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2025 Load Impact Evaluation for Pacific Gas & Electric Company's SmartAC™ Program

CALMAC Study ID – PGE0519

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EXECUTIVE SUMMARY

This report documents ex-post and ex-ante load impact evaluations of Pacific Gas and Electric's (PG&E) SmartAC™ program for 2025. The evaluation produces estimates of the ex-post load impacts for each hour of each event dispatched in program year 2025 (PY2025), and develops ex-ante load impact forecasts for the program through 2028.[1]

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 a Zigbee AC load control switch 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 dispatched, 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 serial test events generally dispatch 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 more serial groups are withheld from the event).[2] During sub-LAP events, all SmartAC™ participants with devices that are associated with a given sub-LAP are dispatched for the event.[3] In PY2025, four events were dispatched: one serial test event with a serial group withheld, and three sub-LAP events with all sub-LAPs dispatched. Of the three sub-LAP events, two were out of market and one included resources dispatched by market awards as well as out of market dispatches.

The primary goals of the evaluation include:

1. Estimate hourly ex-post load impacts for PY2025, 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, local capacity area (LCA), CARE/non-CARE customers, net-metering solar customers (NEM), housing type (i.e., detached vs. shared wall

[1] Given the CPUC's approval to sunset the SmartAC program, we only present ex-ante forecasts up to 2028.

[2] Currently, not all installed devices have a serial number that conforms to this serial group selection process. For these devices, customers are randomly assigned to a serial group at the time of device installation.

[3] In PY2025, all sub-LAPs are dispatched during the event hours of the three sub-LAPs events.

residences), AC usage intensity, and device type (i.e., two-way vs. one-way; by one-way device type: UtilityPro, Gen 1, and Gen 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; and
   e. The persistence of load reductions across event hours for multiple-hour events.

2. Produce ex-ante load impact forecasts for 2026 to 2028 by sub-LAP and LCA on an aggregate and per-customer basis for a typical event day and the monthly system worst load day for May through October. Forecasts are based on the following four sets of weather conditions[4]:
   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 in which at least one serial group is withheld from the event, we use this random sample of SmartAC™ customers as an additional control group. For all events, we use a matched control group consisting of residential customers who are not enrolled in any demand response programs, including SmartAC™ or SmartRate™. Matched control group customers are selected based on the similarity of available customer characteristics (e.g., rate schedule, sub-LAP, AC usage level, 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 full event hour for all SmartAC™ events in PY2025, along with a 90 percent confidence interval (corresponding to the 5th and 95th percentile uncertainty-adjusted load impacts).[5] There were four events dispatched, including one serial event and three sub-LAP events, during which all sub-LAPs were dispatched. The yellow bar indicates the serial test event on September 17th while the blue bars correspond to the sub-LAP events. These results indicate that

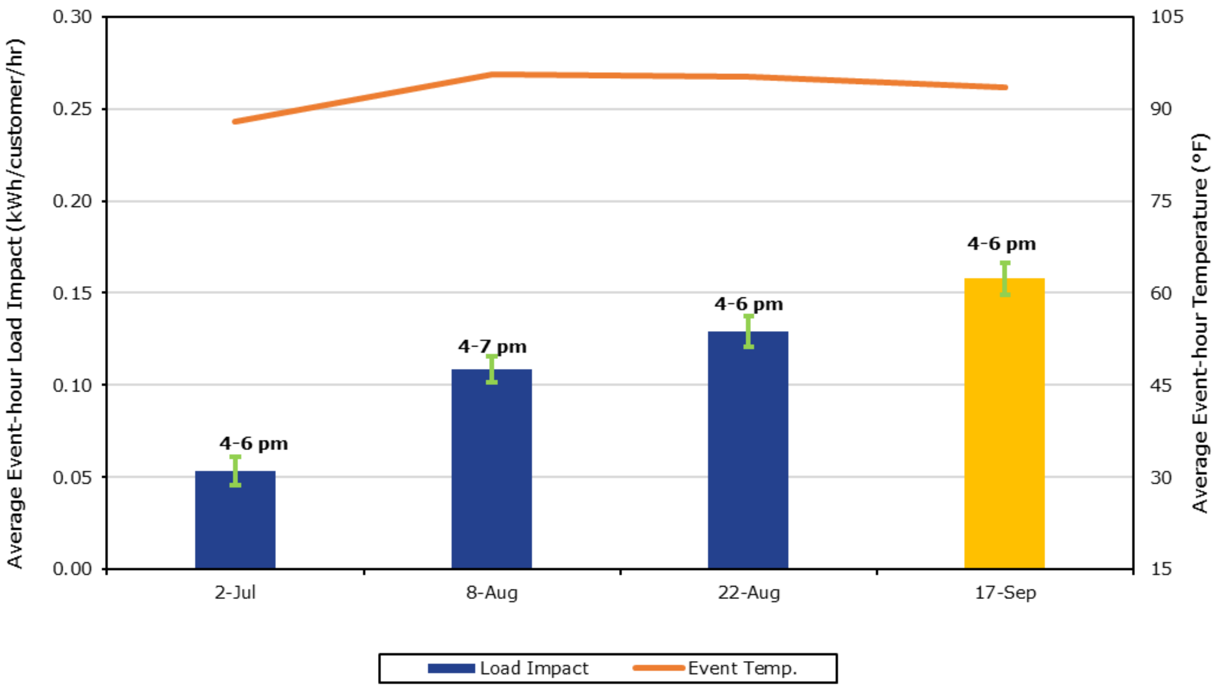
[4] While only the peaking conditions in a 1-in-2 weather year are required, we also include the 1-in-10 weather year conditions as it is often closer to the actual SmartAC™ event temperatures.

[5] All results in this report are presented in prevailing time. The associated protocol table generators include the option to view results in Coordinated Universal Time (UTC).

SmartAC™ customers had statistically significant load reductions on each of the four event days, ranging from 0.05 to 0.16 kWh/customer/hour. The orange solid line represents the average temperatures experienced by the customers during the event. There are two main factors leading to the low load impacts in PY2025; the first being low temperatures throughout the 2025 summer season, and the second being the performance issues of Energate two-way devices for most of the events in PY2025, as in PY2024. Overall, load impacts were 0.09 kWh/customer/hour lower in PY2025 compared to PY2024 for sub-LAP events, largely due to average event-hour temperatures that were 6 degrees lower in PY2025.

The average load reduction feature was set in such a way that Energate two-way devices did not respond well to dispatch signals during some of the PY2024 and PY2025 events. The issue was fixed by the time of the last serial event on September 17th, 2025. Notably, the average event-hour load impact significantly improved during the serial event compared to the sub-LAP event on August 22nd, despite the slightly lower average event-hour temperature.

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



In addition to the overall load impacts, we examine patterns of load impacts at the sub-LAP level and how load impacts are distributed across customer subgroups.

ES.4 Ex-Ante Load Impacts

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

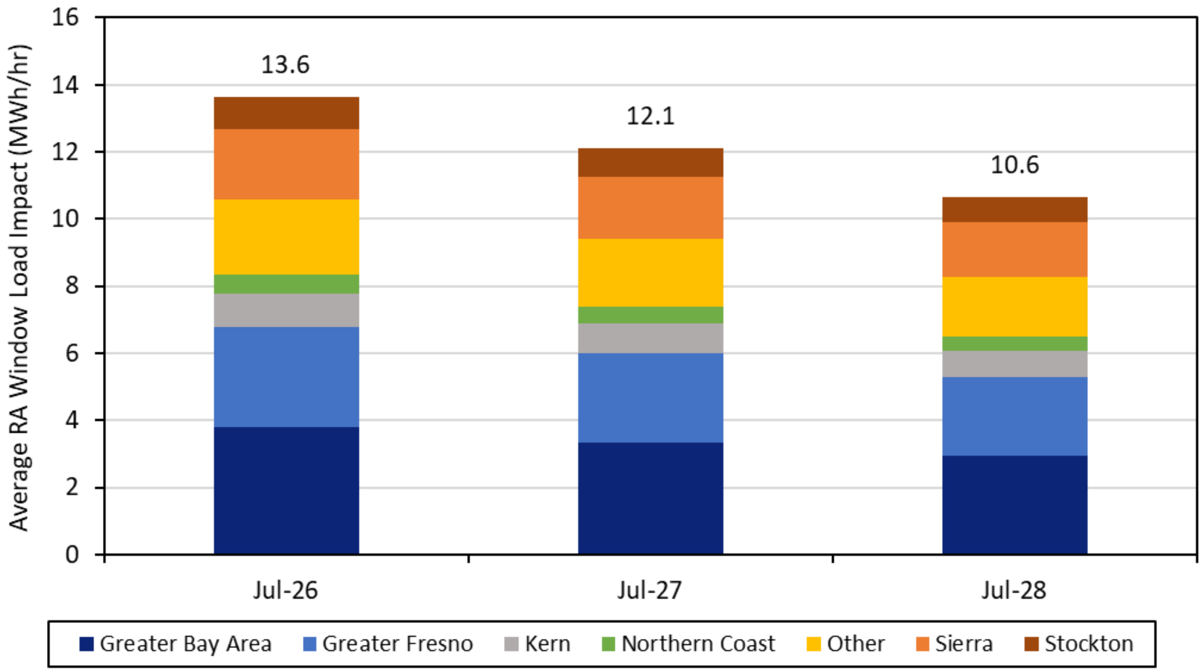
Estimating ex-ante load impacts requires three key pieces of information:

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

2. *Reference loads* by customer type; and
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.

Figure ES-2 summarizes the ex-ante program load impact forecast for 2026 to 2028 for SmartAC™ by plotting the average aggregate load impacts for the first four hours of the resource adequacy (RA) window over time by LCA.[6] For this comparison we use the PG&E 1-in-2 scenario for July system worst days. The trend of declining aggregate load impacts is driven by declining enrollments due to program attrition and SmartAC™ being closed to new participants (as of 2024). Aggregate load impacts steadily decline by about 11 percent per year, consistent with the percentage decline in enrollments.

Figure ES-2: Aggregate Load Impacts over RA Window for PG&E 1-in-2 July System Worst Day Scenario (2026-2028)



[6] The Load Impact Protocol (LIP) 24-Hour Slice-of-Day requirements state that a four consecutive hour dispatch is required in ex-ante within Availability Assessment Hours on the worst day of each month. The first 4 hours of the RA window are reported for ex-ante to better reflect ex-post event window (most events in recent years ended by 8 p.m.).

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 2025. The evaluation produces estimates of the ex-post load impacts for each hour of each event dispatched in program year 2025 (PY2025), and it develops ex-ante load impact forecasts for the program through 2028.

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 a Zigbee AC load control switch 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. During past years, as part of the second phase of the Reliability Order Instituting Rulemaking decision (D.21-12-015), PG&E was authorized to offer SmartAC™ customers with one-way devices a $25 incentive for PG&E to upgrade their switch to a two-way Zigbee device. Enrollment in the SmartAC™ program has been closed since 2024.[7]

When events are dispatched, 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 percent 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 dispatch 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 more serial groups are withheld from the event).[8] During sub-LAP 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 dispatched for testing purposes.

[7] PG&E proposed closing the SmartAC program to new enrollments in its "Application for Pacific Gas and Electric Company (U 39 E) for approval of its demand response program, pilots, and budgets for programs years 2023-2027". The proposal was approved by the CPUC in Decision 23-12-005.

[8] Currently, not all installed devices have a serial number that conforms to this serial group selection process. For these devices, customers are randomly assigned to a serial group at the time of device installation.

Table 1.1 shows the details for each event in PY2025.[9] There were four SmartAC™ events dispatched in PY2025; three sub-LAP events and one serial test event on September 17th. There was no emergency events dispatched in 2025. Of the three sub-LAP events, two were out of market dispatches and one was a combination of market award dispatches and out of market dispatches.

There are some notable differences in the way customers were dispatched in sub-LAP events in PY2025. All sub-LAPs were dispatched for the same hours on all event days. On August 22nd, the dispatches of sub-LAPs PGNP, PGSI, PGST, PGKN, PGF1, and PGZP were CAISO market awards, while the dispatches of the remaining sub-LAPS were due to testing. All events besides the July 2nd event happened alongside SmartRate™ events. The event on August 8th lasted three hours, whereas the other events each ran for two hours.

Table 1.1: PY2025 SmartAC™ Events

Date	SmartRate™ Event?	Reason	Event Hours (p.m.)	Device Type Dispatched	Sub-LAPs/Serial Groups Dispatched	# Customers Dispatched
7/2	No	Test	4-6	Both	All Sub-LAPs	52,394
8/8	Yes	Test	4-7	Both	All Sub-LAPs	48,906
8/22	Yes	Market	4-6	Both	PGNP, PGSI, PGST, PGKN, PGF1, PGZP	48,787
		Test			PGHB, PGNC, PGFG, PGNB, PGSF, PGEB, PGSB, PGP2, PGCC	
9/17	Yes	Test	4-6	Both	All Sub-LAPs, Serial Group 7 withheld	43,433

SmartAC™ customers are permitted to be dually enrolled in SmartAC™ and the SmartRate™ program if they were enrolled before October 26, 2018, but subsequent new dual participation is prohibited. As of May 2025, SmartAC™ had over 58,000 active enrolled residential customers; approximately 3,200 of these customers were dually enrolled in SmartAC™ and SmartRate™. During days in which both SmartAC™ and SmartRate™ events are dispatched, the SmartRate™ customers are withheld from our summary of SmartAC™ events and the response from dually enrolled customers is attributed to the SmartRate™ program. As of January 2024, enrollment in the SmartAC™ program is no longer open to new participants.

The primary goals of the evaluation include:

1. Estimate hourly ex-post load impacts for PY2025, 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, local capacity area (LCA), CARE/non-CARE customers, net-metering solar customers (NEM), housing type (i.e., detached vs. shared wall residences), AC usage intensity, and device type (i.e., two-way vs. one-way; by one-way device type: UtilityPro, Gen 1, and Gen 2);

[9] All results in this report are presented in prevailing time. The associated protocol table generators include the option to view results in Coordinated Universal Time (UTC).

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;[10] and

e. The persistence of load reductions across event hours for multiple hour events.

2. Produce ex-ante load impact forecasts for 2026 to 2028 by sub-LAP and LCA on an aggregate and per-customer basis for a typical event day and the monthly system worst load day for May through October. Forecasts are based on the following four sets of weather conditions[11]:

   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, additional analysis and contain electronic versions of the required Protocol table generators.

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

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 any demand response programs. We match control-group customers based on the similarity of available customer characteristics (e.g., sub-LAP, rate schedule, AC usage level, CARE status, NEM status) as well as usage patterns on non-event days.

[10] 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.

[11] While only the peaking conditions in a 1-in-2 weather year are required, we also include the 1-in-10 weather year conditions as it is often closer to the actual SmartAC™ event temperatures.

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, rate schedule, housing type, CARE status, NEM status);
- Billing-based *interval load data* (i.e., hourly loads for each treatment and potential control group customer) for PY2025 (May 1 through September 30);
- *Weather data* (i.e., hourly temperatures and other variables for PY2025, 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

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 nearest neighbor matching to identify four control customers for each treatment customer that have the closest match in terms of average daily usage (based on monthly billing data), weather station and average cooling degree days, and customer characteristics such as CARE status, NEM status, dwelling type, and rate schedule. Following the first-stage matching, we obtain interval load data for the treatment customers and the pared-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 of the 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.[12] 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.[13] Finally, we require that SmartAC™ customers are matched to a control customer residing in the same sub-LAP area with a similar rate schedule (i.e., TOU rates vs. other rates).

[12] In the PY2025 evaluation, we also included an additional sample of 150,000 residential customers' interval data as candidates for potential controls in the second stage matching process.

[13] 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.

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:

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*

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

To produce estimates of ex-post load impacts, we estimate the following panel model for each hour of the day and sub-LAP:

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

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 treated SmartAC customer (1) or Control (0) customer on the i^{th} event day (control customers include SmartAC customers in withheld serial groups)
$Evt_{i,d}$	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*
AC_c	Variable indicating customer *c*'s level of AC usage (no AC, low, medium, or high)
β_0	Estimated constant coefficient
$\beta_{1,i}$	Estimated load impact for event *i*
$\beta_{2,j}$	Estimated coefficient for weather variable *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 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[14]. The $\beta_{1,i}$ coefficients represent the estimated load impacts for each hour of every event day.[15]

For the serial test events, there is an additional control group that was not dispatched, which consists of SmartAC™ customers with device serial numbers ending in 7 on September 17th. We estimate load impacts for the serial test event and the sub-LAP events using one model, consistent with previous evaluations.

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 percent of non-event days). We estimate the distribution of load impacts across different customer subgroups by interacting the event variables with indicator variables for customer subgroups of interest (e.g., CARE vs. non-CARE).[16] While this approach produces subgroup load impacts for each event, these results are not necessarily representative of the system-wide results but are limited to the sub-LAPs dispatched for sub-LAP events. This is not an issue in PY2025 as compared to previous years since all sub-LAPs were dispatched for the three sub-LAP events. Also, the matching procedure used for sub-LAP events does not guarantee that treatments and matched control customers have the same subgroup status.

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

[14] 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). Similar to the previous year's evaluation, we have allowed the relationship between weather and loads to vary by AC usage level.

[15] For PY2025, we keep the negative or statistically insignificant coefficients in the report and indicate those coefficients as such.

[16] Due to the drop in customer enrollment, we estimate the load impacts across customer subgroups for all sub-LAPs in PY2025, rather than by sub-LAP and subgroup as in previous program years.

around the estimated impacts. These methods use the estimated load-impact parameter values and the associated variances to derive scenarios of hourly load impacts.

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

2.2 Developing Ex-Ante Load Impacts

Ex-ante load impacts represent forecasts of load impacts that are expected to occur when program events are dispatched 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
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 2026 through 2028, both for the monthly system worst 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. Sub-LAP;
2. LCA;
3. Customers enrolled in only SmartAC™ vs. customers dually enrolled in SmartAC™ and SmartRate™; and
4. One-way versus two-way device.

PG&E provided the enrollment forecasts and ex-ante weather conditions for each required scenario. This forecast also accounts for the closure of SmartAC™ to new enrollments.

