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Christensen ASSOCIATES

2025 Load Impact Evaluation for Pacific Gas & Electric Company's Automated Response Technology Program

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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") Automated Response Technology ("ART") program for program year 2025 ("PY2025"). The evaluation produces estimates of the ex-post load impacts for each of the fourteen events dispatched in PY2025, estimates the effects of Daily Load Shifting ("DLS") strategies implemented as part of the ART program, and develops ex-ante load impact forecasts for ART events from 2026 through 2036. The evaluation conforms to the Load Impact Protocols adopted by the California Public Utilities Commission (CPUC) in April 2008 (D.08-04-050).

ES.1 Resources Covered

The ART program is a voluntary residential demand response program for customers with smart home technologies that officially launched on September 18, 2024. The program offers third-party "Providers" incentives for participating in Demand Response ("DR") events when requested by PG&E through the dispatch of smart technologies, also known as distributed energy resources ("DER"). Customers with smart technologies can enroll through a PG&E-contracted Provider.

ART events are based on the CAISO market award dispatch, PG&E system emergencies, or near-emergencies for distribution service. Total demand response event hours can be up to four hours daily. To demonstrate capacity for the purpose of calculating capacity payments, PG&E will have the option to dispatch up to one test event, not exceeding three hours in duration, per month for sub-LAP resources that did not dispatch in the given month. ART is available year-round for all hours and seven days a week. During PY2025, fourteen events were called. All customers were called on ten of the fourteen events, while the remaining four events dispatched only some of the customers. Customers enrolled in the program can have either smart thermostat technology, electric vehicle chargers, battery storage, the California Energy Commission ("CEC") flex application, or Heat Pump Water Heaters (HPWHs). However, in PY2025, only smart thermostat technologies were able to be dispatched for events.

If a customer is on a time-varying rate, the Provider must implement a DLS strategy using the automated technology to shift usage from high- to low- priced periods. The customer has the option to opt out of the DLS strategy, which currently applies to Time-of-Use ("TOU") rates and in the future could apply to real time pricing ("RTP") rates. All customers, whether they are in DLS or not, participate in DR events. In PY2025, only customers with smart thermostat technologies were able to have DLS strategies implemented.

The primary goals of the evaluation include:

1. Estimate ex-post load impacts for PY2025, including:
    a. Hourly and average daily load impacts for each ART event; and
    b. The distribution of hourly and average daily load impacts by customer segment, including Sub-Load Aggregation Point ("sub-LAP"), local capacity area ("LCA"), California Alternate Rates for Energy ("CARE") status, rate type, and smart thermostat device manufacture (e.g., NEST Thermostats).
2. Estimate ex-post load impact of DLS strategies implemented by Providers, including:

a. Hourly and average daily load impacts for monthly average weekday; and

b. The distribution of hourly and average daily load impacts by customer segment, including rate type and smart thermostat device manufacture (e.g., NEST Thermostats).

3. Produce ex-ante load impact forecasts of ART events for 2026 to 2036 by sub-LAP, LCA, and technology type on an aggregate and per-customer basis for the monthly system worst day for January through December. Forecasts are based on the following two sets of weather conditions:

a. PG&E's peaking conditions in a 1-in-2 weather year; and

b. CAISO peaking conditions in a 1-in-2 weather year.

ES.2 Ex-Post Load Impacts

In this evaluation, we estimated ex-post event load impacts by comparing ART 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 all events, we used a matched control group consisting of residential customers who are not enrolled in any demand response programs. Matched control group customers were selected based on the similarity of available customer characteristics (e.g., sub-LAP and NEM status) as well as usage patterns on non-event days.

We then estimated event-day load impacts using a regression-based difference-in-differences ("D-in-D") 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 ART customers and the control group on event-like non-event days, thus representing a D-in-D evaluation approach.

In PY2025, all ex-post results are confidential because only one third party provider was dispatched in ART.

Table ES1 summarizes the ex-post load impact estimates (in kWh/customer/hour) for all events in PY2025.[1] There were fourteen events called in PY2025: ten were system-wide while in the other four events were limited to specific sub-LAPs. All events were called in the afternoon, however, hours varied by event. All events were within the 3 to 8 p.m. range.[2] No event was longer than two hours. Events can be called either as market awards or as test events. In PY2025, two events were called as market awards, eleven events were called as test events, and one event was called as both a test event and market award.[3]

[1] PY2025 is defined as November 2024 through October 2025.

