load impacts where the time of day varied – load impacts for the direct load control of residential CAC units are highly sensitive to the hour in which the event is dispatched. Here, average event day load impacts are calculated using 8/2/2017, 8/3/2017, 8/28/2017, 8/31/2017, and 9/1/2017.[26] All five of these events were dispatched from 4 to 8 PM. Note that load impacts for these event days reflect a wide of temperature conditions. The five 2017 Summer Saver events included in the Average Event Day estimate yield an aggregate load reduction of 5.7 MW.

The Average Event Day load impact, per premise, in 2016 and 2017 were both approximately 0.42 kW. They were calculated using similar event windows (3-7 PM in 2016 and 4-8 PM in 2017) and were dispatched under similar weather conditions. The key driver of the difference between *ex post* load impacts in 2016 and 2017 is the number of residential customers

[26] Note that 8/1/2017 was another day that had a 4-8 PM event but is not included in this average. Load impacts for this day had to be estimated using an alternate (day-matching) methodology since both research groups A and B were dispatched (there was no control group held back on that day).

enrolled in the program. Approximately one-third of the participants in the program were removed from participation on the basis of low electricity usage; the intent of this action was to remove customers from the program who do not use their CAC unit.

Table 5-2: Summer Saver Residential *Ex post* Load Impact Estimates

Year	Date	Impact			Mean17 (°F)
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2016	6/20/2016	0.27	0.32	6.20	82
	7/22/2016	0.56	0.67	12.87	80
	8/15/2016	0.45	0.54	10.39	80
	9/26/2016	0.34	0.40	7.69	80
	9/27/2016	0.18	0.21	4.06	84
	Average*	**0.36**	**0.42**	**8.13**	**81**
2017	8/1/2017	0.31	0.37	5.72	76
	8/2/2017	0.19	0.23	3.12	78
	8/3/2017	0.32	0.39	5.33	80
	8/7/2017	0.14	0.17	2.34	74
	8/8/2017	0.20	0.24	3.34	75
	8/28/2017	0.31	0.36	5.04	76
	8/29/2017	0.36	0.42	5.87	78
	8/31/2017	0.43	0.51	7.02	82
	9/1/2017	0.50	0.59	8.18	84
	9/2/2017	0.59	0.71	9.78	84
	9/5/2017	0.19	0.22	3.11	74
	9/11/2017	0.19	0.22	3.09	78
	9/12/2017	0.11	0.13	1.85	75
	9/25/2017	0.03	0.03	0.48	70
	9/26/2017	0.03	0.03	0.46	69
	9/28/2017	0.05	0.06	0.88	70
	10/24/2017	0.38	0.45	6.29	82
	Average**	**0.35**	**0.42**	**5.74**	**80**

* Reflects the average 2016 Summer Saver event (all events 3-7 PM)

** Reflects the average 4-8 PM weekday 2017 Summer Saver event

5.3.2 Summer Saver Commercial *Ex post* Load Impact Estimates

Table 5-3 presents *ex post* load impact estimates for commercial customers for each 2017 event day (excluding the two EM&V cool weather event days) and the Average Event Day. The 2016 *ex post* load impacts are shown for comparison. The commercial segment of the program is smaller than the residential segment; commercial customers represent about 24% of total

Summer Saver participants and approximately 39% of enrolled CAC tonnage. Not only are the numbers of enrolled customers and cooling tons smaller, but the per premise load impacts for commercial customers are smaller than those of residential customers. This is due in part to the fact that enrolled commercial CAC units are, on average, cycled less than the residential CAC units – either 30% or 50% (as opposed to 50% or 100% in the case of the residential segment). Commercial load impacts are also lower than residential load impacts due to the timing of Summer Saver events, which in 2017 are timed when per premise load is ramping down towards the commercial daily minimum usage that occurs in the evening and overnight hours, as opposed to during the residential daily maximum usage that occurs at the same time.

Commercial aggregate impacts vary from a low of -0.16 MW (not statistically significant) on September 25 to a high of 1.65 MW on August 3. Commercial load impact peaks occurs on a different day than the residential segment, the highest commercial load impact of 0.37 kW per premise occurs on August 3 (a Thursday) while the highest residential load impact occurred on September 2, the Saturday of Labor Day weekend.

Table 5-3: Summer Saver Commercial *Ex post* Load Impact Estimates

Year	Date	Impact			Mean17 (°F)
		Per CAC Unit (kW)	Per Premise (kW)	Aggregate (MW)	
2016	6/20/2016	0.16	0.39	1.72	80
	7/22/2016	0.16	0.37	1.66	79
	8/15/2016	0.13	0.31	1.38	79
	9/26/2016	0.10	0.24	1.08	81
	9/27/2016	0.04	0.10	0.45	84
	Average*	**0.12**	**0.28**	**1.26**	**81**
2017	8/1/2017	0.08	0.19	0.83	80
	8/2/2017	0.09	0.20	0.90	83
	8/3/2017	0.16	0.37	1.65	81
	8/7/2017	-0.01	-0.01	-0.06	75
	8/8/2017	0.08	0.20	0.89	77
	8/28/2017	0.10	0.24	1.06	81
	8/29/2017	0.00	0.00	-0.01	83
	8/31/2017	0.11	0.26	1.15	85
	9/1/2017	0.06	0.15	0.66	90
	9/2/2017	0.09	0.20	0.90	91
	9/5/2017	0.02	0.05	0.22	79
	9/11/2017	0.03	0.08	0.35	78
	9/12/2017	0.01	0.02	0.07	75
	9/25/2017	-0.01	-0.03	-0.16	75
	9/26/2017	0.04	0.09	0.42	75
	9/28/2017	0.01	0.01	0.05	76
	10/24/2017	0.14	0.33	1.49	99
	Average**	**0.09**	**0.21**	**0.93**	**84**

* Reflects the average 2016 Summer Saver event (all events 3-7 PM)

** Reflects the average 4-8 PM weekday 2017 Summer Saver event

5.4 Summer Saver Ex ante Evaluation Methodology

The primary task in estimating *ex ante* load impacts—which is often of more practical concern—is to make the best use of historical data on loads and load impacts to predict future program performance. The data and models used to estimate *ex post* impacts are typically the key inputs to the *ex ante* analysis.

Ex ante load impacts were developed using relatively recent *ex post* load impacts. While reliably estimated load impacts are available going back ten years, the older load impact estimates are not likely to be as relevant as the most recent ones, due to the fact that the program’s fleet has been aging over the past ten years without any significant program efforts or plans to refresh older equipment in field. *Ex post* load impacts from 2015, 2016, and 2017 were used as the foundational data for developing the *ex ante* model that estimates Summer Saver load impacts’ weather response.

In 2017, the majority of events were called markedly later in the day than in previous years. In estimating *ex ante* load impacts, a single model is fit that estimates the weather responsiveness of average *ex post* load impacts. Since events were called so late in the day in 2017, the average load impacts used for 2017 events are defined as the average load impact across the window 6 to 8 PM. Summer Saver events called in 2015 and 2016 occurred earlier in the day, and here the average load impacts use in *ex ante* estimation are defined as the average load impact across the window 3 to 5 PM. The benefit of these selections of the hours included in the averages are that none of the hours included in them are first-hour load impacts (which are usually much lower than impacts later in events) and that they result in the greatest amount of data points available for estimating the model. We refer in the remainder of this section to this set of average load impacts, the 3 to 5 PM average *ex post* impacts from 2015-2016 and the 6 to 8 PM average *ex post* impacts from 2017 as the core 2015-2017 *ex post* impacts.

Another important quality of the core 2015-2017 *ex post* load impacts used in estimating *ex ante* load impacts is that all *ex post* impacts in the estimation dataset reflect important changes to the program; the drop of the bottom 30% of electricity users that occurred in 2017 and the upcoming drop of NEM customers in 2018.

The methodology for estimating *ex ante* impacts in 2017 is the same for residential and commercial participants. The core 2015-2017 average *ex post* impact was modeled as a function of the average temperature for the first 17 hours of each event day—midnight to 5 PM (mean17). This 17-hour average is used to capture the impact of heat buildup leading up to and including the event hours. Per ton load impacts have historically been used in the Summer Saver load impact evaluation so that the load impacts would be scalable to *ex ante* scenarios where the tonnage and number of devices per premise may be different.

The regressions only include one explanatory variable; more complicated models were not found to perform better in prior Summer Saver evaluations, owing mostly to the relatively limited dataset of *ex post* load impacts that is available for *ex ante* estimation. Equation 5-1 presents the model that was used to predict average *ex post* impacts as a function of weather. This model is estimated separately by customer class (residential and commercial) and cycling strategy. The estimated parameters from the models are used to predict load impacts under 1-in-2 and 1-in-10-year *ex ante* weather conditions.

Equation 5-1 *Ex ante* Model for Predicting *Ex post* Load Impacts' Weather Response

$$impact_d = b_0 + b_1 \cdot mean17_{\mathrm{d}} + \varepsilon_d$$

Variable	Definition
$Impact_d$	Core 2015-2017 average *ex post* impact
b_0	Estimated constant
b_1	Estimated parameter coefficient
$mean17_d$	Average temperature over the 17 hours prior to the start of the event for each event day
ε_d	The error term for each day *d*

5.5 Summer Saver Ex ante Load Impact Estimates

The model described in the previous section was used to estimate load impacts based on *ex ante* event weather conditions and enrollment projections for the years 2018–2028. As was the case in the prior Summer Saver evaluation, program enrollment is expected to change substantially in the upcoming year of the forecast horizon. Therefore, this section will show annual load impact estimates for the 2018–2028 forecast horizon, under the assumptions of how the program will change in future years. The most significant changes will occur on the residential side, with NEM customers no longer permitted to enroll in Summer Saver starting in 2018.

Tables 5-4 summarizes the average and aggregate load impact estimates per premise under SDG&E-specific peaking conditions and CAISO peaking conditions for 2018. For residential customers, 2018 reflects the most significant changes to enrollment due to the drop of residential NEM customers from the program. The per premise load impacts are highest under both CAISO and SDG&E system September monthly peak conditions for residential and commercial. Similarly, the per premise impacts are lowest for the May monthly peak for all scenarios and customer types.

For a typical event day in a 1-in-2 year under SDG&E-specific weather conditions, the impact per premise is 0.41 kW for residential customers and 0.60 kW under 1-in-10 weather conditions. The hottest weather conditions are expected in the month of September, where under the SDG&E-specific 1-in-2 conditions per premise load impacts peak at 0.65 kW and at 0.76 kW under 1-in-10 conditions. Large differences between 1-in-2 and 1-in-10 load impacts are driven by large differences in mean17, which vary by 5 or 6 degrees across some of the above conditions; a difference of 5 degrees on average over 17 hours represents a very large difference in temperature conditions and air conditioning requirements.

Load impacts for commercial customers follow similar patterns. Under the SDG&E peaking scenarios, typical event day per premise load impacts are 0.37 kW under the 1-in-2 assumption and 0.53 kW under the 1-in-10 assumption. In September, commercial per premise load impacts peak at 0.61 kW under 1-in-2 conditions and 0.68 under 1-in-10 conditions. While the commercial load impacts are very similar to residential impacts, they on the one hand reflect lower cycling strategies and on the other reflect more CAC units enrolled in the program per premise. The net effect is that commercial load impacts are similar, but somewhat lower, than residential. The milder cycling strategies also yield less-sensitive load impacts for commercial participants as compared to residential participants.

The aggregate program load reduction potential for residential customers is 5.1 MW for a typical event day under SDG&E-specific 1-in-2 year weather conditions in 2018 and 1.7 MW for commercial customers. Under SDG&E-specific 1-in-10 year weather conditions, the aggregate impacts for residential and commercial customers are 7.5 MW and 2.5 MW, respectively. The aggregate impacts under CAISO weather conditions are slightly lower for both weather year types.

Table 5-4: Summer Saver 2018 *Ex ante* Load Impact Estimates by CAISO and SDG&E-specific Weather and Day Type

Customer Type	Day Type	Per Premise Impact (kW)				Aggregate Impact (MW)			
		CAISO 1 in 2	SDGE 1 in 2	CAISO 1 in 10	SDGE 1 in 10	CAISO 1 in 2	SDGE 1 in 2	CAISO 1 in 10	SDGE 1 in 10
Residential	Typical Event Day	0.41	0.42	0.57	0.62	5.0	5.1	7.0	7.5
	May Monthly Peak	0.06	0.16	0.41	0.46	0.7	1.9	5.0	5.7
	June Monthly Peak	0.08	0.07	0.64	0.53	0.9	0.8	7.8	6.4
	July Monthly Peak	0.27	0.40	0.46	0.50	3.3	4.8	5.5	6.1
	August Monthly Peak	0.60	0.55	0.56	0.66	7.3	6.7	6.8	8.0
	September Monthly Peak	0.68	0.67	0.64	0.79	8.3	8.1	7.8	9.6
	October Monthly Peak	0.29	0.40	0.50	0.54	3.5	4.8	6.1	6.5
Commercial	Typical Event Day	0.37	0.39	0.51	0.55	1.7	1.8	2.4	2.6
	May Monthly Peak	0.05	0.16	0.38	0.44	0.2	0.7	1.8	2.1
	June Monthly Peak	0.06	0.07	0.55	0.46	0.3	0.3	2.6	2.1
	July Monthly Peak	0.24	0.36	0.39	0.43	1.1	1.7	1.8	2.0
	August Monthly Peak	0.53	0.49	0.50	0.60	2.5	2.3	2.4	2.8
	September Monthly Peak	0.63	0.63	0.60	0.71	2.9	3.0	2.8	3.3
	October Monthly Peak	0.26	0.36	0.48	0.50	1.2	1.7	2.2	2.3

5.6 Comparison of Ex ante and Ex post results

Ex post and *ex ante* load impacts may differ for a variety of reasons, including differences in weather conditions, the timing and length of the event window, and other factors such as changes in expected enrollment. Table 5-5 presents an overall comparison of 2017 *ex post* load impacts and the *ex ante* load impacts as estimated for 2018, to indicate how different *ex post* and *ex ante* load impacts can be. Only the months of August through October are shown for comparison, since there were no events taking place in May or June 2017. July is not included because there were no commercial events that took place in July 2017. It is important to note that the 2018 *ex ante* impacts reflect the drop of the residential solar users but the *ex post* estimates do not.

Generally speaking, the 2017 August and September *ex post* average aggregate impacts are lower than the 2018 *ex ante* impacts due to the high number of events called at very low temperatures. The October the 2017 *ex post* impact is higher than the 2018 October *ex ante* impacts due to the high temperature experienced during the event called in October.

Table 5-5 Comparison of 2017 *Ex post* Load Impacts to 2018 *Ex ante* Load Impacts by Month

Month	2017 *Ex post* Average Aggregate Impacts* (MW)	2018 *Ex ante* Impact** SDG&E 1 in 2 (MW)
August	6.0	9.0
September	3.8	11.1
October	7.8	6.5

*Average of 2016 events by month

**For RA hours of 1-6 PM

6 Summary of the Opt-in Peak Time Rebate Program (PTR) and Residential Small Customer Technology Deployment (SCTD) Program[27]

6.1 Program Overview

6.1.1 Opt-in PTR Program Description

The PTR program provides customers with notification on a day-ahead basis that a PTR event will occur on the following day. The PTR program is marketed as Reduce Your Use. In emergency situations, an PTR event can be called on a day-of basis to help address an emergency, but day-of events are not the primary design or intended use of the program. PTR is a two-level incentive program, providing a basic incentive level ($0.75/kWh) to customers that reduce energy use through manual means and a premium incentive ($1.25/kWh) to customers

[27] The PTR and SCTD evaluation was conducted by Itron. This section of the Executive Summary contains excerpts from the following evaluation: ITRON (2018). "2017 Impact Evaluation of San Diego Gas & Electric's Residential Peak Time Rebate and Small Customer Technology Deployment Programs".

that reduce energy usage through automated demand response (DR) enabling technologies. The PTR bill credit is calculated based on their event day reduction in electric usage below their established customer-specific reference level (CRL). The program is marketed under the name Reduce Your Use (RYU) and is an opt-in program for residential customers. CPUC Decision D-13-07-003 directed SDG&E to require residential customers to enroll in PTR to receive a bill credit beginning in 2014. Prior to 2014, the PTR program was a default program for all SDG&E residential customers with an opt-in component whereby customers could receive notification of events.

6.1.2 SCTD Program Description

The program provides demand response enabling technology to residential. In past years, SDG&E offered at no cost to qualifying customers the Ecobee Smart Si thermostat. This thermostat is signaled by SDG&E through Wi-Fi through use of an Ecobee utility portal. In 2017 only one cycling strategy was used with the free thermostats, namely a four-degree temperature setback. Beginning in 2017, SDG&E added a BYOT element to the program. The eligible thermostats include the Nest Learning Thermostat, the Nest Thermostat E, the Ecobee 3 Thermostat, and the Ecobee 4 Thermostat. These can be purchased on SDG&E's website or the individual vendors' websites.

Although PTR events were seven hours long (11 a.m. to 6 p.m.), SCTD thermostats can be signaled between 11:00 a.m. and 9:00 p.m. but for more than four hours in a row. Typically, SCTD events run from 2 p.m. – 6 p.m.

Since PTR is opt-in, customers must enroll to receive a bill credit. Not all SCTD customers enrolled themselves in PTR. If the customer did not enroll in PTR their thermostat was curtailed but they did not receive a bill credit. SCTD customers receive a $50 e-gift card for enrolling and will receive a $25 e-gift card at the end of each summer they stay enrolled and their thermostat stays connected.

SDG&E also offers an air-conditioning cycling program called Summer Saver. Residential customers are either enrolled on a 50% cycling option or a 100% cycling option. Some of these customers are also enrolled in PTR and receive the higher bill credit of $1.25. The Summer Saver program is run by a third-party aggregator.

6.2 PTR and SCTD Residential Ex post Evaluation Methodology and Validation

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

6.2.1 Control Group Selection

Control groups were used to measure impacts from the PTR and SCTD programs. The use of control groups helps to improve the estimation of reference loads and impacts when obfuscating conditions exist, such as: a) few events, with the potential of these events being the hottest days during the summer, b) some events occurring during non-cooling months and/or months where hot weather is not typical, c) small average impacts relative to the overall size of the average participant load during the events. To develop control groups for this evaluation, Itron used a Stratified Propensity Score Matching (SPSM) method.

6.2.2 Pre-Matching Stratification and Design

Prior to generating propensity scores, the participant sites were stratified to control for variables that may observationally influence participation. Strata were defined using a combination of three major participant characteristics: PTR participation, SCTD participation, and having Net Energy Metering (NEM). Each of the six possible participant combinations of these characteristics were also stratified by climate zone (coastal and inland). In total, this provided 12 different strata from which to develop control groups.

PTR Participant	Net Energy Metered	SCTD Participant	Climate Zones
✓	✓	×	Inland, Coastal
✓	×	×	Inland, Coastal
✓	✓	✓	Inland, Coastal
✓	×	✓	Inland, Coastal
×	×	✓	Inland, Coastal
×	✓	✓	Inland, Coastal

Using these customer segments and strata, the SPSM methodology used a logistic regression (logit) model to estimate the probability of participation within each stratum. The matching routine paired each participant with a non-participant that had the most similar estimated probability of participation.

The control group selection used the hourly interval data for a random sample of 600,000 non-participant customers. The PSM selected the control group using variables developed from interval data. The matching was performed separately for all PTR and SCTD participants by the stratification detailed above, as well as for the other various participant subgroups, namely SCTD, Summer Saver, and Low Income.

After experimenting with various combinations, the final set of variables based on interval data for the months of June through September of 2017 were chosen. The logit model included: monthly hot day morning kWh usage, monthly hot day event hours kWh usage, monthly hot day evening kWh usage, monthly Saturday event hours kWh usage, and dummy variables for Low Income status, presence of an electric vehicle, enrollment in Summer Saver and usage size category.

The second stage of matching saw the additional inclusion of hourly kWh usage during the event hours for summer hot days and coefficients of variation of kWh usage during event hours.
Propensity Score Matching Results

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

6.2.3 PTR *Ex post* Methodology

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

Expressed symbolically, the model is as follows:

$$
\begin{aligned}
kWh_t = \beta_0 &+ \sum\nolimits_d \beta_1^d \times DOW_d + \sum\nolimits_m \beta_2^m \times Month_m + \sum\nolimits_h \beta_3^h \times Hour_h \\
&+ \sum\nolimits_d \sum\nolimits_h \beta_4^{h,d} \times Hour_h \times DOW_d + \sum\nolimits_m \sum\nolimits_h \beta_5^{h,m} \times Hour_h \times Month_m \\
&+ \beta_6 \times CDH65 + \sum\nolimits_h \beta_7^h \times Hour_h \times CDH65_h \\
&+ \sum\nolimits_{e=1,2,3} \sum\nolimits_h \beta_{8,e}^h \times Hour_h \times Event_e \\
&+ \sum\nolimits_{e=1,2,3} \sum\nolimits_h \beta_{9,e}^h \times Hour_h \times Event_e \times InactivePart \\
&+ \sum\nolimits_{e=1,2,3} \sum\nolimits_h \beta_{10,e}^h \times Hour_h \times Event_e \times ActivePart + \varepsilon_t
\end{aligned}
$$

Where

kWh_t	Is the kWh in hour *t*
β_0	Is the intercept
β_1^d	Is the set coefficient for day of week (DOW*)* *d*
β_2^m	Is the set of coefficient for month *m*
β_3^h	Is the set of coefficients for hour *h*
$\beta_4^{h,d}$	Is the set of coefficients for the interaction of hour *h* and DOW *d*
$\beta_5^{h,m}$	Is the set of coefficients for the interaction of hour *h* and month *m*
β_6	Is the coefficient for cooling degree hours (CDH)
β_7^h	Is the set of coefficients for CDH interacted with hour *h*
$\beta_{8,e}^h$	Is the set of coefficients that measure how much energy the non-participants would consume during the three event days, e=1,2,3, and in hour *h*
$\beta_{9,e}^h$	Is the set of coefficients for the program impacts on the inactive participants during the three event days, e=1,2,3, and in hour *h*
$\beta_{10,e}^h$	Is the set of coefficients for the program impacts on the active participants during the three event days, e=1,2,3, and in hour *h*
ε_t	Is the error

The program impacts were modeled using three sets of dummy variables, one for each event day. In year 2017, three events were called for three consecutive days, on Thursday, Friday and Saturday. It has long been noticed that the residential customers' energy consumption behaviors are different during weekdays and weekends. Therefore, it is expected that they react differently to a weekday DR event and a weekend DR event, and the difference is more likely to be due to behavior difference than to weather difference. For the two week-day events, by modeling the impacts using dummy variables, the model estimates the impact energy without attributing any of the impact difference to weather change. If more events were called in 2017, the model can allocate the weather sensitive impact better, but with only two week-day events, it is either attributing all impacts to weather or none. The purpose of the *ex post* analysis is to quantify the impact, and hence the dummy model serves the purpose better.

