2019 Load Impact Evaluation for Pacific Gas & Electric Company's SmartAC™ Program

CALMAC Study ID PGE0443

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Table of Contents

List of Tables

List of Figures

Executive Summary

This report documents *ex-post* and *ex-ante* load impact evaluations of Pacific Gas and Electric's (PG&E) SmartAC™ program for 2019. The evaluation produces estimates of the *ex-post* load impacts for each hour of each event called in 2019, and it develops *ex-ante* load impact forecasts for the program through 2030.

ES.1 Resources Covered

SmartAC™ is a direct load control central air conditioner (AC) cycling program for residential customers that was integrated into the CAISO wholesale market in program year 2018. SmartAC™ program participants receive a one-time incentive for allowing PG&E to cycle their AC for up to 6 hours per day in response to CAISO market awards, during periods of system or local area emergencies for PG&E capacity, or for limited testing for a maximum of 100 hours per summer (May 1 through October 31). Upon enrollment in SmartAC™, PG&E installs an AC control switch (*i.e.*, Energate LC2200) on the participant's central AC unit that communicates bi-directionally over the AMI network. Legacy technology, installed prior to August 2017, is capable of one-way communication over commercial paging systems and includes programmable communicating thermostats (PCT) and switches. When events are called, PG&E sends signals to the PCTs and switches.

PG&E employs a combination of events including system-wide serial events or at the Sub-Load Aggregation Point (sub-LAP) level. System-wide events include all participants and can be initiated based on CAISO or PG&E emergencies or for testing purposes. System-wide test events generally call all SmartAC™ customers throughout the service territory except for a random sample of SmartAC customers that serve as the control group based on the last digit of the factory programmed serial number of their installed device (*i.e.*, one or two serial groups are withheld from the event). During sub-LAP level events all SmartAC™ participants with devices that are associated with a given sub-LAP are dispatched for the event. Two of the events during PY2019 were serial test events, while the remaining eight events were CAISO market awards.

The primary goals of the evaluation include:

1. Estimate hourly *ex-post* load impacts for the 2019 program year, including:
    a. Hourly and average daily load impacts for each event;
    b. The distribution of hourly and average daily load impacts by customer segment, including: sub-LAP, CARE/non-CARE customers, net-metering solar customers (NEM), housing type (*i.e.*, single family vs. multifamily customers), AC usage intensity, device type (*i.e.*, Two-way vs. One-way; by One-way device type: ExpressStat, UtilityPro, Gen 1, and Gen 2), and by marketing cohort
    c. Load Impact estimates for SmartAC™-only customers as compared to customers who are dually enrolled in SmartAC™ and SmartRate™;

    d. The opt-out/override rate by customer segment; and
    e. The persistence of load reductions across event-hours for multiple hour events.
2. Produce *ex-ante* load impact forecasts for 2020-2030 by local capacity area (LCA) on an aggregate and per customer basis for a typical event day and the monthly system peak load day for May through October. Forecasts are based on the following four sets of weather conditions:
    a. PG&E's peaking conditions in a 1-in-2 weather year;
    b. PG&E's peaking conditions in a 1-in-10 weather year;
    c. CAISO peaking conditions in a 1-in-2 weather year; and
    d. CAISO peaking conditions in a 1-in-10 weather year.

ES.2 Evaluation Methodologies

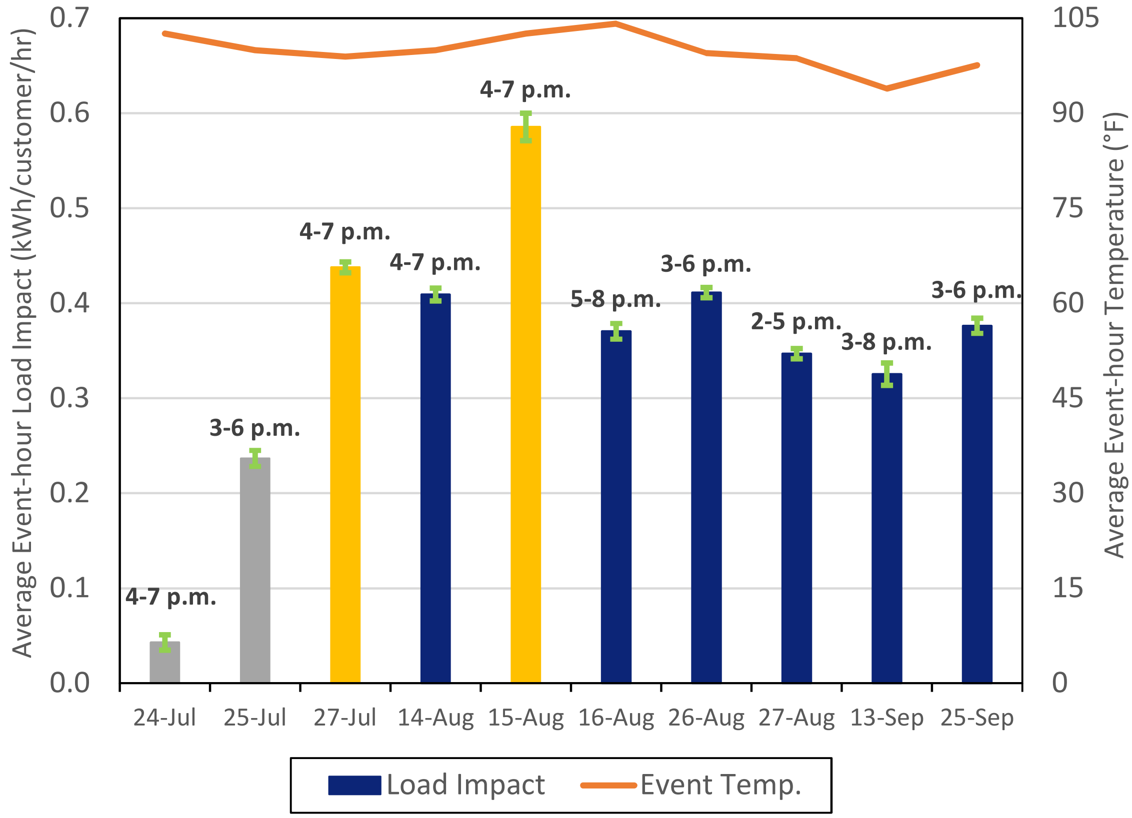
In this evaluation, we estimate load impacts by comparing SmartAC™ customer loads to that of a control group on event days, net of the differences in loads on non-event days with comparable weather conditions. For system-wide serial test events where at least one serial group is withheld from the event, we use this random sample of SmartAC™ customers as the control group. Otherwise we use a matched control group consisting of residential customers who are not enrolled in SmartAC™ or SmartRate™. Matched control group customers are selected based on the similarity of available customer characteristics (*e.g.*, sub-LAP, AC usage, CARE status, NEM status) as well as usage patterns on non-event days.

We then estimate event-day load impacts using a regression-based difference-in-differences method, which produces estimates of standard errors, and thus confidence intervals around the estimated event-hour or event-day usage reductions. This approach also adjusts for differences in usage between the treated SmartAC™ customers and the control group on event-like non-event days, thus representing a difference-in-differences evaluation approach.

ES.3 Ex-Post Load Impacts

Figure ES.1 summarizes the *ex-post* load impact estimates (in kWh/customer/hour) for the average event-hour for all ten SmartAC™ events in PY2019, along with an 80 percent confidence interval (corresponding to the 10th and 90th percentile uncertainty-adjusted load impacts). The gold bars indicate the two serial test events, while the blue and gray bars correspond to the eight sub-LAP events. There were statistically significant load reductions on each of the ten events, ranging from 0.04 to 0.59 kWh/customer/hour. The gray bars indicate two events with dispatch issues on July 24th and 25th, explaining the low load impact relative to the other events. Moreover, the serial events had higher load impacts on average.

Figure ES.1: Average Event-Hour Load Impacts by Event



In addition to the overall load impacts, we examined patterns of load impacts at the sub-LAP level for sub-LAP events and at the LCA level for serial events. We also examined how load impacts are distributed across customer subgroups. Our results were largely consistent with previous findings, while new results indicate that load impacts are higher for new two-way devices compared to one-way devices for serial and sub-LAP events.

ES.4 Ex-Ante Load Impacts

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

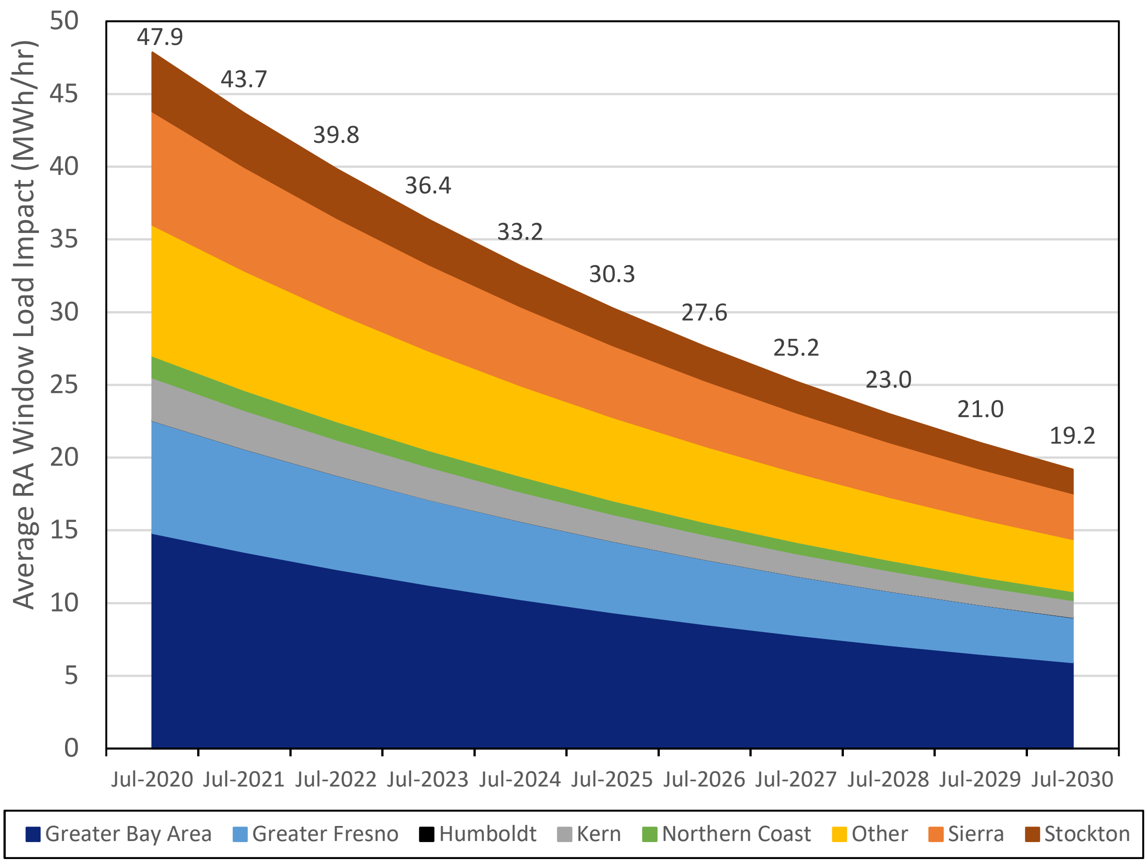
Estimating *ex-ante* load impacts requires three key pieces of information:

1. An *enrollment forecast* provided by PG&E for relevant components of the program, which consists of forecasts of the number of customers by required type of customer;
2. *Reference loads* by customer type, simulated from regression models plus *ex-ante* weather conditions provided by PG&E; and

3. A forecast of *load impacts per customer*, again by relevant customer type, where the load impact forecast also varies with weather conditions and is based on *ex-post* results from current or past program years.

Figure ES.2 summarizes the *ex-ante* load impact forecast for 2020 to 2030 for SmartAC™ customers by plotting the average aggregate load impacts for the Resource Adequacy (RA) window over time. For this comparison we use the PG&E 1-in-2 scenario for July peak days. The large declines in aggregate load impacts over time are being driven by the enrollment forecast provided by PG&E, which assumes consistent program attrition of approximately 9 percent per year from 2020 to 2030.

Figure ES.2: Aggregate RA Window Load Impacts 2020-2030 for PG&E 1-in-2 July Peak Scenario



1. Introduction and Purpose of the Study

This report documents *ex-post* and *ex-ante* load impact evaluations of Pacific Gas and Electric's (PG&E) SmartAC™ program for 2019. The evaluation produces estimates of the *ex-post* load impacts for each hour of each event called in 2019, and it develops *ex-ante* load impact forecasts for the program through 2030.

SmartAC™ is a direct load control central air conditioner (AC) cycling program for residential customers that was integrated into the CAISO wholesale market in program year 2018. SmartAC™ program participants receive a one-time incentive for allowing PG&E to cycle their AC for up to 6 hours per day in response to CAISO market awards, during periods of system or local area emergencies for PG&E capacity, or for limited testing for a maximum of 100 hours per summer (May 1 through October 31).

Upon enrollment in SmartAC™, PG&E installs an AC control switch (*i.e.*, Energate LC2200) on the participant's central AC unit that communicates bi-directionally over the AMI network. Legacy technology, installed prior to August 2017, is capable of one-way communication over commercial paging systems and includes programmable communicating thermostats (PCT) and switches. When events are called, PG&E sends signals to the PCTs and switches. As dictated by the tariff, PG&E cycles the AC unit for residential customers for approximately 50% of the compressor run-time during each half-hour. Switches and some PCTs are cycled using adaptive algorithms.

PG&E employs a combination of events including system-wide serial events or at the Sub-Load Aggregation Point (sub-LAP) level. System-wide events include all participants and can be initiated based on CAISO or PG&E emergencies or for testing purposes. System-wide test events generally call all SmartAC™ customers throughout the service territory except for a random sample of SmartAC customers that serve as the control group based on the last digit of the factory programmed serial number of their installed device (*i.e.*, one or two serial groups are withheld from the event). During sub-LAP level events all SmartAC™ participants with devices that are associated with a given sub-LAP are dispatched for the event. Historically, sub-LAP "addressing" was done by sending a signal to new SmartAC™ devices after installation to associate these devices with the appropriate sub-LAP. Since the CAISO wholesale market integration of the SmartAC™ program in 2018, a majority of SmartAC™ events are sub-LAP-level events, while a select number of serial events are called for testing purposes.

Table 1-1 shows the details for each event day in program year 2019 (PY2019). Two of the events, on July 27, 2019 and August 15, 2019 were serial test events, while the remaining eight events were CAISO market awards. There were two SmartAC™ sub-LAP events on August 27, 2019 and September 13, 2019 during which the event hours differed across sub-LAPs. Otherwise, sub-LAPs that were dispatched for the same event were dispatched for the same event hours. Both system wide test events were dispatched from 4 to 6:30 p.m. in PY2019 in order to ease the customer experience, since it can take up to 30 minutes for all devices to restore normal AC function.[1]

Table 1-1: PY2019 SmartAC™ Events

Date	Hours	Reason	SmartRate Event?	Sub-LAPs/Serial Groups Dispatched	# Customers Dispatched
24-Jul	4 to 7 p.m.	Market Award	Yes	PGF1, PGKN, PGZP	21,809
25-Jul	3 to 6 p.m.	Market Award	No	PGF1, PGKN, PGZP	25,313
27-Jul	4 to 7 p.m.	System-wide test	No	All	100,857
14-Aug	4 to 7 p.m.	Market Award	Yes	PGEB, PGNB, PGP2, PGSB, PGSI	46,192
15-Aug	4 to 7 p.m.	System-wide test	No	Except Serial Group 2	87,476
16-Aug	5 to 8 p.m.	Market Award	Yes	PGF1, PGKN, PGZP	21,660
26-Aug	3 to 6 p.m.	Market Award	Yes	PGF1, PGKN, PGNC, PGNP, PGSI, PGST, PGZP	53,727
27-Aug	3 to 5 p.m. (PGNC only) 2 to 5 p.m.	Market Award	Yes	PGF1, PGKN, PGNC, PGNP, PGSI, PGST, PGZP	53,662
13-Sep	3 to 6 p.m. (PGNB only) 5 to 8 p.m.	Market Award	Yes	PGNB, PGP2, PGSB	13,108
25-Sep	3 to 6 p.m.	Market Award	No	PGEB, PGP2, PGSB	31,997

SmartAC™ customers have historically been eligible to also enroll in the SmartRate™ program. A CPUC decision permits the legacy dual participants if they enrolled before October 26, 2018, but subsequent new dual participation is prohibited. As of May 2019, SmartAC™ had over 105,000 active enrolled residential customers; approximately 12,800 of these customers were dually enrolled in SmartAC™ and SmartRate™. On days when both a SmartAC™ event and a SmartRate™ event is called, the SmartRate™ customers are withheld from SmartAC™ events and the response from dually enrolled customers is attributed to the SmartRate™ program.

The primary goals of the evaluation include:

1. Estimate hourly *ex-post* load impacts for the 2019 program year, including:
    a. Hourly and average daily load impacts for each event;
    b. The distribution of hourly and average daily load impacts by customer segment, including: sub-LAP, CARE/non-CARE customers, net-metering solar customers (NEM), housing type (*i.e.*, single family vs. multifamily customers),

[1] The systems that control the devices are programmed to restore normal AC function randomly over the course of 30 minutes. Consequently, some devices returned ACs to normal function at 6:30 p.m., while the rest returned to normal function throughout the following 30 minutes from 6:30 to 7 p.m.

AC usage intensity, device type (*i.e.*, Two-way vs. One-way; by One-way device type: ExpressStat, UtilityPro, Gen 1, and Gen 2), and by marketing cohort[2];

   c. Load Impact estimates for SmartAC™-only customers as compared to customers who are dually enrolled in SmartAC™ and SmartRate™;
   d. The opt-out / override rate by customer segment[3]; and
   e. The persistence of load reductions across event-hours for multiple hour events.[4]

2. Produce *ex-ante* load impact forecasts for 2020-2030 by LCA on an aggregate and per customer basis for a typical event day and the monthly system peak load day for May through October. Forecasts are based on the following four sets of weather conditions:
   a. PG&E's peaking conditions in a 1-in-2 weather year;
   b. PG&E's peaking conditions in a 1-in-10 weather year;
   c. CAISO peaking conditions in a 1-in-2 weather year; and
   d. CAISO peaking conditions in a 1-in-10 weather year.

The evaluation conforms to the Load Impact Protocols adopted by the California Public Utilities Commission (CPUC) in April 2008 (D.08-04-050).

This report is organized as follows: Section 2 describes the evaluation methods used in the study; Section 3 contains *ex-post* load impact results; Section 4 contains *ex-ante* forecasts; Section 5 compares *ex-post* and *ex-ante* estimates to those from previous years; and Section 6 provides recommendations. Appendices describe the results of our control-group matching process, approaches used to evaluate the quality of results, and contain electronic versions of the required Protocol table generators.

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[2] Since 2015, PG&E has employed a targeted marketing strategy to recruit SmartAC™ customers with the greatest potential for producing large load reductions. PG&E defines these customers as medium and high AC usage customers.

[3] The opt-out rate is the portion of program participants who request by phone or website to override the control of their AC device during specific events.

[4] In the PY2018 report, we instead analyzed the persistence of load impacts across consecutive event days. This is not possible for PY2019 because there are few consecutive event days of the same type (*i.e.*, serial events versus sub-LAP events); comparing load impacts on consecutive event days would amount to comparing the load impacts from serial events vs. sub-LAP events. Moreover, it is difficult to distinguish the persistence across event hours from the hours called for events, because there is a strong correlation between the hour of the event and the hour of day (*e.g.*, HE 18 is the second event hour in 34 of 61 events).

2. Study Methodology

The primary objectives of this evaluation were outlined in Section 1. This section describes the data and methods used to produce *ex-post* load impacts and *ex-ante* forecasts.

2.1 Ex-post Load Impact Evaluation: Sub-LAP Events

For the sub-LAP events, we estimate load impacts by comparing SmartAC™ customer loads to that of a quasi-experimental matched control group of non-SmartAC™ customers on event days, net of the differences in loads on event-like non-event days. This regression-based approach, known as the difference-in-differences (D-in-D) method, can be used to produce estimates of standard errors to develop confidence intervals about the estimated event-hour or event-day load impacts. The eligible control-group customers consist of residential customers who are not enrolled in SmartAC™ or SmartRate™. We match control-group customers based on the similarity of available customer characteristics (*e.g.*, sub-LAP, AC usage, CARE status, NEM status) as well as usage patterns on non-event days.