2.2.1 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 PG&E) 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 2025. Average load profiles are created for each sub-LAP 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:

$$avgkW_{d,h} = \beta_0 + \sum_{h=1}^{24} \beta_{1,h}(CDD65_d \times H_h) + \sum_{h=1}^{24} \beta_{2,h}(CDD65_d^2 \times H_h) + \sum_{h=1}^{24} \beta_{3,h} H_h + \sum_{h=1}^{24} \beta_{4,h}(Mon_d \times H_h) + \sum_{h=1}^{24} \beta_{5,h}(Fri_d \times H_h) + \sum_{d=1}^{5} D_d + \sum_{d=1}^{6} M_d + \varepsilon_{d,h}$$

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

Table 2.3: Ex-Ante Reference Loads Model Terms

Symbol	Description
$avgkW_{d,h}$	Average load (kWh/customer/hour) on day *d* during hour *h*
$CDD65_d$	The cooling degrees on day *d*
$CDD65_d^2$	The cooling degrees on day *d* squared
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)
β_0	Estimated constant coefficient
$\beta_{1,h}$	Estimated increase in average load during hour *h* that results from a one degree increase in cooling degrees
$\beta_{2,h}$	Estimated increase in average load during hour *h* that results from a one degree increase in squared cooling degrees
$\beta_{3,h}$	Estimated average load during hour *h*
$\beta_{4,h}$	Estimated difference in average load during hour *h* on Mondays
$\beta_{5,h}$	Estimated difference in average load during hour *h* on Fridays
D_d	Day-of-the-week fixed effects
M_d	Month 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, while the $\beta_{2,h}$ coefficients represent the estimated increase in average loads during hour *h* due to an increase in squared cooling degrees by one. We estimate this model separately for each sub-LAP and enrollment segment to be consistent with the load impact model described in Section 2.2.2. We then aggregate results from the sub-LAP level models to LCA based on the share of customers in each sub-LAP and LCA in PY2025.

Reference loads are simulated by applying the cooling degree days from the weather scenarios provided by PG&E to the estimated $\beta_{1,h}$ and $\beta_{2,h}$ 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 worst load (or typical event day) for a Wednesday event.

2.2.2 Load Impacts

The ex-ante 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 ex-ante per-customer load impacts are then coupled with the appropriate simulated ex-ante reference loads to develop the load impact forecast.

We develop an ex-ante forecast that projects program performance during sub-LAP events. We include load impacts from all sub-LAP and serial events in PY2023, PY2024, and PY2025 and develop a model that estimates the relationship between ex-post load impacts (for both serial and sub-LAP events) and event day temperatures and simulate the model results for sub-LAP events.

We model the relationship between load impacts and weather conditions as follows:

$$Impact_{s,h,evt\ i} = \beta_0 + \beta_{1,h} Mean17_{s,evt\ i} \times H_h + \beta_2 Temperature_{s,h,evt\ i} + \delta_s Serial_{evt\ i} \times subLAP_s + \mu_s subLAP_s + \varepsilon_{s,h,evt\ i}$$

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

Table 2.4: Ex-Ante Load Impacts Model Terms

Symbol	Description
$Impact_{s,h,evt\ i}$	Estimated load impact in sub-LAP *s* during hour *h* on event *i*
$Mean17_{s,evt\ i}$	Average temperature over the first 17 hours of the day
H_h	Variable indicating if the hour is *h* (1) or not (0)
$Temperature_{s,h,evt\ i}$	Average temperature during hour *h*
$Serial_{evt\ i}$	Variable indicating if event *i* is a serial event (1) or not (0)
$subLAP_s$	Variable indicating if the sub-LAP is *s* (1) or not (0)
β_0	Estimated constant coefficient
$\beta_{1,h}$	Estimated increase in load impact in hour *h* from a 1 degree increase in the average temperature over the first 17 hours of the day
β_2	Estimated increase in load impact from a 1 degree increase in event-hour temperature
δ_s	Estimated difference in load impacts in sub-LAP*s* during serial events
μ_s	Estimated difference in load impacts for sub-LAP *s*
$\varepsilon_{s,h,evt\ i}$	Error term (robust)

The $\beta_{1,h}$ coefficients represent the estimated increase in load impact during hour *h* that results from a one-degree increase in the average temperature over the first seventeen hours of the event day. The β_2 coefficient is the estimated increase in load impact that results from a one-degree increase in average event-hour temperature. The δ coefficient measures the additional load impacts during serial events, which may vary by sub-LAP, and the μ coefficients allow load impacts to vary by sub-LAP. The standard errors from this model are the basis for the uncertainty-adjusted load impacts.

We build our ex-ante load impact forecasts based on a combination of sub-LAP and serial events dispatched in 2023, 2024, and 2025. Due to poor performance issues observed with Energate two-way devices in PY2024 and PY2025 – and with this issue expected to be resolved by the end of PY2025 – we excluded the Energate devices from the PY2024 and PY2025 ex-post results and used Eaton two-way devices as proxies for all two-way devices. The load impacts simulated using this model are for sub-LAP events to reflect the nature of how events will be dispatched for the SmartAC™ program in future program years.[17]

In addition, we separately estimate the model using load impacts for one-way and two-way devices. We simulate ex-ante results using different weather scenarios and compute the aggregate load impacts by using the enrollment forecast for one-way and two-way devices. We assume that load impacts are comparable for SmartAC™-only and dually enrolled customers based on our examination of the relative performance of these customers in past evaluations.

The snapback during 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 sub-LAP. 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 2025 and the temperatures in the various weather scenarios). We 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 fact that all sub-LAPs were dispatched for sub-LAP events in PY2025, and that all event hours are the same for a given event day, we can capture the average hourly load impacts across all sub-LAPs for all event hours. There is only one serial event day, which represents the typical event day in 2025.[18] 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 three concurrent SmartRate™ event days 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. Our validity assessment focuses on comparisons of treatment and control-group loads for selected event-like

[17] To simulate the load impacts for sub-LAP events, we set $Serial_{evti}$ equal to zero so that the incremental load impacts during serial events are not included in the simulated load impacts.

[18] We chose the September 17th event as the typical event day because Energate device dispatch issue was fixed for all sub-LAPs for this event.

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.[19]

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 use 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 that ranks from 25% to 75% 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 are 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

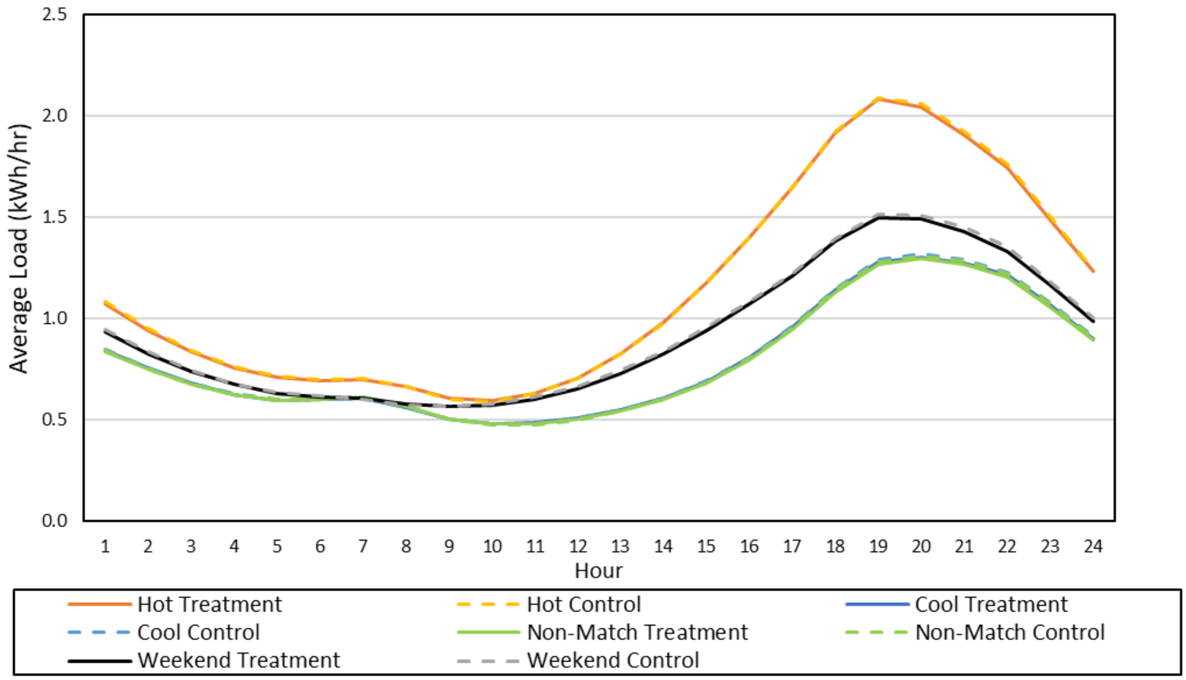
Comparison Days	MPE	MAPE	MPE RA Window	MAPE RA Window
Hot Days	0.4%	0.5%	0.4%	0.4%
Cool Days	0.3%	0.5%	0.8%	0.8%
Non-Matching Cool Days	0.4%	0.7%	1.0%	1.0%
Weekend Days	1.0%	1.2%	1.1%	1.1%

Figure 3.1: illustrates the load profiles for selected event-like days for treatment and matched control customers. 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, 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 (yellow), 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. Cool days that are used in matching have comparable loads to cool days that are not used in matching[20] and the control loads on each type of day tracks the treatment loads very closely.

[19] 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.

[20] In Figure 3.1, the blue cool matching lines are overlapping with the green non-matching lines.

Figure 3.1: Treatment and Control Non-Event Day Load Profiles



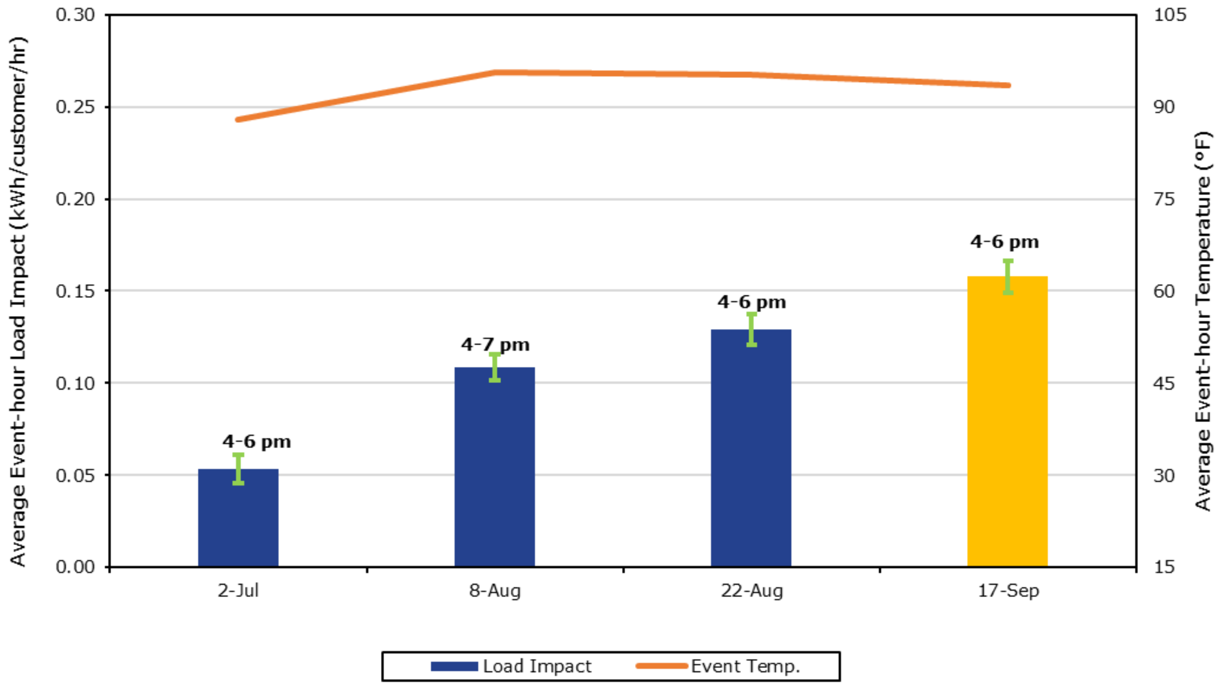
3.2 Overall Load Impacts

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.

The ex-post load impacts are summarized for all full event hours for the four event days in Figure 3.2. The bars indicate the magnitude of the average per-customer load impact (in kWh/customer/hour) during the full event hours dispatched for each event, while the labels show the maximal range of full event hours over which all customers were dispatched.[21] The gold bars indicates the average per-customer load impact during the full event hours of the serial test events on September 17th. The blue bars represent the sub-LAP events. The green bands correspond to 90 percent confidence intervals around these estimates (i.e., the 5th and 95th percentile scenarios from the uncertainty-adjusted load impacts). The orange solid line represents the average temperatures experienced by the customers during the event.

[21] In PY2025, all sub-LAPs were dispatched during the same event hours for each sub-LAP event. Thus, the average load impacts and event hours are representative across all sub-LAPs.

Figure 3.2: Average Event-Hour Load Impacts by Event



Overall results range from 0.05-0.16 kWh/customer/hour

These results indicate that SmartAC™ customers have statistically significant load reductions on all four event days, ranging from 0.05 kWh/customer/hour on July 2nd to 0.16 kWh/customer/hour on September 17th, with an average of 0.11 kWh/customer/hour.

Temperature and device performance issues drive the variation in per-customer load impacts

July 2nd event has the lowest impact due to lower temperature. The load impact during the last serial event (September 17th) is higher than those during the previous two sub-LAP events in August despite lower average event temperature (93.5°F on September 17th vs. 95.6°F on August 8th and 95.3°F on August 22nd), which is driven by the improved performance of Energate two-way devices.

The serial test event has higher impacts compared to the PY2024 serial event with comparable temperature

The average temperature of the serial event in PY2025 is comparable to the serial event on October 2nd in PY2024, which had an average load impact of 0.13 kWh/customer/hour with an average event hour temperature of 92.8°F. Meanwhile, the serial event on September 17th in PY2025 had an average load impact of 0.16 kWh/customer/hour with an average event hour temperature of 93.5°F.

The number of dispatched customers, average event temperatures, and device performance drive large variation in aggregate event load 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 of customers dispatched, as well as average load impacts (per-customer and in aggregate), reference loads, and percentage load impacts across the full event hours for which each sub-LAP was dispatched for each event day. The event dates highlighted in light green are for sub-LAP events, and the event date highlighted in light orange is for the serial test event. The number of dispatched customers is the lowest on the serial event day (September 17th) as there is a withheld serial group. Aggregate load impacts, which averaged 5.3 MWh/hour, ranged from 2.79 MWh/hour on July 2nd to 6.85 MWh/hour on September 17th.

Table 3.2: Average Event-Hour Load Impacts by Event

Date	SmartRate™ Event?	Type of Event	Event Hours (p.m.)	Sub-LAPs/Serial Groups Dispatched	# Called	Average Event Hour				
						Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
7/2	No	Test	4-6	All Sub-LAPs	52,394	1.69	0.05	3.1%	2.79	88.0
8/8	Yes	Test	4-7	All Sub-LAPs	48,906	2.25	0.11	4.8%	5.30	95.6
8/22	Yes	Market	4-6	PGNP, PGSI, PGST, PGKN, PGF1, PGZP	48,787	2.18	0.13	5.9%	6.29	95.3
		Test		PGHB, PGNC, PGFG, PGNB, PGSF, PGEB, PGSB, PGP2, PGCC						
9/17	Yes	Test	4-6	All Sub-LAPs, Serial Group 7 withheld	43,433	1.87	0.16	8.4%	6.85	93.5

Percentage load impacts range from 3.1 percent to 8.4 percent on event days

There is variation in the percentage load impacts ranging from 3.1 percent of reference loads on July 2nd to 8.4 percent on September 17th. There is no strong correlation between percentage load impact and event temperatures. The September 17th event has the highest percentage load impacts as the Energate device performance has improved for all sub-LAPs.

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. Except for the August 8th event, the other events were two hours long. Load impacts are generally comparable across two-hour events. The per-customer load impacts are consistent between the first and second event hours across all event days, largely due to the similar temperatures between the first two event hours. On August 8th, the load impact is slightly lower in the third hour with lower temperature.

Table 3.3: Persistence of Load Impacts Across Consecutive Events

Date	Full Event Hours (p.m.)	Smart-Rate™ Event?	Impact (kW/Cust)			Avg. Temp (°F)		
			Hour 1	Hour 2	Hour 3	Hour 1	Hour 2	Hour 3
7/2	4-6	No	0.05	0.06		88.4	87.5	
8/8	4-7	Yes	0.11	0.11	0.10	96.9	96.2	93.8
8/22	4-6	Yes	0.13	0.13		96.2	94.4	
9/17	4-6	Yes	0.16	0.16		94.5	92.5	

3.3 Sub-LAP Event Load Impacts

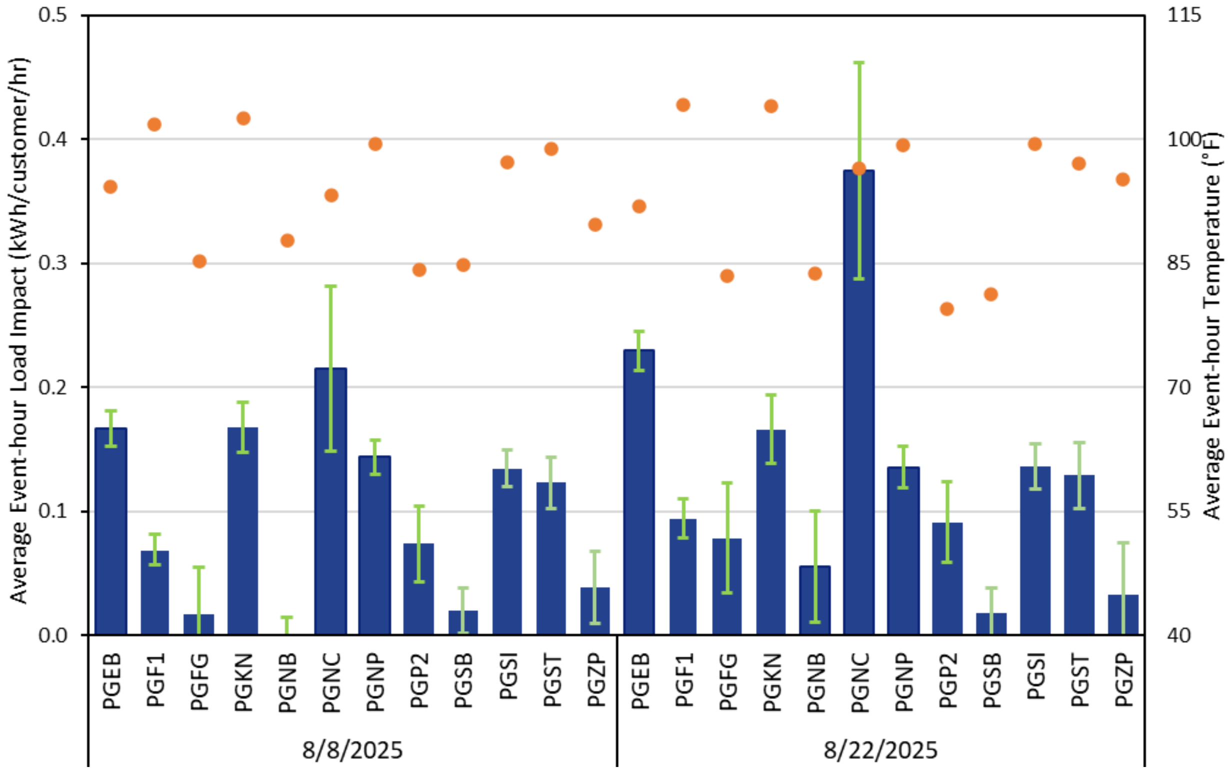
Next, we examine the results for sub-LAP events at the sub-LAP level. Figure 3.3 summarizes the sub-LAP level ex-post load impacts for the August 8th and August 22nd events, for which all sub-LAPs were dispatched during the same event hours. The bars indicate the magnitude of the average per-customer load impacts (in kWh/customer/hour) across the sub-LAP-specific event hours. The green bands correspond to 90 percent confidence intervals around these estimates (i.e., the 5th and 95th percentile scenarios from the uncertainty-adjusted load impacts). The orange scatter plot represents the average temperatures experienced by the customers in each sub-LAP during the event hours.

