Public Version. Redactions in 2019 Statewide Load Impact Evaluation of Non-Residential Critical Peak Pricing Programs and Appendices

AEG Applied Energy Group

2019 STATEWIDE LOAD IMPACT EVALUATION OF CALIFORNIA NON-RESIDENTIAL CRITICAL PEAK PRICING PROGRAMS

Ex-Post and Ex-Ante Load Impacts

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Report prepared for:
PACIFIC GAS & ELECTRIC COMPANY
SAN DIEGO GAS & ELECTRIC COMPANY
SOUTHERN CALIFORNIA EDISON

Energy Solutions. Delivered.

This work was performed by

Applied Energy Group, Inc.
500 Ygnacio Valley Blvd., Suite 250
Walnut Creek, CA 94596

Project Director: K. Marrin

Project Manager: A. Nguyen

Project Team: A. Duer
T. Williams
X. Zhang

in consultation with Pacific Gas & Electric Company, San Diego Gas & Electric Company, Southern California Edison, and the Demand Response Measurement & Evaluation Committee.

ABSTRACT

This report documents the load impact evaluation of the non-residential Critical Peak Pricing (CPP) programs operated by the three California Investor-Owned Utilities (IOUs)—Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E)—for Program Year 2019 (PY2019). The CPP programs provide participating customers with lower rates during non-CPP summer season hours and higher rates during CPP periods when an event is called. As such, customers benefit financially from the longer periods of the lower rates for electricity consumed outside of the CPP periods. While the rates are similar at the three utilities, they are referred to by different names, e.g., Peak Day Pricing (PDP) at PG&E and CPP at SCE and SDG&E. The primary goals of this evaluation study are to 1) estimate the ex-post load impacts for PY2019, and 2) estimate ex-ante load impacts for the programs for years 2020 through 2030.

The three California IOUs began defaulting their large commercial and industrial customer accounts onto CPP rates twelve years ago. Specifically, SDG&E began CPP default in 2008 followed by PG&E and SCE in 2010. Small and Medium Business (SMB) customers have been able to participate on a voluntary basis on CPP rates since 2014, however, all three utilities have begun, or completed their defaults of SMB customers within the past several years. In 2018, SDG&E completed their default of all SMB customers onto the CPP rates. In 2019 SCE began and completed the default of all their SMB customers with demands below 200 kW, along with large pumping and agricultural customers onto the CPP rate. PG&E has suspended the PDP default until the transition to new Time-of-Use (TOU) period is implemented in 2019-2020, so that the new customers are not subject to the PDP default right before or even simultaneously with a new TOU period. All newly-enrolled customers receive bill protection for the first 12 months.

Each utility called a different number of events in PY2019. PG&E called a total of nine events, and SCE called twelve events. SDG&E did not call any events in PY2019. All events were called on weekdays, between June 1st and September 30th, and between 2 and 6 PM for PG&E and 4 and 9 PM for SCE. Some other program provisions including the notification period for events, the specific hours when CPP events can be called, and the number and duration of CPP events can vary by utility.

AEG estimated hourly ex-post load impacts for each program and event during 2019, using regression analysis of subgroup-level hourly load, weather, and event data. The estimated load impacts are reported by IOU, for each event, and by customer size. Load impacts for the average event day are also reported by industry type and CAISO local capacity area (LCA), where relevant. In addition, AEG estimated ex-post impacts associated with Technical Assistance and Technology Incentives (TA/TI) and Automated Demand Response (AutoDR) participants[1], and for CPP participants that received vs. did not receive notification. Estimated aggregate ex-post load impacts for an average event were 14.3 MW for PG&E and 4.9 MW for SCE. SDG&E did not call any events

AEG developed ex-ante load impact forecasts by combining enrollment forecasts provided by the IOUs, and per-customer load impacts generated from the analysis of current ex-post load impact estimates. The forecast numbers of nominated customer service accounts and aggregate ex-ante load impacts presented in the report reflect several program changes expected to take place beginning in 2020. Estimated

[1] TA/TI and AutoDR participants are customers that have received technology incentives for the purchase and installation of load control equipment and technology that enables a customer's ability to automatically curtail its load during a DR event.

aggregate ex-ante load impacts for a typical event day in 2020 for a utility 1-in-2 weather scenario were 3.3 MW for PG&E, 8.0 MW for SCE, and 2.1 MW for SDG&E.

EXECUTIVE SUMMARY

This report documents the load impact evaluation of the non-residential Critical Peak Pricing (CPP) programs operated by the three California Investor-Owned Utilities (IOUs)—Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E)—for Program Year 2019 (PY2019). The CPP programs provide participating customers with lower rates during non-CPP summer season hours and higher rates during CPP periods when an event is called. As such, customers benefit financially from longer periods of lower rates for electricity consumed outside of the CPP periods. While the rates are similar at the three utilities, they are referred to by different names, e.g., Peak Day Pricing (PDP) at PG&E and CPP at SCE and SDG&E. Additionally, some program provisions including the notification period for events, the specific hours when CPP events can be called, and the number and duration of CPP events vary by utility, as illustrated in Table ES-1.

Table ES-1 Event Hours and Allowed Number of Events by Utility

Utility	Notification	Event hours	Events / year	Season
PG&E	Day ahead before 2 PM	2 to 6 PM	9 to 15	Year-round
SCE	~ 24-hour notice	4 to 9 PM	12	Year-round non-holiday weekdays
SDG&E	Day ahead before 3 PM	2 to 6 PM	Maximum of 18	Year-round

Research Objectives

The primary research objectives of the 2019 impact evaluation were to estimate both ex-post and ex-ante impacts for the non-residential CPP programs. Specifically, the evaluation report provides:

- PY2019 ex-post impacts for the average participant, and all participants in aggregate, for each hour of each event day, as well as for the average event day for each IOU's CPP program.
- Ex-ante impacts for each year over a 12-year[2] time horizon, based on each IOU's and CAISO's 1-in-2 and 1-in-10 weather conditions for a typical event day and each monthly system peak day. In addition, the report provides impacts for the average participant, and all participants in aggregate, for all program operating hours and for the resource adequacy (RA) window from 4-9 PM. Finally, the report provides impacts as a portfolio forecast, which excludes load impacts of customers dually enrolled in another DR program.
- Estimates of changes in hourly consumption resulting from changes in SDG&E's TOU and event periods implemented as of December 1st, 2017.

Program Descriptions

The three California IOUs began defaulting their large commercial and industrial customer accounts onto CPP rates twelve years ago. Specifically, SDG&E began CPP default in 2008 followed by PG&E and SCE in 2010.[3] Newly enrolled customers receive bill protection for the first 12 months. Most of the largest

[2] Eleven-year forecasts for SCE and PG&E companies.

[3] Most of the defaulted customers were previously served under tariffs with TOU energy and/or demand charges, such that they already had varying incentives to reduce load during peak periods on all summer weekdays.

customers at PG&E and SDG&E currently have the option of reserving a level of generation capacity (a capacity reservation level, or CRL) to protect a portion of their load on CPP event days.[4] Small-to-Medium Business (SMB) customers have been able to participate on a voluntary basis on CPP rates since 2014. In 2018, SDG&E completed their default of all SMB customers onto the CPP rates, while PG&E suspended the PDP default until the transition to new Time-of-Use (TOU) period is implemented in 2019-2020, so that the new customers are not subject to the PDP default right before or even simultaneously with the new TOU period. SCE's default of SMB customers with demands below 200 kW, along with large pumping and agricultural customers, onto the CPP rate occurred in March 2019. Moreover, in 2019, SCE changed the CPP event window from 2-6 PM to 4-9 PM and eliminated the CRL and CPP lite options.

PY2019 Event Days and Participant Counts

Each utility called a different number of events in PY2019. PG&E called a total of nine events, SCE called twelve events, and SDG&E did not call any events. All events were called on weekdays and between June 1st and September 30th.

Table ES-2 presents the number of service accounts enrolled in CPP, or PDP, during a typical summer event by industry and utility. Table ES-3 presents the number of service accounts enrolled in CPP, or PDP, during an average summer event by size of maximum customer demand, including small (< 20 kW), medium (20 kW ≤ x < 200 kW), and large (> 200 kW).[5]

Table ES-2 Enrolled Service Accounts, by Utility and Industry Group, Typical Event Day

Industry Type	PG&E	SCE	SDG&E
1. Agriculture, Mining & Construction	6,455	11,730	394
2. Manufacturing	4,744	13,247	1,123
3. Wholesale, Transport, Other Utilities	17,646	18,626	969
4. Retail Stores	10,801	23,829	1,899
5. Offices, Hotels, Finance, Services	39,677	124,974	7,279
6. Schools	2,653	4,469	817
7. Institutional/Government	21,742	45,848	1,999
8. Other/Unknown	13,678	29,660	447
Total	**117,397**	**272,383**	**14,927**

Table ES-3 Enrolled Service Accounts, by Utility and Industry Group, Typical Event Day

Industry Type	PG&E	SCE	SDG&E
Small < 20 kW	91,156	235,219	-
Medium 20 ≤ x < 200 kW	24,994	34,963	13,402
Large ≥ 200 kW	1,246	2,201	1,525
Total	**117,397**	**272,383**	**14,927**

[4] Effective March 2019, SCE no longer offers the CRL and CPP lite option.

[5] Since SDG&E did not call any events, the counts represent PY2019 enrollment instead of a typical event day.

Evaluation Methods

AEG's approach to the ex-post analysis is described at a high level below and summarized in Figure ES-1.

- For subgroups where it was feasible, AEG developed a matched control group. For subgroups where it was not feasible, we employed a within subjects' design leveraging event-like days in 2019. Table ES-4 presents the methodology used to estimate impacts for each subgroup.
- Then, AEG estimated subgroup level models for each IOU, size, and industry. In some cases, we also estimated separate models for those who were notified of event and those who were not notified of events. All subgroup level models were ultimately selected using our optimization process.
- Finally, we estimated the ex-post impact for each customer so that they could be aggregated easily into the various reporting subgroups required for the analysis.

Figure ES-1 Ex-Post Analysis Approach

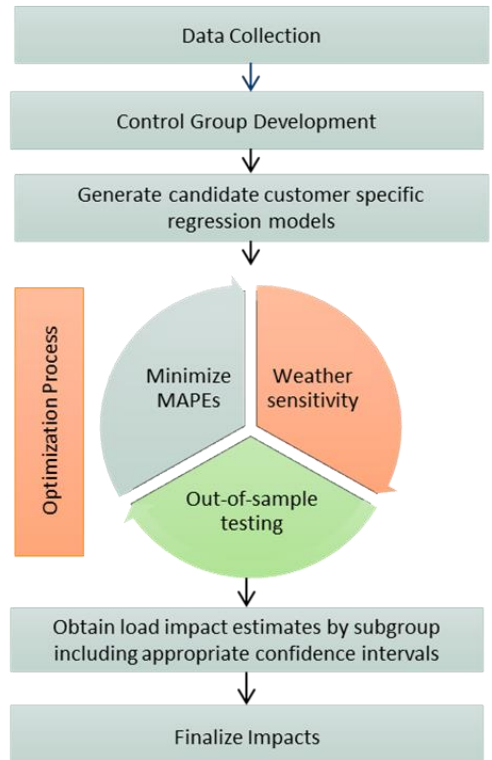

Table ES-4 presents the methodology AEG employed by utility and size group. We based the methodology on the total non-participant to participant ratio in each group. In general, a non-participant to participant ratio of at least 3 to 1 is needed to obtain a good match, therefore for groups with a ratio less than three, we employed a within subjects' design.[6] The within subjects' design leverages the participant's own load on event-like days to estimate the reference load.

Table ES-4 Analysis Method by Subgroup

Utility	Size Group	Analysis Method
PG&E	< 20 kW	Within Subjects
	20 kW ≤ x < 200 kW	Within Subjects
	≥ 200 kW	Matched Control
SCE	0 to 20 kW	Within Subjects
	20 kW ≤ x < 200 kW	Within Subjects
	≥ 200 kW	Matched Control
SDG&E	20 kW ≤ x < 200 kW	Within Subjects
	≥ 200 kW	Within Subjects

CPP is implemented differently within each IOU's territory. This, and the differences in methods, required the ex-post analysis to be conducted independently for each IOU. However, AEG used the same set of candidate models and optimization strategies across all three IOUs which maintained consistency in the results while allowing for customization of the models.

[6] In addition to having small non-participant pools, the potential control group customers for the defaulted groups are made up of customers that opted out of the CPP rate. They are likely to be different than those that stayed on the rate and may introduce substantial self-selection bias into the analysis.

Results

The results from the State PY2019 CPP, or PDP, evaluation are summarized at the state-level as well as the utility-level in the subsections that follow.

State-Level Ex-Post Impacts

Table ES-5 presents the total enrollments, reference loads, load impacts, and event temperatures for PG&E's and SCE's programs. In addition, the table presents the statewide total impacts for a typical event day. Given that SDG&E did not call any events, this PY2019 statewide total likely underestimates what might be achievable across the state should a statewide event be needed. PG&E clearly has the largest contribution to the overall state level total of 14.3 MW, contributing 75% of the load reduction while SCE contributes 25%.

Table ES-5 Total State Level Ex-Post Impacts by Utility: Typical Event Day

Utility	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
PG&E - PDP	117,396	1,226	14.3	1.2%	97.5
SCE - CPP	272,383	1,629	4.9	0.3%	87.9
SDG&E - CPP	NA	NA	NA	NA	NA
Statewide	**389,779**	**2,855**	**19.2**	**0.7%**	**92.7**

Statewide, the total MW impact dropped by more than half from 52 MW in PY2018 to 19.2 MW in PY2019. Impacts for both utilities that called events dropped substantially, and SDG&E did not call any events in PY2019. Reduction in impacts is concentrated mainly in the large groups since the small and medium groups contributed little to the overall MW in PY2018 and PY2019.

- For PG&E's large group specifically, we see about a 43% decrease in impacts. We also saw a 30% reduction in enrollment, but an increase in the reference load and a decrease in the percent impacts. This indicates that as enrollment has dropped over the past year, the group has retained larger customers, but those large customers are reducing less on a per customer basis.
- In SCE's large group the impacts dropped by about 50% in PY2019. We believe the primary driver of the reduction in impacts is the change in the event window from 2-6 PM to 4-9 PM. First, the on-peak period shift resulted in a reduction of 25% in the average per-customer reference load and a corresponding reduction in the overall potential load available. Second, the events are occurring later in the day, when many businesses are already shutting down and likely have less discretionary load available to reduce.

In Table ES-6 below, we also present the impacts by customer size. Similar to PY2018, the large participants contribute more than 99% of the total impacts across the state, with medium and small customers essentially contributing zero.[7] Recall that SDG&E did not call any events in PY2019, so the table reflects only the contributions of PG&E and SCE.

[7] The small negative value here is most likely a modeling artifact resulting from an imperfect quantification of weather effects and/or omitted variable bias. We have no reason to think that customers are actually increasing their load in response to events.

Table ES-6 Total State Level Ex-Post Impacts by Customer Size: Typical Event Day

Size	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
Large	3,447	899	20.7	2.3%	93.1
Medium	59,957	1,433	(1.5)	-0.1%	92.1
Small[8]	326,375	522.8	(0.1)	0.0%	95.2
Statewide	**389,779**	**2,855**	**19.1**	**0.7%**	**93.5**

Ex-Ante Impacts

We also present the state level ex-ante impacts for a Utility 1-in-2 weather year for program years 2020 and 2030 in Table ES-7. Keep in mind that the RA window for the 2020-2030 ex-ante forecast is 4-9 PM. SCE's event window aligns with the RA window, however, both PG&E's and SDG&E's event windows will remain 2-6 PM, which means that the PDP and CPP programs are only available during the first two hours of the RA window while all other hours are non-event hours. This results in significantly lower (and sometimes even negative) impacts within the RA window.

In program year 2020 the utilities forecast approximately 12.2 MW of load reduction to be available during the RA window. In 2020, SCE expects to contribute approximately 65% of the overall impacts, PG&E contributing 15%, and SDG&E contributing 20%. SCE is the main contributor because it is the only utility that has changed the CPP event window to overlap with the RA window.

By 2030 the IOUs forecast a total of 20.3 MW of demand response on a typical event day with all utilities predicting an increase in MW driven primarily by increased enrollment.

Table ES-7 Total State Level Ex-Ante Impacts by Utility: Typical Event Day

Utility	PY 2020 Enrollment	PY 2020 Load Impact (MW)	PY 2030 Enrollment	PY 2030 Load Impact (MW)
PG&E- PDP	113,154	1.8	183,765	4.6
SCE - CPP	252,481	8.0	397,481	12.6
SDG&E - CPP	14,160	2.5	13,302	3.1
Statewide	**379,795**	**12.2**	**594,548**	**20.3**

In Table ES-8, we also present the ex-ante impacts for 2020 and 2030 by customer size. In the ex-ante scenario, the large customers still contribute most of the impacts. In 2030 the increase in impacts is largely driven by the increased enrollment in the large groups across the three IOU programs.

Table ES-8 Total State Level Ex-Ante Impacts by Customer Size: Typical Event Day

Size	PY 2020 Enrollment	PY 2020 Load Impact (MW)	PY 2030 Enrollment	PY 2030 Load Impact (MW)
Large	5,134	14.0	8,305	23.3
Medium	67,443	-1.3	104,095	-2.2
Small[9]	307,218	-0.5	482,147	-0.8
Statewide	**379,795**	**12.2**	**594,548**	**20.3**

[8] SDG&E's Small CPP participants are included in the SCTD evaluation and are therefore excluded from the total.

[9] SDG&E's Small CPP participants are included in the SCTD evaluation and are therefore excluded from the total.

Event Communication

It is also important to keep in mind that not all the customers that were enrolled in CPP, or PDP, received communication regarding events. As customers were defaulted onto the rates, each utility established mechanisms to reach out to customers to obtain contact information that could be used to provide day ahead event notification, however, in many cases customers did not respond to the utility outreach and therefore were unaware of the events throughout the summer. Table ES-9 shows the percentage of participants that were notified by utility and size group on a typical event day.

Interestingly, we saw very little difference in impacts among the medium and small customers within SCE and PG&E programs regardless of the percent of customers that were notified. For both utilities the impacts in those groups were nearly, or indistinguishable, from zero even though PG&E notified more than 90% of participants, and SCE notified just over half.

Table ES-9 Percent of Service Accounts Notified, by Utility and Size Group, Typical Event Day

Size Group	PG&E % Notified	SCE % Notified	SDG&E % Notified[10]
Small < 20 kW	92%	54%	-
Medium 20 kW ≤ x < 200 kW	95%	61%	NA
Large ≥ 200 kW	94%	89%	NA
Total	**92%**	**55%**	**NA**

Key Findings by Utility

The key results for each utility on a typical event day are summarized in Table ES-10 (PG&E), Table ES-11 (SCE), and Table ES-12 (SDG&E). While the large customers participating in PG&E's PDP program in 2019 demonstrate large and consistent load impact reduction as a group, the medium and small default customer groups show little or no load reduction. Similarly, the large customer group in SCE's CPP Program demonstrates large and consistent load impact reduction. The small and medium customers defaulted by SCE, however, show no or little load reduction, respectively.

Table ES-10 Key Results for PG&E's Peak Day Pricing Program for PY2019[11]

Utility	Size Group	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
PG&E	Large	1,246	472.1	13.7	2.9%	97.5
	Medium	24,994	571.5	-0.1	0.0%	96.1
	Small	91,156	182.4	0.6	0.4%	95.2
ALL PG&E		**117,396**	**1,226.0**	**14.2**	**1.2%**	**96.3**

[10] SDG&E did not notify any customers because no events were called in PY2019.

[11] The small negative value for the small participants is most likely a modeling artifact resulting from an imperfect quantification of weather effects and/or omitted variable bias. We have no reason to think that customers are actually increasing their load in response to events.

Table ES-11 Key Results for SCE's Critical Peak Pricing Program for PY2019

Utility	Size Group	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
SCE	Large	2,201	426.9	7.0	1.6%	88.7
	Medium	34,963	861.8	(1.4)	(0.2%)	88.0
	Small	235,219	340.4	(0.7)	(0.2%)	87.1
ALL SCE		**272,383**	**1,629.1**	**4.9**	**0.3%**	**87.9**

Table ES-12 Key Results for SDG&E's Critical Peak Pricing Program for PY2019

Utility	Size Group	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
SDG&E	Large	1,525	NA	NA	NA	NA
	Medium	13,042	NA	NA	NA	NA
ALL SDG&E		**14,927**	**NA**	**NA**	**NA**	**NA**

Recommendations

AEG has developed four recommendations for future research and evaluation related to the non-residential CPP programs.

- Investigate the experiences of small and medium participants. Through future or ongoing process evaluations, ensure that special care is taken to better understand the experiences of small and medium customers on the CPP rates. Participant surveys and focus groups can be used to understand aspects of participation including, awareness and understanding of the rate, awareness of participation, awareness of events, ability to respond to events, and actions taken during events. Conducting research while maintaining statistically significant samples by key industry group and size may provide invaluable insights for both program staff and future impact evaluations.
- Investigate the effect of notifications on customer impacts. Again, through the use of participant surveys and/or focus groups, conduct research to better understand participant choices regarding notification, their awareness of notifications, and how they respond to notifications on event days.
- Consider opportunities to improve robustness of within-subjects designs. For most of the subgroups, we elected not to develop a matched control group for this evaluation because of the small ratios of participants to non-participants and the opt-out nature of the CPP, or PDP, rates which would likely lead to poor matches and introduce self-selection bias. Unfortunately, the within-subjects design may also have led to the introduction of bias, particularly among those groups with very small impacts due to a lack of truly comparable event like days. Since all utilities expect their participant population to grow (and the non-participant pools to continue to shrink) we recommend considering the following opportunities to mitigate this bias in the future. We propose two options for consideration:
    - Intentionally call test events on cooler days and, unless absolutely necessary, try not to call events on all the hottest days of the season. This will provide the models with better information as to how participants would behave during events on a wider range of temperatures and improve their performance.

  - Consider using the non-notified participants as a control group for the notified participants when appropriate. This would accurately estimate the incremental effect of notification, rather than the overall program impact, but this may not be undesirable given that we know the impacts for non-notified customers are very small.

- Consider utilizing customer-specific regression models for the large groups. In PY2019, PG&E's and SCE's large groups were evaluated using subgroup level models with matched control groups. As previously stated, the opt-out nature of the CPP, or PDP, rates can introduce self-selection bias. For the large groups, very high variation in customer usage can lead to both poor matches and poor model estimations. This is especially true for groups with extremely large customers. We recommend utilizing customer-specific models for all large customers or only the extremely large (outlier) customers. For groups with very high variation, customer-specific regression models can better estimate weather response, seasonal usage, and load impacts and control for unobservable customer-specific effects that are more difficult to account for in subgroup level models.

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1

INTRODUCTION

This report documents the load impact evaluation of the non-residential Critical Peak Pricing (CPP) programs operated by Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E) for PY2019.

Research Objectives

The key objectives of this study are to estimate both ex-post and ex-ante impacts for the non-residential CPP programs. More specifically,

- Provide PY2019 ex-post impacts for the average participant and all participants in aggregate for each hour of each event day and for the typical event day, for each IOU's CPP program.
- Provide ex-ante impacts for each year over a 12-year[12] time horizon, based on each IOU's and CAISO's 1-in-2 and 1-in-10 weather conditions for a typical event day and each monthly system peak day. Provide impacts for the average participant and all participants in aggregate for all program operating hours and the resource adequacy (RA) window from 4-9 PM. Also provide impacts as a portfolio forecast, which excludes load impacts of customers dually enrolled in another DR program.
- Estimate the changes in hourly consumption resulting from SDG&E's changes in TOU and event periods implemented as of December 1st, 2017.

Report Organization

The remainder of this report is organized into the following sections:

- Section 2 describes the CPP program as it is implemented by each IOU. The section also presents information regarding the total number of accounts enrolled in each program.
- Section 3 describes the methods used to estimate the ex-post and ex-ante impacts for the 2019 program year.
- Section 4 presents the ex-post impact evaluation results.
- Section 5 presents the ex-ante impact evaluation results.
- Section 6 presents key findings and recommendations.

[12] Eleven-year forecasts for SCE and PG&E companies.

2

PROGRAM DESCRIPTION

This section describes the CPP programs as they are implemented by each IOU in 2019 along with any changes to the program since PY2017. We also present information regarding the PY2019 event days, and the total number of participants at each utility, by industry.

Program Implementation

California's CPP programs provide participating customers with lower rates during non-CPP summer season hours and higher rates during CPP periods when an event is called. These "dynamic" pricing rates are designed to encourage price-responsive demand reductions during the higher priced critical periods. Customers benefit financially from the longer periods of the lower rates for electricity consumed outside of the CPP periods. New customers on the program may also be eligible for bill protection for an initial period, such as 12 months, so that their energy costs on CPP do not exceed their pre-CPP costs while they learn how to respond.

The rates are similar at the three utilities, though they are referred to by different names (*e.g.*, Peak Day Pricing, or PDP, at PG&E). All CPP tariffs are designed for bundled service customers. Customers on the CPP tariffs offered by the IOUs are also eligible to participate in Technical Assistance and Technology Incentives (TA/TI) and Automated Demand Response (AutoDR) programs. Various program provisions vary by utility, including the notification period for events, the specific hours when CPP events can be called, and the number and duration of CPP events. The key parameters are summarized for each utility in Table 2-1.

Table 2-1 Event Hours and Allowed Number of Events by Utility

Utility	Notification	Event hours	Events / year	Season
PG&E	Day ahead before 2 PM	2 to 6 PM	9 to 15	Year-round
SCE	~ 24-hour notice	4 to 9 PM	12	Year-round non-holiday weekdays
SDG&E	Day ahead before 3 PM	2 to 6 PM	Maximum of 18	Year-round

The three California IOUs began defaulting their large commercial and industrial customer accounts onto CPP rates twelve years ago. Specifically, SDG&E began CPP default in 2008 followed by PG&E and SCE in 2010.[13] Small and Medium Business (SMB) customers have been able to participate on a voluntary basis on CPP rates since 2014. In 2018, SDG&E completed their default of all SMB customers onto the CPP rates, while PG&E suspended the PDP default until the transition to new Time-of-Use (TOU) period is implemented in 2019-2020, so that the new customers are not subject to the PDP default right before or even simultaneously with the new TOU period. SCE's default of SMB customers with demands below 200 kW, along with large pumping and agricultural customers, onto the CPP rate occurred in March 2019.

[13] Most of the defaulted customers were previously served under tariffs with TOU energy and/or demand charges, such that they already had varying incentives to reduce load during peak periods on all summer weekdays.

Table 2-2 below summarizes the groups of customers included in the *ex-post* and *ex-ante* portions of this study. Note that the analysis of SDG&E's small CPP customers will be carried out in a different study.

Table 2-2 Analyses included in Evaluation by Utility and Customer size

Size Group	PG&E	SCE	SDG&E
Large (≥ 200 kW)	*Ex-post* and *ex-ante*	*Ex-post* and *ex-ante*	*Ex-post* and *ex-ante*
Medium (20 ≤ x < 200 kW)	*Ex-post* and *ex-ante*	*Ex-post* and *ex-ante*	*Ex-post* and *ex-ante*
Small (< 20 kW)	*Ex-post* and *ex-ante*	*Ex-post* and *ex-ante*	Excluded[14]

Newly enrolled customers receive bill protection for the first 12 months. Most of the largest customers at PG&E and SDG&E have the option of reserving a level of generation capacity (a capacity reservation level, or CRL) to protect a portion of their load on CPP event days.[15]

PY2019 Event Days

Table 2-3 below summarizes the CPP events called by each utility in 2019. All events were called on weekdays between June 1st and September 30th. Note that SDG&E did not call any events in 2019.

Table 2-3 PY2019 CPP Event Dates by Utility

Date	Day of Week	PG&E	SCE	SDG&E
6/11/2019	Tuesday	X		
7/12/2019	Friday		X	
7/15/2019	Monday		X	
7/16/2019	Tuesday		X	
7/24/2019	Wednesday	X		
7/26/2019	Friday	X		
8/13/2019	Tuesday	X		
8/14/2019	Wednesday	X	X	
8/15/2019	Thursday		X	
8/16/2019	Friday	X		
8/22/2019	Thursday		X	
8/23/2019	Friday		X	
8/26/2019	Monday	X		
8/27/2019	Tuesday	X	X	
9/5/2019	Thursday		X	
9/6/2019	Friday		X	
9/12/2019	Thursday		X	
9/13/2019	Friday	X	X	
Total		**9**	**12**	**0**

[14] Approximately 1,000 customers with maximum demands less than 20 kW were included in SDG&E's 20 to 200 kW group because they were participating on SDG&E's Medium CPP Tariff

[15] Effective March 2019, SCE no longer offers the CRL and CPP lite option.

Program Changes

Several program changes have been proposed by the IOUs. Some of the key changes are as follows:

- In 2018, PG&E put the defaults for PDP on hold for 2018 and 2019 until the TOU period transition change is implemented in November 2020. Additionally, in 2019, enrollment decreased by 19% as a result of customer transitions to Community Choice Aggregation (CCA). In 2019, PG&E also stopped providing in-season support[16] to participants.
- In 2019, SCE defaulted approximately 235,000 small and 35,000 medium commercial customers with demands below 200kW, along with large pumping and agricultural customers, onto the CPP rate. All defaulted customers receive bill protection for up to one year. In addition, SCE's event window changed to 4-9 PM effective March 1, 2019, the change was approved in July of 2018 in Rate Design Window Decision (D18-07-006). Additional changes to SCE's CPP are that the Capacity Reservation Level (CRL) and CPP lite options have been eliminated and are no longer available to new or existing CPP customers.
- SDG&E saw no new changes to the CPP rate in PY2019.

PY2019 Participant Counts

Next, we present counts of participants by utility, industry type, and size category. We also present information regarding what percent of the enrolled population received notification of events. The participant counts represent the participation on a typical event day, actual counts varied by event.

Table 2-4 presents the industry-type definitions and corresponding NAICS codes. There are eight categories of industries. Table 2-5 presents the number of service accounts enrolled in CPP, or PDP, during a typical summer event by industry and utility. Table 2-6 presents the number of service accounts enrolled in CPP, or PDP, during a typical summer event by size group, small (< 20 kW), medium (20 kW ≤ x < 200 kW), and large (≥ 200 kW).[17]

Table 2-4 Industry Type Definitions

Industry Type	NAICS Codes
1. Agriculture, Mining & Construction	11, 21, 23
2. Manufacturing	31-33
3. Wholesale, Transport, Other Utilities	22, 42, 48-49
4. Retail Stores	44-45
5. Offices, Hotels, Finance, Services	51-56, 62, 72
6. Schools	61
7. Institutional/Government	71, 81, 92
8. Other/Unknown	NA

[16] In-season support provided additional communication around event notification and performance.

[17] Since SDG&E did not call any events, the counts represent PY2019 enrollment instead of a typical event day.