[2] The time in the report refers to the prevailing time.

[3] Six of the fourteen sub-LAPs on August 22, 2025, were called for a market award event, while the remaining sub-LAPs were called for a test event during the same hours.

Table ES1: Average Event-Hour Load Impacts by Event

Date	Type of Event	Event Hours (p.m.)	Sub-Lap Dispatched	# Dis-patched	Average Event Hour				
					Reference (kWh/ cust/hr)	Impact (kWh/ cust/hr)	% Impact	Aggregate Impact (MWh/hr)	Avg. Temp (°F)
11/22/24	Test	5 - 6	All	16,852	[redacted]	[redacted]	[redacted]	[redacted]	59.7
12/20/24	Test	5 - 6	All	18,705	[redacted]	[redacted]	[redacted]	[redacted]	50.5
1/23/25	Test	4 - 5	All	18,704	[redacted]	[redacted]	[redacted]	[redacted]	65.0
2/26/25	Test	3 - 4	All	18,694	[redacted]	[redacted] [4]	[redacted]	[redacted]	72.6
3/26/25	Test	6 - 8	All	19,001	[redacted]	[redacted]	[redacted]	[redacted]	60.3
4/20/25	Test	7 - 8	All	20,000	[redacted]	[redacted]	[redacted]	[redacted]	65.0
5/21/25	Test	7 - 8	All	21,212	[redacted]	[redacted]	[redacted]	[redacted]	71.3
6/26/25	Test	6 - 8	All	23,326	[redacted]	[redacted]	[redacted]	[redacted]	73.8
7/11/25	Market Award	4 - 6	PGEB, PGF1, PGKN, PGNB, PGNP, PGP2, PGSB, PGSI, PGST, PGZP	25,067	[redacted]	[redacted]	[redacted]	[redacted]	89.2
7/29/25	Test	4 - 6	PGCC, PGHB, PGFG, PGNC, PGSF	1,750	[redacted]	[redacted]	[redacted]	[redacted]	71.2
8/22/25	Test & Market Award	4 - 6	All	33,474	[redacted]	[redacted]	[redacted]	[redacted]	88.8
9/17/25	Market Award	4 - 6	PGEB, PGF1, PGFG, PGKN, PGNB, PGNP, PGP2, PGSB, PGSI, PGST, PGZP	36,648	[redacted]	[redacted]	[redacted]	[redacted]	90.2
9/23/25	Test	4 - 6	PGHB, PGNC, PGSF, PGCC	1,174	[redacted]	[redacted]	[redacted]	[redacted]	83.7
10/29/25	Test	4 - 6	All	41,872	[redacted]	[redacted]	[redacted]	[redacted]	77.7

Program enrollments increased steadily during PY2025 so participating customers and aggregate program impacts increased steadily as well. The first full event, November 22, 2024, called 16,852 customers. There were 41,872 customers called to the final event on October 29, 2025. Load impacts occur mostly between May through September since only cooling-based demand response was enabled during PY2025. [redacted].[5]

The large range of per-customer impacts is largely due to differences in temperature, as average event-hour temperatures ranged from 71.2 degrees to 90.2 degrees during the summer months, and the specific sub-LAPs dispatched. [redacted].[6] The large range of aggregate impacts is due to a combination of differences in temperature, sub-LAPs dispatched,

4 [redacted]

5 [redacted]

6 [redacted]

aggregate program enrollment over the course of PY2025, and the number of customers called on a specific event date.

ES.3 Daily Load Shifting Impacts

We estimated Daily Load Shifting ("DLS") impacts by comparing the hourly loads of ART customers on a TOU rate with that of a matched control group. Matched control group customers are selected based on the similarity of average monthly electricity usage, available customer characteristics (e.g., rate schedule, electric vehicle ("EV") ownership status, and NEM status) as well as solar panel size.

Table ES2 summarizes the average DLS impacts for each month of PY2025. We summarize average weekday impacts from 5-8 p.m., since this period corresponds with when most customers on TOU rates are at the peak price. Enrollments ranged from 14,414 customers in November 2024 to 32,810 customers in October 2025. This is partially responsible for the aggregate impacts increasing over the course of the program year.