Temperature differences do not fully explain the variation in load impacts

Load impact ranges from insignificant for PGNB on August 8th to 0.37 kWh/customer/hour for PGNC on August 22nd.[22] Figure 3.3 illustrates that event temperatures do not fully explain the variation in load impacts. PGEB has a higher temperature at 94°F on August 8th but a lower load impact than on August 22nd at 92°F because the performance of Energate devices for this sub-LAP has improved on August 22nd. In other sub-LAPs, Energate devices still have dispatch issues on both August 8th and August 22nd. More details about the Energate performance issue are discussed in Section 3.7.

[22] The load impacts estimated for PGNC are less reliable due to low customer counts.

Figure 3.3: Load Impacts by Sub-LAP on August 8 and August 22, 2025



Sub-LAP event load impacts range from insignificant impacts to 0.37 kWh/customer/hour

Table 3.4 provides the number of customers dispatched, the average event load impacts (per-customer and in aggregate), reference loads, and percentage load impacts for each sub-LAP event in 2025. Across all sub-LAP events, apart from PGNC[23], the highest impacts occurred in PGEB on August 22nd at 0.23kWh/customer/hour. Temperatures are lower for most sub-LAPs compared to the usual temperatures for event dispatch.

PGEB has the highest aggregate load impacts

The number of customers dispatched varies across sub-LAPs. The highest load impact is 2.2 MWh/hour, which occurred on August 22nd for PGEB. This is driven by both high per-customer load impacts and high enrollment counts.

[23] All negative load impacts shown in Table 3.4 are statistically insignificant and are likely indicative of noise in estimation and not reflective of increases in usage in response to an event. A combination of low temperatures and device performance issues likely results in insignificant load impacts. In addition, for PGNC, low customer counts due to enrollment decline also make the estimates less reliable.

Table 3.4: Average Event-Hour Load Impacts by Sub-LAP and Event for Sub-LAP Events

Date	Sub-LAP	Full Event Hours (p.m.)	# Dispatched	Average Event Hour				
				Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Aggregate Impact (MWh/hr)	Avg. Temp (°F)
7/2	PGEB	4-6	10,125	1.25	0.04	2.9%	0.36	78.6
	PGF1		9,579	2.27	0.07	2.9%	0.62	97.7
	PGFG		1,031	0.90	-0.03	-3.2%	-0.03	75.3
	PGKN		2,908	2.24	0.09	4.1%	0.26	101.2
	PGNB		828	0.85	0.00	-0.3%	0.00	77.3
	PGNC		372	2.07	0.13	6.1%	0.05	84.9
	PGNP		7,846	1.83	0.08	4.6%	0.67	94.9
	PGP2		2,320	1.08	0.01	0.6%	0.02	69.7
	PGSB		5,075	0.86	-0.01	-1.6%	-0.07	69.2
	PGSI		6,774	1.97	0.07	3.4%	0.46	95.4
	PGST		4,068	2.12	0.08	4.0%	0.34	94.0
	PGZP		1,309	1.66	0.10	6.2%	0.13	87.0
8/8	PGEB	4-7	9,613	2.13	0.17	7.8%	1.60	94.3
	PGF1		8,689	2.67	0.07	2.6%	0.60	101.9
	PGFG		988	1.76	0.02	0.9%	0.02	85.2
	PGKN		2,619	2.75	0.17	6.1%	0.44	102.6
	PGNB		791	1.62	-0.03	-1.7%	-0.02	87.7
	PGNC		332	2.37	0.21	9.1%	0.07	93.2
	PGNP		7,178	2.38	0.14	6.0%	1.03	99.4
	PGP2		2,298	1.79	0.07	4.1%	0.17	84.2
	PGSB		5,009	1.52	0.02	1.3%	0.10	84.9
	PGSI		6,324	2.29	0.13	5.9%	0.85	97.3
	PGST		3,671	2.53	0.12	4.9%	0.45	98.8
	PGZP		1,236	2.00	0.04	1.9%	0.05	89.7
8/22	PGEB	4-6	9,586	1.90	0.23	12.1%	2.20	91.9
	PGF1		8,662	2.85	0.09	3.3%	0.82	104.2
	PGFG		985	1.46	0.08	5.4%	0.08	83.5
	PGKN		2,614	2.99	0.17	5.6%	0.43	104.0
	PGNB		788	1.36	0.06	4.1%	0.04	83.7
	PGNC		330	2.27	0.37	16.5%	0.12	96.5
	PGNP		7,163	2.22	0.14	6.1%	0.97	99.2
	PGP2		2,293	1.47	0.09	6.2%	0.21	79.4
	PGSB		5,000	1.26	0.02	1.4%	0.09	81.2
	PGSI		6,311	2.27	0.14	6.0%	0.86	99.5
	PGST		3,666	2.45	0.13	5.3%	0.47	97.1
	PGZP		1,232	2.50	0.03	1.3%	0.04	95.2

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

Figure 3.4 shows an example of the aggregate hourly reference loads, observed loads, and estimated load impacts using the August 8th sub-LAP event, in which all sub-LAPs were dispatched from 4 to 7 p.m. Table 3.5 contains these hourly results in the manner required by the Protocols, including hourly temperatures and uncertainty adjusted load impacts (not displayed in Figure 3.4). Load impacts peak at 5.62 MWh during the second event hour (5 to 6 p.m.), and there is statistically significant post-event snapback. During the first hour after the event, loads increased by 5.94 MWh/hour.

Figure 3.4: Hourly Load Impacts on August 8, 2025

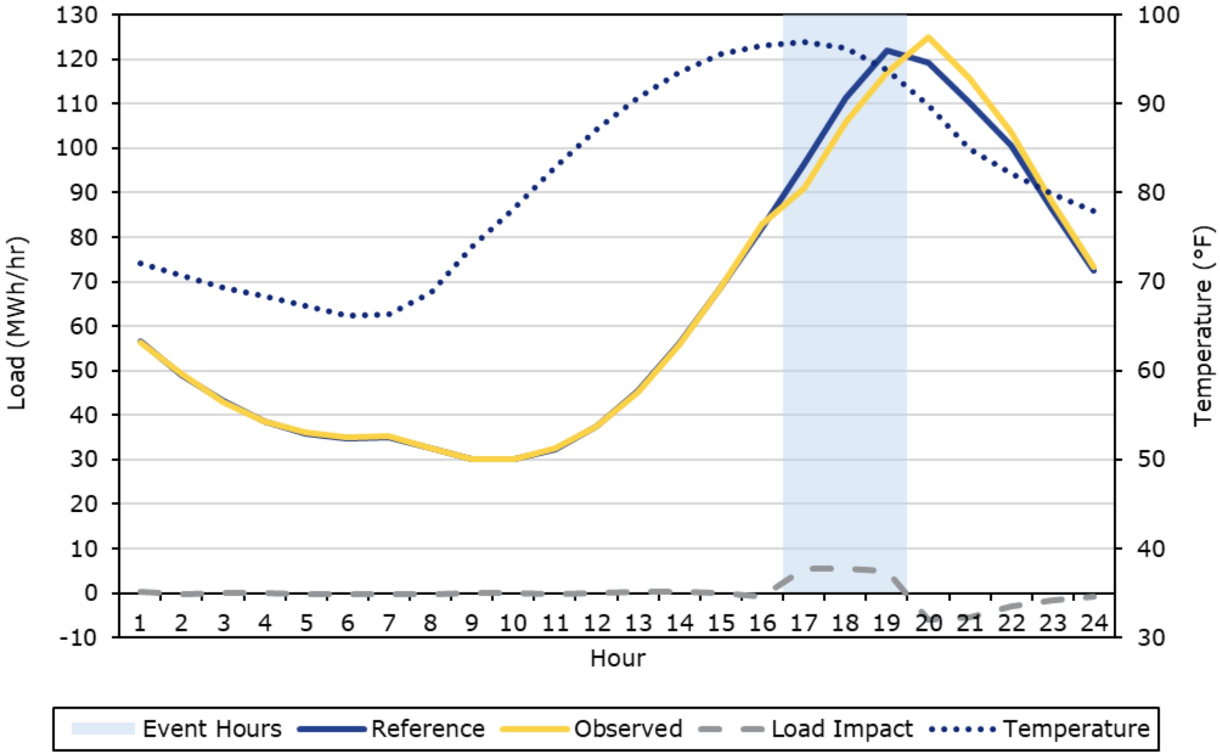


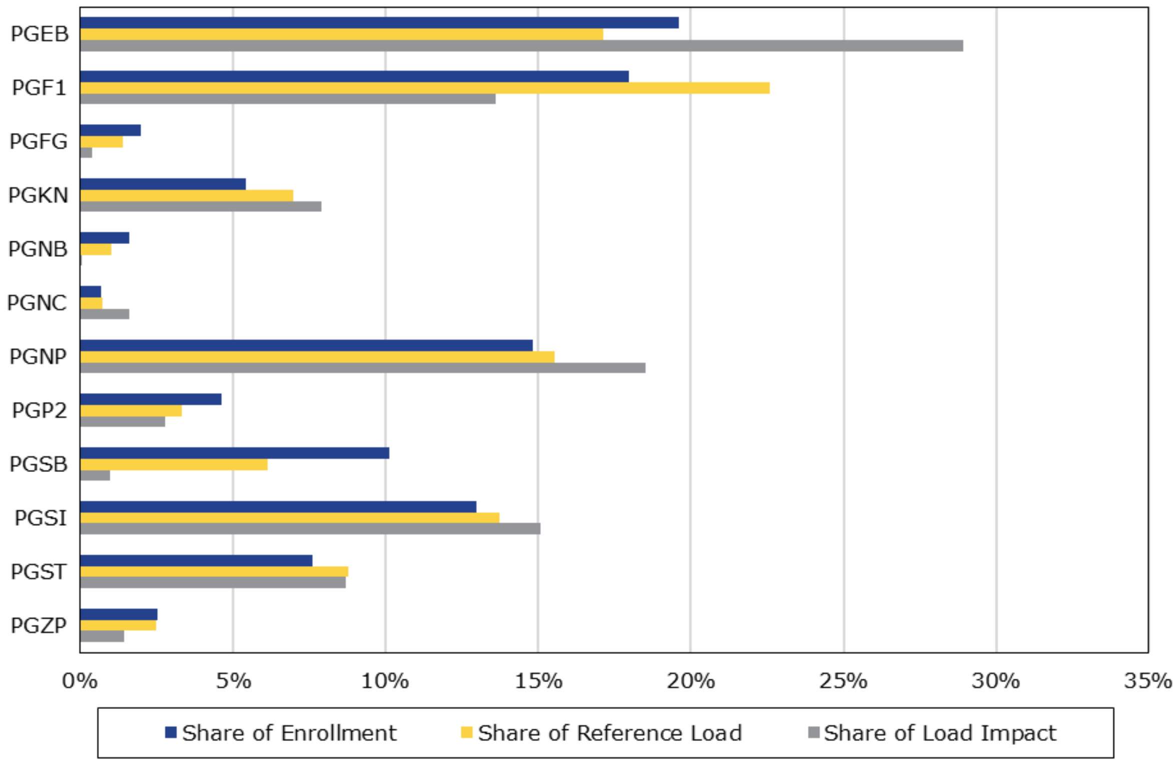
Table 3.5: Hourly Load Impacts and Uncertainty Adjusted Estimates on August 8, 2025

Hour Ending	Estimated Reference Load (MWh/hour)	Observed Event Day Load (MWh/hour)	Estimated Load Impact (MWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (MWh/hour)- Percentiles 5th %ile	50th%ile	95th %ile	Standard Errors	Statistically Significant
1	56.6	56.3	0.24	72.0	-0.28	0.24	0.77	0.32	No
2	49.1	49.2	-0.13	70.8	-0.64	-0.13	0.37	0.31	No
3	43.1	43.0	0.09	69.3	-0.36	0.09	0.55	0.28	No
4	38.5	38.4	0.04	68.3	-0.37	0.04	0.44	0.25	No
5	35.8	36.0	-0.28	67.3	-0.63	-0.28	0.07	0.21	No
6	34.7	34.9	-0.21	66.2	-0.51	-0.21	0.10	0.18	No
7	35.1	35.2	-0.18	66.4	-0.47	-0.18	0.10	0.17	No
8	32.5	32.7	-0.14	68.7	-0.45	-0.14	0.16	0.18	No
9	30.2	30.1	0.10	74.0	-0.21	0.10	0.41	0.19	No
10	30.1	30.0	0.08	78.2	-0.26	0.08	0.41	0.20	No
11	32.2	32.5	-0.26	82.9	-0.61	-0.26	0.10	0.22	No
12	37.5	37.4	0.07	87.1	-0.32	0.07	0.45	0.24	No
13	45.5	45.2	0.31	90.7	-0.13	0.31	0.74	0.26	No
14	56.1	55.7	0.39	93.5	-0.09	0.39	0.87	0.29	No
15	68.6	68.6	0.06	95.6	-0.47	0.06	0.59	0.32	No
16	82.1	83.0	-0.88	96.5	-1.44	-0.88	-0.33	0.34	Yes
17	96.5	91.1	5.44	96.9	4.87	5.44	6.02	0.35	Yes
18	111.4	105.7	5.62	96.2	5.01	5.62	6.22	0.37	Yes
19	121.8	117.0	4.84	93.8	4.20	4.84	5.47	0.39	Yes
20	119.1	125.1	-5.94	89.8	-6.58	-5.94	-5.29	0.39	Yes
21	110.3	115.6	-5.35	84.9	-5.97	-5.35	-4.72	0.38	Yes
22	100.5	103.5	-3.04	82.2	-3.66	-3.04	-2.43	0.37	Yes
23	86.2	87.8	-1.67	79.8	-2.25	-1.67	-1.08	0.35	Yes
24	72.6	73.4	-0.83	77.9	-1.38	-0.83	-0.29	0.33	Yes
By Period:	Estimated Reference Energy Use (MWh/hour)	Observed Event Day Energy Use (MWh/hour)	Estimated Change in Energy Use (MWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (MWh/hour) - Percentiles 5th %ile	50th %ile	95th %ile	Standard Errors	Statistically Significant
Daily	1,525.9	1,527.6	-1.65	81.2	-6.61	-1.65	3.31	3.01	No
Avg. Event Hour***	109.9	104.6	5.30	95.6	4.95	5.30	5.65	0.21	Yes

PGEB, PGF1, PGNP and PGSI produced 76 percent of load reductions

Next, we look at how load impacts are distributed across sub-LAPs. We focus this analysis on the load impacts from all the sub-LAP events this year (July 2nd, August 8th, and August 22nd) during event hours. Figure 3.5 compares the sub-LAP shares of estimated aggregate event-hour load impacts, reference loads, and enrollments. Out of customers dispatched for the events, PGEB, PGF1, PGNP, and PGSI have 65 percent of enrolled customers and produce 76 percent of the total load reductions. The share of load impacts for PGEB, PGKN, PGNC, PGNP, and PGSI exceeds the share of enrollments and reference loads.

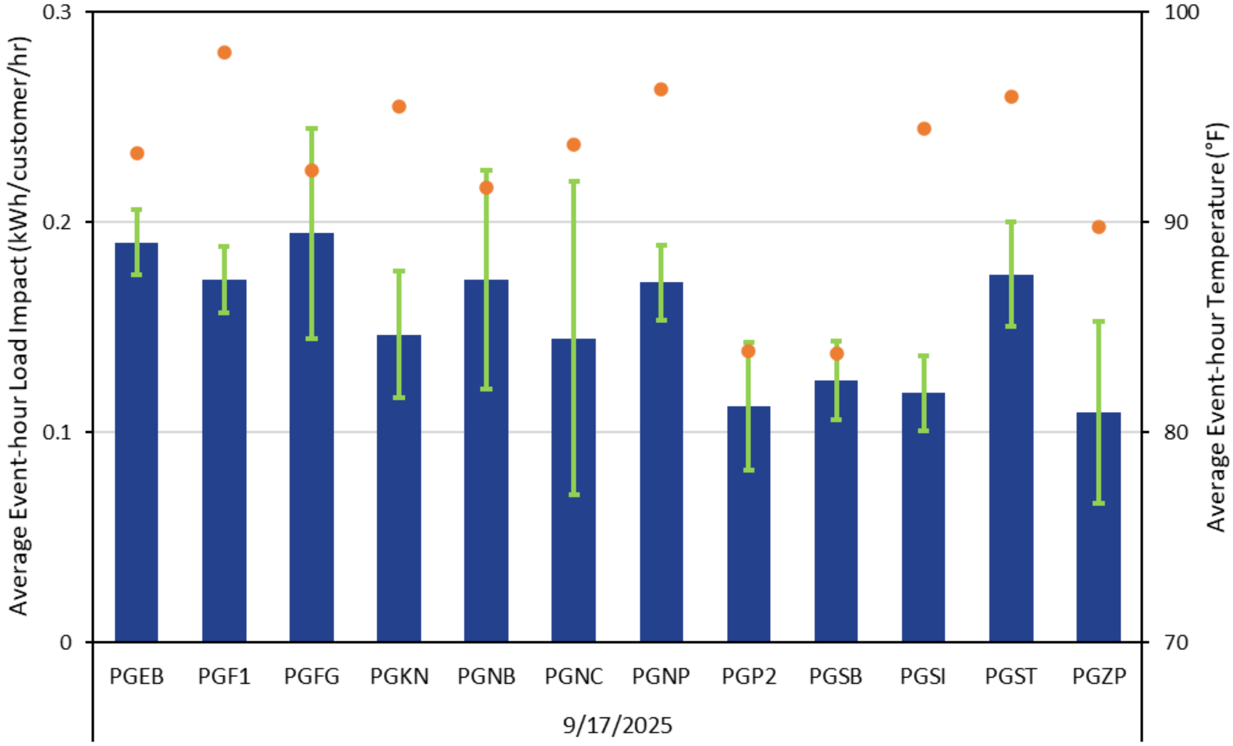
Figure 3.5: Share of Load Impacts by Sub-LAP for July 2, August 8, and August 22, 2025



3.4 Serial Test Event Load Impacts

Next, we examine the results for the serial test event on September 17th. Figure 3.6 and Table 3.6 summarize the load impacts by sub-LAP. The bars indicate the magnitude of the average per-customer load impacts (in kWh/customer/hour) across the full serial event hours. The green bands correspond to 90 percent confidence intervals around these estimates (i.e., the 5th and 95th percentile scenarios from the uncertainty-adjusted load impacts). The orange scatter plot represents the average event temperatures for each sub-LAP.