6.2.4 SCTD Residential *Ex post* Methodology

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

6.3 PTR and SCTD Residential Ex post Load Impact Estimates

In 2017, SDG&E called a total of three PTR events and three SCTD events. The events were on the same days for both programs: August 31st, September 1st, and September 2nd. The event hours for PTR were from 11 a.m. to 6 p.m. and the event hours for SCTD were from 2 p.m. to 6 p.m. Table 6-1 through Table 6-6 present a high-level summary of the major sub-groups for the PTR and SCTD programs, respectively.

Table 6-1: PTR *Ex post* Load Impact Estimates – By 2017 Event Date (11 a.m. to 6 p.m.)

Customer Category	Mean Active Participants	Mean Reference Load (kW)	Mean Observed Load (kW)	Mean Impact (kW)	% Load Reduction	Aggregate Load Reduction (MW)	Mean °F
August 31st, 2017	80,342	1.18	1.05	0.13	11.1%	10.57	90.9
September 1st, 2017	80,630	1.41	1.30	0.11	7.7%	8.78	95.7
September 2nd, 2017	80,745	1.57	1.52	0.05	3.3%	4.15	94.3
Average 2017 Event	80,572	1.39	1.29	0.10	7.0%	7.84	93.6

Table 6-2: SCTD Residential *Ex post* Load Impact Estimates by Thermostat Type – Average 2017 Event (2 p.m. to 6 p.m.)*

Event Date	Active Participants	Mean Reference Load (kW)	Mean Observed Load (kW)	Mean Impact (kW)	% Load Reduction	Aggregate Load Reduction (MW)	Mean °F
All	17,617	2.18	1.64	0.54	24.7%	9.48	94.1
BYOT	4,680	2.13	1.67	0.69	29.2%	3.22	92.7
Free	12,940	2.15	1.63	0.52	24.2%	6.74	94.6

* Participants excluding Summer Saver load control.

Table 6-3: PTR Dually Enrolled in Summer Saver *Ex post* Load Impact Estimates – Average 2017 Event (3 p.m. to 6 p.m.)

Customer Category	Mean Active Participants	Mean Reference Load (kW)	Mean Observed Load (kW)	Mean Impact (kW)	% Load Reduction	Aggregate Load Reduction (MW)	Mean °F
All	2,217	2.10	1.92	0.18	8.4%	0.39	96.8
Summer Saver – 50% Cycling	751	2.43	2.39	0.04	1.7%	0.03	97.9
Summer Saver – 100% Cycling	1,465	1.93	1.69	0.23	12.2%	0.34	96.3

6.4 PTR Ex ante Evaluation Methodology

Ex ante impacts for the PTR program for four participant segments (Opt-In PTR-Only, PTR Dually Enrolled in Summer Saver, PTR Dually Enrolled in SCTD, and SCTD-Only) were estimated by combining the regression model results from the *ex post* impacts with two other sources of data. The first data source was a 10-year forecast of enrollment for four separate participant segments. The second data source was two separate versions of weather scenarios containing hourly weather for different types of weather years and day types for each month of the year, one from SDG&E and the second from CAISO. The results presented in this section use the weather conditions based on SDG&E estimates.

The *ex ante* estimation process involved three main steps. The first step required estimating a similar model as the *ex post* regression model. Several changes were made to the *ex post* methodology for *ex ante* forecasting. These were: 1) excluding the event on September 2nd, which was a Saturday. Customers behave differently on weekends, and they are expected to respond differently for a weekday event than a weekend event. Therefore, the weekend event was excluded from the *ex ante* analysis, since the major task here is to predict what would happen in the future when a weekday event is called. 2) For PTR, two dummy variables were used to model the impacts. The similar hourly weather conditions across the two weekday events was causing the model to give too much importance to temperature. Because the temperatures for the *ex ante* scenarios are very different from those on the actual event days, the model estimated impacts that were much larger than were experienced on the actual events even though the temperature were lower. To resolve this problem, we have used the average load impacts from the *ex post* analysis and applied them to the modeled reference loads estimated using the *ex ante* temperatures. For PTR, it is assumed that the impact does not change as weather changes, but depends more on the date; while for SCTD, the impact is estimated as a function of cooling degree hours. Since the SCTD program encourages customers to adjust their thermostats, it is intuitive that the impact would be weather dependent, rather than date dependent. 3) Given that there are only two weekday event days, and the two days were both very hot, the temperatures for some hours were very similar across the two days, especially for the inland areas. To estimate the impact as a function of weather variable for SCTD, it is required that there is variation in weather across the two days. Therefore, for SCTD *ex ante* model, the weighted average temperature was used, using number of customers in the whole population as weights.

In the second step, the re-estimated parameters were combined with the weather scenarios from the various year and day types to calculate per participant average reference loads, observed loads, and load impacts. The standard errors from the impact variable parameters were used to calculate the uncertainty estimates.

The last step was to combine estimated per-participant impacts for the different weather scenarios and multiply them by the forecast of enrolled participants to generate the total program impacts. SDG&E forecasts that the PTR-only enrollments will stay constant through the end of 2018, when the program will be discontinued. By the end of 2018, the PTR program is expected to grow to over 82,000 participants (driven by dual enrollments from SCTD), and the SCTD program is expected to grow to over 28,000 participants. By the end of 2021, the SCTD program is forecasted to grow to over 56,000 participants. These projections are then expected to remain relatively constant throughout the remainder of the *ex ante* forecast period.

The enrollment forecasts were based on total participants by participant segment, whereas the weather scenarios and estimated impacts have more detailed information. Consequently, the alignment of these data sources called for making certain assumptions about the allocation of program participants. Total participants from the forecast were allocated to climate zones and, for the SCTD and Summer Saver groups, to the cycling strategies based on the relative shares as of the event days from 2017. Additionally, since the weather scenarios were provided by climate zone, an average weather scenario was created using an average where the same participant shares were used as weights. Note that this weighting was program segment specific. For example, the overall weather for the SCTD 100% cycling participants was based on the shares by climate zone for that group. The shares used for the allocation of the enrollment forecast are presented in Table 7-4. Lastly, it should be noted that in 2018 and beyond, the SCTD program will be renamed to the AC Saver Day Ahead program. After 2018, participants with Net Energy Metering customers will not be able to participate in demand response.

Table 6-4: Shares for Allocation of Enrollment Forecast

Participant Segment		Coastal	Inland	All
PTR-Only	**All**	53%	47%	100%
PTR Dually Enrolled in Summer Saver	**100% Cycle**	16%	50%	67%
	50% Cycle	3%	30%	33%
	All	19%	81%	100%
PTR Dually Enrolled in Residential SCTD	**4 Degree Setback**	10%	9%	19%
	50% Cycle	31%	50%	81%
	All	41%	59%	100%
SCTD-Only	**4 Degree Setback**	44%	56%	100%
	50% Cycle	19%	14%	33%
	All	25%	42%	67%

6.5 PTR and SCTD Residential Ex ante Load Impacts Estimates

6.5.1 PTR Only

Table 7-5 shows show the *ex ante* average load impact estimates for the average PTR-only customer on an average weekday, monthly system peak day, and a typical event day based on 1-in-2 and 1-in-10 weather year conditions for 2018. The average weekday and monthly system peak days are presented for June, July, and August, while the typical event day is presented for the month of August. For both 1-in-2 typical event day and 1-in-10 typical event day scenario, the estimated load reduction for the average participant is 0.055 kW during the Resource Adequacy hours (1:00pm to 6:00 pm), and the estimated aggregate load reduction is 3.98 MW. These estimates represent approximately 3.9% and 3.6% of the reference load, respectively, for each weather scenario.

Table 6-5: 2018 *Ex ante* Average Hourly Load Impact Results – PTR-Only

			1 in 10					1 in 2				
	Day / Type	Month	Avg. Hourly Reference Load (kWh)	Average Hourly Observed Load (kWh)	Average Hourly Impact (kWh)	Percent Load Reduc-tion	Average Total Hourly Impact (MWh)	Avg. Hourly Reference Load (kWh)	Avg. Hourly Observed Load (kWh)	Avg. Hourly Impact (kWh)	Percent Load Reduc-tion	Avg. Total Hourly Impact (MWh)
ALL	Average Weekday	Jun	1.00	0.95	0.055	5.5%	3.98	0.88	0.82	0.055	6.3%	3.98
		Jul	1.40	1.34	0.055	4.0%	3.98	1.29	1.24	0.055	4.3%	3.98
		Aug	1.34	1.28	0.055	4.1%	3.98	1.31	1.26	0.055	4.2%	3.98
	Monthly System Peak Day	Jun	1.28	1.22	0.055	4.3%	3.98	1.04	0.98	0.055	5.3%	3.98
		Jul	1.60	1.54	0.055	3.5%	3.98	1.45	1.39	0.055	3.8%	3.98
		Aug	1.56	1.5	0.055	3.6%	3.98	1.48	1.42	0.055	3.7%	3.98
	Typical Event Day	Aug	1.54	1.48	0.055	3.6%	3.98	1.42	1.36	0.055	3.9%	3.98

6.5.2 PTR Dually Enrolled in Summer Saver

Table 6-6Table 7-6 shows show the *ex ante* load impact estimates for the average PTR customer dually enrolled in Summer Saver for the various combinations of day types and weather scenarios for 2018. As a reminder, the control group for these dually enrolled participants are Summer Saver participants that are not dually enrolled in PTR, and the forecasted impacts are incremental savings over and above those realized from the Summer Saver program. Since the PTR model does not model the impact as a function of the weather variables, the predicted impacts are constant for all weather scenarios. Therefore, for both 1-in-2 and 1-in-10 typical event days, the estimated incremental load reduction for the average participant is 0.182 kW during event hours. These estimates are much higher than the PTR-only group. The estimated aggregate load reductions are 0.47 MW, which is about 9.1% in the 1-in-2 scenario and 8.4% in the 1-in-10 scenario. Note that the percentage reductions are different due to the different reference load predicted.

The 100% cycling group has an estimated load reduction during event hours of 0.252 kW, representing a 13.2% reduction from the reference load under the 1-in-2 scenario and a 12.3% reduction under the 1-in-10 conditions. The 50% cycling group has much lower estimated load reductions of 0.017 kW, about 0.8% and 0.7% of the reference load for 1-in-2 and 1-in-10 scenarios, respectively.

Table 6-6: *Ex ante* Average Hourly Load Impact Results – PTR Dually Enrolled in Summer Saver

Day / Type	Month	1 in 10					1 in 2				
		Average Hourly Reference Load (kWh)	Average Hourly Observed Load (kWh)	Average Hourly Impact (kWh)	Percent Load Reduc-tion	Average Total Hourly Impact (MWh)	Average Hourly Reference Load (kWh)	Average Hourly Observed Load (kWh)	Average Hourly Impact (kWh)	Percent Load Reduc-tion	Average Total Hourly Impact (MWh)
Average Weekday	Jun	1.60	1.41	0.182	11.4%	0.47	1.38	1.20	0.182	13.1%	0.47
	Jul	2.03	1.85	0.182	8.9%	0.47	1.89	1.70	0.182	9.6%	0.47
	Aug	1.92	1.74	0.182	9.5%	0.47	1.87	1.69	0.182	9.7%	0.47
Monthly System Peak Day	Jun	1.95	1.76	0.182	9.3%	0.47	1.63	1.45	0.182	11.1%	0.47
	Jul	2.32	2.14	0.182	7.8%	0.47	2.08	1.90	0.182	8.7%	0.47
	Aug	2.17	1.99	0.182	8.4%	0.47	2.11	1.93	0.182	8.6%	0.47
Typical Event Day	Aug	2.16	1.98	0.182	8.4%	0.47	2.00	1.82	0.182	9.1%	0.47

6.5.3 PTR Dually Enrolled in Residential SCTD

Table 6-7 shows show the *ex ante* load impact estimates for the average PTR customer dually enrolled in SCTD for the various combinations of day types and weather scenarios for 2018. For a 1-in-2 typical event day, the estimated load reduction for the average dual PTR-SCTD participant is 0.608 kW during Resource Adequacy hours. For a 1-in-10 typical event day, the estimated load reduction is 0.659 kW. The average estimated aggregate load reductions are 5.07 MW (33.8%) and 5.50 MW (31.2%), respectively. The impacts were predicted to be different because the SCTD *ex ante* forecasts model the impact as a function of the weather variable. This is because the SCTD customers are assumed to save energy by adjusting their thermostats, and hence the energy-saving should intuitively be weather-dependent.

For those who had Free Thermostats, the average reduction is 0.574 kW (31.9%) and 0.625 kW (29.7%), for 1-in-2 and 1-in-10 scenarios, respectively. While for those BYOT participants, the average reduction is at 0.753 kW (41.8%) and 0.805 kW (37.6%).

Table 6-7: *Ex ante* Average Hourly Load Impact Results – PTR Dually Enrolled in SCTD

Day / Type	Month	1 in 10					1 in 2				
		Average Hourly Reference Load (kWh)	Average Hourly Observed Load (kWh)	Average Hourly Impact (kWh)	Percent Load Reduction	Average Total Hourly Impact (MWh)	Average Hourly Reference Load (kWh)	Average Hourly Observed Load (kWh)	Average Hourly Impact (kWh)	Percent Load Reduction	Average Total Hourly Impact (MWh)
Average Weekday	Jun	1.35	0.83	0.519	38.3%	4.33	1.36	0.90	0.467	34.2%	3.90
	Jul	1.74	1.16	0.571	32.9%	4.76	1.63	1.10	0.531	32.6%	4.43
	Aug	1.66	1.09	0.576	34.6%	4.80	1.62	1.06	0.564	34.8%	4.71
Monthly System Peak Day	Jun	1.76	1.13	0.627	35.7%	5.23	1.37	0.84	0.534	39.0%	4.46
	Jul	2.19	1.53	0.657	30.0%	5.48	1.81	1.22	0.593	32.7%	4.95
	Aug	2.15	1.49	0.659	30.7%	5.49	1.97	1.33	0.642	32.6%	5.36
Typical Event Day	Aug	2.11	1.45	0.659	31.2%	5.50	1.80	1.19	0.608	33.8%	5.07

6.5.4 SCTD Only

Table 7-8 shows the *ex ante* load impact estimates for the average customer only enrolled in the SCTD program for the various combinations of day types and weather scenarios for 2018. For a 1-in-2 typical event day, the estimated load reduction for the average SCTD-only participant is 0.451 kW during the resource availability hours. For a 1-in-10 typical event day, the estimated load reduction is slightly higher, at 0.474 kW. The estimated aggregate load reductions are 4.49 MW (24.4%) and 4.72 MW (22.0%), respectively. As the enrollment in the SCTD programs continues to grow, these aggregate estimates will increase.

For the SCTD-only customers, those who received free thermostats are forecasted to reduce usage by 0.379 kW for the 1-in-2 weather condition, and by 0.396 kW for the 1-in-10 weather condition, which are about 20.7% and 18.6% of the corresponding reference usages, respectively. On the other hand, the BYOT customers are forecasted to reduce usage by 0.602 kW (31.8%), and 0.635 kW (28.9%), respectively. The forecasted program impact for the BYOT group is higher than that for group who received free thermostats.

Table 6-8: *Ex ante* Average Hourly Load Impact Results - SCTD Only

		1 in 10					1 in 2				
Day / Type	Month	Average Hourly Reference Load (kWh)	Average Hourly Observed Load (kWh)	Average Hourly Impact (kWh)	Percent Load Reduc-tion	Average Total Hourly Impact (MWh)	Average Hourly Reference Load (kWh)	Average Hourly Observed Load (kWh)	Average Hourly Impact (kWh)	Percent Load Reduc-tion	Average Total Hourly Impact (MWh)
Average Weekday	Jun	1.40	0.98	0.417	29.9%	4.16	1.40	1.01	0.398	28.4%	3.97
	Jul	1.79	1.35	0.436	24.4%	4.34	1.68	1.26	0.421	25.1%	4.20
	Aug	1.71	1.27	0.438	25.6%	4.36	1.67	1.24	0.433	25.9%	4.32
Monthly System Peak Day	Jun	1.79	1.33	0.465	26.0%	4.63	1.41	0.99	0.423	29.9%	4.21
	Jul	2.22	1.75	0.470	21.2%	4.68	1.86	1.42	0.445	23.9%	4.44
	Aug	2.19	1.72	0.471	21.5%	4.69	2.01	1.54	0.466	23.2%	4.64
Typical Event Day	Aug	2.15	1.67	0.474	22.0%	4.72	1.85	1.40	0.451	24.4%	4.49

6.5.5 Comparison of 2017 and 2016 *Ex ante* Estimates

Table 7-9 shows the comparisons between the *ex ante* estimates in the current evaluation and those reported in the previous evaluation for the forecast year 2018. The current *ex ante* impact estimates are similar for the PTR-only group –the current estimates are 0.06 kW for a 1-in-2 event day and a 1-in-10 event day, while the previous estimates are 0.04 kW and 0.05 kW, respectively. This consistency between the two weather scenarios supports the assumption that PTR-only impacts are relatively insensitive to weather. The percentage load reductions slightly decreased, from approximately 4.2% and 4.7% in the previous analysis to approximately 3.9% and 3.6% in the current analysis for 1-in-2 and 1-in-10 weather condition, respectively.

The estimates for the group dually enrolled in Summer Saver are higher in the current evaluation. The current estimates for incremental Summer Saver impacts are 0.18 kW for both a 1-in-2 event day and a 1-in-10 event day, almost doubled comparing to 0.08 kW and 0.11 kW in the previous evaluation. The percentage load reductions also increase in the current estimates, from approximately 7.8% in the previous analysis to approximately 8.4% in the current analysis for a 1-in-10 year.

The estimated impacts for the SCTD participants in the current analysis increase even more. For the dually enrolled participants, the previous analysis found estimates of 0.26 kW on 1-in-2 event days and 0.34 kW on 1-in-10 event days. The current analysis projects 0.61 kW on 1-in-2 event days and 0.66 kW on 1-in-10 event days, almost double the previous forecasts. The percentage load reduction estimates under the current analysis are also much higher. For example, in the 1-in-2 year, the previous results had load reductions of 19.8%, while the current estimates are 33.8%.

For the SCTD-only participants, the current forecasts are also much higher in both absolute impacts and percentage impacts. The previous analysis found estimates of 0.17 kW (11.4%) on 1-in-2 event days and 0.22 kW (12.3%) on 1-in-10 event days. The current analysis projects 0.45 kW (24.4%) on 1-in-2 event days and 0.47 kW (22.0%) on 1-in-10 event days. Both absolute impacts and percentage impacts are more than double of the previous estimates, except for the percentage impacts for 1-in-10 case, which has almost doubled as well. This is again largely driven by the differences in *ex post* impacts between the two years. The average overall event hour impacts for SCTD-Only in the previous evaluation were 0.31 kW (16.6%). This year, the averages for the Thursday and Friday events (having excluded the Saturday event for *ex ante* purposes) were 0.52 kW (27.1%) and 0.51 kW (22.4%). This increase is assumed to be due to the effect of removing the lower-performing 50% AC Cycling option, as well as the higher incidence of BYOT thermostats signaled, which appear to have higher impacts than the free thermostats.

Table 6-9: Comparison of 2017 and 2016 *Ex ante* Estimates per customer Forecast Year 2018, 1 P.M to 6 P.M.

			Current				Previous			
Participant Segment	**Weather Year**	**Day / Type**	**Average Hourly Reference Load**	**Average Hourly Observed Load**	**Average Hourly Impact**	**Percent Load Reduction**	**Average Hourly Reference Load**	**Average Hourly Observed Load**	**Average Hourly Impact**	**Percent Load Reduction**
PTR Only	**1 in 10**	Monthly System Peak Day	1.56	1.50	0.06	3.6%	1.11	1.06	0.05	4.6%
		Typical Event Day	1.54	1.48	0.06	3.6%	1.15	1.10	0.05	4.7%
	1 in 2	Monthly System Peak Day	1.48	1.42	0.06	3.7%	1.07	1.03	0.05	4.5%
		Typical Event Day	1.42	1.36	0.06	3.9%	0.98	0.94	0.04	4.2%
PTR/SS	**1 in 10**	Monthly System Peak Day	2.17	1.99	0.18	8.4%	1.28	1.18	0.10	7.6%
		Typical Event Day	2.16	1.98	0.18	8.4%	1.36	1.25	0.11	7.8%
	1 in 2	Monthly System Peak Day	2.11	1.93	0.18	8.6%	1.24	1.15	0.09	7.5%
		Typical Event Day	2.00	1.82	0.18	9.1%	1.14	1.06	0.08	7.1%
PTR/SCTD	**1 in 10**	Monthly System Peak Day	2.15	1.49	0.66	30.7%	1.52	1.21	0.32	20.8%
		Typical Event Day	2.11	1.45	0.66	31.2%	1.61	1.27	0.34	21.3%
	1 in 2	Monthly System Peak Day	1.97	1.33	0.64	32.6%	1.47	1.17	0.30	20.6%
		Typical Event Day	1.80	1.19	0.61	33.8%	1.33	1.07	0.26	19.8%
SCTD Only	**1 in 10**	Monthly System Peak Day	2.19	1.72	0.47	21.5%	1.70	1.50	0.20	11.9%
		Typical Event Day	2.15	1.67	0.47	22.0%	1.79	1.57	0.22	12.3%
	1 in 2	Monthly System Peak Day	2.01	1.54	0.47	23.2%	1.64	1.45	0.19	11.8%
		Typical Event Day	1.85	1.40	0.45	24.4%	1.49	1.32	0.17	11.4%

6.6 Relationship between Ex post and Ex ante Estimates

Table 7-10 show comparisons between the *ex ante* and *ex post* estimates from the PY2017 evaluation. For the overall PTR-only group and PTR/SS group, given that the impacts were modeled independent of weather condition, the *ex post* impacts and the *ex ante* impacts are the same. For the PTR-only customers, the average event hour load reduction is estimated to be 0.06 kW, representing a 3.9% reduction in 1-in-2 typical event day weather scenario and a 3.6% reduction in 1-in-10 case, comparing to a 3.8% reduction in *ex post* analysis. For the overall PTR-Summer Saver dually enrolled group, the impact is estimated to be 0.18 kW, about 8.4% in 1-in-10 typical event day weather scenario and 9.1% in 1-in-2 scenario, comparing to 9.1% using *ex post* load as reference. For the 100% cycling sub-group, the average saving is 0.25 kW, and the percentage in 1-in-10, 1-in-2 and *ex post* scenarios are 12.3%, 13.2% and 14.0%, respectively. The 50% cycling sub-group had minimal impacts at about 0.02 kW, and the percentage savings are very similar across the three scenarios, at 0.7%, 0.8% and 0.7%.