The event on July 27, 2019 was a system-wide serial event, which relies on factory-programmed addressing rather than sub-LAP addressing. However, there was not a control group of SmartAC™ customers withheld from the event—all SmartAC™ customers were dipatched for this event. This necessitates using the same approach to estimating load impacts that we use to for sub-LAP events as described above.

2.1.1 Data

To address each of the load impact objectives listed in Section 1, the following data is required:

- *Customer* information for SmartAC™ customers and potential control-group customers (*e.g.*, sub-LAP, LCA, weather station, AC usage level, housing type, CARE status, NEM status);
- Billing-based *interval load data* (*i.e.*, hourly loads for each treatment and potential control group customer) for PY2019 (May 1 through October 31);
- *Weather data* (*i.e.*, hourly temperatures and other variables for PY2019, by weather station);
- *Program event data* (*i.e.*, dates and hours of SmartAC™ and SmartRate™ events and a list of SmartAC™ customers who are dually enrolled in both programs); and
- *Device Information* for SmartAC™ customers (*i.e.*, the type and number of devices installed at each premise and the serial number to determine treatment and control groups for the serial event) as well as SmartAC™ customer opt-outs on each date.

2.1.2 Control Group Selection for Sub-LAP events

The objective in selecting a quasi-experimental matched control group is to identify a group of customers that are as similar as possible to treatment customers, particularly in terms of their hourly load profiles. Due to the high number of potential control customers, we perform the matching in two stages. In the first stage, we use propensity score matching to identify three control customers for each treatment customer that have the closest match in terms of monthly usage (based on billing data), weather station and cooling degree days, and customer characteristics such as CARE status, NEM status, dwelling type, AC usage, and rate schedule. Following the first-stage matching, we obtain interval load data for the treatment customers and the paired-down set of matched control customers.

The first-stage matching allows for a more tractable matching process in the second stage using the interval load data. The second-stage matching process uses propensity score matching to find a single control customer for each SmartAC™ customer with the closest hourly load profile on a selection of non-event, non-holiday weekdays. Moreover, to ensure that customers are matched based on the sensitivity of their energy usage to weather conditions, we perform this matching process using two 24-hour load profiles drawn from different temperature profiles. The first 24-hour load profile reflects usage patterns during the hottest 10 percent of non-event days. The second 24-hour load profile reflects usage over a set of cooler days taken from the middle 50 percent of non-event days. In addition to two 24-hour load profiles, customers are also matched based on CARE-status, NEM-status, dwelling type, and AC usage level.[5] Finally, we require that SmartAC™ customers are matched to a control customer residing in the same sub-LAP area.

Propensity score matching involves estimating a regression to determine each customer's probability (*i.e.*, "propensity") of being assigned treatment based upon observable characteristics. Each SmartAC™ customer is then matched to the control customer with the nearest value in terms of their predicted probability, also known as their "propensity score". For the second stage matching, we assume the probability model is a logistic function of the following form:

$$logit(SmartAC_c) = \beta_0 + \sum_{h=1}^{24} \beta_{1,h} avgkW_{c,h} + \sum_{all\ j} \beta_{2,j} X_{c,j} + \varepsilon_c$$

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

[5] Propensity score matching does not guarantee that treatment customers are matched with a control that has the same CARE status, NEM status, etc. However, this approach leads to a similar distribution across these characteristics for the treatment group and control group.

Table 2-1: Propensity Score Model Terms

Symbol	Description
$SmartAC_c$	Variable indicating whether customer c is a SmartAC (1) or Control (0) customer
$avgkW_{c,h}$	Average load during hour h for customer *c*
$X_{c,j}$	The value of characteristic j for customer c
β_0	Estimated constant coefficient
$\beta_{1,h}$	Estimated coefficient for hour h of 24-hour load profile
$\beta_{2,i}$	Estimated coefficient for customer characteristic j
ε_c	Error term for customer c

We estimate a logistic regression that includes two 24-hour profiles: one that averages customer load across hot days (*i.e.*, the hottest 10 percent of non-event days) and one that averages customer load across a random selection of cooler days (*i.e.*, days that fall between the 25th and 75th percentile of non-event days based on average temperature). Furthermore, we include indicators for CARE status, NEM status, type of dwelling, and AC usage level as customer characteristics in the regression. This model is estimated separately for each sub-LAP.

For the first stage matching, we estimate a similar logistic regression to the one described above, however, this regression is based on monthly billing data and includes the average usage divided by the number of billed days in place of the 24-hour load profiles above, as well as characteristics that include: average cooling degrees per billed day, an indicator for weather station, the share of billed days on each type of rate schedule, an indicator for whether the customer switched rate schedules, an indicator for dwelling type, and an indicator for AC usage.

To assess the validity of the control-group matching processes, we compare the characteristics and non-event-day load profiles of the matched control-group and treatment customers. More details about our matching process, including evaluation of match quality, are provided in Section 3.1 and Appendix A.

2.1.3 Analysis Methods

We estimate the following panel model for each hour of the day and sub-LAP:

$$kW_{c,d} = \beta_0 + \sum_{i=1}^{n}\left(\beta_{1,i} \times SmartAC_{c,d} \times Evt_{i,d}\right) + \sum_{all\ j} \beta_{2,j}\, X_{c,d,j} + C_c + D_d + \varepsilon_{c,d}$$

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

Table 2-2: *Ex-Post* Load Impacts Model Terms

Symbol	Description
$kW_{c,d}$	Load during a given hour for customer *c* on day *d*
$SmartAC_{c,d}$	Variable indicating whether customer *c* is a SmartAC (1) or Control (0) customer
$Evt_{i,d}$	Variable indicating that day *d* is the i^{th} event day (1) or not (0)
$X_{c,d,j}$	The value of weather variable j on day d for customer c
β_0	Estimated constant coefficient
$\beta_{1,i}$	Estimated load impact for event *i*
$\beta_{2,i}$	Estimated coefficient for customer characteristic j
C_c	Customer fixed effects
D_d	Date fixed effects
$\varepsilon_{c,d}$	Error term (correlated at the customer level)

The model includes date and customer fixed effects to account for factors that commonly affect all customers over time (*e.g.*, weather) and time-invariant customer characteristics (*e.g.*, home size). In addition, the model includes time variant weather controls such as the mean temperature across the first 17 hours of the day[6]. The $\beta_{1,i}$ coefficients represent the estimated load impacts for each hour of every event day.

We estimate this model separately for each hour of the day using only event and event-like non-event days (*i.e.*, the hottest 10% of non-event days). The distribution of load impacts across different customer subgroups is reserved for the serial test event on August 15, 2019, since this allows for a system-wide comparison of treatments and controls with the same subgroup status. As previously mentioned, the matching procedure used for sub-LAP events does not guarantee that the dispatched sub-LAPs are representative of the system-wide results nor that treatments and matched controls have the same subgroup status. For sub-LAP events we estimate the load impacts by sub-LAP and for customers who are dually enrolled in SmartRate™ compared to customers who are only enrolled in the SmartAC™ program.

The Load Impact Protocols require the estimation of uncertainty-adjusted load impacts. Thus, in addition to producing point estimates of the *ex-post* load impacts, we show the uncertainty around the estimated impacts. These methods use the estimated load-impact parameter values and the associated variances to derive scenarios of hourly load impacts. Due to variation in event hours across event days, we are not able to estimate the uncertainty associated with the typical event day.

We validated the *ex-post* load impact estimates against simple difference-in-difference calculations from load data. Specifically, for each sub-LAP and event day, we compared the average treatment customer hourly loads to the average control-group hourly loads. The comparisons included events during which the sub-LAP was not dispatched, which allowed us to ensure that the event information we were provided was correct and that our methods did not produce "false positives" (*i.e.*, estimated load impacts for dates/locations in which customers were not dispatched).

[6] The inclusion of weather variables may improve the effectiveness of the date fixed effects, particularly in models that include customers in different weather regions (*e.g.*, models by sub-LAP).

2.2 Ex-post Load Impact Evaluation: Serial Events

For the system-wide test event on August 15, 2019, in which the control group consists of SmartAC customers with device serial numbers ending in 2 (*i.e.*, serial group 2 was not dispatched for the event), we can estimate load impacts by simply comparing the treatment and control customer usage during each hour of the day. This approach relies upon treatment and control-group customer load profiles being statistically equal during pre-event hours. Although this is generally the case for a large number of customers, when estimating load impacts for smaller subgroups significant differences can arise.[7] A D-in-D approach, similar to the model presented in Section 2.1.3, can be used to control for any remaining differences in pre-event hour loads. This approach subtracts the difference between treatment and control loads (SmartAC customers in serial group 2) on select non-event days with comparable weather profiles from the difference on the serial event day.

Consistent with previous evaluations of serial test events, we use a simple D-in-D approach to estimate load impacts. In order to obtain standard errors for the uncertainty-adjusted load impacts, we implement this by estimating a regression model with each customer's usage during a given hour as the dependent variable and with the explanatory variables limited to a constant term and variables indicating 1) customers who are in the treatment group, 2) the day where the event is called, and 3) the treatment customers on the event day. The coefficient on the latter variable is the D-in-D load impact estimate. Once again, we use the estimated load-impact parameter values and the associated variances to derive uncertainty-adjusted load impacts for the Load Impact Protocols.

We estimate this model separately for each hour of the day using only event and event-like non-event days. The distribution of load impacts across different customer subgroups is explored by estimating the above model separately for each subgroup, when there are a sufficient number of treatment and control customers in each subgroup. These variables include CARE status, NEM status, housing type, AC usage level, device type (*i.e.*, Two-way vs. One-way; by One-way device type: ExpressStat, UtilityPro, Gen 1, and Gen 2), customers with multiple devices, marketing cohort, and customers who are dually enrolled in SmartRate™.

2.3 Developing Ex-Ante Load Impacts

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

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

1. An *enrollment forecast* for relevant components of the program, which consists of forecasts of the number of customers by required type of customer;
2. *Reference loads* by customer type; and

[7] This issue was discussed at length in the PY2017 evaluation.

3. A forecast of *load impacts per customer*, again by relevant customer type, where the load impact forecast also varies with weather conditions (if applicable), as determined in the *ex-post* evaluation.

Ex-ante load impacts are developed for the years 2020 through 2030, both for the monthly system peak load as well as a typical event day, under the four scenarios defined by both utility-specific and CAISO peaking conditions in both 1-in-2 (normal) and 1-in-10 (extreme) scenarios. Furthermore, *ex-ante* load impacts are developed for the following subgroups of customers:

1. LCA;
2. Customers enrolled in only SmartAC™ vs. customers dually enrolled in SmartAC™ and SmartRate™; and
3. Busbar (by November 1, 2020).

PG&E provided the enrollment forecasts and *ex-ante* weather conditions for each required scenario.

2.3.1 Reference Loads

The *per-customer reference loads* are simulated based on regression models, which reflect customer load patterns on non-event days and estimate the relationship between load patterns and weather. Reference loads are simulated using the appropriate weather scenario data (*i.e.*, the 1-in-2 and 1-in-10 weather-year conditions provided by the utilities) and month.

The regression model uses data for treatment customers from all non-holiday weekdays that do not coincide with SmartAC™ or SmartRate™ events from May 1 to October 31 in 2019. Average load profiles are created for each LCA and enrollment segment (*i.e.*, SmartAC™-only and dually enrolled customers). The regressions account for differences in loads by hour, day-of-week, or month by including various indicator control variables.

The *ex-ante* reference load regression model is as follows:

$$avgkW_{d,h} = \beta_0 + \sum_{h=1}^{24} \beta_{1,h}(CDD60_d \times H_h) + \sum_{h=1}^{24} \beta_{2,h} H_h + \sum_{h=1}^{24} \beta_{3,h}(Mon_d \times H_h) + \sum_{h=1}^{24} \beta_{4,h}(Fri_d \times H_h) + D_d + M_d + \varepsilon_{d,h}$$

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

Table 2-3: *Ex-Ante* Reference Loads Model Terms

Symbol	Description
$avgkW_{d,h}$	The average load (kWh/customer/hour) on day *d* during hour *h*
$CDD60_d$	The cooling degrees on day *d*
$B_{1,h}$	Estimated increase in average load during hour *h* from an increase of one cooling degree
$B_{2,h}$	Estimated average load during hour *h*
$B_{3,h}$	Estimated difference in average load during hour *h* on Mondays
$B_{4,h}$	Estimated difference in average load during hour *h* on Fridays
H_h	Variable indicating that the hour is *h* (1) or not (0)
Mon_d	Variable indicating that day *d* is a Monday (1) or not (0)
Fri_d	Variable indicating that day *d* is a Friday (1) or not (0)
D_d	Day of the week fixed effects
M_d	Month of the year fixed effects
$\varepsilon_{d,h}$	Error term (robust)

The model includes hour fixed effects to allow loads to vary by hour of the day. Monday and Friday hourly fixed effects allow for differences in load profiles on Mondays and Fridays. Day of the week fixed effects allow the daily load level to vary by day of the week. Month fixed effects allow the daily load level to vary by month of the year. The $\beta_{1,h}$ coefficients represent the estimated increase in average loads during hour *h* due to a one cooling degree day increase. We estimate this model separately for each LCA and enrollment segment.

Reference loads are simulated by applying the cooling degree days from the weather scenarios provided by PG&E to the estimated $\beta_{1,h}$ coefficients along with the other relevant load shape variables and fixed effects. The estimated reference loads for each month and weather scenario are assumed to be the monthly system peak load (or typical event day) for a Wednesday event.

2.3.2 Load Impacts

The *per-customer load impacts* are derived from an analysis of the current and previous *ex-post* load impact evaluations, with a focus on the effect of weather on the estimated load impacts. The resulting per-customer load impacts are then coupled with the appropriate reference loads to develop the forecasted load impacts and event-day reference load profiles.

We modeled the relationship between the load impact and weather conditions as follows:

$$Impact_{l,h,evt\ i} = \beta_0 + \beta_1 Temp_{l,h,evt\ i} + \beta_{2,l} Mean8_{l,evt\ i} \times LCA_l + LCA_l + H_h + \varepsilon_{l,h,evt\ i}$$

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

Table 2-4: *Ex-Ante* Load Impacts Model Terms

Symbol	Description
$Impact_{l,h,evt\ i}$	The estimated per-customer load impact (kWh/customer/hour) in LCA *l* during hour *h* on event *i*
$Temp_{l,h,evt\ i}$	The average temperature in LCA *l* during hour *h* on event *i*
$Mean8_{l,evt\ i}$	The average temperature in LCA *l* over the first eight hours of the day on event *i*
β_1	Estimated increase in per-customer load impact due to a 1 degree increase in the average hourly temperature
$\beta_{2,l}$	Estimated increase in per-customer load impact in LCA *l* due to a 1 degree increase in the average temperature over the first eight hours of the day
LCA_l	Variable indicating if the LCA is *l* (1) or not (0)
H_h	Variable indicating if the hour is *h* (1) or not (0)
$\varepsilon_{l,h,evt\ i}$	Error term (robust)

The model includes LCA and hour fixed effects to allow load impacts to vary by LCA and hour of the day. The β coefficients represent the estimated increase in per-customer load impact (in kWh/hour/customer) that results from a one-degree increase in temperature, either hourly or the average of the first eight hours of the event day. The standard errors from this model are the basis for the uncertainty-adjusted load impacts.

We build our *ex-ante* load impact forecasts based only on a combination of serial events called in 2017 and 2019. There were only two serial events dispatched during PY2019 (July 27th and August 15th), both during the same event hours from 4 to 7 p.m. Because the *ex-ante* load impact forecast must span the resource adequacy window from 4 to 9 p.m., PY2019 does not provide enough variation in serial event hours or temperatures to provide a reasonable forecast across the resource adequacy window nor the months over which the SmartAC™ program events can be called (May through October). Moreover, the other eight events dispatched in 2019 were sub-LAP events, which tend to yield smaller estimated load impacts compared to serial number events due to higher rates of commercial paging system issues or equipment malfunction associated with calling only a subset of PG&E's sub-LAP areas.[8] As a result, serial number events are more representative of the load impacts that would be achieved from system-wide events. In an effort to ensure the load impact forecast reflects current program performance in serial events, we give the PY2019 load impacts twice the weight in our regressions as the PY2017 load impacts.

In addition, we use load impacts that correspond to SmartAC™-only customers, consistent with how this analysis was done in the PY2018 report. To arrive at load impacts for dually enrolled customers, we apply a multiplicative factor of 0.66 based on

[8] Calling specific sub-LAPs historically depended on all devices being properly addressed to sub-LAPs, which is an imperfect process. The installation of new two-way communicating devices, which are not dependent on sub-LAP addressing, will bring sub-LAP event load impacts more in line with serial number event load impacts. However, during PY2019 only 12 percent of SmartAC™ customers had two-way devices.

our examination of the relationship between SmartAC™-only customers and dually enrolled customers during the two serial test events in 2019.

The snapback in the three hours following the event (when the customer's AC unit is running more than it would have in the absence of the event day to bring the home's temperature back to the thermostat's set point) is modeled as a share of the total event-hour load impact, by LCA. That is, larger event-hour load impacts are associated with higher post-event snapback.

As in all recent load impact evaluations, we present results of analyses of the relationship between current *ex-post* and *ex-ante* load impacts, focusing on key factors causing differences between them (*e.g.*, differences between observed temperatures in 2019 and the temperatures in the various weather scenarios). We will also compare current and previous *ex-post* load impacts, and current and previous *ex-ante* load impacts.

3. *Ex-Post* Load Impacts

This section documents the findings from the *ex-post* load impact analysis. The primary load impact results include estimates of the aggregate and per-customer event-hour load impacts for each event. Due to the nature of sub-LAP events (eight out of ten events), where different sub-LAPs are dispatched for different events and, in some cases, different event hours, we are not able to present results for the typical event day. Instead, we average the hourly load impacts across all potential event hours, or in some cases choose an illustrative event hour or event day. Our main findings are summarized in this section in various figures and data tables, while detailed results for each hour, event, and sub-LAP or LCA are available in electronic form in Protocol table generators provided along with this report.

As described in Section 2, all results presented in this section are derived from D-in-D regression analyses of hourly data for SmartAC™ customers and a control group. In addition to the controls described in the estimated model in Section 2.1.3, we control for the six concurrent SmartRate™ events by including separate indicators for customers who are dually enrolled in SmartAC™ and SmartRate™. Furthermore, we drop SmartRate™-only events from the pool of SmartAC™ non-event days to ensure that non-event loads are comparable between SmartAC™ customers and controls on all non-event days.

3.1 Control Group Matching Results

In this section, we present summaries of our control group matching process used to create a control group for the eight sub-LAP events and the system-wide event on July 27th. Our validity assessment focuses on comparisons of treatment and control-group loads for selected event-like non-event days. We also report statistics such as the mean absolute percentage error (MAPE) and mean percent error (MPE), which provide measures of accuracy and bias in the matches, respectively.[9]

Table 3-1 provides the mean percentage error (MPE) and mean absolute percentage error (MAPE) calculated across the average 24-hour load profile as well over the RA window. We evaluate match quality based on the two 24-hour load profiles that we used in matching. The first corresponds to the average load profile over the hottest 10 percent of event-like non-event days, while the second corresponds to a random sample of cooler days taken from the middle 50 percent of days based on temperature. We also evaluate the match quality of the cooler days (*i.e.*, the middle 50 percent of days based on temperature) that were not sampled for use in matching and the weekend non-event days, which helps assess whether there is good match quality on out-of-sample days. Additional results by sub-LAP are presented in Appendix A.