Figure 3.6: Average Event-Hour Load Impacts by Sub-LAP for the Serial Event



Serial event load impacts range from 0.11 to 0.19 kWh/customer/hour

Load impact ranges from 0.11 kWh/customer/hour for PGZP and PGP2 to 0.19 kWh/customer/hour for PGFG and PGEB on September 17th. The lowest average temperature was 83.9 degrees for PGP2 and the highest was 98.1 degrees for PGF1 during the event hours. While PGF1, PGKN, PGNP, and PGST had some of the highest event temperatures on this day, the temperatures are lower than when events usually occur for these sub-LAPs in the past. Accordingly, the observed lower load impacts are not out of the ordinary for these sub-LAPs.

Table 3.6: Average Event-Hour Load Impacts by Sub-LAP for the Serial Event

Date	Event Hours (p.m.)	SmartRate™ Event?	Sub-LAP	# Dispatched	Average Event Hour				
					Reference (kW/Cust)	Impact (kW/Cust)	% Impact	Aggregate Impact (MW)	Avg. Temp (°F)
9/17	4-6	Yes	PGEB	8,580	1.85	0.19	10.3%	1.63	93.3
			PGF1	7,784	2.20	0.17	7.9%	1.35	98.1
			PGFG	868	1.72	0.19	11.3%	0.17	92.5
			PGKN	2,317	2.22	0.15	6.6%	0.34	95.5
			PGNB	706	1.68	0.17	10.3%	0.12	91.6
			PGNC	299	1.54	0.14	9.4%	0.04	93.7
			PGNP	6,327	1.98	0.17	8.7%	1.08	96.4
			PGP2	2,023	1.46	0.11	7.7%	0.23	83.9
			PGSB	4,454	1.33	0.12	9.4%	0.56	83.7
			PGSI	5,568	1.73	0.12	6.9%	0.66	94.5
			PGST	3,268	2.12	0.18	8.3%	0.57	96.0
			PGZP	1,096	1.80	0.11	6.1%	0.12	89.8

Load impacts for the serial event on September 17th are consistent during the full event hours

Figure 3.7 shows the average aggregate hourly reference loads, observed loads, and estimated load impacts for the September 17th serial event from 4 to 6 p.m. Table 3.7 contains the hourly results in the manner required by the Protocols, including hourly temperatures and uncertainty adjusted load impacts (not displayed in Figure 3.7). Load impacts peak at 6.95 MWh during the second hour of this event (5 to 6 p.m.). Figure 3.7 also illustrates that there is post-event snapback for the serial event.

Figure 3.7: Hourly Load Impacts on September 17, 2025

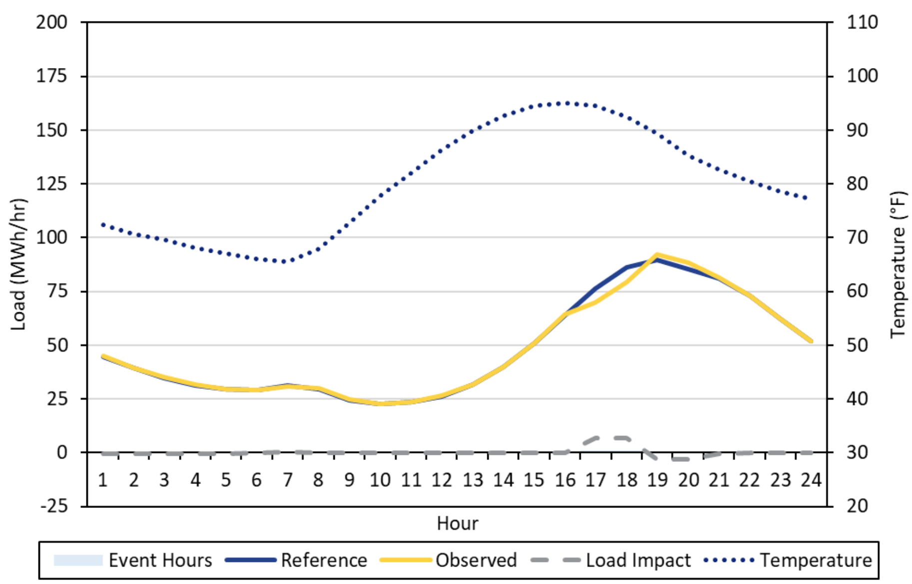


Table 3.7: Hourly Load Impacts and Uncertainty Adjusted Estimates on September 17, 2025

Hour Ending	Estimated Reference Load (MWh/hour)	Observed Event Day Load (MWh/hour)	Estimated Load Impact (MWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (MWh/hour)- Percentiles			Standard Errors	Statistically Significant
					5th %ile	50th%ile	95th %ile		
1	44.7	45.0	-0.27	72.3	-0.72	-0.27	0.19	0.28	No
2	39.4	39.6	-0.26	70.7	-0.70	-0.26	0.18	0.27	No
3	34.7	35.1	-0.39	69.6	-0.78	-0.39	0.01	0.24	No
4	31.5	31.8	-0.30	68.0	-0.65	-0.30	0.05	0.21	No
5	29.4	29.7	-0.27	67.0	-0.57	-0.27	0.04	0.18	No
6	29.3	29.3	0.06	65.9	-0.21	0.06	0.32	0.16	No
7	31.1	30.9	0.18	65.5	-0.07	0.18	0.43	0.15	No
8	29.7	29.8	-0.18	67.9	-0.44	-0.18	0.08	0.16	No
9	24.6	24.7	-0.12	72.6	-0.38	-0.12	0.14	0.16	No
10	22.7	22.9	-0.16	77.7	-0.43	-0.16	0.11	0.17	No
11	23.6	23.7	-0.09	81.9	-0.38	-0.09	0.19	0.17	No
12	26.3	26.5	-0.20	86.3	-0.51	-0.20	0.10	0.19	No
13	31.7	31.8	-0.14	89.9	-0.48	-0.14	0.21	0.21	No
14	40.0	39.9	0.06	92.6	-0.34	0.06	0.46	0.24	No
15	51.0	51.0	-0.02	94.4	-0.47	-0.02	0.43	0.27	No
16	64.0	64.2	-0.20	95.0	-0.69	-0.20	0.30	0.30	No
17	76.4	69.7	6.74	94.5	6.23	6.74	7.26	0.31	Yes
18	86.3	79.3	6.95	92.5	6.42	6.95	7.49	0.32	Yes
19	89.5	92.3	-2.82	89.3	-3.38	-2.82	-2.27	0.34	Yes
20	85.2	88.2	-2.96	85.2	-3.49	-2.96	-2.42	0.33	Yes
21	80.9	81.4	-0.45	82.7	-0.96	-0.45	0.06	0.31	No
22	72.8	72.8	0.01	80.5	-0.48	0.01	0.50	0.30	No
23	62.3	62.2	0.05	78.5	-0.41	0.05	0.51	0.28	No
24	51.9	51.8	0.05	77.2	-0.38	0.05	0.47	0.26	No

By Period:	Estimated Reference Energy Use (MWh/hour)	Observed Event Day Energy Use (MWh/hour)	Estimated Change in Energy Use (MWh/hour)	Weighted Average Temperature (°F)	Uncertainty Adjusted Impact (MWh/hour) - Percentiles			Standard Errors	Statistically Significant
					5th %ile	50th %ile	95th %ile		
Daily	1,158.8	1,153.5	5.29	79.9	1.17	5.29	9.41	2.51	Yes
Avg. Event Hour***	81.4	74.5	6.85	93.5	6.48	6.85	7.22	0.23	Yes

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 different rate groups.[24] Additional results for these subgroups, including the load profiles, can be found in electronic form in Protocol table generators provided along with this report.[25]

The average ex-post load impacts are summarized for each subgroup in Figure 3.8. These comparisons are based on the average load impacts from the serial event on September 17, 2025.[26] 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 90 percent confidence intervals around these estimates. The orange dots represents the average temperatures experienced by customers in each subgroup.

Figure 3.8 shows that there are statistically significant load impacts for every subgroup. Customers in the various subgroups are not evenly distributed across PG&E's service territory, so the differences in load impacts can be driven by location. The subgroup comparison results are

[24] ExpressStat customers are excluded from the analysis because there are too few customers in this subgroup to estimate load impacts reliably.

[25] Ex-post load impacts of SmartAC™ and SmartRate™ dually customers on dual event days are included within the SmartRate report.

[26] We chose the September 17th event because of the improved performance of Energate devices.

broadly consistent with past evaluations. Some differences with PY2024 are likely because of device performance issues. In PY2025, two-way devices have higher performance compared to PY2024 because the performance of Energate devices has improved on September 17, 2025 compared to PY2024. One-way devices have lower performance compared to PY2024 due to one-way devices reaching the end of their service life.

The key findings of the comparison include:

- Gen 1 and Gen 2 switches had higher load impacts than UtilityPro thermostats, however the gap is smaller than previous years, mostly due to lower Gen 2 impacts.
- Load impacts increase with AC usage intensity, with high AC usage customers having significantly higher load impacts than medium and low AC usage customers.
- Two-way devices have higher load impacts than one-way devices.

Figure 3.8: Average Event-Hour Load Impacts by Subgroup

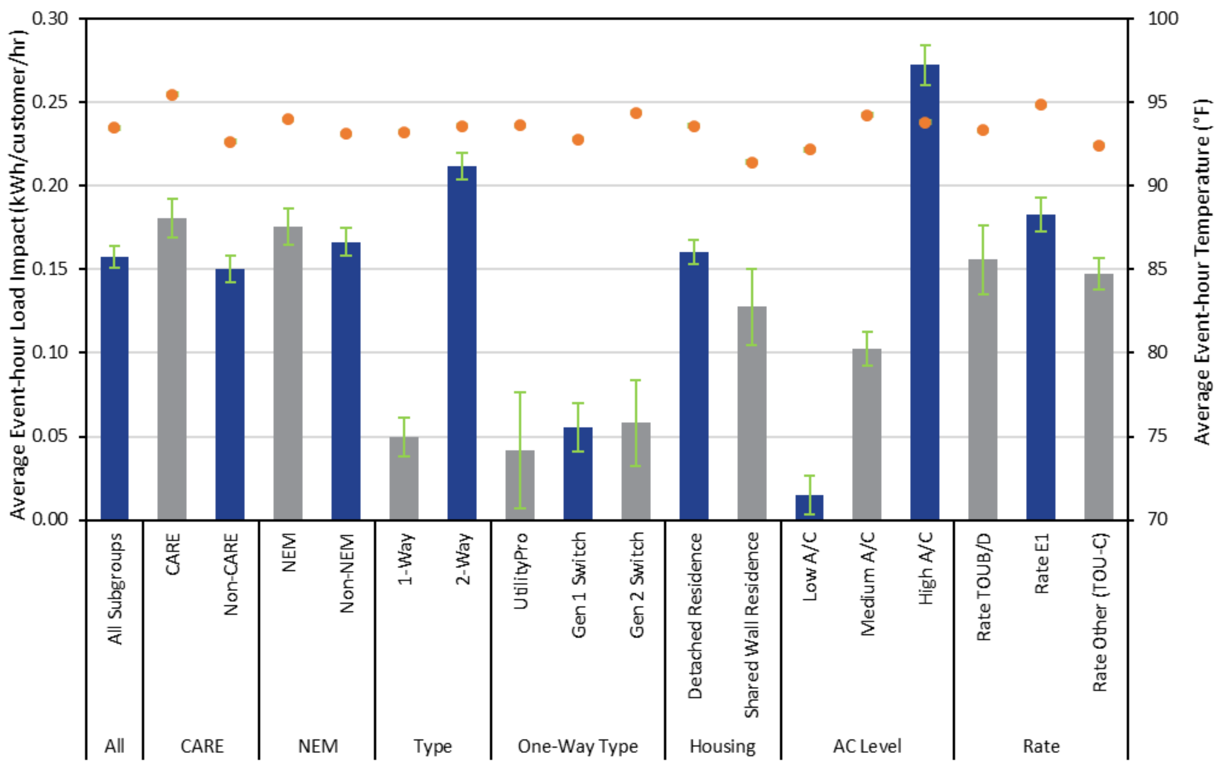


Table 3.8 provides the detailed information underlying Figure 3.8, including the average number of customers dispatched, the total number of enrolled customers in each subgroup, the average load impacts, reference loads, percentage load impacts, and temperatures. Two-way devices have much higher percentage load impacts than one-way devices. Within one-way devices, Gen 1 switch has slightly higher percentage load impacts than Gen 2 switch. Among all the subgroups, two-way devices and high AC usage customers have percentage load impacts larger than 10%.

Table 3.8: Average Event-Hour Load Impacts by Subgroup

Subgroup	# Dis-Patched	# Enrolled	Average Load Impacts				
			Reference (kWh/cust /hour)	Impact (kWh/cust /hour)	% Impact	Agg. Impact (MWh/ hour)	Avg. Temp (°F)
All SmartAC™ Customers	43,433	48,649	1.87	0.16	8.42%	6.85	93.5
CARE	12,462	13,947	2.15	0.18	8.40%	2.25	95.5
Non-CARE	30,302	33,935	1.76	0.15	8.55%	4.56	92.7
NEM	18,231	20,420	1.80	0.18	9.75%	3.20	94.0
Non-NEM	24,533	27,462	1.95	0.17	8.54%	4.09	93.1
One-Way	14,306	15,898	1.89	0.05	2.63%	0.71	93.3
Two-Way	28,929	32,471	1.87	0.21	11.31%	6.13	93.6
UtilityPro	1,601	1,782	1.94	0.04	2.14%	0.07	93.6
Gen 1 Switch	9,640	10,710	1.82	0.06	3.04%	0.53	92.8
Gen 2 Switch	3,259	3,619	2.04	0.06	2.86%	0.19	94.4
Detached Residence	41,468	46,460	1.90	0.16	8.44%	6.66	93.6
Shared Wall Residence	1,954	2,160	1.34	0.13	9.52%	0.25	91.4
Low A/C	6,309	7,049	0.73	0.02	2.07%	0.10	92.2
Medium A/C	15,860	17,749	1.63	0.10	6.30%	1.62	94.3
High A/C	18,779	21,013	2.63	0.27	10.38%	5.12	93.8
Rate TOUB/D	5,647	6,375	2.02	0.16	7.73%	0.88	93.3
Rate E1	16,695	18,657	2.13	0.18	8.61%	3.06	94.9
Rate Other (TOU-C)	21,106	23,617	1.64	0.15	8.98%	3.11	92.4

3.6 Event Override Rate

Customers can override (opt out of) SmartAC™ events. Table 3.9 summarizes the number of overrides by event day, including the number of enrolled customers in the sub-LAPs dispatched for each event. In total, the overrides correspond to insignificant percentage of dispatched customers during PY2025 events.

Table 3.9: Customer Overrides by Event Day

Date	Event Hours (p.m.)	Sub-LAPs Dispatched	Smart-Rate™ Event?	# Overrides	# Dispatched	Override Rate
7/2	4:00-6:00	All Sub-LAPs	No	1	52,394	0.00%
8/8	4:00-7:00	All Sub-LAPs	Yes	2	48,906	0.00%
8/22	4:00-6:00	All Sub-LAPs	Yes	4	48,787	0.01%
9/17	4:00-6:00	All Sub-LAPs, Serial Group 7 withheld	Yes	2	43,433	0.00%
			Total	**9**	**193,520**	**0.00%**

3.7 Comparison of Performance of Two-Way Devices by Manufacturer

In PY2024 and PY2025, the load impacts of two-way devices were abnormally lower than those in previous program years. Investigation showed that Energate devices – the older generation of two-way devices – were the main cause of the poor performance. The newer two-way Eaton devices responded as expected compared to prior program year evaluations. PG&E discovered the root cause was that the HCM event parameters were not set properly in PY2024 and PY2025 compared to PY2023. To confirm this discovery, a test for sub-LAP PGEB was made during the August 22nd event in PY2025. The HCM event parameters for PGEB were set according to the PY2023 settings during event hours, while those for other sub-LAPs were kept the same as in PY2024. Table 3.10 shows the load impacts of Energate devices for PGEB during this event were 0.31kWh/customer/hour, whereas that in other sub-LAPs continued to stay low.[27]

As a result of the test, the HCM event parameters were reset to the PY2023 settings for all sub-LAPs during the serial event on September 17th, 2025. Table 3.10 shows that the performance of Energate devices improved significantly across all large sub-LAPs on September 17th compared to August 22nd, leading to higher overall two-way load impacts despite lower average temperature.