For the dually enrolled PTR-SCTD and SCTD-only group, the impacts were modeled as a function of cooling degree days, and hence the predicted impacts are different given different temperature. For the dually enrolled PTR-SCTD group, the *ex post* estimates are slightly lower than the *ex ante* estimates, both in terms of absolute value and percentage impacts. The *ex post* impact is 0.54 kW (22.8%), and the *ex ante* impacts are 0.66 (31.2%) and 0.61 (33.8%) for the 1-in-10 and 1-in-2 typical event day weather scenarios. The estimates for the BYOT and Free sub-groups also have a similar relationship. For BYOT group, the *ex ante* estimate is 0.81 kW (37.6%) for 1-in-10 weather scenario, and 0.59 kW (24.7%) for *ex post*; while for Free group, the *ex ante* is 0.62 kW (29.7%) for 1-in-10, and 0.52 kW (22.4%) for *ex post*. The SCTD-only *ex post* estimates are also lower than the *ex ante* estimates. The overall event hour load reduction estimate is 0.32 kW (13.3%) for the *ex post*, and 0.47 kW (22.0%) for the 1-in-10 *ex ante*. The BYOT sub-group has averages of 0.36 kW (14.7%) for *ex post*, and 0.62 (30.6%) for the 1-in-10 *ex ante* estimate. The Free sub-group has an *ex post* estimate of 0.29 kW (12.5%), compared to the *ex ante* average of 0.40 (18.6%) for the 1-in-10 typical event day.

Table 6-10: Comparison of *Ex ante* and *Ex post* Estimates

Participant Segment	Control Strategy	Weather Year	Day / Type	Average Hourly Reference Load	Average Hourly Observed Load	Average Hourly Impact	Percent Load Reduction	Average °F
PTR Only		1 in 10	Monthly System Peak Day	1.56	1.50	0.06	3.6%	92.19
			Typical Event Day	1.54	1.48	0.06	3.6%	91.49
		1 in 2	Monthly System Peak Day	1.48	1.42	0.06	3.7%	89.20
			Typical Event Day	1.42	1.36	0.06	3.9%	86.62
		Ex post	*Ex post* Average Event Day	1.44	1.38	0.06	3.8%	92.85
PTR/SS	100	1 in 10	Monthly System Peak Day	2.05	1.80	0.25	12.3%	94.13
			Typical Event Day	2.05	1.79	0.25	12.3%	93.93
		1 in 2	Monthly System Peak Day	2.00	1.75	0.25	12.6%	92.17
			Typical Event Day	1.91	1.65	0.25	13.2%	88.56
		Ex post	*Ex post* Average Event Day	1.81	1.55	0.25	14.0%	96.13
	50	1 in 10	Monthly System Peak Day	2.36	2.34	0.02	0.7%	95.20
			Typical Event Day	2.36	2.34	0.02	0.7%	95.29
		1 in 2	Monthly System Peak Day	2.30	2.28	0.02	0.7%	93.82
			Typical Event Day	2.14	2.12	0.02	0.8%	89.63
		Ex post	*Ex post* Average Event Day	2.37	2.35	0.02	0.7%	97.94
	ALL	1 in 10	Monthly System Peak Day	2.17	1.99	0.18	8.4%	94.49
			Typical Event Day	2.16	1.98	0.18	8.4%	94.38
		1 in 2	Monthly System Peak Day	2.11	1.93	0.18	8.6%	92.72
			Typical Event Day	2.00	1.82	0.18	9.1%	88.92
		Ex post	*Ex post* Average Event Day	2.00	1.82	0.18	9.1%	96.73
PTR/SCTD	BYOT	1 in 10	Monthly System Peak Day	2.20	1.40	0.81	36.6%	92.13
			Typical Event Day	2.14	1.34	0.81	37.6%	91.41
		1 in 2	Monthly System Peak Day	1.97	1.18	0.79	40.1%	89.11
			Typical Event Day	1.80	1.05	0.75	41.8%	86.56
		Ex post	*Ex post* Average Event Day	2.38	1.79	0.59	24.7%	93.16
	FREE	1 in 10	Monthly System Peak Day	2.13	1.51	0.62	29.3%	93.21

Table 7-10: (Cont'd) Comparison of *Ex ante* and *Ex post* Estimates

Participant Segment	Control Strategy	Weather Year	Day / Type	Average Hourly Reference Load	Average Hourly Observed Load	Average Hourly Impact	Percent Load Reduction	Average °F
PTR/SCTD			Typical Event Day	2.10	1.48	0.62	29.7%	92.77
		1 in 2	Monthly System Peak Day	1.97	1.36	0.61	30.8%	90.76
			Typical Event Day	1.80	1.23	0.57	31.9%	87.64
		Ex post	*Ex post* Average Event Day	2.34	1.82	0.52	22.4%	95.14
	ALL	1 in 10	Monthly System Peak Day	2.15	1.49	0.66	30.7%	93.00
			Typical Event Day	2.11	1.45	0.66	31.2%	92.51
		1 in 2	Monthly System Peak Day	1.97	1.33	0.64	32.6%	90.45
			Typical Event Day	1.80	1.19	0.61	33.8%	87.43
		Ex post	*Ex post* Average Event Day	2.35	1.81	0.54	22.8%	94.76
SCTD Only	BYOT	1 in 10	Monthly System Peak Day	2.26	1.62	0.63	28.1%	91.88
			Typical Event Day	2.20	1.56	0.63	28.9%	91.10
		1 in 2	Monthly System Peak Day	2.03	1.41	0.62	30.6%	88.73
			Typical Event Day	1.89	1.29	0.60	31.8%	86.31
		Ex post	*Ex post* Average Event Day	2.43	2.08	0.36	14.7%	92.67
	FREE	1 in 10	Monthly System Peak Day	2.15	1.76	0.39	18.3%	93.24
			Typical Event Day	2.12	1.73	0.40	18.6%	92.81
		1 in 2	Monthly System Peak Day	2.00	1.60	0.39	19.6%	90.81
			Typical Event Day	1.83	1.45	0.38	20.7%	87.67
		Ex post	*Ex post* Average Event Day	2.35	2.06	0.29	12.5%	95.15
	ALL	1 in 10	Monthly System Peak Day	2.19	1.72	0.47	21.5%	92.79
			Typical Event Day	2.15	1.67	0.47	22.0%	92.25
		1 in 2	Monthly System Peak Day	2.01	1.54	0.47	23.2%	90.13
			Typical Event Day	1.85	1.40	0.45	24.4%	87.23
		Ex post	*Ex post* Average Event Day	2.38	2.06	0.32	13.3%	94.33

7 Summary of the Permanent Load Shifting (PLS) Program[28]

7.1 PLS Program Overview

The PLS program provides a one-time incentive payment ($875/kW) to customers who install qualifying PLS-Thermal Energy Storage (TES) technology on typical central air conditioning units or process cooling equipment. Incentives are determined based on the designed load shift capability of the system and the project must undergo a feasibility study prepared by a licensed engineer. The load shift is typically accomplished through shifting of daytime chiller load to overnight hours. All electric customers on time-of-use electricity rates are eligible for the program, including residential, commercial, industrial, agricultural, direct access, and Community Choice Aggregation customers.

To qualify for the PLS program incentive payment, customers must go through the program application, approval and verification process, which includes all of the stages that are required for customers to apply for and receive a verified incentive amount. These stages are:

1. Customer submits complete application;
2. Customer submits feasibility study;
3. IOU reviews feasibility study prior to approval;
4. IOU conducts pre-installation inspection, including pre-installation M&V, and, if customer passes, approves application and sets aside incentive funds;
5. IOU and customer sign agreement (SCE only);
6. Customer submits project design;
7. Customer installs PLS-TES system;
8. Customer submits Commissioning Report;
9. IOU reviews commissioning report and conducts post-installation inspection, tests, cost, and any other verifications; and
10. Customer receives final PLS technology incentive.

After submitting an application, participating customers must provide, in advance of installation, a feasibility study prepared by a licensed engineer. This study must include an estimated cooling profile for each hour for a year based on building simulation models and input

[28] The PLS statewide load impact evaluation was conducted by Nexant. This section of the Executive Summary contains excerpts from the following evaluation: Bell, E. & Bieler , S. & Wein , A., Nexant, Inc. (2018). "2017 Load Impact Evaluation of the California Statewide Permanent Load Shifting Program"

about building specifications, regional temperatures, occupancy, and other inputs. Both retrofit and new construction customers are subject to the energy modeling process unless utility approved cooling usage data is available.

The total incentive amount is determined using a customer's load shift on their maximum cooling demand day—based on the on-peak hours. A conversion factor[29] is used to convert the cooling load shift tons to electricity load shift (kW) for both full and partial storage systems. The incentive levels for the program are $875/kW-shifted for all IOUs.

The incentive payments are intended to offset a portion of the cost of installation, thereby making the system more attractive financially. Under the program rules, the incentive is the lesser of (1) the incentive reservation amount calculated from the approved feasibility study and post-installation approval; (2) 50% of the actual final installed project cost; or (3) $1.5 million. In addition, customers are required to be on a time-of-use electric rate and provide trend data to the IOU's about their TES system for the first five years after installation. In the participation component of the program, customers are required to run their TES system on summer weekdays for five years after installation, thereby realizing electric bill savings, and submit monitored system data to the IOU. The systems are expected to have a lifetime of about 20 years.

Customers are required to run the PLS system during all weekday peak periods during summer months (May1 –October 31) from 11am through 6pm. PLS program participants are also encouraged to shift load during non-summer months if doing so maximizes their energy bill savings.

7.2 PLS Ex post Evaluation Methodology

This year, SDG&E had three operational customers enrolled in the PLS program. Each customer was analyzed separately using a different methodology and then the results of the three analyses were combined.

The first customer was analyzed last year after the April 1 filing and presented several data problems. After determining that there was no change in the customer's status from the previous year, Nexant used the same methodology as last year to estimate the *ex post* impacts for its first customer, outlined below.

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[29] A conversion factor will be used to convert the cooling load shift (tons) to electricity load shift (kW) capacity. This calculation method is applied for both full and partial storage systems. A conversion factor of 0.7 kW/ton will be applied to water-cooled chillers and 1.2 kW/ton will be applied to air-cooled chillers.

The first customer's installation in SDG&E's territory presented several challenges to estimating *ex post* impacts. Records from SDG&E indicate the building with the TES installation changed owners or tenants around the time of the installation. This makes it difficult to find pre-installation data that can be used to generate a reference loads for comparison with observed premise meter data during the post-installation period. Additionally, the building is only partially occupied, so the TES system is not being run at full capacity. This makes it difficult to detect the PLS signature in the premise meter data, as the TES system is being run below the maximum incentivized capacity of 306 kW. In this situation where the PLS signature is small relative to the base load, it is ideal to use operational data directly from TES system; however, the building conducts classified[30] activities, which limited the access of the third-party contractor to collect operational data and conduct operational tests.

In order to demonstrate system performance and calculate the final incentive amount for this customer, the third-party contractor ran the fully charged TES system to depletion on two test days, June 8 and June 9, 2016, and recorded the total ton-hours.[31] The total ten-hours were divided by the seven hour load-shifting period (11 AM to 6 PM) to calculate the average tons the TES system would shift during the on-peak period. The maximum average on-peak tons measured over the two test days was 255 tons, or 306 kW (255 tons * 1.2 kW/ton = 306). Given the TES system's small signature in the premise meter data, the lack of pre-installation premise data for the current customer, and the lack of operational data, Nexant identified approximately 10 proxy days each from June 2014 and non-test days in June 2016 based on similar weather conditions. Proxy days were selected based on their similarity to each test day based on mean17, overnight cooling degree hour (CDH), and cooling degree day (CDD). A simple propensity score model was used to calculate the likelihood that a proxy day had the same weather conditions as the test days. The model was run separately for each test day and each weather metric. Each run identified up to 10 nearest neighbor matches from the group of weekdays in June 2014 and the non-test weekdays in June 2016. The final 2014 and 2016 proxy days were selected if the day was identified as a top ten match across two of the three weather metrics. Figure 2 1 shows a side-by-side comparison of the average 2014 and 2016 proxy day loads with the observed load on the June 8 test day. Figure 2 2 shows the same set of graphs for the June 9 test day.

[30] Classified as in military, defense, or government related.

[31] Other tests may have been conducted. These days were included in the test data from SDG&E and showed full depletion of the ice.

Figure 8-1: Average 2014 and 2016 June Proxy Days and Observed Load – June 8, 2016 Test Day

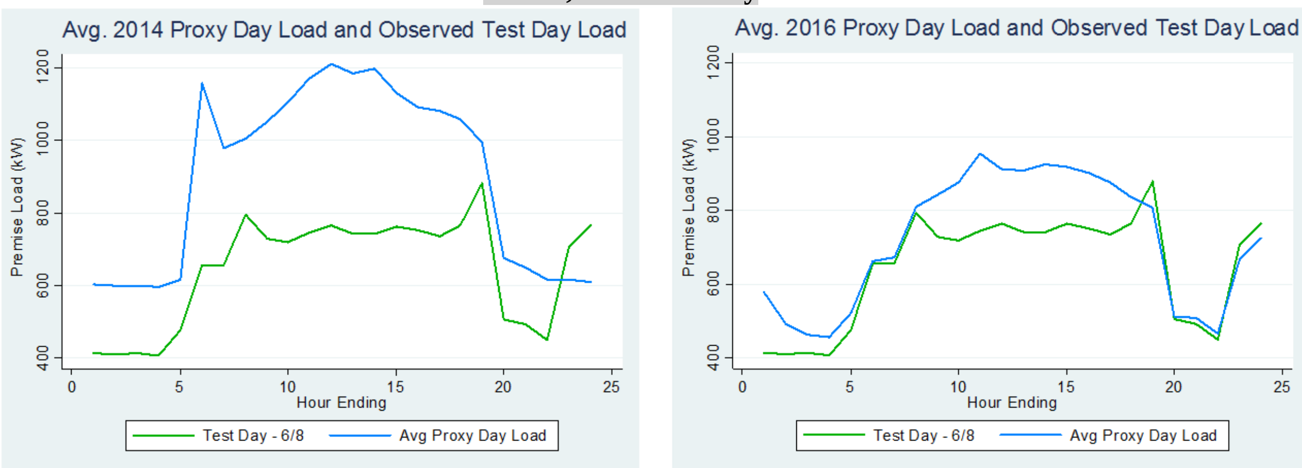
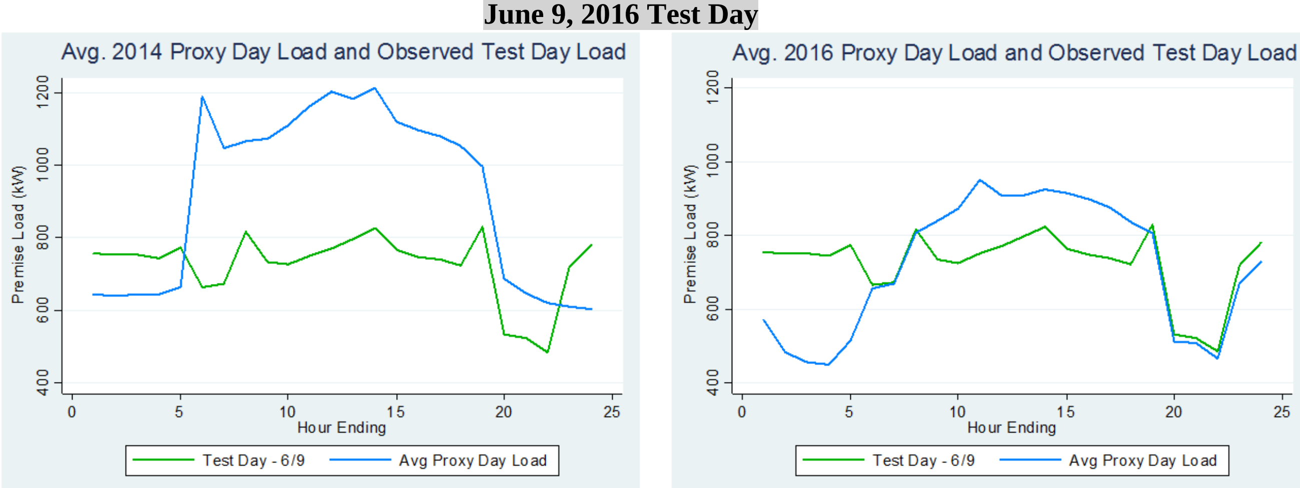


Figure 8-2: Average 2014 and 2016 June Proxy Days and Observed Load – June 9, 2016 Test Day



The difference between the reference and observed loads using the average 2014 and 2016 proxy days represent the upper and lower bounds of the load shift, respectively. The range for the average on-peak shift for the June 8 test day is 146.3 kW to 384 kW and 129.5kW to 369.5kW for the June 9 test day.

The reference load for the average 2014 proxy day is assumed to represent the pre-installation load for the current customer if the building were fully occupied. Given the similarity in load shapes during the off-peak periods for the test days and 2014 proxy days, it is reasonable to assume that the 2014 proxy days represent the typical pre-installation premise loads for the current customer. The 2016 proxy days were selected to generate a lower bound on the impact estimates. Since the customer is not currently running the TES system to its full capacity, it is reasonable to assume that the load on similar, non-test days represent the typical load profile for the customer under the limited occupancy conditions.

The final *ex post* impact is calculated using the average of the 2014 and 2016 proxy day loads for each test day and for an average test day.

For the second and third customer's installation a regression model was used to estimate the relationship between premise level hourly load data for the customer with the operational TES system and several explanatory variables expected to influence the load such as the temperature, time of day, day of the week, month, season, and year.

To construct the model for the second customer, at least four years of premise-level data were used for estimation. The first site became operational between January and May 2016, resulting in approximately two years of pre-TES installation data and two years of post-TES installation data. The time from January 2016 through May 2016 was excluded from the analysis to allow for the installation and testing period to not influence model estimation.

For the third customer, Nexant was unable to use premise-level data for the *ex post* analysis because additional buildings had been added after the time of the pre-installation data, and therefore the load shape had changed too much to separate out the impact of the PLS system.

Because of this, Nexant used operational data for the analysis. This means that the aggregate impact of the PLS system includes both premise-level data and end-use data, and so the percent impact of the PLS system is not well defined because the data type is not consistent across all three sites.

The operational data for SDGE's third customer presented several data challenges. Pre-installation data indicated that the cooling system had three chillers, but one of the chillers was not being used at full capacity during the 2012-2013 time interval in which Nexant was provided with pre-installation data. To ensure only the PLS system impact was captured in the analysis, Nexant excluded the third chiller from the analysis, since its use had changed independently of the installation of the PLS system. Nexant was also provided with auxiliary load in pre-installation data, but not in the post-installation data, and so was not able to include auxiliary data in the analysis. Therefore, Nexant analyzed the impact of the PLS system on two of the customer's chillers. The chiller load was given the same treatment as premise-level load in the model selection and analysis.

The customer's operational data for July also only included five days that could be used for analysis. Of these five days, two days had a significantly higher load than all other post-operational data provided. In order to prevent these outliers from influencing the monthly predictions in the *ex ante* analysis, Nexant created a model that estimated impacts without including the month as a variable.

To construct the model for the third customer, twelve months of data were used for estimation—April 2012 through July 2012, April 2013 through July 2013, and April 2017 through July 2017. The other months were excluded from the analysis because Nexant did not receive post-installation data for the other months. The site became operational October 2016, resulting in approximately eight months of pre-TES installation data and four months of post-TES installation data.

For both customers, many model specifications were systematically evaluated via out-of-sample testing, as discussed below, and the best performing model was used to estimate the relationship between the explanatory variables such as weather and time during the pre-TES installation period. The relationships estimated from the pre-TES installation period were then applied to the observed data—temperature and time related variables—in the post-TES installation period to forecast the reference load; or what we would have expected the customer's load to be in the absence of TES under the specific weather conditions at that time. The load shift is then calculated as the difference between the predicted reference load and the actual observed load for each hour.

Impacts were calculated for every hour of every day in the post-TES installation period. However, the reporting of impacts is limited to the day types required by the load impact protocols—system peak days and the average weekday for each month—and the day with the largest estimated impact for each month.

The model selection process is summarized as follows:

1. Identified 10 days from 2012 and 2013 (5 from each year) with the highest hourly load to use as peak load days prior to TES installation for out of sample testing.
2. Estimated 28 different regression models and used them to predict out-of-sample for the peak load days identified in step 1. This allowed us to identify the regression model that produced the most accurate predictions for peak load days similar to when maximum load shifting is expected. The models vary with respect to how weather variables were defined and with the inclusion of time related variables such as day of the week, month, or season.
3. Selected the most accurate model specification based on out-of-sample testing metrics and used it to estimate the reference load after the TES system was installed.

Nexant first developed a set of candidate models to test. A candidate model could vary based on its specification. The model specifications tested were carefully selected with a focus on load magnitude and shape under peak load conditions when maximum load shifting was expected to occur. The set of candidate models were evaluated using a cross-validation process that assesses the quality of the model based on how well it predicts for excluded peak load days that were not used to estimate the model. The rationale for such a strategy is that, if a model accurately predicts load on peak load days prior to TES installation, it is expected to provide an accurate counterfactual for expected load in the absence of a TES system, after that system is installed.