Table 3-1: Match Quality Statistics

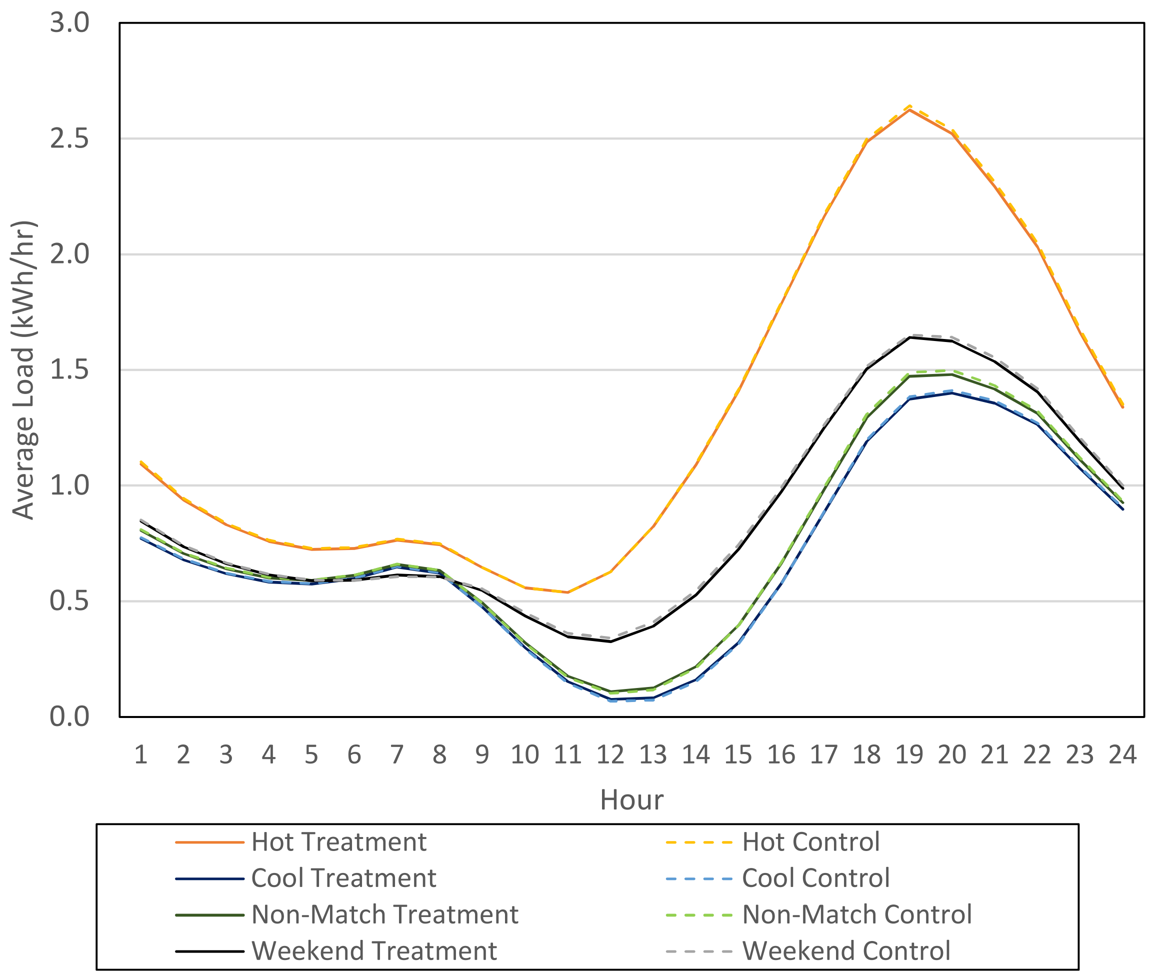
Comparison Days	MPE	MAPE	MPE RA Window	MAPE RA Window
Hot Days	0.5%	0.5%	0.6%	0.6%
Cool Days	-1.2%	1.9%	0.6%	0.6%
Non-Matching Cool Days	-0.3%	1.3%	1.1%	1.1%
Weekend Days	1.4%	1.6%	0.9%	0.9%

Figure 3-1 illustrates the matched load profiles for selected event-like days. This figure contains the average hourly profiles for the treatment and matched control-group customers by day type including hot days, cooler days that were used in matching, the cooler days that were not used in matching, and weekend days (not used in matching). The solid lines represent the average usage of treatment customers on hot days (red), cooler matching days (blue), cooler non-matching days (green), and weekend days (black). Similarly, the dashed lines represent the average usage of the matched control customers on hot days (yellow), cooler matching days (blue), cooler non-matching days (green), and weekend days (gray). Regardless of the comparison day, the average load profiles are nearly identical between treatment and control. Although cool days that are used in matching have slightly lower loads than cool days that are not used in matching, the control loads on each type of day track the treatment loads very closely.[10] Moreover, weekend loads are higher on average compared to loads on cool weekdays, but control and treatment have a similar pattern of usage during weekends on average suggesting that matches based on weekdays can be used for the weekend event on July 27, 2019.

[9] Note that "biased" matches do not necessarily adversely affect the estimated load impacts, as we employ a difference-in-differences estimation methodology that accounts for load differences during the matching period.

[10] Although the cool days that are used in matching are randomly chosen from the set of the middle 50 percent of days based on temperature, it is still possible that fewer hot days were assigned to this group compared to the cool days not used in matching.

Figure 3-1: Treatment and Control Non-Event Day Load Profiles



3.2 Overall Load Impacts

This section summarizes overall results for all SmartAC™ events. In later sections, we focus attention on sub-LAP events, serial events, and discuss how these load impacts are distributed across subgroups of interest, including for customers who are dually enrolled in SmartRate™.

The *ex-post* load impacts are summarized for all ten events in Figure 3-2.[11] The bars indicate the magnitude of the average per customer load impact (in kWh/customer/hour) during the hours dispatched for each event, while the labels show

[11] The load impacts for the serial events on 7/27 and 8/15 do not include the last hour of the event from 6 to 7 p.m., because the signal was terminated at 6:30 pm, making load impacts during this hour much lower than the previous two hours. Including the last hour in the event lowers the average event-hour load impacts on 7/27 and 8/15 to 0.34 and 0.51, respectively.

the maximal range of event hours over which all customers were dispatched.[12] The gold bars indicate the two serial events, while the blue bars correspond to the six sub-LAP events without dispatch issues, and the gray bars indicate two sub-LAP events that had dispatch issues. The green bands correspond to 80 percent confidence intervals around these estimates (*i.e.*, the 10th and 90th percentile scenarios from the uncertainty-adjusted load impacts). The orange line represents the average temperatures experienced by the customers during the event.

Overall results range from 0.04-0.59 kWh/customer/hour

These results indicate that SmartAC™ customers had statistically significant load reductions on each of the ten event days, ranging from 0.04 to 0.59 kWh/customer/hour.

Dispatch issues on July 24th and 25th led to small, statistically significant load impacts

Two sub-LAP events with dispatch issues on July 24th from 4 to 7 p.m. and July 25th from 3 to 6 p.m., indicated with gray bars, had lower load impacts relative to other sub-LAP events. The events dispatched customers in three historically very responsive sub-LAPs: PGF1, PGKN, and PGZP. The low level of per-customer load impacts was due to a system dispatch issue where many SmartAC™ customers in PGF1, PGKN, and PGZP were not actually or fully dispatched for the event leading to an overall load impact that was small compared to historical program performance. Even so, these events had small, statistically significant load impacts of 0.04 kWh/customer/hour on July 24th and 0.24 kWh/customer/hour on July 25th.

Serial Events have higher load impacts than sub-LAP events

The average load impact across serial event hours (excluding 6 to 7 p.m.) was 0.51 kWh/customer/hour while the average load impact across sub-LAP event hours (excluding July 24th and 25th) was 0.37 kWh/customer per hour. Historically load impacts for SmartAC™ serial test events have been higher than load impacts for sub-LAP events, since factory programmed addressing, used for serial event dispatch, is more reliable than sub-LAP addressing. However, as new two-way devices replace old devices this difference is expected to shrink. Indeed, the PY2017 evaluation found average per-customer load impacts across all serial event hours was 0.57 kWh/customer/hour compared to 0.38 kWh/customer/hour across all sub-LAP event hours.

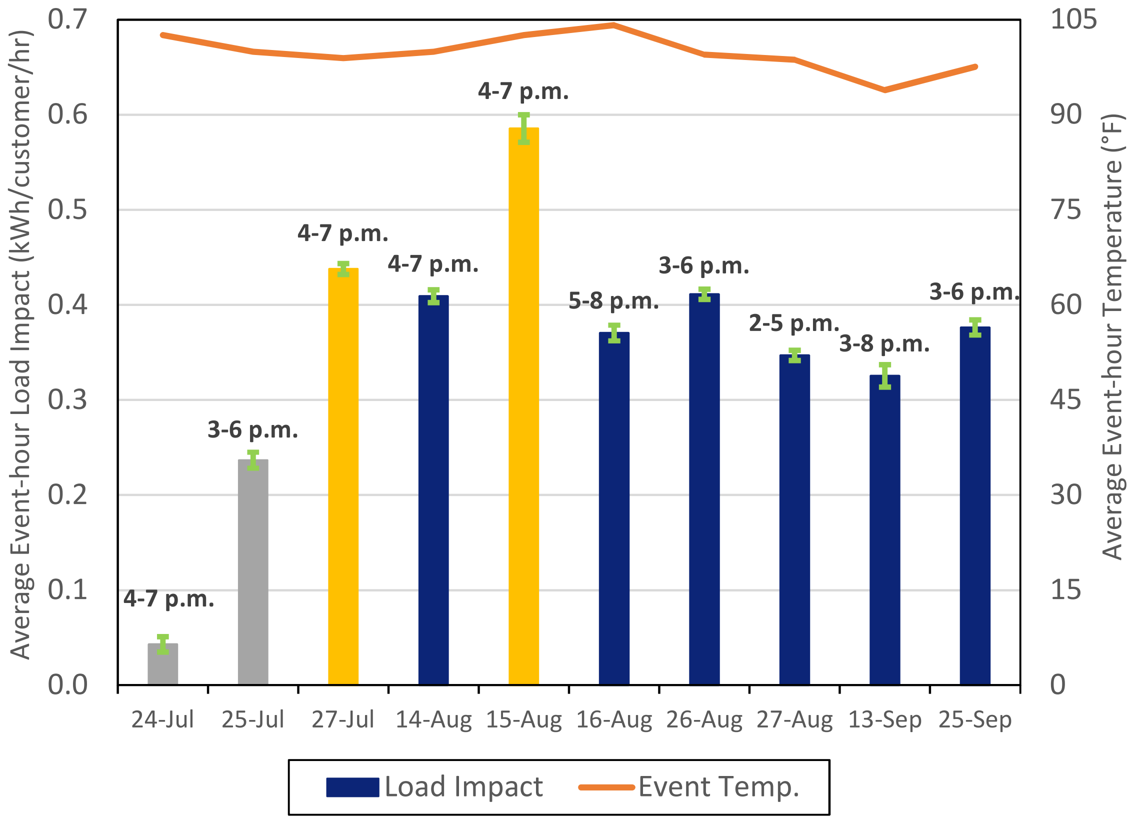
Load impacts average 0.41 kWh/customer/hour for most afternoon events

The load impacts for the eight events without dispatch issues averaged 0.41 kWh/customer/hour. Later sub-LAP events (4 to 8 p.m.) and earlier sub-LAP events (2 to

[12] On the August 27th and September 13th sub-LAP events, sub-LAPs were called for different event hours. In Figure 3-2, we aggregate across hours during which customers were called, while in the protocol table generators the hourly load impacts are aggregated across all called sub-LAPs for each hour of the day. This can dampen the estimated load impacts during hours where only a subset of called sub-LAP areas are called during the hour.

6 p.m.) have comparable average load impacts of 0.39 and 0.38 kWh/customer/hour, respectively.

Figure 3-2: Average Event-Hour Load Impacts by Event



The number of dispatched customers and average event temperature drive large variation in aggregate event impacts

Table 3-2 presents a more complete summary of event information, including the sub-LAPs dispatched, the sub-LAP-specific event hours, the type of event, and the number customers dispatched, as well as average load impacts (per customer and in aggregate), reference loads, and percentage load impacts across the hours for which each sub-LAP was dispatched (in the case of sub-LAP events) for each event day.

The number of dispatched customers and average event temperatures explain over 94 percent of the variation in aggregate load impacts, excluding the two events with dispatch issues. The number of dispatched customers varies dramatically across events, with 13,108 customers dispatched for the sub-LAP event on September 13th to 100,857 customers for the system-wide test event on July 27th. Aggregate load impacts, which averaged 22.19 MWh/hour, ranged from 2.56 MWh/hour on September 13th to 51.22 MWh/hour on August 15th. Although fewer customers were dispatched for the test event on August 15th than July 27th, due to the withheld serial group, the aggregate load impacts are higher because this event was almost four degrees hotter.

Table 3-2: Average Event-Hour Load Impacts by Event

Event Date	Event Hours	sub-LAPs/Serial Groups Dispatched	Type of Event	SmartRate Event?	# Dispatched	Average Event Hour				
						Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
7/24/2019	4 to 7 p.m. (HE17 to HE19)	PGF1, PGKN, PGZP	Market Award	Yes	21,809	3.07	0.04	1.4%	0.94	102.6
7/25/2019	3 to 6 p.m. (HE16 to HE18)	PGF1, PGKN, PGZP	Market Award	No	25,313	2.68	0.24	8.8%	5.99	99.9
7/27/2019	4 to 7 p.m. (HE17 to HE19)	All	System-wide test	No	100,857	2.53	0.44	17.3%	44.15	98.9
8/14/2019	4 to 7 p.m. (HE17 to HE19)	PGEB, PGNB, PGP2, PGSB, PGSI	Market Award	Yes	46,192	2.80	0.41	14.6%	18.90	99.9
8/15/2019	4 to 7 p.m. (HE17 to HE19)	Except Serial Group 2	System-wide test	No	87,476	2.98	0.59	19.6%	51.22	102.6
8/16/2019	5 to 8 p.m. (HE18 to HE20)	PGF1, PGKN, PGZP	Market Award	Yes	21,660	3.31	0.37	11.2%	8.02	104.1
8/26/2019	3 to 6 p.m. (HE16 to HE18)	PGF1, PGKN, PGNC, PGNP, PGSI, PGST, PGZP	Market Award	Yes	53,727	2.62	0.41	15.7%	22.09	99.5
8/27/2019	3 to 5 p.m. (HE16 to HE17) *PGNC only 2 to 5 p.m. (HE15 to HE17)	PGF1, PGKN, PGNC, PGNP, PGSI, PGST, PGZP	Market Award	Yes	53,662	2.16	0.35	16.1%	18.55	98.7
9/13/2019	3 to 6 p.m. (HE16 to HE18) *PGNB only 5 to 8 p.m. (HE 17 to HE20)	PGNB, PGP2, PGSB	Market Award	Yes	13,108	2.30	0.33	14.2%	2.56	93.9
9/25/2019	3 to 6 p.m. (HE16 to HE18)	PGEB, PGP2, PGSB	Market Award	No	31,997	2.16	0.38	17.4%	12.04	97.6

Serial events have relatively high percentage load impacts

In percentage terms, the load impacts range from 11.2 percent of reference loads for the sub-LAP event on August 16th to 19.6 percent for the serial event on August 15th (excluding the two events with dispatch issues). The serial event on July 27th had the third highest load impact of 17.3 percent of reference loads. The sub-LAP event on September 25th had a comparably high percentage load impacts of 17.4 percent.

Load Impacts are persistent across event hours for multiple hour events

Table 3-3 compares average per-customer load impacts and hourly temperatures across hours within each event to analyze whether load impacts persist across event hours. The blue shaded events begin later in the afternoon at 4 p.m. or later. Table 3-3 does not include the events with dispatch issues or the last hour of the serial events. Overall, load impacts are comparable in magnitude across event hours within each event, suggesting that load impacts are persistent across multiple hour events. For all events, the load impact during the second event hour exceed the load impacts during the first event hour. However, for earlier events the load impact during the third hour also exceeds the load impact during the second hour, while the reverse is true for events that begin at 4 p.m. or later. The temperatures across event hours largely explain this difference, with temperatures declining more dramatically between the second and third event hour for later events compared to smaller declines or event increases for earlier events.

Table 3-3: Persistence of Load Impacts Across Event Hours

Event Date	Event Hours	SmartRate™ Event?	Impact (kW/Cust)			Avg. Temp (°F)		
			Hour 1	Hour 2	Hour 3	Hour 1	Hour 2	Hour 3
27-Jul	4 to 7 p.m.	No	0.39	0.48		98.7	99.2	
14-Aug	4 to 7 p.m.	Yes	0.36	0.45	0.41	100.2	100.3	99.3
15-Aug	4 to 7 p.m.	No	0.50	0.68		102.5	102.6	
16-Aug	5 to 8 p.m.	Yes	0.38	0.40	0.32	105.2	104.7	102.5
26-Aug	3 to 6 p.m.	Yes	0.35	0.43	0.45	98.7	99.8	100.1
27-Aug	3 to 5 p.m. (PGNC only) 2 to 5 p.m.	Yes	0.27	0.36	0.40	96.8	98.9	99.1
13-Sep	3 to 6 p.m. (PGNB only) 5 to 8 p.m.	Yes	0.35	0.40	0.23	96.4	94.4	90.9
25-Sep	3 to 6 pm.m.	No	0.31	0.41	0.42	96.9	98.0	97.9

3.3 Sub-LAP Event Load Impacts

Next, we examine the results for sub-LAP events at the sub-LAP level. Figure 3-3 summarizes the sub-LAP level *ex-post* load impacts by event. The bars indicate the magnitude of the average per customer load impacts (in kWh/customer/hour) across the sub-LAP-specific event hours. The gold bars highlight the load impacts for PGKN, which had dispatch issues in PY2018. The green bands correspond to 80 percent confidence intervals around these estimates (*i.e.*, the 10th and 90th percentile scenarios from the uncertainty-adjusted load impacts). The orange line represents the average temperatures experienced by the customers in each sub-LAP during the event hours.

Sub-LAP event load impacts range from 0.25 to 0.59 kWh/customer/hour

Figure 3-3 illustrates that there is considerable variation across sub-LAP areas within the same event, as well as within sub-LAP across events. Sub-LAP event load impacts range from 0.25 to 0.59 kWh/customer/hour (excluding the first two events with dispatch issues). Several sub-LAPs that achieve the highest per-customer load impacts include PGEB, PGKN, PGP2, PGSB, and PGST.

PGKN has highest sub-LAP load impacts in PY2019 compared to the lowest in PY2018

During PY2018, there was a malfunctioning transmitter in Bakersfield, which caused PGKN to underperform during events relative to other sub-LAPs. During PY2019, PG&E replaced numerous devices in PGKN with two-way devices to improve dispatch reliability. The yellow bars highlight the average per customer load impacts for PGKN during five sub-LAP events in PY2019. The two-way devices have improved per-customer load impacts for PGKN, which was a high-performing sub-LAP in past evaluations. In particular, the events on July 16th, 26th, and 27th have load impacts that range from 0.55 to 0.59 kWh/customer/hour, or 17.3 to 23.9 percent of reference loads.