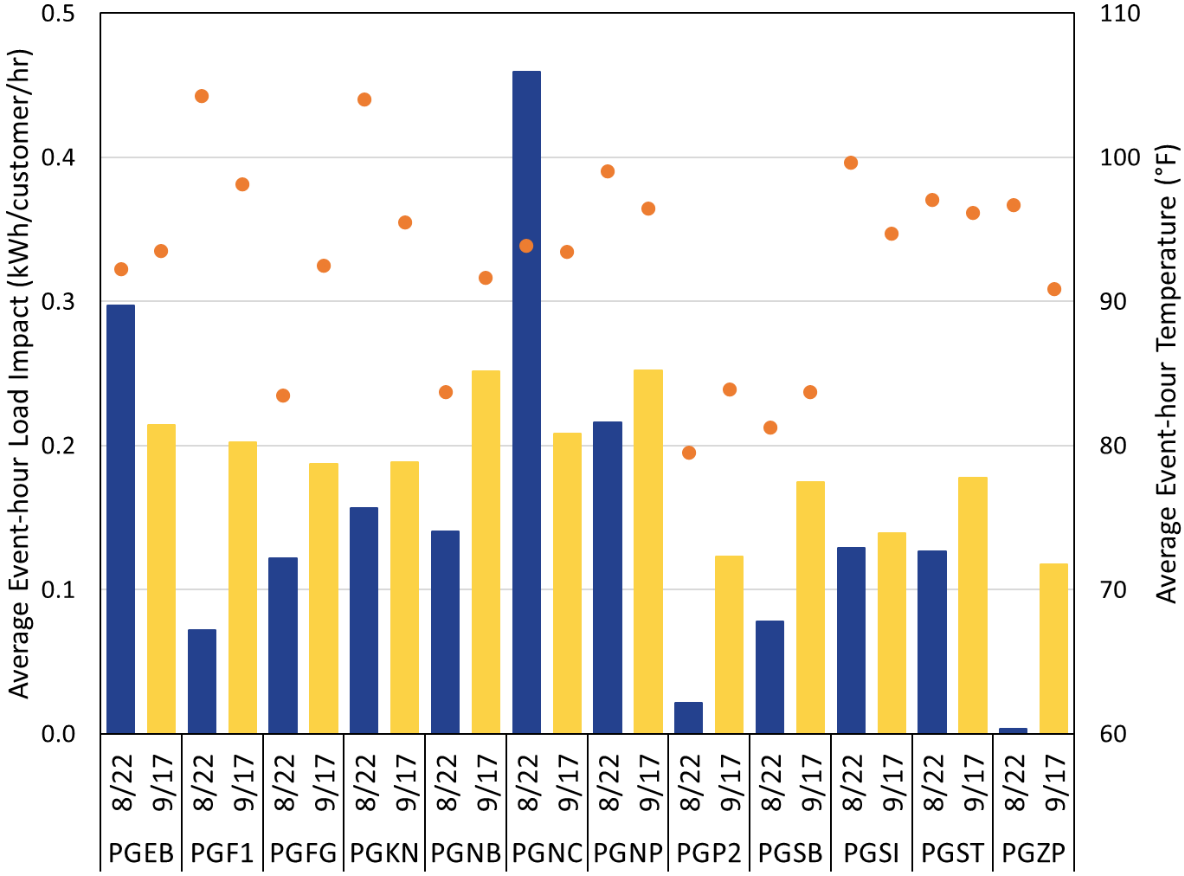
[27] The estimates at device manufacture level for two-way devices is less reliable for sub-LAPs with low customer counts such as PGNC, PGFG, and PGZP.

Table 3.10: Per-Customer Load Impacts by Two-Way Device Manufacturer

Date	Sub-LAP	Energate Dispatch #	Eaton Dispatch #	Average Event Hour			
				Energate Impact (kWh/cust/hr)	Eaton Impact (kWh/cust/hr)	Overall Two-Way Impact (kWh/cust/hr)	Avg. Temp (°F)
8/22	PGEB	2,919	4,803	0.31	0.24	0.30	92.3
	PGF1	4,608	2,315	0.03	0.28	0.07	104.2
	PGFG	255	462	0.13	0.09	0.12	83.5
	PGKN	1,310	1,010	0.05	0.27	0.16	104.0
	PGNB	52	572	[redacted]	[redacted]	0.14	83.7
	PGNC	108	89	[redacted]	[redacted]	0.46	93.9
	PGNP	1,294	3,409	0.01	0.25	0.22	99.1
	PGP2	191	1,309	0.02	0.12	0.02	79.5
	PGSB	612	3,030	0.01	0.04	0.08	81.2
	PGSI	2,381	2,051	0.13	0.18	0.13	99.7
	PGST	1,333	1,254	0.05	0.23	0.13	97.1
	PGZP	392	524	-0.23	0.27	0.00	96.7
9/17	PGEB	2,634	4,274	0.22	0.22	0.21	93.5
	PGF1	4,146	2,068	0.24	0.11	0.20	98.1
	PGFG	228	405	0.21	0.20	0.19	92.5
	PGKN	1,155	905	0.19	0.14	0.19	95.5
	PGNB	48	516	[redacted]	[redacted]	0.25	91.6
	PGNC	98	80	[redacted]	[redacted]	0.21	93.4
	PGNP	1,162	2,970	0.30	0.19	0.25	96.4
	PGP2	174	1,141	-0.05	0.18	0.12	83.9
	PGSB	543	2,677	0.23	0.16	0.17	83.7
	PGSI	2,106	1,795	0.14	0.15	0.14	94.7
	PGST	1,197	1,116	0.17	0.25	0.18	96.1
	PGZP	351	465	0.17	0.17	0.12	90.9

Figure 3.9 illustrates the improvement of load impacts across sub-LAPs between August 22nd and September 17th events. Apart from PGEB where the Energate performance issue had been resolved by August 22nd and PGNC where load impact measures are unreliable due to small customer dispatched numbers, the remaining sub-LAPs all demonstrate higher two-way load impacts during the serial event on September 17th than on August 22nd.

Figure 3.9: Comparison of Two-Way Load Impacts between August 22 and September 17



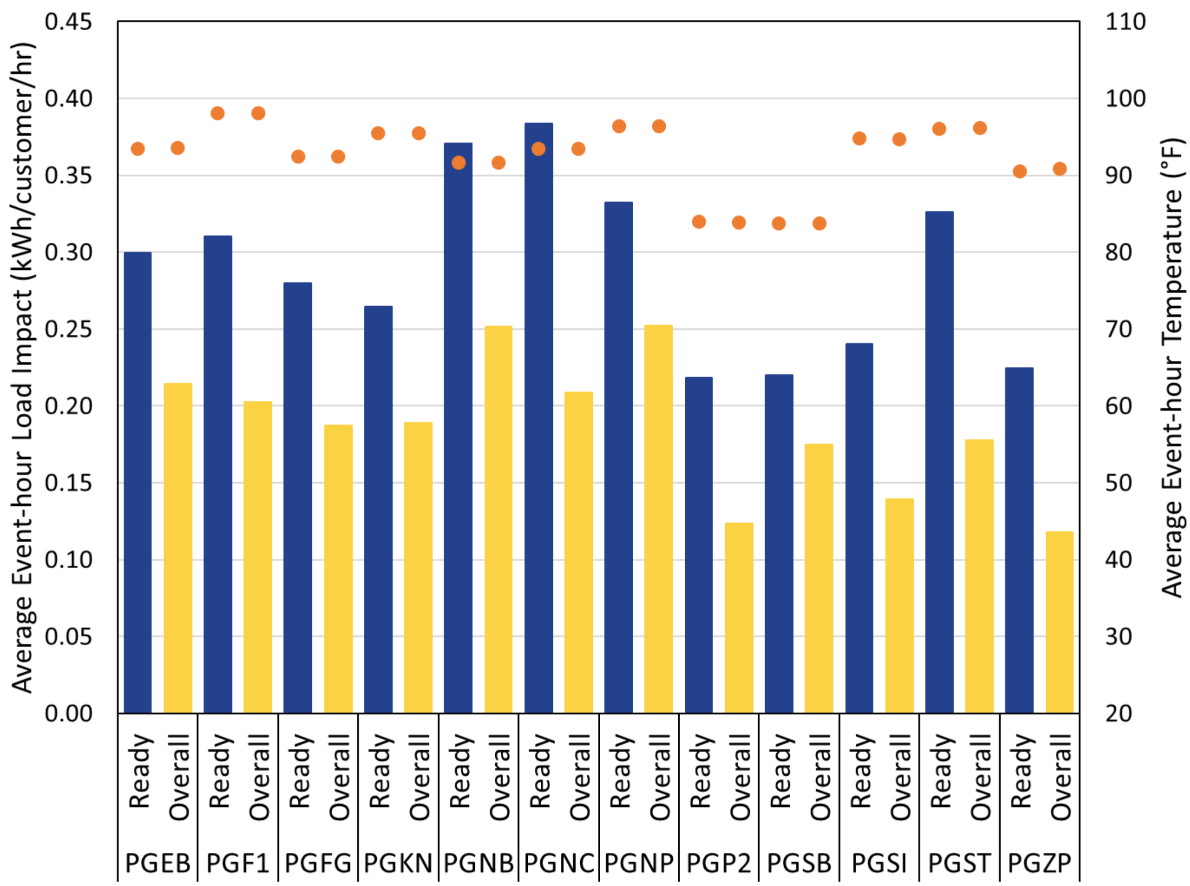
3.8 Performance of "Ready" Devices

Two-way devices respond to dispatch calls with a "Ready" or "Not Ready" status. Those devices with "Not Ready" status may not be responsive to event dispatch. Historically, "Not Ready" two-way devices were due to devices being removed or disconnected at the customer's premise. While PG&E is able to detect the status of a "Not Ready" device it would still require a technician to initiate a site visit to re-connect or replace a new device on the customer's AC unit. Additional causes for a "Not Ready" status could include obstruction between the meter and the device or varying software related impacts. The presence of devices with "Not Ready" status can decrease the average per-customer load impacts for two-way devices. This section presents the performance of two-way devices if we include only devices with "Ready" status. Table 3.11 and Figure 3.10 show the comparison of the performance of "Ready" devices to the overall two-way impacts by sub-LAP on the September 17th serial event day when the Energate device performance has improved. In all sub-LAPs, over two thirds of the two-way devices are in "Ready" status. Per-customer load impacts are at least 0.05 kWh/customer/hour higher across sub-LAPs for devices with a "Ready" status than when all two-way devices are included.

Table 3.11: Per-Customer Load Impacts by Device Status

Date	Sub-LAP	Two-Way Ready Dispatch #	Two-Way Overall Dispatch #	Average Event Hour		
				Two-Way Ready Impact (kWh/cust/hr)	Two-Way Overall Impact (kWh/cust/hr)	Difference in Impact (kWh/cust/hr)
9/17	PGEB	4,737	6,497	0.30	0.21	0.09
	PGF1	3,784	5,563	0.31	0.20	0.11
	PGFG	433	551	0.28	0.19	0.09
	PGKN	1,279	1,860	0.26	0.19	0.08
	PGNB	401	541	0.37	0.25	0.12
	PGNC	117	141	0.38	0.21	0.18
	PGNP	2,481	3,353	0.33	0.25	0.08
	PGP2	889	1,200	0.22	0.12	0.09
	PGSB	2,244	3,044	0.22	0.17	0.05
	PGSI	2,432	3,423	0.24	0.14	0.10
	PGST	1,374	1,896	0.33	0.18	0.15
	PGZP	563	758	0.22	0.12	0.11

Figure 3.10: Load Impacts between Ready 2-Way and Overall 2-Way



4. EX-ANTE LOAD IMPACTS

This section provides the SmartAC™ ex-ante load impact forecast for the period from 2026 to 2028. 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. The PY2025 ex-ante forecast also reflects SmartAC™ performance during sub-LAP events, consistent with recent evaluations.

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: figures showing the PG&E's enrollment forecast by LCA; a figure showing the forecast of aggregate load impacts; 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.

Figure 4.1 shows PG&E's enrollment forecast by LCA from 2026 to 2028. The total enrollments in July of each year are displayed above the chart.

PG&E expects enrollments to steadily decrease in 2026 through 2028 for the SmartAC™ program. As of January 2026, there were approximately 53,000 enrolled customers. Similar to last year, PG&E decided not to de-enroll roughly 20,000 customers using one-way devices. Instead, PG&E plans to replace one-way devices primarily for maintenance purposes, with up to 1,500 one-way devices to be replaced by two-way devices in 2026. Additionally, new enrollments are not allowed. As such, PG&E forecasts an annual attrition rate of approximately 11.4 percent in 2026 based on historical enrollment trends, which would yield a customer base of approximately 37,000 customers by the end of the program in October 2028. PG&E also projects a 25% annual attrition rate for SmartRate™ dual enrollments.

Figure 4.1: Changes in Enrollment by LCA (2026-2028)

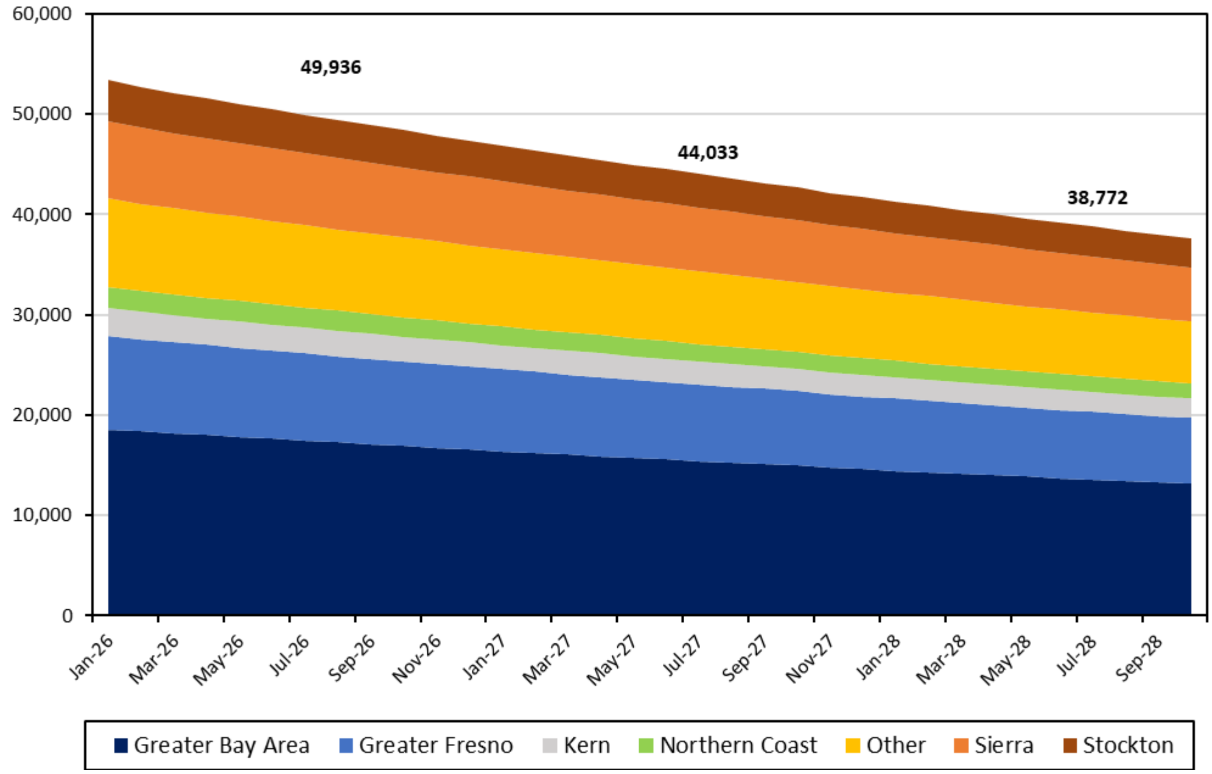


Figure 4.2 illustrates the changes in aggregate load impacts during the first four hours of the Resource Adequacy (RA) window (4 to 8 p.m.) over the forecast period by comparing load impacts for all SmartAC™ customers by LCA for the PG&E 1-in-2 scenario for a July system worst day. Aggregate load impacts decrease by about 11 percent per year, which is consistent with the percentage decline of enrollments.

Figure 4.2: Aggregate Load Impacts over RA Window by LCA for PG&E 1-in-2 July System Worst Day Scenario (2026-2028)

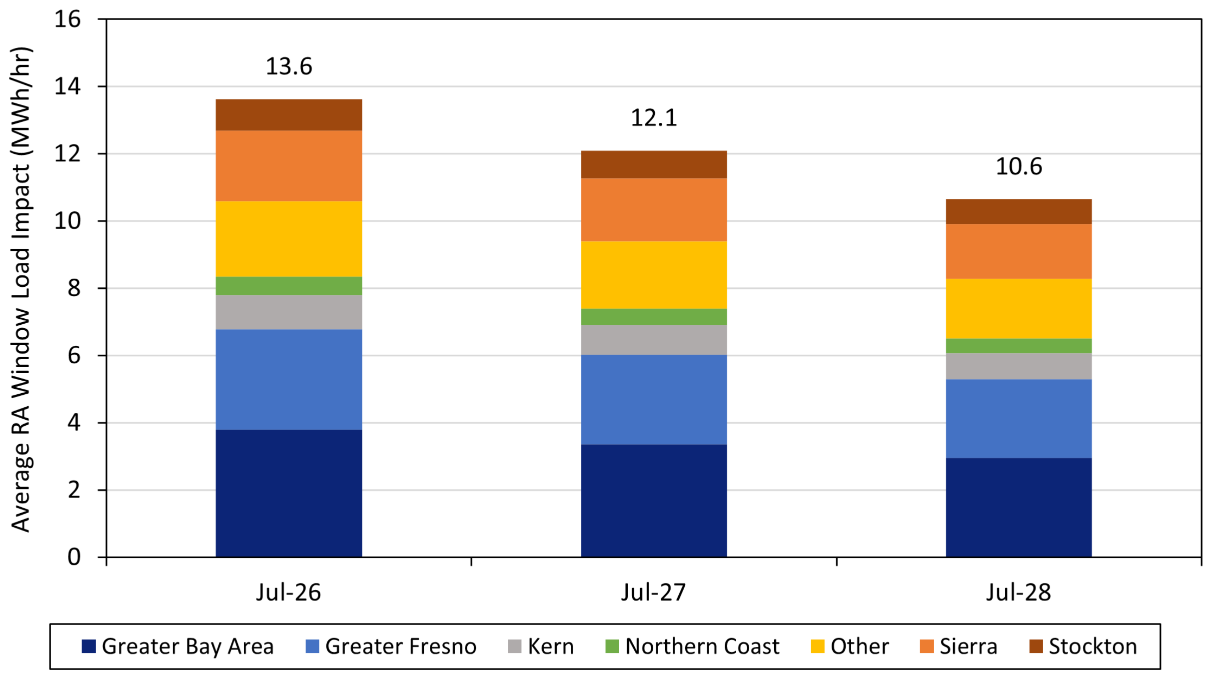


Figure 4.3 illustrates the aggregate reference loads, observed loads, and load impacts for all SmartAC™ customers on a July system worst day in 2026 for the PG&E 1-in-2 weather scenario. Ex-ante load impacts peak during the second event hour. The average July event window load impact is 13.6 MWh/hour, or 11.1 percent of the average event window (the first four hours of the RA window) reference loads.