A good model can be said to predict load accurately if it yields an unbiased and precise fit to that of the withheld peak load day. The evaluation used a quantitative model selection process that employs a method called leave one out cross validation (LOOCV) over a set of peak load days. That set of days, as noted in step 1 above, is selected to be as similar as possible to days when a maximum load shift is expected. LOOCV is outlined below:

1. For each of the m candidate models, conduct LOOCV over peak load days:
   a. For each of the n peak load days:
      i. Develop explanatory variables using data from all peak load days except the nth;
      ii. Fit mth model using explanatory variables and predict load based on the observed characteristics of the nth day;
      iii. Record predicted load and actual load on the nth peak load day not used to fit the model; and
2. Compute metrics to measure bias and goodness-of-fit for each model.

The quality of a model is evaluated based on the bias and precision of its prediction of load compared to the actual load on the excluded peak load days. Table 8-1 shows the metrics computed in step 2. All metrics were computed over the relevant PLS program hours, as that was the principal period over which we had to estimate load shifting.

Table 8-2: Control Group Accuracy Statistics

Statistic Type	Statistic Level	Statistic	Formula	Description	Typical Values
Bias	Program	Average Percent Error	$\frac{\sum \hat{y}_{i,t}}{\sum y_{i,t}} - 1$	Sums up predicted and actual value for peak load days for the customer; calculates error statistics from these values.	Expressed in percentage terms. Can be positive or negative. The closer to zero, the better.
Bias	Program	SD(APE)	$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(APE_t - \overline{APE})^2}$	Measures the average deviation in average percent error on individual peak load days.	Expressed in percentage terms. Can only be positive. The smaller the number, the better.
Goodness-of-fit	Program	Absolute Sum of Errors	$\sum \lvert \hat{y}_{i,t} - y_{i,t} \rvert$	Sums up absolute errors for peak days.	Expressed in kWh terms. Can only be positive. The smaller the number, the better.

The statistics above use the following nomenclature:

- y - observed kWh
- $\hat{y}$ - predicted kWh
- i - customer
- t - each individual peak load day
- n - total number of peak load days

The final model was selected on the basis of average percent error, taking into account both its absolute value and its deviation across the excluded days, provided that the absolute sum of errors was acceptable relative to other potential models. The final model and its associated explanatory variables are summarized below.

Mathematically, the regression can be expressed by:

$$kW_t = A + \sum_{i=1}^{24}\sum_{j=1}^{5} B_{ij} \times Hour_i \times DOW_j + \sum_{i=1}^{24} C_i \times Hour_i \times Summer \quad \sum_{i=1}^{24} D_i \times Hour_i \times CDH_t$$
$$+ \sum_{i=1}^{24} E_i \times Hour_i \times OvernightCDH_t$$

7.3 PLS Ex post Evaluation Estimates

There were three PLS installations within SDG&E's territory that were available for evaluation this year. The first installation in SDG&E's territory was installed in March 2015, however due to the ownership change for the building and its classified status, the final post-installation activities and commissioning report were not completed until spring 2016. The installation is located in San Diego, and the installation site comprises a single building that is part of a larger office park. The second installation was installed in May 2016, and is comprised of a 40,000 square foot laboratory facility. The third installation was installed in October 2016 and is comprised of a 10,350 square foot building that is part of a college campus located in San Diego.

Due to a lack of post-operational data, the results for the 2017 evaluation only include all three utilities in the average June weekday results. Two customers are included for the months of April through July for both average weekdays and monthly system peakdays, and one customer is included in all of the result months. Figure 3-9 shows the aggregate *ex post* load impact table for an average June weekday where all three customers are included. An average June weekday experienced an aggregate load shift of 899 kW and a maximum hourly load shift of 934 kW occurring in hour ending 14. The load impact is likely larger in the hotter peak summer months, but the data availability challenges limit what can be reported in the *ex post* section of the report. Modeling techniques will be applied for the *ex ante* analysis that help to reflect the full load shifting potential of the program during the months not included in the *ex post*.

The upper and lower confidence intervals on the graph (green dashed lines) represent the uncertainty around the load impact estimate. The upper and lower bounds of the 90% confidence interval are 1,076 kW and 793 kW, respectively. This range represents the point estimate of the load impact plus or minus 18%. Similarly, Figure 3-10 shows the *ex post* load impact for the average customer on an average June weekday. On an average June weekday the average PLS customer experienced a load shift of 300 kW and a maximum hourly load shift of 311 kW during hour ending 14. The upper and lower bounds of the 90% confidence interval are 359 kW and 264 kW, respectively.

Figure 8-3: *Ex post* Load Impact Table— Aggregate Impact June Average Weekday

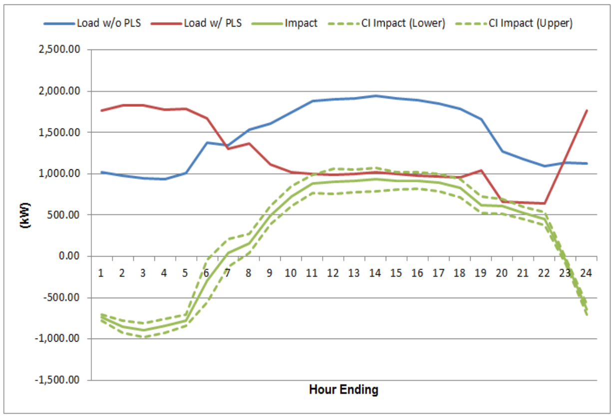
Menu Options

Impact Type	Aggregate Impact
Day Type	Average Weekday
Month	June

Date	N/A
Day of the Week	N/A

Event Day Information

Event Start	11 AM
Event End	6 PM
Average Temp. for Event Window	76
Mean17	68
Load Reduction for Event Window*	899.09
% Load Reduction for Event Window**	48%



Hour Ending	Load w/o PLS (kW)	Load w/ PLS (kW)	Impact (kW)	Impact (%)	Temp. (°F)	Uncertainty Adjusted Impact - Percentiles 10%	30%	50%	70%	90%
1	1,024.20	1,763.36	-739.16	-72%	62	-766.95	-750.53	-739.16	-727.79	-711.37
2	974.04	1,826.52	-852.49	-88%	61	-908.23	-875.30	-852.49	-829.67	-796.74
3	943.04	1,833.23	-890.19	-94%	61	-956.53	-917.33	-890.19	-863.04	-823.85
4	933.53	1,776.56	-843.03	-90%	61	-910.57	-870.66	-843.03	-815.39	-775.49
5	1,007.51	1,782.68	-775.17	-77%	61	-826.71	-796.26	-775.17	-754.08	-723.63
6	1,378.18	1,676.56	-298.38	-22%	61	-499.93	-380.86	-298.38	-215.91	-96.84
7	1,347.67	1,305.62	42.05	3%	61	-92.38	-12.96	42.05	97.06	176.48
8	1,530.30	1,370.35	159.95	10%	62	69.58	122.97	159.95	196.93	250.32
9	1,610.20	1,111.92	498.28	31%	64	409.79	462.07	498.28	534.49	586.77
10	1,748.67	1,018.75	729.92	42%	67	637.29	692.01	729.92	767.82	822.54
11	1,881.69	999.51	882.18	47%	71	796.86	847.27	882.18	917.09	967.50
12	1,898.93	990.93	907.99	48%	73	791.00	860.12	907.99	955.86	1,024.98
13	1,910.54	995.46	915.08	48%	76	806.06	870.47	915.08	959.68	1,024.09
14	1,950.46	1,016.03	934.43	48%	77	823.90	889.20	934.43	979.65	1,044.95
15	1,913.88	998.02	915.86	48%	79	832.30	881.67	915.86	950.05	999.41
16	1,894.07	975.61	918.45	48%	79	841.07	886.79	918.45	950.12	995.83
17	1,855.59	963.13	892.45	48%	78	810.66	858.99	892.45	925.92	974.25
18	1,787.50	961.24	826.27	46%	77	738.73	790.45	826.27	862.09	913.81
19	1,661.84	1,037.26	624.59	38%	74	548.82	593.59	624.59	655.59	700.35
20	1,270.76	663.89	606.86	48%	71	537.80	578.60	606.86	635.12	675.92
21	1,179.34	651.31	528.04	45%	67	470.19	504.37	528.04	551.71	585.88
22	1,096.15	641.78	454.37	41%	64	391.97	428.84	454.37	479.91	516.77
23	1,140.81	1,196.03	-55.22	-5%	63	-84.54	-67.22	-55.22	-43.22	-25.89
24	1,122.52	1,764.12	-641.59	-57%	63	-692.51	-662.43	-641.59	-620.76	-590.68
Event	**1886.58**	**987.49**	**899.09**	**48%**	**76.2**	**848.17**	**878.25**	**899.09**	**919.92**	**950.01**

*Data for all three customers only available for June Average Weekday. Data for two customers only available for April-June for both daytypes. Data for one customer available for all months and daytypes.

**Percent impacts will not match feasibility studies since end use data is combined with premise level data.

Table 8-3 compares the monthly system peak day aggregate impact with the average weekday impact estimated for each month the customer is required to shift load (June 1 to September 30). The average impact across the peak hours and the maximum hourly impact are also presented. The July monthly system peak saw the highest impacts with an average shift of 1,100 kW and an hourly maximum of 1,134 kW. Because PLS is not an event based program and the TES system runs at all hours during the program operational months, the average weekday impacts are more indicative of the day-to-day usage. The highest average weekday impact of 899 kW was observed in June. It should again be noted that only June average weekdays represent all three customer loads, and August and September only represent the load impacts of one customer.

Table 8-3: Comparison of Monthly System Peak Day and Average Weekday Impacts (aggregate)

Month	Monthly System Peak Day (kW)		Average Weekday (kW)	
	Average Hourly Impact	Maximum Hourly Impact	Average Hourly Impact	Maximum Hourly Impact
June	934.67	1,089.18	899.09	934.43
July	1,101.81	1,134.65	652.77	715.11
August	151.19	259.06	137.57	189.11
September	132.17	280.23	156.09	197.37

7.4 PLS Ex ante Evaluation Methodology

The PLS program evaluation forecasts load impacts for three different types of projects:

- **Operational** - customers with installed and operational PLS systems;
- **Identified** - those for which customers have completed an application or feasibility study.

In past years, Nexant has analyzed impacts for both identified projects, those for which customers have already completed an application or feasibility study, and unidentified projects, or projects in which applications are projected to be submitted during the funding cycle. Because the PLS program is not open to new applicants, Nexant only analyzed identified and operational projects in the PY2017 evaluation.

Applications are submitted by potential PLS participants to initiate their enrollment in the program. Each application includes an initial estimate of the proposed PLS-TES installation's load shifting capacity. Feasibility studies are more in-depth analyses conducted by qualified engineers and include a technical and cost analysis of the proposed project. Completion of a feasibility study is the next step in the PLS approval process after the initial application has been submitted and approved. As of this writing, a total of 30 applications have been received by the 3 IOUs, 10 have been withdrawn, 1 project is awaiting approval, 12 projects have completed feasibility studies, and 7 installations are operational.

For identified projects, the *ex ante* load impacts were allocated to specific local capacity areas[32] (LCAs) because the location of the PLS-TES system installation was known. While this information on where identified projects will be installed reduces some uncertainty in the forecast, there is still substantial uncertainty regarding whether the project will successfully go through the entire verification process given that, as of January 2018, seven projects have become operational. The identified projects also have an expectation of the installation date—either in the application or the feasibility study, if available—but those dates may change throughout the verification process.

Because the number and size of identified projects varies between each IOU, the approach used to evaluate program impacts was tailored to the amount of information that was available for each IOU. Primarily, the number and diversity of applications determines the methodology used to generate load impacts for identified projects.

[32] LCA is the CAISO-defined term that represents each transmission-constrained load pocket in the California IOU service territories.

7.4.1 Operational Projects

There were two similar methods used for *ex ante* estimation for operational sites, depending on whether *ex post* estimation used premise level meter data or operational data.

Ex post based on premise level data. The methodology for *ex ante* estimation for the operational sites using premise level data is based off the *ex post* estimation, but contains three extra modeling steps—developing a model to estimate the relationship between temperature and the *ex post* load shift, predict the reference load under *ex ante* conditions using the same model used for *ex post*, and predicting the *ex ante* load impacts based on the *ex ante* weather conditions—all as functions of outdoor air temperature and time. This methodology was used to estimate *ex ante* for the two installations in SDG&E's territory and includes the following steps:

1. Identify 10 days from the two most recent pre-installation years (5 from each year) with the highest hourly load to use as peak load days prior to TES installation for out of sample testing.
2. Estimate 28 different regression models and used them to predict out-of-sample for the peak load days identified in step 1. This allowed us to identify the regression model that produced the most accurate results on peak load days similar to when a maximum load shifting is expected. The models vary in how weather variables were defined, and in the inclusion of time related variables such as day of the week, month, or season.
3. Select the most accurate model specification based on out-of-sample testing metrics (same as those used in the *ex post* model selection) and use the selected model to estimate the reference load after the TES system was installed.
4. Calculate the estimated *ex post* load impacts based by subtracting the observed load from the estimated reference load during the post-PLS installation period.
5. Develop a model of the relationship between temperature, time, and *ex post* load impacts.
6. Forecast reference load under *ex ante* weather conditions based on the selected model from Step 3.
7. Forecast *ex ante* impacts based on the model developed in Step 5 under *ex ante* weather conditions, and combine with reference load to create to create *ex ante* load impacts.

7.4.2 Identified Projects

The PY2017 PLS program evaluation used the same single, consistent, methodology as the 2016 evaluation to estimate *ex ante* load impacts for identified projects for SDG&E. This approach is based on the fact that the size, installation date, and location were known for each specific project. At the time of the evaluation, SDG&E had two projects. *Ex ante* conversion factors (discussed in detail in the next report section) were used to convert the expected load shift from the application/feasibility study to *ex ante* weather conditions.

This kW load shift amount represents the peak load shift that can be expected under hot, maximum cooling load, weather conditions. The kW load shift was multiplied by the *ex ante* conversion factors, which converted the load shift under the incentive payment, maximum cooling load, and weather conditions to the *ex ante* load impact estimates for monthly system peak days and average weekdays under 1-in-2 year and 1-in-10 year weather conditions—as per the California DR Load Impact Protocols. The conversion factors are the same as those used in PY2015 and PY2016. These conversion factors were re-estimated for the PY2014 evaluation based on updated building simulation models and newly developed 1-in-2 and 1-in-10 year weather data that addressed the new requirement for reporting results for the CAISO system peak in addition to the IOU system peak.

Over time, the load shifting capacity of the PLS-TES technologies is expected to degrade as the system ages. The forecasts assume that five years after each forecasted PLS-TES installation, the *ex ante* impacts begin to degrade at a rate of 2.5% per year. This assumption was made in consultation with program managers and it is consistent with last year's evaluation.

The *ex ante* conversion factors were used to convert the load shift under the incentive payment, maximum cooling load, and weather conditions to the load shift that can be expected under the various *ex ante* temperature scenarios. The *ex ante* temperature scenarios include the monthly system peak days and average weekdays under 1-in-2 year and 1-in-10 year weather conditions for the utility specific and CAISO peak. Essentially, the conversion factors facilitate the estimation of the PLS-TES load impacts under a variety of different weather conditions with ease and efficiency.

It is important to note that these conversion factors were developed with building simulation models of space cooling installations. Some of the applications that have been received thus far also include process cooling installations, which have load profiles that frequently differ from the typical space cooling profile. Unfortunately, the process cooling installations do not make good candidates for generalized modeling because they are highly customized by industry and location; in addition, while space cooling loads exhibit significant seasonality due to temperature variation, process cooling loads may vary seasonally by temperature and changes in the underlying production process. For example, agricultural customer process cooling loads tend to follow the harvest schedule in addition to being temperature sensitive. The weather sensitivity of the currently modeled process cooling applications was analyzed, and the range of sensitivity in terms of the percentage difference in cooling load between 1-in-2 and 1-in-10 monthly peak days exhibit similar upper and lower limits to commercial AC cycling programs. For the sake of simplicity, lack of generalizability of the process cooling installations, and similarity in weather sensitivity ranges, space cooling building simulation models were used to develop the conversion factors applied to both space cooling and process cooling installations.

Finally, because local weather conditions influence the load shift that is actually experienced, the *ex ante* load impacts are dependent on the specific geographic region in which an installation is located. Considering that the location and installation date were provided in the application for identified projects, the forecast for identified projects incorporates this information by having the project come online on the expected installation date and by assigning the *ex ante* load impacts for that project to the customer's LCA.

7.5 Estimating Ex ante Weather Conditions

The CPUC Load Impact Protocols require that *ex ante* load impacts be estimated assuming weather conditions associated with both normal and extreme utility operating conditions. Normal conditions are defined as those that would be expected to occur once every 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 *ex ante* weather 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 for all three utilities. They were updated again in 2017 for SDG&E along with the development of the new CAISO based conditions. Both sets of estimates used a common methodology, which was documented in a report delivered to the IOUs. The PY2017 PLS program evaluation uses the most recently developed *ex ante* weather conditions that are available for each utility, which means that 2017 updates for SDG&E's *ex ante* weather conditions were incorporated for its operational projects where the *ex ante* impacts were based off the *ex post* results. However, identified (not yet operational) projects that rely on building simulation models to calculate the *ex ante* impacts are all based on the 2015 *ex ante* weather conditions. Building simulation models are based on specific sets of weather data, and are not simple updates, requiring extensive calibration and quality checks. Given the uncertainty regarding these identified sites actually completing installation, and the final specifications of the installation (which often vary compared to the initial application and feasibility study), the benefit of creating new building simulation models for the two SDG&E applicants isn't enough to outweigh the costs of creating the model. This is especially the case now that the program has been closed, as the cost of the previous building simulation models were able to be spread out across several years of evaluations. Based on all of these factors, Nexant has recommended the original building simulation models based on the 2015 *ex ante* weather data be used because the newer data wouldn't necessarily improve the accuracy or precision of the forecast, nor would it be an efficient use of the evaluation budget.

Table 8-1 and 8-2 show the values for each weather scenario, weather year and month for a variable equal to the average temperature from midnight to 5 PM (referred to as mean17) for each day type. For SDG&E, the CAISO weather is cooler under both 1-in-2 year and 1-in-10 year weather conditions. There are instances for SDG&E where the CAISO 1-in-2 weather conditions are higher temperature than the CAISO 1-in-10 weather conditions for the average weekday. This is driven by the process of how the CAISO weather conditions are selected, and the relationship between the CAISO peaking conditions and the local utility weather.

Table 8-1: 2015 SDG&E Enrollment Weighted *Ex ante* Weather Values (mean17)

Day Type		SDG&E Based Weather		CAISO Based Weather	
		1-in-2	1-in-10	1-in-2	1-in-10
Typical Event Day		73.1	79.0	72.3	75.7
Peak Day	May	68.0	78.1	64.7	72.2
	June	70.3	77.8	71.2	73.6
	July	72.7	78.7	70.9	75.4
	August	74.2	78.7	73.5	76.0
	September	75.0	80.7	73.6	77.6
	October	70.0	76.3	68.0	72.6
Average Weekday	May	61.6	65.7	62.1	61.4
	June	63.7	67.3	63.5	65.6
	July	67.4	69.2	70.5	68.2
	August	68.5	70.3	67.6	69.5
	September	67.1	70.4	67.8	69.8
	October	63.2	66.0	63.1	65.5

Table 8-2: 2017 SDG&E Enrollment Weighted *Ex ante* Weather Values (mean17)

Day Type		SDG&E Based Weather		CAISO Based Weather	
		1-in-2	1-in-10	1-in-2	1-in-10
Typical Event Day		**75.7**	**79.8**	**75.1**	**78.8**
Peak Day	May	69.7	77.0	66.7	75.6
	June	67.5	77.2	67.3	79.7
	July	75.0	76.6	72.0	75.6
	August	78.0	81.1	79.3	78.5
	September	82.2	84.0	81.9	81.4
	October	74.9	78.7	72.4	77.9
Average Weekday	May	62.8	65.0	63.5	63.5
	June	64.9	68.6	64.6	68.6
	July	69.5	72.15	70.6	72.2
	August	71.9	74.0	73.0	74.0
	September	70.4	74.9	70.4	74.9
	October	65.4	69.5	64.5	69.5

7.6 PLS Ex ante Load Impact Estimates

Table8-3 shows the impacts for the 1-in-2 and 1-in-10 utility-specific and CAISO weather conditions for the May through October system peak days. The difference between utility specific and CAISO peaks tend to vary by month. Impacts range from the CAISO-specific, September 1-in-2 monthly peak day in 2018 being 9% greater than the utility specific comparable peak at 2.2 MW and 2.0 MW, respectively, to the utility specific July 1-in-10 monthly peak day in 2018 being 10% greater than the CAISO specific comparable peak at 2.0 MW and 1.8 MW, respectively. Year-over-year, the difference between the utility specific peak and the CAISO peak appears to remain fairly constant. For example, the utility specific September 1-in-10 monthly peak load impact is typically around 4% higher than the comparable CAISO specific impact.