Figure 3-3: Average Event-Hour Load Impacts by Sub-LAP and Event for Sub-LAP Events

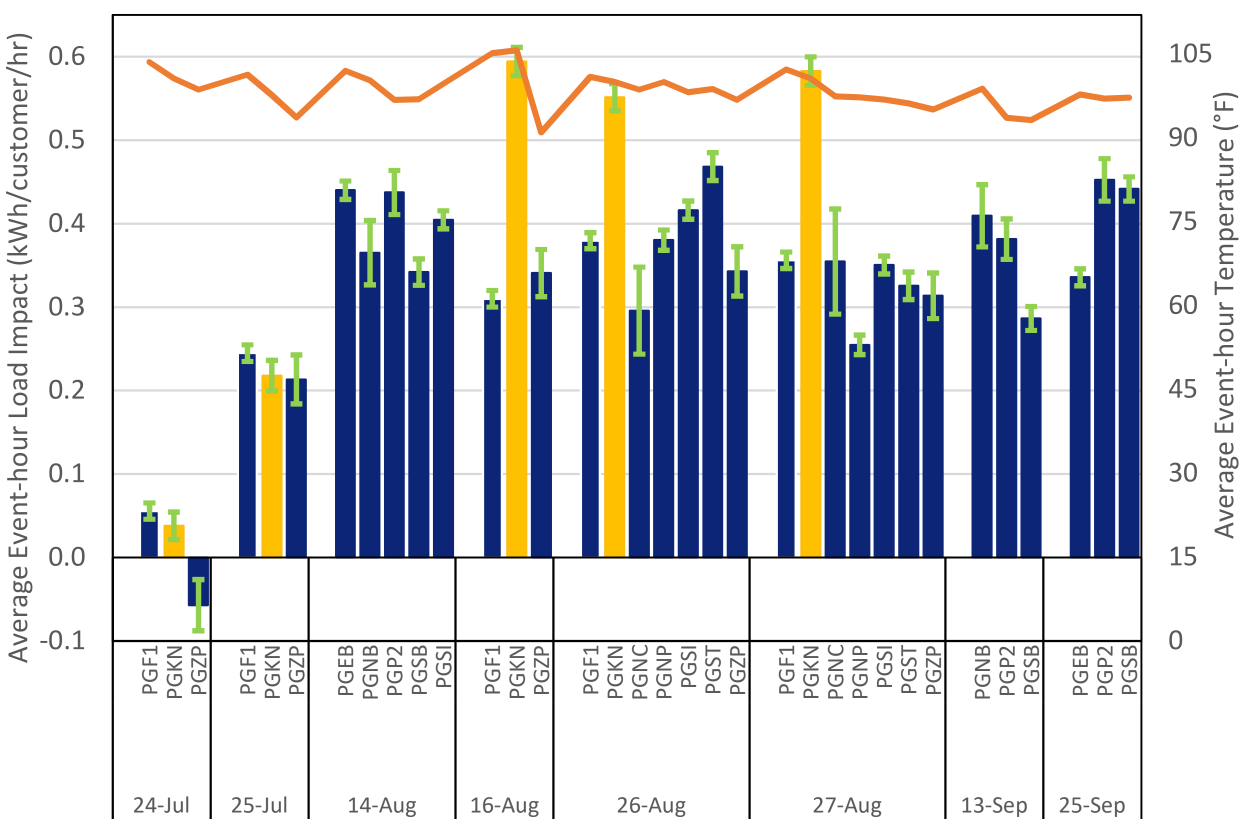


Table 3-4: Average Event-Hour Load Impacts by Sub-LAP and Event for Sub-LAP Events

Event Date	Sub-LAP	Event Hours	SmartRate Event?	# Dispatched	Average Event Hour				
					Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
24-Jul	PGF1	4-7 p.m.	Yes	15,598	3.15	0.06	1.8%	0.87	103.6
	PGKN			4,445	2.86	0.04	1.3%	0.17	100.7
	PGZP			1,766	2.85	-0.06	-2.0%	-0.10	98.6
25-Jul	PGF1	3-6 p.m.	No	17,990	2.83	0.24	8.6%	4.41	101.3
	PGKN			5,154	2.39	0.22	9.1%	1.12	97.7
	PGZP			2,169	2.14	0.21	10.0%	0.46	93.7
14-Aug	PGEB	4-7 p.m.	Yes	18,563	2.97	0.44	14.8%	8.17	102.0
	PGNB			1,355	2.86	0.37	12.8%	0.49	100.3
	PGP2			3,682	2.79	0.44	15.7%	1.61	96.8
	PGSB			8,202	2.46	0.34	13.9%	2.80	96.9
	PGSI			14,390	2.76	0.40	14.7%	5.82	99.7
16-Aug	PGF1	5-8 p.m.	Yes	15,489	3.37	0.31	9.2%	4.80	105.2
	PGKN			4,418	3.43	0.59	17.3%	2.63	105.7
	PGZP			1,753	2.47	0.34	13.8%	0.60	91.0
26-Aug	PGF1	3-6 p.m.	Yes	15,381	2.81	0.38	13.5%	5.84	100.9
	PGKN			4,398	2.71	0.55	20.4%	2.42	100.0
	PGNC			618	2.17	0.30	13.7%	0.18	98.6
	PGNP			11,358	2.55	0.38	14.9%	4.32	100.0
	PGSI			14,321	2.48	0.42	16.8%	5.96	98.2
	PGST			5,912	2.69	0.47	17.4%	2.77	98.7
	PGZP			1,739	2.40	0.34	14.3%	0.60	96.8
27-Aug	PGF1	2-5 p.m.	Yes	15,366	2.49	0.36	14.3%	5.47	102.2
	PGKN			4,390	2.44	0.58	23.9%	2.56	100.7
	PGNC	3-5 p.m.		618	2.05	0.35	17.3%	0.22	97.4
	PGNP	2-5 p.m.		11,350	1.89	0.25	13.5%	2.89	97.3
	PGSI			14,305	1.99	0.35	17.6%	5.01	96.8
	PGST			5,897	2.11	0.33	15.4%	1.92	96.2
	PGZP			1,736	1.87	0.31	16.8%	0.54	95.1
13-Sep	PGNB	3-6 p.m.	Yes	1,337	2.30	0.41	17.8%	0.55	98.8
	PGP2	5-8 p.m.		3,636	2.49	0.38	15.3%	1.39	93.6
	PGSB			8,135	2.21	0.29	13.0%	2.33	93.2
25-Sep	PGEB	3-6 p.m.	No	20,123	2.21	0.34	15.2%	6.76	97.8
	PGP2			3,656	2.21	0.45	20.5%	1.65	97.0
	PGSB			8,218	2.02	0.44	21.8%	3.63	97.2

PGEB has the highest aggregate load impacts

Table 3-4 provides the detailed information underlying Figure 3-3, including the number customers dispatched, the average event load impacts (per customer and in aggregate), reference loads, and percentage load impacts for each sub-LAP for each event. The number of dispatched customers varies dramatically across sub-LAPs leading to aggregate load impacts that range from 0.18 MWh/hour for PGNC to 8.17 MWh/hour for PGEB. In percentage terms, the load impacts range from 9.2 percent of reference loads for PGF1 to 23.9 percent of reference loads for PGKN.

Load impacts are similar across sub-LAP event hours with large post-event snapback

Figure 3-4 shows an example of the aggregate hourly reference loads, observed loads, and estimated load impacts using the August 26th sub-LAP event (there is no typical event day), in which a large share (*i.e.*, 53 percent or 53,727 customers) of enrolled SmartAC™ customers were dispatched. Table 3-5 contains the hourly results for August 26th in the manner required by the Protocols, including hourly temperatures and uncertainty adjusted load impacts. Notice that the load impacts peak at 24.3 MWh during the third hour of this event (5:00 to 6:00 p.m.) when temperatures also peak. Furthermore, there is statistically significant post-event snapback, when loads increase by 15.2 MWh the first hour after the event. Snapback peaks at 16.7 MWh the second hour after the event and declines over the course of the evening.

Figure 3-4: Hourly Load Impacts and Uncertainty Adjusted Estimates-August 26, 2019

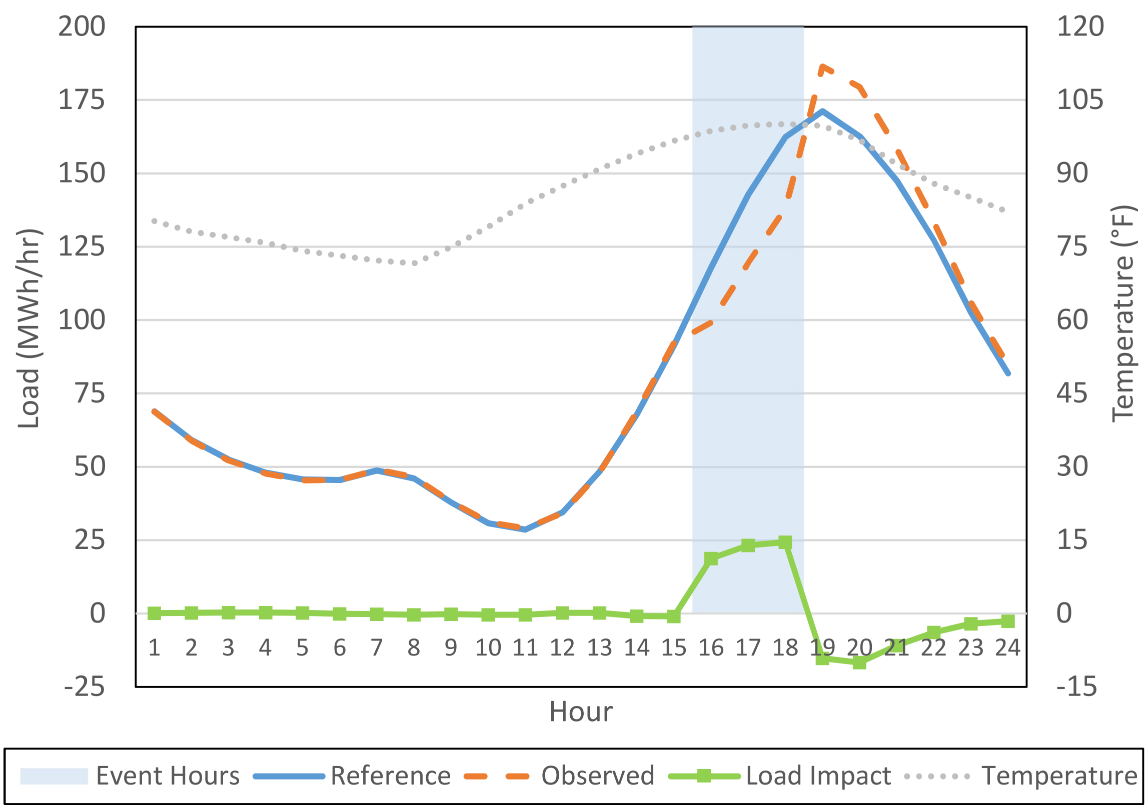


Table 3-5: Hourly Load Impacts and Uncertainty Adjusted Estimates-August 26, 2019

Hour Ending	Reference Load (MWh/hour)	Event Day Load (MWh/hour)	Estimated Load Impact (MWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (MWh/hour)- Percentiles				
					10th%ile	30th%ile	50th%ile	70th%ile	90th%ile
1	68.9	68.8	0.1	80.3	-0.2	0.0	0.1	0.3	0.4
2	59.1	58.9	0.2	78.1	0.0	0.1	0.2	0.3	0.5
3	52.5	52.1	0.4	77.0	0.1	0.3	0.4	0.5	0.6
4	48.0	47.7	0.3	75.8	0.1	0.3	0.3	0.4	0.6
5	45.7	45.4	0.3	74.1	0.1	0.2	0.3	0.3	0.5
6	45.5	45.5	0.0	73.2	-0.2	-0.1	0.0	0.0	0.2
7	48.7	48.9	-0.2	72.2	-0.4	-0.3	-0.2	-0.1	0.0
8	46.1	46.5	-0.4	71.6	-0.6	-0.5	-0.4	-0.3	-0.2
9	37.8	38.0	-0.2	74.9	-0.4	-0.3	-0.2	-0.1	0.1
10	30.8	31.3	-0.4	79.0	-0.8	-0.6	-0.4	-0.3	-0.1
11	28.6	29.0	-0.4	83.8	-0.8	-0.6	-0.4	-0.3	-0.1
12	34.5	34.3	0.2	87.4	-0.2	0.0	0.2	0.4	0.6
13	48.4	48.1	0.3	90.9	-0.2	0.1	0.3	0.5	0.7
14	67.9	68.7	-0.9	94.1	-1.3	-1.1	-0.9	-0.7	-0.4
15	91.4	92.3	-0.9	96.6	-1.4	-1.1	-0.9	-0.7	-0.4
16	117.9	99.2	18.7	98.7	18.2	18.5	18.7	18.9	19.2
17	142.7	119.5	23.2	99.8	22.7	23.0	23.2	23.4	23.7
18	162.4	138.1	24.3	100.1	23.8	24.1	24.3	24.5	24.8
19	171.2	186.4	-15.2	99.7	-15.7	-15.4	-15.2	-15.0	-14.7
20	162.7	179.4	-16.7	96.8	-17.2	-16.9	-16.7	-16.5	-16.2
21	147.5	158.4	-10.9	91.9	-11.3	-11.1	-10.9	-10.7	-10.4
22	127.2	133.5	-6.4	87.9	-6.8	-6.5	-6.4	-6.2	-5.9
23	102.5	106.0	-3.5	85.1	-3.8	-3.6	-3.5	-3.3	-3.1
24	81.8	84.4	-2.6	82.1	-3.0	-2.8	-2.6	-2.5	-2.3
By Period:	Estimated Reference Energy Use (MWh/hour)	Observed Event Day Energy Use (MWh/hour)	Estimated Change in Energy Use (MWh/hour)	Cooling Degree Hours (Base 75° F)	Uncertainty Adjusted Impact (MWh/hour) - Percentiles				
					10th	30th	50th	70th	90th
Daily	1,969.8	1,960.5	9.3	260.0	5.4	7.7	9.3	10.9	13.2
Avg. Event Hour	141.0	118.9	22.1	73.5	21.8	22.0	22.1	22.2	22.4

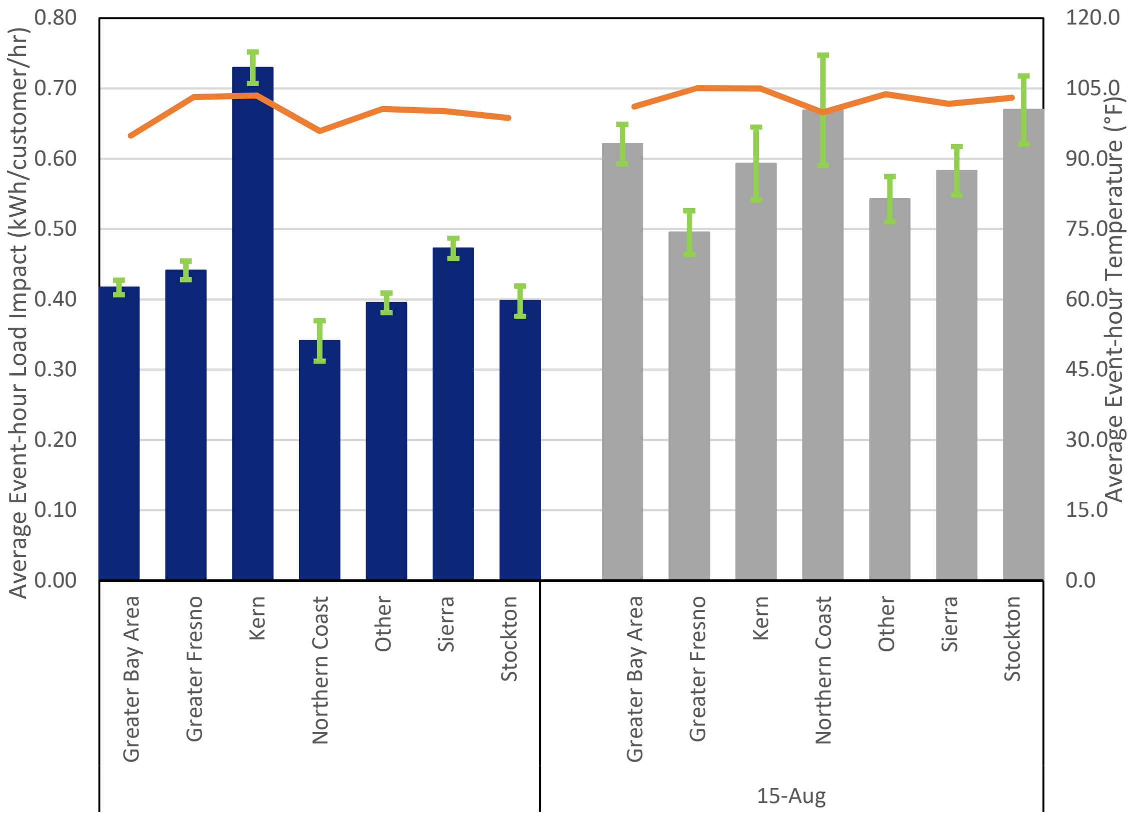
3.4 Serial Event Load Impacts

Next, we examine the results for serial events at the LCA level. Figure 3-5 summarizes the LCA level *ex-post* load impacts by event. The bars indicate the magnitude of the average per customer load impacts (in kWh/customer/hour) across the full event hours during which customers were dispatched (4 to 6.pm). The green bands correspond to 80 percent confidence intervals around these estimates (*i.e.*, the 10th and 90th percentile scenarios from the uncertainty-adjusted load impacts). The orange line represents the average temperatures experienced by the customers in each LCA during the event hours.

Serial event load impacts range from 0.34 to 0.73 kWh/customer/hour

Figure 3-5 illustrates that there is more consistency in per-customer load impacts across LCAs for serial events, with the exception of Kern on the July 27th event, which is significantly higher. Load impacts range from 0.34 to 0.73 kWh/customer/hour for serial events. The August 15th event, which was hotter on average, produced per-customer load impacts that averaged 0.60 kWh/customer/hour, compared to 0.46 kWh/customer/hour for the July 27th event.

Figure 3-5: Average Event-Hour Load Impacts by LCA and Event for Serial Events



Greater Bay Area has the highest aggregate load impacts

Table 3-6 provides the detailed information underlying Figure 3-5, including the number customers dispatched, the average event load impacts (per customer and in aggregate), reference loads, and percentage load impacts for each LCA for each serial event. Greater Bay Area has by far the highest number of customers leading to the highest aggregate load impacts of 18.23 MWh/hour on August 15th. Kern has the highest load impacts in percentage terms on July 27th with load impacts that are 24 percent of reference loads.

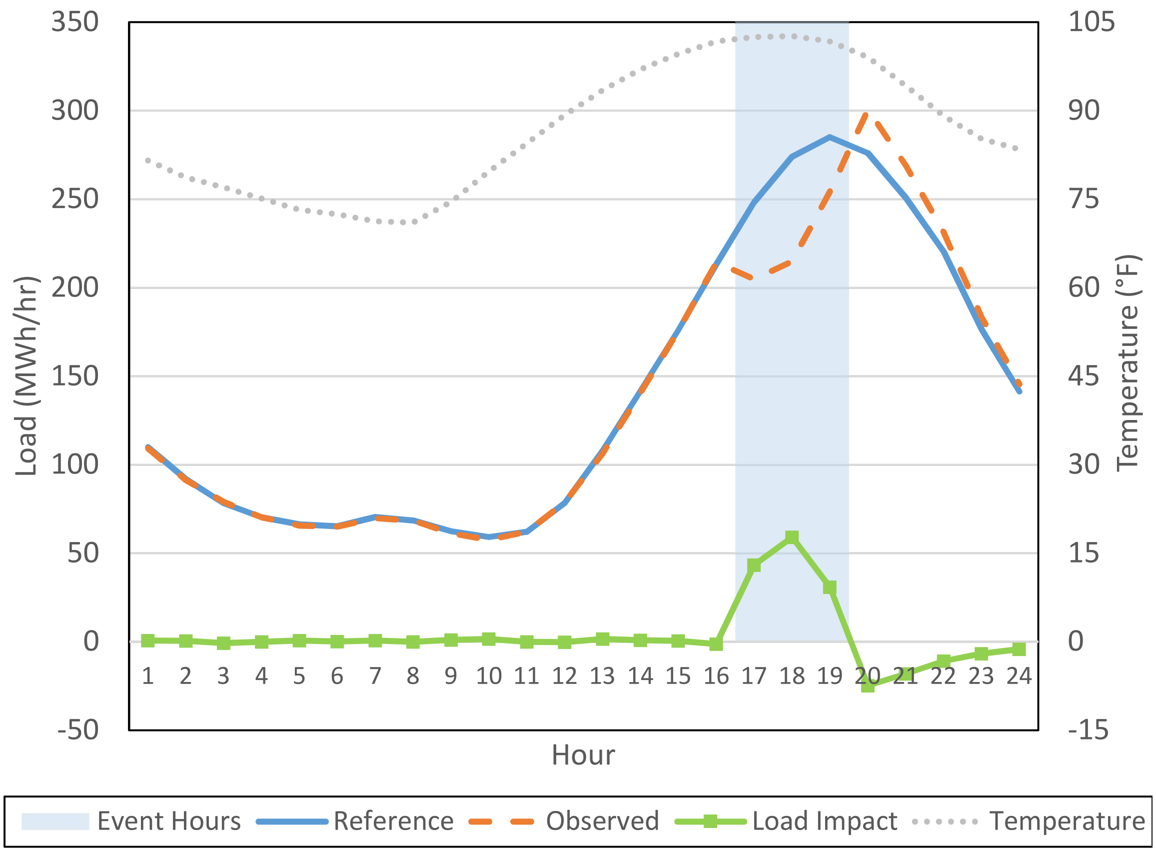
Table 3-6: Average Event-Hour Load Impacts by LCA and Event for Serial Events

Event Date	LCA	Event Hours	# Dispatched	Average Event Hour				
				Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
27-Jul	Greater Bay Area	4-7 p.m. Dispatch 4-6:30 p.m.	32,927	2.10	0.42	19.8%	13.73	94.9
	Greater Fresno		17,972	3.03	0.44	14.6%	7.93	103.2
	Kern		5,149	3.04	0.73	24.0%	3.76	103.5
	Northern Coast		4,294	1.95	0.34	17.5%	1.46	95.9
	Other		16,674	2.56	0.39	15.4%	6.59	100.6
	Sierra		16,215	2.69	0.47	17.6%	7.66	100.2
	Stockton		7,626	2.69	0.40	14.8%	3.03	98.7
15-Aug	Greater Bay Area	4-7 p.m. Dispatch 4-6:30 p.m.	29,361	2.93	0.62	21.2%	18.23	101.1
	Greater Fresno		14,422	3.07	0.50	16.1%	7.14	105.1
	Kern		3,930	2.96	0.59	20.0%	2.33	105.0
	Northern Coast		3,653	3.07	0.67	21.8%	2.44	99.8
	Other		15,163	2.99	0.54	18.1%	8.23	103.8
	Sierra		14,280	2.87	0.58	20.3%	8.32	101.7
	Stockton		6,713	3.18	0.67	21.0%	4.49	103.0

Load impacts for serial events peak during the second hour and decline during third hour of event

Figure 3-6 shows the average aggregate hourly reference loads, observed loads, and estimated load impacts using the serial event on August 15th. Table 3-7 contains the hourly results in the manner required by the Protocols, including hourly temperatures and uncertainty adjusted load impacts. Notice that the load impacts peak at 59.1 MWh during the second hour of this event (5:00 to 6:00 p.m.) and are markedly lower during the third hour of the event at 30.9 MWh. This resulted from event dispatch that ended 30 minutes prior to the scheduled end of the event at 7 p.m.