Figure 4.3: Aggregate Hourly Loads and Load Impacts for July System Worst Day, *PG&E 1-in-2 Scenario* in 2026: All SmartAC™ Customers

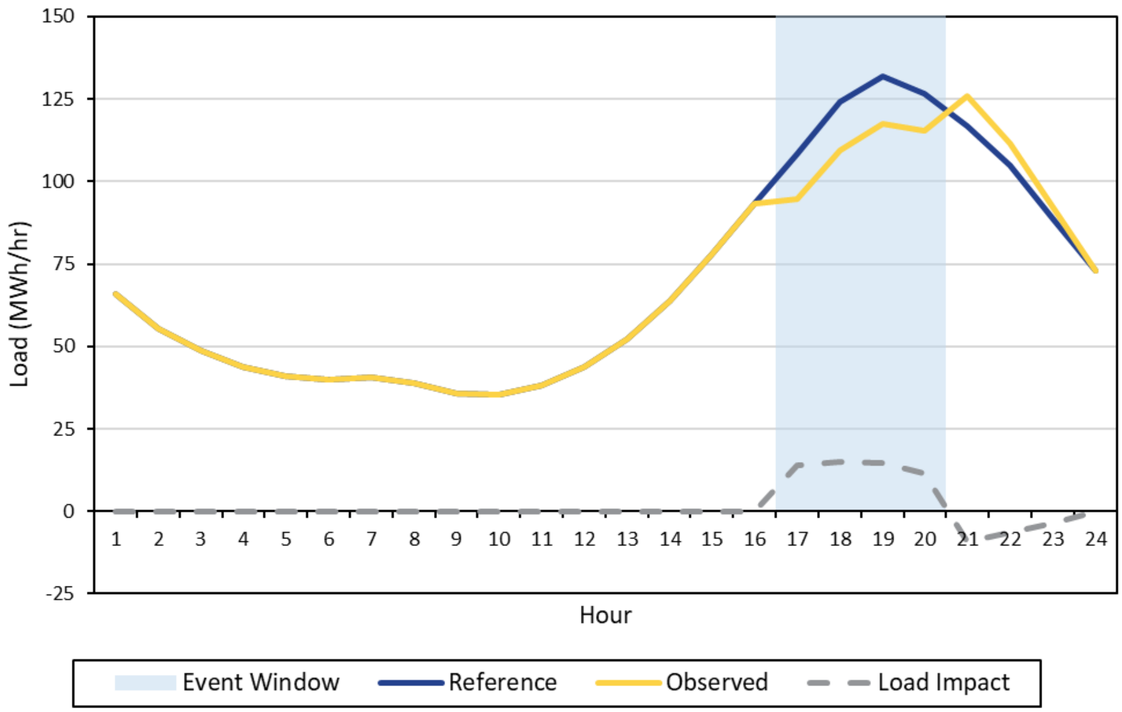


Figure 4.4 illustrates the aggregate reference loads, observed loads, and load impacts for SmartAC™-only customers on a July system worst day in 2026 for the PG&E 1-in-2 weather scenario. The shape of the ex-ante loads and load impacts is similar to the results for all SmartAC™ program customers. The average event window load impact is 12.9 MWh/hour, or 11.0 percent of the average event window reference loads.

Figure 4.4: Aggregate Hourly Loads and Load Impacts for July System Worst Day, *PG&E 1-in-2* Scenario in 2026: SmartAC™-only Customers

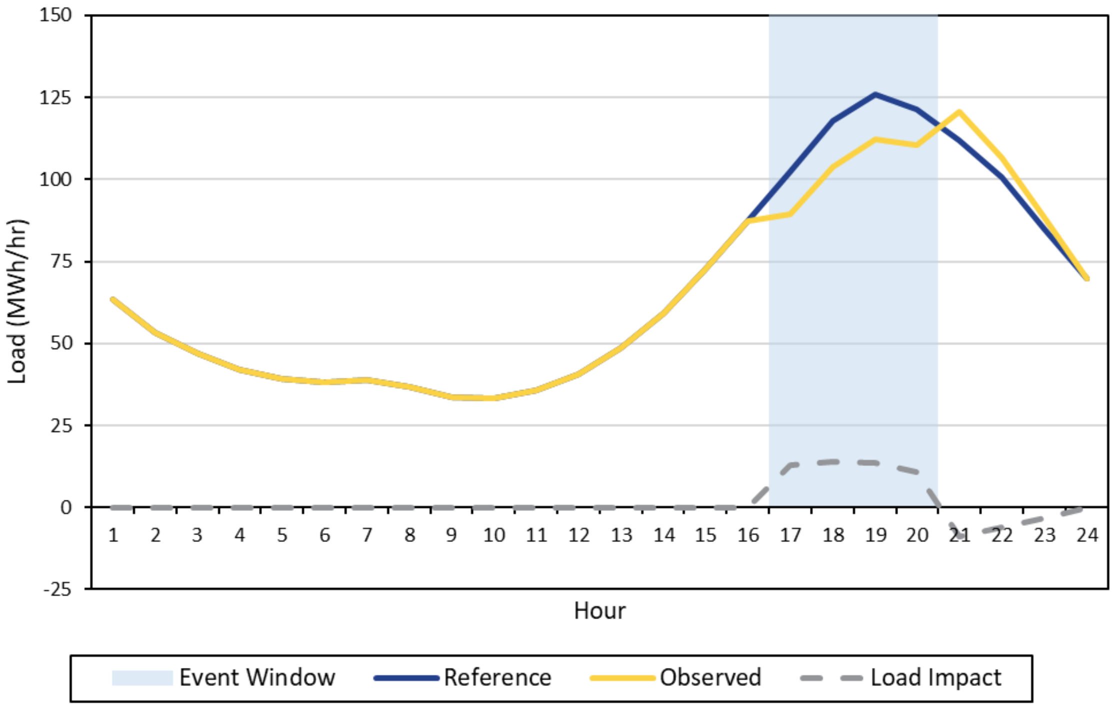


Figure 4.5 illustrates the aggregate reference load, observed load, and load impact for customers who are dually enrolled in SmartAC™ and SmartRate™ on a July system worst day in 2025 for the PG&E 1-in-2 weather scenario. The shape of the reference loads differs for dually enrolled customers, with a peak at Hour (Ending) 18 instead of 19 compared to SmartAC™-only customers. The magnitude of the aggregate loads and load impacts is much smaller compared to SmartAC™-only customers due to lower enrollments. The average event window load impact is 0.8 MWh/hour, or 12.8 percent of the average event window reference loads.

Figure 4.5: Aggregate Hourly Loads and Load Impacts for July System Worst Day, *PG&E 1-in-2* Scenario in 2026: Dually Enrolled Customers

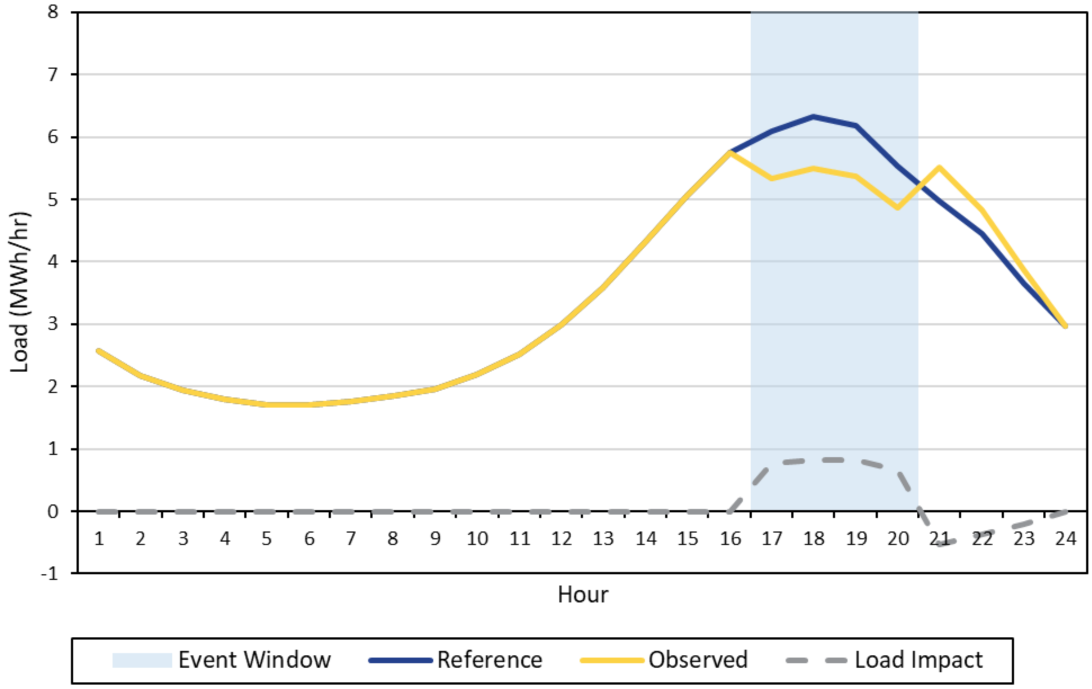


Table 4.1 summarizes average loads and load impacts, percentage load impacts, and average temperatures for the RA window on a July system worst day in 2026 for the PG&E 1-in-2 weather scenario by LCA and enrollment segment. Per-customer load impacts range from 0.22 kWh/customer/hour for Greater Bay Area to 0.39 for Kern. The differences are mainly due to temperatures and event performance in these LCAs. There is large variation in aggregate load impacts due to the distribution of enrolled customers across LCAs. Greater Bay Area has the largest aggregate load impacts of 3.8 MWh/hour. Dually enrolled customers in Northern Coast have the largest percentage load impact of 20.4 percent.

Table 4.1: Average RA Window Load Impacts for *PG&E 1-in-2* July System Worst Day in 2026 by LCA and Enrollment Segment

Enrollment Segment	LCA	Enrolled	Average RA Window Hour				
			Reference (kW/cust/hr)	Impact (kW/cust/hr)	% Load Impact	Aggregate Impact (MW/hr)	Avg. Temp (°F)
All	Greater Bay Area	17,438	1.98	0.22	11.0%	3.8	91.5
	Greater Fresno	8,709	3.08	0.34	11.2%	3.0	103.3
	Kern	2,565	2.94	0.39	13.3%	1.0	103.3
	Northern Coast	2,002	1.87	0.28	14.7%	0.6	88.5
	Other	8,200	2.65	0.27	10.4%	2.3	100.1
	Sierra	7,207	2.49	0.29	11.7%	2.1	100.0
	Stockton	3,815	2.79	0.24	8.8%	0.9	99.2
	Total	**49,936**	**2.46**	**0.27**	**11.1%**	**13.6**	**98.1**
Dually Enrolled	Greater Bay Area	407	1.92	0.26	13.7%	0.1	94.0
	Greater Fresno	654	2.85	0.38	13.3%	0.2	103.3
	Kern	210	2.83	0.39	13.8%	0.1	103.3
	Northern Coast	77	1.48	0.30	20.4%	0.0	90.7
	Other	546	2.37	0.27	11.4%	0.1	100.1
	Sierra	306	2.22	0.30	13.5%	0.1	100.0
	Stockton	299	2.39	0.24	10.1%	0.1	99.2
	Total	**2,499**	**2.42**	**0.31**	**12.8%**	**0.8**	**100.3**
SmartAC Only	Greater Bay Area	17,031	1.98	0.22	10.9%	3.7	91.5
	Greater Fresno	8,055	3.10	0.34	11.0%	2.8	103.3
	Kern	2,355	2.95	0.39	13.2%	0.9	103.3
	Northern Coast	1,925	1.89	0.27	14.5%	0.5	88.4
	Other	7,654	2.67	0.28	10.3%	2.1	100.1
	Sierra	6,901	2.50	0.29	11.6%	2.0	100.0
	Stockton	3,516	2.82	0.25	8.7%	0.9	99.2
	Total	**47,437**	**2.46**	**0.27**	**11.0%**	**12.9**	**98.0**

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 first four hours of the Resource Adequacy (RA) window in 2026 across months and weather scenarios. The highest load impact comes from the PG&E 1-in-10 scenario in September (18.04 MWh/hour), and the second highest load impact comes from the PG&E 1-in-10 scenario in June (16.51 MWh/hour). For the CAISO 1-in-10 scenario, the load impacts are also highest in September (15.89 MWh/hour).

Figure 4.6: Aggregate Load Impacts over RA Window in 2026 by Month and Weather Scenario

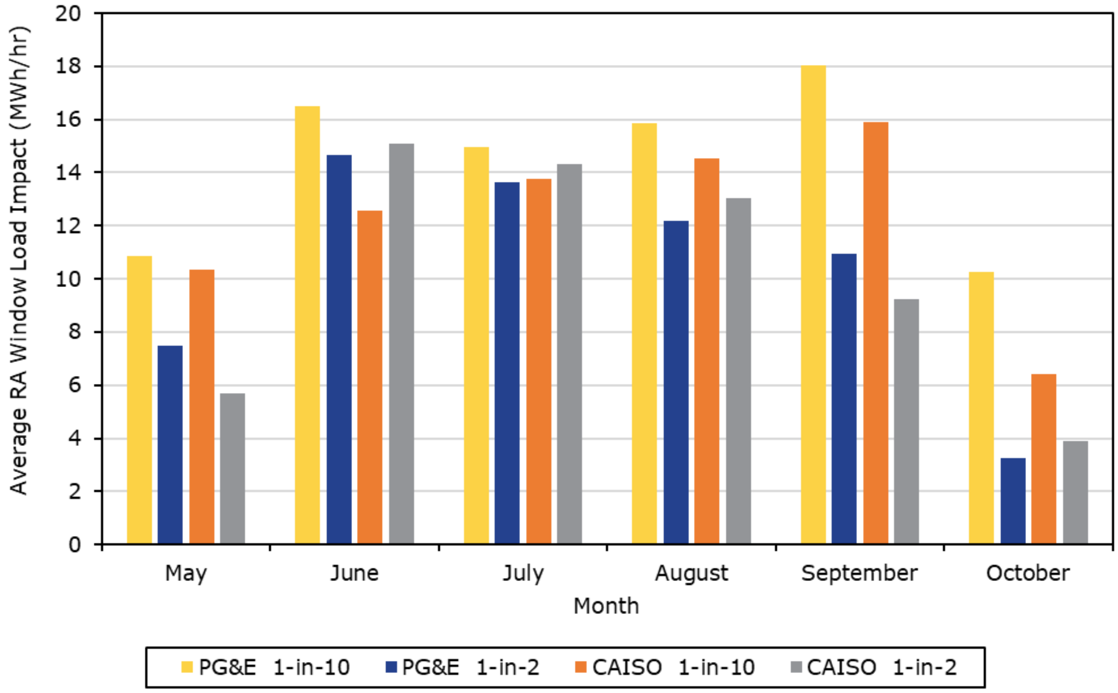
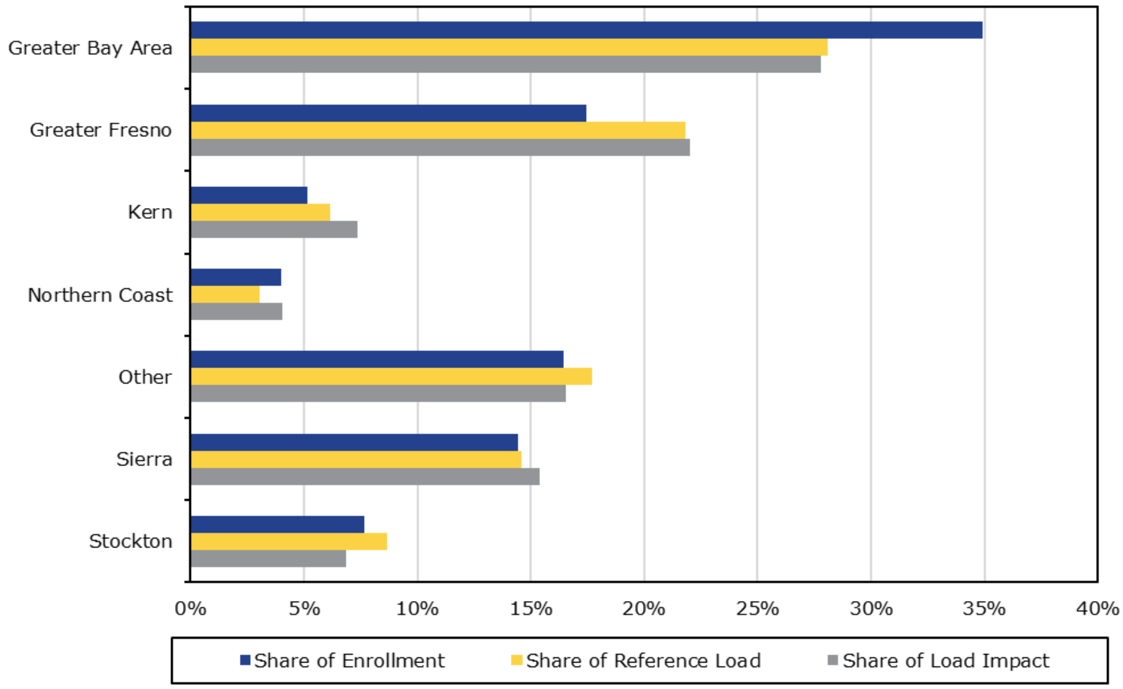


Figure 4.7 compares the LCA shares of average event window load impacts, reference loads, and enrollments on a July system worst day for the PG&E 1-in-2 scenario in 2026. The load impacts for the SmartAC™ program are highest in the Greater Bay Area with 28 percent of aggregate load impacts, 35 percent of enrolled customers, and 28 percent of reference loads. The top four LCAs in terms of enrollments and load impacts, including the Greater Bay Area, Greater Fresno, Other, and Sierra, contribute 82 percent of the aggregate load reductions for SmartAC™. Greater Fresno, Kern, and Sierra have a higher share of load impacts compared to the share of enrollments or reference loads. The rest of the LCAs have a similar or lower share of load impacts compared to the share of enrollments or reference loads.

Figure 4.7: RA Window Load Impacts for *PG&E 1-in-2* July System Worst Day in 2026 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 PY2025. The term "previous" refers to findings in reports for PY2024. In the final comparison above, we illustrate the linkage between the PY2025 ex-post load impacts and the "current" ex-ante forecast.

5.1 Previous vs. Current Ex-Post

In this section we compare ex-post load impacts from the current and previous studies. We compare results for sub-LAP events to the results from PY2024.

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, averaged across the most common event hours from 4 to 6 p.m. The bottom row of the table compares average load impacts across sub-LAPs that had events in both years. On average, about 13,000 more customers were dispatched for sub-LAP events in 2025 relative to 2024, since all sub-LAPs and all device types were dispatched during the same event hours of each sub-LAP event in PY2025 whereas in PY2024, only one type of devices were dispatched in many events. The reference loads in PY2024 are slightly higher than PY2025. Overall, load impacts were 0.09 kWh/customer/hour lower in PY2025, largely due to average event-hour temperatures that were 6 degrees lower in PY2025. Of the twelve sub-LAPs that had sub-LAP events in both years, eleven sub-LAPs had lower load impacts in PY2025 compared to PY2024. This is mostly driven by much lower average event-hour temperatures in PY2025 compared to PY2024. Overall, the average percentage load impacts in PY2025 are lower compared to the prior year. However, the sub-LAPs PGEB, PGKN, PGSI, and PGNC exhibit higher percentage load impacts in PY2025 than in PY2024.