Table 8-3: SDG&E *Ex ante* Load Impact Estimates (1 to 6 PM) on Monthly Peak Days for May–October 2017–2027 (kW) – Base Scenario

Peak Type	Forecast Year	May		June		July		August		September		October	
		1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Utility Specific	2018	1,082	1,337	989	1,343	1,677	1,971	1,863	2,092	2,049	2,305	1,902	2,035
	2019	1,528	1,846	1,451	1,843	1,677	1,971	1,863	2,092	2,049	2,305	1,902	2,035
	2020	1,528	1,846	1,451	1,843	1,677	1,971	1,863	2,092	2,049	2,305	1,902	2,035
	2021	1,523	1,836	1,446	1,832	1,665	1,960	1,850	2,077	2,033	2,289	1,893	2,023
	2022	1,512	1,821	1,436	1,815	1,649	1,943	1,832	2,056	2,013	2,266	1,878	2,006
	2023	1,487	1,788	1,410	1,781	1,618	1,906	1,796	2,016	1,976	2,223	1,846	1,971
	2024	1,462	1,756	1,384	1,748	1,587	1,869	1,761	1,977	1,940	2,182	1,815	1,937
	2025	1,438	1,725	1,359	1,716	1,557	1,834	1,727	1,939	1,905	2,141	1,785	1,904
	2026	1,414	1,695	1,335	1,685	1,527	1,799	1,694	1,902	1,871	2,101	1,755	1,871
	2027	1,391	1,666	1,311	1,654	1,499	1,765	1,662	1,866	1,838	2,063	1,726	1,840
	2028	1,368	1,637	1,288	1,624	1,471	1,732	1,631	1,831	1,806	2,025	1,698	1,809
CAISO Specific	2018	931	1,335	953	1,423	1,621	1,763	1,934	1,984	2,211	2,196	1,676	1,959
	2019	1,321	1,864	1,386	1,933	1,621	1,763	1,934	1,984	2,211	2,196	1,676	1,959
	2020	1,321	1,864	1,386	1,933	1,621	1,763	1,934	1,984	2,211	2,196	1,676	1,959
	2021	1,315	1,855	1,380	1,921	1,611	1,751	1,920	1,971	2,196	2,180	1,668	1,947
	2022	1,305	1,841	1,370	1,903	1,596	1,735	1,900	1,951	2,174	2,157	1,655	1,930
	2023	1,282	1,809	1,345	1,868	1,564	1,702	1,863	1,914	2,133	2,114	1,626	1,895
	2024	1,259	1,778	1,320	1,834	1,533	1,670	1,826	1,877	2,093	2,072	1,599	1,860
	2025	1,237	1,747	1,297	1,800	1,502	1,638	1,791	1,841	2,054	2,031	1,571	1,827
	2026	1,215	1,718	1,273	1,768	1,472	1,608	1,757	1,807	2,016	1,991	1,545	1,794
	2027	1,194	1,689	1,251	1,736	1,444	1,578	1,723	1,773	1,978	1,952	1,519	1,762
	2028	1,173	1,660	1,228	1,705	1,415	1,549	1,690	1,739	1,942	1,914	1,494	1,731

7.6.1 Relationship between *Ex post* and *Ex ante* Estimates

Table 8-4 compares the current *ex post* results from the 2017 program year evaluation with last year's 2016 program year *ex ante* forecast for 2017. This comparison shows how similar or different the forecast was from what actually took place. Most of the differences observed between the 2017 forecast and the 2017 *ex post* evaluation are due to the differences in evaluation methodology. For the *ex post* evaluation, Nexant was not able to evaluate the full load impact for one of the customers due to a lack of available data. The unavailable data accounts for a large amount of the difference observed between the *ex post* and *ex ante* estimates. Additionally, *ex ante* estimates were based off of premise-level data and building simulations for identified projects, and so there was a large amount of uncertainty around the actual load shift that would be observed in 2017, as discussed further below.

Table 8-4: Comparison of 2017 *Ex post* to Prior Year *Ex ante* Estimates (June Average Weekday – Utility Specific)

Analysis	Accounts	Reference Loads (MW)	Percent Reductions	Aggregate Impacts (MW)
2017 *Ex post*	3	1.89	48%	0.90
2017 *Ex ante* 1-in-2	3	1.85	91%	1.69
2017 *Ex ante* 1-in-10	3	1.94	90%	1.75

Error! Reference source not found.8-5 provides an analysis of how the current *ex ante* results differ from the current *ex post* results. Four key factors contribute to the differences between the *ex post* and the *ex ante* forecast. The weather and event window provide small differences. However, the enrollment and methodology are interrelated and provide more significant differences. Technically, the enrollment forecast is a function of the methodology for forecasting program growth based on anticipated utilization of available budgets. Given PLS is a growing program with low enrollment rates, yet a large impact per customer, very small changes to the enrollment forecast can have a large influence on program MW. In 2018, two more customers are expected to enroll in the program. After that point, there is expected to be significant departure from the *ex post* results observed this year. The other factor related to the methodology is the specific analysis method used for the estimation of load impacts. In 2017 *ex post* data was available for the three operational customers; however, no such data exists for the projects projected to come online in the future. To address this, generalizable building simulation models and assumptions about the number and size of future projects are necessary. This is meant to represent the best estimate from program staff, but also involves a significant amount of uncertainty.

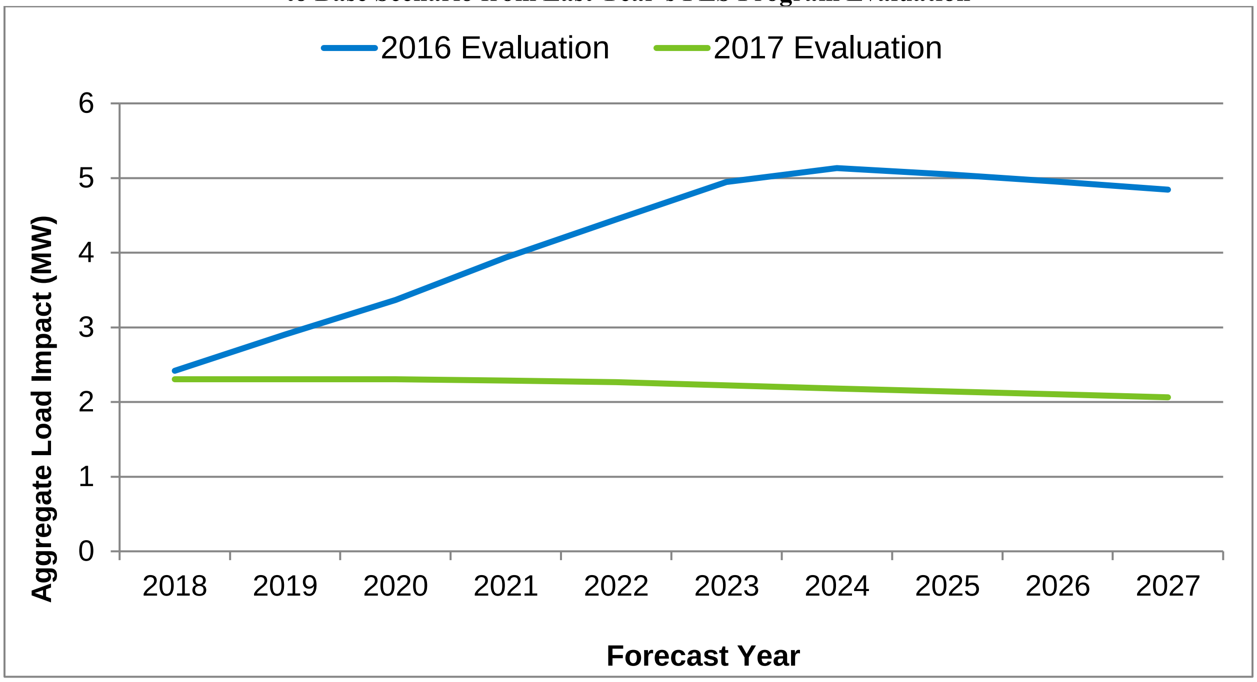
Table 8-5: Summary of Factors Underlying Differences between 2017 *Ex post* and 2018 *Ex ante* Impacts (June Average Weekday – Utility Specific)

Factor	*Ex post*	*Ex ante*	Expected Impact
Weather	Average weekday Mean17 = 68 Note: Mean17 is the average temperature between midnight and 5pm (hour ending 17). This metric helps to account for heat buildup during the day, which can affect cooling load.	Program specific Mean17 for 1-in-2 average weekday = 64 and 63 for SDG&E and CAISO weather, respectively Program specific mean17 for 1-in-10 average weekday = 67 and 66 for SDG&E and CAISO weather, respectively	*Ex ante* estimates are sensitive to temperature– impacts will be lower based on 1-in-2 SDG&E weather and more similar based on 1-in-10 PG&E weather and CAISO weather
Event window	Program hours from 11 AM to 6 PM	Resource adequacy window is from 1 to 6 PM	In some cases average *ex ante* impacts will be lower because in many cases the impacts are largest in the 12-1 PM hour that isn't included
Enrollment	Three customers	2018+ includes additional identified customers	*Ex ante* estimates will start to increase significantly in 2018+ as the program is projected to grow
Methodology	2017 impacts based on partial operational data for one customer and premise-level data for the other two customers	2018+ combines impacts based on operational data and building simulations for identified and unidentified customers	2018+ rely on a variety of assumptions and a different approach. Results are not directly comparable

7.6.2 Comparison of 2016 and 2017 *Ex ante* Estimates

Figure 8-4**Error! Reference source not found.** compares the *ex ante* load impact estimates from this evaluation to those from last year's PLS program evaluation, for the September 1-in-10 monthly system peak day. In last year's evaluation, there were no additional identified projects other than the projects evaluated in the 2017 *ex post*. However, there were several unidentified projects expected to come online through 2024. This year, two additional identified projects are expected to come online in 2018, but there are no additional unidentified projects since the program has been cancelled. Therefore, last year's predictions are much higher compared to this year after 2018 because of the additional unidentified customers that were expected to come online.

Figure 8-4: SDG&E Comparison of September 1-in-10 Monthly System Peak Day Load Impacts (1 to 6 PM) to Base Scenario from Last Year's PLS Program Evaluation



8 Summary of the Default Small Commercial CPP & TOU Rates[33]

8.1 Default Small Commercial CPP & TOU Rates) Overview

Most small business (SMB) customers across the U.S. have the same price throughout the day and do not have an incentive to consider the timing of their energy consumption and the degree to which consumption during peak hours drives energy and infrastructure costs. Between November 2015 and April 2016, SDG&E transitioned over 120,000 small business customers onto time of use rates with a critical peak component (CPP-TOU). While customers were defaulted onto TOU-CPP rates, they could elect to opt-out to a time-of-use (TOU) rate and 5% of them did. In tandem, SDG&E also transitioned small agricultural customers from flat rates onto time of use rates and offered a CPP-TOU rate on a voluntary (opt-in) basis. By April 2016, electricity rates without a time varying component were no longer available for small commercial and agricultural customers.

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[33] The small commercial CPP and TOU rate evaluation was conducted by Demand Side Analytics (DSA). This section of the Executive Summary contains excerpts from the following evaluation: Bode, J. & Lemarchand, A. (2018). "SDG&E Small Commercial Demand Response Evaluation Program Year 2017"

The transition to time varying rates encourages customers to consider when they consume power in addition to how much they consume. Customers can save by modifying when they use energy and by reducing energy use. The rates also better align the prices customers face and with the cost of supplying power. Prior to the transition, SDG&E implemented an outreach and education campaign designed to increase awareness and improve understanding of the new rate.

Two distinct interventions were assessed as part of the evaluation:

- TOU-CPP – Critical peak prices are designed to incentivize customers to reduce or shift electricity use from peak hours on a handful of days that drive the need for building additional power infrastructure. Customers receive rate reductions during summer non-event days to offset the higher prices during critical peak events (less than 1% of hours). At SDG&E the CPP rates are layered on top of TOU rates.
- TOU rates – TOU rates provide a daily signal to customers regarding when electricity production costs are lower or higher and provide them an incentive to reduce or shift their use.

8.2 Default Small Commercial CPP & TOU Rates Ex post Evaluation Methodology

The primary challenge of impact evaluation is the need to accurately detect changes in energy consumption while systematically eliminating plausible alternative explanations for those changes, including random chance. Did the introduction of time of use rates or smart learning thermostats cause a change in energy consumption and critical peak period demand? Or can the differences be explained by other factors? To estimate energy savings, it is necessary to estimate what energy consumption would have been in the absence of the intervention—the counterfactual or reference load.

The change in energy use patterns was estimated using two primary methods:

- ✓ <u>Difference in differences with a matched control group</u>. This approach was used as the primary method for event impacts for critical peak events delivered by CPP-TOU and thermostat participants. The matched control group was developed using non-participants and relied on out of sample testing. A total of 12 matching models were specified and hot non-event days were split into a training and testing days. The matching model used various combinations of hot non-event load data and customer characteristics. The quality of the match was assessed by comparing actual versus estimated aggregate hourly loads in the testing data. The analysis was implemented using a difference in differences panel regression with fixed effects. The technique corrects for remaining differences between the treatment and the matched control group, if any.

- ✓ Synthetic control groups. This approach was used as the primary method for estimating day to day energy savings (a non-dispatchable resource) for TOU impacts and commercial thermostats. The approach is implemented on a time series of aggregated loads. It relies on multiple non-equivalent control segments, plus weather and day characteristics, to estimate the counterfactual. The model weighs the various control segments based on their predictive power. A total of 20 models, 10 without and 10 with synthetic controls were tested side by side using pre-transition data. The data was split in half, with one half used to developed the model, and the other half used to assess the accuracy of the model. Approaches that included synthetic controls outperformed models that relied exclusively on pre and post data on energy use and weather.

Figure 8-1 summarizes the out of sample testing process used to select matched control groups. Essentially, the out of sample process is an iterative approach whereby data is systematically left out of the matching model then used to assess model performance—a well performing matching model should produce matches for loads on days which were not used for the match. The final match control group is identified based on least bias (% Bias) and best fit (Relative RMSE) metrics.

Figure 8-1: Out of Sample Process for Matching Model Selection

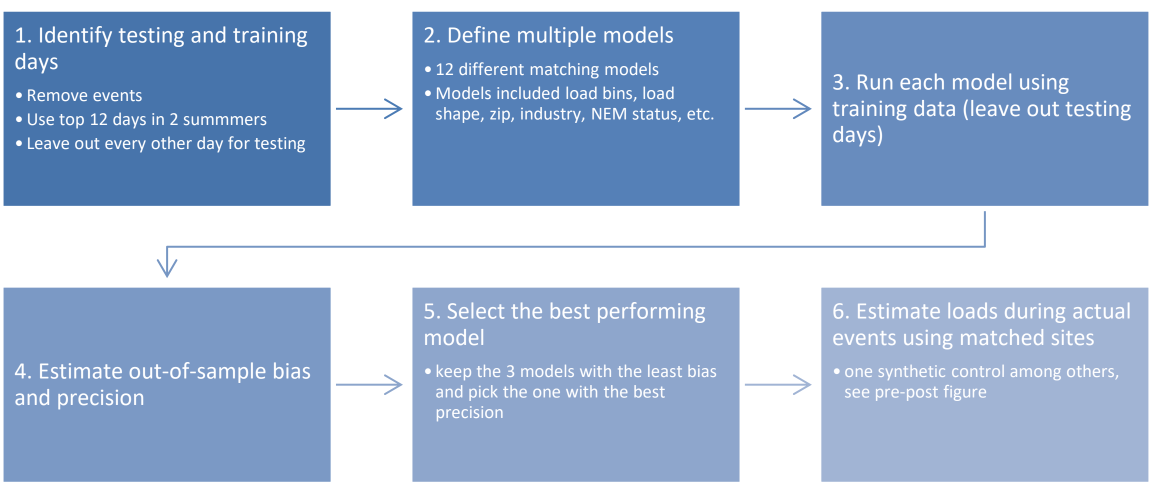


Figure 8-2: Out of Sample Process for Pre-post Model with Synthetic Controls

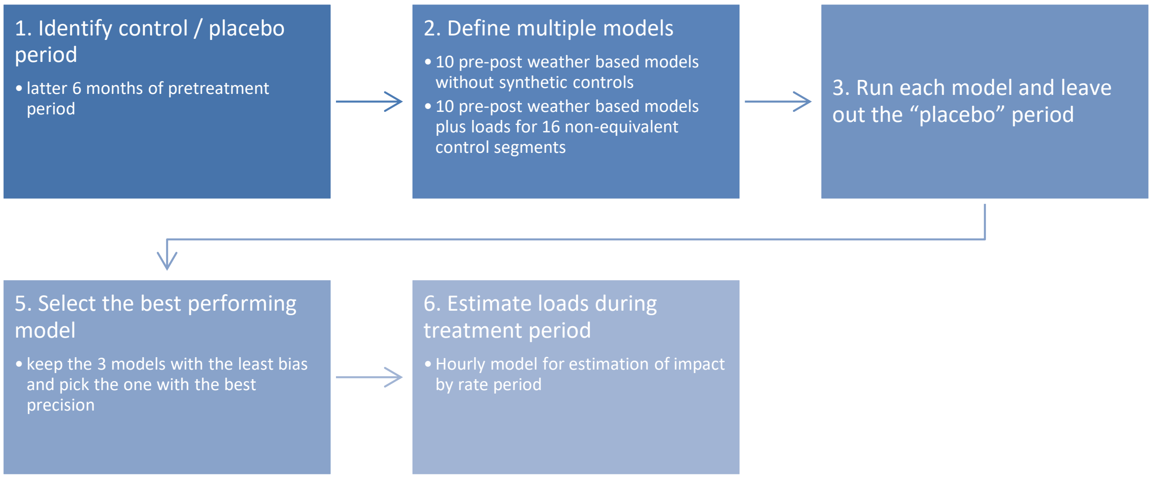


Figure 8-2 summarizes the multi-step out of sample process used to select pre-post models before finally estimating counterfactual post-treatment loads. For energy savings, the out-of-sample approach uses the first half of the pre-treatment period to predict loads for the second half of the pre-treatment period. This was done with each model tested and then model performance was assessed by comparing model estimates to actual loads. A total of 20 models were tested. The first 10 models were weather did not include external control groups but relied on participant load patterns and weather data before the intervention to model the counterfactual (i.e., within-subjects models). The second 10 models were these same weather-based models with the addition of 16 different non-equivalent comparison groups. The non-equivalent control groups did not experience the same TOU rate transition as the small commercial group. The model assigns weights to the various non-equivalent comparison groups based on their predictive power, creating a synthetic control group out of multiple external controls.

Error! Reference source not found.8-1 summarizes the data sources, segmentation and estimation methods used for each program. The segmentation was defined in advance of the analysis and is of particular importance because the evaluation used a bottom up approach to estimate impacts and to ensure that aggregate impacts across segments equaled the sum of the parts. Because impacts for each segment were added together, the segmentation was structured to be mutually exclusive and completely exhaustive. In other words, every customer was assigned to exactly one segment. By design, the segmentation differentiated customers who were expected deliver demand reductions and energy savings – such as customers who sign up for event notification or technology to automate response – from customers who were expected to deliver little or no demand reductions and energy savings. Additional segments were analyzed, after the fact, as part of exploratory analysis, but the core results presented are based on the segmentation detailed below.

Table 8-1: Evaluation Methods

	TOU	CPP
Data sources / samples	▪ 3 years (2015-2017) of hourly data for: ✓ ~6400 TOU participants ✓ ~117k CPP-TOU participants ✓ ~3,310 Ag TOU participants ✓ 5,000 residential customers ✓ X,000 large and medium customers who did experience a change in rates	▪ Hottest 20 weekdays and weekends over two summers, plus any additional event days for: ✓ 117k Small Comm participants ✓ 6400 CPP-TOU opt outs (used for match control group) ✓ 31 Ag participants ✓ 3,310 Ag participants
Segmentation	▪ Rate ▪ Enrollment in event notification (Y/N) ▪ Enabling technology (Y/N) ▪ Dual enrollment (by program) ▪ Net metering status (Y/N)	
Estimation method: ***Ex post***	Energy savings - Synthetic control group for each segment using medium business and residential segments to establish counterfactual	Event impacts – Diff-in-diff panel regression using matched control from opt-outs for each segment
Estimation method: ***Ex ante***	NA	▪ Weather normalized customer regressions by segment for reference loads ▪ Apply average percent impacts from 2017 to load profiles for various temperature conditions

8.3 Default CPP Ex post Load Impact Estimates

CPP event impacts were assessed by site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in

Table **8-2**8-2, was developed based on rate class, program, and technology characteristics which may influence impacts. Analysis was performed at the segment level so these granular impacts could therefore be summed, yielding aggregate impacts in addition to the segment specific impacts.

The segmentation criteria were defined as follows:

- **Rate class:** what type of rate was the site on throughout the study period?
- **Notification:** did the customer associated with the site receive any event notifications for any site?
- **Technology:** did the site have smart thermostat enabling technology installed?
- **Dual enrollment:** was the site enrolled in other demand response programs during the study period (Summer Saver, PTR, CBP)?
- **Solar:** was the site on a net metered rate during the study period?

Table 8-2: Critical Peak Pricing Population Segments

Rate class	Notification	Tech	Dually enrolled	Solar	Total Sites	Sites in analysis
Small Commercial	No	No	No	No	40,397	40,348
				Yes	499	495
			Yes	No	1,393	1,392
				Yes	19	18
		Yes	No	No	268	268
				Yes	11	10
			Yes	No	29	29
	Yes	No	No	No	70,248	70,147
				Yes	878	865
			Yes	No	2,424	2,423
				Yes	40	40
		Yes	No	No	797	797
				Yes	37	36
			Yes	No	74	74
				Yes	4	4
TOTAL SMALL COMMERCIAL					**117,118**	**116,945**
Small Agricultural	No	No	No	No	16	11
				Yes	1	1
	Yes	No	No	No	22	17
				Yes	1	1
			Yes	No	2	1
TOTAL SMALL AGRICULTURAL					**42**	**31**

Sites are premise and service point combinations

Table **8-2** summarizes the total number of sites in each segment and the final number of sites used for analysis once data cleaning was completed[34]. For most segments the vast majority of sites were included in the analysis. Aggregate *ex post* analysis results were scaled up to match the total number of sites before data cleaning.

Because other programs also modify loads, those event days cannot be used for counterfactual estimation for dually enrolled CPP participants. Days which were not CPP events but which were events for other DR programs were excluded for dual participants, leaving fewer days for counterfactual estimation. High load days from both 2016 and 2017 were used to develop the CPP counterfactual.

Table **8-3**8-3 shows the three PY 2017 CPP event days, including the maximum daily temperature weighted by participating sites. These consecutive events occurred during a statewide heat wave on the Thursday, Friday, and Saturday before Labor Day. Though the SDG&E peak often differs from the rest of the state, Friday September 1 was the system peak for both SDG&E and CAISO. The second highest load day for both systems was Saturday September 2, which was even hotter than the previous day and which was also a weekend.