Figure 3-6: Hourly Load Impacts and Uncertainty Adjusted Estimates-August 15, 2019



Post-event snapback for serial events is lower as a share of event load impacts

Figure 3-6 also illustrates that there is significant post-event snapback for serial events, when loads increase by 24.7 MWh the first hour after the event and decline over the course of the evening. Moreover, post-event snapback as a share of event load impacts is lower for serial events compared to the sub-LAP event example in Figure 3-4. For the two serial events, the peak post-event snapback from 7 to 8 p.m. is 42 percent of the peak load impacts during 5 to 6 p.m. For the sub-LAP event on August 26th, the peak post-event snapback during 7 to 8 p.m. is 69 percent of the peak load impact during 5 to 6 p.m.

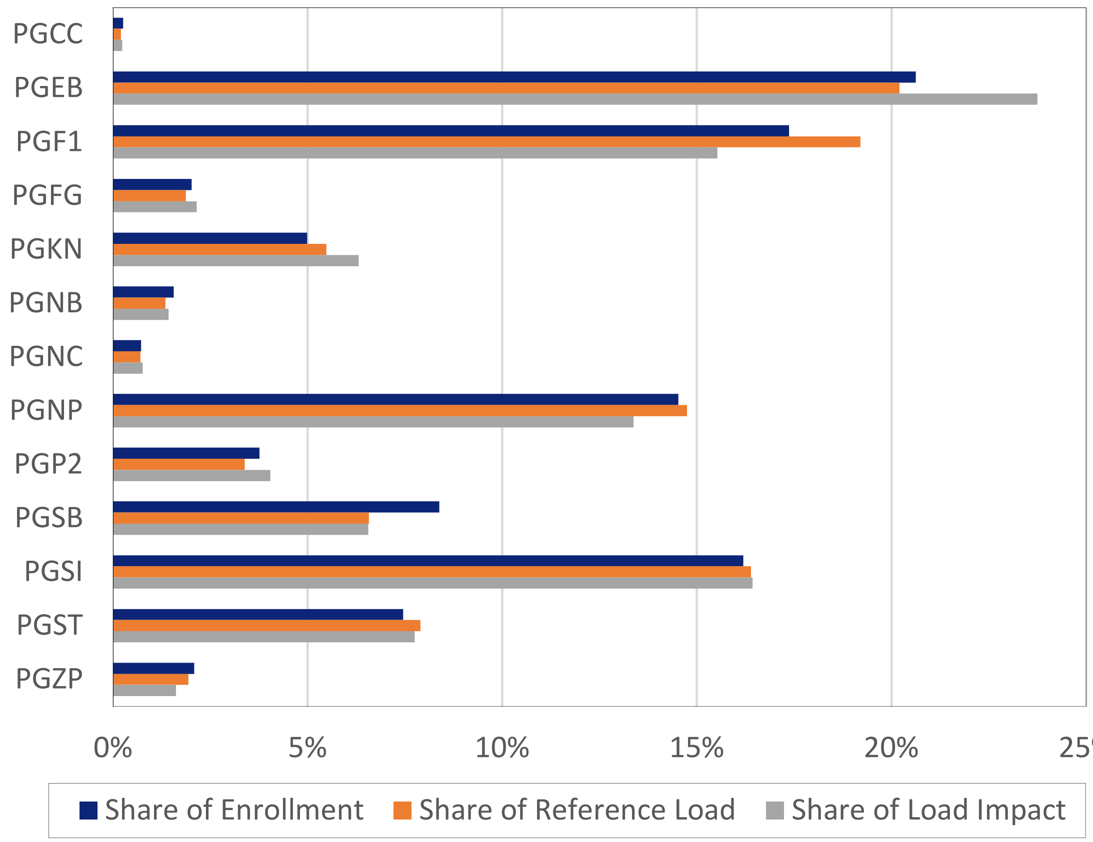
Table 3-7: Hourly Load Impacts and Uncertainty Adjusted Estimates-August 15, 2019

Hour Ending	Reference Load (MWh/hour)	Event Day Load (MWh/hour)	Estimated Load Impact (MWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (MWh/hour)- Percentiles				
					10th%ile	30th%ile	50th%ile	70th%ile	90th%ile
1	109.9	109.2	0.7	81.5	-0.4	0.3	0.7	1.2	1.9
2	91.7	91.3	0.5	78.7	-0.5	0.1	0.5	0.9	1.5
3	78.3	78.9	-0.7	77.0	-1.5	-1.0	-0.7	-0.3	0.2
4	70.3	70.4	-0.1	75.1	-0.9	-0.4	-0.1	0.2	0.7
5	66.4	65.7	0.7	73.2	0.0	0.4	0.7	1.0	1.4
6	65.3	65.1	0.2	72.5	-0.4	0.0	0.2	0.5	0.9
7	70.5	69.8	0.7	71.3	0.0	0.4	0.7	1.0	1.4
8	68.5	68.4	0.1	71.0	-0.7	-0.2	0.1	0.4	0.8
9	62.3	61.2	1.2	74.5	0.3	0.8	1.2	1.5	2.0
10	59.2	57.6	1.6	79.7	0.5	1.1	1.6	2.0	2.6
11	62.1	62.2	-0.1	84.5	-1.3	-0.6	-0.1	0.4	1.2
12	78.5	78.7	-0.3	89.2	-1.7	-0.8	-0.3	0.3	1.1
13	108.1	106.5	1.6	93.5	0.0	1.0	1.6	2.3	3.2
14	141.7	140.8	1.0	97.0	-0.7	0.3	1.0	1.7	2.7
15	176.1	175.6	0.5	99.6	-1.3	-0.3	0.5	1.2	2.3
16	213.2	214.5	-1.2	101.7	-3.0	-2.0	-1.2	-0.5	0.6
17	248.1	204.8	43.3	102.5	41.5	42.6	43.3	44.0	45.1
18	274.0	214.9	59.1	102.7	57.3	58.3	59.1	59.8	60.8
19	285.1	254.2	30.9	101.8	29.1	30.2	30.9	31.6	32.6
20	276.0	300.8	-24.7	99.1	-26.4	-25.4	-24.7	-24.1	-23.0
21	251.0	269.1	-18.1	94.2	-19.8	-18.8	-18.1	-17.5	-16.5
22	220.3	231.1	-10.8	89.1	-12.4	-11.4	-10.8	-10.1	-9.2
23	176.7	183.4	-6.7	85.3	-8.1	-7.3	-6.7	-6.1	-5.3
24	141.3	145.4	-4.1	83.4	-5.4	-4.7	-4.1	-3.6	-2.8
By Period:	Estimated Reference Energy Use (MWh/hour)	Observed Event Day Energy Use (MWh/hour)	Estimated Change in Energy Use (MWh/hour)	Cooling Degree Hours (Base 75° F)	Uncertainty Adjusted Impact (MWh/hour) - Percentiles				
					10th	30th	50th	70th	90th
Daily	3,394.6	3,319.5	75.1	290.7	60.3	69.1	75.1	81.2	90.0
Avg. Event Hour	269.1	224.7	44.4	81.9	43.4	44.0	44.4	44.8	45.4

PGEB, PGF1, PGNP and PGSI produced 69 percent of the PY2019 load reductions

Next, we look at how load impacts are distributed across sub-LAPs. We focus this analysis on the load impacts from the serial events on July 27th and August 15th, because all sub-LAPs were dispatched for these events. Figure 3-7 compares the sub-LAP shares of estimated aggregate event-hour load impacts, reference loads, and enrollments. The load impacts for SmartAC™ customers are mainly driven by four sub-LAPs (PGEB, PGF1, PGNP, and PGSI), which collectively produced 69 percent of the PY2019 load reductions. Furthermore, PGEB and PGKN have a considerably higher share of load impacts than of enrollments or reference loads, while PGF1, PGNP, and PGSB have appreciably lower shares of load impacts compared to the share of enrollments and reference loads.

Figure 3-7: Share of Load Impacts by Sub-LAP for Serial Events



3.5 Subgroup Load Impacts

This section summarizes how SmartAC™ load impacts are distributed across subgroups of interest including: CARE/non-CARE customers, NEM/non-NEM customers, housing type, AC usage intensity, device type (one-way versus two-way and by one-way device type), and by marketing cohort. We also compare load impacts for customers who are only enrolled in SmartAC™ to customers who are also enrolled in SmartRate™. These comparisons are based on load impacts from the serial event on August 15th during the two full event hours from 4 to 6 p.m. Additional results for these subgroups, including the load profiles, can be found in electronic form in Protocol table generators provided along with this report.

One factor to consider when making subgroup comparisons is that customers within a given subgroup may disproportionately reside within certain sub-LAPs. For example, CARE customers tend to live in hotter locations and therefore have more AC load to curtail than non-CARE customers. Thus, a finding that CARE customers have higher load impacts may not reflect a behavioral difference from non-CARE customers as much as a difference in circumstances.

The *ex-post* load impacts for the August 15th serial test event are summarized for each subgroup in Figure 3-8. The blue and gray bars indicate the magnitude of the average per customer load impact (in kWh/customer/hour) within each subgroup. The green bands correspond to 80 percent confidence intervals around these estimates. The orange line represents the average temperatures experienced by customers in each subgroup.

Most sub-group comparisons are consistent with PY2018 results

There are statistically significant load impacts for every subgroup except for customers with ExpressStat devices. PG&E has been systematically replacing or decommissioning ExpressStat devices, leading to few devices remaining for this estimation.

The pattern of load impacts is similar to subgroup comparisons from the PY2018 report, which were based on sub-LAP events, including the following:

- SmartAC™-only customers have significantly higher load impacts than dually enrolled customers.
- Customers enrolled in SmartAC™ after 2014 (when PG&E's SmartAC™ marketing methods changed) have substantially higher per-customer load impacts than customers enrolled earlier.
- CARE customers have significantly higher per-customer load impacts than non-CARE customers, although the differences are closer in magnitude than in PY2018.
- The device-type results are also similar, with the thermostats (*i.e.*, ExpressStat and UtilityPro) performing more poorly than the Gen 1 or Gen 2 switches. Moreover, UtilityPro devices lead to significant load impacts, while ExpressStat devices do not; and the Gen 2 switches lead to significantly higher per-customer load impacts compared to the Gen 1 switches.
- Load impacts increase with AC usage intensity, with medium AC usage having significantly higher load impacts than low AC usage and high AC usage having significantly higher load impacts than medium AC usage.

NEM comparisons differ from PY2018 results, but are consistent with PY2017

Some results that differ from those presented in the PY2018 but are consistent with the PY2017 report include the NEM results. In PY2018, the NEM customers had substantially lower load impacts than non-NEM customers based on sub-LAP event load impacts. In PY2019, our results for the serial test event suggest that while the NEM customer load impacts are lower in magnitude, they are not significantly different from the non-NEM load impacts, which is consistent with the PY2017 results.

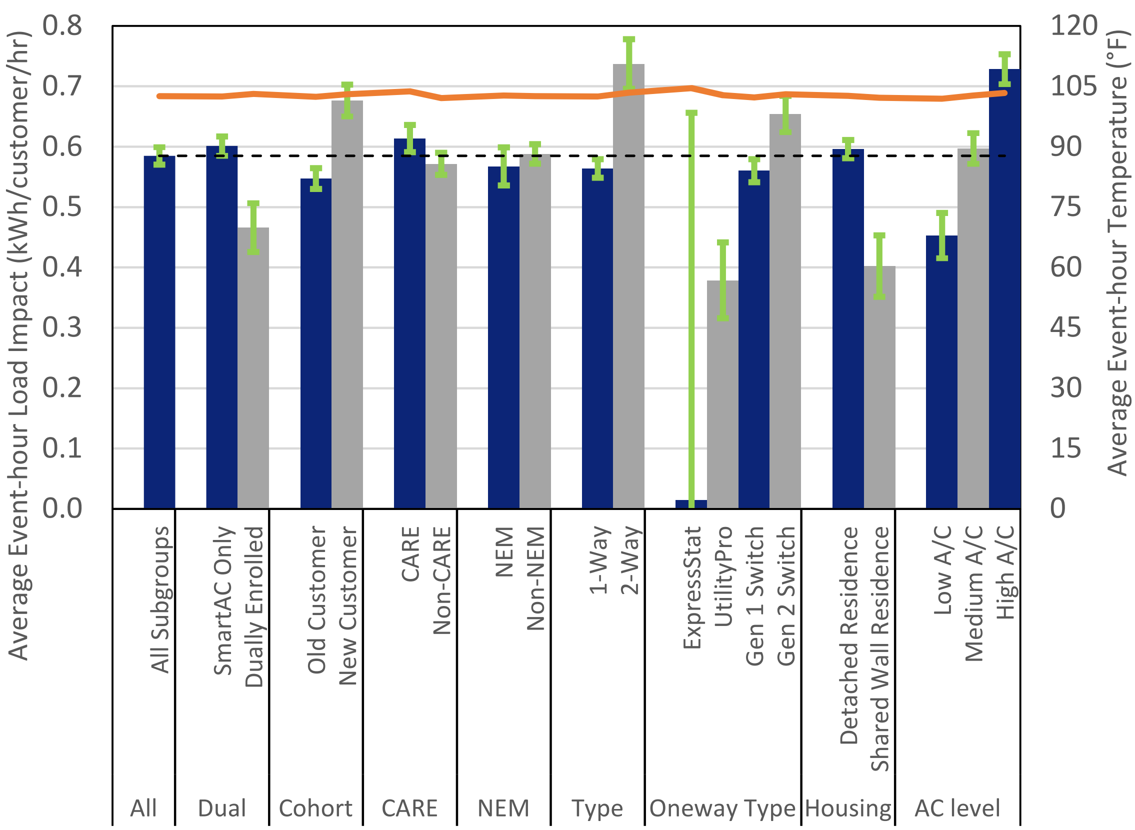
Different housing types have statistically different load impacts

The categories of housing type, provided by PG&E, include detached residences and shared wall residences.[13] In PY2018, the load impacts were significantly higher for detached residences compared to shared wall residences but were close in magnitude based off results from sub-LAP event. In PY2019, we find that detached residences outperform shared wall residences to a greater extent for the serial test event. These results are consistent with the single-family results compared to the multi-family residence results in the PY2017 report.

Two-way customers have significantly higher load impacts than one-way customers

We contribute new subgroup analysis in this report by comparing customer load impacts for the newer two-way devices to the legacy one-way devices. We find that during the serial test event, two-way devices led to significantly higher load impacts than one-way devices. Two-way devices had load impacts of 0.74 kWh/customer/hour—higher than any other subgroup. We present further device type analysis later in this section.

Figure 3-8: Average Event-Hour Load Impacts by Subgroup-August 15, 2019



[13] There is also a category called common area, but there are very few SmartAC™ customers classified as common area, which prevents the reliable estimation of results for this subgroup.

Comparing subgroups by percentage load impacts can lead to different results

Table 3-8 provides the detailed information underlying Figure 3-8, including the number of customers dispatched for the August 15th event, the total number of enrolled customers in each subgroup, the average load impacts, reference loads, percentage load impacts, and temperatures. The main takeaway from this table is that comparing subgroups by percentage load impacts can lead to different results than level load impacts. That is, while some subgroups have higher load impacts, they may have higher reference loads as well, which can lead to comparable or even lower percentage impacts. This is true for CARE customers, NEM customers, and AC usage level.

Table 3-8: Average Event-Hour Load Impacts by Subgroup-August 15, 2019

Subgroup	Avg. # Dispatched	Enrolled Customers	Average Load Impacts (4-6 p.m.)				
			Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
All SmartAC™ Customers	87,522	100,227	2.98	0.58	19.6%	51.19	102.6
SmartAC™ Only	77,099	88,016	3.02	0.60	19.9%	46.34	102.5
Dually Enrolled	10,423	12,211	2.69	0.47	17.3%	4.86	103.2
Old Customer	63,861	72,902	2.91	0.55	18.8%	34.94	102.4
New Customer	23,661	27,325	3.16	0.68	21.4%	16.01	103.1
CARE	25,696	30,356	3.15	0.61	19.5%	15.76	103.7
Non-CARE	61,826	69,871	2.91	0.57	19.7%	35.34	102.1
NEM	20,782	23,209	2.20	0.57	25.8%	11.79	102.7
Non-NEM	66,740	77,018	3.20	0.59	18.4%	39.24	102.5
One-Way	78,604	87,811	2.93	0.56	19.2%	44.34	102.5
Two-Way	8,918	12,416	3.35	0.74	22.0%	6.57	103.5
ExpressStat	106	117	3.04	0.01	0.5%	0.00	104.6
UtilityPro	4,378	4,835	3.18	0.38	11.9%	1.66	102.8
Gen 1 Switch	54,110	59,543	2.86	0.56	19.6%	30.32	102.3
Gen 2 Switch	18,369	20,293	3.10	0.65	21.1%	12.02	103.1
Detached Residence	82,844	94,852	3.03	0.60	19.7%	49.38	102.6
Shared Wall Residence	4,606	5,292	2.24	0.40	17.9%	1.85	102.2
Low A/C	13,983	15,721	2.21	0.45	20.5%	6.33	101.9
Medium A/C	26,275	30,162	3.06	0.60	19.5%	15.69	102.8
High A/C	30,770	35,828	3.85	0.73	18.9%	22.42	103.4

3.5.1 Two-way Devices

This section compares results for customers with new two-way communicating devices to customers with legacy technology capable of one-way communication including thermostats and Gen1 and Gen2 switches. We contrast results for each device type for the average event-hour for serial test events compared to sub-LAP events (excluding the two events with dispatch issues).

Table 3-9 summarizes the per-customer and aggregate results for customers with two-way and one-way devices for serial and sub-LAP type events, including the number of customers dispatched and enrolled on average, the average event load impacts (per customer and in aggregate), reference loads, and percentage load impacts. Only 14 percent of SmartAC™ customers had two-way devices during PY2019, which accounts for the large aggregate load impacts for one-way devices compared to two-way devices.

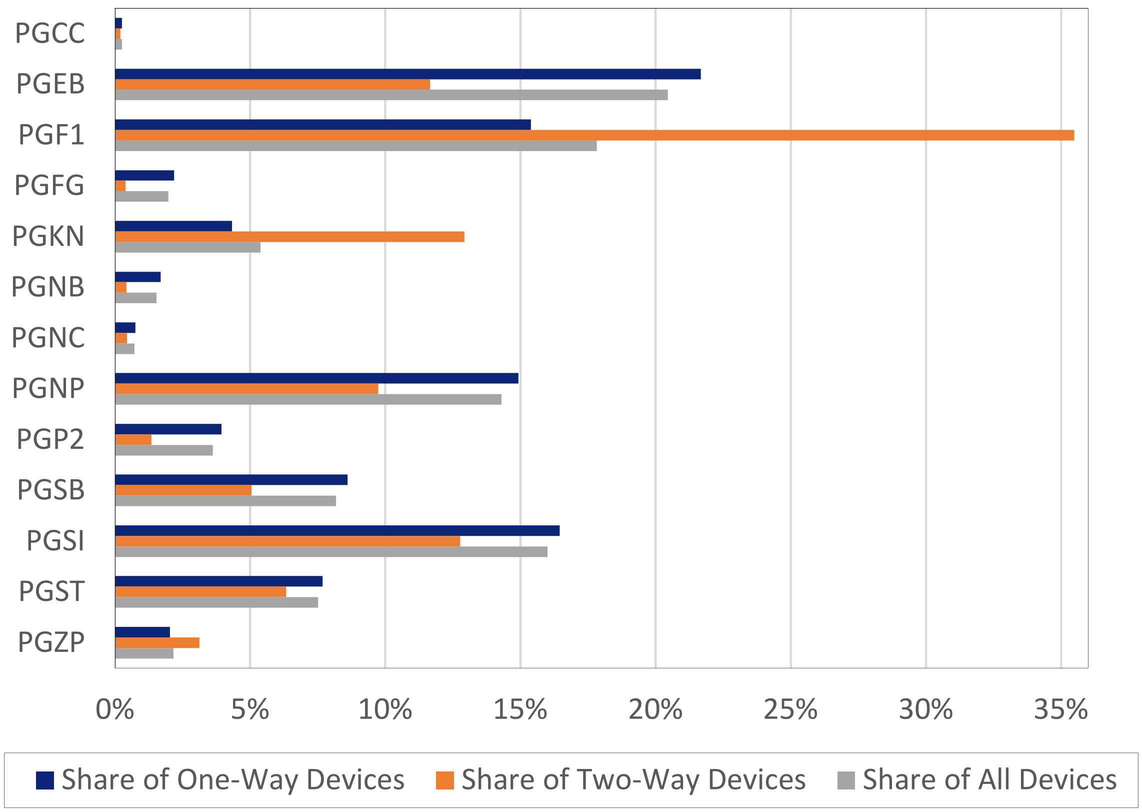
Two-way devices led to significantly higher load impacts for serial and sub-LAP events both in per-customer terms and as a percentage of reference loads. Two-way devices generated per-customer load impacts of 0.62 kWh/customer/hour during serial events compared to 0.49 kWh/customer/hour for one-way devices and 0.55 kWh/customer/hour during sub-LAP events compared to 0.36 kWh/customer/hour for one-way devices. Since paging for one-way devices differs between serial events (*i.e.*, based on factory programmed addressing) and sub-LAP events (*i.e.*, based on sub-LAP addressing after device installation), we would expect more of a performance advantage for two-way devices relative to one-way devices on sub-LAP events compared to serial events. Indeed, average per-customer load impacts are 0.19 kWh/customer/hour higher for two-way devices relative to one-way devices on sub-LAP events compared to a difference of 0.13 kWh/customer/hour for serial events. In percentage terms, per-customer load impacts for one-way devices are 65 percent of the per-customer load impacts for two-way devices on sub-LAP events compared to 78 percent for serial events. One contributing factor to the higher per-customer load impacts for two-way devices is slightly higher average event temperatures experienced by these customers.