Table 2-5 Enrolled Service Accounts, by Utility and Industry Group, Typical Event Day

Industry Type	PG&E	SCE	SDG&E
1. Agriculture, Mining & Construction	6,455	11,730	394
2. Manufacturing	4,744	13,247	1,123
3. Wholesale, Transport, Other Utilities	17,646	18,626	969
4. Retail Stores	10,801	23,829	1,899
5. Offices, Hotels, Finance, Services	39,677	124,974	7,279
6. Schools	2,653	4,469	817
7. Institutional/Government	21,742	45,848	1,999
8. Other/Unknown	13,678	29,660	447
Total	**117,397**	**272,383**	**14,927**

Table 2-6 Enrolled Service Accounts, by Utility and Size Group, Typical Event Day

Size Group	PG&E	SCE	SDG&E
Small < 20 kW	91,156	235,219	-
Medium 20 kW ≤ x < 200 kW	24,994	34,963	13,402
Large ≥ 200 kW	1,246	2,201	1,525
Total	**117,397**	**272,383**	**14,927**

It is also important to keep in mind that not all the customers that were enrolled in CPP, or PDP, received communication regarding events. As customers were defaulted onto the rates, each utility established mechanisms to reach out to customers to obtain contact information that could be used to provide day ahead event notification, however, in many cases customers did not respond to the utility outreach and therefore were unaware of the events throughout the summer. Table 2-7 shows the percentage of participants that were notified by utility and size group on a typical event day.

Table 2-7 Percent of Service Accounts Receiving Notification, by Utility and Size Group, Typical Event Day

Size Group	PG&E % Notified	SCE % Notified	SDG&E % Notified[18]
Small < 20 kW	92%	54%	-
Medium 20 kW ≤ x < 200 kW	95%	61%	NA
Large ≥ 200 kW	94%	89%	NA
Total	**92%**	**55%**	**NA**

[18] SDG&E did not notify any customers because no events were called in PY2019.

3

STUDY METHODS

This section presents the methods used to estimate the ex-post and ex-ante impacts for the CPP programs for the three IOUs.

Ex-Post Impact Analysis

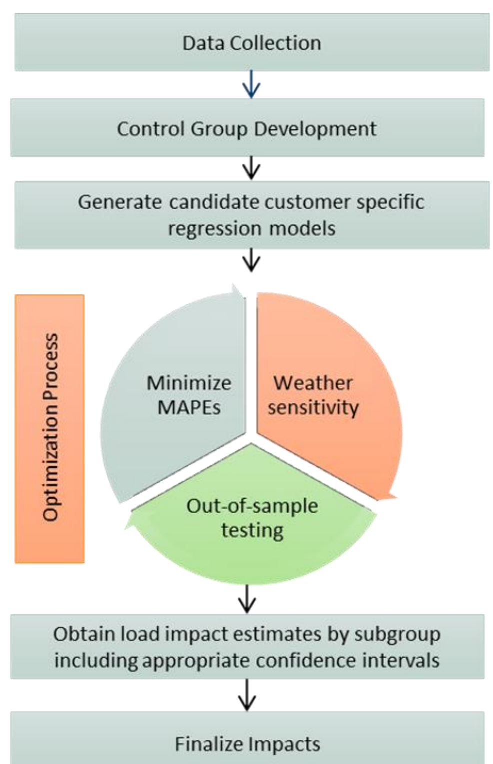
The primary objectives of the ex-post analysis are presented below.

For each of the three IOUs, at both the aggregate and per-participant levels, the objectives include to:

- Develop hourly and daily load impact estimates for each CPP event day called in PY2019 for the following:
    - PG&E large customers (≥ 200 kW) and Small-to-Medium Business (SMB) customers (< 200 kW),
    - SCE large non-residential customers (≥ 200 kW), and SMB customers (< 200 kW), and
    - SDG&E large customers (≥ 200 kW) and medium customers (20 kW ≤ x < 200 kW)[19].
- Provide estimates by various segments: LCA, industry group, dual enrollment in other DR programs, participation in Auto DR or TA and TI, and other industrial classifications such as busbar.
- Estimate the effect of utility notification of events.

In addition, AEG provides an impact analysis of the SDG&E changes in TOU periods and season. As of December 1, 2017, SDG&E implemented new TOU periods and moved the month of May into the winter season. We will address this objective in a separate section below (SDG&E Additional TOU Ex-post Analysis).

Figure 3-1 Ex-Post Analysis Approach



Overview of AEG's Approach

AEG's approach to the ex-post analysis is described at a high level below and summarized in Figure 3-1.

- For subgroups where it was feasible, AEG developed a matched control group. For subgroups where it was not feasible, AEG employed a within subjects' design leveraging event-like days in 2019. Table 3-1 presents the methodology used to estimate impacts for each subgroup.
- Then, AEG estimated subgroup level models for each IOU, size, and industry. All subgroup level

[19] SDG&E also requires results for customers with maximum demand less than or equal to 500 kW v. greater than 500 kW.

models were ultimately selected using our optimization process combined with industry expertise and experience.

- Finally, we estimated the ex-post impact for each customer so that they could be aggregated easily into the various reporting subgroups required for the analysis.

Table 3-1 presents the methodology employed by utility and size group.[20] We based the methodology employed on the total non-participant to participant ratio in each group. In general, a non-participant to participant ratio of at least 3 to 1 is required to obtain a good match, therefore for groups with a ratio less than three, we employed a within subjects' design.[21] The within subjects' design leverages the participant's own load on event-like days to estimate the reference load.

Table 3-1 Analysis Method by Subgroup

Utility	Size Group	Analysis Method
PG&E	< 20 kW	Within Subjects
	20 kW ≤ x < 200 kW	Within Subjects
	≥ 200 kW	Matched Control
SCE	0 to 20 kW	Within Subjects
	20 kW ≤ x < 200 kW	Within Subjects
	≥ 200 kW	Matched Control
SDG&E	20 kW ≤ x < 200 kW	Within Subjects
	≥ 200 kW	Within Subjects

CPP is implemented differently within each IOU's territory. This, and the differences in methods necessitate the ex-post analysis to be conducted independently for each IOU. However, AEG used the same set of candidate models and optimization strategies across all three IOUs which maintains consistency in the results while allowing for customization of the models.

Detailed Description of Methods

In the subsections that follow we describe the analysis steps in more detail.

Data Collection

To address each of the load impact objectives, AEG collected 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).
- Monthly billing data for CPP customers and potential control group customers.
- Billing-based interval load data (i.e., hourly loads) for sampled CPP customers 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).

[20] For SDG&E, there are no ex-post impacts since no events were called. However, AEG developed baseline models using a similar approach to inform the ex-ante forecast.

[21] In addition to having small non-participant pools, the potential control group customers for the defaulted groups are made up of customers that opted out of the CPP rate. They are likely to be different than those that stayed on the rate and may introduce substantial self-selection bias into the analysis.

- Notification data indicating whether each participant was notified on each event day.

Sample Selection

In the interest of efficiency, AEG utilized a sampling approach to limit the amount of data requested and received. Since regression models will be estimated at subgroup levels for each IOU, size, and industry, the sample was designed based on this subgrouping. For PG&E and SCE, we pulled a sample of 5,000 customers from the following subgroups:

- PG&E
  - Small: Wholesale/Transport/Utilities, Retail stores, Offices/Hotels/Finance/Services, Institutional/Government, and Other
  - Medium: Offices/Hotels/Finance/Services
- SCE
  - Small: Agriculture/Mining/Construction, Manufacturing, Wholesale/Transport/Utilities, Retail stores, Offices/Hotels/Finance/Services, Institutional/Government, and Other
  - Medium: Offices/Hotels/Finance/Services

For PG&E and SCE's subgroups not mentioned above and all SDG&E subgroups, a census sample was utilized.

Event-like Days Selection

The selection of comparable non-event days, or event-like days, is essential to several of the evaluation activities. These were used in the matched control group development and the out-of-sample testing in model optimization.

The event-like days included 5 to 15 days which are comparable to called event days in weather, day of the week, and month of the year. We used a Euclidean distance metric (similar to what we describe below) to select days that are as similar as possible to actual event days using multiple weather-based criteria.

Matched Control Group Development

To create the matched control groups, we used a Stratified Euclidean Distance Matching (SEDM) technique. The basic steps were as follows:

Step 1 is to define both the participant and non-participant populations and the treatment and pre-treatment periods for each participant. Once the participant and non-participant populations are identified, both populations can be assigned to strata or filters that are categorical in nature. For CPP participants, we used size and industry type as key filters. This ensured that customers with similar usage characteristics were matched to one another, capturing some of the unobservable attributes that affect the way customers use energy.

Step 2 is to perform the one-to-one match based on hourly demand data of comparable event-like days. To determine how close each participant is to a potential match, we used a Euclidean distance metric. The Euclidean distance is defined as the square root of the sum of the squared differences between the matching variables. Any number of relevant variables could be included in the Euclidean distance. For this one-to-one match, we included three demand variables:

- The average demand on event-like days during the typical event window,

- The maximum demand on event-like days,
- And the average demand on event-like days during the hours outside the typical event window.

We then weighted the variables to reflect the relative importance of the estimates, with typical system peak hour having the most weight and the average demand outside the typical event window having the least weight. The Euclidean distance for this set of variables can be calculated using the equation below.

$$ED = \sqrt{w_1(avgevnt_{Ti} - avgevnt_{Ci})^2 + w_2(peak_{Ti} - peak_{Ci})^2 + w_3(avgnonevnt_{Ti} - avgnonevnt_{Ci})^2}$$

After calculating the distance metric within each group for each possible combination of participant and control customer, the control customer with the smallest distance is matched to each participant without replacement. We can then select the closest matches for each of our participants, creating a one-to-one match of control customers to participants.

Develop Candidate Regression Models

Given the evaluation timeline, it would be difficult to develop models individually for the 64 industry and size subgroups across the three IOUs. Therefore, we developed a set of candidate models which were fit to all subgroups and utilized an algorithm developed in previous Statewide DR evaluations to select the best model for each subgroup.

We can think of regression models as being made up of building blocks, which are in turn made up of one or more explanatory variables. These different sets of variables can be combined in different ways to represent different types of customers. The blocks can be generally categorized into either "baseline" variables, or "impact" variables and could be made up of a single variable (e.g., cooling degree hours, CDH), or a group of variables (e.g., days of the week). The baseline portion of the model explains variation in usage unrelated to demand response events, while the impact portion explains the variation in usage related to a DR event.[22]

The candidate models fit into two basic categories:

- Weather sensitive models which include weather effects and calendar effects.
- Non-weather sensitive models that include the morning load adjustment and calendar effects.

Table 3-2 below presents the listing of the different variables and variable combinations we used to develop the candidate models.

[22] Any unexplained variation will end up in the error term.

Table 3-2 Variables Included in Candidate Regression Models

Type of Variable	Variable	Description
Dependent	kWh $_{i,t}$	Hourly consumption for customer *i* in hour/day *t*
Baseline Fixed effect	α_i	Indicator variable for each customer *i*
Baseline Calendar	Day of Week $_t$	Indicator variable for each day of the week
Baseline Calendar	Weekday $_t$	Indicator variable taking on the value of 1 for each weekday and 0 for weekends and holidays
Baseline Calendar	Month of Year $_t$	Indicator variable for each month of the year
Baseline Weather	CDH $_{i,t}$	Cooling degree hours[23] for customer *i* in hour/day *t*
Baseline Weather	Meantemp $_{i,t}$	Mean temperature for customer *i* on day *t*
Baseline Adjustment	Average Load $_{i,t}$	Average hourly load for a specified window[24] for customer *i* on day *t*
Baseline Adjustment	Other DR $_{i,t}$	Indicator variable that takes on a value of 1 if a customer *i* is dually enrolled and participated in another DR event on day *t*
Impact	Event $_{i,t}$	Indicator that takes on a value of 1 if customer *i* participated in an event on day *t*
Impact Interaction	(Event * Notification) $_{i,t}$	Interaction between event and notification that takes on a value of 1 if customer *i* was notified of an event on day *t*
Impact Interaction	(Event * CDH) $_{i,t}$	Interaction between event and CDH for customer *i* on day *t*
Impact Interaction	(Event * month) $_{i,t}$	Interaction between event and month for customer *i* on day *t*

Various combinations of the variables above resulted in 24 potential candidate models.

Optimization and Model Selection Process

Our optimization process incorporates the validation of the subgroup regression models. The subgroup models are designed to:

1. Accurately predict the actual participant load on event days, and
2. Accurately predict the reference load, or what participants would have used on event days in absence of an event.

To meet these two specific goals, our optimization process includes an analysis of both the in-sample and out-of-sample mean absolute percent error (MAPE) and the mean percent error (MPE) for each of the candidate regression models for each subgroup. We use out-of-sample tests to show how well each of the candidate models could predict a participant's load on non-event days that were as similar as possible to actual event days; this test gives us an estimate of how well each model could predict the reference load. We use in-sample tests to show how well each model performs on the actual event days; therefore, it helps us understand how well the model is able to match the actual load. Our optimization procedure has several steps, which are described below:

- First, we identify the out-of-sample event-like days as described above.

[23] Depending on the service territory, base temperatures can be one or more of the following: 60, 70, 80, 85, 95.

[24] The specified window can be one or more of the following: HE5-HE10, HE11-HE13, HE13-HE16, HE21-HE23.

- After identifying the event-like days, those days are removed from the analysis dataset and the candidate models are fit to the remaining data.
- Next, the results of the candidate models are used to predict the usage on the out-of-sample days. Then we assess the error and bias in the reference load by calculating the MAPE and MPE between the actual usage and the predicted usage on the out-of-sample days.
- Finally, we compare the actual and predicted loads on the event days from the given program year. We also calculate the MAPE and MPE on these days to assess the error and bias in the predicted load.

The final step of the process is to select the candidate model with the minimum weighted MAPE and MPE for each subgroup. This model then becomes the final model specification. We describe the steps in more detail in the model validity subsection (see Appendix B).

Obtain Load Impacts and Confidence Intervals by Segment

The following example illustrates the process of estimating the impacts from the final model for a single subgroup. There were ultimately 64 subgroups in the actual analysis, each with their own final model specification determined by the optimization process (see Appendix B). Nevertheless, the process will be the same in each case.

Let's assume that this subgroup is weather sensitive and that the final model specification includes calendar and weather effects in the baseline portion of the model. In this simple example below, α_t, δ_t, and CDH_t, make up the baseline blocks of the model, and explain variation in kwh_t unrelated to demand response events. The remaining variables, $EVNT$, and the interaction term $(\alpha_t * EVNT)$ are the impact blocks and explain the variation in kwh_t related to a DR event.[25] An hourly model like equation (1) below can be equivalently estimated as one model with hourly dummy variables, or as 24 separate hourly models.

$$kwh_{it} = \beta_0 + \alpha_t + \delta_t + CDH_t + EVNT + (\alpha_t * EVNT) + \varepsilon_{it} \quad (1)$$

Where:

kwh_{it} is the consumption of customer i in hour t

β_0 is the intercept

α_t is a vector of segment indicators, i.e. AutoDR, LCA, etc.

δ_t is a vector of calendar variables, i.e. month, year, and day of week

CDH_t represents the cooling degree hours for hour t

$EVNT$ is a dummy variable indicating that hour t was on a CPP or PDP event day

$(\alpha_t * EVNT)$ is an interaction between the event indicator and the segment indicator variables

ε_{it} is the error for participant i in time t

This type of time-series model is likely to have auto-correlated errors which will be handled either directly through modeling the appropriate autoregressive process or more simply by using the Newey-West error correction.

We used the model above to estimate the load impacts as follows:

[25] Any unexplained variation will end up in the error term.

- First, we obtained the actual and predicted load for each participant on each hour and day based on the specification defined in equation (1).
- Next, we used the estimated coefficients and the baseline portion of the model to predict what this participant would have used on each day and hour, if there had been no events. We call this prediction the reference load.
- We calculated the difference between the reference load (the estimate based on the baseline blocks) and the predicted load (the estimate based on the baseline + impact blocks) on each event day. This difference represents our estimated load impact for each participant.

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 estimated load impact.

Assess model validity and finalize impacts

As we mention above, we selected and validated the subgroup regression models during our optimization process. The first aspect of our process includes assessing the accuracy of the model for the in-sample period, meaning that we assess the ability of the models to predict the actual load on each event day. The second aspect of our validation approach includes out-of-sample testing using a set of event-like days. This process allows us to assess the ability of the models to accurately predict the reference load.

To select similar non-event days, we used a Euclidean Distance matching approach. Euclidean distance is a simple and highly effective way of creating matched pairs. We used three different Euclidean distance metrics to select similar non-event days: (1) daily maximum temperature; (2) average daily and daily maximum temperatures; and (3) average daily temperature. The Euclidean distance metrics used can be calculated by Equation 5 through 7 below.

$$ED_1 = \sqrt{(MaxTemp_{event} - MaxTemp_{non-event})^2} \tag{5}$$

$$ED_2 = \sqrt{(MeanTemp_{event} - MeanTemp_{non-event})^2 + (MaxTemp_{event} - MaxTemp_{non-event})^2} \tag{6}$$

$$ED_3 = \sqrt{(MeanTemp_{event} - MeanTemp_{non-event})^2} \tag{7}$$

Next, we estimated the MAPE and MPE, for the event window, for each customer, and for each candidate model, both for the in-sample period and for the out-of-sample period. This results in thousands of in-sample and out-of-sample tests. Recall that the goal of the tests is to find the best model for each subgroup in terms of its ability to predict the reference load and the actual load for each customer. Therefore, we will collapse the tests into a single metric, which can be calculated for each subgroup and each candidate model.

The metric is defined in Equation 8 below:

$$\boldsymbol{metric_{ic}} = (0.4 * EvntMAPE) + (0.4 * EvntlikeMAPE) + (0.1 * EvntMPE) + (0.1 * EvntlikeMPE) \tag{8}$$

Where,

$$MAPE = \frac{100\%}{n} \sum_{h=1}^{n} \left| \frac{Actual_h - Estimate_h}{Actual_h} \right| \tag{9}$$

$$MPE = \frac{100\%}{n} \sum_{h=1}^{n} \frac{Actual_h - Estimate_h}{Actual_h} \tag{10}$$

Once we compute a single metric for each subgroup and candidate model combination, we can then select the best model for each customer by choosing the model specification with the smallest overall metric.

SDG&E Additional TOU Ex-post Analysis

As of December 2017, SDG&E implemented new TOU periods for all its customers and moved the month of May into the Winter season. We estimated impacts to test if any material changes have resulted during the second year of implementation. For consistency with the 2018 analysis, we again performed a simple regression analysis and examined changes in consumption in each hour from the previous TOU periods to the current TOU periods. The analysis is described in more detail below:

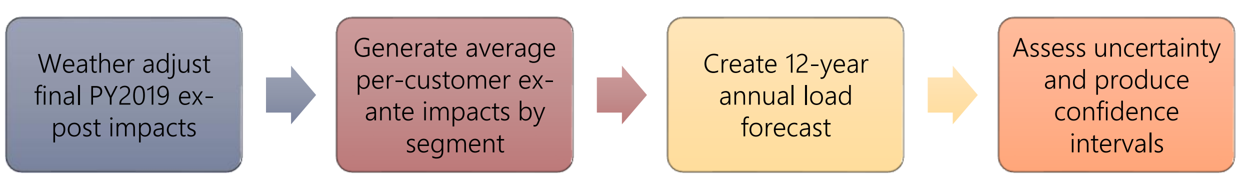
- We appended the 2019 interval data to the 2017 and 2018 interval data for all the 2019 participants.
- Next, we ran a simple regression model that included calendar variables, weather, and a 2018/2019 indicator. This indicator variable captures the impact of the TOU period changes, on average, on non-event[26] days.
- Then we looked at those impacts by day-type to assess whether customers changed their consumption in response to the changes in the TOU periods.

Ex-Ante Impact Analysis

The main goal of the ex-ante analysis is to produce an annual twelve-year[27] forecast of the load impacts expected from the CPP programs. Separate forecasts are to be produced for each LCA (as applicable), each busbar (as applicable), and bundled v. direct access (as applicable). We will produce a set of impacts under each of the different weather scenarios required: monthly peak day and typical event day for 1-in-2 weather year and 1-in-10 weather year for each of the IOUs and the CAISO. A portfolio forecast that excludes the forecasted load impacts of dually enrolled customers will also be provided. An annual twelve-year forecast will be produced for each of the following:

- PG&E large customers (≥ 200 kW) and SMB customers (< 200 kW);
- SCE large non-residential customers (≥200 kW) and SMB non-residential customers (< 200 kW); and,
- SDG&E large customers (≥ 200 kW) and medium customers (20 kW ≤ x < 200 kW)[28].

Our approach achieves these goals by first determining the appropriate weather-adjusted, per-customer impact for each of the segments of interest, and then multiplying that impact by the number of participants for each year specified by the enrollment forecast. First, we describe the various steps involved in implementing this approach in detail. Then we address uncertainty in the forecast and the calculation of confidence intervals. The figure below provides an overview of the ex-ante analysis approach.



[26] We only perform this update on non-event days since SDG&E did not call any events in PY2019.

[27] Eleven-year forecasts for SCE and PG&E companies.

[28] SDG&E also requires results for customers with a maximum demand less or equal to 500 kW v. greater than 500 kW.

Detailed Description of Methods

In the subsections that follow we describe the analysis steps in more detail.

Weather-Adjusted Impacts

The first step in the ex-ante analysis was to use the ex-post regression models to predict weather-adjusted impacts for each segment of interest. This will produce a set of impacts under each of the required weather scenarios. To do this, we carried out the following steps:

- For each program, the analysis begins with the coefficients estimated in the subgroup regression models developed for the ex-post analysis.
- Then, the actual weather from the program year is replaced with the 1-in-2 and 1-in-10 weather data to predict a customer's load for each of these scenarios assuming no events are called. The result was a weather-adjusted reference load for each customer for each weather scenario required.
- Next, the weather-adjusted event day load is predicted 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 by changing the event indicator variables from zero to one.
- Finally, the load impact for each customer is calculated by subtracting the weather-adjusted event-day load from the weather-adjusted reference load.

Generation of Per-Customer Average Impacts by Segment

Once weather-adjusted impacts were predicted for each customer, for each of the desired weather scenarios, it became a relatively simple exercise to average the individual impacts and generate per-customer average impacts by segment of interest.

Since we are dealing with very small, sometimes insignificant, impacts in the small and medium customer groups, we performed an additional check on the average event window impacts, checking for negative weather-adjusted impacts. These small negative impacts are most likely a modeling artifact resulting from an imperfect quantification of weather effects and/or omitted variable bias. We have no reason to think that customers are increasing their load in response to events. For these cases wherein we found negative average event window impacts, we set the estimates to zero. Note that negative average impacts in the RA window for PG&E and SDG&E are plausible given that the RA window coincides with post-event hours wherein snapback effects are likely to occur.

Creation of 12-Year[29] Annual Load Impact Forecasts

The next step in the analysis will be to use the set of per-customer average impacts to create an annual forecast of load impacts over the next 12 years. For PG&E and SCE, the 2019 ex-post weather adjusted per customer subgroup level impacts were multiplied by the number of customers in each IOU's enrollment forecast by month and year to develop the 12-year load forecast.

Since SDG&E did not call any events in PY2019, we did not have ex-post regression models to predict weather-adjusted impacts. Instead, we used a combination of both PY2018 and PY2019 estimates to produce per-customer average impacts needed for the 12-year load forecast. To do this, we carried out the following steps:

- A 12-month baseline was estimated using the PY2019 program population.

[29] Eleven-year forecasts for SCE and PG&E companies.

- In place of the ex-post regression models, we estimated baseline regression models for each of SDG&E's 16 subgroups, following our optimization and model selection process[30]. Since we did not have any event days for event-like day selection, we used the event-like days selected for SDG&E in the Capacity Bidding Program (CBP) analysis.
- Then, the actual weather from the program year is replaced with the 1-in-2 and 1-in-10 weather data to predict a customer's load for each of these scenarios. The result was a weather-adjusted reference load for each customer for each weather scenario required.

- The PY2018 weather-adjusted impact estimates were used as a replacement.
  - To determine the appropriateness of using PY2018 impact estimates, we checked for enrollment overlap between PY2018 and PY2019, i.e., continuing PY2018 enrollment.
  - For each customer, the PY2018 weather-adjusted impact estimates were merged to the PY2019 reference load estimates in order to generate per-customer average impacts by segment.

[30] Since SDG&E did not have any event days, we only performed the in-sample test, using event-like days to estimate MAPEs in place of event days.

4

EX-POST RESULTS

This section presents the ex-post impacts for each IOU, by size, industry, LCA, dual participation, participation in Auto DR or TA/TI, and receipt of event notification for the 2019 CPP, or PDP, programs.

PG&E

This section presents the ex-post load impact analysis for PG&E. The primary load impact results include estimates of average event-hour load impacts, in aggregate and per-customer, for the typical event day, which is simply the average of all the event days, as well as for each individual event. Detailed results for each hour for each event are available in electronic form in Protocol table generators provided along with this report.

Table 4-1 below summarizes the overall program level event-hour impacts on each event including the number of participants enrolled during each event, the aggregate and per-customer reference load and load impacts, the percent impact, and the average temperature.

Table 4-1 PG&E All Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
6/11/2019	124,280	1,292.1	8.7	10.4	0.1	0.7%	99.2
7/24/2019	118,258	1,220.8	17.4	10.3	0.1	1.4%	96.4
7/26/2019	118,217	1,146.5	17.9	9.7	0.2	1.6%	93.6
8/13/2019	116,978	1,206.8	14.1	10.3	0.1	1.2%	94.4
8/14/2019	116,855	1,260.8	14.6	10.8	0.1	1.2%	98.2
8/16/2019	116,549	1,242.5	15.5	10.7	0.1	1.2%	97.8
8/26/2019	115,615	1,236.3	14.8	10.7	0.1	1.2%	96.0
8/27/2019	115,463	1,236.6	16.6	10.7	0.1	1.3%	95.4
9/13/2019	114,354	1,191.7	9.0	10.4	0.1	0.8%	94.8
Typical Event Day	**117,397**	**1,226.0**	**14.3**	**10.4**	**0.1**	**1.2%**	**96.2**

Results for Large Customers (≥ 200 kW)

This section summarizes results for all large PG&E program participants, defined as customers with maximum demand equal to, or greater than, 200 kW. The results are presented as follows:

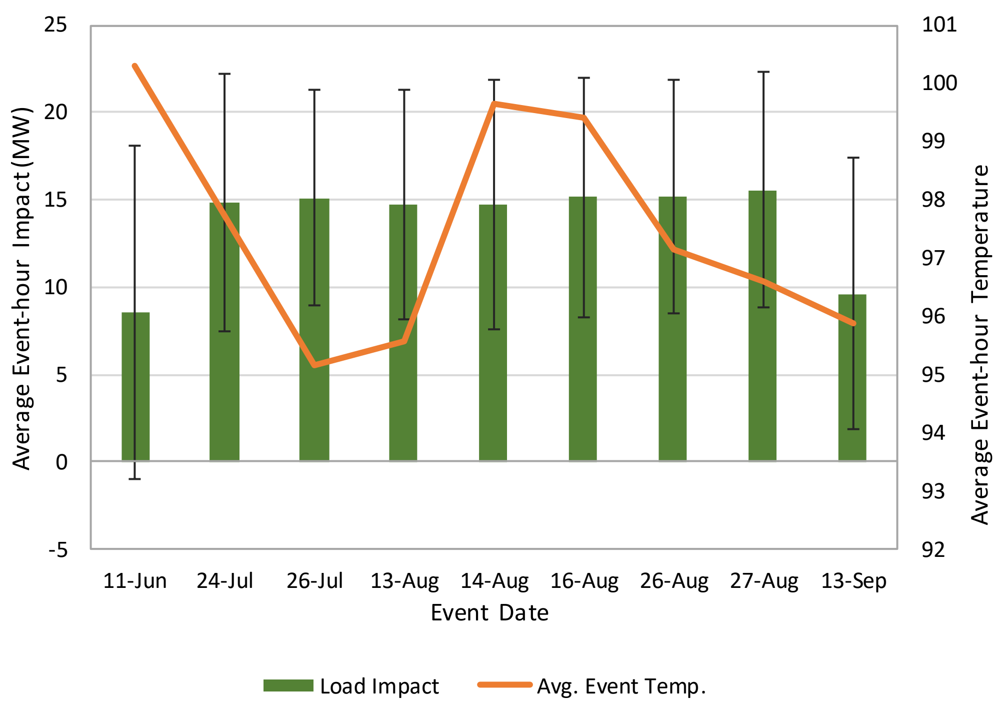
- Average event-hour impacts for each individual event day
- Hourly load impacts for a typical event day
- Average event-hour impacts on a typical event day by industry group and LCA

Results for dually enrolled customers, AutoDR customers, and for those that were notified (vs. not notified) are presented in subsequent subsections.

Figure 4-1 presents the average event-hour ex post load impacts for each individual event day for all of PG&E's large PDP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

These results indicate that large customers had statistically significant load reductions on eight of the nine event days, ranging from 8.6 to 15.6 MW. The average load impact was 13.7 MW, with seven out of nine event days having a load impact greater than 14.5 MW.

Figure 4-1 PG&E Large all Participants: Average Event-Hour Impacts by Event



Error! Not a valid bookmark self-reference. summarizes the event-hour impacts on each event including the number of participants enrolled during each event, the aggregate and per-customer reference load and load impacts, the percent impact, and the average temperature. Load impacts as a percent of the reference load were 2.9% on average across the nine events. In addition, enrollment dropped over time from 1,272 participants during the first event on June 11th to 1,233 participants on the last September 13th event.