Table 5.1: Previous vs. Current Ex-Post Load Impacts (4-6 p.m.)

sub-LAP	Avg. # dispatched		Reference (kW/cust)		Load Impact (kW/cust)		Share of Reference Load		Avg Temp (°F)	
	2024	2025	2024	2025	2024	2025	2024	2025	2024	2025
PGEB	9,521	10,125	2.61	1.76	0.23	0.19	8.7%	10.6%	97.0	88.7
PGF1	7,529	9,579	3.48	2.54	0.16	0.06	4.5%	2.5%	106.7	101.3
PGFG	1,121	1,031	2.53	1.38	0.33	0.02	13.2%	1.7%	91.7	81.8
PGKN	2,520	2,908	3.48	2.61	0.17	0.15	5.0%	5.7%	107.9	102.8
PGNB	875	828	2.43	1.31	0.32	0.05	13.3%	3.5%	95.3	83.2
PGNC	194	372	2.90	2.14	0.00	0.11	0.0%	5.3%	96.5	91.7
PGNP	4,004	7,846	3.06	2.09	0.29	0.12	9.3%	5.5%	104.8	97.8
PGP2	1,892	2,320	2.36	1.46	0.18	0.09	7.7%	6.1%	88.6	78.2
PGSB	3,962	5,075	2.25	1.24	0.15	0.05	6.7%	4.3%	88.2	78.7
PGSI	3,750	6,774	2.97	2.14	0.14	0.12	4.6%	5.6%	102.9	97.5
PGST	2,232	4,068	3.26	2.33	0.19	0.12	5.9%	5.1%	104.2	96.6
PGZP	963	1,309	3.18	2.01	0.24	0.04	7.5%	1.8%	100.8	90.9
Common Sub-LAPs	**38,563**	**52,235**	**2.92**	**2.02**	**0.20**	**0.11**	**7.0%**	**5.6%**	**99.99**	**93.34**

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. The comparison includes average load impacts across the first four hours of the RA window from 4 to 8 p.m.

Table 5.2 reports the average event window load impacts for the July 2026 peak day under PG&E 1-in-2 weather conditions. As discussed previously, we expect the performance issues of Energate two-way devices to be resolved in future years, so we dropped these devices from the ex-ante forecast model in PY2024 and PY2025 and used Eaton devices as proxies for all two-way devices. This leads to higher forecasted two-way impacts in PY2025. However, due to the continued decline in performance of one-way devices, the forecasted one-way impacts are lower in PY2025 than PY2024. Overall, the per-customer load impacts are the same in both forecasts.

The enrollments in the PY2025 forecast of 2026 are slightly higher than the PY2024 forecast, so aggregate load impacts are higher in the PY2025 forecast.

Table 5.2: Previous vs. Current Ex-Ante Load Impacts (RA Window)

Level	Outcome	July System Worst Day 2026	
		PY2024 Utility 1-in-2	PY2025 Utility 1-in-2
Total	Enrollments	48,440	49,936
	Reference (MW)	122	123
	Load Impact (MW)	13	14
	Avg. RA Window Temp (°F)	98	98
	Avg. Daily Temp (°F)	85	85
	% Load Impact	10.7%	11.1%
Per Participant	Reference (kW)	2.51	2.46
	Load Impact (kW)	0.27	0.27

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 during sub-LAP events contained in the current study. In PY2025, all sub-LAPs were dispatched during the same event hours of each event day. We compare these load impacts to the forecast for an August system worst day for the PG&E 1-in-2 Scenario to get a closer match of temperatures to the August 8th event.

Table 5.3 provides a comparison of the PY2024 ex-ante forecast of 2025 load impacts to the ex-post load impacts on August 8, 2025. There are about 100 fewer customers in ex-post compared to the ex-ante forecast. The per-customer load impact is 0.14 kwh/customer/hour lower in ex-post than ex-ante due to a lower average event-hour temperature and dispatch issues of Energate devices. The reference loads are also lower on August 8th compared to the forecast due to lower temperature. The percentage load impacts are higher in the ex-ante forecast compared to the ex-post estimate.

Table 5.3: Previous Ex-Ante vs. Current Ex-Post Load Impacts (4-7 p.m.)

Level	Outcome	PY2024 Ex-Ante	PY2025 Ex-Post
Total	Enrollments	49,017	48,906
	Reference (MW)	114.1	110.7
	Load Impact (MW)	12.6	5.7
	Avg. Evt Hour Temp (°F)	98.0	95.6
	Avg. Daily Temp (°F)	84.2	81.5
	% Load Impact	11.0%	5.2%
Per Participant	Reference (kW)	2.33	2.26
	Load Impact (kW)	0.26	0.12

5.4 Current Ex-Post vs. Current Ex-Ante

In this section, we compare the ex-post findings by device type to the ex-ante forecast for 2026 contained in the current study during the common event hours from 4 to 6 p.m.

Table 5.4 compares the ex-post load impacts across all sub-LAP events in 2025, by device type, to the ex-ante load impact forecast for an August system worst day with PG&E 1-in-2 weather conditions in 2026. Per-customer load impacts are higher for both device types in the forecast compared to ex-post load impacts because the temperatures are higher. In addition, for two-way devices, the forecast removed the dispatch issues of Energate devices, based on the assumption that future events will no longer have the same issues. The enrollment forecast for 2026 is lower than ex-post since enrollment in the program is expected to decline through the end of October 2028.

Table 5.4: Current Ex-Post vs. Ex-Ante Load Impacts (4-6 p.m.)

Level	Outcome	PY2025 Sub-LAP Event Load Impacts			PY2025 Forecast of 2026		
		One-Way	Two-Way	All	One-Way	Two-Way	All
Total	Enrollments	17,239	34,860	52,099	15,505	33,913	49,418
	Reference (MW)	35.0	70.2	105.3	34.8	76.9	111.7
	Load Impact (MW)	0.9	4.4	5.3	2.3	10.9	13.2
	Avg. Event Temp (°F)	93.2	93.3	93.3	99.1	99.4	99.3
	Avg. Daily Temp (°F)	80.3	80.3	80.3	84.2	84.4	84.3
	% Load Impact	2.4%	6.3%	5.0%	6.6%	14.2%	11.8%
Per Participant	Reference (kW)	2.03	2.01	2.02	2.25	2.27	2.26
	Load Impact (kW)	0.05	0.13	0.10	0.15	0.32	0.27

Table 5.5 documents the various potential reasons for differences between the ex-post and ex-ante load impacts. The main reason for higher per-customer load impacts in the PY2025 ex-ante forecast includes dropping Energate devices in the forecast model and higher event temperatures. The aggregate load impacts in ex-ante are higher than ex-post due to higher per-customer load impacts. Per-customer reference loads are lower in the ex-post results compared to forecasts due to lower daily temperatures in ex-post than in the forecast. Percentage load impacts are higher in the forecast because of much higher load impacts compared to the difference in reference loads.

Table 5.5: Comparison of Ex-Post and Ex-Ante Factors

Factor	Ex-Post	Ex-Ante	Expected Impact
Weather	Average event-hour temperature of 93.2°F for one-way devices, 93.3°F for two-way devices, and 93.3°F overall.	Average event-hour temperature of 99.1°F for one-way devices, 99.4°F for two-way devices, and 99.3°F overall.	The higher overall temperature in ex-ante may produce high per customer load impacts (ceteris paribus).
Device Composition	About 67% of devices dispatched are two-way devices.[28]	About 69% are two-way devices.	Similar ex-ante percentage of two-way devices is due to low forecasted swap-out rate.
Enrollment	52,099	49,418	Lower ex-ante enrollments but higher per-customer impacts increase the aggregate load impacts.
Methodology	Difference-in-Differences with matched control group.	Simulated load impacts from the ex-post using events in 2023-2025.	Incorporating events in PY2023 and removing Energate dispatch issues in PY2024 and PY2025 increase the per-customer load impacts.

6. RECOMMENDATIONS

Evidence suggests that Energate device performance has improved by the time of the serial event on September 17th, 2025 compared to PY2024. We recommend PG&E continue to monitor the status of two-way devices in the system and to identify and remedy dispatch problems such as devices with "Not Ready" status. If there are future opportunities for device swap-out, we recommend PG&E to prioritize customers with high AC usage intensity to maximize the benefit.

For some sub-LAPs, temperatures in the ex-ante scenarios are significantly different than those experienced during ex-post events for the past few years. We recommend that future revisions of the ex-ante temperatures create a better alignment between ex-post and ex-ante sub-LAP weather scenarios to make ex-ante forecasts more helpful for program planning and operation.

[28] There are more two-way devices dispatched since all sub-LAPs and devices were dispatched in PY2025, and since the number of two-way devices is higher among the customers.

7. APPENDICES

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

Appendix C 3. PGE_2025_SAC_Ex_Post_PUBLIC

Appendix D 4. PGE_2025_SAC_Ex_Ante_PUBLIC

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 as 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 1.9 percent for all hours and 1.6 percent for the RA window. Table A-1 demonstrates that all ME and MAE values are less than 0.06 kWh/customer/hour in absolute terms.

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)
PGEB	Hot Days	0.2%	0.00	0.9%	0.01	0.2%	0.00	0.5%	0.03
	Cool Days	0.2%	0.00	0.7%	0.01	0.7%	0.00	0.7%	0.02
	Non-Matching Cool Days	-0.2%	0.00	1.0%	0.01	0.7%	0.00	0.7%	0.02
	Weekend Days	0.4%	0.00	1.0%	0.01	0.6%	0.01	0.6%	0.02
PGF1	Hot Days	1.2%	0.02	1.2%	0.02	0.8%	0.00	0.8%	0.03
	Cool Days	1.4%	0.01	1.5%	0.02	1.6%	0.00	1.6%	0.02
	Non-Matching Cool Days	1.8%	0.02	1.9%	0.02	2.1%	0.00	2.1%	0.02
	Weekend Days	1.9%	0.02	1.9%	0.02	1.7%	0.01	1.7%	0.02
PGFG	Hot Days	-1.3%	-0.01	1.6%	0.01	-0.7%	0.00	1.2%	0.03
	Cool Days	-1.1%	-0.01	1.6%	0.01	-0.6%	0.00	1.2%	0.02
	Non-Matching Cool Days	-0.7%	0.00	2.0%	0.01	-0.5%	0.00	1.3%	0.02
	Weekend Days	0.4%	0.00	1.9%	0.01	-0.7%	0.01	1.0%	0.02
PGKN	Hot Days	-0.1%	0.00	0.7%	0.01	0.2%	0.00	0.4%	0.03
	Cool Days	-0.2%	0.00	0.9%	0.01	0.5%	0.00	0.8%	0.02
	Non-Matching Cool Days	0.0%	0.00	1.0%	0.01	0.6%	0.00	0.7%	0.02
	Weekend Days	0.8%	0.01	1.0%	0.01	0.5%	0.01	0.7%	0.02
PGNB	Hot Days	-6.1%	-0.05	6.1%	0.05	-5.8%	0.00	5.8%	0.03
	Cool Days	-6.3%	-0.04	6.3%	0.04	-5.1%	0.00	5.1%	0.02
	Non-Matching Cool Days	-6.2%	-0.04	6.2%	0.04	-4.7%	0.00	4.7%	0.02
	Weekend Days	-5.9%	-0.04	5.9%	0.04	-4.3%	0.01	4.3%	0.02
PGNC	Hot Days	-5.4%	-0.05	5.4%	0.05	-2.0%	0.00	2.2%	0.03
	Cool Days	-5.3%	-0.03	5.3%	0.03	-4.8%	0.00	4.9%	0.02
	Non-Matching Cool Days	-4.9%	-0.03	4.9%	0.03	-4.2%	0.00	4.2%	0.02
	Weekend Days	1.4%	0.01	3.0%	0.02	1.2%	0.01	1.5%	0.02

Sub-LAP	Comparison Days	24 Hour Load Profile				RA Window			
		MPE (%)	ME (kW)	MAPE (%)	MAE (kW)	MPE (%)	ME (kW)	MAPE (%)	MAE (kW)
PGNP	Hot Days	0.4%	0.01	0.6%	0.01	0.5%	0.00	0.7%	0.03
	Cool Days	0.2%	0.00	0.9%	0.01	0.7%	0.00	0.8%	0.02
	Non-Matching Cool Days	0.4%	0.00	0.8%	0.01	1.1%	0.00	1.1%	0.02
	Weekend Days	1.2%	0.01	1.2%	0.01	1.6%	0.01	1.6%	0.02
PGP2	Hot Days	2.1%	0.02	2.1%	0.02	3.0%	0.00	3.0%	0.03
	Cool Days	1.5%	0.01	1.7%	0.01	3.1%	0.00	3.1%	0.02
	Non-Matching Cool Days	0.7%	0.01	1.3%	0.01	1.4%	0.00	1.4%	0.02
	Weekend Days	2.2%	0.02	2.3%	0.02	3.3%	0.01	3.3%	0.02
PGSB	Hot Days	0.3%	0.00	0.7%	0.01	-0.1%	0.00	0.4%	0.03
	Cool Days	0.1%	0.00	0.7%	0.00	0.6%	0.00	0.6%	0.02
	Non-Matching Cool Days	0.4%	0.00	0.5%	0.00	0.8%	0.00	0.8%	0.02
	Weekend Days	1.0%	0.01	1.3%	0.01	0.8%	0.01	0.8%	0.02
PGSI	Hot Days	0.5%	0.01	0.5%	0.01	0.4%	0.00	0.4%	0.03
	Cool Days	0.4%	0.00	0.5%	0.00	0.3%	0.00	0.4%	0.02
	Non-Matching Cool Days	0.0%	0.00	0.5%	0.00	0.3%	0.00	0.4%	0.02
	Weekend Days	0.9%	0.01	1.1%	0.01	0.8%	0.01	0.8%	0.02
PGST	Hot Days	-0.5%	0.00	0.6%	0.01	0.0%	0.00	0.3%	0.03
	Cool Days	-0.4%	0.00	0.5%	0.00	0.0%	0.00	0.1%	0.02
	Non-Matching Cool Days	-0.7%	0.00	0.9%	0.01	0.3%	0.00	0.5%	0.02
	Weekend Days	0.3%	0.00	0.7%	0.01	0.5%	0.01	0.5%	0.02
PGZP	Hot Days	2.2%	0.03	2.2%	0.03	1.7%	0.00	1.7%	0.03
	Cool Days	2.1%	0.02	2.2%	0.02	2.4%	0.00	2.4%	0.02
	Non-Matching Cool Days	2.4%	0.02	2.4%	0.02	2.7%	0.00	2.7%	0.02
	Weekend Days	3.2%	0.03	3.2%	0.03	2.1%	0.01	2.1%	0.02

Appendix B. Scatterplots of Load Impacts and Temperature

Figure C.1 through Figure C.12 show scatterplots of hourly ex-post and ex-ante load impacts compared to average temperatures from PY2025 for all sub-LAPs by device type. PGCC is dropped from this analysis as it no longer receives CAISO market awards in 2024 due to low customer count. The red dots show the hourly ex-post load impacts of sub-LAP events in 2025. The blue dots show the hourly ex-post load impacts of sub-LAP events in 2023 and 2024, while the blue line shows the linear relationship between load impacts and hourly temperatures in all three years. The green dots and line show the hourly ex-ante load impacts from the PY2025 forecast. The results are limited to the hours where ex-post and ex-ante have overlapping event hours from 4 to 8 p.m. For the ex-ante load impacts we use the June, July, August, September, and October peak month weather conditions for the PG&E 1-in-10 weather scenario for 2025.

Event temperatures tend to be lower for PY2025 for most sub-LAPs. In PY2025, one-way devices tend to have worse performance than in previous years. For one-way devices, given similar temperatures, the forecasted ex-ante load impacts are broadly in line with the results from ex-post. On the other hand, for two-way devices, the forecasted ex-ante load impacts are generally higher than the fitted line for ex-post because we assume going forward the performance issue with Energate devices will be resolved.