Table 3-9: Average Event-Hour Load Impacts by Device Type and Event Type

Event Type	Device Type	Avg. # Dispatched	Avg. # Enrolled	Average Event Hour				
				Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
Serial Test Event	One-Way	83,509	88,160	2.68	0.49	18.3%	40.87	100.5
	Two-Way	10,658	12,408	3.17	0.62	19.7%	6.65	101.9
Sub-LAP Event	One-Way	32,204	78,794	2.46	0.36	14.5%	11.52	99.1
	Two-Way	4,520	10,551	2.99	0.55	18.3%	2.48	100.4

To examine why two-way customers would have higher event temperatures compared to one-way customers, Figure 3-9 shows the distribution of device types across sub-LAPs. Three sub-LAPs had a higher share of two-way devices relative to their share of overall customers including PGF1, PGKN, and PGZP. These sub-LAPs tend to experience higher average event temperatures, which explains why two-way customers endure higher temperatures during system-wide serial events.

Figure 3-9: Distribution of Device Types Across Sub-LAPs



3.5.2 Dually Enrolled Customers

This section compares results for customers who are only enrolled in the SmartAC™ program to customers who are dually enrolled in SmartAC™ and SmartRate™. We present results for the average event-hour for each event day. Additional results for these customers can be found in electronic form in Protocol table generators provided along with this report.

Table 3-10 summarizes the per-customer and aggregate results for SmartAC™-only and dually enrolled customers for each event, including the number of customers dispatched, the average event load impacts (per customer and in aggregate), reference loads, and percentage load impacts. The blue shading indicates the two serial test events. Fewer than 14 percent of SmartAC™ customers were dually enrolled in

SmartRate™ during PY2019, which explains why the aggregate load impacts from SmartAC™-only customers dwarf the load impacts for dually enrolled customers.

On a per-customer basis, the load impacts are higher for dually enrolled customers than SmartAC™-only customers during all sub-LAP events. Since PG&E concentrated legacy device replacement efforts on SmartRate customers, there is a higher proportion of dually enrolled customers with new two-way devices, which generate higher per-customer load impacts. Almost 18 percent of the dually enrolled customers during PY2019 had two-way devices compared to 11 percent of SmartAC™-only customers.

During the two serial test events, SmartAC™-only customers have significantly higher per-customer load impacts than dually enrolled customers due to the fact that two-way devices have less of a performance advantage during serial events, as discussed in Section 3.5.1.

Table 3-10: Average Event-Hour Load Impacts by Event, SmartAC™-only vs. Dually Enrolled

Enrollment Segment	Event Date	SmartRate Event?	# Dispatched	Average Event Hour				
				Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
Dually Enrolled	7/24/2019	Yes	3,516	2.74	0.30	11.1%	1.1	102.5
	7/25/2019	No	3,512	2.55	0.37	14.6%	1.3	99.7
	7/27/2019	No	12,346	2.49	0.19	7.8%	2.4	100.4
	8/14/2019	Yes	3,936	2.43	0.60	24.5%	2.4	100.5
	8/15/2019	No	10,423	2.71	0.40	14.8%	4.2	103.0
	8/16/2019	Yes	3,462	2.89	0.43	14.9%	1.5	104.1
	8/26/2019	Yes	9,837	2.50	0.58	23.2%	5.7	99.4
	8/27/2019	Yes	9,825	2.24	0.48	21.3%	4.7	98.3
	9/13/2019	Yes	181	1.82	0.53	29.2%	0.1	97.0
	9/25/2019	No	1,991	1.99	0.47	23.3%	0.9	97.9
SmartAC Only	7/24/2019	Yes	21,809	3.07	0.05	1.6%	1.1	102.6
	7/25/2019	No	21,801	2.70	0.22	8.0%	4.7	100.0
	7/27/2019	No	88,511	2.65	0.36	13.6%	32.0	98.9
	8/14/2019	Yes	46,192	2.80	0.41	14.8%	19.1	99.9
	8/15/2019	No	77,053	3.13	0.52	16.7%	40.2	102.2
	8/16/2019	Yes	21,660	3.35	0.40	11.9%	8.6	104.9
	8/26/2019	Yes	53,727	2.63	0.42	15.9%	22.5	99.5
	8/27/2019	Yes	53,662	2.16	0.35	16.2%	18.7	98.7
	9/13/2019	Yes	11,771	2.32	0.37	16.0%	2.4	95.4
	9/25/2019	No	30,006	2.17	0.37	16.9%	11.0	97.5

3.6 Event Override Rate

Customers can override (opt-out of) SmartAC™ events. Table 3-11 summarizes the number of overrides by event day, including the number of enrolled customers in the sub-LAPs dispatched for each event. Although the number of overrides includes all SmartAC™ customers who opt-out on a given event day, including some customers who were not dispatched for the event, over 87 percent of the overrides correspond to customers dispatched for events. In total, the overrides correspond to only 0.2 percent of dispatched customers during PY2019 events. There were no events with high override rates, all were far below one percent. Additional tables in the appendix break down the override rates by location for each event.

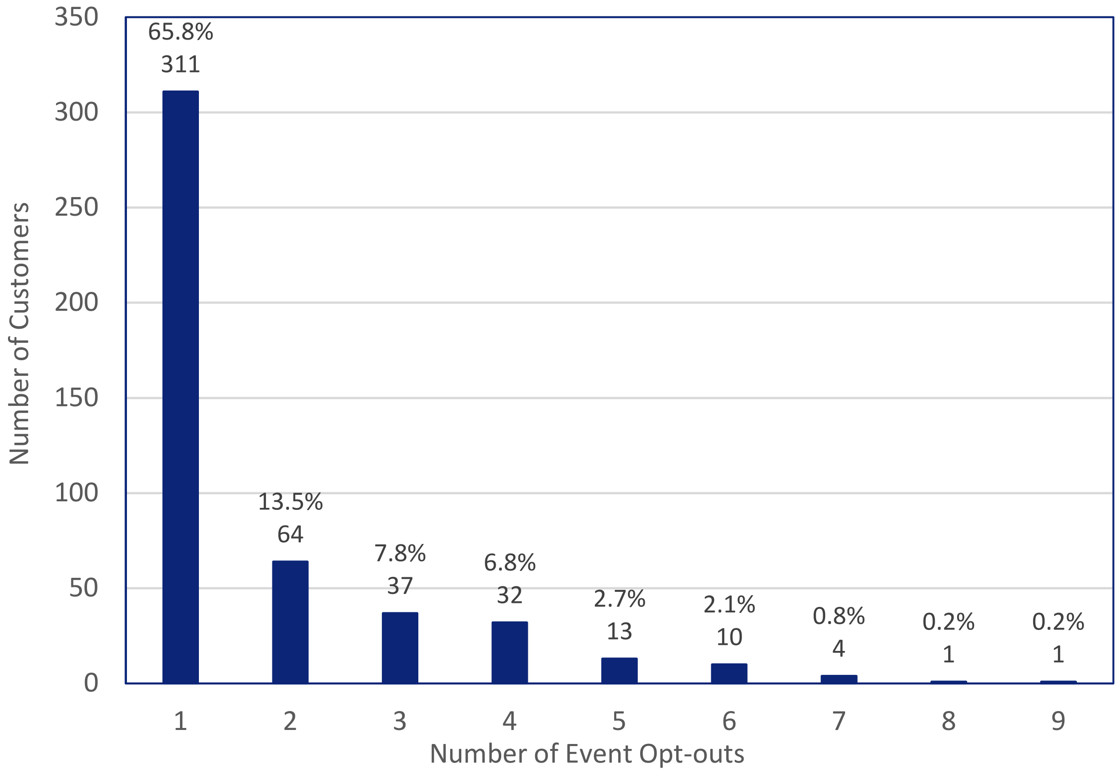
Table B-1 shows the override rates by sub-LAP for the 8 sub-LAP events. There were no sub-LAPs or sub-LAP events with high override rates. Table B-2 shows the override rates by LCA for the 2 serial events with similarly low override rates by LCA and event.

Table 3-11: Customer Overrides by Event Day

Date	Hours	Sub-LAPs Dispatched	SmartRate Event?	Overrides	Enrollment	Override Rate
24-Jul	4-7 p.m.	PGF1, PGKN, PGZP	Yes	34	21,809	0.2%
25-Jul	3-6 p.m.	PGF1, PGKN, PGZP	No	25	25,313	0.1%
27-Jul	4-7 p.m.	All	No	105	100,857	0.1%
14-Aug	4-7 p.m.	PGEB, PGNB, PGP2, PGSB, PGSI	Yes	110	46,192	0.2%
15-Aug	4-7 p.m.	Except Serial Group 2	No	196	87,476	0.2%
16-Aug	5-8 p.m.	PGF1, PGKN, PGZP	Yes	68	21,660	0.3%
26-Aug	3-6 p.m.	PGF1, PGKN, PGNC, PGNP, PGSI, PGST, PGZP	Yes	92	53,727	0.2%
27-Aug	2-5 p.m.	PGF1, PGKN, PGNC, PGNP, PGSI, PGST, PGZP	Yes	127	53,662	0.2%
13-Sep	3-8 p.m.	PGNB, PGP2, PGSB	Yes	43	13,108	0.3%
25-Sep	3-6 p.m.	PGEB, PGP2, PGSB	No	48	31,997	0.2%
			Total	**848**	**455,801**	**0.2%**

Figure 3-10 illustrates the extent to which customers opted-out of multiple events. Most customers only exercised their ability to override during one event—311 customers or 66 percent opted-out of one event compared to 473 customers who opted-out of one or more events. Only 13 percent of customers opt-out during four or more events.

Figure 3-10: Number of Event Day Overrides by Customer



4. *Ex-Ante* Load Impacts

This section provides the *ex-ante* SmartAC™ load impact forecasts for the period from 2020 to 2030. The forecasts are based on analyses of per-customer load impacts from *ex-post* evaluations, weather-sensitive reference loads, and incorporation of PG&E's forecasts of program enrollments. Results are presented for customers who are enrolled in SmartAC™-only and for customers who are dually enrolled in SmartAC™ and SmartRate™. We present the following: a figure showing the PG&E's enrollment forecast by LCA; a table and figures showing the hourly reference loads and load impacts on a typical event day; a figure summarizing how *ex-ante* load impacts vary by month and weather scenario; and a figure showing the share of load impacts on a typical event day by LCA. Detailed results for each hour, weather scenario, month, forecast year, and enrollment segment (*i.e.*, SmartAC™-only and dually enrolled customers) are available in electronic form in Protocol table generators provided along with this report.

The enrollment forecast provided by PG&E anticipates a high level of program attrition throughout 2020 to 2030 of approximately 9 percent per year due to PG&E's decision to minimize marketing efforts to back-fill attrition. Figure 4-1 illustrates this attrition over the forecast period for the July peak month by LCA. Enrollments are expected to decline across all LCAs. Moreover, dually enrolled customers, which are not depicted here, are expected to maintain a proportionate share of declining SmartAC™ enrollments over the forecast period.

Figure 4-1: Changes in Enrollment by LCA (2020-2030)

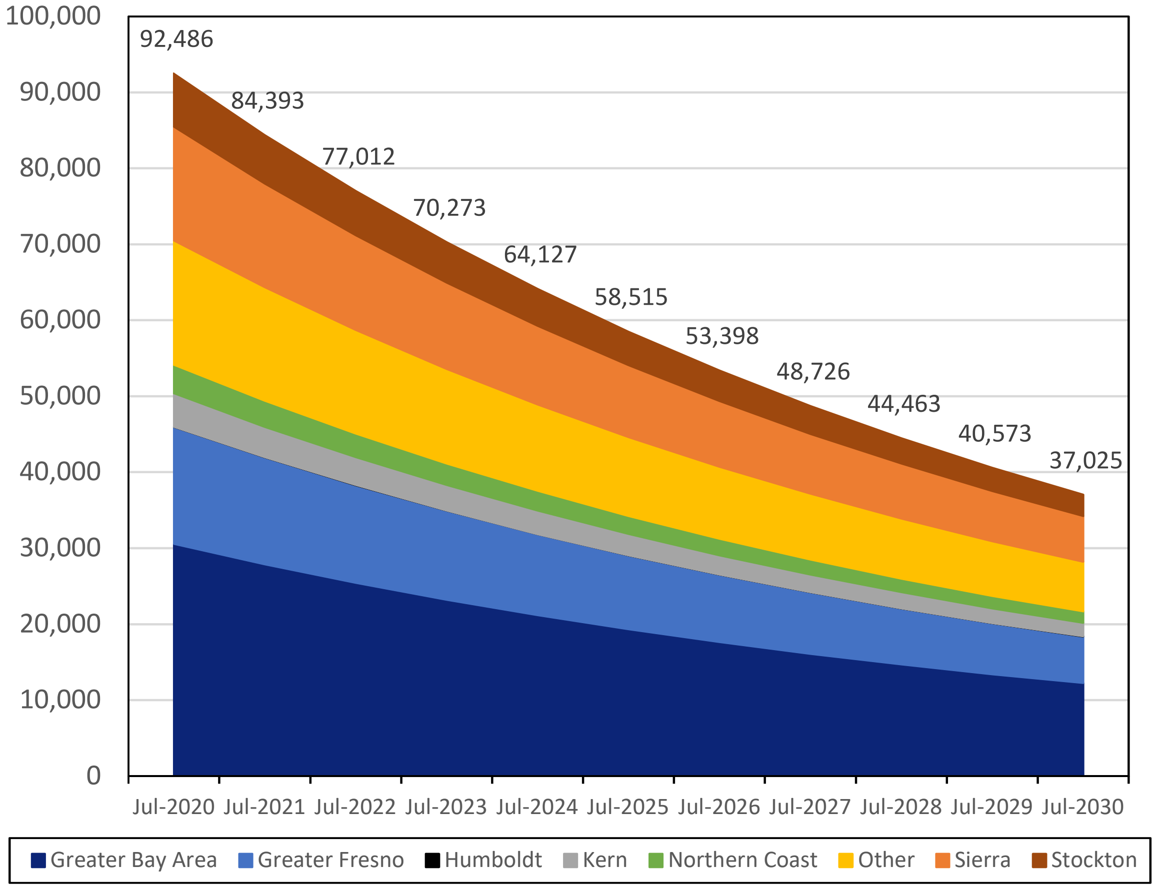


Figure 4-2 illustrates the changes in aggregate load impacts during the Resource Adequacy (RA) window (4 to 9 p.m.) over the forecast period by comparing load impacts for all SmartAC™ customers by LCA for the PG&E 1-in-2 scenario for a July peak day. The declining aggregate load impacts are commensurate with the enrollment forecast. Load impacts decline by 60 percent from 47.9 MWh/hour in 2020 to 19.2 MWh/hour in 2030.

Figure 4-2: Changes in Aggregate RA Window Load Impacts by LCA for PG&E 1-in-2 July Peak Scenario (2020-2030)

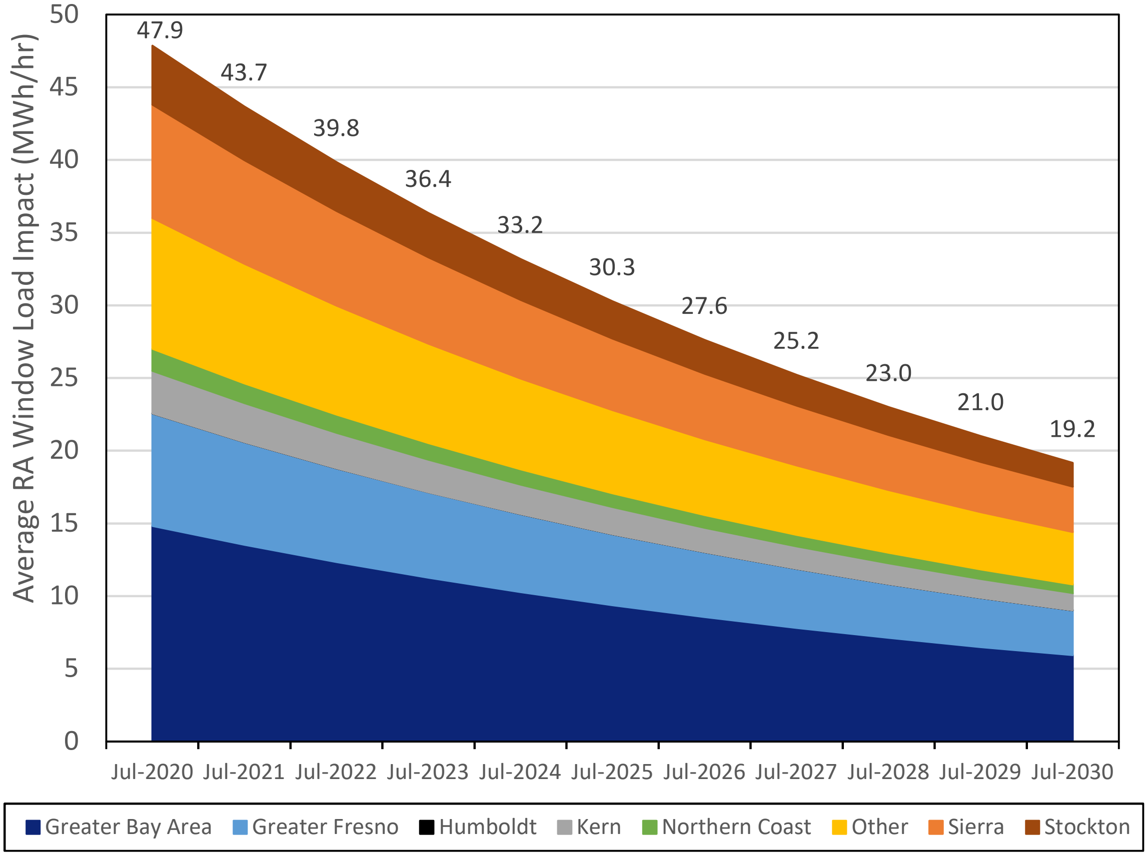


Figure 4-3 illustrates the aggregate reference load, observed load, and load impact for all SmartAC™ customers on a July peak day in 2020 for the PG&E 1-in-2 weather scenario. The shape of the *ex-ante* loads is similar to the *ex-post* results in Figure 3-6, however the shape of the event load impacts is flatter due to the longer duration of the RA window. Furthermore, the *ex-ante* loads and load impacts are slightly smaller in magnitude compared to Figure 3-6 due to declining program enrollments. The average RA window load impact is 47.9 MWh/hour, or 21 percent of the average RA window reference loads.