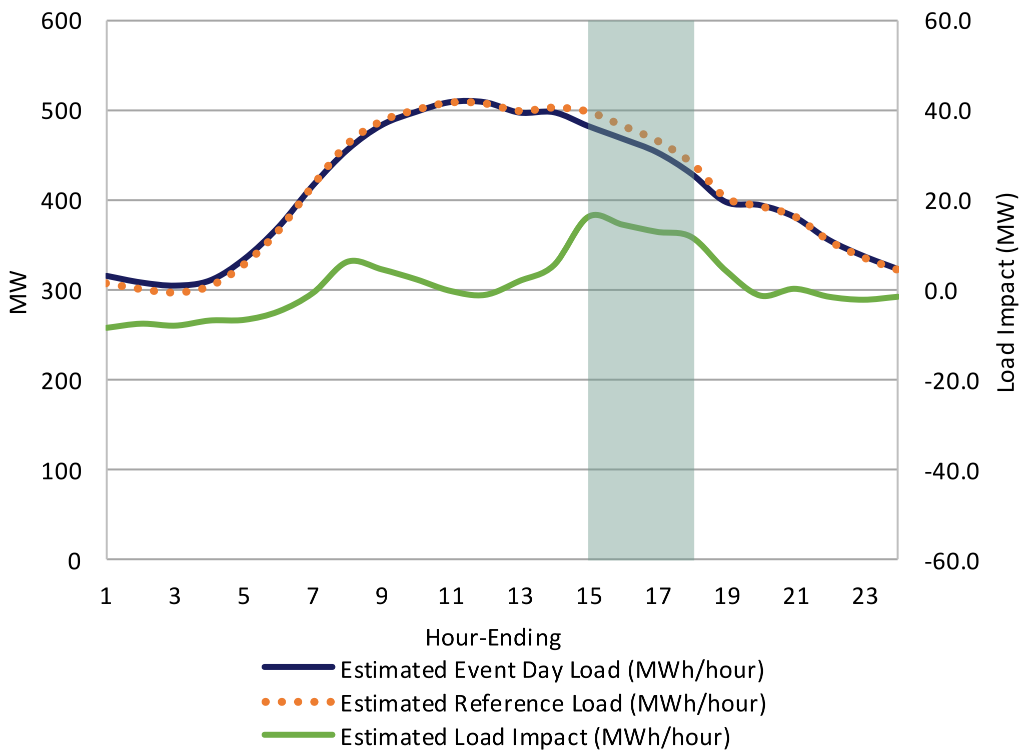
In addition, it is interesting to note that the June 11th event had the highest number of participants, and the highest temperature, but the lowest impact. Given that large customers are generally insensitive to weather, it may be that fewer customers participated in the first event of the season.

Table 4-2 PG&E Large all Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
6/11/2019	1,272	504.0	8.6	396.2	6.7	1.7%	100.3
7/24/2019	1,251	469.5	14.9	375.3	11.9	3.2%	97.7
7/26/2019	1,250	430.8	15.1	344.6	12.1	3.5%	95.2
8/13/2019	1,243	469.2	14.7	377.5	11.9	3.1%	95.6
8/14/2019	1,243	477.4	14.7	384.1	11.8	3.1%	99.6
8/16/2019	1,243	468.7	15.1	377.1	12.2	3.2%	99.4
8/26/2019	1,240	475.0	15.2	383.0	12.3	3.2%	97.2
8/27/2019	1,239	464.2	15.6	374.7	12.6	3.4%	96.6
9/13/2019	1,233	490.3	9.6	397.6	7.8	2.0%	95.9
Typical Event Day	**1,246**	**472.1**	**13.7**	**378.9**	**11.0**	**2.9%**	**97.5**

Figure 4-2 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. The highest load impact tends to occur during the first event hour. In addition, hourly load impacts do not show evidence of pre-cooling or post-event snapback. This is more typical of large participants that tend to be less weather sensitive and participate using a mix of end-uses rather than being cooling dominated like SMB or residential customers. The load impacts outside the event windows are very small and do not suggest that large customers are responding to events by shifting event-hour loads to hours outside the event window.

Figure 4-2 PG&E Large all Participants: Hourly Typical Event Day Load Impacts



PG&E Large: by Industry

Next, we look at load impacts for PG&E large customers by industry group. Table 4-3 summarizes aggregate event-hour results for the typical event day for eight industry groups, including the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load, and the average event temperature. Insignificant impacts are highlighted in red font.

Enrollments are concentrated in the Agriculture, Mining, & Construction and Wholesale, Transport, other utilities groups. These two groups represent 42% of the total enrolled customers. The largest estimated load impacts, however, are from Manufacturing and Offices, Hotels, Finance, Services Industries with impacts of 4.4 MW and [redacted] MW, respectively. These two groups contribute to 78% of total load reduction. (See Figure 4-3.) Note also that the average event temperature experienced by the Agriculture, Mining and Construction industry was significantly higher than any other industry at 99 degrees. In California the mining operations tend to be located inland (i.e. Barstow, Boron) which are much hotter than the rest of the state and most of PG&E's agricultural customers are in the central valley. Two of the industries, Schools and Institutional/Government, show negative impacts.

In Figure 4-3, we present the share of the total enrollment, impacts, and reference load by industry.[31]

[31] Note that the total share of impacts is based upon the absolute value of the impacts to properly normalize for both positive and negative impacts.

Table 4-3 PG&E Large: Average Event-Hour Impacts by Industry on a Typical Event Day

Industry	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
1. Agriculture, Mining & Construction	275	48.7	2.0	4.2%	99.0
2. Manufacturing	195	64.6	4.4	6.8%	96.8
3. Wholesale, Transport, other utilities	249	44.8	1.9	4.3%	97.5
4. Retail stores	51	15.7	0.0	0.1%	98.3
5. Offices, Hotels, Finance, Services	208	[redacted]	[redacted]	[redacted]	97.4
6. Schools	107	17.7	(1.1)	-6.0%	98.0
7. Institutional/Government	107	[redacted]	[redacted]	[redacted]	95.4
8. Other or unknown	54	27.2	0.3	1.2%	96.6

Figure 4-3 PG&E Large: Contributions by Industry on a Typical Event Day

[redacted]

PG&E Large: by LCA

Next, we look at load impacts for PG&E large customers by LCA. Table 4-4 summarizes aggregate event-hour results for the typical event day for seven of PG&E's eight LCAs. (Humboldt does not have any large participants.) The tables include the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load and the average event temperature. Again, insignificant estimates are highlighted in red font.

As one might expect enrollments are concentrated in the Greater Bay and Fresno Areas with about 50% of all participants coming from the two areas combined. The largest estimated load impacts, 3.7 MW, come from the Greater Fresno Area, with impacts in other areas being substantially lower. Impacts in the Greater Bay Area are likely to be low relative to their overall participation due to the milder weather experienced there compared to the Greater Fresno Area which tends to experience more extreme summer heat. This is also demonstrated by the greater average event temperatures (>100ºF) for the Greater Fresno and Kern Areas. (See Table 4-4.)

In Figure 4-4, we present the share of the total enrollment, impacts, and reference load by LCA.[32]

Table 4-4 PG&E Large: Average Event-Hour Impacts by LCA on a Typical Event Day

LCA	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
Greater Bay Area	236	[redacted]	[redacted]	[redacted]	91.6
Greater Fresno Area	371	83.0	3.7	4.4%	101.5
Kern	120	26.1	1.5	5.6%	100.1
Sierra	166	40.9	1.5	3.8%	97.7
Stockton	119	34.4	1.1	3.2%	98.6
Northern Coast	69	12.3	0.9	7.0%	97.0
Other	165	41.6	1.8	4.4%	95.8

Figure 4-4 PG&E Large: Contributions by LCA on a Typical Event Day

[redacted]

[32] Note that the total share of impacts is based upon the absolute value of the impacts to properly normalize for both positive and negative impacts when they are present.

Results for Medium Customers (20 ≤ x < 200 kW)

This section summarizes results for all medium PG&E program participants, defined as customers with maximum demand equal to or greater than 20 kW but less than 200 kW. The results are presented in the same format as the previous section. Again, results for dually enrolled customers, AutoDR customers, and for those that were notified (vs. not notified) are presented in subsequent sub-sections.

Figure 4-5 presents the average event-hour ex-post load impacts for each individual event day for all of PG&E's medium PDP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

These results indicate that medium PDP participants had statistically significant changes in usage on only four out of the nine event days. Furthermore, the point estimates are both positive and negative with an average per customer impact of negative 0.004. AEG believes that this pattern of impacts suggests that the medium customers are not responding to PDP events and that their true impacts are in fact zero. Table 4-5 shows enrollment dropped over time from 26,109 participants during the first event to 24,541 participants on the last event.

Figure 4-5 PG&E Medium all Participants: Average Event-Hour Impacts by Event

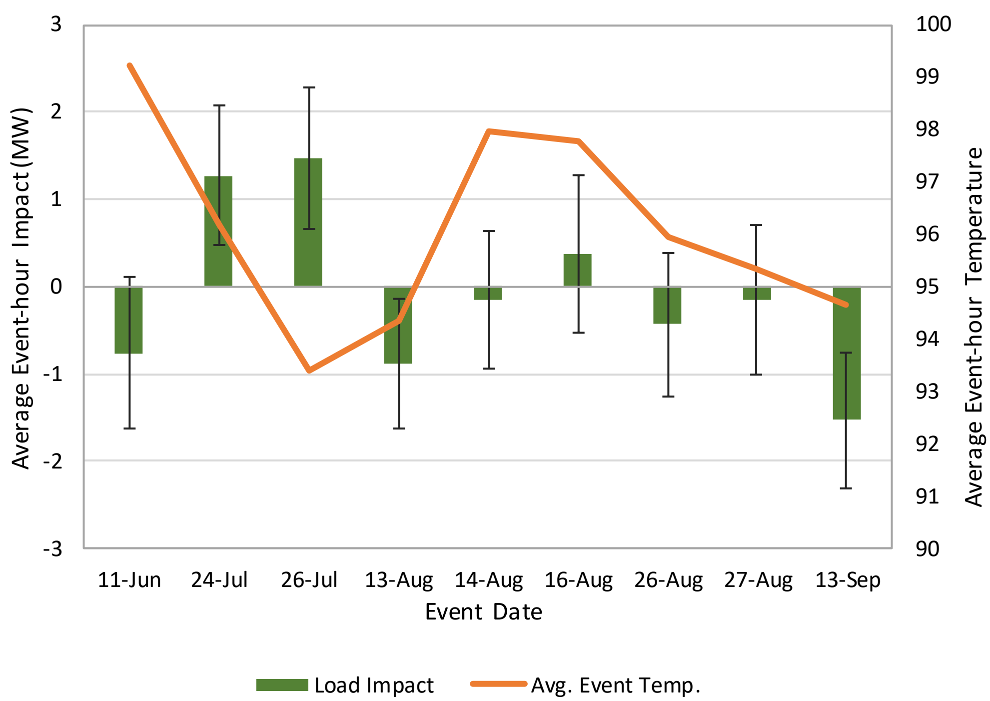
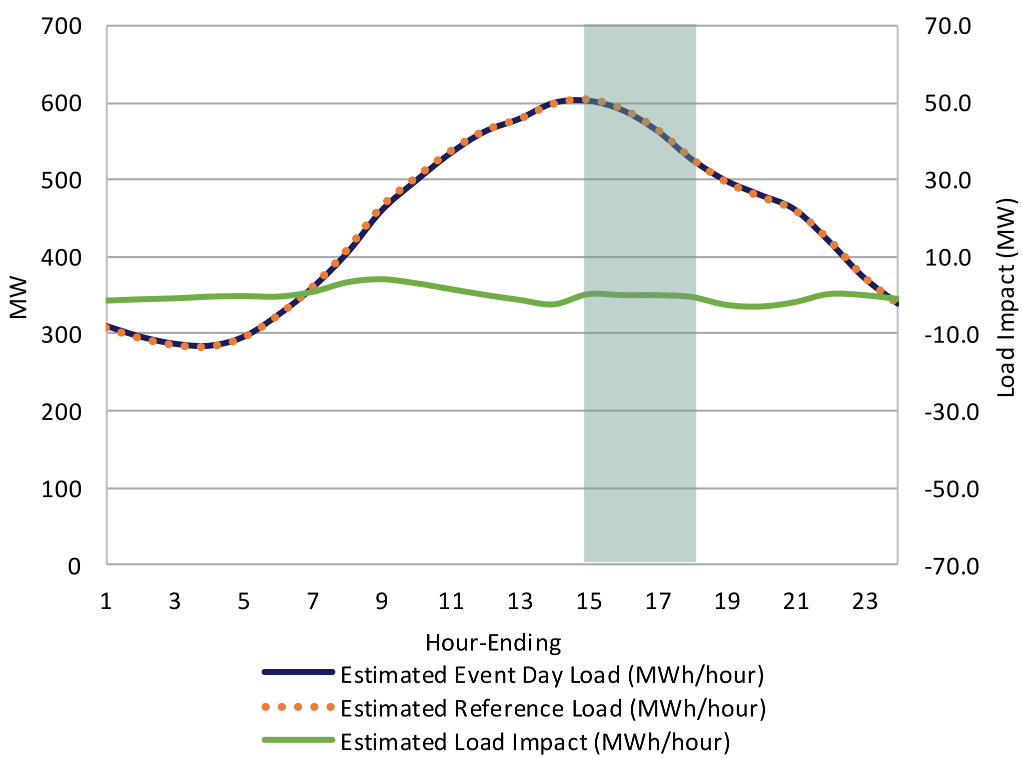


Table 4-5 PG&E Medium all Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
6/11/2019	26,109	590.5	(0.8)	22.6	(0.0)	-0.1%	99.2
7/24/2019	25,116	562.4	1.3	22.4	0.1	0.2%	96.2
7/26/2019	25,109	541.4	1.5	21.6	0.1	0.3%	93.4
8/13/2019	24,923	558.5	(0.9)	22.4	(0.0)	-0.2%	94.3
8/14/2019	24,903	592.9	(0.2)	23.8	(0.0)	0.0%	98.0
8/16/2019	24,859	591.1	0.4	23.8	0.0	0.1%	97.8
8/26/2019	24,707	581.5	(0.4)	23.5	(0.0)	-0.1%	95.9
8/27/2019	24,680	586.0	(0.1)	23.7	(0.0)	0.0%	95.3
9/13/2019	24,541	539.2	(1.5)	22.0	(0.1)	-0.3%	94.6
Typical Event Day	**24,994**	**571.5**	**(0.1)**	**22.9**	**(0.0)**	**0.0%**	**96.1**

Figure 4-6 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. The impacts in this case are extremely flat and the observed and reference loads show no visible differences on event days during the event window.

Figure 4-6 PG&E Medium all Participants: Hourly Typical Event Day Load Impacts



PG&E Medium: by Industry

Next, we look at load impacts for PG&E's medium customers by industry group. Table 4-6 summarizes aggregate event-hour results for the typical event day for eight industry groups, including the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load, and the average event temperature. Enrollments are concentrated in the Offices, Hotels, Finance & Services. This group represents 38% of the total enrolled customers. Several of the industries, show negative impacts, however, they are very small at the per-customer level and are most likely a result of modeling noise and omitted variable bias.

Table 4-6 PG&E Medium: Average Event-Hour Impacts by Industry on a Typical Event Day

Industry	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
1. Agriculture, Mining & Construction	861	16.0	0.9	5.3%	95.8
2. Manufacturing	1,277	27.3	0.1	0.3%	96.7
3. Wholesale, Transport, other utilities	2,762	51.5	0.6	1.1%	96.0
4. Retail stores	3,534	96.1	1.5	1.6%	95.3
5. Offices, Hotels, Finance, Services	9,583	235.7	(1.1)	-0.5%	95.4
6. Schools	1,221	48.5	(0.8)	-1.6%	95.9
7. Institutional/Government	4,144	68.7	(0.7)	-1.0%	94.2
8. Other or unknown	1,612	27.6	(0.5)	-1.9%	96.1

PG&E Medium: by LCA

Finally, we examine load impacts for PG&E's medium customers by LCA. Table 4-7 summarizes aggregate event-hour results for the typical event day for PG&E's eight LCAs. The tables include the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load and the average event temperature. Insignificant estimates are shown in red font. As one might expect enrollments are concentrated to the Greater Bay and Fresno Areas with about 50% of the participants coming from those two areas.

Table 4-7 PG&E Medium: Average Event-Hour Impacts by LCA on a Typical Event Day

LCA	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
Greater Bay Area	3,456	82.1	(0.2)	-0.2%	91.1
Greater Fresno Area	6,456	148.4	0.3	0.2%	101.4
Humboldt	44	0.6	0.0	0.3%	79.1
Kern	2,348	58.3	0.1	0.1%	100.0
Sierra	3,500	78.8	(0.1)	-0.1%	97.0
Stockton	2,386	56.0	(0.1)	-0.1%	98.4
Northern Coast	1,940	44.1	(0.1)	-0.2%	96.8
Other	4,863	103.3	(0.0)	0.0%	94.3

Results for Small Customers (< 20 kW)

This section summarizes results for all small PG&E program participants, defined as customers with maximum demand less than 20 kW. The results are presented in the same format as the previous section. Again, results for dually enrolled customers, AutoDR customers, and for those that were notified (vs. not notified) are presented in subsequent sub-sections.

Figure 4-7 presents the average event-hour ex post load impacts for each individual event day for all of PG&E's small PDP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

It is critical to point out that the per-customer impacts for these participants (shown in Figure 4-7 and associated Table 4-8) are incredibly small ranging from -0.01% to 0.76%. In addition, the small customers only achieve statistically significant impacts on five of the nine event days. The smaller the impacts are, the more difficult it becomes to accurately capture those impacts within the model. We suspect that the impacts for this group may simply be a modeling artifact due to an inability of the models to perfectly capture the weather sensitivity due to modeling noise or potentially omitted variable bias. Similar to the medium participants, AEG believes that this pattern of impacts suggests that the small customers are not responding to PDP events and that their true impacts are in fact zero.

Table 4-8 shows enrollment dropped over time from 96,899 participants during the first event to 88,580 participants on the last event.

Figure 4-7 PG&E Small all Participants: Average Event-Hour Impacts by Event

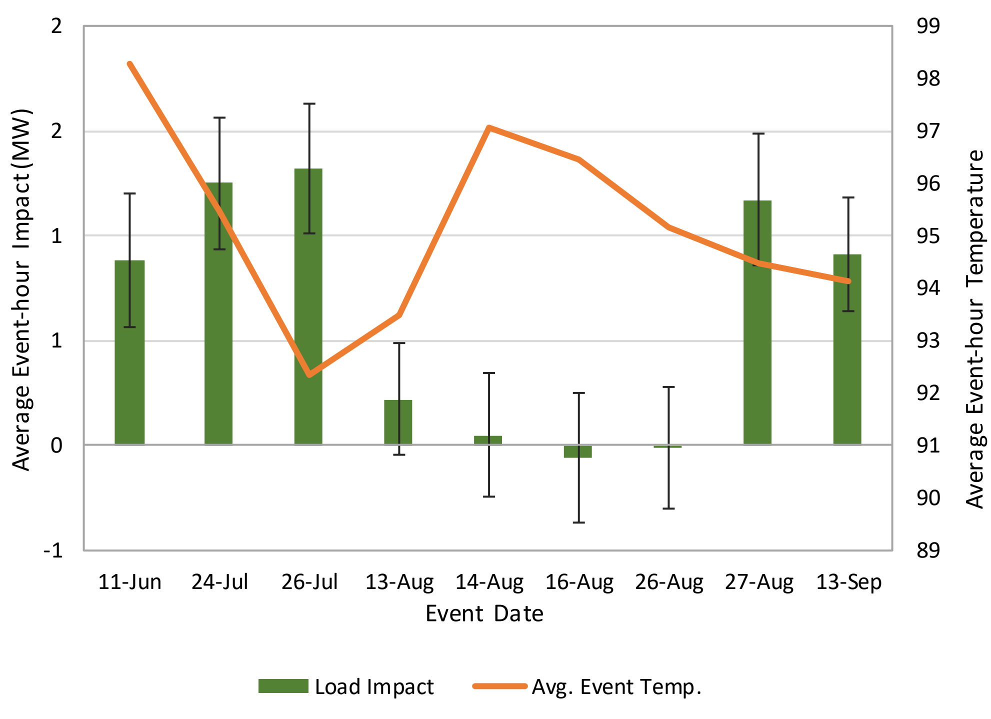
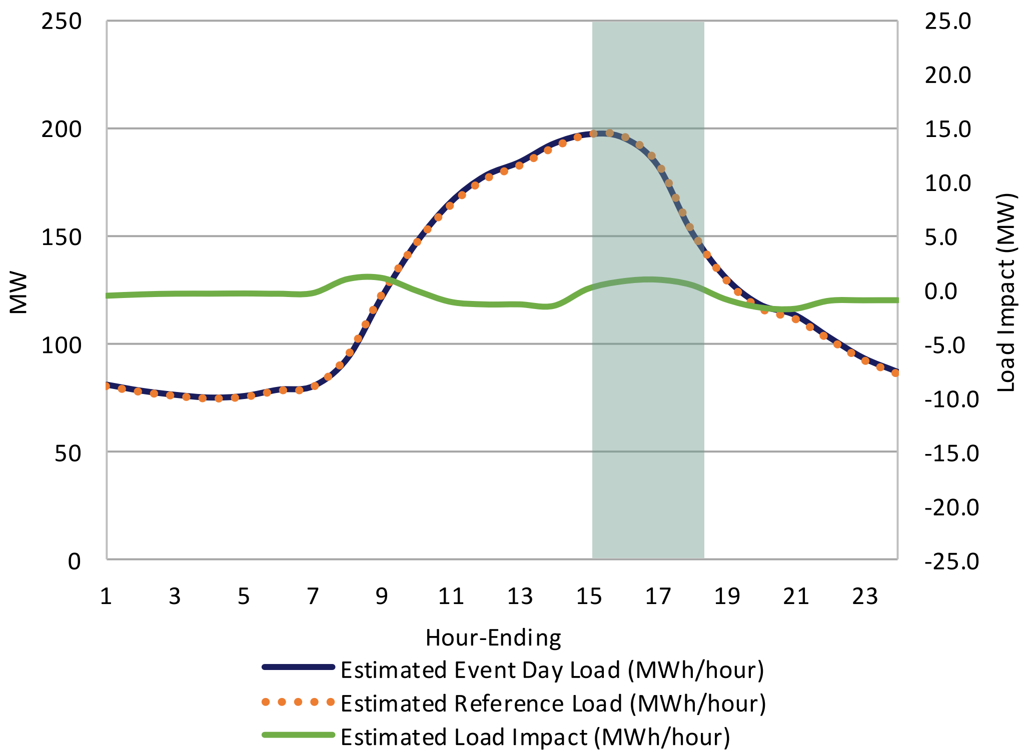


Table 4-8 PG&E Small Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
6/11/2019	96,899	197.5	0.9	2.0	0.0	0.4%	98.3
7/24/2019	91,891	188.9	1.3	2.1	0.0	0.7%	95.5
7/26/2019	91,858	174.3	1.3	1.9	0.0	0.8%	92.4
8/13/2019	90,812	179.1	0.2	2.0	0.0	0.1%	93.5
8/14/2019	90,709	190.5	0.0	2.1	0.0	0.0%	97.1
8/16/2019	90,447	182.7	(0.1)	2.0	(0.0)	-0.0%	96.5
8/26/2019	89,668	179.9	(0.0)	2.0	(0.0)	-0.0%	95.2
8/27/2019	89,544	186.3	1.2	2.1	0.0	0.6%	94.5
9/13/2019	88,580	162.3	0.9	1.8	0.0	0.6%	94.1
Typical Event Day	**91,156**	**182.4**	**0.6**	**2.0**	**0.0**	**0.4%**	**95.2**

Figure 4-8 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. The impacts in this case are extremely flat and the observed and reference loads show no visible differences on event days during the event window.

Figure 4-8 PG&E Small all Participants: Hourly Typical Event Day Load Impacts



PG&E Small: by Industry

Next, we look at load impacts for PG&E's small customers by industry group. Table 4-9 summarizes aggregate event-hour results for the typical event day for eight industry groups, including the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load, and the average event temperature. Enrollments are concentrated in the Offices, Hotels, Finance & Services and Institutional/Government groups. These two groups represent 45% of the total enrolled customers. Several of the industries, show negative impacts, however, again they are very small at the per-customer level and are most likely a result of modeling noise and omitted variable bias.

Table 4-9 PG&E Small: Average Event-Hour Impacts by Industry on a Typical Event Day

Industry	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
1. Agriculture, Mining & Construction	5,319	7.6	(0.0)	-0.3%	95.2
2. Manufacturing	3,273	6.8	0.1	1.4%	96.3
3. Wholesale, Transport, other utilities	14,635	16.3	(0.0)	0.0%	95.1
4. Retail stores	7,215	24.2	0.2	1.0%	95.4
5. Offices, Hotels, Finance, Services	29,886	72.5	0.7	1.0%	94.1
6. Schools	1,325	3.5	(0.2)	-4.7%	96.0
7. Institutional/Government	17,491	33.3	0.0	0.1%	95.1
8. Other or unknown	12,012	18.2	(0.2)	-1.3%	95.0

PG&E Small: by LCA

Finally, we examine the load impacts for PG&E's small customers by LCA. Table 4-10 summarizes aggregate event-hour results for the typical event day for PG&E's eight LCAs. The table includes the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load and the average event temperature. As one might expect enrollments are concentrated to the Greater Bay and Fresno Areas with about 44% of the participants coming from those two areas. However, again they are very small at the per-customer level and are most likely a result of modeling noise and omitted variable bias.

Table 4-10 PG&E Small: Average Event-Hour Impacts by LCA on a Typical Event Day

LCA	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
Greater Bay Area	9,863	21.3	0.1	0.5%	90.0
Greater Fresno Area	22,236	49.2	0.1	0.2%	101.1
Humboldt	228	0.2	0.0	0.3%	85.4
Kern	6,838	15.8	0.0	0.2%	99.7
Sierra	15,108	27.8	0.1	0.4%	96.0
Stockton	8,735	17.4	0.1	0.3%	98.1
Northern Coast	7,939	13.6	0.1	0.5%	95.6
Other	20,209	37.1	0.2	0.5%	92.2

Dually Enrolled Customers

Next, we present the impacts for PG&E's dually enrolled customers. On a typical event day, a total of 94 customers were dually enrolled in either PG&E's Capacity Bidding Program (CBP) or the Base Interruptible Program (BIP). These customers demonstrate consistent positive impacts ranging from 0.6 MW to 0.7 MW (3.4% to 4.5%) and impacts across each individual day was insignificant, however the overall impact on the typical event day was significant.

Figure 4-9 presents the average event-hour ex-post load impacts for each individual event day for the dually enrolled customers. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

Figure 4-9 PG&E Dually Enrolled Participants: Average Event-Hour Impacts by Event

[redacted]

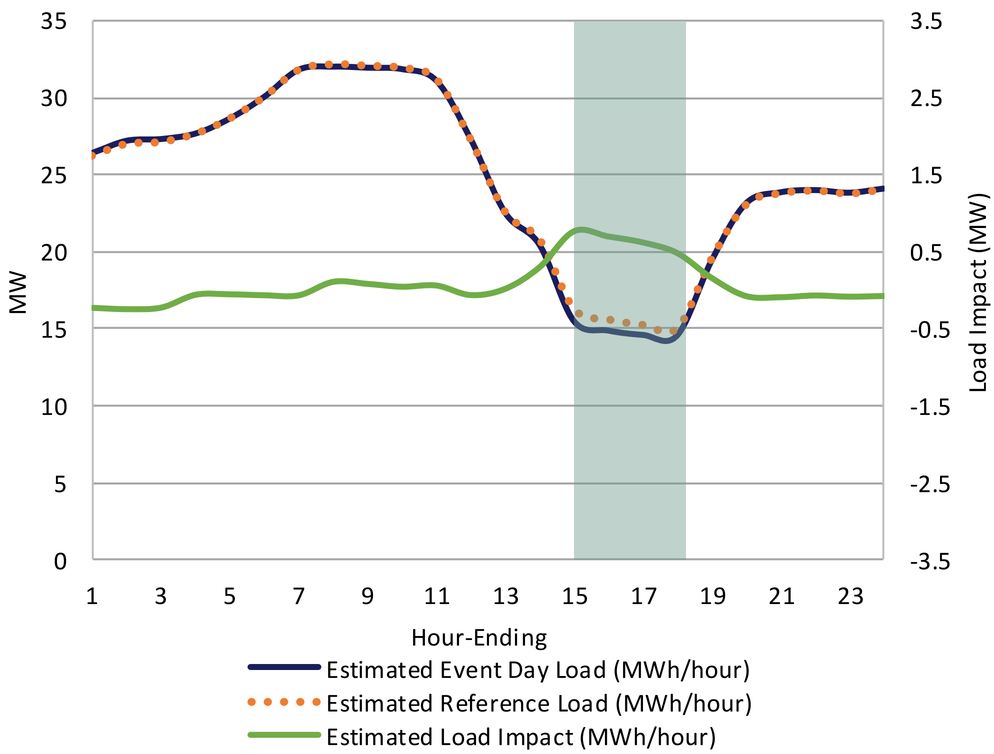
Table 4-11, presents both the aggregate and per-customer impacts, the percent impacts, the number of participants enrolled, and the temperature on each day. Insignificant impacts are identified in red font.

Table 4-11 PG&E Dually Enrolled Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW) Ref. Load	Aggregate (MW) Load Impact	Per-Customer (kW) Ref. Load	Per-Customer (kW) Load Impact	% Load Impact	Avg. Event Temp.
6/11/2019	94	15.6	0.6	166.2	6.1	3.6%	101.0
7/24/2019	94	15.2	0.7	161.7	7.3	4.5%	99.6
7/26/2019	94	15.0	0.7	159.7	7.3	4.5%	99.3
8/13/2019	94	15.0	0.6	159.4	6.9	4.3%	97.3
8/14/2019	94	16.5	0.7	175.3	6.9	3.9%	100.9
8/16/2019	94	14.6	0.7	155.8	7.1	4.5%	102.9
8/26/2019	94	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	99.2
8/27/2019	94	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	100.0
9/13/2019	94	17.2	0.6	183.3	6.2	3.4%	96.3
Typical Event Day	**94**	**15.6**	**0.6**	**165.7**	**6.8**	**4.1%**	**99.6**

Figure 4-10 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. Notice that impacts outside the event window are very small relative to the event window impacts indicating a consistent load reduction without shifting of load into non-event hours.

Figure 4-10 PG&E Dually Enrolled Participants: Hourly Typical Event Day Load Impacts



Automated Demand Response Customers

Next, we present the impacts for PG&E's Automated Demand Response (AutoDR) customers. PG&E's AutoDR customers have load reduction equipment installed at their facilities which automates their response during events. On a typical event day, a total of 87 customers were participating in the AutoDR program. These customers demonstrate consistent positive impacts ranging from 2.5 to 4.0 MW. However, none of the impacts were statistically significant due to the low number of participants.