Table 8-3: Critical Peak Pricing Events in 2017

Event day	Day of week	Event start	Event end	Max day temp (F)	SDG&E system load (MW)
8/31/2017	Thursday	11:00 AM	6:00 PM	89.4	4,190
9/1/2017	Friday	11:00 AM	6:00 PM	94.1	4,481
9/2/2017	Saturday	11:00 AM	6:00 PM	94.6	4,353

Weekend loads are typically different than weekday patterns, reflecting different activities and usage patterns for these different types of day. Because of this, the weekday events have been summarized separately from the weekend event which may not be comparable. Table 8-4 summarizes the load impacts by segment for the two weekday events (August 31 and September 1) for the 11am to 6pm event window. In aggregate, these events delivered 4.57 MW of load reduction across the small commercial and small agricultural rate classes. The small CPP portfolio total, excluding impacts for commercial thermostats and customer dually enrolled in other DR programs, was 4.31 MW. While aggregate impacts were significant, segmentation of load impacts actually show that impacts concentrated in key segments. Customers who signed up for event notification delivered the vast share of demand reductions. Percentage impacts for weekday events were about 50% higher for the groups that received some form of event

[34] The cleaning algorithm ensured that complete data was available for the study period. Sites for which high quality matches could not be found were also excluded.

notification. Customers who did not sign up for notification also delivered reductions, albeit smaller ones. There were multiple indirect channels where sites that did not directly sign up for notification could become aware of them. SDG&E publicized the events via mass media channels – radio and TV – and customers at many smaller sites that did not sign up for notification also had a medium and large facilities that were signed for event notification. Though very small in absolute, solar segments produced very high percentage impacts, primarily because they have smaller net loads (i.e., a small denominator).

Table 2-4: CPP Weekday Event Impacts (11 am to 6pm)

Rate class	Notifi-cation	Tech	Dually enrolled	Solar	Sites	Load without DR (MW)	Load w DR (MW)	Impact (MW)	% Impact	Std. Error	t	Significant (90% CI)
Small Commercial	No	No	No	No	40,397	141.39	139.77	-1.63	-1.1%	0.242	-6.70	Yes
				Yes	499	0.61	0.65	0.04	6.4%	0.035	1.10	No
			Yes	No	1,393	7.43	7.46	0.02	0.3%	0.052	0.42	No
				Yes	19	0.03	0.03	0.00	3.1%	0.007	0.14	No
		Yes	No	No	268	2.00	1.88	-0.11	-5.7%	0.031	-3.73	Yes
				Yes	11	0.06	0.05	-0.01	-11.9%	0.005	-1.33	No
			Yes	No	29	0.23	0.24	0.01	5.9%	0.010	1.36	No
	Yes	No	No	No	70,248	273.10	270.40	-2.71	-1.0%	0.321	-8.42	Yes
				Yes	878	1.98	1.96	-0.02	-1.0%	0.064	-0.30	No
			Yes	No	2,424	13.71	13.68	-0.03	-0.2%	0.079	-0.36	No
				Yes	40	0.18	0.18	0.00	0.3%	0.018	0.03	No
		Yes	No	No	797	6.70	6.59	-0.11	-1.7%	0.050	-2.21	Yes
				Yes	37	0.24	0.22	-0.01	-5.2%	0.011	-1.11	No
			Yes	No	74	0.52	0.50	-0.03	-5.4%	0.015	-1.89	Yes
				Yes	4	0.00	0.01	0.00	45.5%	0.006	0.35	No
TOTAL SMALL COMMERCIAL					**117,118**	**448.19**	**443.61**	**-4.57**	**-1.0%**	**0.423**	**-10.76**	**Yes**
TOTAL SMALL COMMERCIAL (portfolio only)					**112,062**	**417.11**	**412.80**	**-4.31**	**-1.0%**	**0.408**	**-10.53**	**Yes**
Small Agricultural	No	No	No	No	16	0.01	0.01	0.01	71.7%	0.004	0.99	No
				Yes	1	0.00	0.00	0.00	2469.0%	0.001	-1.99	Yes
	Yes	No	No	No	22	0.01	0.01	0.00	-31.4%	0.003	-1.17	No
				Yes	1	0.00	0.00	0.00	12.7%	0.000	-0.68	No
			Yes	No	2	0.00	0.00	0.00	-94.5%	0.000	-1.59	No
TOTAL SMALL AGRICULTURAL					**42**	**0.02**	**0.02**	**0.00**	**-2.3%**	**0.006**	**-0.06**	**No**

Sites are premise and service point combinations
Very high percent impacts for some solar subgroups a function of low net loads.

Table 8-5 summarizes the load impacts by segment for the single weekend event, Saturday, September 2, for the 11am to 6pm event window. In aggregate, this event delivered 2.08 MW of load reduction across the small commercial and small agricultural rate classes.

The impact for this weekend event was substantially lower in overall magnitude than the weekend impacts due to lower weekend loads and small load increases among customers who did not sign up for notification. The call for event reduction made the news on the weekday events but not on the weekend. This stands in contrast to the impacts produced by those receiving notification produced impacts—notified participants produced weekend impacts similar in magnitude to their weekday impacts. This further underscores the influence of notification on impacts delivered.

Table 8-5: CPP Weekend Event Impacts

Rate class	Notifi-cation	Tech	Dually enrolled	Solar	Sites	Load without DR (MW)	Load w DR (MW)	Impact (MW)	% Impact	Std. Error	t	Significant (90% CI)
Small Commercial	No	No	No	No	40,397	105.75	106.19	0.45	0.4%	0.395	1.13	No
				Yes	499	-0.03	-0.03	0.00	8.1%	0.138	-0.02	No
			Yes	No	1,393	5.90	6.10	0.20	3.4%	0.082	2.44	Yes
				Yes	19	-0.01	-0.01	-0.01	100.7%	0.011	-0.45	No
		Yes	No	No	268	1.43	1.42	-0.01	-0.7%	0.042	-0.24	No
				Yes	11	0.01	0.01	0.00	29.1%	0.010	0.26	No
			Yes	No	29	0.21	0.23	0.02	9.1%	0.015	1.33	No
	Yes	No	No	No	70,248	208.02	205.14	-2.88	-1.4%	0.518	-5.55	Yes
				Yes	878	-0.37	-0.30	0.07	-18.3%	0.075	0.88	No
			Yes	No	2,424	10.73	10.95	0.22	2.0%	0.129	1.70	Yes
				Yes	40	-0.05	-0.03	0.02	-44.1%	0.030	0.77	No
		Yes	No	No	797	5.33	5.16	-0.17	-3.2%	0.082	-2.06	Yes
				Yes	37	0.02	0.00	-0.02	-88.1%	0.013	-1.49	No
			Yes	No	74	0.42	0.45	0.04	8.5%	0.021	1.66	Yes
				Yes	4	0.00	0.00	-0.01	-381.9%	0.006	-1.15	No
TOTAL SMALL COMMERCIAL					**117,118**	**337.38**	**335.30**	**-2.08**	**-0.6%**	**0.695**	**-2.99**	**Yes**
TOTAL SMALL COMMERCIAL (portfolio only)					**112,062**	**313.39**	**311.03**	**-2.36**	**-0.8%**	**0.670**	**-3.52**	**Yes**
Small Agricultural	No	No	No	No	16	0.01	0.02	0.01	49.5%	0.003	1.38	No
				Yes	1	0.00	0.00	0.00	62.7%	0.001	-0.70	No
	Yes	No	No	No	22	0.01	0.01	0.00	-12.3%	0.003	-0.30	No
				Yes	1	0.00	0.00	0.00	44.2%	0.000	-2.26	Yes
			Yes	No	2	0.00	0.00	0.00	-99.8%	0.000	-6.07	Yes
TOTAL SMALL AGRICULTURAL					**42**	**0.02**	**0.02**	**0.00**	**0.6%**	**0.005**	**0.02**	**No**

Sites are premise and service point combinations

Very high percent impacts for some solar subgroups a function of low net loads.

8.4 Default Small Commercial CPP & TOU Rates Ex ante Evaluation Methodology

A key objective of the 2017 evaluation is to quantify the relationship between demand reductions, temperature and hour of day. *Ex ante* impacts are estimated load reductions as a function of weather conditions, time of day, and forecasted changes in enrollment. By design, they reflect planning conditions defined by normal (1-in-2) and extreme (1-in-10) peak demand weather conditions. The historical load patterns and performance during actual events are used the reductions for a standardized set of weather conditions.

At a fundamental level, the process of estimating *ex ante* impacts included five main steps:

1. Estimate the relationship between customer loads (absent DR) and weather
2. Use the models to predict customers loads (absent DR) for 1-in-2 and 1-in-10 weather year conditions
3. Apply the average percent reductions, at an hourly level, from historical events. The average reduction was employed because experience with small business default CPP is limited and there is less of a history of program performance across events.
4. Estimate reductions for 1-in-2 and 1-in-10 weather year conditions
5. Incorporate the enrollment forecast

8.5 *Default Small Commercial CPP Ex ante Load Impact Estimates*

Table 8-6 summarizes the *ex ante* demand reduction capability by forecast year and planning condition. The tables reflect dispatchable demand reductions available from 1 pm to 6 pm on August monthly peaking conditions for 1-in-2 and 1-in-10 weather conditions. They align with the planning conditions used for resource adequacy attribution. To avoid double counting, the table only includes resources that are not dually enrolled in other DR programs or the technology deployment, known as portfolio impacts.

Table 8-6: Small CPP Portfolio Impacts for August Monthly Peak Day (1-6 PM)

Year	Accts	CAISO		SDG&E	
		1-in-2	1-in-10	1-in-2	1-in-10
2018	112,032	4.83	4.75	4.73	4.96
2019	111,587	4.81	4.73	4.71	4.94
2020	110,387	4.75	4.68	4.66	4.89
2021	108,612	4.68	4.60	4.58	4.81
2022	106,289	4.58	4.50	4.48	4.70
2023	103,455	4.46	4.38	4.36	4.58
2024	100,154	4.31	4.24	4.22	4.43
2025	96,436	4.15	4.09	4.07	4.27
2026	92,355	3.98	3.91	3.90	4.09
2027	87,970	3.79	3.73	3.71	3.89
2028	83,342	3.59	3.53	3.52	3.69
2028	78,532	3.38	3.33	3.31	3.48

8.6 *Comparison of 2016 and 2017 Ex ante Estimates*

Table 8-7 compares the demand reductions from 2017 events to the reduction expected under the 1-in-2 and 1-in-10 weather conditions used for planning. The small differences between *ex post* and *ex ante* values are due to different reporting hours, weather conditions and day of week effects. In 2017, small CPP customers delivered 4.31 MW during the dispatch period of 11am to 6pm. However, demand reductions were larger, 4.81 MW, for the 1-6 pm period used for resource adequacy and planning. When similar hours are compared, the *ex post* impacts align well with the *ex ante* resource estimates. Because 2017 event day weather conditions were between an SDG&E 1-in-2 and a 1-in-10 weather year, the realized demand reductions fall between the two *ex ante* values. Some small differences are also due to differences in customer loads by day of week. The two 2017 events included a Friday, when business loads tend to be lower than in other weekdays. In contrast, the *ex ante* estimates assume an average weekday. Finally, the CAISO *ex ante* weather conditions are cooler. CAISO peak days are more heavily influenced by larger utilities and do not always coincide with SDG&E peaks.

Table 8-7: Small CPP Comparison of *Ex post* and *Ex ante* Load Impacts for 2017

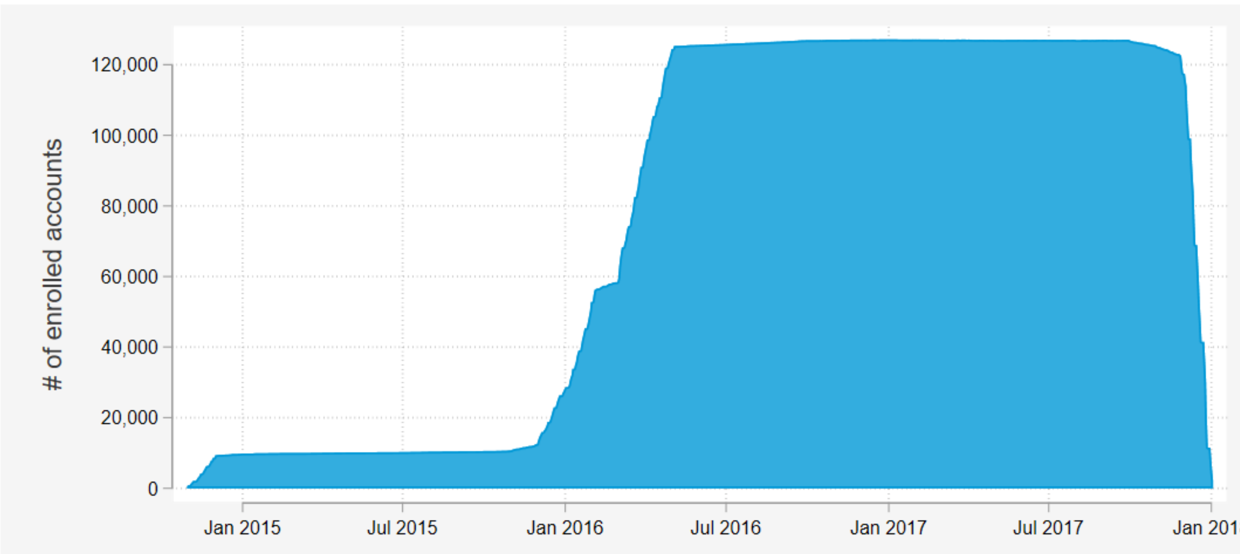
Result Type	Day Type and Period	Accts	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex post Avg. Weekday	Event Period (11am to 6pm)	111,889	417.1	4.31	1.0%	91.5
	Resource Adequacy Period (1 to 6pm)	111,889	410.4	4.81	1.2%	91.5
Ex ante SDG&E	1-in-2 Weather August Peak (1 to 6pm)	112,032	408.9	4.73	1.2%	88.9
	1-in-10 Weather August Peak (1 to 6pm)	112,032	427.5	4.96	1.2%	92.7
Ex ante CAISO	1-in-2 Weather August Peak (1 to 6pm)	112,032	416.9	4.83	1.2%	88.8
	1-in-10 Weather August Peak (1 to 6pm)	112,032	411.0	4.75	1.2%	88.6

*Table shows portfolio impacts. To avoid double counting, it excluded commercial thermostats and customers dually enrolled in other DR programs.

8.7 *Time of Use Pricing Demand and Consumption Impacts (Non-Dispatchable)*

By April 2016, all electric rate options available for small commercial and agricultural customers had a time varying component. Rates that did not differentiate prices by time of day were no longer available. Over 130,000 small customer sites were defaulted onto CPP-TOU rates. Though roughly 5% of these customers opted-out, they were placed on TOU rates so the full population is now on rates with a TOU component. Figure 8-3 shows this cumulative enrollment in TOU, including both CPP-TOU and TOU. This analysis assesses the energy impacts for sites transitioned between November 2015 and April 2016, but excludes the handful of customers who were already on TOU rates previously or who transitioned afterwards.

Figure 8-3: Small Non-Residential TOU Enrollment[35]



TOU impacts were assessed by site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in Table, was developed based on rate class, rate type (inclusion of CPP), and technology characteristics which may influence impacts. Analysis was performed at the segment level so these granular impacts could therefore be summed, yielding aggregate impacts in addition to the segment specific impacts.

The segmentation criteria were defined as follows:

[35] includes CPP-TOU

- **Rate class:** what type of rate class (agricultural or commercial) was the site on throughout the study period?
- **Rate:** was the site on a rate with a CPP component during the study period?
- **Tech:** did the site have commercial thermostats installed?
- **Solar:** was the site on a net metered rate during the study period?
- **Notification:** did the customer associated with the site receive any event notifications for any site?

Table8-7 summarizes the total number of sites in each segment and the final number of sites used for analysis once data cleaning was completed[36]. For most segments the vast majority of sites were included.

Table 8-7: Time of Use Population Segments

Rate class	CPP	Tech	Solar	Notify	Total Sites	Sites in analysis
Small Commercial	No	No	No	No	3,243	3,053
				Yes	1,160	1,050
			Yes	No	97	83
				Yes	48	44
		Yes	No	No	80	76
				Yes	14	14
			Yes	No	15	14
				Yes	2	2
	Yes	No	No	No	45,107	41,674
				Yes	74,339	65,987
			Yes	No	691	537
				Yes	963	836
		Yes	No	No	332	309
				Yes	880	746
			Yes	No	17	14
				Yes	43	37
TOTAL					**127,031**	**114,476**
Small Agricultural	No	No	No	No	2,461	2,417
				Yes	795	770
			Yes	No	139	134
				Yes	42	33
		Yes	No	No	1	0
	Yes	No	No	No	33	29
				Yes	36	27
			Yes	No	2	2

[36] The cleaning algorithm ensured that complete data was available for the study period. The key reason for excluding a site was lack of pretreatment data: only sites with a full 12 months of data from November 2014 through October 2015 were included.

Rate class	CPP	Tech	Solar	Notify	Total Sites	Sites in analysis
				Yes	1	1
		TOTAL			3,510	3,413

8.8 Demand and Energy Saving Impacts

The impact estimation model was run at the hourly level, by segment, allowing for time and segment differentiated results. Table 8-8 summarizes the energy and demand savings by rate period for three key rate groups. Notably, energy consumption increased for the small agricultural customers. However, there is an important caveat. The transition to TOU rates coincided with drought conditions and changes to irrigation restrictions. This exogenous factor may have had an influence on water pumping behaviors and in turn on electricity usage, meaning the increase in electricity usage in the treatment period may be due to factors other than the TOU transition.

For small commercial customers, a 0.6% decrease in energy usage overall was detected. This decrease was significant for all but one segment and equates to an aggregate energy savings of nearly 8.80 GWh and 6.82 MW. Though the energy savings are small in percentage terms, they are applied to a very large pool of customers, resulting in a large volume of energy savings. Percent savings are highest in off-peak periods—especially in the summer—but savings were observed in all rate periods. Percent savings are also highest for sites on TOU rates, e.g. without a CPP component.

Table 8-8: Time of Use Impacts by Rate Period

Rate group	Season	Day type	Rate period	Sites	Aggregate impacts			Average site impacts		
					Percent reduction	Demand reduction (MW)	Energy savings (GWh)	Demand reduction (kW)	95% CI Lower Bound	95% CI Upper Bound
Small Commercial: TOU	Summer	Weekday	Peak	4,588	0.4%	0.03	0.02	0.006	-0.063	0.075
			Off-peak	4,588	3.2%	0.16	0.34	0.034	-0.034	0.102
		Weekends & Holidays	Off-peak	4,588	3.9%	0.18	0.24	0.039	-0.027	0.106
	Winter	Weekday	Peak	4,588	1.8%	0.19	0.17	0.042	-0.042	0.126
			Off-peak	4,588	2.5%	0.18	0.39	0.039	-0.044	0.123
		Weekends & Holidays	Off-peak	4,588	1.7%	0.11	0.14	0.023	-0.060	0.107
Small Commercial: TOU-CPP	Summer	Weekday	Peak	119,078	0.1%	0.19	0.17	0.002	-0.004	0.007
			Off-peak	119,078	-0.1%	-0.15	-0.32	-0.001	-0.007	0.004
		Weekends & Holidays	Off-peak	119,078	1.8%	2.63	3.48	0.022	0.016	0.028
	Winter	Weekday	Peak	119,078	0.4%	0.89	0.78	0.007	0.002	0.013
			Off-peak	119,078	0.1%	0.21	0.44	0.002	-0.004	0.007
		Weekends & Holidays	Off-peak	119,078	1.7%	2.20	2.95	0.018	0.012	0.024
SMALL COMMERCIAL TOTAL				123,666	0.6%	6.82	8.80	0.06	0.04	0.07
Small Agricultural: all	Summer	Weekday	Peak	3,444	-12%	-0.66	-0.59	-0.193	-0.227	-0.158
			Off-peak	3,444	-15%	-0.99	-2.16	-0.288	-0.322	-0.255
		Weekends & Holidays	Off-peak	3,444	-16%	-0.89	-1.17	-0.258	-0.293	-0.223
	Winter	Weekday	Peak	3,444	8%	0.39	0.34	0.114	0.074	0.155
			Off-peak	3,444	1%	0.05	0.12	0.016	-0.023	0.055
		Weekends & Holidays	Off-peak	3,444	0%	0.00	0.00	0.001	-0.040	0.041
SMALL AGRICULTURAL TOTAL				3,444	-6.6%	-2.09	-3.46	-0.61	-0.70	-0.52

Sites are premise and service point combinations
Positive percentages indicate energy savings.

Table8-8 and Table8-9 summarize percent and aggregate GWh energy savings, respectively, by rate period for each study segment. Grey text indicates impacts that are not significant. Savings vary widely by segment and rate period and some segments increased energy usage overall. Large percent impacts were detected for a few, very small segments with distributed generation due to small net loads (percent impacts are a percent of net load).

The greatest savings, 14.3 GWh, were produced by the TOU-CPP segment with no solar or commercial thermostat technology but which opted to receive event notification[37]. Energy usage for most other groups either increased or did not significantly change, resulting in aggregate savings of 8.8 GWh across all segments.

[37] Because a single customer can manage sites multiple sites the notification classification was applied at the customer level, resulting in a handful of non-CPP sites being classified as receiving notification

Table 8-8: Time of Use Impacts by Rate Period and Segment (percent savings)

Rate	Tech	Solar	Notify	Sites	Summer Weekday Peak	Summer Weekday Off-peak	Summer Weekends & Holidays Off-peak	Winter Weekday Peak	Winter Weekday Off-peak	Winter Weekends & Holidays Off-peak	Overall
Small Commercial: TOU	No	No	No	3,189	-0.4%	-0.2%	1.9%	1.8%	1.0%	1.0%	0.7%
			Yes	1,144	-1.0%	4.4%	3.7%	1.5%	5.5%	3.0%	2.7%
		Yes	No	97	210.0%	34.8%	65.6%	163.8%	16.5%	28.9%	58.6%
			Yes	47	-58.2%	-34.3%	-52.6%	-65.3%	-44.9%	-76.1%	-51.8%
	Yes	No	No	80	3.2%	5.0%	7.3%	3.2%	0.2%	-0.2%	3.2%
			Yes	14	3.2%	12.4%	11.1%	10.3%	16.1%	20.0%	10.6%
		Yes	No	15	20.1%	22.4%	27.7%	7.3%	4.3%	6.5%	15.2%
			Yes	2	-77.1%	-46.7%	-469.1%	-134.7%	-43.1%	-78.2%	-75.5%
Small Commercial: TOU-CPP	No	No	No	43,124	-0.2%	-1.4%	0.3%	-0.5%	-1.6%	-0.5%	-0.6%
			Yes	73,198	0.3%	0.5%	2.5%	1.0%	1.2%	2.9%	1.2%
		Yes	No	569	-88.0%	-18.4%	-45.8%	-133.1%	-37.4%	-86.5%	-45.9%
			Yes	929	-49.2%	-12.1%	-30.6%	-83.6%	-27.6%	-76.5%	-32.5%
	Yes	No	No	321	-3.8%	-6.4%	-7.3%	-1.4%	-2.9%	-4.3%	-4.0%
			Yes	878	-1.5%	-2.0%	-0.2%	-0.6%	-1.6%	-0.5%	-1.1%
		Yes	No	17	-20.9%	-9.0%	-26.9%	-142.3%	-24.3%	-420.4%	-32.2%
			Yes	42	-1.3%	-6.8%	3.2%	-7.7%	-21.8%	-50.0%	-10.0%
TOTAL				**123,666**	**0.1%**	**0.0%**	**1.9%**	**0.5%**	**0.3%**	**1.7%**	**0.6%**

Sites are premise and service point combinations

Positive percentages indicate energy savings. Estimates not significant at the 90% level have been greyed out.