Figure 4-3: Aggregate Hourly Loads and Load Impacts for July Peak, *PG&E 1-in-2 Scenario* in 2020-All SmartAC™ customers

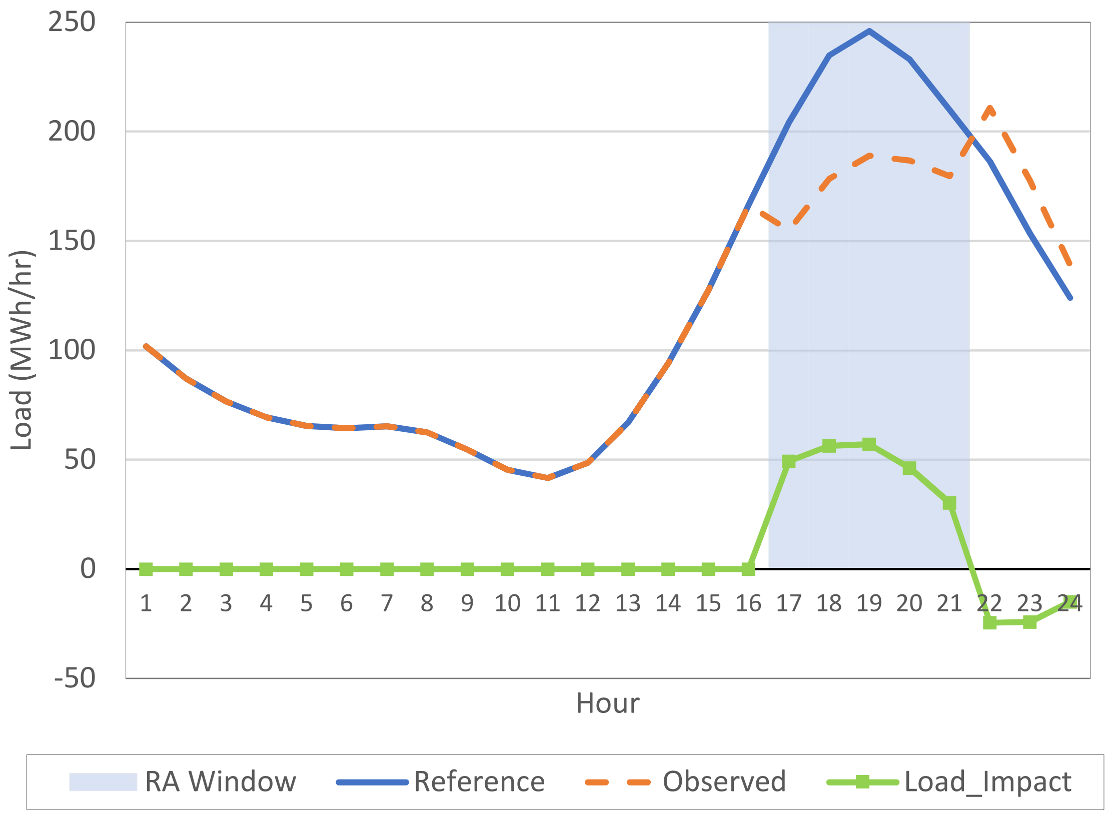


Figure 4-4 illustrates the aggregate reference load, observed load, and load impact for SmartAC™-only customers on a July peak day in 2020 for the PG&E 1-in-2 weather scenario. The shape of the *ex-ante* loads and load impacts is similar to the results for all SmartAC™ program customers. The average RA window load impact is 43.7 MWh/hour, or 22 percent of the average RA window reference loads.

Figure 4-4: Aggregate Hourly Loads and Load Impacts for July Peak, *PG&E 1-in-2* Scenario in 2020: SmartAC™-only customers

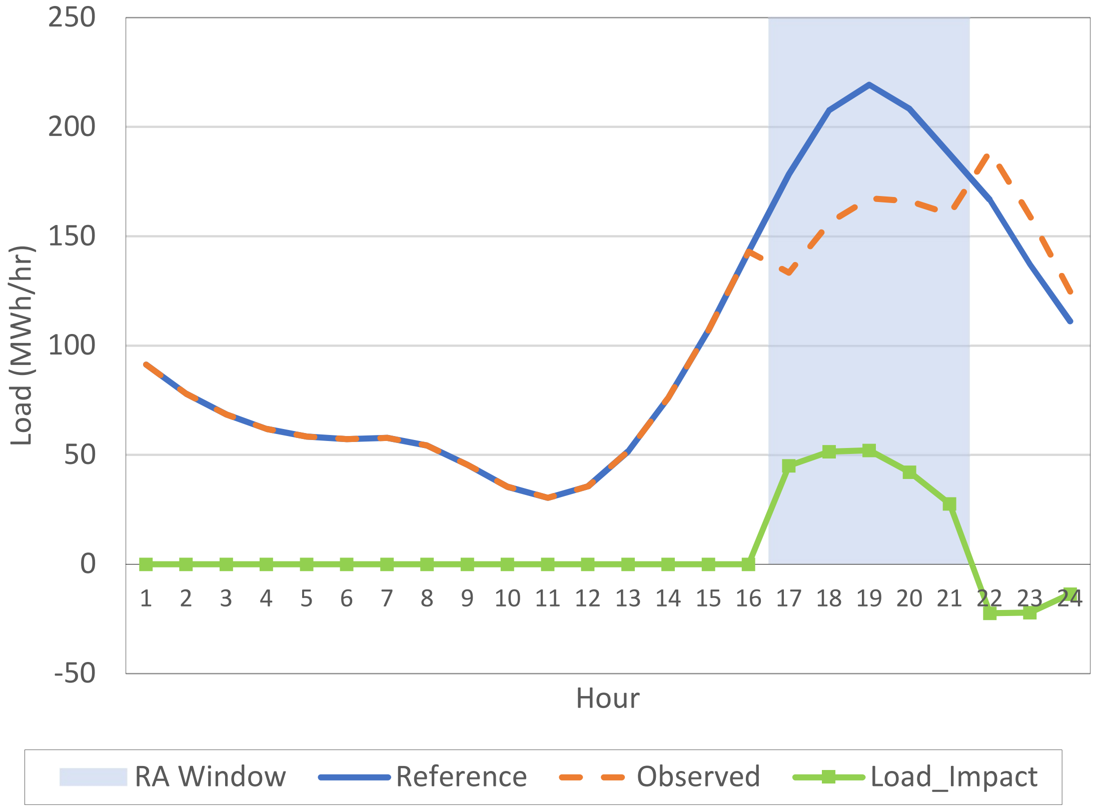


Figure 4-5 illustrates the aggregate reference load, observed load, and load impact for customers who are dually enrolled in SmartAC™ and SmartRate™ on a July peak day in 2020 for the PG&E 1-in-2 weather scenario. The shape of the *ex-ante* reference load is flatter than for SmartAC™-only customers, with a slightly less pronounced peak. The magnitude of the loads and load impacts are much smaller compared to SmartAC™-only customers due to lower dual enrollments, however dually enrolled customers are still less responsive than SmartAC™-only customers based on the methodology employed. See Section 2.3.2 for more details of our load impacts modeling approach. The average RA window load impact is 4.2 MWh/hour, or 16 percent of the average RA window reference loads.

Figure 4-5: Aggregate Hourly Loads and Load Impacts for July Peak, *PG&E 1-in-2* Scenario in 2020-Dually Enrolled Customers

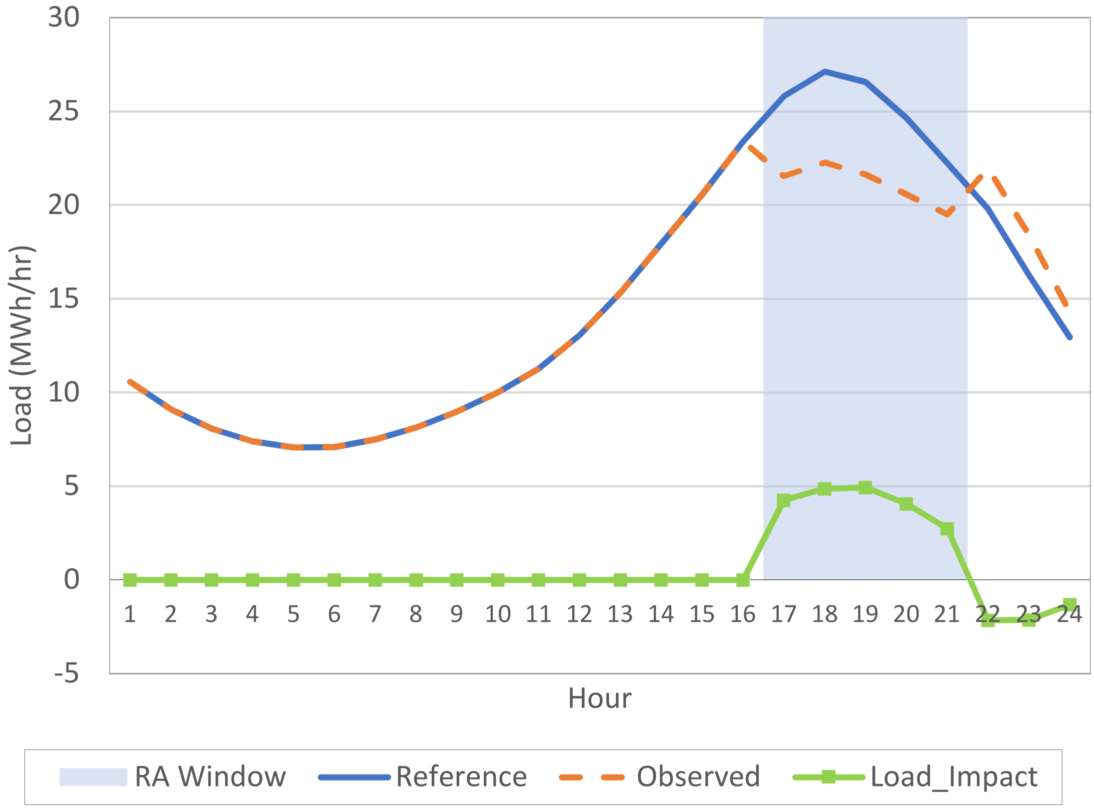


Table 4-1 summarizes average loads and load impacts, percentage load impacts, and average temperature for the RA window on a July peak day in 2020 for the PG&E 1-in-2 weather scenario by LCA and enrollment segment. Per-customer load impacts range from 0.29 to 0.70 (kWh/customer/hour) with a large variation in aggregate load impacts due to the distribution of enrolled customers across LCAs. The Greater Bay area will have the largest aggregate load impacts of 14.8 MWh/hour and the largest percentage reduction of 25.4 percent from SmartAC™-only customers the Greater Bay Area. The highest per-customer load impact is 0.70 kWh/customer/hour which corresponds to SmartAC™-only customers in Kern.

Table 4-1: Average RA Window Load Impacts for *PG&E 1-in-2* Typical Event Day by LCA and Enrollment Segment

Enrollment Segment	LCA	Enrolled	Average RA Window Hour				
			Reference (kW/Cust)	Impact (kW/Cust)	% Load Impact	Aggregate Impact (MW)	Avg. Temp (°F)
All	Greater Bay Area	30,582	1.93	0.49	25.1%	14.8	90.2
	Greater Fresno	15,380	3.02	0.50	16.6%	7.7	103.8
	Humboldt	2	2.10	0.52	24.9%	0.0	94.8
	Kern	4,413	3.00	0.66	22.2%	2.9	102.8
	Northern Coast	3,747	1.85	0.40	21.8%	1.5	88.1
	Other	16,390	2.52	0.55	21.8%	9.0	100.4
	Sierra	14,970	2.55	0.52	20.4%	7.8	98.4
	Stockton	7,002	2.89	0.58	20.0%	4.0	99.9
	Total	**92,486**	**2.44**	**0.52**	**21.2%**	**47.9**	**96.9**
Dually Enrolled	Greater Bay Area	1,852	1.79	0.37	20.7%	0.7	94.3
	Greater Fresno	2,082	2.65	0.35	13.1%	0.7	103.9
	Kern	589	2.86	0.46	16.0%	0.3	94.8
	Northern Coast	271	1.48	0.29	19.6%	0.1	102.8
	Other	3,317	2.19	0.39	17.6%	1.3	89.9
	Sierra	1,512	2.12	0.33	15.7%	0.5	100.2
	Stockton	1,522	2.54	0.41	16.2%	0.6	97.0
	Total	**11,146**	**2.27**	**0.37**	**16.5%**	**4.2**	**96.2**
SmartAC Only	Greater Bay Area	28,730	1.94	0.49	25.4%	14.2	100.0
	Greater Fresno	13,298	3.08	0.53	17.1%	7.0	90.0
	Humboldt	2	2.10	0.52	24.9%	0.0	103.8
	Kern	3,824	3.02	0.70	23.1%	2.7	94.8
	Northern Coast	3,476	1.88	0.41	21.9%	1.4	102.8
	Other	13,073	2.61	0.59	22.6%	7.7	88.0
	Sierra	13,458	2.60	0.54	20.9%	7.3	100.5
	Stockton	5,480	2.99	0.62	20.9%	3.4	98.5
	Total	**81,340**	**2.46**	**0.54**	**21.8%**	**43.7**	**96.3**

Figure 4-6 illustrates the seasonality and variation by weather scenario in the forecasted load impacts by comparing aggregate load impacts for the average hour in the Resource Adequacy (RA) window in 2020 across months and weather scenarios. The load impact is highest in July in three out of the four weather scenarios, with a maximum load impact of 58 MWh/hour from the PG&E 1-in-10 scenario. For the CAISO 1-in-2 scenario, the load impacts are highest in June (46 MWh/hour). The loads impacts are always the lowest in October, with a minimum of 18 MWh/hour from the PG&E 1-in-2 scenario.

Figure 4-6: Aggregate Load Impacts over RA Window in 2020 by Month and Weather Scenario

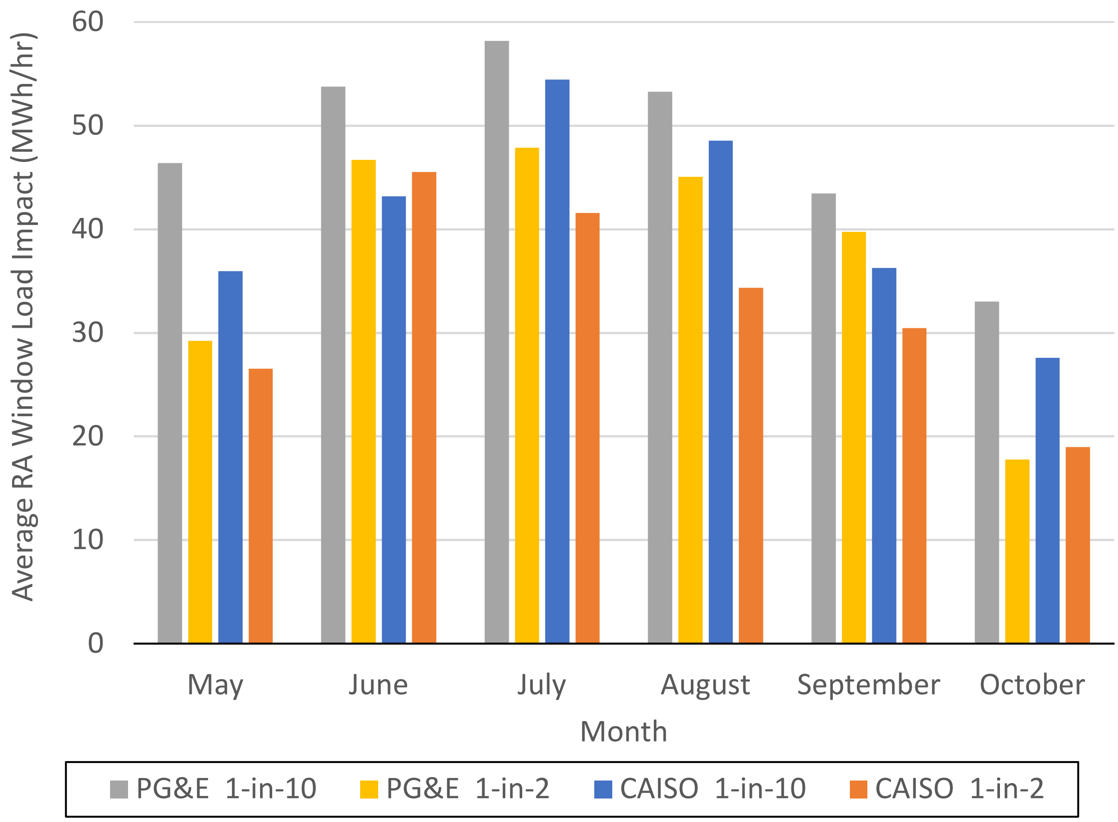
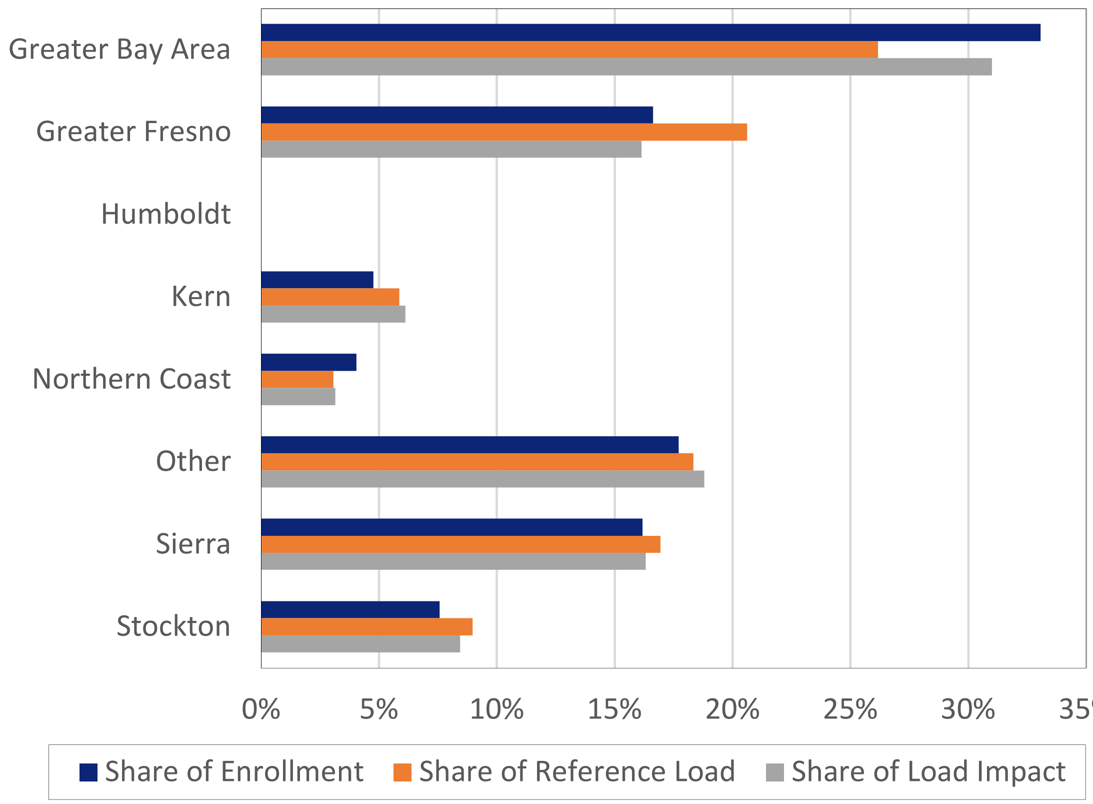


Figure 4-7 compares the LCA shares of average RA window load impacts, reference loads, and enrollments on a July peak day for the PG&E 1-in-2 scenario in 2020. The load impacts for the SmartAC™ program are highest in the Greater Bay Area with 31 percent of aggregate load impacts, 33 percent of enrolled customers, and 26 percent of reference loads. The top four LCA's, including the Greater Bay Area, Greater Fresno, Other LCAs, and Sierra, contribute 82 percent of the aggregate load reductions for SmartAC™. Kern, Other LCAs, Sierra and Stockton all have higher shares of load impacts than enrollments, suggesting that they are relatively more responsive on a per-customer basis. The remaining LCAs have a lower share of load impacts compared to enrollments.

Figure 4-7: RA Window Load Impacts for *PG&E 1-in-2* Typical Event Day by LCA



5. Load Impact Reconciliations

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

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

The term "current" refers to the present study, which includes *ex-post* and *ex-ante* results for PY2019. The term "previous" refers to findings in reports for PY2018 and PY2017. In the final comparison above, we illustrate the linkage between the PY2019 *ex-post* load impacts and the "current" *ex-ante* forecast for 2019.

5.1 Previous vs. Current Ex-Post

In this section we compare *ex-post* load impacts from the current and previous studies. We focus on comparing results for sub-LAP events to the results from PY2018 (all events were sub-LAP events) and the results for serial events to the results from PY2017, since there were no serial events in PY2018.

Table 5-1 compares the average per-customer reference loads, load impacts, and temperatures for sub-LAP events for the current and previous program years across the most common event hours from 4 to 6 p.m. No sub-LAP events were called in either year for the following sub-LAPS: PGCC, PGHB, and PGSF. For the eight sub-LAPs that had sub-LAP events in both years, the load impacts were higher across the board in PY2019 compared to PY2018, but this is mainly due to higher event temperatures in PY2019. PGF1 and had comparable per-customer load impacts and event temperatures, while PGSI and PGZP had higher load impacts despite comparable and lower event temperatures (respectively). The remaining sub-LAPs had higher event temperatures.