Figure 4-11 presents the average event-hour ex post load impacts for each individual event day for all of PG&E's AutoDR participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

Figure 4-11 PG&E AutoDR Participants: Average Event-Hour Impacts by Event

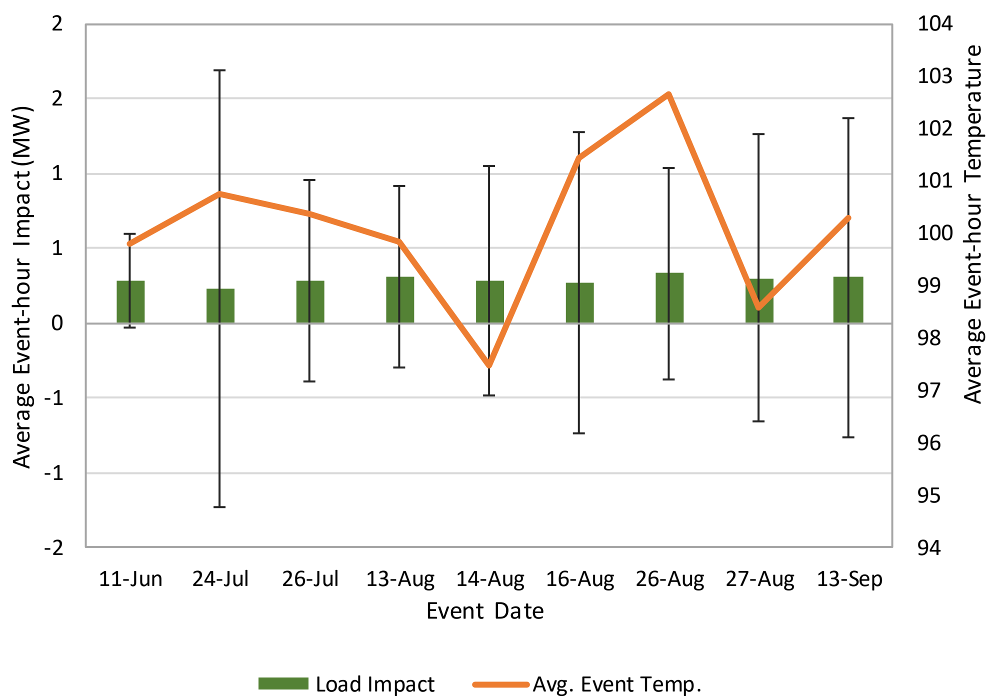


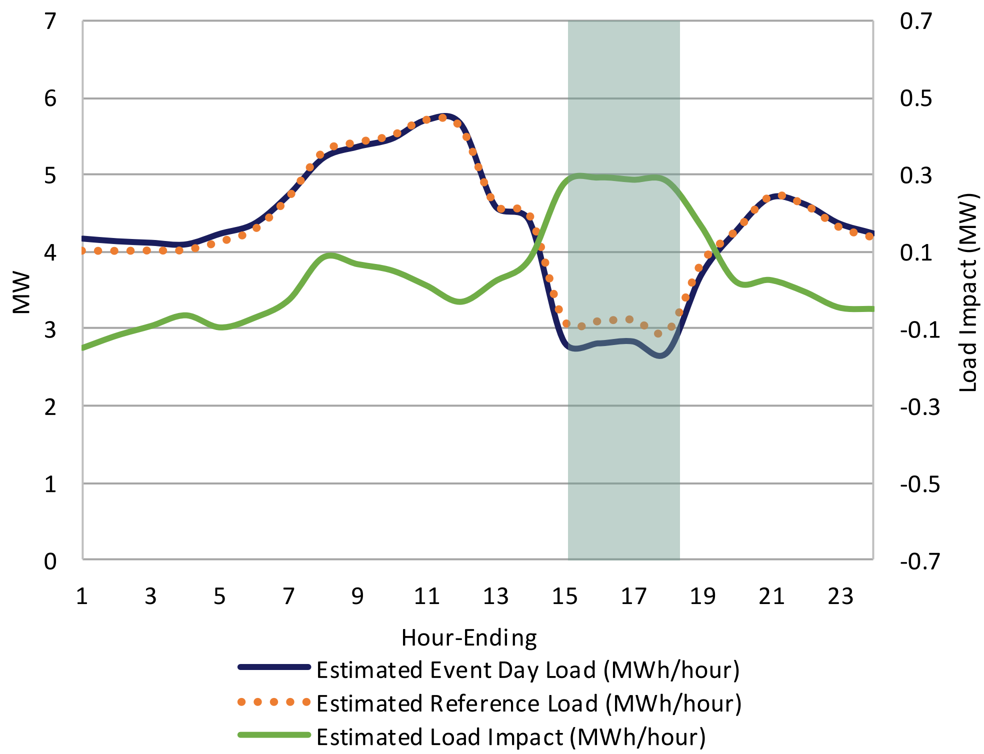
Table 4-12 presents both the aggregate and per-customer impacts, the percent impacts, the number of participants enrolled, and the temperature on each day.

Table 4-12 PG&E AutoDR Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
6/11/2019	87	2.5	0.2	28.2	2.7	9.4%	100.8
7/24/2019	87	2.7	0.3	31.0	3.2	10.5%	100.4
7/26/2019	87	3.3	0.3	37.4	3.6	9.6%	99.8
8/13/2019	87	4.0	0.3	46.4	3.3	7.1%	97.5
8/14/2019	87	3.5	0.3	40.4	3.1	7.7%	101.4
8/16/2019	87	3.3	0.3	38.3	3.8	10.0%	102.7
8/26/2019	87	2.6	0.3	30.0	3.5	11.6%	98.6
8/27/2019	87	2.9	0.3	33.3	3.5	10.5%	100.3
9/13/2019	87	3.1	0.3	35.6	3.3	9.5%	100.1
Typical Event Day	**87**	**3.1**	**0.3**	**35.4**	**3.3**	**9.2%**	**99.8**

Figure 4-12 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. Notice that impacts outside the event window are very small relative the event window impacts indicating a consistent load reduction without shifting of load into non-event hours.

Figure 4-12 PG&E AutoDR Participants: Hourly Typical Event Day Load Impacts



Notified vs. Non-Notified Customers

PDP is a default rate for PG&E's non-residential customers and as such, participants are notified of an event if their contact information is provided to PG&E. However, customers that do not receive notification probably do not know that an event is occurring and would therefore find it difficult to respond. Customers can receive day ahead notifications for events by setting up their account to receive alerts either by email, or by text message. PG&E discontinued their in-season support this year, which provided additional information including post event feedback to participants.

Table 4-13 and Table 4-14 present the percentage of service accounts receiving notification by size group and the per customer impacts by size group, and notification, on a typical event day, respectively.

In looking at Table 4-13, we note that relative to last year PG&E increased the percentage of service accounts receiving notification from 88% to 92%. And, like last year, approximately 95% of the load impacts come from customers that are receiving notification. However, when we compare the difference in per customer impacts by size, in Table 4-14, we can see that the key difference, at a per customer level, comes from the large customers. The small and medium customers show negligible reductions regardless of whether they are notified of events suggesting that for these groups, notifications and/or increasing notifications will not improve the impacts.

Table 4-13 Percent of Service Accounts Receiving Notification, by Size Group: Typical Event Day

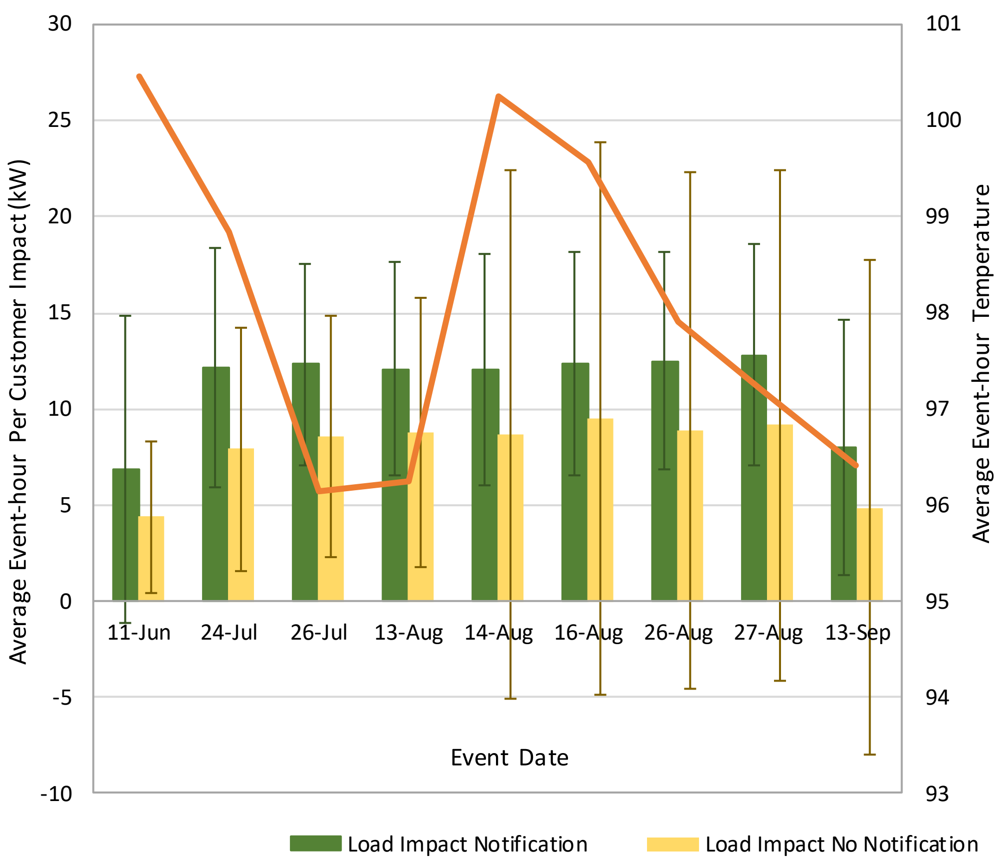
Size Group	PG&E % Notified
Small < 20 kW	92%
Medium 20 kW ≤ x < 200 kW	95%
Large ≥ 200 kW	94%
Total	**92%**

Table 4-14 Per Customer Impacts by Size Group and Notification: Typical Event Day

Notification	Size group	# Customers	Per-Customer Ref. Load (kW)	Per-Customer Load Impact (kW)	Aggregate Load Impact (MW)
No	0 to 20 kW	7,255	1.3	0.0	0.2
	20 to 199.99 kW	1,245	20.1	(0.0)	(0.0)
	200 kW and above	77	241.4	7.8	0.6
	All	**8,577**	**6.2**	**0.1**	**0.8**
Yes	0 to 20 kW	83,902	2.1	0.0	0.4
	20 to 199.99 kW	23,749	23.0	(0.0)	(0.1)
	200 kW and above	1,169	388.0	11.2	13.1
	All	**108,819**	**10.8**	**0.1**	**13.5**

In Figure 4-13 below we compare the average event hour impacts on each event day, by notification, for the large customers PY2019. Large customers who are notified of events provide more load reduction on average, than those that are not notified of events. It is interesting however, that even customers that are not notified of events are showing significant load reductions. This suggests that it is possible some customers are keeping up to date on events through other means such as checking the PG&E website, or perhaps as part of a larger company/organization that distributes notifications to various sites.

Figure 4-13 Comparison Average Event-Hour of Impacts by Level of Communication; Large Customers



SCE

This section presents the ex-post load impact analysis for SCE. 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. Detailed results for each hour for each event are available in electronic form in Protocol table generators provided along with this report.

Table 4-15 summarizes the overall, program level, event-hour impacts on each event, including the number of participants enrolled during each event, the aggregate and per-customer reference load and load impacts, the percent impact, and the average temperature.

Table 4-15 SCE All Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
7/12/2019	275,081	1,602.2	5.3	5.8	0.0	0.3%	89.7
7/15/2019	275,082	1,625.3	5.3	5.9	0.0	0.3%	88.9
7/16/2019	275,082	1,608.5	4.8	5.8	0.0	0.3%	86.1
8/14/2019	272,567	1,662.8	5.1	6.1	0.0	0.3%	90.3
8/15/2019	272,565	1,642.3	4.8	6.0	0.0	0.3%	89.6
8/22/2019	272,566	1,563.0	3.2	5.7	0.0	0.2%	84.1
8/23/2019	272,565	1,548.2	4.4	5.7	0.0	0.3%	85.6
8/27/2019	272,566	1,677.2	4.6	6.2	0.0	0.3%	88.7
9/5/2019	270,129	1,709.4	5.4	6.3	0.0	0.3%	88.6
9/6/2019	270,129	1,671.7	5.3	6.2	0.0	0.3%	88.2
9/12/2019	270,130	1,603.5	4.9	5.9	0.0	0.3%	85.7
9/13/2019	270,130	1,635.6	5.5	6.1	0.0	0.3%	89.8
Typical Event Day	**272,383**	**1,629.1**	**4.9**	**6.0**	**0.0**	**0.3%**	**87.9**

Results for Large Customers (≥ 200 kW)

This section summarizes results for all large SCE program participants, defined as customers with maximum demand equal to or greater than 200 kW. The results are presented as follows:

- Average event-hour impacts for each individual event day
- Hourly load impacts for a typical event day
- Average event-hour impacts on a typical event day by industry group and LCA

Results for dually enrolled customers, AutoDR customers, and for those that were notified (vs. not notified) are presented in subsequent subsections.

Figure 4-14 presents the average event-hour ex post load impacts for each individual event day for all of SCE's large CPP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

These results indicate that large customers had statistically significant load reductions on each of the twelve event days, ranging from 6.2 MW to 7.6 MW. The load impact averaged 7 MW, with one-third of the event days (4 days) having a load impact lower than 7 MW.

Table 4-16 summarizes the event-hour impacts on each event, including the number of participants enrolled during each event, the aggregate and per-customer reference load and load impacts, the percent impact, and the average temperature. Load impacts as a percent of the reference load were 1.6% on average across the twelve events. Enrollment dropped slightly over time by 149 participants, or 7%.

Figure 4-14 SCE Large all Participants: Average Event-Hour Impacts by Event

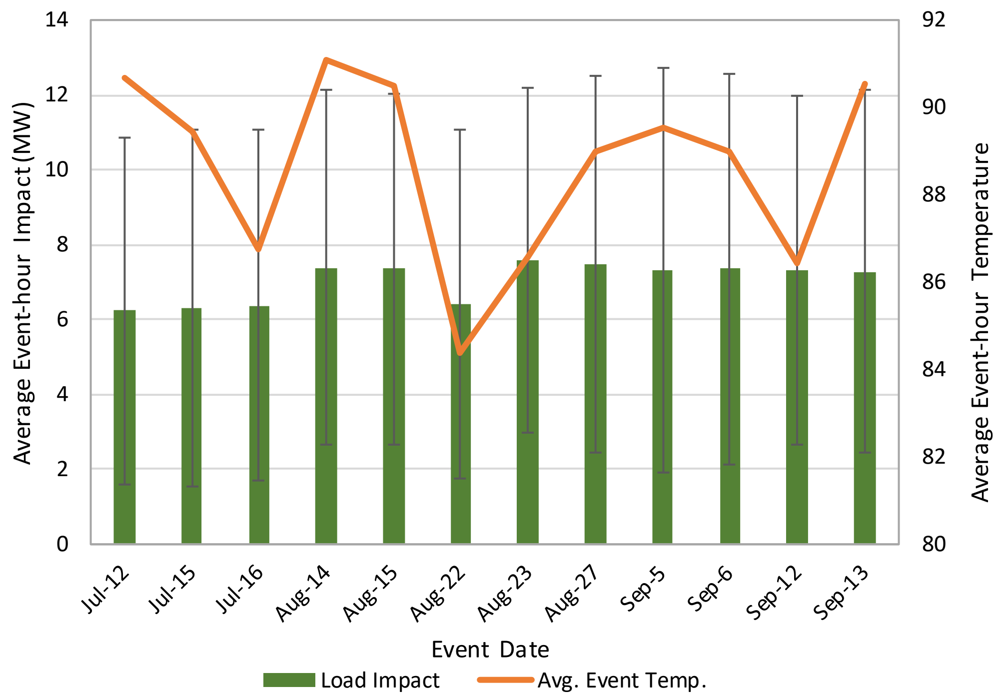
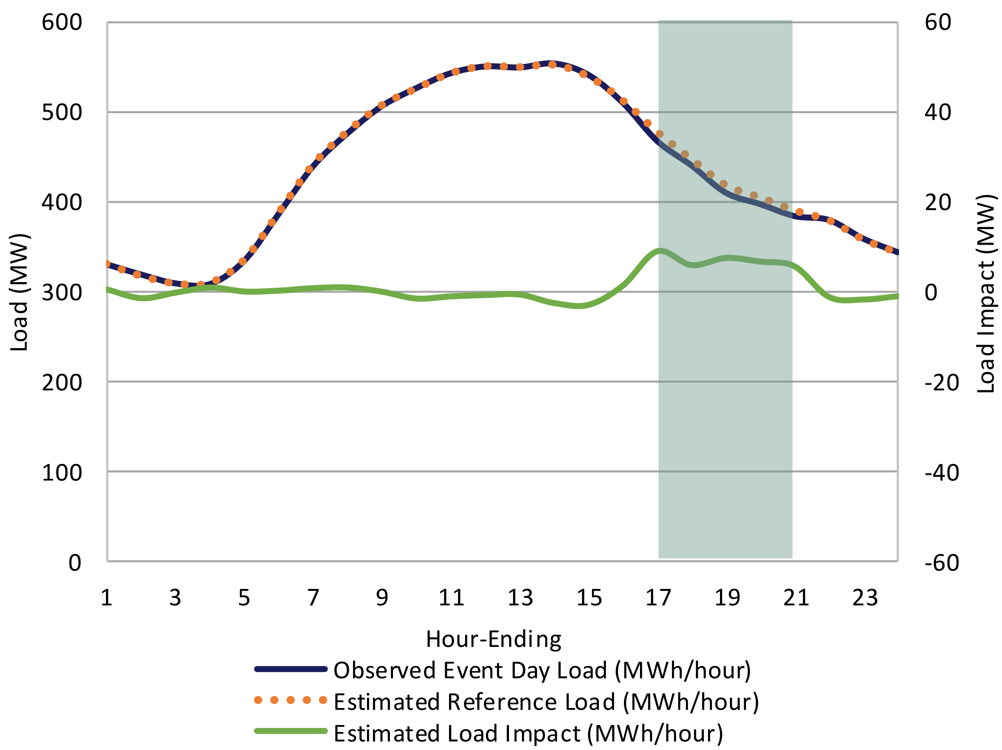


Table 4-16 SCE Large all Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
7/12/2019	2,230	410.7	6.2	184.2	2.8	1.5%	90.7
7/15/2019	2,231	426.6	6.3	191.2	2.8	1.5%	89.5
7/16/2019	2,231	424.8	6.4	190.4	2.9	1.5%	86.8
8/14/2019	2,199	432.3	7.4	196.6	3.4	1.7%	91.1
8/15/2019	2,198	431.5	7.3	196.3	3.3	1.7%	90.5
8/22/2019	2,198	417.9	6.4	190.1	2.9	1.5%	84.4
8/23/2019	2,198	405.7	7.6	184.6	3.4	1.9%	86.6
8/27/2019	2,198	440.0	7.5	200.2	3.4	1.7%	89.0
9/5/2019	2,181	450.0	7.3	206.3	3.4	1.6%	89.5
9/6/2019	2,180	434.0	7.3	199.1	3.4	1.7%	89.0
9/12/2019	2,181	428.0	7.3	196.2	3.4	1.7%	86.4
9/13/2019	2,181	421.6	7.3	193.3	3.3	1.7%	90.5
Typical Event Day	**2,201**	**426.9**	**7.0**	**194.0**	**3.2**	**1.6%**	**88.7**

Figure 4-15 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. The highest load impact tends to occur during the first event hour. In addition, hourly load impacts do not show evidence of pre-cooling or post-event snapback. This is typical of large participants that tend to be less weather sensitive and participate using a mix of end-uses rather than cooling dominate SMB or residential customers. The load impacts outside the event windows are very small and do not suggest that large customers are responding to events by shifting event-hour loads to hours outside the event window.

Figure 4-15 SCE Large all Participants: Hourly Typical Event Day Load Impacts



SCE Large: by Industry

Next, we look at load impacts for SCE large customers by industry group. Table 4-17 summarizes aggregate event-hour results for the typical event day for eight industry groups, including the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load, and the average event temperature. Insignificant impacts are highlighted in dark red font.

Enrollments are concentrated in the Manufacturing and Offices, Hotels, Finance and Services groups. These two groups represent 47% of the total enrolled customers. The largest estimated load impact is from Manufacturing with an impact of 6.6 MW. Manufacturing is also the only industry group that has statistically significant impacts.

In Figure 4-16, we present the share of the total enrollment, impacts, and reference load by industry.[33]

[33] Note that the total share of impacts is based upon the absolute value of the impacts to properly normalize for both positive and negative impacts.

Table 4-17 SCE Large: Average Event-Hour Impacts by Industry on a Typical Event Day

Industry	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
1. Agriculture, Mining & Construction	141	16.0	0.2	1.1%	94.3
2. Manufacturing	557	106.6	6.6	6.2%	89.0
3. Wholesale, Transport, other utilities	420	88.7	0.1	0.1%	90.9
4. Retail stores	144	36.5	(0.1)	-0.3%	86.5
5. Offices, Hotels, Finance, Services	487	102.9	(0.3)	-0.3%	83.6
6. Schools	190	24.5	0.3	0.9%	86.2
7. Institutional/Government	185	33.8	0.5	1.5%	87.1
8. Other or unknown	77	[redacted]	[redacted]	[redacted]	82.6

Figure 4-16 SCE Large: Contributions by Industry on a Typical Event Day

[redacted]

SCE Large: by LCA

Next, we look at load impacts for SCE large customers by LCA. Table 4-18 summarizes aggregate event-hour results for the typical event day for the three SCE LCAs. The tables include the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load and the average event temperature. Insignificant estimates are highlighted in red font.

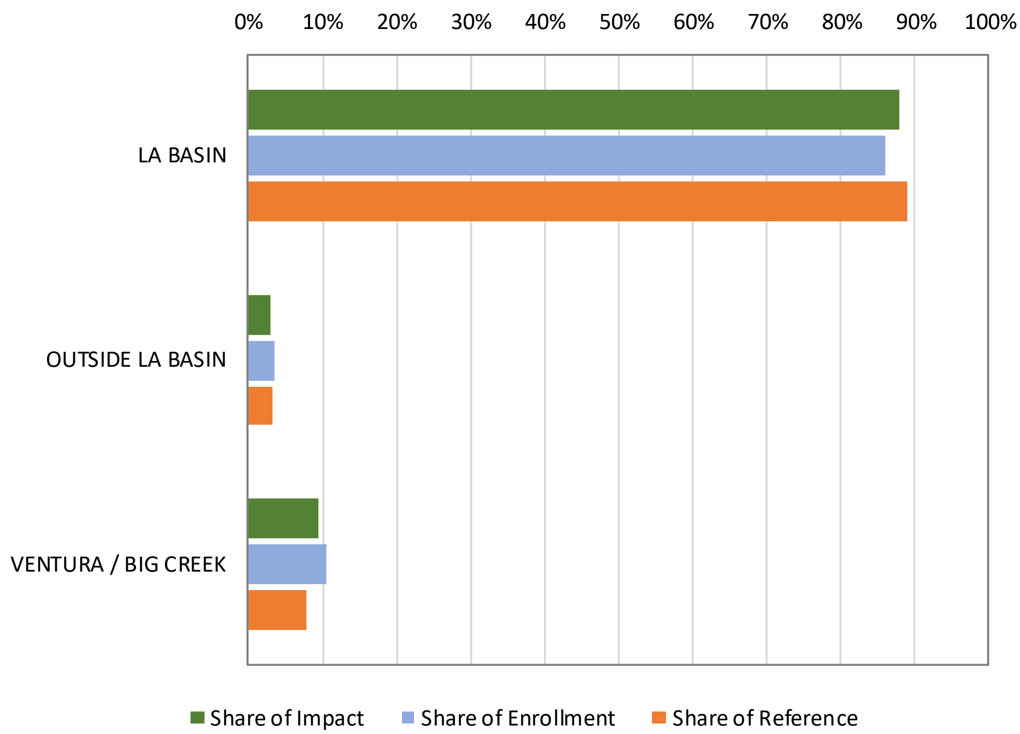
As one might expect, enrollments are concentrated in the LA Basin comprising about 86% of the participants. The largest estimated load impact, 6.2 MW, comes from the LA Basin, with impacts in other areas being substantially lower. However, each LCA experienced about the same percent impact (2%).

In Figure 4-17, we present the share of the total enrollment, impacts, and reference load by LCA.[34]

Table 4-18 SCE Large: Average Event-Hour Impacts by LCA on a Typical Event Day

LCA	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
LA Basin	1,890	380.4	6.2	2%	86.9
Outside LA Basin	79	13.8	0.2	2%	92.7
Ventura / Big Creek	232	32.8	0.7	2%	89.2

Figure 4-17 SCE Large: Contributions by LCA on a Typical Event Day



Results for Medium Customers (20 < x ≤ 200 kW)

This section summarizes results for all medium SCE program participants, defined as customers with maximum demand greater than 20 kW but less than or equal to 200 kW. The results are presented in the same format as the previous section. Again, results for dually enrolled customers, AutoDR customers, and for those that were notified (vs. not notified) are presented in subsequent sub-sections.

Figure 4-18 presents the average event-hour ex post load impacts for each individual event day for all of SCE's medium CPP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

[34] Note that the total share of impacts is based upon the absolute value of the impacts in order to properly normalize for both positive and negative impacts when they are present.

These results indicate that medium CPP participants had statistically significant load increases on six of the twelve event days (ranging from 0.3 MW to 1.0 MW) the remaining six event days were insignificant. Furthermore, the point estimates at the per customer level are very close to zero with the ranging from -0.00 to -0.08 kWh. We suspect that the negative impacts indicate that the model may not be able to accurately quantify the impacts, either because of omitted variable bias, or simply because of the variability. AEG believes that these impacts suggest that the medium customers are not responding to CPP events and that their true impacts are in fact zero.[35]

Figure 4-18 SCE Medium all Participants: Average Event-Hour Impacts by Event

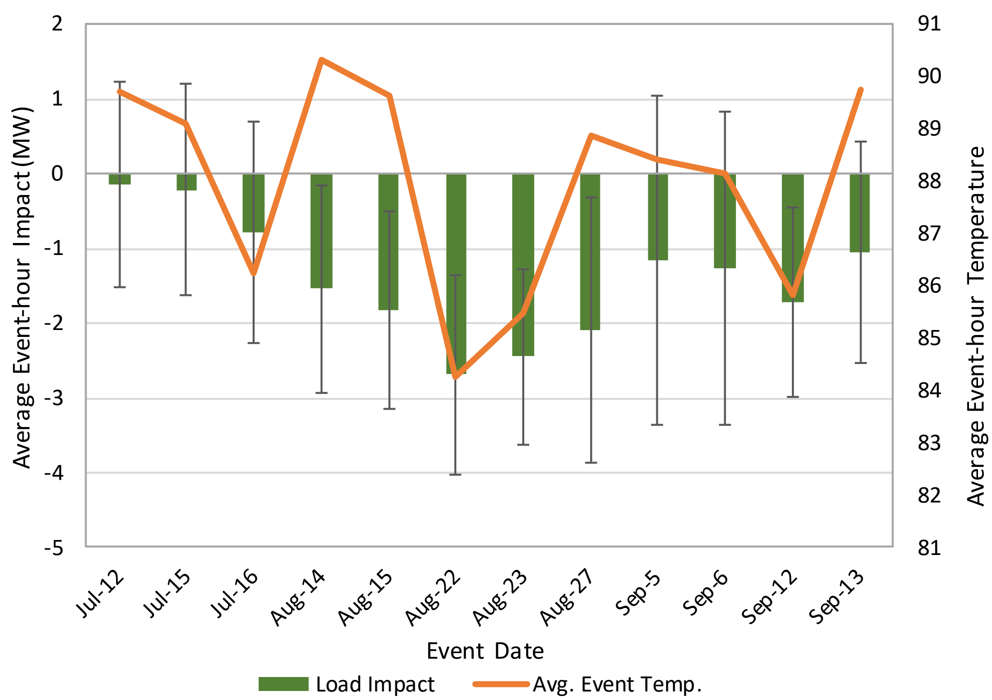


Table 4-19 summarizes the event-hour impacts on each event, including the number of participants enrolled during each event, the aggregate and per-customer reference load and load impacts, the percent impact, and the average temperature. Insignificant point estimates appear in red font.

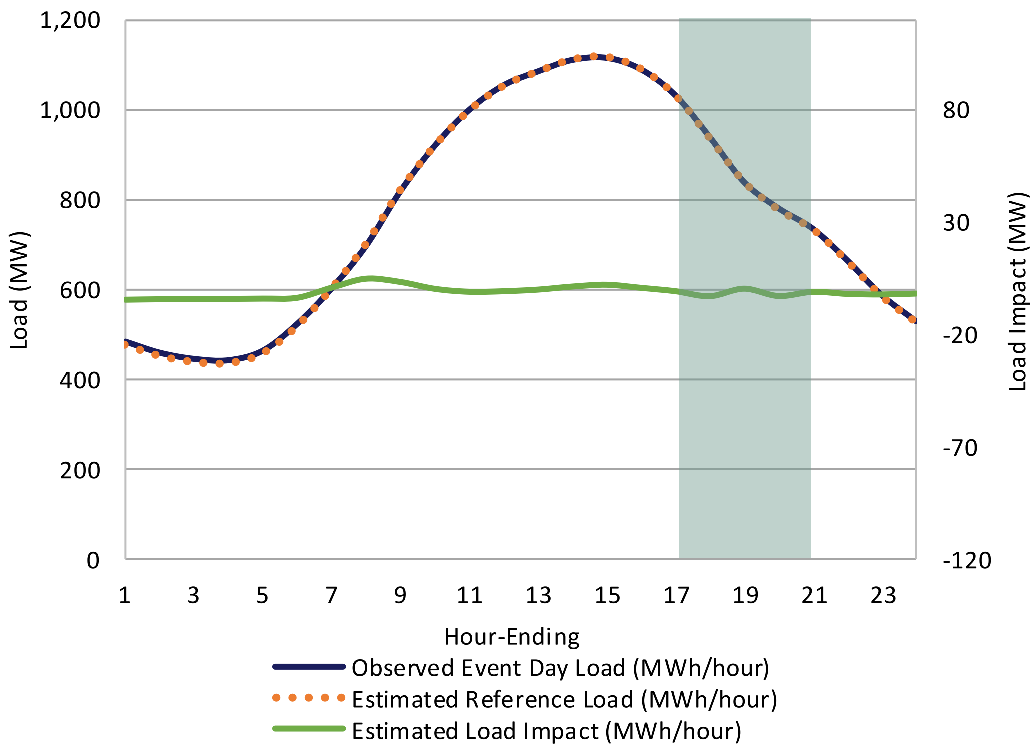
[35] The individual hourly impacts are both positive and negative with the negatives being slightly larger than the positives resulting in a negative impact on average.