Table 8-9: Time of Use Impacts by Rate Period and Segment (GWh savings)

					Summer			Winter			
					Weekday		Weekends & Holidays	Weekday		Weekends & Holidays	
Rate	Tech	Solar	Notify	Sites	Peak	Off-peak	Off-peak	Peak	Off-peak	Off-peak	Overall
Small Commercial: TOU	No	No	No	3,189	(0.010)	(0.008)	0.040	0.107	0.090	0.047	0.266
			Yes	1,144	(0.031)	0.258	0.134	0.040	0.313	0.108	0.822
		Yes	No	97	0.062	0.085	0.057	0.030	0.029	0.019	0.282
			Yes	47	(0.029)	(0.062)	(0.035)	(0.026)	(0.066)	(0.042)	(0.260)
	Yes	No	No	80	0.012	0.022	0.018	0.009	0.001	(0.000)	0.062
			Yes	14	0.003	0.014	0.007	0.007	0.016	0.011	0.058
		Yes	No	15	0.019	0.032	0.020	0.005	0.005	0.004	0.086
			Yes	2	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.015)
Small Commercial: TOU-CPP	No	No	No	43,124	(0.076)	(0.625)	0.083	(0.135)	(0.791)	(0.139)	(1.684)
			Yes	73,198	0.628	1.391	3.932	1.409	2.905	4.068	14.333
		Yes	No	569	(0.113)	(0.370)	(0.228)	(0.171)	(0.600)	(0.381)	(1.862)
			Yes	929	(0.139)	(0.480)	(0.230)	(0.273)	(0.892)	(0.512)	(2.527)
	Yes	No	No	321	(0.058)	(0.112)	(0.075)	(0.017)	(0.044)	(0.037)	(0.343)
			Yes	878	(0.066)	(0.105)	(0.006)	(0.019)	(0.077)	(0.014)	(0.288)
		Yes	No	17	(0.004)	(0.009)	(0.002)	(0.007)	(0.019)	(0.014)	(0.055)
			Yes	42	(0.001)	(0.010)	0.001	(0.007)	(0.038)	(0.020)	(0.074)
TOTAL				123,666	0.194	0.019	3.714	0.949	0.829	3.095	8.801

Sites are premise and service point combinations

Positive percentages indicate energy savings. Estimates not significant at the 90% level have been greyed out.

9 Summary of the Commercial Thermostats Program[38]

9.1 Commercial Thermostats Overview

The commercial thermostat program currently provides Ecobee devices free of charge to commercial customers. The technology deployment program has been in operations since 2014. However, beginning in 2017, customers are required to be on a CPP-TOU rate – either CPP-D (large commercial), TOU-A-P (small commercial), or CPP-D-Ag (agricultural). Because the requirement to be on a CPP-TOU rate was not in place before, a significant number of participants are not enrolled in a CPP-TOU rate. The devices are curtailed on the CPP event days or on Reduce Your Use (RYU) days for customers not enrolled on a CPP-TOU rate. The thermostats can be dispatched at any time between 11 am to 6 pm (on-peak hours) for a maximum of four consecutive hours. Historically, they have been dispatched from 2-6 pm.

[38] The Commercial thermostat evaluation was conducted by Demand Side Analytics (DSA). This section of the Executive Summary contains excerpts from the following evaluation: Bode, J. & Lemarchand, A. (2018). "SDG&E Small Commercial Demand Response Evaluation Program Year 2017"

Currently, there are over 14,000 devices installed at over 3,000 non-residential sites. This includes nearly 1,100 “quasi-residential” sites, most of which deployed thermostats within a one-week period at the end of July 2015, as indicated by the sharp increase in enrolled sites in that time frame (see large jump in the blue chart). The full program population also includes small, medium, and large non-residential sites. Together, these sites produced significant, consistent impacts during all three RYU days, on the order of 5.4% during the 2 pm to 6 pm window, with larger impacts on weekdays than on weekends. This is in contrasts to reductions of 1.0% for small non-residential sites without enabling technology but on a CPP rate (covered in a previous section). Those sites, which experienced events on the same day as the commercial thermostat population, produced impacts which were significant overall but much smaller in magnitude than those produced by sites with enabling technology.

The Ecobee thermostats used as the enabling device receive a signal from SDG&E to curtail usage during events. Across the enrolled devices there was a variety of curtailment strategies, including raising thermostat temperatures by a designated number of degrees and cycling the thermostat on and off at regular intervals. Both of these approaches are intended to reduce energy usage by air conditioning units. However, to receive the curtailment signals, the devices must be connected to the internet and registered in the SDG&E dispatch portal. This is initially set up during the device installation process, but connectivity can be affected by internet reliability. Once connected, the device can receive and execute curtailment signals, and it can also communicate event notifications to users before the beginning of an event. Participating, connected devices were sent event notifications 24 hours prior to an event.

Commercial thermostat event impacts were assessed by site (premise and service point combination). Sites were grouped together into segments to assess potential differences in impacts for various groups. The segmentation, summarized in Table 9-1, was developed based on rate size and on rate characteristics which may influence impacts. The analysis was performed at the segment level so these granular impacts could therefore be summed, yielding aggregate impacts in addition to the segment specific impacts.

The segmentation criteria were defined as follows:

- Rate: was the site on a rate with a CPP component during the study period?

- Rate size: what size (demand level for rate[39]) was the site classified as throughout the study period?

Table 9-1 also summarizes the total number of sites in each segment and the final number of sites used for event analysis once data cleaning was completed. As one might expect, smaller sites are more numerous but larger sites have more devices per site. Of particular note is the quasi-residential group, which comprises over 1,000 sites with an average of one device per site. Analysis of loads showed that usage across quasi-residential sites was very highly correlated and analysis of participant data showed that over 80% of these devices were installed for the same customer – a commercial short-term housing operator – at the same location, in the same period. Another 17% were installed by two customers in a similar geographically clustered manner. Because of this, the quasi-residential customers were analyzed separately from the other segments using an approach more suited to highly correlated data.

Another attribute of the commercial thermostat sites is the long installation period which spanned over three-year period. This long installation period was an important consideration for the energy savings analysis (which requires pre-installation data, as covered in the next chapter). This is not the case for the event impact analysis which develops a counterfactual load estimate using non-event days from the time frame as event days.

Table 9-1: Commercial Thermostats Population Segments*

Rate	Size	Total sites	Avg devices per site	Sites in event analysis
TOU	Large	38	39	33
	Medium	87	14	86
	Small	112	5	95
	Quasi residential	1,099	1	1,099
TOU-CPP	Large	68	39	58
	Medium	506	11	484
	Small	1,253	3	1,218
TOTAL		**3,163**	**5**	**3,073**

*Sites are premise and service point combinations

Table 9-2 shows the three PY 2017 CPP event days, including the maximum daily temperature weighted by participating commercial thermostat sites. These consecutive

[39] Small sites are on AS rates (such as ATOU and ASTODPSW) and have maximum demand below 20 kW—classification was assigned by rate. Medium and large sites are on AL rates or PA CP2 rates (such as ALTOU or PATODCP2). Medium sites were distinguished from Large sites by applying a maximum demand cutoff of 200 kW.

events occurred during a statewide heat wave on the Thursday, Friday, and Saturday before Labor Day. Though the SDG&E peak often differs from the rest of the state, Friday September 1 was the system peak for both SDG&E and CAISO. The second highest load day for both systems was Saturday September 2, which was hotter than the previous day.

Table 9-2: Commercial Thermostat Events in 2017

Event day	Day of week	Event start	Event end	Max daily temp (F)	SDG&E system load (MW)
8/31/2017	Thursday	2:00 PM	6:00 PM	85.3	4,190
9/1/2017	Friday	2:00 PM	6:00 PM	90.8	4,481
9/2/2017	Saturday	2:00 PM	6:00 PM	90.9	4,353

9.2 Commercial Thermostats Analysis Method

The primary analysis method was a differences-in-differences panel regression with a matched control group. The statistical matching approach used to select a matched control for the roughly 2,200 non-residential SCTD sites among a control candidate pool of roughly 11,000 TOU sites, e.g., who were not enrolled in CPP or other DR programs which might interfere with prediction of SCTD event impacts. A difference-in-difference regression model was then used to assess impacts and standard errors for each event and each study segment.

A population comprising about 1,100 quasi-residential sites was analyzed separately using a regression model that used non-event days to estimate the counterfactual. Quasi-residential customers were mainly temporary apartments for a specific industry at a handful of buildings, with a high level of distributed solar penetration. While there were roughly 1,100 apartments, there were only eight distinct locations, each of which had highly correlated and predictable loads within the building. Because of their unique nature, a control group was not feasible.

To identify which model best predicted customer loads absent demand reductions, an out of sample approach was still used to select the regression model. The model selection relied on testing how well each model estimated loads for hot non-event days out-of-sample. Because there was, in fact, no event, it was possible to assess how close model estimates were to the correct answer and the most accurate model. A total of ten weather-based models were tested.

9.3 Commercial Thermostats Ex post Load Impact Estimates

Weekend loads are typically different than weekday patterns, reflecting different activities and usage patterns for these different types of day. Because of this, the weekday events have been summarized separately from the weekend event which may not be comparable.

Table 9-3 summarizes the load impacts by segment for the two weekday events (August 31 and September 1) for the 2pm to 6pm event window. In aggregate, these events delivered 3.86 MW of load reduction across all rates including quasi-residential and Small Commercial CPP participants. Impacts were significant in aggregate and across every segment except large customers on TOU only rates. While the largest percent impacts were estimated for small and quasi-residential customers the largest aggregate savings were estimated for the large and medium CPP sites, delivered 0.91 MW and 1.05 MW of reductions, respectively. Impacts were also differently distributed among segments for the weekday and weekend events.

Table 9-3: Commercial Thermostats Weekday Event Impacts

Rate	Size	Sites	Load without DR (MW)	Load w DR (MW)	Impact (MW)	% Impact	Std. Error	t	Significant (90% CI)
TOU	Large	38	16.34	16.21	-0.12	-0.8%	0.40	-0.27	No
	Medium	87	3.11	2.93	-0.19	-6.1%	0.12	-1.58	No
	Small	112	0.86	0.76	-0.10	-12.1%	0.02	-4.20	Yes
	Quasi residential	1,099	0.84	0.32	-0.52	-62.3%	0.04	-12.40	Yes
TOU-CPP	Large	68	19.34	18.12	-1.22	-6.3%	0.26	-3.95	Yes
	Medium	506	21.56	20.40	-1.16	-5.4%	0.25	-4.38	Yes
	Small	1,253	9.64	9.09	-0.55	-5.7%	0.08	-6.70	Yes
TOTAL (w/ Small CPP)		**3,163**	**71.68**	**67.82**	**-3.86**	**-5.4%**	**0.63**	**-6.09**	**Yes**
TOTAL (w/o Small CPP)		**1,910**	**62.04**	**58.73**	**-3.32**	**-5.3%**	**0.56**	**-5.95**	**Yes**

Sites are premise and service point combinations

Table 9-4 summarizes the load impacts by segment for the one weekend events (September 2) for the 2pm to 6pm event window. In aggregate, these events delivered 1.29 MW of load reduction—about 40% of the reduction measured for the weekday events. Also of note, while most other segments produced weekend load reductions about 20% to 50% lower than weekday reductions, the quasi-residential group contributed about 0.5 MW on the weekend and the weekday events. This group, largely consisting of managed residential sites, produced over a third of the weekend impacts

Table 9-4: Commercial Thermostats Weekend Event Impacts (2-6pm)

Rate	Size	Sites	Load without DR (MW)	Load w DR (MW)	Impact (MW)	% Impact	Std. Error	t	Significant (90% CI)
TOU	Large	38	11.30	12.14	0.84	7.4%	0.37	1.94	Yes
	Medium	87	2.43	2.36	-0.07	-2.8%	0.11	-0.59	No
	Small	112	0.63	0.52	-0.11	-17.3%	0.04	-2.57	Yes
	Quasi residential	1,099	0.98	0.49	-0.49	-50.2%	0.09	-5.77	Yes
TOU-CPP	Large	68	16.44	16.15	-0.30	-1.8%	0.46	-0.54	No
	Medium	506	19.44	18.61	-0.83	-4.3%	0.32	-2.51	Yes
	Small	1,253	7.57	7.23	-0.34	-4.5%	0.12	-2.65	Yes
TOTAL (w/ Small CPP)		**3,163**	**58.79**	**57.50**	**-1.29**	**-2.2%**	**0.79**	**-1.63**	**No**
TOTAL (w/o Small CPP)		**1,910**	**51.23**	**50.27**	**-0.96**	**-1.9%**	**0.69**	**-1.38**	**No**

Sites are premise and service point combinations

9.4 Commercial Thermostats Ex ante Load Impact Estimates

A key objective of the 2017 evaluation is to quantify the relationship between demand reductions, temperature and hour of day. *Ex ante* impacts are estimated load reductions as a function of weather conditions, time of day, and forecasted changes in enrollment. By design, they reflect planning conditions defined by normal (1-in-2) and extreme (1-in-10) peak demand weather conditions. The historical load patterns and performance during actual events are used the reductions for a standardized set of weather conditions.

- At a fundamental level, the process of estimating *ex ante* impacts included five main steps:
- Estimate the relationship between customer loads (absent DR) and weather
- Use the models to predict customers loads (absent DR) for 1-in-2 and 1-in-10 weather year conditions
- Apply the average percent reductions, at an hourly level, from historical events. The average reduction was employed because experience with small business default CPP is limited and there is less of a history of program performance across events.
- Estimate reductions for 1-in-2 and 1-in-10 weather year conditions
- Incorporate the enrollment forecast

Table 9-5 summarizes the *ex ante* demand reduction capability by forecast year and planning condition. The tables reflect dispatchable demand reductions available from 1 pm to 6 pm on August monthly peaking conditions for 1-in-2 and 1-in-10 weather conditions. They align with the planning conditions used for resource adequacy attribution. The enrollment forecast was developed by SDG&E and shows moderate increases in the number of thermostats over time.

Table 9-5: Commercial Thermostats Portfolio Impacts for August Monthly Peak Day

	Accts	CAISO		SDG&E	
		1-in-2	1-in-10	1-in-2	1-in-10
2017	3,297	2.87	2.86	2.83	2.94
2018	3,385	2.97	2.95	2.92	3.04
2019	3,477	3.07	3.05	3.02	3.14
2020	3,574	3.18	3.16	3.13	3.25
2021	3,675	3.29	3.27	3.24	3.37
2022	3,781	3.41	3.39	3.35	3.49
2023	3,781	3.41	3.39	3.35	3.49
2024	3,781	3.41	3.39	3.35	3.49
2025	3,781	3.41	3.39	3.35	3.49
2026	3,781	3.41	3.39	3.35	3.49
2027	3,781	3.41	3.39	3.35	3.49
2028	3,781	3.41	3.39	3.35	3.49

9.5 Commercial Thermostats Comparison between Ex post and Ex ante Estimates

Table 9-6 compares the demand reductions from 2017 events to the reduction expected under the 1-in-2 and 1-in-10 weather conditions used for planning. The small differences between *ex post* and *ex ante* values are due to different reporting hours, weather conditions and customer counts. In 2017, small CPP customers delivered 3.86 MW during the dispatch period of 2pm to 6pm. However, because thermostat resources were not dispatched from 1 to 2pm, demand reductions are smaller, 2.76 MW, for the 1-6 pm period used for resource adequacy and planning. When similar hours are compared, the *ex post* impacts align well with the *ex ante* resource estimates. The remaining differences are due to different number of sites (6.8%) because of weather. As expected, available resources are larger under 1-in-10 SDG&E peaking conditions than under 1-in-2 conditions. However, this pattern does not hold for CAISO peak days, which are more heavily influenced by larger utilities and do not always coincide with SDG&E peaks.

Table 9-6: Commercial Thermostat Comparison of *Ex post* and *Ex ante* Load Impacts for 2017

Result Type	Day Type and Period	Accts	Load without DR (MW)	Load Reduction (MW)	% Reduction	Daily Max Temp (F)
Ex post Avg. Weekday	Event Period (2 to 6pm)	3,073	71.7	3.86	5.4%	89.0
	Resource Adequacy Period (1 to 6pm)	3,073	73.5	2.76	3.8%	89.0
Ex ante SDG&E	1-in-2 Weather August Peak (1 to 6pm)	3,297	69.4	2.83	4.1%	88.1
	1-in-10 Weather August Peak (1 to 6pm)	3,297	72.4	2.94	4.1%	92.1
Ex ante CAISO	1-in-2 Weather August Peak (1 to 6pm)	3,297	70.7	2.87	4.1%	88.3
	1-in-10 Weather August Peak (1 to 6pm)	3,297	69.9	2.86	4.1%	88.2

*Table shows portfolio impacts. To avoid double counting, it excluded commercial thermostats and customers dually enrolled in other DR programs.

10 Summary of the Voluntary Residential CPP Rate[40]

10.1 Voluntary Residential CPP Rate Overview

This section documents the program year 2017 (PY 2017) load impacts for SDG&E's time varying pricing tariffs for residential customers, including:

a. Voluntary CPP-TOU residential customers (non-event) (TOU-DR)
b. Voluntary CPP-TOU residential customers (event) (TOU-DR-P)

These are collectively referred to as the residential smart pricing project (SPP) rates. The SPP rates became active in February of 2015. The current TOU periods for the residential SPP rates are:

[40] The Voluntary Residential CPP evaluation was conducted by Christensen. This section of the Executive Summary contains excerpts from the following evaluation: Crowley, N., Hansen, D. & Clark, M. Christensen Associates (2018). "2017 Load Impact Evaluation of San Diego Gas and Electric's Voluntary Residential Critical Peak Pricing (CPP) and Time-of-Use (TOU) Rates"

Summer (May 1- Oct 31)
On-Peak 11 a.m. – 6 p.m. weekdays, excluding holidays
Semi-Peak 6 a.m. – 11 a.m. and 6 p.m. – 10 p.m. weekdays, excluding holidays
Off-Peak 10 p.m. – 6 a.m. weekdays, and all hours on weekends & holidays
CPP: 11a.m.-6p.m. all days.

Winter (Nov 1 – April 30)
On-Peak 5 p.m. – 8 p.m. weekdays, excluding holidays
Semi-Peak 6 a.m. – 5 p.m and 8 p.m. – 10 p.m. weekdays, excluding holidays
Off-Peak 10 p.m. – 6 a.m. weekdays, and all hours on weekends & holidays
CPP: 11a.m.-6p.m. all days.

Starting in May 2018, SDG&E has proposed a terminology change in which the current *semi-peak* period will be re-labeled *off-peak*, and the current *off-peak* period will be called the *super off-peak* period. The proposed changes are the following:

1. Change the summer on-peak period to 4 p.m. to 9 p.m. on weekdays;
2. Change the winter on-peak period to 4 p.m. to 9 p.m. on weekdays;
3. Change the super off-peak period to 12 a.m. to 6 a.m. on weekdays and 12 a.m. to 2 p.m. on weekends and holidays;
4. All hours not in the above on-peak and super-off-peak periods are off-peak;
5. The CPP period is reduced to 2 p.m. to 6 p.m. year-round[41]

Critical Peak Pricing (CPP) events are called in conjunction with SDG&E's Reduce Your Use (RYU) program. Up to 18 RYU events can be triggered per year, on any day of the week, at any time during the year. A CPP event period adder of $1.16/kWh applies on event days. In return, enrollees receive credits on their electric commodity cost during all TOU pricing periods on non-RYU event days. Participants are generally notified of events by 3 p.m. on the business day prior to the event, and several notification options are available, including email and text. For the first full season following their enrollment, CPP participants are eligible for *bill protection*, which guarantees that their bill will be no larger than what it would have been under their otherwise applicable tariff.

10.2 Voluntary Residential CPP Rate Ex post Evaluation Methodology

The *ex post* load impact evaluations for the TOU-DR (TOU henceforth) and TOU-DR-P (CPP henceforth) rates apply difference-in-differences methods that involve selecting quasi-

[41] Please refer to SDG&E's Electric Schedules: http://regarchive.sdge.com/tm2/pdf/ELEC_ELEC-SCHEDS_EECC-TOU-DR-P.pdf, and http://regarchive.sdge.com/tm2/pdf/ELEC_ELEC-SCHEDS_TOU-DR.pdf for additional details.

experimental matched control groups and then comparing the usage of treatment and control group customers on relevant days or time periods, where the comparisons are then adjusted by their usage differences on pre-treatment or non-event days. The control groups were selected by matching each treatment customer to one of an initial sample of eligible non-treatment customers in relevant population segments (*e.g.*, climate zone, CARE status, and enrollment in RYU), based on the closest match of load profiles. This difference-in-differences approach with matched control groups is available for this study since both rates are new, meaning that customers' pre-treatment data are recent, and hourly interval load data are available for all of SDG&E's customers.