For PGKN, which had major dispatch issues in PY2018, has made a dramatic improvement in PY2019 with the highest average per-customer load impacts of 0.48 kWh/customer/hour. Previously we accounted for the PY2018 dispatch issues in the PY2018 forecast by scaling down the serial load impacts for Kern, however this dramatic improvement during PY2019 has led us to eliminate this scaling factor from our forecast procedure.

The bottom row of the table compares average load impacts across sub-LAPs that had events in both years. Overall, almost 9,000 fewer customers were dispatched for sub-LAP events in 2019 relative to 2018 due to program attrition. There was an increase in per-customer reference loads and load impacts, but overall load impacts outpaced reference loads leading to an increase in percentage load impact from 12.3 to 14.4 percent of reference loads.

Table 5-1: Current vs. Previous *Ex-Post* Load Impacts for sub-LAP events (4-6 p.m.)

sub-LAP	Avg. # Dispatched		Reference (kW/cust)		Load Impact (kW/cust)		Avg Temp (°F)	
	PY2018	PY2019	PY2018	PY2019	PY2018	PY2019	PY2018	PY2019
PGEB	21,069	20,123	1.85	2.62	0.31	0.40	92.7	100.2
PGF1	17,370	17,990	2.71	3.04	0.34	0.34	102.5	102.6
PGFG	2,078		1.16		0.11		78.0	
PGKN	5,602	5,154	2.81	2.82	0.03	0.48	102.6	100.8
PGNB		1,346		2.63		0.40		100.3
PGNC	727	618	2.05	2.29	0.25	0.31	95.1	97.8
PGNP	15,183	11,355	2.40	2.63	0.21	0.37	98.7	100.0
PGP2		3,656		2.53		0.46		97.3
PGSB		8,218		2.27		0.39		97.3
PGSI	16,617	14,345	2.49	2.63	0.36	0.43	99.2	99.0
PGST	7,542	5,907	2.49	2.78	0.40	0.46	97.6	98.6
PGZP	2,267	2,169	2.46	2.38	0.20	0.32	99.9	94.2
Common Sub-LAPs	**86,377**	**77,661**	**2.38**	**2.74**	**0.29**	**0.39**	**98.2**	**100.2**

Table 5-2 compares the average per-customer reference loads, load impacts, and temperatures for serial events from 4 to 6 p.m. (the full dispatch hours for 2019 serial events) for the current program year to PY2017, the last year where serial test events were called. Since serial event load impacts form the basis for the *ex-ante* load impact forecast, we compare results by LCA. Overall, load impacts and reference loads have decreased since 2017, with load impacts decreasing more as a percent of 2017 levels compared to reference loads. Moreover, this decrease cannot be explained by weather as event temperatures in 2019 are comparable or event greater than for 2017 serial events.

The bottom row of the table compares average load impacts across all LCAs. In addition to decreasing per-customer load impacts and reference loads there is a sharp decline in program enrollments of 17 percent between PY2017 and PY2019. Although overall serial event load impacts decreased by 0.14 kWh/customer/hour, or 21 percent of the average level in PY2017, percentage load impacts have only decreased by 2.7 percent from 21.2 to 18.5 percent of reference loads.

Table 5-2: Current vs. Previous *Ex-Post* Load Impacts for serial events by LCA (4-6 p.m.)

sub-LAP	Avg. # Enrolled		Reference (kW/cust)		Load Impact (kW/cust)		Avg Temp (°F)	
	PY2017	PY2019	PY2017	PY2019	PY2017	PY2019	PY2017	PY2019
Greater Bay Area	37,876	32,850	2.74	2.52	0.64	0.52	95.4	98.0
Greater Fresno	22,679	17,522	3.36	3.05	0.59	0.47	104.6	104.1
Kern	6,588	4,762	3.27	3.00	0.78	0.66	103.5	104.2
Northern Coast	5,168	4,077	2.57	2.51	0.52	0.50	93.7	97.9
Other	20,330	17,270	3.12	2.78	0.67	0.47	102.4	102.2
Sierra	19,419	16,151	3.16	2.78	0.68	0.53	100.8	100.9
Stockton	8,901	7,935	3.29	2.94	0.65	0.53	101.3	100.9
All LCA	**120,961**	**100,566**	**3.05**	**2.75**	**0.65**	**0.51**	**100.0**	**100.8**

5.2 Previous vs. Current Ex-Ante

In this section, we compare the *ex-ante* forecast from the previous study to the *ex-ante* forecast contained in the current study. We focus on average load impacts across the RA window from 4 to 9 p.m.

Table 5-3 reports the average event-hour load impacts for the July 2020 peak day under PG&E 1-in-2 weather conditions. The aggregate load impact forecast decreased across years from 53.9 MWh/hour in the previous study to 47.9 MWh/hour in the current study. This decrease is being driven by lower program enrollment forecast, as per-customer load impacts are the same for this scenario. The RA window per-customer reference load are higher in the current study, while the temperature is slightly lower. When combined with changes in enrollment forecasts, these changes lead to aggregate reference loads that are markedly lower in the current study.

Table 5-3: Previous vs. Current *Ex-Ante* Load Impacts, *PG&E 1-in-2 July 2020 Peak Day*

Level	Outcome	PY2018	PY2019
Total	# SAIDs	103,471	92,486
	Reference (MW)	240.4	225.5
	Load Impact (MW)	53.9	47.9
	Avg. Temp (°F)	98.3	97.8
	% Load Impact	22.4%	21.2%
Per SAID	Reference (kW)	2.32	2.44
	Load Impact (kW)	0.52	0.52

5.3 Previous Ex-ante vs. Current Ex-Post

In this section, we compare the *ex-ante* forecast from the previous study to the *ex-post* results from the two serial events contained in the current study. We limit the load impacts to the serial event hours during PY2019 from 4 to 6 p.m., which fall within the RA window from 4 to 9 p.m.

Table 5-4 provides a comparison of the *ex-ante* forecast of 2019 load impacts for the PG&E 1-in-2 scenario for the typical event day from the previous study to the *ex-post* load impacts for serial events estimated as part of the current study. This scenario was chosen because the scenario temperature was closest to serial event temperatures in 2019. Overall, the per-customer *ex-post* load impacts are slightly lower than the previous *ex-ante* forecast, while per-customer reference loads were considerably higher. As a result, load impacts during 2019 were much lower as a percent of reference loads compared to the forecast. The aggregate load impacts are much lower than forecasted, mainly as a result of approximately 3,000 fewer customers enrolled compared to the enrollment forecast.

Table 5-4: Comparison of Previous *Ex-Ante* and Current *Ex-Post* Impacts (4-6 p.m.)

Level	Outcome	PY2018 Forecast of 2019	PY2019 Serial Event Load Impacts
Total	# SAIDs	103,471	100,566
	Reference (MW)	223.14	276.87
	Load Impact (MW)	59.55	51.28
	Avg. Temp (°F)	99.9	100.8
	% Load Impact	26.7%	18.5%
Per SAID	Reference (kW)	2.16	2.75
	Load Impact (kW)	0.58	0.51

5.4 Current Ex-Post vs. Current Ex-Ante

In this section, we compare the *ex-post* findings from the current study to the *ex-ante* forecast contained in the current study in a similar fashion as the previous comparison during the event hours from 4 to 6 p.m.

Table 5-5 compares the *ex-post* serial event load impacts to the *ex-ante* load impact forecast for an August Peak day for the CAISO 1-in-10 weather conditions. The *ex-post* per-customer load impacts are somewhat smaller than the forecast, which is based in part on serial events in PY2017. Per-customer reference loads exceed the forecast but are closer than the previous forecast. The biggest difference is reflected in the large discrepancy between the enrollment forecast for 2020 and PY2019 enrollments. By 2020, there is forecast to be almost 9,000 fewer customers in the SmartAC™ program. This leads to aggregate load impacts that are similar in magnitude despite lower per-customer load impacts in 2019.

Table 5-5: Comparison of Current *Ex-Post* and *Ex-Ante* Load Impacts

Level	Outcome	PY2019 Forecast of 2020	PY2019 Serial Event Load Impacts
Total	# SAIDs	91,783	100,566
	Reference (MW)	228.37	276.87
	Load Impact (MW)	54.80	51.28
	Avg. Temp (°F)	100.9	100.8
	% Load Impact	24.0%	18.5%
Per SAID	Reference (kW)	2.49	2.75
	Load Impact (kW)	0.60	0.51

6. Recommendations

The rollout of new two-way devices has led to improved per-customer load impacts in 2019 relative to 2018. Moreover, two-way devices coming online in PGKN have dramatically improved the dispatch challenges experienced in PY2018. As a result, this sub-LAP had the highest per-customer load impacts in 2019. Continued replacement of old one-way devices with two-way devices would further improve the per-customer response for the SmartAC™ program making it a more dependable resource in the CAISO wholesale market.

While we understand that sub-LAP events are the source of value from CAISO market awards, we recommend that there continue to be some serial group or system-wide events called going forward. Until a much higher share of SmartAC customers have new two-way devices installed there will continue to be significant differences between load impacts on serial and sub-LAP events due to differences in dispatch effectiveness for one-way devices. Because system-wide and serial group events take advantage of factory programmed addressing for one-way devices and because of the inherent randomization, these events will enable a more complete program evaluation and should produce more accurate forecasts of the program's capacity as a whole.

Appendices

The following Appendices accompany this report. Appendix A presents further information about how we evaluated the quality of our *ex-post* load impact evaluation and *ex-ante* forecast. The additional appendices consist of Excel files that can produce the tables required by the Protocols.

Appendix C   SmartAC™ *Ex-post* Load Impact Tables

4a. PGE_2019_SmartAC_Ex_Post_PUBLIC.xlsx

4a. PGE_2019_SmartAC_Ex_Post_CONFIDENTIAL.xlsx

Appendix D   SmartAC™ *Ex-ante* Load Impact Tables

4b. PGE_2019_SmartAC_Ex_Ante_PUBLIC.xlsx

(There is no confidential information in Appendix D.)

Appendix A. Additional Control Group Matching Results

Table A-1 provides the mean percentage error (MPE) and mean absolute percentage error (MAPE) calculated across the average 24-hour load profile as well over the RA window. Also included are the mean error (ME) and mean absolute error (MAE) which show the errors in terms of kWh/customer/hour differences rather than percentage differences. Again, we evaluate match quality based on 24-hour load profiles for hot days and cooler days used in matching as well as days not using in matching.

The MPE and MAPE are higher by sub-LAP than the overall results. The average MAPE is 7.8 percent for all hours and 3.1 percent for the RA window. A few sub-LAPs have MPEs and MAPEs that are well above 10 percent in absolute terms for some types of non-event days. This is mainly an artifact of the formula the MPE and MAPE, whereby average per-customer load levels close to zero during midday lead to high percentage errors for these hours due to a near-zero denominator.[14] Table A-1 demonstrates that most ME and MAE values are less than 0.05 kWh/customer/hour. Moreover, hot non-event days generally have lower MAPEs, which average 2.8 percent for all hours and 1.8 percent for the RA window. PGCC (highlighted in yellow) is one exception with MAPEs above 10 percent and MAEs around 0.1 kWh/customer/hour, however this sub-LAP has few customers which makes finding a good match more difficult.

Table A-1: Match Quality Statistics by Sub-LAP

Sub-LAP	Comparison Days	24 Hour Load Profile				RA Window			
		MPE (%)	ME (kW)	MAPE (%)	MAE (kW)	MPE (%)	ME (kW)	MAPE (%)	MAE (kW)
PGCC	Hot Days	-1.0%	0.01	11.5%	0.08	1.4%	0.03	4.7%	0.04
	Cool Days	21.1%	-0.01	55.0%	0.11	-8.5%	0.02	15.5%	0.03
	Non-Matching Cool Days	51.4%	-0.03	75.7%	0.12	-19.8%	0.02	25.2%	0.04
	Weekend Days	-45.5%	0.00	56.5%	0.09	-2.7%	0.02	12.0%	0.04
PGEB	Hot Days	1.6%	0.02	1.6%	0.02	1.5%	0.03	1.5%	0.04
	Cool Days	1.2%	0.01	1.5%	0.01	1.6%	0.02	1.6%	0.03
	Non-Matching Cool Days	2.6%	0.01	2.6%	0.01	2.3%	0.02	2.3%	0.04
	Weekend Days	2.9%	0.02	3.2%	0.02	1.8%	0.02	1.8%	0.04
PGF1	Hot Days	0.4%	0.00	0.7%	0.01	0.1%	0.03	0.3%	0.04
	Cool Days	-2.0%	0.00	2.9%	0.01	-0.1%	0.02	0.5%	0.03
	Non-Matching Cool Days	-1.0%	0.00	1.8%	0.01	0.2%	0.02	0.4%	0.04
	Weekend Days	0.7%	0.00	0.8%	0.01	0.1%	0.02	0.4%	0.04
PGFG	Hot Days	1.1%	0.02	2.1%	0.02	2.0%	0.03	2.0%	0.04
	Cool Days	2.3%	0.01	3.4%	0.01	3.0%	0.02	3.0%	0.03

[14] Average per-customer loads near zero during midday result from the large number of NEM customers, which can bring load levels below zero in some cases.

	Non-Matching Cool Days	1.6%	0.00	3.5%	0.01	2.7%	0.02	2.7%	0.04
	Weekend Days	3.0%	0.02	4.1%	0.02	1.9%	0.02	1.9%	0.04
PGKN	Hot Days	0.6%	0.01	0.6%	0.01	1.0%	0.03	1.0%	0.04
	Cool Days	0.6%	0.01	0.8%	0.01	1.3%	0.02	1.3%	0.03
	Non-Matching Cool Days	0.1%	0.00	0.6%	0.01	1.2%	0.02	1.2%	0.04
	Weekend Days	0.9%	0.01	1.1%	0.01	0.8%	0.02	0.8%	0.04
PGNB	Hot Days	5.7%	0.06	5.7%	0.06	4.8%	0.03	4.8%	0.04
	Cool Days	6.7%	0.03	7.9%	0.04	8.5%	0.02	8.5%	0.03
	Non-Matching Cool Days	7.1%	0.03	8.6%	0.04	9.6%	0.02	9.6%	0.04
	Weekend Days	7.1%	0.05	7.1%	0.05	7.6%	0.02	7.6%	0.04
PGNC	Hot Days	4.2%	0.05	5.5%	0.06	5.9%	0.03	5.9%	0.04
	Cool Days	6.1%	0.03	7.3%	0.04	6.6%	0.02	6.6%	0.03
	Non-Matching Cool Days	4.5%	0.02	6.8%	0.03	7.8%	0.02	7.8%	0.04
	Weekend Days	5.7%	0.04	6.4%	0.04	5.8%	0.02	5.8%	0.04
PGNP	Hot Days	0.7%	0.01	0.8%	0.01	0.5%	0.03	0.5%	0.04
	Cool Days	-0.2%	0.00	1.1%	0.00	0.7%	0.02	0.7%	0.03
	Non-Matching Cool Days	1.7%	0.01	2.1%	0.01	1.6%	0.02	1.6%	0.04
	Weekend Days	1.6%	0.01	2.2%	0.01	0.9%	0.02	0.9%	0.04
PGP2	Hot Days	-0.1%	0.00	1.0%	0.01	0.4%	0.03	0.4%	0.04
	Cool Days	-0.9%	0.00	1.5%	0.01	0.4%	0.02	0.4%	0.03
	Non-Matching Cool Days	-0.6%	0.00	1.5%	0.01	0.9%	0.02	0.9%	0.04
	Weekend Days	1.5%	0.01	2.0%	0.02	2.1%	0.02	2.1%	0.04
PGSB	Hot Days	-0.5%	0.00	1.0%	0.01	0.7%	0.03	0.7%	0.04
	Cool Days	-4.3%	0.00	5.0%	0.01	1.3%	0.02	1.3%	0.03
	Non-Matching Cool Days	-6.7%	-0.01	7.3%	0.01	1.2%	0.02	1.2%	0.04
	Weekend Days	0.3%	0.00	1.3%	0.01	1.6%	0.02	1.6%	0.04
PGSI	Hot Days	-0.5%	0.00	0.7%	0.01	0.0%	0.03	0.2%	0.04
	Cool Days	1.4%	-0.01	6.5%	0.01	-0.5%	0.02	0.5%	0.03
	Non-Matching Cool Days	-5.5%	0.00	5.7%	0.01	0.4%	0.02	0.4%	0.04
	Weekend Days	1.0%	0.00	1.5%	0.01	0.3%	0.02	0.3%	0.04
PGST	Hot Days	1.0%	0.01	1.0%	0.01	0.5%	0.03	0.5%	0.04
	Cool Days	2.2%	0.01	2.2%	0.01	0.5%	0.02	0.5%	0.03
	Non-Matching Cool Days	2.2%	0.01	2.2%	0.01	1.5%	0.02	1.5%	0.04
	Weekend Days	2.6%	0.02	2.6%	0.02	1.0%	0.02	1.0%	0.04
PGZP	Hot Days	-2.6%	-0.02	3.6%	0.03	-1.2%	0.03	1.4%	0.04
	Cool Days	8.7%	-0.02	42.6%	0.02	-1.6%	0.02	1.7%	0.03
	Non-Matching Cool Days	-23.1%	-0.02	23.5%	0.02	-1.7%	0.02	1.9%	0.04
	Weekend Days	-2.1%	-0.01	2.9%	0.02	-1.8%	0.02	2.1%	0.04

Appendix B. Event Overrides by Event and Location

Table B-1 shows customers overrides by sub-LAP for sub-LAP events and Table B-2 displays overrides by LCA for serial events. All override rates are below one percent and are limited to customers who were dispatched for an event and elected to override the event.

Table B-1: Overrides by Sub-LAP and Event for Sub-LAP events

Date	Hours	sub-LAP	SmartRate Event?	Overrides	Enrollment	Override Rate
24-Jul	4-7 p.m.	PGF1	Yes	6	15,598	0.0%
		PGKN		3	4,445	0.1%
		PGZP		2	1,766	0.1%
25-Jul	3-6 p.m.	PGF1	No	14	17,990	0.1%
		PGKN		4	5,154	0.1%
		PGZP		2	2,169	0.1%
14-Aug	4-7 p.m.	PGEB	Yes	41	18,563	0.2%
		PGNB		4	1,355	0.3%
		PGP2		8	3,682	0.2%
		PGSB		17	8,202	0.2%
		PGSI		22	14,390	0.2%
16-Aug	5-8 p.m.	PGF1	Yes	28	15,489	0.2%
		PGKN		10	4,418	0.2%
		PGZP		4	1,753	0.2%
26-Aug	3-6 p.m.	PGF1	Yes	10	15,381	0.1%
		PGKN		8	4,398	0.2%
		PGNC		1	618	0.2%
		PGNP		27	11,358	0.2%
		PGSI		24	14,321	0.2%
		PGST		11	5,912	0.2%
		PGZP		5	1,739	0.3%
27-Aug	2-5 p.m.	PGF1	Yes	23	15,366	0.1%
		PGKN		15	4,390	0.3%
	3-5 p.m.	PGNC		1	618	0.2%
	2-5 p.m.	PGNP		35	11,350	0.3%
		PGSI		32	14,305	0.2%
		PGST		8	5,897	0.1%
		PGZP		7	1,736	0.4%
13-Sep	3-6 p.m.	PGNB	Yes	2	1,337	0.1%
	5-8 p.m.	PGP2		6	3,636	0.2%
		PGSB		11	8,135	0.1%
25-Sep	3-6 p.m.	PGEB	No	20	20,123	0.1%
		PGP2		8	3,656	0.2%
		PGSB		19	8,218	0.2%
Total				**438**	**267,468**	**0.2%**

Table B-2: Overrides by LCA and Event for Serial Events

Date	Hours	LCA	Overrides	Enrollment	Override Rate
27-Jul	4-7 p.m.	Greater Bay Area	33	32,927	0.1%
		Greater Fresno	17	17,972	0.1%
		Kern	5	5,149	0.1%
		Northern Coast	9	4,294	0.2%
		Other	18	16,674	0.1%
		Sierra	17	16,215	0.1%
		Stockton	6	7,626	0.1%
15-Aug	4-7 p.m.	Greater Bay Area	95	29,361	0.3%
		Greater Fresno	11	14,422	0.1%
		Kern	8	3,930	0.2%
		Northern Coast	9	3,653	0.2%
		Other	31	15,163	0.2%
		Sierra	33	14,280	0.2%
		Stockton	9	6,713	0.1%
Total			**301**	**188,379**	**0.2%**