Table 4-19 SCE Medium all Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
7/12/2019	35,399	856.6	(0.2)	24.2	(0.0)	0.0%	89.7
7/15/2019	35,399	864.3	(0.2)	24.4	(0.0)	0.0%	89.1
7/16/2019	35,399	849.0	(0.8)	24.0	(0.0)	-0.1%	86.2
8/14/2019	34,997	879.5	(1.5)	25.1	(0.0)	-0.2%	90.3
8/15/2019	34,996	863.8	(1.8)	24.7	(0.1)	-0.2%	89.6
8/22/2019	34,997	816.2	(2.7)	23.3	(0.1)	-0.3%	84.3
8/23/2019	34,996	817.2	(2.4)	23.3	(0.1)	-0.3%	85.5
8/27/2019	34,997	884.1	(2.1)	25.3	(0.1)	-0.2%	88.9
9/5/2019	34,593	907.4	(1.2)	26.2	(0.0)	-0.1%	88.4
9/6/2019	34,594	892.1	(1.3)	25.8	(0.0)	-0.1%	88.1
9/12/2019	34,594	840.4	(1.7)	24.3	(0.0)	-0.2%	85.8
9/13/2019	34,594	870.9	(1.0)	25.2	(0.0)	-0.1%	89.8
Typical Event Day	**34,963**	**861.8**	**(1.4)**	**24.6**	**(0.0)**	**-0.2%**	**88.0**

Figure 4-19 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. Note that there is no visible difference between the actual observed load and the reference load again suggesting that the impacts for medium customers are likely to be zero.

Figure 4-19 SCE Medium all Participants: Hourly Typical Event Day Load Impacts



SCE Medium: by Industry

Next, we look at load impacts for SCE's medium customers by industry group. Table 4-20 summarizes aggregate event-hour results for the typical event day for eight industry groups, including the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load, and the average event temperature. Many of the industry-level impacts are statistically insignificant, however the point estimates are shown below for informative purposes. Insignificant estimates are highlighted in red font. Enrollments are concentrated in the Offices, Hotels, Finance & Services; Wholesale, Transport, other utilities; and Manufacturing groups. These three groups represent 48% of the total enrolled customers.

Table 4-20 SCE Medium: Average Event-Hour Impacts by Industry on a Typical Event Day

Industry	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
1. Agriculture, Mining & Construction	1,024	15.7	0.1	0.7%	88.9
2. Manufacturing	3,561	76.1	0.9	1.2%	88.4
3. Wholesale, Transport, other utilities	3,461	77.6	0.4	0.6%	90.0
4. Retail stores	4,717	144.8	(0.7)	-0.5%	87.8
5. Offices, Hotels, Finance, Services	17,108	443.6	(2.1)	-0.5%	86.6
6. Schools	940	22.3	0.2	0.9%	87.2
7. Institutional/Government	3,923	77.7	(0.3)	-0.4%	88.9
8. Other or unknown	229	4.1	(0.0)	-0.8%	85.2

SCE Medium: by LCA

Finally, we present the load impacts for SCE's medium customers by LCA. Table 4-21 summarizes aggregate event-hour results for the typical event day for SCE's three LCAs. The tables include the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load and the average event temperature. As one might expect, enrollments are concentrated in the LA Basin with 82% of the participants coming from that area.

Table 4-21 SCE Medium: Average Event-Hour Impacts by LCA on a Typical Event Day

LCA	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
LA Basin	29,636	734.6	(1.2)	0%	86.1
Outside LA Basin	1,370	34.6	(0.1)	0%	90.1
Ventura / Big Creek	3,957	92.7	(0.1)	0%	88.2

Results for Small Customers (< 20 kW)

This section summarizes results for all small SCE program participants, defined as customers with maximum demand equal to less than 20 kW. The results are presented in the same format as the previous section. Again, results for dually enrolled customers, AutoDR customers, and for those that were notified (vs. not notified) are presented in subsequent sub-sections.

Figure 4-20 presents the average event-hour ex post load impacts for each individual event day for all of SCE's small CPP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

The small CPP participants did not have any statistically significant changes in load across the twelve event days. The per-customer point estimates are extremely small, approximately -0.003 kWh. Given that there were no significant impacts in the small group we must conclude that the small customers are not responding to CPP events.

Figure 4-20 SCE Small all Participants: Average Event-Hour Impacts by Event

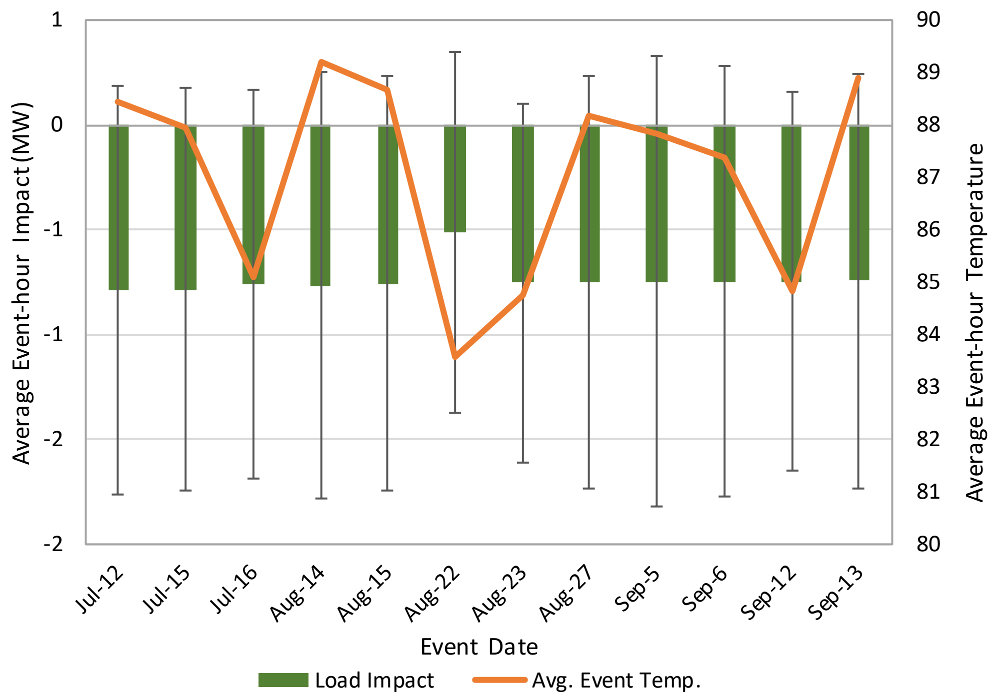


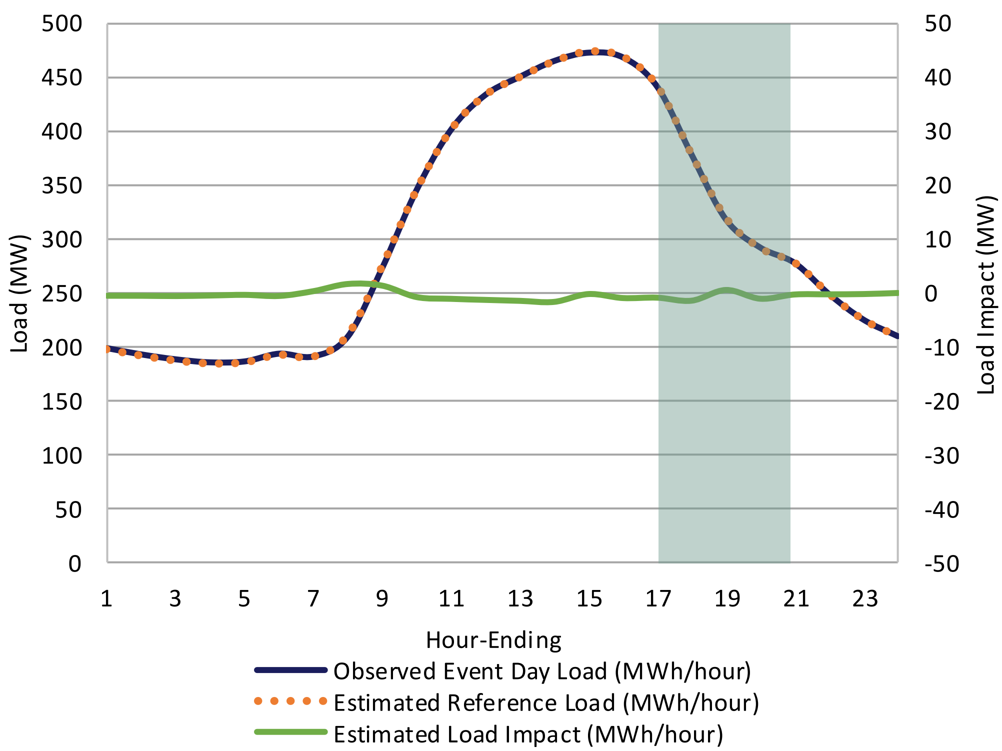
Table 4-22 summarizes the event-hour impacts on each event including the number of participants enrolled during each event, the aggregate and per customer reference load and load impacts, the percent impact, and the average temperature. Insignificant point estimates are indicated with red font.

Table 4-22 SCE Small all Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
7/12/2019	237,452	334.9	(0.8)	1.4	(0.0)	-0.2%	88.4
7/15/2019	237,452	334.4	(0.8)	1.4	(0.0)	-0.2%	87.9
7/16/2019	237,452	334.7	(0.8)	1.4	(0.0)	-0.2%	85.1
8/14/2019	235,371	350.9	(0.8)	1.5	(0.0)	-0.2%	89.2
8/15/2019	235,371	346.9	(0.8)	1.5	(0.0)	-0.2%	88.7
8/22/2019	235,371	328.9	(0.5)	1.4	(0.0)	-0.2%	83.6
8/23/2019	235,371	325.4	(0.8)	1.4	(0.0)	-0.2%	84.7
8/27/2019	235,371	353.1	(0.8)	1.5	(0.0)	-0.2%	88.2
9/5/2019	233,355	352.0	(0.8)	1.5	(0.0)	-0.2%	87.8
9/6/2019	233,355	345.6	(0.8)	1.5	(0.0)	-0.2%	87.4
9/12/2019	233,355	335.1	(0.7)	1.4	(0.0)	-0.2%	84.8
9/13/2019	233,355	343.1	(0.7)	1.5	(0.0)	-0.2%	88.9
Typical Event Day	**235,219**	**340.4**	**(0.7)**	**1.4**	**(0.0)**	**-0.2%**	**87.1**

Figure 4-21 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. Again, there is no evidence of load impact during the event window.

Figure 4-21 SCE Small all Participants: Hourly Typical Event Day Load Impacts



SCE Small: by Industry

Next, we look at load impacts for SCE's small customers by industry group. Table 4-23 summarizes aggregate event-hour results for the typical event day for eight industry groups, including the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load, and the average event temperature. Enrollments are concentrated in the Offices, Hotels, Finance and Services group. This group represents about 45% of the total enrolled customers. Several of the industries show negative impacts.

Table 4-23 SCE Small: Average Event-Hour Impacts by Industry on a Typical Event Day

Industry	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
1. Agriculture, Mining & Construction	10,565	13.2	0.3	2.3%	90.0
2. Manufacturing	9,129	12.3	0.2	1.8%	86.0
3. Wholesale, Transport, other utilities	14,745	19.8	(0.4)	-1.9%	88.4
4. Retail stores	18,968	52.9	(0.2)	-0.3%	87.2
5. Offices, Hotels, Finance, Services	107,379	153.1	0.4	0.3%	86.9
6. Schools	3,339	7.5	(0.1)	-1.2%	85.9
7. Institutional/Government	41,740	64.4	(1.1)	-1.7%	87.8
8. Other or unknown	29,355	17.2	0.1	0.6%	84.2

SCE Small: by LCA

Finally, we present the load impacts for SCE's small customers by LCA. Table 4-24 summarizes aggregate event-hour results for the typical event day for SCE's three LCAs. The tables include the number of enrolled customers, the reference and observed loads, the estimated load impacts as a percentage of the reference load and the average event temperature. None of the impacts are statistically significant. As one might expect enrollments are concentrated to the LA Basin, with about 83% of the participants coming from there.

Table 4-24 SCE Small: Average Event-Hour Impacts by LCA on a Typical Event Day

LCA	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Avg. Event Temp.
LA Basin	194,287	283.3	(0.6)	0%	84.1
Outside LA Basin	9,327	13.0	(0.1)	0%	90.5
Ventura / Big Creek	31,605	44.2	(0.1)	0%	86.6

Dually Enrolled Customers

Next, we present the impacts for SCE's dually enrolled customers. On a typical event day, a total of 108 customers were dually enrolled in either SCE's Capacity Bidding Program (CBP) or Base Interruptible Program (BIP). These customers demonstrate consistent positive impacts ranging from [redacted], however none of the impacts were found to be statistically significant.

Figure 4-22 presents the average event-hour ex-post load impacts for each individual event day for SCE's dually enrolled participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

Figure 4-22 SCE Dually-Enrolled Participants: Average Event-Hour Impacts by Event

Associated Table 4-25, on the following page, presents both the aggregate and per customer impacts, the percent impacts, the number of participants enrolled, and the temperature on each day.

Table 4-25 SCE Dually Enrolled Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
7/12/2019	109	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	92.1
7/15/2019	110	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	90.8
7/16/2019	110	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	87.7
8/14/2019	109	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	92.2
8/15/2019	107	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	90.9
8/22/2019	109	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	84.6
8/23/2019	107	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	86.6
8/27/2019	109	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	89.3
9/5/2019	107	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	90.1
9/6/2019	107	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	89.6
9/12/2019	108	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	87.9
9/13/2019	108	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	91.8
Typical Event Day	**108**	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	**89.5**

Figure 4-23 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day. Notice that impacts outside the event window are very small relative the event window impacts indicating a consistent load reduction without shifting of load into non-event hours.

Figure 4-23 SCE Dually Enrolled Participants: Hourly Typical Event Day Load Impacts

[redacted]

Automated Demand Response Customers

Next, we present the impacts for SCE's Automated Demand Response (AutoDR) customers. SCE's AutoDR customers have load reduction equipment installed at their facilities which automates their response during events. On a typical event day, a total of 88 customers were participating in the AutoDR program. These customers demonstrate consistent positive impacts ranging from [redacted]. Unfortunately, none of the impacts were statistically significant.

Figure 4-24 presents the average event-hour ex-post load impacts for each individual event day for SCE's AutoDR CPP participants. The green bars indicate the magnitude of the aggregate load impact and the black bands correspond to 90 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by the participants during the event hours.

Figure 4-24 SCE AutoDR Participants: Average Event-Hour Impacts by Event

[redacted]

Table 4-26 presents both the aggregate and per-customer impacts, the percent impacts, the number of participants enrolled, and the temperature on each day.

Table 4-26 SCE AutoDR Participants: Average Event-Hour Impacts by Event

Event Date	# Enrolled	Aggregate (MW)		Per-Customer (kW)		% Load Impact	Avg. Event Temp.
		Ref. Load	Load Impact	Ref. Load	Load Impact		
7/12/2019	88	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	91.5
7/15/2019	89	18.1	0.0	202.9	0.3	0.1%	90.1
7/16/2019	89	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	87.0
8/14/2019	88	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	91.2
8/15/2019	87	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	90.0
8/22/2019	88	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	84.1
8/23/2019	86	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	85.8
8/27/2019	88	19.5	0.0	221.3	0.5	0.2%	88.6
9/5/2019	86	18.5	0.1	215.5	0.6	0.3%	89.2
9/6/2019	87	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	89.1
9/12/2019	87	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	87.2
9/13/2019	87	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	91.0
Typical Event Day	**88**	**18.6**	**0.0**	**212.5**	**0.5**	**0.3%**	**88.7**

Figure 4-25 shows the aggregate hourly reference loads, observed loads, and estimated load impacts on the typical event day.

Figure 4-25 SCE AutoDR Participants: Hourly Typical Event Day Load Impacts

Notified vs. Non-Notified Customers

Participants on SCE's CPP Rate are not required to receive event notification. Customers that do not receive notification probably do not know that an event is occurring and would therefore find it difficult to respond proactively to events. Customers can receive day-ahead notifications for events by setting up their account to receive alerts either by phone, email, or by text message.

Table 4-27 and Table 4-28 present the percentage of service accounts receiving notification by size group and the per customer impacts by size group, and notification, on a typical event day, respectively.

In looking at Table 4-27, we note that relative to last year the percentage of service accounts receiving notification decreased from 65% to 55%. This decrease is attributable to the drastic increase in the number of small and medium participants that joined the program during the default. And, relative to 87% last year, 100% of the load impacts come from customers are receiving notification.

Table 4-27 Percent of Service Accounts Receiving Notification, by Size Group: Typical Event Day

Size Group	SCE % Notified
Small < 20 kW	54%
Medium 20 kW ≤ x < 200 kW	61%
Large ≥ 200 kW	89%
Total	**55%**

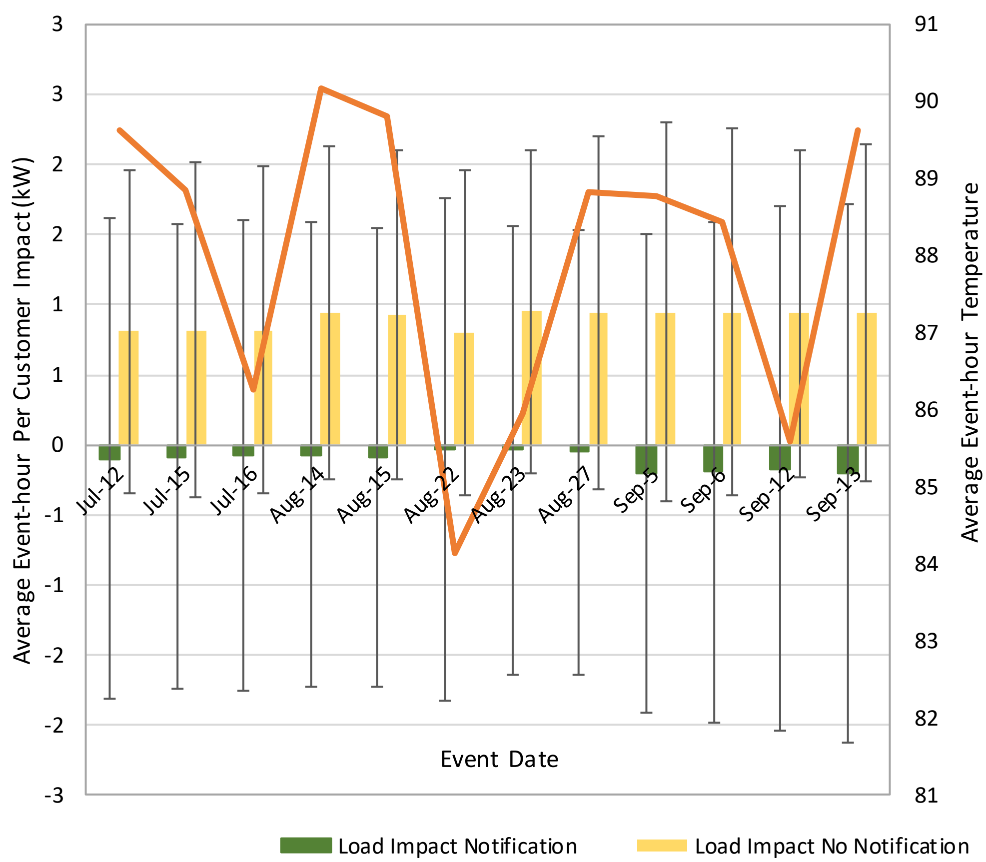
When we compare the difference in per customer impacts by size, in Table 4-28 we can see that the key difference, at a per customer level, comes from the large customers. The small and medium customers show negligible reductions regardless of whether they are notified of events suggesting that for these groups, notifications and/or increasing notifications will not improve the impacts.

Table 4-28 Per Customer Impacts by Size Group and Notification: Typical Event Day

Notification	Size group	# Customers	Per-Customer Ref. Load (kW)	Per-Customer Load Impact (kW)	Aggregate Load Impact (MW)
No	0 to 20 kW	107,215	1.3	0.0	0.4
	20 to 199.99 kW	13,300	24.0	(0.1)	(0.8)
	200 kW and above	226	159.3	(0.4)	(0.1)
	All	**120,742**	**4.1**	**(0.0)**	**(0.4)**
Yes	0 to 20 kW	128,004	1.5	(0.0)	(1.2)
	20 to 199.99 kW	21,663	25.1	(0.0)	(0.7)
	200 kW and above	1,974	198.0	3.6	7.1
	All	**151,641**	**7.5**	**0.0**	**5.3**

In Figure 4-26 below we compare the average event hour impacts on each event day, by notification, for the large customers PY2019. Large customers who are notified of events provide much more load reduction on average, than those that are not notified of events while those that are not notified do not provide any measurable load reductions.

Figure 4-26 Comparison Average Event-Hour of Impacts by Level of Communication: Large Customers



SDG&E

This section presents the analysis of TOU Period Changes for SDG&E. Ex-post impacts are not included in this report since SDG&E did not call any events in PY2019.

SDG&E Analysis of TOU Period Changes

As of December 2017, SDG&E implemented new TOU periods for all its customers and moved the month of May into the Winter season. To estimate the impact of these changes, we performed a simple regression analysis and examined changes in consumption in each hour from the previous TOU periods to the current TOU periods. The changes were as follows:

- The underlying TOU period (on event and non-event days) moved from 11 AM – 6 PM to 4-9 PM.
- The CPP event window moved from 11 AM – 6 PM to 2-6 PM.

In PY2018, we looked for changes in consumption on both non-event days and on event days in both the large and medium segments. The analysis of non-event days did not show any material changes in consumption resulting from the changes in the TOU window. However, the analysis of event days did suggest that customers are responding to the new CPP event window.

In PY2019, we performed a similar analysis to test if any material changes have resulted during the second year of period change implementation. Note that SDG&E did not call any events in PY2019, so we were only able to perform the second-year analysis for non-event days. Also note that we only performed the analysis on PY2019 CPP customers, so the program populations in both analyses are not entirely the same.

Figure 4-27 and Figure 4-28 show the comparison of the PY2018 and PY2019 results for Large and Medium customers, respectively. We show the model's prediction of 2018 and 2019 average non-event day consumption under the new TOU window (in blue) vs. the old TOU window (in yellow). The orange dotted line represents the difference between the two. The blue shaded region highlights the new TOU period 4-9 PM.

The second-year analysis of non-event days did suggest that customers are responding to the changes in the TOU window. While the PY2019 participant population is notably smaller than PY2018, on average, these key observations suggest that the PY2019 participant population have changed their consumption patterns in response to the TOU window change:

- The change in consumption is highest in HE17 (4-5 PM) for Large customers and HE18 (5-6 PM) for Medium customers. Both hours are within the new TOU window. The Large customers can be seen maintaining this change in consumption throughout the new TOU window despite having smaller impacts in HE20-HE21 (7-9 PM). The Medium customers, however, only show this same pattern in the early hours of the new TOU window HE17-HE19 (4-7 PM).
- Interestingly, the analysis also detects a smaller change in consumption patterns starting in HE11 (10 AM) for both groups. Given that the old TOU window previously started at 11 AM, this suggests that the PY2019 participant population is still exhibiting some awareness of the old TOU window.

Figure 4-27 Changes in Consumption Large Customers: New vs. Old TOU Window, PY2018 v. PY2019

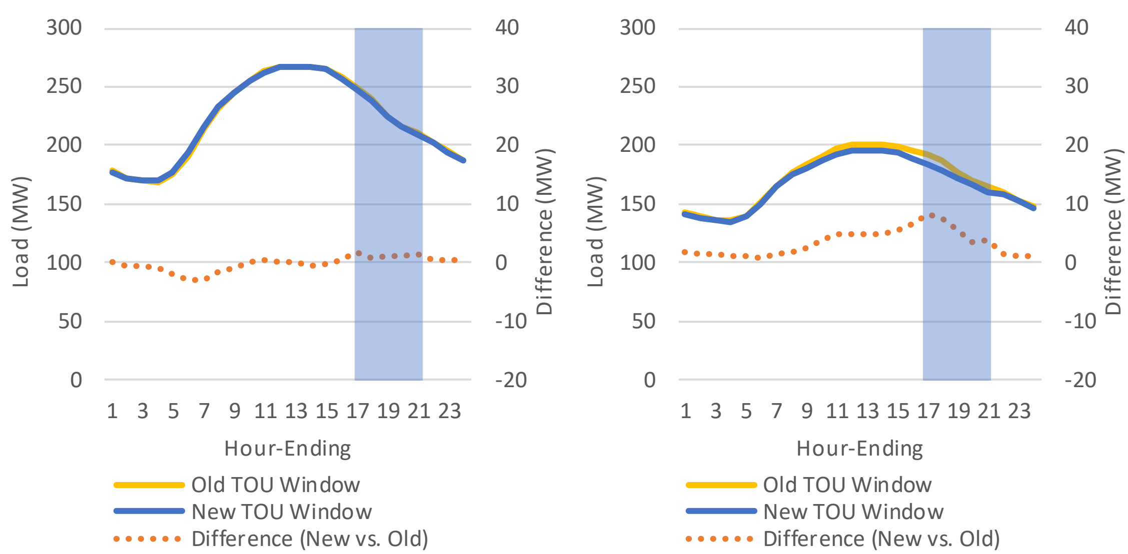
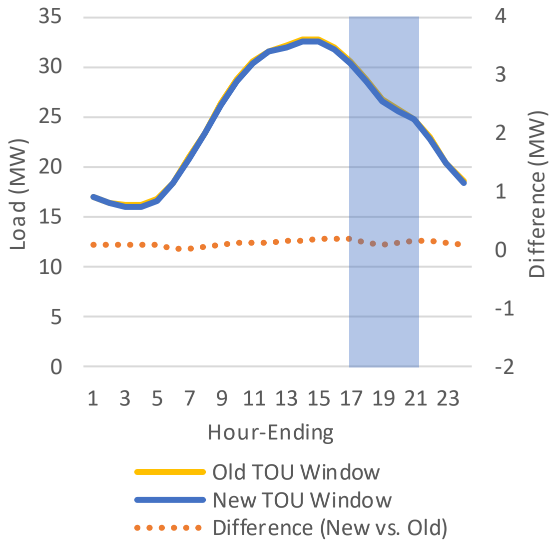
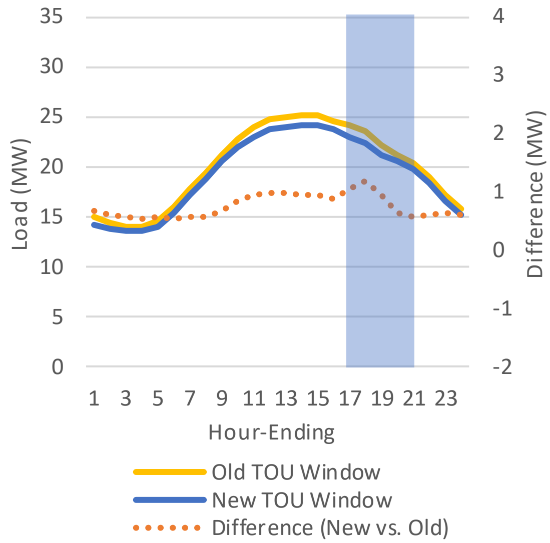


Figure 4-28 Changes in Consumption Medium Customers: New vs. Old TOU Window, PY2018 v. PY2019





5

EX-ANTE RESULTS

This section presents the ex-ante results, which include the load impact forecasts for the 1-in-2 and 1-in-10 weather conditions for each utility and product. For each utility we first present a summary of the enrollment forecast and load impacts. Then, we discuss the relationship between ex-post and ex-ante estimates.

It should be noted that in 2018 the resource adequacy (RA) window shifted to 4-9 PM instead of 2-6 PM. SCE has aligned their CPP event window with the RA window. However, both PG&E's and SDG&E's event windows will remain unchanged, which means that the PDP and CPP programs are only available during the first two hours of the RA window while all other hours are non-event hours. This results in significantly lower (and sometimes even negative) impacts within the RA window.

PG&E

Enrollment and Load Impact Summary

Table 5-1 summarizes the average event-hour load impact forecasts for non-residential PDP participants on a typical events day in 2020. 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. As we noted above, because of the differences between the actual program availability (2-6 PM) and the RA window (4-9 PM) the ex-ante impacts are much smaller than the ex-post impacts, and for some subgroups can be either positive or negative. As we noted in the ex-post analysis, the largest impacts come from the large group, even though they have the fewest participants. The small and medium groups show either zero or negative impacts.

Table 5-1 PG&E Typical Event Enrollment and Impacts by Size: 2020

Size	# of Accts	Aggregate Impact (MW)				Per Customer Impact (kW)			
		Utility Peak		CAISO Peak		Utility Peak		CAISO Peak	
		1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Large	1,326	5.1	5.0	5.0	5.0	4.0	3.9	4.0	4.0
Medium	24,302	-1.2	-1.5	-0.4	-1.2	0.0	-0.1	0.0	-0.1
Small	87,561	-0.5	-0.7	-0.3	-0.6	0.0	0.0	0.0	0.0
Total PDP	**125,513**	**3.3**	**2.7**	**4.3**	**3.3**	**0.0**	**0.0**	**0.0**	**0.0**

In Table 5-2 below we also present the program level impacts by month for a PG&E 1-in-2 weather year for 2020, 2021, and 2030. Enrollment is consistent across months with some fluctuations in spring and fall. Impacts are lowest in the winter months, highest in the shoulder months, and moderate in the summer months. Winter impacts are intentionally conservative using a derating factor of 50% while impacts dip in the summer during the hottest months because of larger negative impacts in the post event window.

Table 5-2 PG&E Monthly Program Level Enrollment and Impacts for Selected Years: PG&E 1-in-2

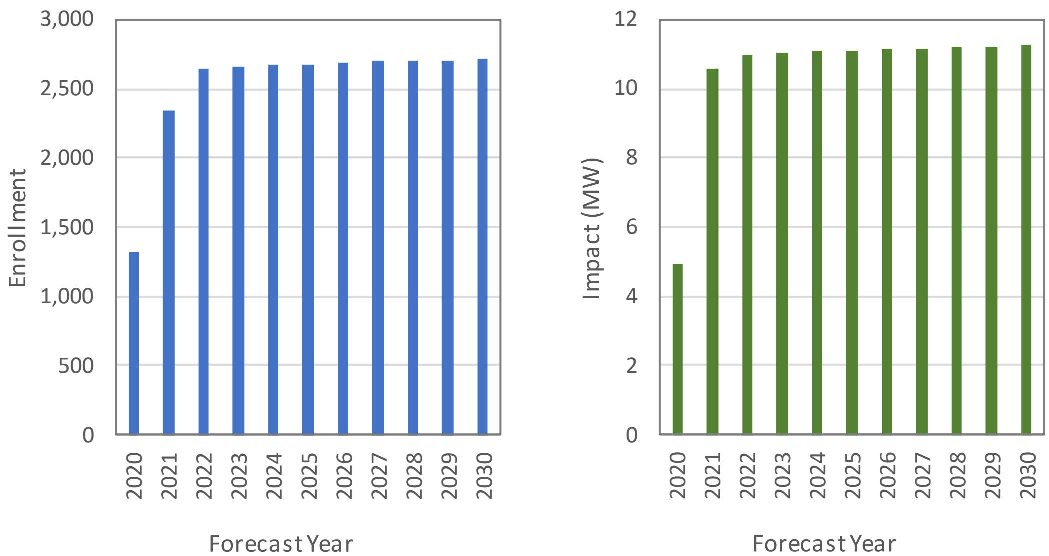
	2020		2021		2030	
	Enrollment	**Impact (MW)**	**Enrollment**	**Impact (MW)**	**Enrollment**	**Impact (MW)**
January	113,117	2.0	162,703	2.5	183,788	4.8
February	113,117	2.0	162,703	2.5	183,788	4.8
March	113,117	2.0	163,729	4.7	183,793	4.8
April	113,117	2.0	163,729	4.7	183,793	4.8
May	113,117	5.0	163,729	10.6	183,793	11.3
June	113,117	3.2	163,729	8.2	183,793	8.2
July	113,117	2.4	163,729	7.0	183,793	6.7
August	113,117	3.4	163,729	8.4	183,793	8.5
September	113,117	4.1	163,729	9.3	183,793	9.6
October	113,117	6.2	163,729	12.9	183,793	13.7
November	162,672	2.5	158,381	4.8	185,080	4.8
December	162,672	2.5	158,381	4.8	185,080	4.8

In the following sections, we present the enrollment and MW forecast, the Typical Event day load shape, and the total share of impacts by LCA for each of the three size groups under the PG&E 1-in-2 weather scenario.