Figure C.1: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGEB

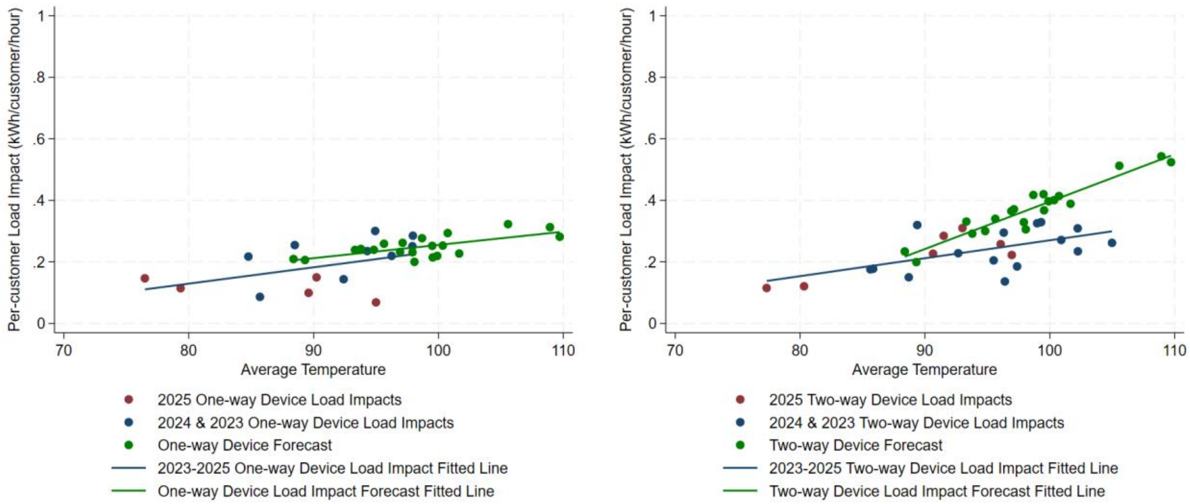


Figure C.2: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGF1

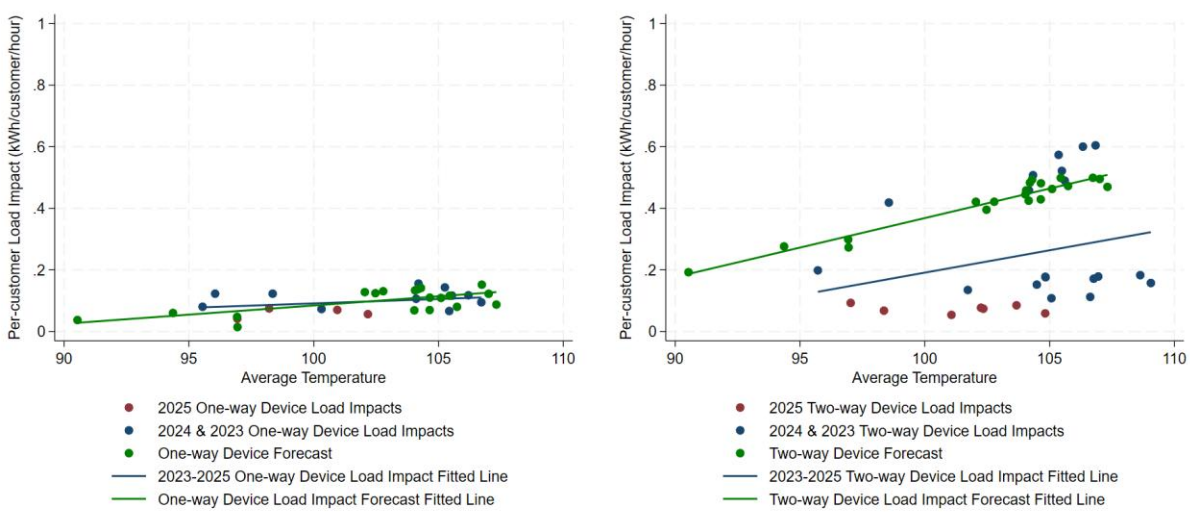


Figure C.3: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGFG

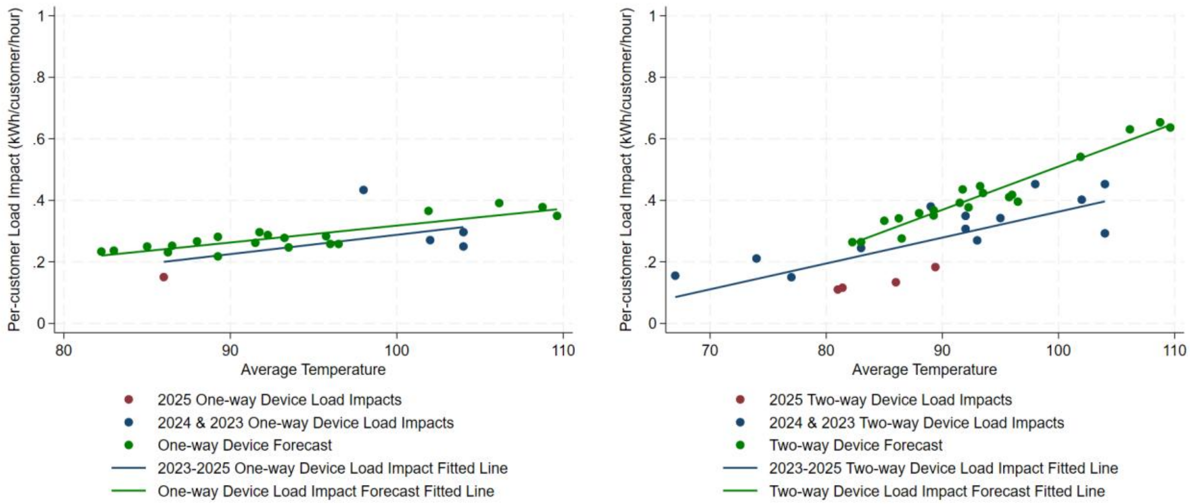


Figure C.4: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGKN

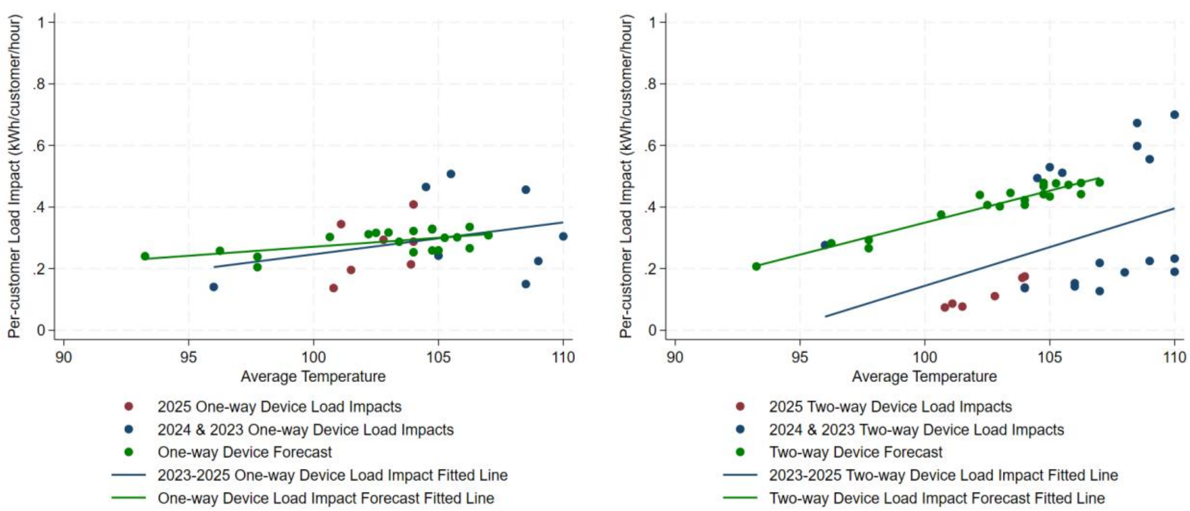


Figure C.5: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGNB

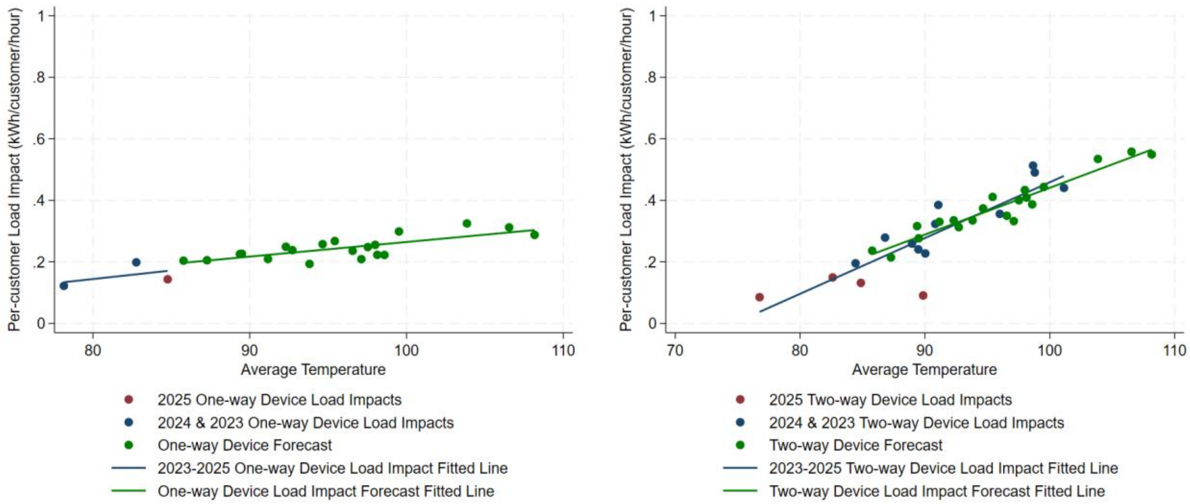


Figure C.6: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGNC

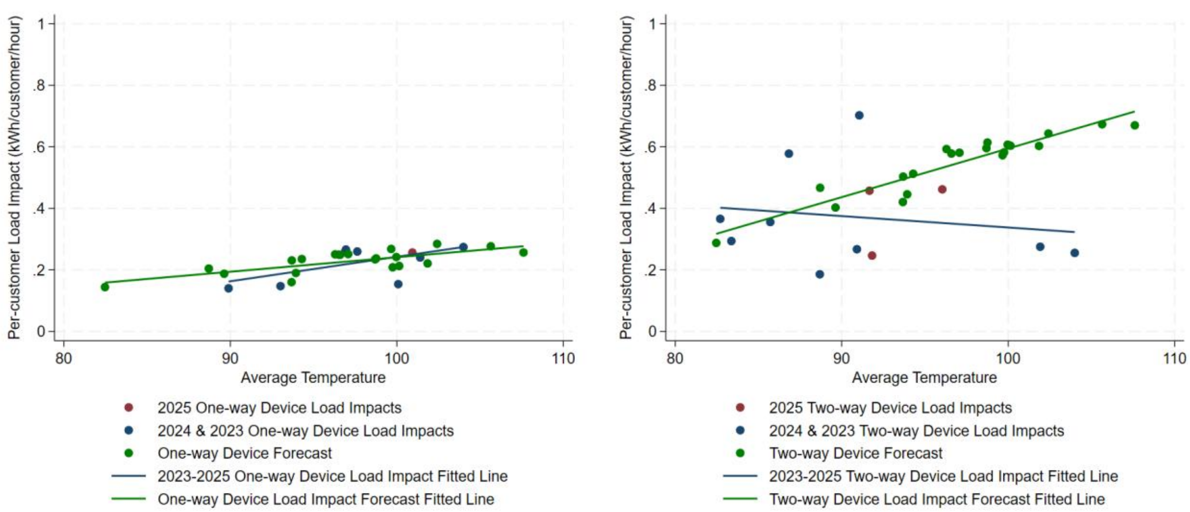


Figure C.7: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGNP

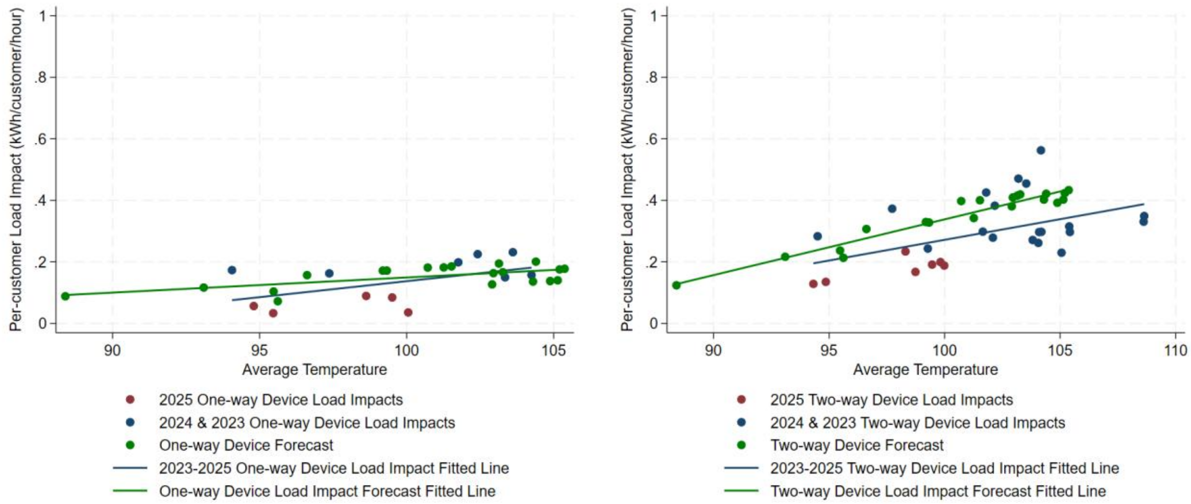


Figure C.8: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGP2

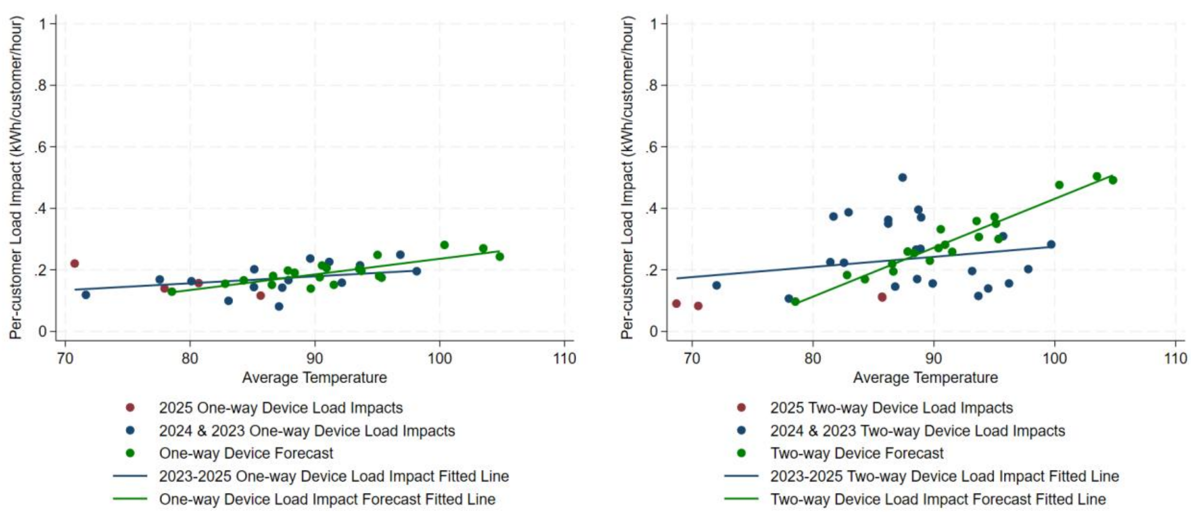


Figure C.9: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGSB

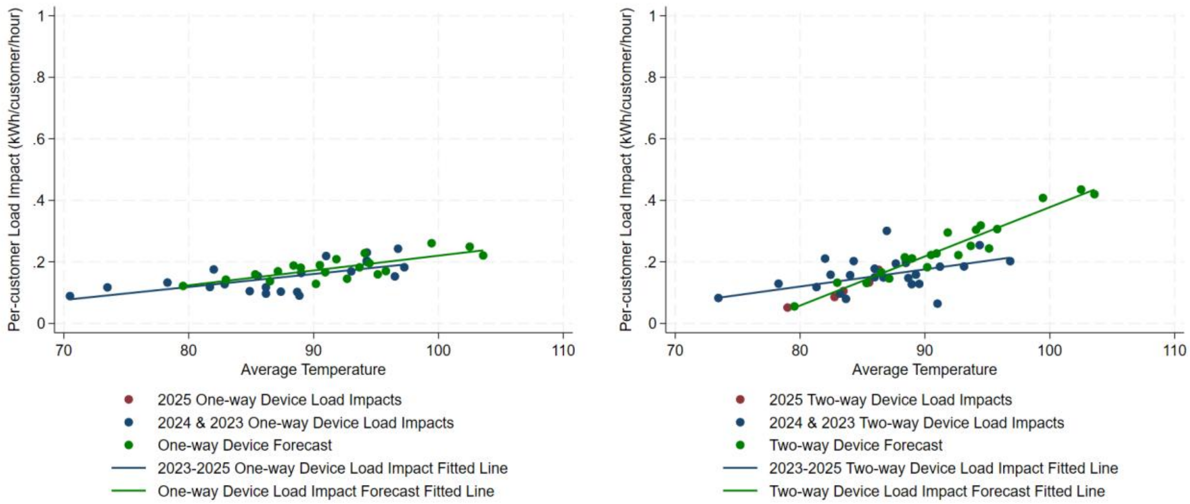


Figure C.10: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGSI

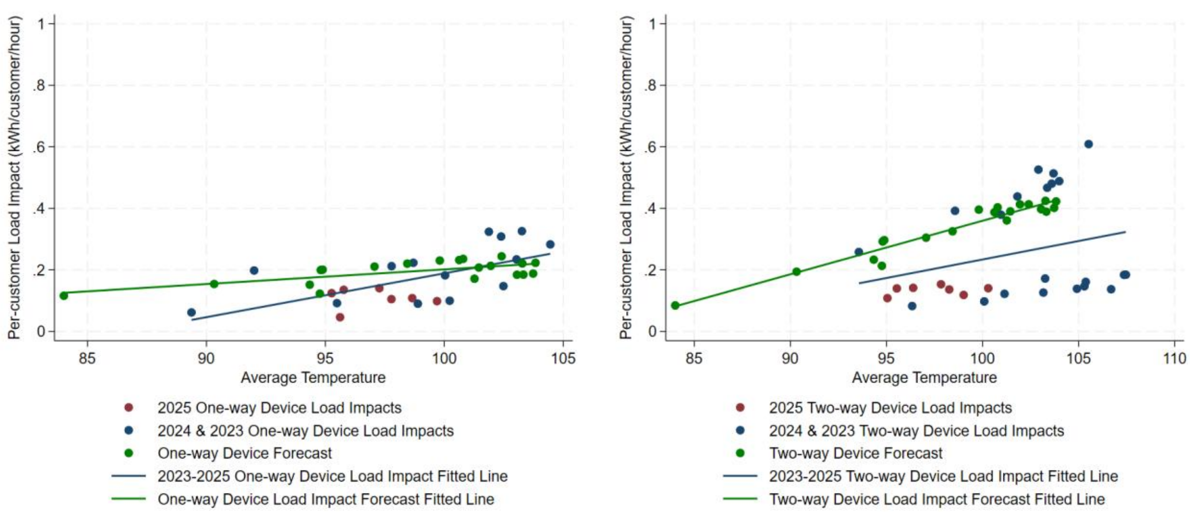


Figure C.11: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGST

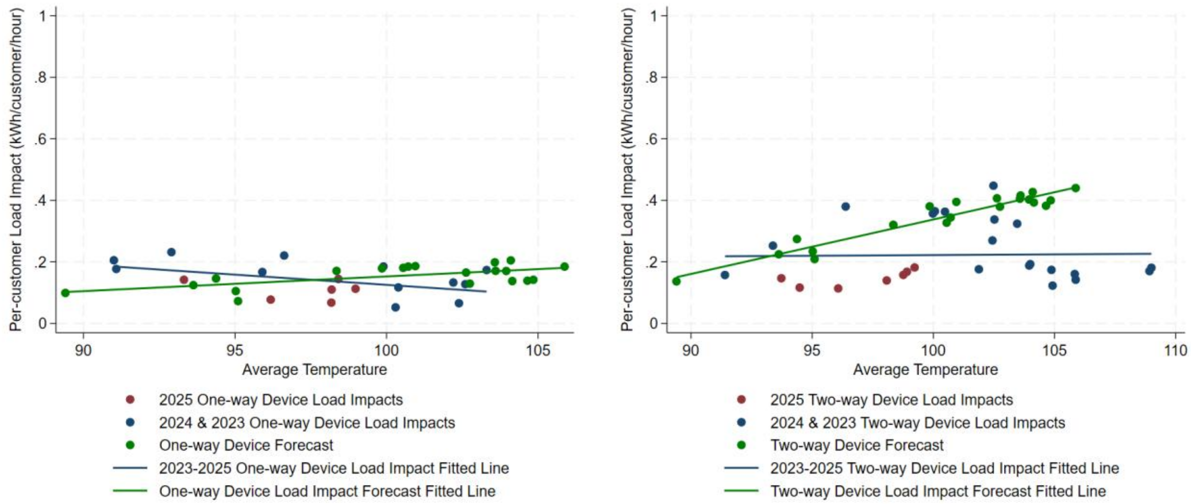


Figure C.12: Scatterplot of Hourly Load Impacts vs. Average Temperature, PGZP