10.2.1 *Ex post* models for estimating CPP load impacts

The load impact estimation model for CPP accounts for customer-specific and date-specific fixed effects (which include weather and day-type factors) and effectively estimates the CPP load impact as the difference between CPP and control-group customer loads on event days, controlling for the aforementioned fixed effects. This can be described as a difference-in-differences estimate (the difference between treatment and control group usage on event days, adjusted for differences on non-event days). The primary customer-level fixed-effects regression model used in the analysis is shown below, where the equation is estimated separately for each of the 24 hours. This model in general produces load impact estimates for each hour of every event, though only one event was called in 2016:

$$kW_{c,d} = \beta_0 + \Sigma_{Evts(i)} (\beta_{1,i} \text{ x } CPP_{c,d} \text{ x } Evt_{i,d}) + \beta_2 \text{ x CPP}_{c,d} + \Sigma_{Cust} (\beta_{3,Cust} \text{ x } C_c)$$
$$+ \Sigma_{day} (\beta_{4,day} \text{ x } D_{day,d}) + \beta_5 \text{ x } SS\_Evt_{c,d} + \beta_6 \text{ x } SCTD\_Evt_{c,d} + \varepsilon_{c,d}$$

The variables and coefficients in the equation are described in the following table:

Symbol	Description
$kW_{c,d}$	Load in a particular hour for customer *c* on day *d*
$CPP_{c,d}$	Variable indicating whether customer *c* is a CPP (1) or Control (0) customer on day *d*
$Evt_{i,d}$	Variable indicating that day *d* is the i^{th} event day (1=i^{th} event, 0 if not)
$SCTD\_Evt_{c,d}$	Variable indicating that day *d* is a *SCTD* event day (1= event, 0 if not) for customer *c*
$SS\_Evt_{c,d}$	Variable indicating that day *d* is *a Summer Saver* event day (1=event, 0 if not) for customer *c*
β_0	Estimated constant coefficient
$\beta_{1,d}$	Estimated load impact for event *d*
β_2	Estimated TOU response
$\beta_{3,Cust}$ and $\beta_{4,day}$	Customer and day fixed-effects
$\beta_{5,d}$	Estimated average *SCTD* load impact for event *d*
$\beta_{6,d}$	Estimated average *Summer Saver* load impact for event *d*
C_c	Variable indicating that the observation is for customer *c*
$D_{day,d}$	Date indicator variable (1 = date *d* equals date *day*)
$\varepsilon_{c,d}$	Error term

Since only one event was called, we can produce estimates of load impacts for the average event by customer type (e.g., Climate zone and CARE status) simply by estimating separate models for each type and reporting the estimated impacts.

10.2.2 *Ex post* models for estimating TOU load impacts

To obtain TOU load impacts (for both the TOU-only and CPP customers), we estimate a distinct model for each required result. For example, to get the average TOU load impacts on August non-holiday weekdays, we estimate a model that includes only days of that day type.[42] In this case, we simplify the model to include customer and day fixed effects, plus a variable to estimate the load impact (i.e., the coefficient β_1). Separate models are estimated by hour, month, day-type (i.e., average weekday versus peak month day), applicable customer groups (e.g., climate zone and CARE status), where the customer-level fixed-effects models are of the following form:[43]

[42] In cases where insufficient numbers of observations were available, we modified the approach by combining day-types. For example, for TOU-only customers, we combined observations for all summer weekdays to estimate a constant summer percentage load impact. Day-type specific reference load is calculated as the day-type observed load divided by one minus the percentage load impact (*i.e.,* Ref=Obs/(1-PctLI)). We can then apply the estimated percentage load impact to reference loads for the average weekday for each month to obtain monthly load impact *levels*.

[43] Note that the customer and day fixed effects remove the need for us to include stand-alone TOU_c and $Post_d$ variables. The former is perfectly collinear with the customer's fixed effect and the latter is perfectly collinear with a combination of day fixed effects.

$$kW_{c,d} = \beta_0 + \beta_1 \text{ x } (TOU_c \text{ x } Post_d) + \Sigma_{Cust} (\beta_{2,Cust} \text{ x } C_c) + \Sigma_{days} (\beta_{3,day} \text{ x } D_{day}) + \beta_4 \text{ x } Evt_{c,d} + \beta_5 \text{ x } SS\_Evt_{c,d} + \beta_6 \text{ x } SCTD\_Evt_{c,d} + \varepsilon_{c,d}$$

The variables and coefficients in the equation are described in the following table:

Symbol	Description
$kW_{c,d}$	Load in a particular hour for customer *c* on day *d*
TOU_c	Variable indicating whether customer *c* is a TOU or CPP (1) or Control (0) customer
$Evt_{c,d}$	Variable indicating whether day *d* is an event day for customer *c* [44]
$Post_d$	Variable indicating that day *d* is in the post-enrollment period
$SCTD\_Evt_{c,d}$	Variable indicating that day *d* is a *SCTD* event day (1= event, 0 if not) for customer *c*
$SS\_Evt_{c,d}$	Variable indicating that day *d* is *a* Summer Saver event day (1=event, 0 if not) for customer *c*
β_0	Estimated constant coefficient
β_1	Estimate of TOU load impact
$\beta_{2,Cust}$ and $\beta_{3,day}$	Estimated customer and day fixed effects
β_4	Estimate of average event-day load impact
β_5 and β_6	Estimated average *SCTD* and SS event event-day load impacts
C_c	Variable indicating that the observation is associated with customer *c*
D_{day}	Variable indicating that the observation is for day *d*
$\varepsilon_{c,d}$	Error term

10.2.3 Control Group Matching

The matching process differed for customers on the two rates. Since the TOU/CPP (TOU-DR-P) customers experienced TOU rates on all non-event days, and the CPP rate on event days, we treat those customers as CPP customers when evaluating CPP load impacts, and as TOU customers when evaluating TOU impacts. For analyzing CPP impacts, the TOU/CPP customers were matched to potential control group customers using loads on selected event-like non-event days (*e.g.*, days with temperatures most like those on the event day) in 2016.[45]

For analyzing TOU impacts, for both TOU/CPP and TOU-only customers, the treatment customers were matched on the basis of loads in the pre-treatment period (November 2014 through September 2015). The TOU customers were matched separately by season, based on two pairs of hourly loads for each season – one for all weekdays, and one for a subset of the hottest (or coldest) weekdays. Matching for the *winter* season used data for November 2014 through April 2015, while that for the *summer* season used data for May through September of 2015.

[44] For CPP customers, the *Evt* variable indicates that a day is a CPP event day. For TOU customers who are also enrolled to receive RYU alerts, that variable indicates that a day is a PTR/RYU event day.

[45] The event-like non-event days in 2016 were 7/20, 7/21, 7/26, 7/27, 7/28, 8/16, 8/17, 9/28, 9/29, and 9/30.

Matching was based on Euclidean distance minimization between treatment and potential control group customer loads. This approach minimizes the difference between a standardized usage metric of the treatment and potential control group customers. In this case, the standardized metric combines the 48 hourly load difference statistics for the two average weekday load profiles for the TOU customers into a single value equal to the square root of the sum of squared differences between the load statistics. That is, each enrolled customer is compared to each potential control group customer, using the distance measure. When the minimum distance statistic is found, the potential control group customer associated with that value is selected as the match for that TOU customer. Potential control group customers were allowed to be matched to multiple enrolled customers.

10.2.4 Validity assessment

Because a control-group approach is employed, the validity assessment focuses on comparisons of treatment and control-group loads for selected event-like non-event days (for CPP) or pre-treatment loads (TOU). We also report statistics such as the relative root mean square error and mean percent error, which provide formal estimates of the percent differences between treatment and control group loads.

10.3 Voluntary Residential CPP Rate & TOU Ex post Load Impacts

This section summarizes the findings from the *ex post* load impact evaluation analysis of the CPP portion of the TOU-DR-P rate. In total, three events were called in 2017, August 31 (Thurs), September 1 (Fri) and September 2 (Sat). For CPP, the primary load impact results include average estimated event-hour load impacts (i.e., the average of the hourly load impacts estimated for the seven-hour event window from 11 a.m. to 6 p.m.), in aggregate and per-customer, for the two weekday events on August 31 and September 1, 2017. Results of the analysis of the TOU portion of the rate (i.e., peak load impacts on non-event days) are presented in Section 10.3.2, along with results for the TOU rate.

10.3.1 Voluntary Residential CPP Rate *Ex post* Load Impact Estimates

For the CPP event called on August 31 and September 1, 2017, average event-hour reference loads[46] and load impacts, at an aggregate and per-customer basis are calculated.

[46] Reference loads represent estimates of the counter-factual loads that would have prevailed on an event day if the event had not been called. Mechanically, the *reference* loads are constructed by adding the estimated load impacts (developed in the difference-in-differences regression analysis) to the *observed* load of the treatment customers on the relevant event day. Alternatively, if percentage load impacts are estimated, then the *reference* loads are calculated by dividing the *observed* load by one minus the percentage load impact.

Table 10-1 summarizes reference load and load impact results for CPP customers, by climate zone. The first two columns show the climate zone and numbers of enrolled customers. The next two columns show aggregate estimated reference loads and load impacts for the average event hour, in MW. The next two columns show the same variables for the average customer, in units of kW. The last two columns show the load impacts as a percentage of the reference loads and the average temperature during the event window.

Table 10-1: Average CPP Event-Hour Load Impacts – *Aug. 31 and Sep. 1 Events*

Climate Zone	Enrolled	Aggregate		Per-Customer		% Load Impact	Ave. Event Temp.
		Ref. Load (MW)	Load Impact (MW)	Ref. Load (kW)	Load Impact (kW)		
Coastal	2,847	3.36	0.47	1.18	0.17	14%	89
Inland	2,089	3.43	0.44	1.64	0.21	13%	95
All	**4,935**	**6.76**	**0.90**	**1.37**	**0.18**	**13%**	**92**

Program enrollment was 4,935 customers, skewed somewhat toward the Coastal climate zone.[47] The aggregate reference load was 6.76 MWh/h. Per-customer load impacts averaged 0.17 kWh/h for customers in the Coastal climate zone, representing 14 percent of their reference load, and 0.21 kWh/h, or 13 percent, for the Inland climate zone. Average event-window temperatures were somewhat cooler in the Coastal zone, at 89 degrees, than the 95-degree temperature for the Inland zone.

10.3.2 TOU *Ex post* Load Impact Estimates

This sub-section shows load impact results for those customers enrolled in the TOU (TOU-DR) rate. Table 10-2 summarizes the average reference loads and load impacts for the TOU peak period (*i.e.*, 11 a.m. to 6 p.m. for May through October, and 5 to 8 p.m. for November through April), for the average weekday *by month*, on an aggregate and per-customer basis. The months are shown starting with the first month included in the analysis (October 2016).[48] Enrollment continued throughout the period, with the numbers of enrolled customers rising from 653 in October 2016 to 1,559 in September 2017.[49] Due to the relatively small number of treatment

[47] This enrollment number differs from the number of customers that were used in the regression models, for whom all required data were available (*e.g.*, all selected event-like days, as well as the event day).
[48] Winter month (Nov. 2016-Apr. 2017) are shaded in blue. Due to the relatively small enrollment numbers and therefore aggregate load levels, the aggregate loads are shown in units of kWh per hour, or kW.
[49] The enrollment numbers shown differ from the number of customers used in the regression models, which use only those customers with sufficient program-year and pre-treatment period load data needed for matching to control groups and estimating load impacts. Specifically, there were 296 incremental customers on the DR-TOD rate with

customers, percentage load impacts were constrained in estimation to be the same across months in each season. The estimated seasonal percentage load impacts were approximately 6.0 percent in summer and negative 3.1 percent (*i.e.*, a load increase) in winter.[50]

Table 10-2: TOU Peak Load Impacts for TOU Customers – *Average Weekday by Month*

			Aggregate		Per-Customer			
Month	Climate Zone	Enrolled	Peak Ref. Load (kW)	Peak Load Impact (kW)	Peak Ref. Load (kW)	Peak Load Impact (kW)	% Peak Load Impact	Ave. Peak Temp.
Oct-16	All	653	0.47	0.03	0.71	0.042	6.0%	76
Nov-16	All	689	0.71	-0.02	1.03	-0.031	-3.0%	65
Dec-16	All	726	0.88	-0.03	1.21	-0.037	-3.0%	59
Jan-17	All	755	0.88	-0.03	1.16	-0.035	-3.0%	56
Feb-17	All	795	0.79	-0.02	0.99	-0.030	-3.1%	59
Mar-17	All	860	0.75	-0.02	0.88	-0.027	-3.1%	65
Apr-17	All	897	0.71	-0.02	0.79	-0.024	-3.1%	67
May-17	All	934	0.57	0.03	0.61	0.036	6.0%	69
Jun-17	All	1,002	0.77	0.05	0.77	0.046	6.0%	74
Jul-17	All	1,130	1.19	0.07	1.06	0.064	6.0%	80
Aug-17	All	1,412	1.46	0.09	1.04	0.063	6.1%	79
Sep-17	All	1,559	1.37	0.08	0.88	0.053	6.0%	78

Table 10-3 shows results by season and climate zone. Because of relatively low enrollment in October 2016 and the discontinuity between that month and the summer of 2017, the results for the summer season include only May through September of 2017. Summer peak load impacts were similar in percentage terms for the two climate zones. However, during the winter month peak periods, Coastal customers *increased* usage almost three times higher than Inland customers, though the increases were not statistically significant.

quality load data that were used in estimating the TOU load impacts. The aggregate TOU load impacts are then scaled to total enrollments.

[50] The estimated load increases in the winter season were not statistically significant.

Table 10-3: TOU Peak Load Impacts for TOU Customers – *Average Weekday by Season & Climate Zone*

Season	Climate Zone	Enrolled (Average)	Aggregate: Peak Ref. Load (MWh/h)	Aggregate: Peak Load Impact (MWh/h)	Per-Customer: Peak Ref. Load (kWh/h)	Per-Customer: Peak Load Impact (kWh/h)	% Peak Load Impact	Ave. Peak Temp.
Summer	Coastal	692	0.60	0.03	0.81	0.038	4.6%	76
	Inland	515	0.52	0.03	0.97	0.061	6.3%	78
	All	**1,207**	**1.12**	**0.06**	**0.88**	**0.048**	**5.4%**	**77**
Winter	Coastal	443	0.46	-0.02	1.05	-0.047	-4.5%	63
	Inland	344	0.33	-0.01	0.95	-0.015	-1.6%	62
	All	**787**	**0.79**	**-0.03**	**1.01**	**-0.033**	**-3.3%**	**62**

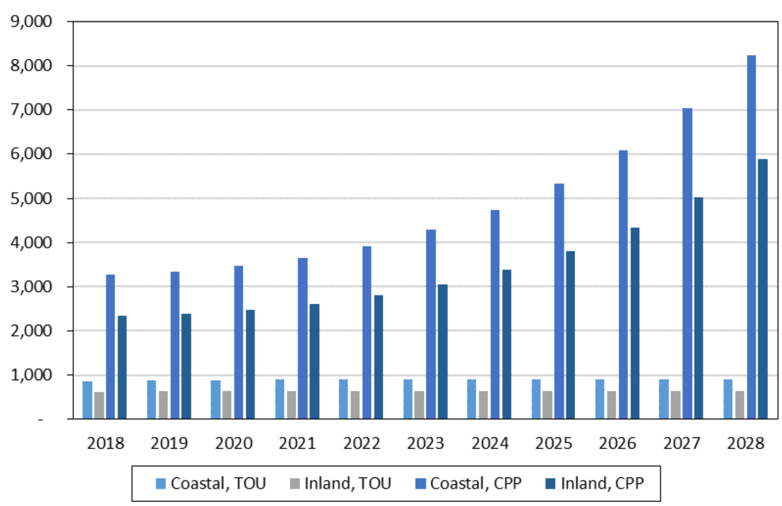
10.4 Voluntary Residential CPP Rate & TOU Ex ante Load Impacts

Ex ante load impacts represent forecasts of load impacts that are expected to occur when program events are called in future years (CPP), or in TOU peak periods (TOU), under standardized weather conditions. The forecasts are based on analyses of per-customer load impact findings from *ex post* evaluations, development of weather-sensitive reference loads, and incorporation of utility forecasts of program enrollments.

10.4.1 Voluntary Residential CPP Enrollment Forecast

Figure 10-1 shows SDG&E's enrollment forecasts for the TOU and CPP rates. Enrollment is anticipated to be essentially flat for TOU after 2019, while enrollment in CPP is forecasted to nearly triple by the end of the forecast period. Enrollment is expected to be somewhat greater in the Coastal climate zone than in the Inland for both rates.

Figure 10-1: Enrollments in TOU and CPP



10.4.2 Residential CPP *Ex ante* Load Impacts

Figure 10-2 illustrates the aggregate reference load, event-day load, and estimated load impact for an August peak day in 2018 in the SDG&E 1-in-2 weather scenario. The average event-period percentage load impact is 9 percent.

Figure 10-2: Aggregate Hourly Loads and CPP Load Impacts (MWh/h) – (*August 2019 SDG&E 1-in-2 Peak Day*)

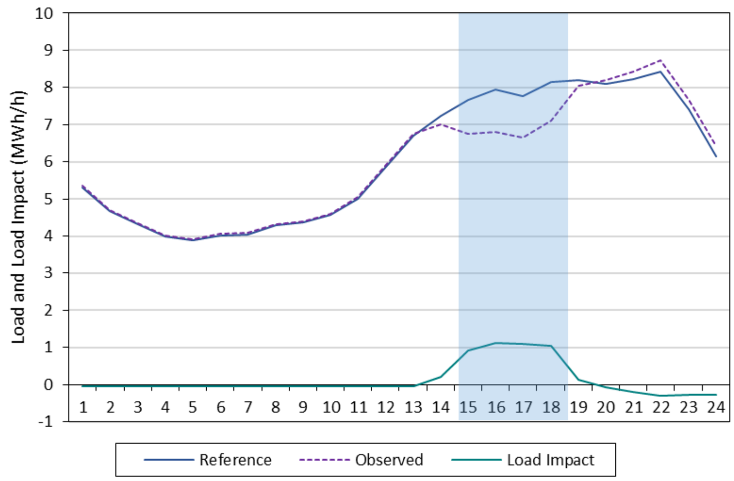
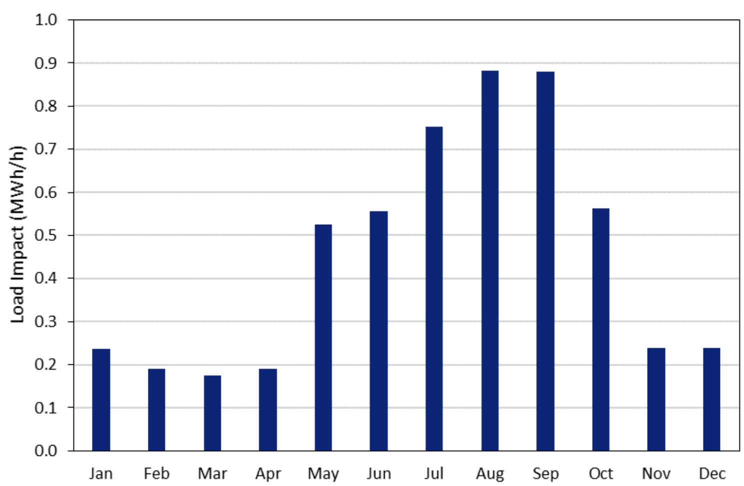


Figure 10-3 shows the monthly pattern of aggregate average *ex ante* load impacts (RA window) in 2019 for the SDG&E 1-in-2 peak day. Load impacts are greatest in the summer months, reaching a maximum in August.

Figure 10-3: Aggregate CPP Load Impacts (MWh/h), by Month – (*2019 SDG&E 1-in-2 Peak Day, RA Window*)



10.4.3 Residential TOU *Ex ante* Load Impacts

Figure 10-4 shows aggregate loads and load impacts for TOU and CPP customers, in 2019 for an August SDG&E 1-in-2 peak day. The average peak load impact is 9 percent of the reference load.

Figure 10-4: Aggregate Hourly Loads and TOU Load Impacts (MWh/h) – *TOU-DR and TOU-DR-P Customers,* (*August 2019 SDG&E 1-in-2 Peak Day*)

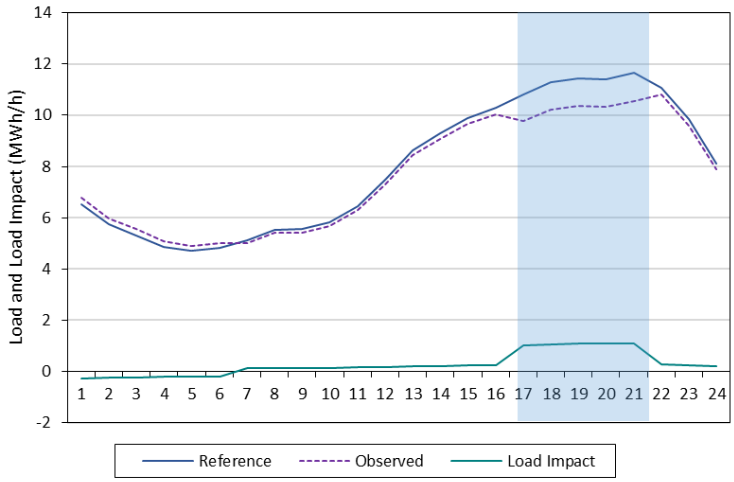
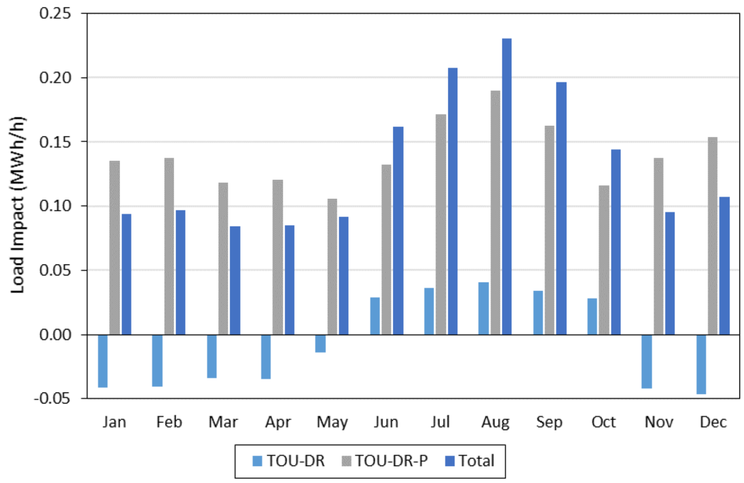


Figure 10-5 shows the monthly distributions of the peak load impacts (RA window) for TOU and CPP customers. Load impacts for CPP customers in particular are greatest in the summer months. Results for the winter months vary considerably. Customers on the CPP rate respond with a decrease in usage over the RA window, while TOU-only customers *increase* their usage both during the RA window and during the TOU period.

Figure 10-5: Aggregate TOU Load Impacts (MWh/h) by Month – *TOU-DR and TOU-DR-P Customers,* (*2019 SDG&E 1-in-2 Average Weekday,* RA Window)



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