Large Customers (≥ 200 kW)

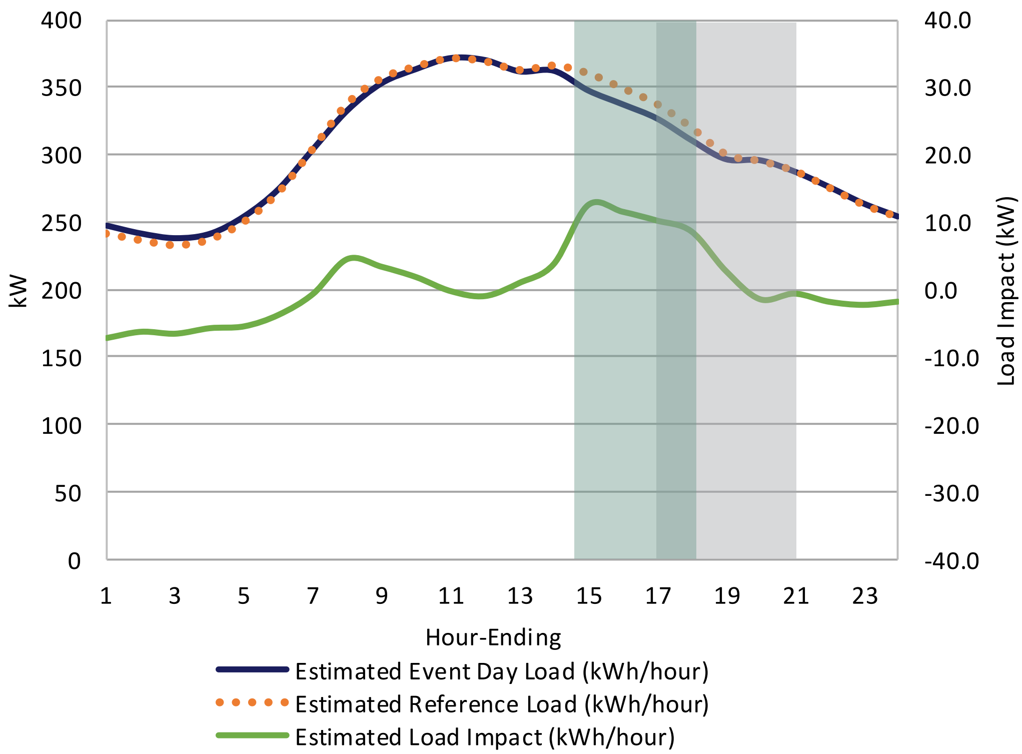
In Figure 5-1 we present the enrollment forecast and the ex-ante impact forecast side-by-side. The enrollment forecast shows a sharp increase in participants from about 1,300 in 2020 to just over 2,600 by 2022 thereafter increasing slightly throughout the forecast horizon. This gain in participation is expected to come from the default schedule being resumed in 2020. Similarly, the ex-ante MW forecast increases from about 3.5 MW in 2020, to 7.4 MW in 2022, and then increases to 7.6 MW by 2030.

Figure 5-1 PG&E Large Enrollment and Impact Forecast PG&E 1-in-2: 2020 to 2030



In Figure 5-2 we present the typical event day load shape for PG&E's large participants during forecast year 2020. In the load shape graph, the blue line represents the estimated event day load, the orange line represents the reference load, or what the participants would consume without an event, and the green line is the estimated load impact, or the difference between the two. In addition, we have added a grey shaded area to represent the RA window, and a green shaded area to represent the CPP availability window. CPP impacts are only available during two hours of RA window, and RA impacts are further reduced by increases in load during the post event period.

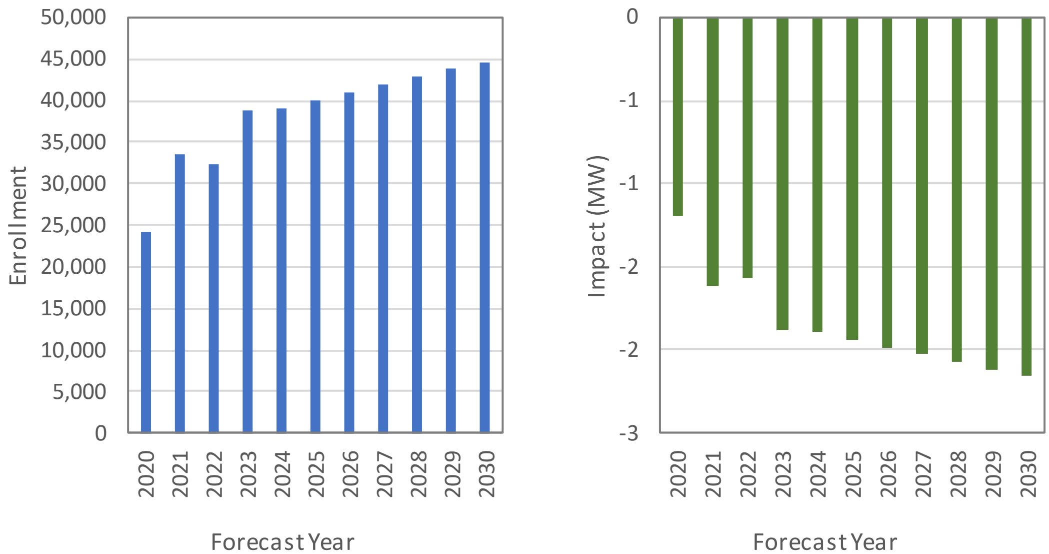
Figure 5-2 PG&E Large Typical Event Day Load Shape PG&E 1-in-2: 2020



Medium Customers (20 ≤ x < 200 kW)

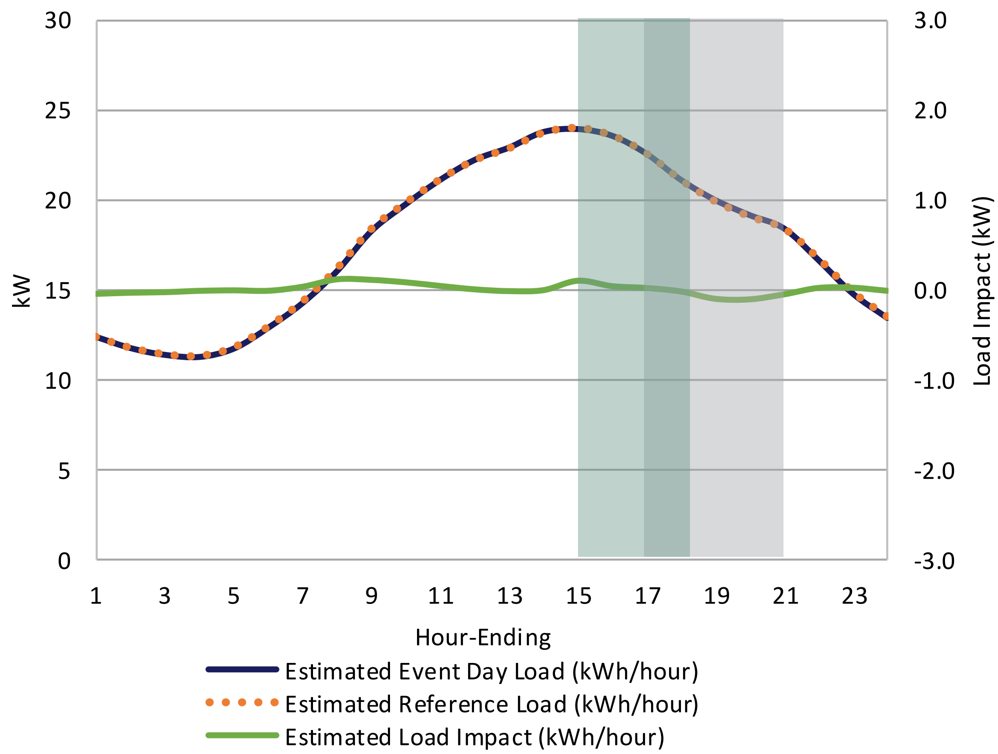
In Figure 5-3, we present the enrollment forecast and the ex-ante impact forecast side-by-side. The enrollment forecast shows an increase in participants from just shy of 25,000 in 2020 to nearly 35,000 in 2021 and ultimately reaching nearly 45,000 by 2030. This increase in participation is consistent with the default schedule. PG&E has suspended the PDP default until the transition to new Time-of-Use (TOU) period is implemented in 2019-2020, so that the new customers are not subject to the PDP default right before or even simultaneously with the new TOU period. For medium participants, the ex-ante forecast is actually negative as a result of small positive impacts in the last two hours of the CPP window, and larger negative impacts in the hours directly after the event, as 3 out of the 5 hours in RA window are non-event hours. The ex-ante MW forecast decreases from -1.2 MW in 2020 to -2.2 MW in 2030.

Figure 5-3 PG&E Medium Enrollment and Impact Forecast PG&E 1-in-2: 2020 - 2030



In Figure 5-4, we present the typical event day load shape for PG&E's medium participants during forecast year 2020. In the load shape graph, the blue line represents the estimated event day load, the orange line represents the reference load, or what the participants would consume without an event, and the green line is the estimated load impact, or the difference between the two. In addition, we have added a grey shaded area to represent the RA window, and a green shaded area to represent the CPP availability window. CPP impacts are only available during two hours of RA window, and RA impacts are further reduced by increases in load during the post event period.

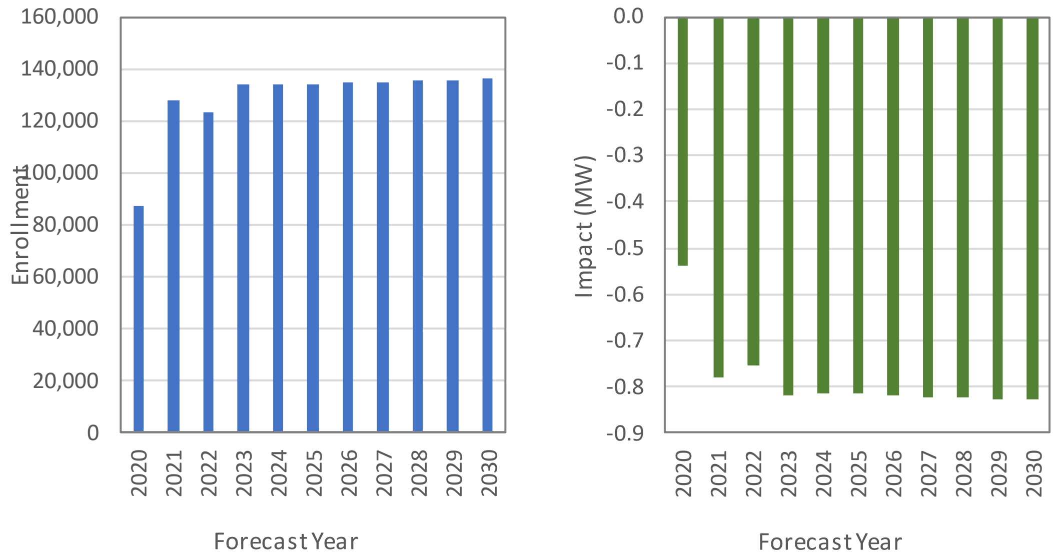
Figure 5-4 PG&E Medium Typical Event Day Load Shape PG&E 1-in-2: 2020



Small SMB Customers (< 20 kW)

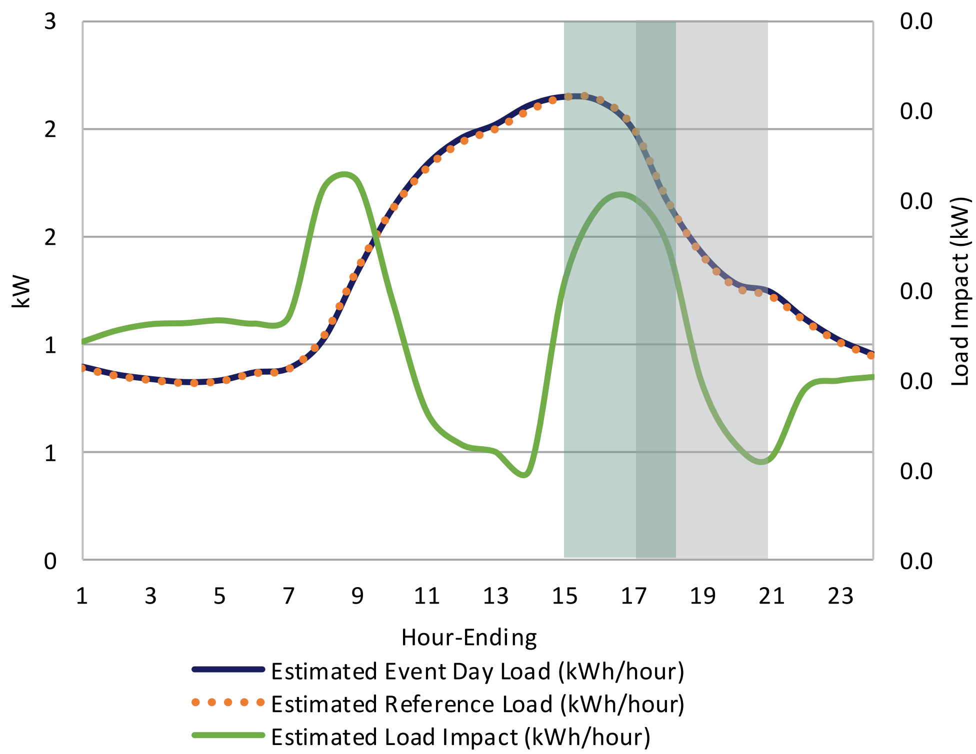
In Figure 5-5 we present the enrollment forecast and the ex-ante impact forecast side-by-side. The enrollment forecast shows an increase in participants from about 88,000 in 2020 to slightly above 127,000 in 2021, decreasing slightly to 123,000 in 2022 and subsequently holding steady through 2030. This increase in participation is consistent with the default schedule. PG&E has suspended the PDP default until the transition to new Time-of-use (TOU) period is implemented in 2019-2020, so that the new customers are not subject to the PDP default right before or even simultaneously with the new TOU period. For small participants the ex-ante forecast is actually negative as a result of small positive impacts in the last two hours of the CPP window, and larger negative impacts in the hours directly after the event, as 3 out of the 5 hours in RA window are non-event hours.

Figure 5-5 PG&E Small Enrollment and Impact Forecast: 2020 - 2030



In Figure 5-6 we present the typical event day load shape for PG&E's small participants during forecast year 2020. In the load shape graph, the blue line represents the estimated event day load, the orange line represents the reference load, or what the participants would consume without an event, and the green line is the estimated load impact, or the difference between the two. In addition, we have added a grey shaded area to represent the RA window, and a green shaded area to represent the CPP availability window. CPP impacts are only available during two hours of RA window, and RA impacts are further reduced by increases in load during the post event period.

Figure 5-6 PG&E Small Typical Event Day Load Shape PG&E 1-in-2: 2020



SCE

Enrollment and Load Impact Summary

Table 5-3 summarizes the average event-hour load impact forecasts for non-residential CPP participants on a typical event day in 2020. 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. As we noted in the ex-post analysis, the largest impacts come from the Large group, even though they have the fewest participants. As in the ex-post due to insignificant estimates the medium and small groups provide zero impact.

Table 5-3 SCE Typical Event Enrollment and Impacts by Size: 2020

Size	# of Accts	Aggregate Impact (MW)				Per Customer Impact (kW)			
		Utility Peak		CAISO Peak		Utility Peak		CAISO Peak	
		1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Large	2,525	8.0	7.7	8.0	7.8	3.2	3.1	3.2	3.1
Medium	30,298	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Small	219,658	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total CPP	**252,481**	**8.0**	**7.7**	**8.0**	**7.8**	**0.0**	**0.0**	**0.0**	**0.0**

In Table 5-4 below we also present the program level impacts by month for a SCE 1-in-2 weather year for 2020, 2021, and 2030. Enrollment is consistent across all months. Impacts are weather sensitive with the highest impacts occurring in October, and the lowest impacts occurring in December, January, February, and March.

Table 5-4 SCE Monthly Program Level Enrollment and Impacts for Selected Years: SCE 1-in-2

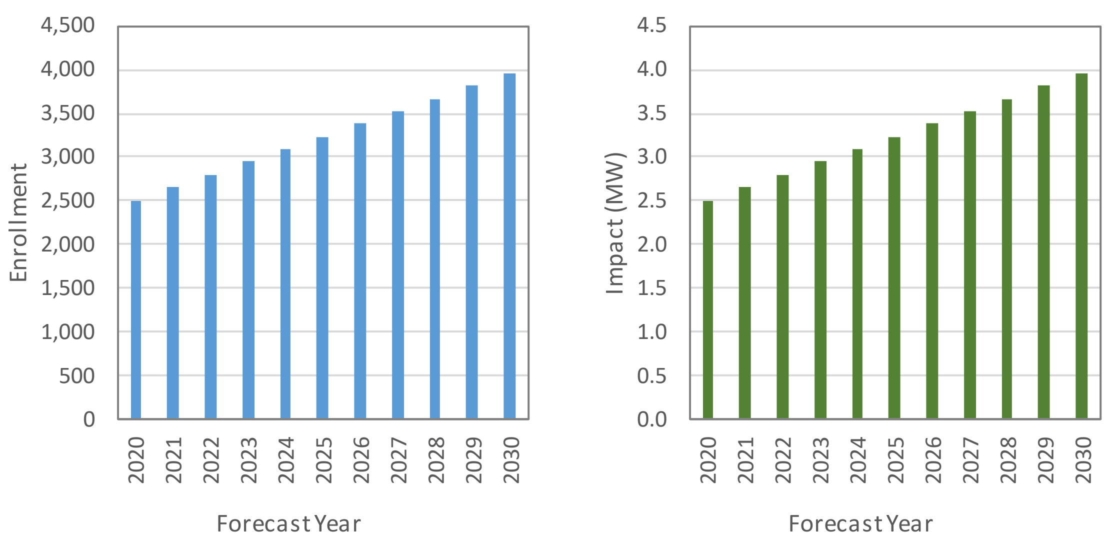
	2020		2021		2030	
	Enrollment	Impact (MW)	Enrollment	Impact (MW)	Enrollment	Impact (MW)
January	252,481	7.4	266,981	7.8	397,481	11.6
February	252,481	7.4	266,981	7.8	397,481	11.6
March	252,481	7.4	266,981	7.8	397,481	11.7
April	252,481	8.0	266,981	8.5	397,481	12.7
May	252,481	8.2	266,981	8.7	397,481	12.9
June	252,481	7.9	266,981	8.4	397,481	12.5
July	252,481	7.9	266,981	8.3	397,481	12.4
August	252,481	8.0	266,981	8.5	397,481	12.6
September	252,481	8.0	266,981	8.5	397,481	12.6
October	252,481	8.5	266,981	9.0	397,481	13.4
November	252,481	7.6	266,981	8.1	397,481	12.0
December	252,481	7.4	266,981	7.8	397,481	11.6

In the following sections, we present the enrollment and MW forecast, the typical event day load shape, and the total share of impacts by LCA for each of the three size groups for the SCE 1-in-2 weather scenario.

Large Customers (≥ 200 kW)

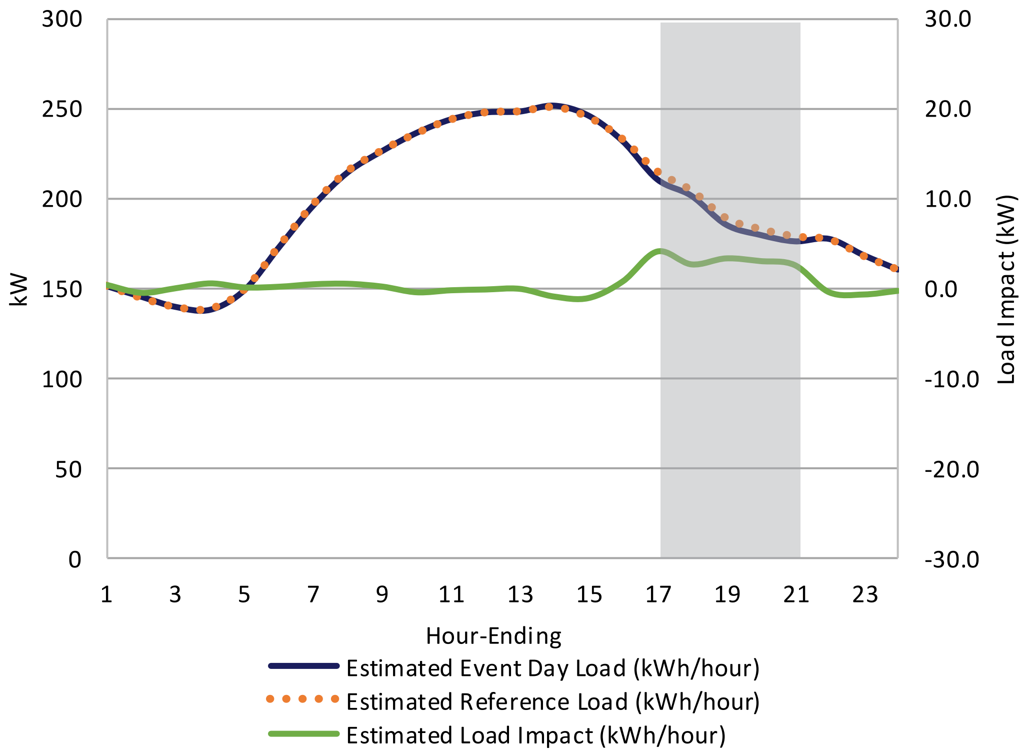
In Figure 5-7 we present the enrollment forecast and the ex-ante impact forecast side-by-side. The enrollment forecast shows a slow, steady, increase in participants from about 2,500 in 2020 to around 4,000 by 2030. This increase in participation is primarily from annual defaults. Similarly, the ex-ante MW forecast steadily increases from around 2.5 MW in 2020 to nearly 4 MW by 2030.

Figure 5-7 SCE Large Enrollment and Impact Forecast SCE 1-in-2: 2020 - 2030



In Figure 5-8, we present the typical event day load shape for SCE's large participants during forecast year 2020. In the load shape graph, the blue line represents the estimated event day load, the orange line represents the reference load, or what the participants would have consumed without an event, and the green line is the estimated load impact, or the difference between the two. The grey shaded area represents the RA window which is the same as SCE's event window.

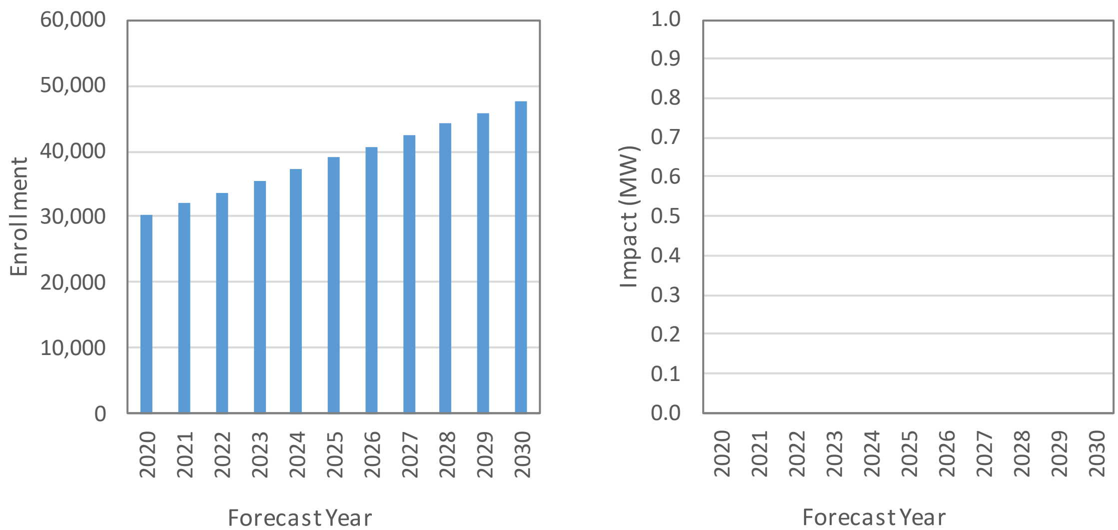
Figure 5-8 SCE Large Typical Event Day Load Shape SCE 1-in-2: 2020



Medium SMB Customers (20 ≤ x < 200 kW)

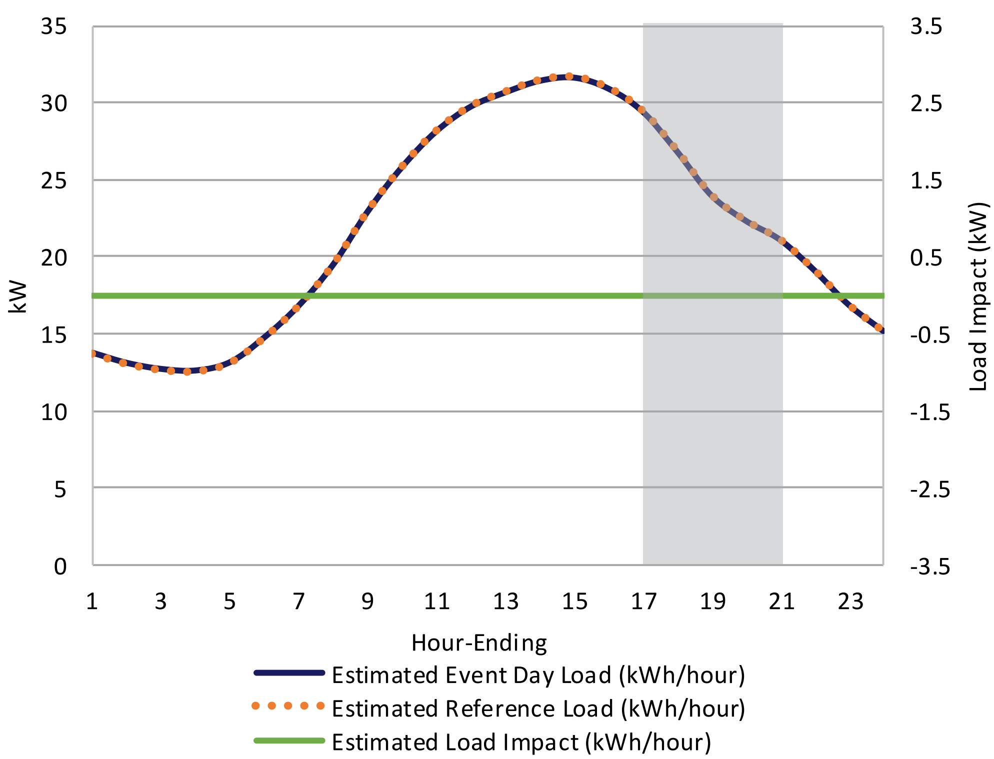
In Figure 5-9 we present the enrollment forecast and the ex-ante impact forecast side-by-side. The enrollment forecast shows a slow, steady, increase in participants from about 30,000 in 2020 to around 48,000 by 2030. This increase in participation is primarily from annual defaults. Given the insignificant impacts in the ex-post, ex-ante impacts are assumed to be zero throughout the forecast.

Figure 5-9 SCE Medium Enrollment and Impact Forecast SCE 1-in-2: 2020 - 2030



In Figure 5-10 we present the typical event day load shape for SCE's medium participants during forecast year 2020. In the load shape graph, the blue line represents the estimated event day load, the orange line represents the reference load, or what the participants would have consumed without an event, and the green line is the estimated load impact, or the difference between the two. The grey shaded area represents the RA window.

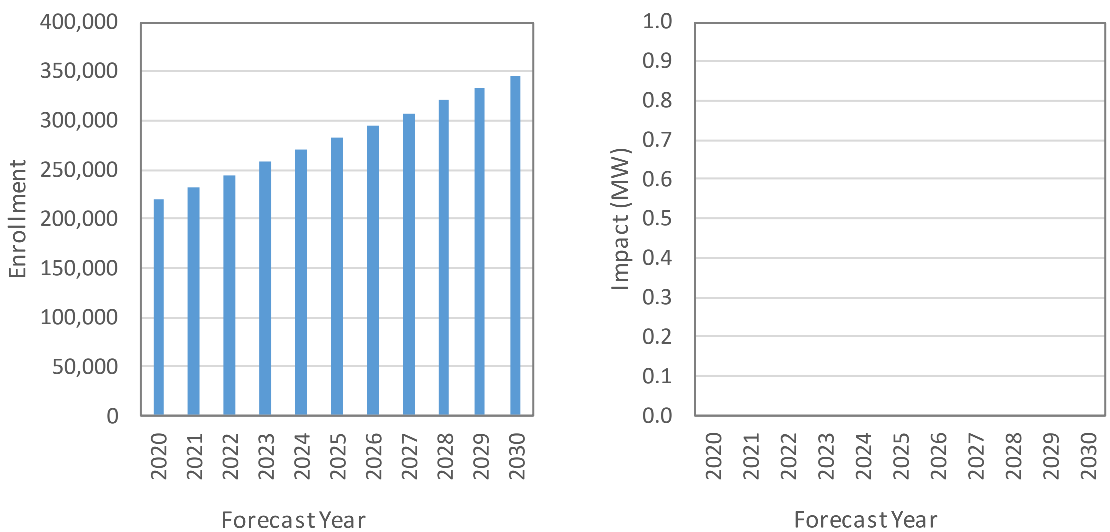
Figure 5-10 SCE Medium Typical Event Day Load Shape SCE 1-in-2: 2020



Small SMB Customers (< 20 kW)

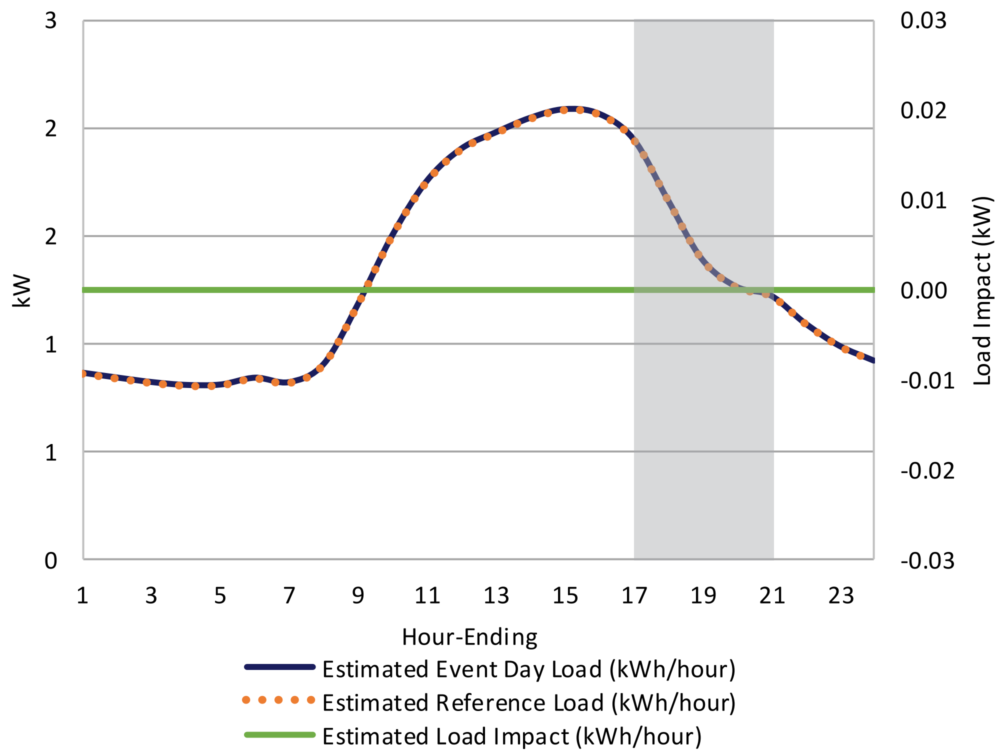
In Figure 5-11 below, we present the enrollment forecast and the ex-ante impact forecast side-by-side. The enrollment forecast shows a slow, steady, increase in participants from about 250,00 in 2020 to nearly 350,000 by 2030. This increase in participation is primarily from annual defaults. Given the insignificant impacts in the ex-post, ex-ante impacts are assumed to be zero throughout the forecast.

Figure 5-11 SCE Small Enrollment and Impact Forecast SCE 1-in-2: 2020 - 2030



In Figure 5-12, we present the typical event day load shape for SCE's small participants during forecast year 2020. In the load shape graph, the blue line represents the estimated event day load, the orange line represents the reference load, or what the participants would have consumed without an event, and the green line is the estimated load impact, or the difference between the two. The grey shaded area represents the RA window.

Figure 5-12 SCE Small Typical Event Day Load Shape SCE 1-in-2: 2020



SDG&E

Enrollment and Load Impact Summary

Table 5-5 summarizes the average event-hour load impact forecasts for non-residential CPP participants on a typical event day in 2020. 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 5-5 SDG&E Typical Event Enrollment and Impacts by Size: 2020

Size	# of Accts	Aggregate Impact (MW)				Per-Customer Impact (kW)			
		Utility Peak		CAISO Peak		Utility Peak		CAISO Peak	
		1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
Large	1,289	3.3	3.2	3.3	3.2	2.5	2.5	2.5	2.5
Medium	12,840	(1.2)	0.3	0.0	(0.5)	(0.1)	0.0	0.0	(0.0)
Total CPP	**14,129**	**2.1**	**3.5**	**3.3**	**2.7**	**0.1**	**0.3**	**0.2**	**0.2**

In Table 5-6 below we also present the program level impacts by month for an SDG&E 1-in-2 weather year for 2020, 2021, and 2030. Enrollment is consistent across all months. Impacts are also consistent across the forecast.

Table 5-6 SDG&E Monthly Program Level[36] Enrollment and Impacts for Selected Years: SDG&E 1-in-2

	2020		2021		2030	
	Enrollment	**Impact (MW)**	**Enrollment**	**Impact (MW)**	**Enrollment**	**Impact (MW)**
January	14,129	2.4	14,025	2.4	13,274	2.9
February	14,129	2.4	14,025	2.4	13,274	2.9
March	14,129	2.4	14,025	2.4	13,274	2.9
April	14,129	2.3	14,025	2.4	13,274	2.9
May	14,129	2.3	14,025	2.3	13,274	2.9
June	14,129	2.3	14,025	2.4	13,274	2.9
July	14,129	4.2	14,025	4.2	13,274	5.2
August	14,129	2.5	14,025	2.6	13,274	3.4
September	14,129	5.4	14,025	5.5	13,274	6.2
October	14,129	1.2	14,025	1.2	13,274	1.9
November	14,129	2.3	14,025	2.4	13,274	2.9
December	14,129	2.4	14,025	2.4	13,274	2.9

In the following sections, we present the enrollment and MW forecast, and the typical event day load shape for the CAISO 1-in-2 weather scenario for large and the Utility 1-in-10 scenario for medium[37].

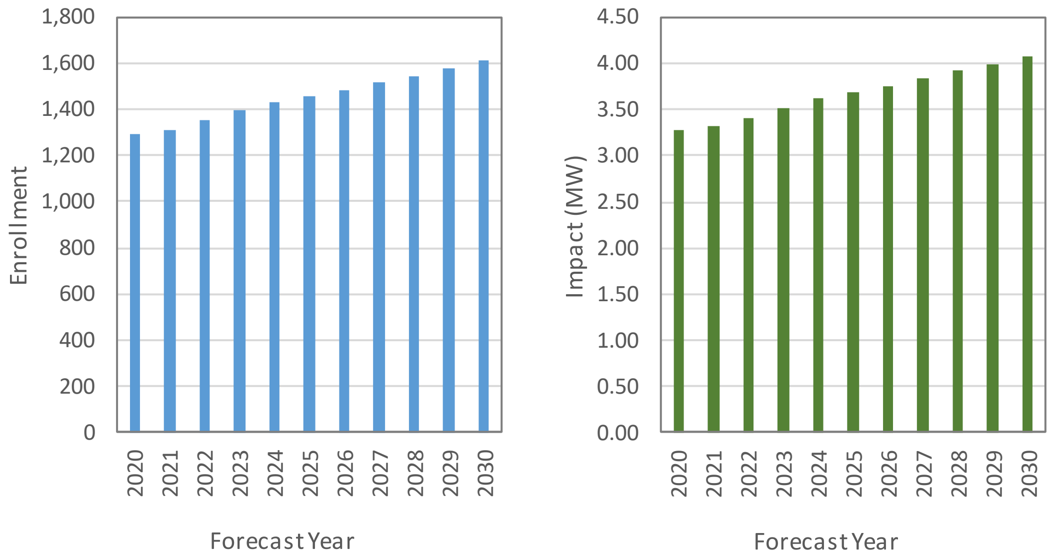
Large Customers (≥ 200 kW)

In Figure 5-13 we present the enrollment forecast and the ex-ante impact forecast side-by-side. The enrollment forecast shows a steady increase in participants from about 1,270 in 2020 to just over 1,600 in 2030. Additional participation comes mainly from population growth. The ex-ante MW forecast increases from just over 3 MW to about 4 MW throughout the forecast.

[36] Includes all large and medium customers.

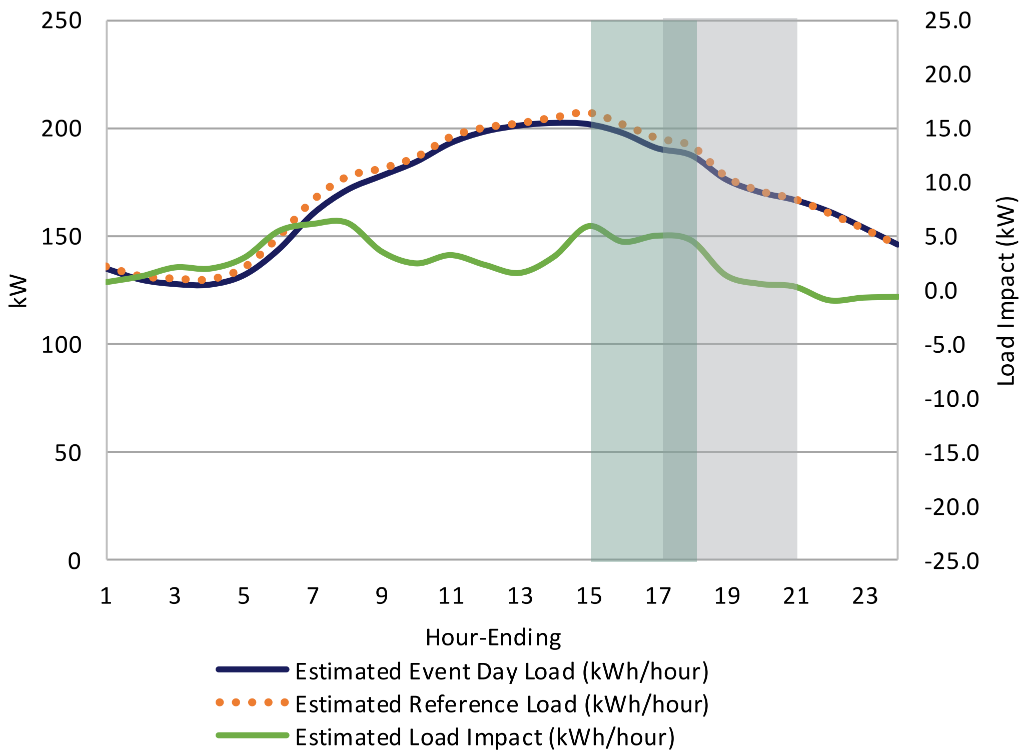
[37] Utility 1-in-10 scenario results were shown because those represent the only positive impacts of the 4 weather scenarios.

Figure 5-13 SDG&E Large Enrollment and Impact Forecast SDG&E 1-in-2: 2020 - 2030



In Figure 5-14, we present the typical event day load shape for SDG&E's large participants during forecast year 2020. In the load shape graph, the blue line represents the estimated event day load, the orange line represents the reference load, or what the participants would consume without an event, and the green line is the estimated load impact, or the difference between the two. In addition, we have added a grey shaded area to represent the RA window, and a green shaded area to represent the CPP availability window. CPP impacts are simply not available during the RA window, and RA impacts are further reduced by increases in load during the post event period.

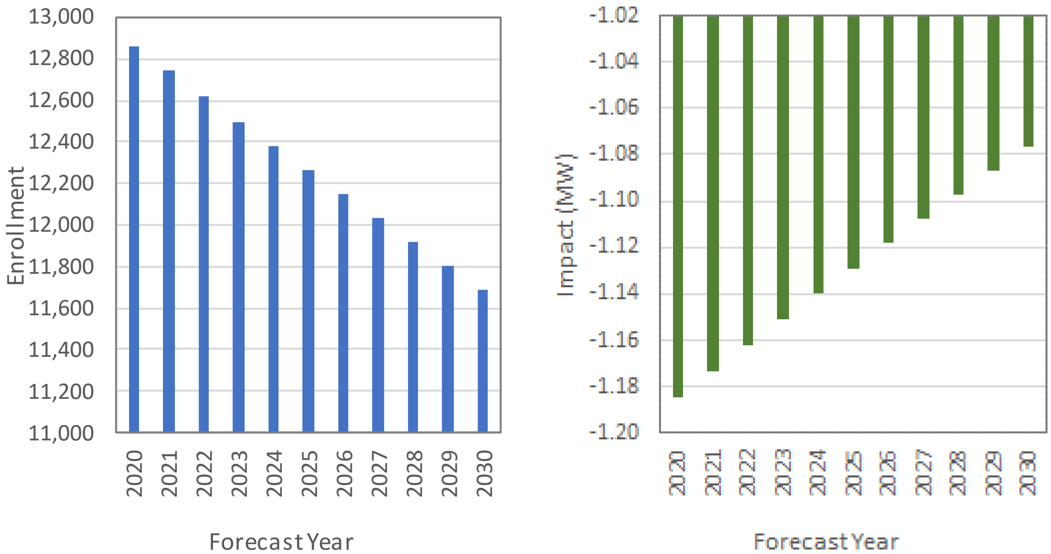
Figure 5-14 SDG&E Large Typical Event Day Load Shape SDG&E 1-in-2: 2020



Medium SMB Customers (20 ≤ x < 200 kW)

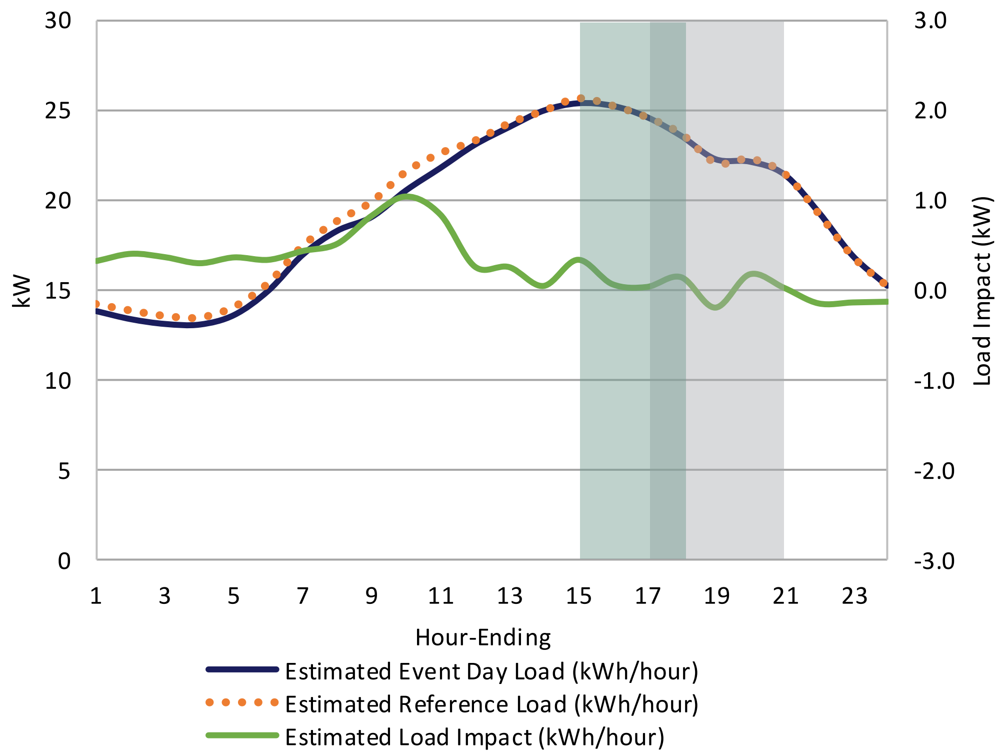
In Figure 5-15 we present the enrollment forecast and the ex-ante impact forecast side-by-side. The enrollment forecast shows a steady decrease in participants from about 12,800 in 2020 to about 11,700 in 2030. Reduction in participation comes mainly from opt-outs. The ex-ante MW forecast is negative but increasing slightly over time.

Figure 5-15 SDG&E Medium Enrollment and Impact Forecast SDG&E 1-in-10: 2020 - 2030



In Figure 5-16, we present the typical event day load shape for SDG&E's large participants during forecast year 2020. In the load shape graph, the blue line represents the estimated event day load, the orange line represents the reference load, or what the participants would consume without an event, and the green line is the estimated load impact, or the difference between the two. In addition, we have added a grey shaded area to represent the RA window, and a green shaded area to represent the CPP availability window. CPP impacts are simply not available during the RA window, and RA impacts are further reduced by increases in load during the post event period.

Figure 5-16 SDG&E Medium Typical Event Day Load Shape SDG&E 1-in-10: 2020



Reconciliations of Ex-Post and Ex-Ante Results

To make the relationship between ex-post and ex-ante estimates more easily understood and transparent, in this section we discuss the following:

- How current ex-post results differ from last year's ex-post results.
- How current ex-post results differ from last year's forecast.
- How current ex-ante results differ from last year's forecast.
- How current ex-ante results differ from the current ex-post results.

As discussed in the ex-ante section above, it is important to keep in mind that PG&E and SDG&E's event windows remain 2-6 PM which does not align with the RA window of 4-9 PM, while SCE's event window does.

PG&E

Previous and Current Ex-Post

Table 5-7 summarizes the non-residential PDP average event-hour ex-post load impact results for the past two years on a typical event day. The table includes the number of participating accounts, the average event-hour reference loads, and average event temperature by size group. Both per-customer and aggregate results are presented.

Table 5-7 PG&E Non-Residential PDP: Previous and Current Ex-Post, Typical Event Day

	Ex-Post Year	# of Accts	Aggregate (MW)		Per-Customer (kW)		% Impact	Event Temp (˚F)
			Ref. Load	Load Impact	Ref. Load	Load Impact		
Large	2018	1,712	445.5	23.9	260.2	14.0	5.4%	93.1
	2019	1,246	472.1	13.7	378.9	11.0	2.9%	97.5
Medium	2018	34,014	750.0	4.9	22.0	0.1	0.3%	93.2
	2019	24,994	571.5	-0.1	22.9	0.0	0.0%	96.1
Small	2018	119,004	243.7	-0.1	2.0	0.0	0.0%	93.0
	2019	91,156	182.4	0.6	2.0	0.0	0.4%	95.2

Comparing this year's ex-post with last year's ex-post, we see a decrease in enrollment across all three groups and a corresponding decrease in impacts in both the large and medium groups, with insignificant impacts in the medium group. In the small group, the impacts increased slightly from 0.0 % to 0.4% however, the per customer impacts are still extremely small.

In the large group specifically, we see about a 43% decrease in impacts. We also saw a 30% reduction in enrollment, but an increase in the reference load, and a decrease in the percent impacts. This indicates that as enrollment has dropped over the past year, the group has retained larger customers, but those large customers are reducing less on a per customer basis.

Previous and Current Ex-Ante and Ex-Post

Table 5-8 compares the current year's analysis with the previous year's analysis of non-residential PDP ex-post and ex-ante typical event-hour impacts. The ex-post represents events on typical event days and ex-ante results represent events on monthly system peak days in August. In addition, the ex-ante results reflect the utility peak 1-in-2 weather scenario.

Table 5-8 PG&E Non-Residential PDP: Previous and Current Ex-Ante and Ex-Post

	Model	Year	# of Accts	Aggregate (MW)		Per-Customer (kW)		% Impact	Event Temp (˚F)
				Ref. Load	Load Impact	Ref. Load	Load Impact		
LARGE	Previous	Ex-Post 2018	1,712	445.5	23.9	260.2	14.0	5.4%	93.1
		Ex-Ante 2019	1,602	391.5	10.0	244.4	6.2	2.5%	92.6
	Current	Ex-Post 2019	1,246	472.1	13.7	378.9	11.0	2.9%	97.5
		Ex-Ante 2020	1,254	392.9	5.0	313.3	4.0	1.3%	94.1
MEDIUM	Previous	Ex-Post 2018	34,014	750.0	4.9	22.0	0.1	0.3%	93.2
		Ex-Ante 2019	30,130	593.4	0.3	19.7	<0.1	0.0%	91.4
	Current	Ex-Post 2019	24,994	571.5	(0.1)	22.9	0.0	0.0%	96.1
		Ex-Ante 2020	24,302	490.4	(1.1)	20.2	<0.1	0.0%	93.9
SMALL	Previous	Ex-Post 2018	119,004	243.7	(0.1)	2.0	<0.1	0.0%	93.0
		Ex-Ante 2019	105,345	162.8	(0.7)	1.5	<0.1	0.0%	91.2
	Current	Ex-Post 2019	91,156	182.4	0.6	2.0	0.0	0.4%	95.2
		Ex-Ante 2020	87,561	132.2	(0.5)	1.5	<0.1	0.0%	92.8

Table 5-8 shows the following trends for the non-residential PDP:

- Current Ex-Post Compared with Previous Ex-Ante: The aggregate ex-post impacts were lower for both the large and medium groups in PY2019. Both these populations had lower enrollment but significant increases in the per-customer reference load, indicating that the remaining participants are larger on average than they were in PY2018. We suspect these larger customers are not responding to the rate in the same way as the previous year's participants. The small customers saw an increase in impacts despite the drop in participation. However, the per-customer impacts are still extremely small, this could be simply a modeling artifact, or it could be that the remaining participants are more responsive to the rate.
- Current Ex-Ante Compared with Previous Ex-Ante: The current ex-ante estimates for PY2020 are lower than previous ex-ante estimates for PY2019 for all three size groups due to lower enrollment. Specific to the large customers, in addition to lower enrollment assumptions, lower per customer impacts in PY2019 ex-post are also driving reductions in forecasted impacts.
- Current Ex-Ante Compared with Current Ex-Post: The current ex-ante analysis is expecting a decrease in enrollment in PY2020 for all size groups as the PDP default is put on hold until the new TOU period

is implemented. In addition, the differences between the PDP event window and the RA window significantly reduces impacts between the ex-post and the ex-ante.

SCE

Previous and Current Ex-Post

Table 5-9 summarizes the non-residential CPP average event-hour ex-post load impact results for the past two years on a typical event day. The table includes the number of participating accounts, the average event-hour reference loads, and average event temperature by size group. Both per-customer and aggregate results are presented.

Table 5-9 SCE Non-Residential CPP: Previous and Current Ex-Post, Typical Event Day

	Ex-Post Year	# of Accts	Aggregate (MW)		Per-Customer (kW)		% Impact	Event Temp (˚F)
			Ref. Load	Load Impact	Ref. Load	Load Impact		
LARGE	2018	2,251	583.7	14.2	259.3	6.3	2.4%	89.9
	2019	2,201	426.9	7.0	194.0	3.2	1.6%	88.7
MEDIUM	2018	659	45.9	0.2	69.7	0.4	0.5%	89.4
	2019	34,963	861.8	(1.4)	24.6	0.0	(0.2%)	88.0
SMALL	2018	106	0.2	<0.1	1.9	<0.1	2.3%	88.9
	2019	235,219	340.4	(0.7)	1.4	0.0	(0.2%)	87.1

Comparing this year's ex-post with last year's ex-post, we see a slight decrease in enrollment across the large group, and a dramatic increase in enrollment in the small and medium groups due to the default schedule.

The impacts in the large group dropped by about 50% from 14.2 MW in PY2018 to 7.0 MW in PY2019. We believe the primary driver of the reduction in impacts is the change in the event window from 2-6 PM to 4-9 PM. First, the shift resulted in a reduction of 25% in the average per-customer reference load and a corresponding reduction in the overall potential load available. Second, the events are occurring later in the day, when many businesses are already shutting down and likely have less discretionary load available to reduce.

The impacts in the small and medium group are insignificant (essentially zero) in PY2019 relative to small non-negative impacts in PY2018. This is attributable to the analysis of a completely different population of participants as SCE defaulted their SMB customers in PY2019.

Previous and Current Ex-Ante and Ex-Post

Table 5-10 compares the current year's analysis with the previous year's analysis of non-residential CPP ex-post and ex-ante average event-hour impacts. The ex-post results represent events on typical event days and ex-ante results represent events on monthly system peak days in August. In addition, the ex-ante results reflect the utility peak 1-in-2 weather scenario.

Table 5-10 SCE Non-Residential CPP: Previous and Current Ex-Ante and Ex-Post[38]

	Model	Year	# of Accts	Aggregate (MW)		Per-Customer (kW)		% Impact	Event Temp (°F)
				Ref. Load	Load Impact	Ref. Load	Load Impact		
LARGE	Previous	Ex-Post 2018	2,251	583.7	14.2	259.3	6.3	2.4%	89.6
		Ex-Ante 2019	3,243	774.6	18.8	238.8	5.8	2.4%	88.9
	Current	Ex-Post 2019	2,201	426.9	7.0	194.0	3.2	1.6%	88.7
		Ex-Ante 2020	2,525	499.6	8.0	197.9	3.2	1.6%	89.5
MEDIUM	Previous	Ex-Post 2018	659	45.9	0.2	69.7	0.4	0.5%	89.4
		Ex-Ante 2019	41,580	917.0	6.9	22.1	0.2	0.7%	88.7
	Current	Ex-Post 2019	34,963	861.8	(1.4)	24.6	0.0	(0.2%)	88.0
		Ex-Ante 2020	30,298	752.4	0.0	24.8	0.0	0.0%	89.1
SMALL	Previous	Ex-Post 2018	106	0.2	<0.1	1.9	<0.1	2.3%	88.9
		Ex-Ante 2019	255,420	448.1	1.0	1.8	<0.1	0.2%	90.5
	Current	Ex-Post 2019	235,219	340.4	(0.7)	1.4	0.0	(0.2%)	87.1
		Ex-Ante 2020	219,658	329.8	0.0	1.5	0.0	0.0%	88.4

Table 5-10 shows the following trends for the non-residential CPP:

- Current Ex-Post Compared with Previous Ex-Ante: For the large group, the previous ex-ante forecasted a higher enrollment and a higher aggregate impact (18.8 MW) when compared to the current ex-post (7.0 MW). The key driver for the shortfall was that the previous ex-ante forecast assumed that customers would respond to the new event window in the same way they responded to the previous window, i.e. the weather adjusted percent reduction from PY2018 ex-post was used to create previous ex-ante estimates. What we actually saw was that customers did not respond to the new event window in a similar manner (likely due to the fact that large C&I customers are not using as much energy in the evening hours as many businesses begin to shut down for the day) and we see impacts decreasing by about 50% relative to PY2019. Given that the default of SMB customers would result in dramatically different populations in the medium and small groups, the previous ex-ante was based on class average load shapes[39] applying PG&E's 2018 ex-post per customer impacts. Therefore, it is not surprising to see some differences between the PY2019 ex-post and the previous ex-ante.
- Current Ex-Ante Compared with Previous Ex-Ante: Differences between the current ex-ante and the previous ex-ante are driven largely by (1) enrollment estimates being lower than previously forecasted,

[38] Previous ex-ante for large customers represents a 2018 August Peak Day. The previous ex-ante for the SMB customers represents a 2020 August Peak Day. To provide a more apples-to-apples comparison with the previous study, we also use 2020 impacts for the current study for SMB customers.

[39] SCE's Dynamic Load Profiles

and (2) the ex post impacts for 2019 which are lower than expected because customers are ramping down their usage between 4-9 PM which is the new event window.

- Current Ex-Ante Compared with Current Ex-Post: The current ex-ante is in line with the ex-post on a per customer basis across all three groups. Key changes in the ex-ante vs. the ex-post result from changes in enrollment.

SDG&E

Previous and Current Ex-Post

Table 5-11 summarizes the non-residential CPP average event-hour ex-post load impact results for the past two years on a typical event day. Given that SDG&E did not call any events in 2019, we have included only a comparison of the enrollment. In both groups, enrollment increased slightly.

Table 5-11 SD&E Non-Residential CPP: Previous and Current Ex-Post, Typical Event Day

	Ex-Post Year	# of Accts	Aggregate (MW)		Per-Customer (kW)		% Impact	Event Temp (˚F)
			Ref. Load	Load Impact	Ref. Load	Load Impact		
LARGE	2018	1,211	348.1	6.9	287.5	5.7	2.0%	88.5
	2019	1,525	NA	NA	NA	NA	NA	NA
MEDIUM	2018	12,854	437.5	1.9	34.0	0.2	0.4%	88.2
	2019	13,402	NA	NA	NA	NA	NA	NA

Previous and Current Ex-Ante and Ex-Post

Table 5-12 compares the current year's analysis with the previous year's analysis of non-residential CPP ex-post and ex-ante average event-hour impacts. The ex-post results represent events on typical event days and ex-ante results represent events on monthly system peak days in August. In addition, the ex-ante results reflect the utility peak 1-in-2 weather scenario.

Table 5-12 SDG&E Non-Residential CPP: Previous and Current Ex-Ante and Ex-Post

	Model	Year	# of Accts	Aggregate (MW) Ref. Load	Aggregate (MW) Load Impact	Per-Customer (kW) Ref. Load	Per-Customer (kW) Load Impact	% Impact	Event Temp (˚F)
LARGE	Previous	Ex-Post 2018	1,211	348.1	6.9	287.5	5.7	2.0%	88.5
		Ex-Ante 2019	1,471	378.5	4.4	257.3	3.0	1.2%	82.5
	Current	Ex-Post 2019	1,525	NA	NA	NA	NA	NA	NA
		Ex-Ante 2020	1,289	232.1	3.2	180.1	2.5	1.4%	82.6
MEDIUM	Previous	Ex-Post 2018	12,854	437.5	1.9	34.0	0.2	0.4%	88.2
		Ex-Ante 2019	12,603	372.1	(0.7)	29.6	(0.1)	0.0%	82.3
	Current	Ex-Post 2019	13,402	NA	NA	NA	NA	NA	NA
		Ex-Ante 2020	12,840	287.4	(0.7)	22.4	(0.1)	0.0%	82.3

Table 5-12 shows the following trends for the non-residential CPP on an August peak day:

- Current Ex-Post Compared with Previous Ex-Ante: We cannot make any comparisons since no event days were called in PY2019.
- Current Ex-Ante Compared with Current Ex-Post: We cannot make any comparisons since no event days were called in PY2019.
- Current Ex-Ante Compared with Previous Ex-Ante: Note that since we did not perform an ex-post analysis due to no events being called in PY2019, the per-customer impact estimates were taken from PY2018 estimates. As a result, the per-customer impacts should be the same in both years and we do see that in the medium customers. However, there is a slight decrease in per-customer impacts in the large group and this is due to 237 PY2018 participants shifting from medium to Large in PY2019. Since the medium customers showed negative per-customer impacts in PY2018, the subgrouping shift of these 237 participants (15% of PY2019 large enrollment) caused a 0.5 kW decrease in per-customer impacts. Paired with lower forecasted enrollments, we see 1.2 MW decrease in aggregate impacts for the large customers.

6

KEY FINDINGS AND RECOMMENDATIONS

State Level Findings

In this section we present the state level findings from the Statewide PY2019 CPP, or PDP, evaluation.

Ex-Post Impacts

In addition, the table presents the statewide total impacts for a typical event day. Given that SDG&E did not call any events, this PY2019 statewide total likely underestimates what might be achievable across the state should a statewide event be needed. PG&E clearly has the largest contribution to the overall state level total of 14.3 MW, contributing 75% of the load reduction while SCE contributes 25%.

Table 6-1 presents the total enrollments, reference loads, load impacts, and event temperatures for PG&E's and SCE's programs. In addition, the table presents the statewide total impacts for a typical event day. Given that SDG&E did not call any events, this PY2019 statewide total likely underestimates what might be achievable across the state should a statewide event be needed. PG&E clearly has the largest contribution to the overall state level total of 14.3 MW, contributing 75% of the load reduction while SCE contributes 25%.

Table 6-1 Total State Level Ex-Post Impacts by Utility: Typical Event Day

Utility	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
PG&E- PDP	117,396	1,226	14.3	1.2%	97.5
SCE - CPP	272,383	1,629	4.9	0.3%	87.9
SDG&E - CPP	NA	NA	NA	NA	NA
Statewide	**389,779**	**2,855**	**19.2**	**0.7%**	**92.7**

Statewide, the total MW impact dropped by more than half from 52 MW in PY2018 to 19.2 MW in PY2019. Impacts for both utilities that called events dropped substantially, and SDG&E did not call any events in PY2019. Reduction in impacts is concentrated mainly in the large groups since the small and medium groups contributed little to the overall MW in PY2018 and PY2019.

- For PG&E's large group specifically, we see about a 43% decrease in impacts. We also saw a 30% reduction in enrollment, but an increase in the reference load, and a decrease in the percent impacts. This indicates that as enrollment has dropped over the past year, the group has retained larger customers, but those large customers are reducing less on a per customer basis.
- In SCE's large group the impacts dropped by about 50% in PY2019. We believe the primary driver of the reduction in impacts is the change in the event window from 2-6 PM to 4-9 PM. First, the on-peak period shift resulted in a reduction of 25% in the average per-customer reference load and a corresponding reduction in the overall potential load available. Second, the events are occurring later in the day, when many businesses are already shutting down and likely have less discretionary load available to reduce.

In Table 6-2 below, we also present the impacts by customer size. Similar to PY2018, the large participants contribute more than 99% of the total impacts across the state, with medium and small customers essentially contributing zero.[40] Recall that SDG&E did not call any events in PY2019, so table reflects only the contributions of PG&E and SCE.

Table 6-2 Total State Level Ex-Post Impacts by Customer Size: Typical Event Day

Size	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
Large	3,447	899	20.7	2.3%	93.1
Medium	59,957	1,433	(1.5)	-0.1%	92.1
Small	326,375	522.8	(0.1)	0.0%	95.2
Statewide	**389,779**	**2,855**	**19.1**	**0.7%**	**93.5**

Ex-Ante Impacts

We also present the state level ex-ante impacts for a Utility 1-in-2 weather year for program years 2020 and 2030 in Table 6-3. Keep in mind that RA window for the 2020-2030 ex-ante forecast is 4-9 PM. SCE's event window aligns with the RA window, however, both PG&E's and SDG&E's event windows will remain 2-6 PM, which means that the PDP and CPP programs are only available during the first two hours of the RA window while all other hours are non-event hours. This results in significantly lower (and sometimes even negative) impacts within the RA window.

In program year 2020 the utilities forecast approximately 12.2 MW of load reduction to be available during the RA window. In 2020, SCE expects to contribute approximately 65% of the overall impacts, with PG&E contributing 15%, and SDG&E contributing 20%. SCE is the main contributor because it is the only utility that has changed the CPP event window to overlap with the RA window.

By 2030 the IOUs forecast a total of 20.3 MW of demand response on a typical event day with all utilities predicting an increase in MW driven primarily by increased enrollment.

Table 6-3 Total State Level Ex-Ante Impacts by Utility: Typical Event Day

Utility	PY 2020 Enrollment	PY 2020 Load Impact (MW)	PY 2030 Enrollment	PY 2030 Load Impact (MW)
PG&E- PDP	113,154	1.8	183,765	4.6
SCE - CPP	252,481	8.0	397,481	12.6
SDG&E - CPP	14,160	2.5	13,302	3.1
Statewide	**379,795**	**12.2**	**594,548**	**20.3**

In Table 6-4 we also present the ex-ante impacts for 2020 and 2030 by customer size. In the ex-ante scenario, the large customers still contribute most of the impacts. In 2030 the increase in impacts is largely driven by the increased enrollment in the large groups across the three IOU programs.

[40] The small negative value here is most likely a modeling artifact resulting from an imperfect quantification of weather effects and/or omitted variable bias. We have no reason to think that customers are actually increasing their load in response to events.

Table 6-4 Total State Level Ex-Ante Impacts by Customer Size: Typical Event Day

Size	PY 2020 Enrollment	PY 2020 Load Impact (MW)	PY 2030 Enrollment	PY 2030 Load Impact (MW)
Large	5,134	14.0	8,305	23.3
Medium	67,443	-1.3	104,095	-2.2
Small	307,218	-0.5	482,147	-0.8
Statewide	**379,795**	**12.2**	**594,548**	**20.3**

Event Communication

It is also important to keep in mind that not all the customers that were enrolled in CPP, or PDP, received communication regarding events. As customers were defaulted onto the rates, each utility established mechanisms to reach out to customers to obtain contact information that could be used to provide day ahead event notification, however, in many cases customers did not respond to the utility outreach and therefore were unaware of the events throughout the summer. Table 6-5 shows the percentage of participants that were notified by utility and size group on a typical event day.

Interestingly, we saw very little difference in impacts among the medium and small customers within SCE and PG&E programs regardless of the percent of customers that were notified. For both utilities the impacts in those groups were nearly, or indistinguishable from, zero even though PG&E notified more than 90% of participants, and SCE notified just over half.

Table 6-5 Percent of Service Accounts Notified, by Utility and Size Group, Typical Event Day

Size Group	PG&E % Notified	SCE % Notified	SDG&E % Notified[41]
Small < 20 kW	92%	54%	-
Medium 20 kW ≤ x < 200 kW	95%	61%	NA
Large ≥ 200 kW	94%	89%	NA
Total	**92%**	**55%**	**NA**

Key Findings by Utility

The key results for each utility on a typical event day are summarized in Table 6-6 (PG&E), Table 6-7 (SCE), and Table 6-8 (SDG&E). While the large customers participating in PG&E's PDP program in 2019 demonstrate large and consistent load impact reduction as a group, the medium and small default customer groups show little or no load reduction. Similarly, the large customer group in SCE's CPP Program demonstrates large and consistent load impact reduction. The small and medium customers defaulted by SCE, however, show no or little load reduction, respectively.

[41] SDG&E did not notify any customers because no events were called in PY2019.

Table 6-6 Key Results for PG&E's Peak Day Pricing Program for PY2019

Utility	Size Group	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
PG&E	Large	1,246	472.1	13.7	2.9%	97.5
	Medium	24,994	571.5	-0.1	0.0%	96.1
	Small	91,156	182.4	0.6	0.4%	95.2
ALL PG&E		**117,396**	**1,226.0**	**14.2**	**1.2%**	**96.3**

Table 6-7 Key Results for SCE's Critical Peak Pricing Program for PY2019

Utility	Size Group	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
SCE	Large	2,201	426.9	7.0	1.6%	88.7
	Medium	34,963	861.8	(1.4)	(0.2%)	88.0
	Small	235,219	340.4	(0.7)	(0.2%)	87.1
ALL SCE		**272,383**	**1,629.1**	**4.9**	**0.3%**	**87.9**

Table 6-8 Key Results for SDG&E's Critical Peak Pricing Program for PY2019

Utility	Size Group	# Enrolled	Ref. Load (MW)	Load Impact (MW)	% Load Impact	Event Temp
SDG&E	Large	1,525	NA	NA	NA	NA
	Medium	13,042	NA	NA	NA	NA
ALL SDG&E		**14,927**	**NA**	**NA**	**NA**	**NA**

Recommendations

AEG has developed four recommendations for future research and evaluation related to the non-residential CPP programs.

- Investigate the experiences of small and medium participants. Through future or ongoing process evaluations, ensure that special care is taken to better understand the experiences of small and medium customers on the CPP rates. Participant surveys and focus groups can be used to understand aspects of participation including, awareness and understanding of the rate, awareness of participation, awareness of events, ability to respond to events, and actions taken during events. Conducting research while maintaining statistically significant samples by key industry group and size may provide invaluable insights for both program staff and future impact evaluations.
- Investigate the effect of notifications on customer impacts. Again, through the use of participant surveys and/or focus groups, conduct research to better understand participant choices regarding notification, their awareness of notifications, and how they respond to notifications on event days.
- Consider opportunities to improve robustness of within-subjects designs. For most of the subgroups, we elected not to develop a matched control group for this evaluation because of the small ratios of participants to non-participants and the opt-out nature of the CPP, or PDP, rates which would likely lead to poor matches and introduce self-selection bias. Unfortunately, the within-subjects design may also have led to the introduction of bias, particularly among those groups with very small impacts due

to a lack truly comparable event like days. Since all utilities expect their participant population to grow (and the non-participant pools to continue to shrink) we recommend considering the following opportunities to mitigate this bias in the future. We propose two options for consideration:

- Intentionally call test events on cooler days and, unless absolutely necessary, try not to call events on all the hottest days of the season. This will provide the models with better information as to how participants would behave during events on a wider range of temperatures and improve their performance.
- Consider using the non-notified participants as a control group for the notified participants when appropriate. This would accurately estimate the incremental effect of notification, rather than the overall program impact, but this may not be undesirable given that we know the impacts for non-notified customers are very small.

- Consider utilizing customer-specific models for the large groups. In PY2019, PG&E's and SCE's large groups utilized subgroup level models with matched control groups. As previously stated, the opt-out nature of the CPP, or PDP, rates can introduce self-selection bias. For the large groups, very high variation in customer usage can lead to both poor matches and poor model estimations. This is especially true for groups with extremely large customers. We recommend utilizing customer-specific models for all large customers or only the extremely large (outlier) customers. For groups with very high variation, customer-specific regression models can better estimate weather response, seasonal usage, and load impacts and control for unobservable customer-specific effects that are more difficult to account for in subgroup level models.

A

TABLE GENERATORS

PG&E PDP Ex-Post Table Generator

PG&E PDP Ex-Ante Table Generator

SCE CPP Ex-Post Table Generator

SCE CPP Ex-Ante Table Generator

SDG&E CPP Ex-Post Table Generator

SDG&E CPP Ex-Ante Table Generator

B

MODEL VALIDITY

We selected and validated segment-specific regression models during our optimization process; participants are segmented into groups based on size, industry type and, for some, notification type. The segment-specific models are designed to be able to:

- Accurately predict the actual participant load on event days, and
- Accurately predict the reference load, or what customers would have used on event days, in absence of an event.

To meet these two specific goals, our optimization process included an analysis of both the in-sample and out-of-sample MAPE and the MPE for each of the candidate regression models for each group. We used the out-of-sample tests to show how well each of the candidate models could predict a customer's load on non-event days that were as similar as possible to actual event days; this test gave us an estimate of how well each model could predict the reference load. We used the in-sample tests to show how well each model performed on the actual event days; therefore, it helped us understand how well the model was able to match the actual load. Our optimization procedure had several steps, which are described below:

- First, we identified the out-of-sample event-like days as several 2019 days that are similar to event days, but were not event days, based on temperature, month, and day of the week.
- After identifying the event-like days, those days were removed from the analysis dataset and the candidate models were fit to the remaining data.
- Next, the results of the candidate models were used to predict the usage on the out-of-sample days. Then we assessed the error and bias in the reference load by calculating the MAPE and MPE between the actual usage and the predicted usage on the out-of-sample days.
- Finally, we compared the actual and predicted loads on the event days from 2019. We also calculated the MAPE and MPE on these days to assess the error and bias in the predicted load.

The final step of the process was to select the final model specification using the candidate model with the minimum weighted MAPE and MPE for each segment. We describe the steps in more detail in the subsections that follow.

Selecting Event-Like Days

To select similar non-event days, we used a Euclidean Distance matching approach. Euclidean distance is a simple and highly effective way of creating matched pairs. To determine how close event day temperature is to a potential event-like day, we calculated a Euclidean distance metric defined as the square root of the sum of the squared differences between the matching variables. Any number of relevant variables could be included in the Euclidean distance; in this program year, we used three different Euclidean distance metrics to select similar non-event days: (1) average daily temperature; (2) daily maximum temperature; (3) daily minimum temperature. The Euclidean distance metrics used can be calculated by Equation B1 below.

$$ED = \sqrt{(MeanTemp_{event} - MeanTemp_{non-event})^2 + (MaxTemp_{event} - MaxTemp_{non-event})^2 + (MinTemp_{event} - MinTemp_{non-event})^2} \quad \text{(B1)}$$

In Figure B-1 to Error! Reference source not found. we show comparisons of the distributions of average daily temperature of event days and event-like days. We show a single utility level comparison for PG&E and SCE, in Figure B-1 and Figure B-2 respectively, because these dates were chosen at the utility level, i.e. all segments have the same set of event and event-like dates. Event-like dates for SDG&E were chosen at the size level, where the 0-199 kW size participants utilize some 2017 event-like dates in addition to the 2018 event like dates.

Figure B-1 PG&E Average Daily Temperatures of Event Days v. Event-Like Days

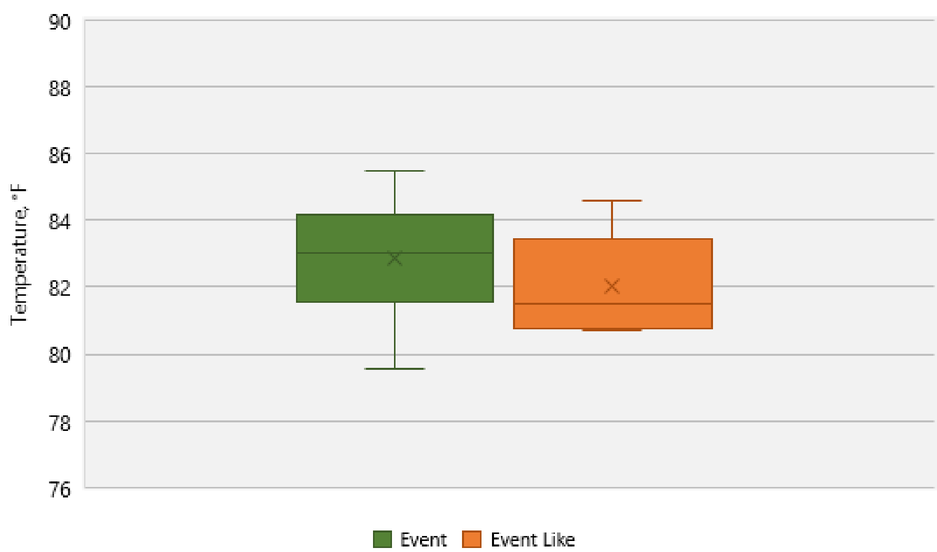


Figure B-2 SCE Average Daily Temperatures of Event Days v. Event-Like Days

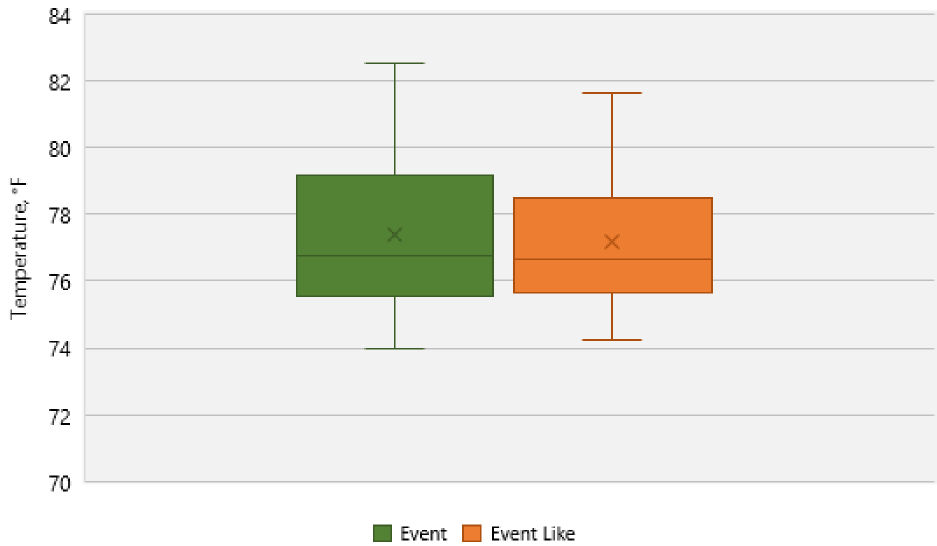
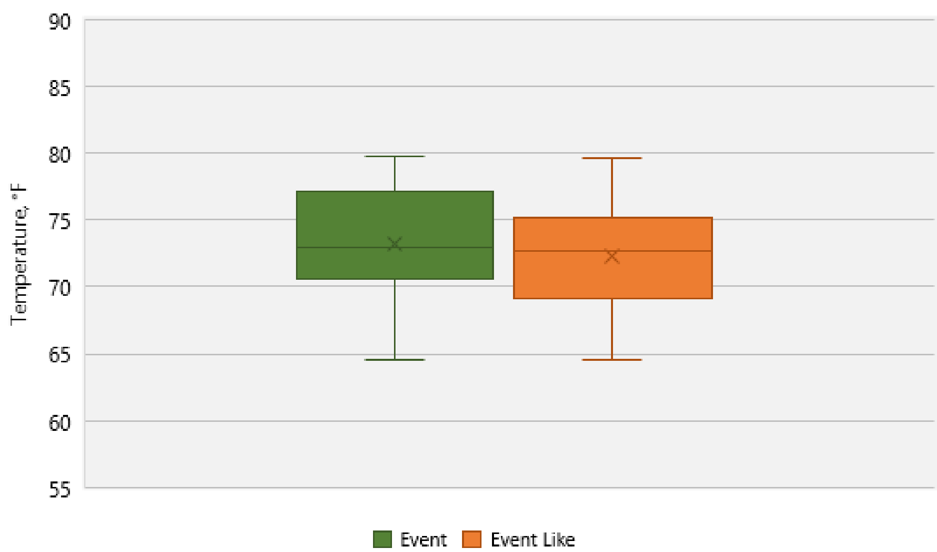


Figure B-3 SDG&E Average Daily Temperatures of Event Days v. Event-Like Days, CBP Events[42]



Optimization Process and Results

Next, we estimated the MAPE and MPE, for the entire day, for each customer, and for each candidate model, both for the in-sample period and for the out-of-sample period. Recall that the goal of the tests is to find the best model for each customer in terms of its ability to predict the reference load, and its ability

[42] Since SDG&E did not have any event days for event-like day selection, we used the event-like days selected for SDG&E in the Capacity Bidding Program (CBP) analysis.

to predict the actual load. Therefore, we collapsed the tests into a single metric, which could be calculated for each customer and each candidate model.

The metric is defined in the equation below:

$$metric_{ic} = (0.5 * DailyEvntMAPE) + (0.5 * DailyEvntlikeMAPE)$$

Once we computed a single metric for each customer and candidate model combination, we then selected the best model for each customer by choosing the model specification with the smallest overall metric. The results of the optimization process are shown in the following tables and figures.

Table B-9 presents the weighted average MAPE and MPE for the final set of per customer models for each utility, by size. Across all three IOUs, programs, and products, all MAPE and MPE estimates are below 2.5%. Most of the MPE values are negative, indicating that the models tend to under-predict the load rather than over-predict; however, the MPE values are still very small indicating a relatively low level of bias.

Table B-9 Weighted Average MAPE and MPE by Utility and Size

	Size	Out-of-Sample		In-Sample	
		MAPE	**MPE**	**MAPE**	**MPE**
PG&E	0-19.99	1.00%	-0.30%	0.70%	-0.07%
	20-199.99	1.00%	-0.31%	0.62%	-0.08%
	200+	1.76%	-0.61%	0.97%	-0.53%
SCE	0-19.99	1.38%	0.38%	1.50%	-0.06%
	20-199.99	1.09%	0.22%	1.34%	-0.06%
	200+	0.89%	0.18%	0.90%	-0.06%
SDG&E	0-199.99	NA	NA	2.31%	-0.89%
	200+	NA	NA	2.13%	1.17%

Figure B-4 to Figure B-8 present the average event-like day predicted loads (dotted lines) and actual loads (solid lines) from the in-sample and out-of-sample tests, by product and utility. In each case, the predicted load is very close to the actual load. This tells us that on average, the customer-specific regression models do a very good job estimating what customer loads would be like on event-like days, and therefore are able to produce very accurate reference loads.

Figure B-4 PG&E Actual and Predicted Loads on Event Days

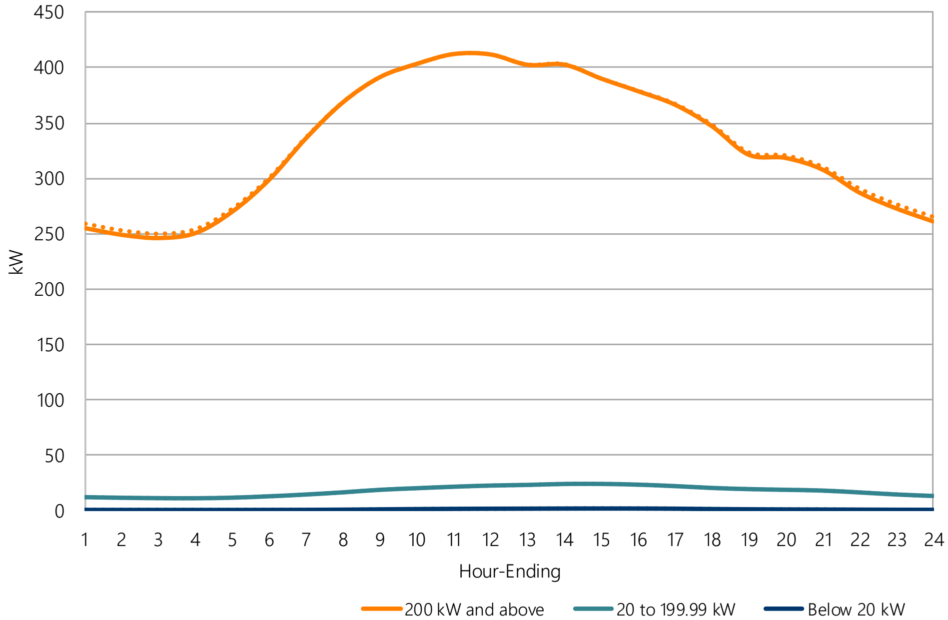


Figure B-5 PG&E Actual and Predicted Loads on Event-Like Days

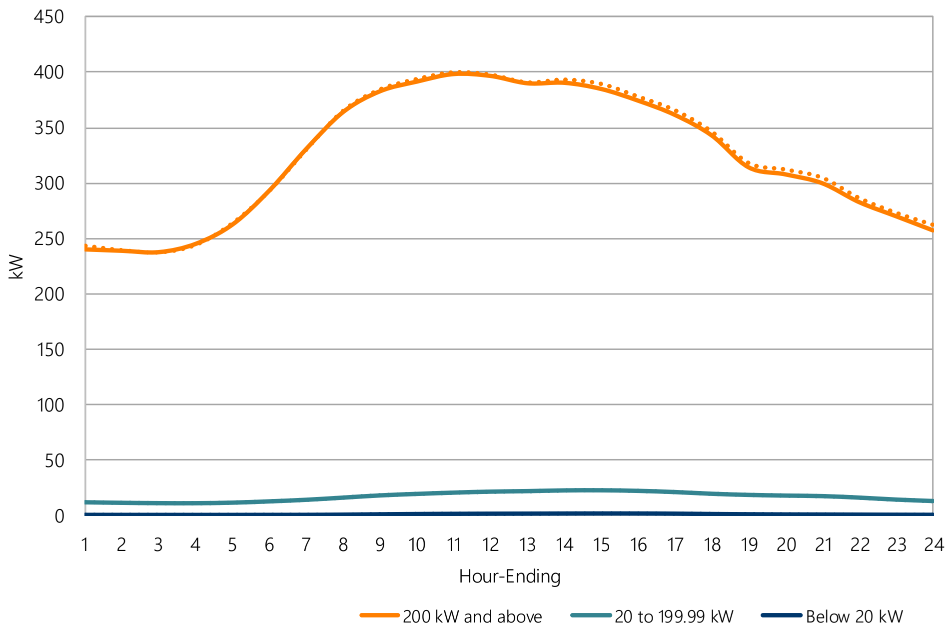


Figure B-6 SCE Actual and Predicted Loads on Event Days

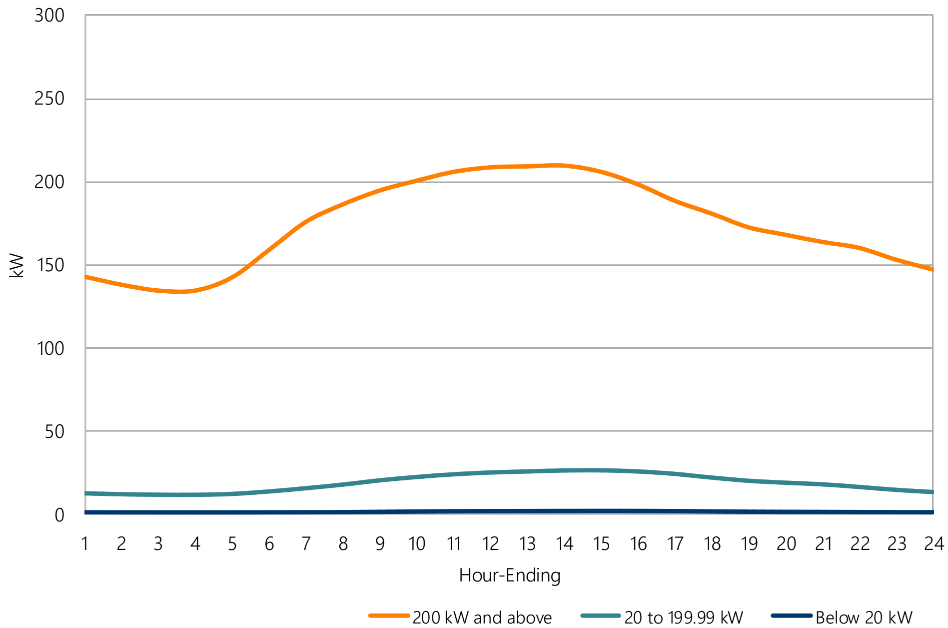


Figure B-7 SCE Actual and Predicted Loads on Event-Like Days

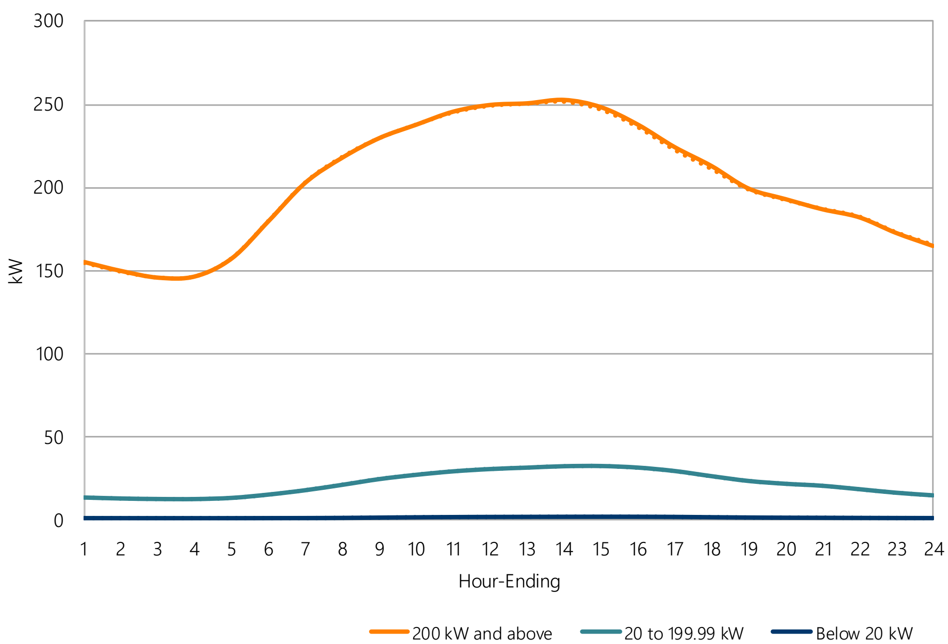
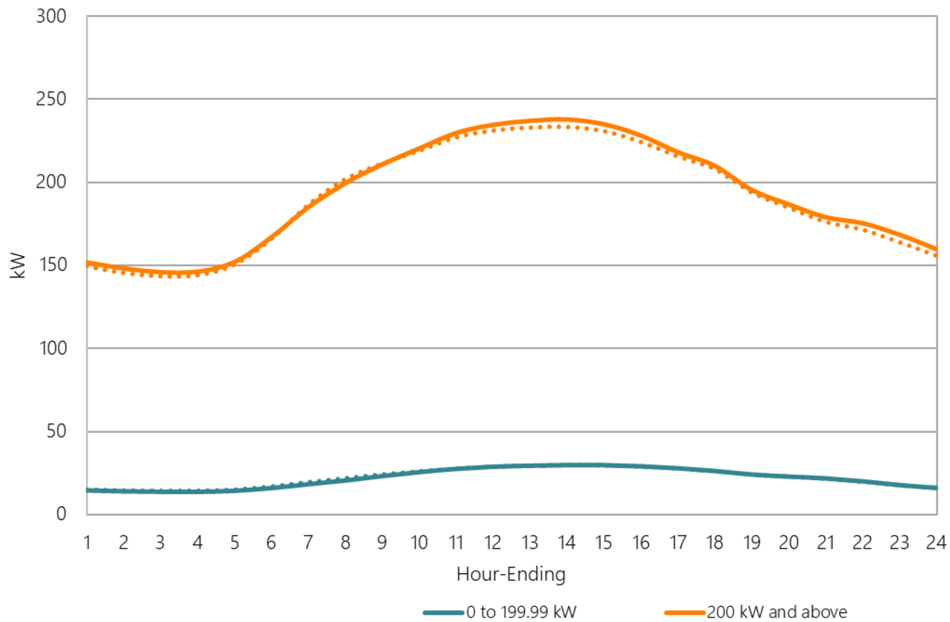


Figure B-8 SDG&E Actual and Predicted Loads on Event-Like Days



Additional Checks

Visual inspection can be a simple but highly effective tool. During the inspection, we looked for specific aspects of the subgroup level predicted and reference load shapes to tell us how well the models performed. For example,

- We checked to make sure that the reference load is closely aligned with the actual and predicted loads during the early morning and late evening hours when there is likely to be little effect from the event. Large differences can indicate that there is a problem with the reference load either over- or under-estimating usage in absence of the event.
- We closely examined the reference load for odd increases or decreases in load that could indicate an effect that is not properly being captured in the models. If we found such an increase or decrease, we investigated the cause and attempted to control for the effect in the models.
- We also looked for bias, both visually and mathematically. Bias is the consistent over- or under-prediction of the actual load. We may see bias that is temperature-related, under-predicting on hot days, and over-predicting on cool days. We have also seen bias that is time-based, over-predicting in the beginning of the year, and under-predicting at the end of the year. Identification of bias and its source often allows us to adjust the models to capture and isolate the bias-inducing effects within the model specification.

Applied Energy Group, Inc.
500 Ygnacio Valley Road, Suite 250
Walnut Creek, CA 94596

P: 510.982.3525