Similarly to the event impacts, DLS impacts are also heavily impacted by temperature. [redacted], correlating with temperatures that were 17 degrees higher. August and September, which were the hottest months, had the highest per customer impacts. The aggregate load impacts were the highest in September [redacted].

Table ES2: Average Peak Period Load Shift Impacts by Month

Day Type	Peak Period Hours (p.m.)	# TOU Customers	Average Event Hour				
			Reference (kWh/ cust/hr)	Impact (kWh/ cust/hr)	% Impact	Aggregate Impact (MWh/hr)	Avg. Temp (°F)
November	5-8	14,414	[redacted]	[redacted]	[redacted]	[redacted]	56.6
December	5-8	15,794	[redacted]	[redacted]	[redacted]	[redacted]	53.2
January	5-8	15,863	[redacted]	[redacted]	[redacted]	[redacted]	53.2
February	5-8	15,843	[redacted]	[redacted]	[redacted]	[redacted]	56.6
March	5-8	16,494	[redacted]	[redacted]	[redacted]	[redacted]	57.9
April	5-8	17,244	[redacted]	[redacted]	[redacted]	[redacted]	64.1
May	5-8	17,926	[redacted]	[redacted]	[redacted]	[redacted]	71.5
June	5-8	19,699	[redacted]	[redacted]	[redacted]	[redacted]	73.1
July	5-8	23,658	[redacted]	[redacted]	[redacted]	[redacted]	74.3
August	5-8	27,389	[redacted]	[redacted]	[redacted]	[redacted]	78.6
September	5-8	29,689	[redacted]	[redacted]	[redacted]	[redacted]	76.7
October	5-8	32,810	[redacted]	[redacted]	[redacted]	[redacted]	66.6

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 customer segments;
2. *Reference loads* by required customer segment; and
3. A forecast of *load impacts per customer*, again by required customer segment, where the load impact forecast also varies with weather conditions (if applicable), as determined in the ex-post evaluation.

Figure ES1 summarizes the ex-ante program load impact forecast for 2026 to 2036 for ART by plotting the average aggregate load impacts for the resource adequacy (RA) window over time by technology type.[7] Table ES3 summarizes the changes in load impacts, reference loads, and enrollments on a per customer and aggregate basis over the forecast period.

For this comparison we use the PG&E 1-in-2 scenario for August system worst days. Aggregate load impacts increase across all technology types from 2026 to 2036. The trend of increasing aggregate load impacts is driven by increased enrollments, while the slight decline in per–customer impacts is due to larger expected enrollment growth in technologies such as CEC flex app and HPWHs that have low assumed demand response capabilities. The reference loads are largely consistent throughout the forecast since we assume that per–customer reference loads for all technologies, but batteries are the same. For battery customers, we estimate separate reference loads; however, given the relatively small enrollment share of batteries, the resulting difference is not material at the hundredth decimal place in kWh.

Figure ES1: Aggregate Load Impacts over RA Window for PG&E 1-in-2 August System Worst Day (2026-2036)

[redacted]

[7] 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. For PG&E, the first 4 hours of the RA window are reported for ex ante. LIP Filing Guide 5.1, p. 11.

Table ES3: Load Impacts over RA Window for PG&E 1-in-2 August System Worst Day (2026-2036)

Year	# Enrolled	Per-Customer		Aggregate	
		Event Load Impact (kWh/cust/hr)	Event Ref. Load (kWh/cust/hr)	Event Load Impact (MWh/hr)	Event Ref. Load (MWh/hr)
2026	75,299	0.45	1.89	33.67	142.66
2027	103,956	0.43	1.89	44.99	196.98
2028	129,081	0.43	1.89	55.00	244.57
2029	151,049	0.42	1.89	63.72	286.07
2030	171,302	0.42	1.89	71.81	324.39
2031	191,225	0.42	1.89	79.88	362.02
2032	210,812	0.42	1.89	87.91	399.02
2033	230,232	0.42	1.89	95.94	435.70
2034	249,272	0.42	1.89	103.97	471.63
2035	268,134	0.42	1.89	111.97	507.21
2036	286,818	0.42	1.89	119.97	542.48

ES.5 Key Findings and Recommendations

We find impacts that vary significantly by month in PY2025 due to significant changes in enrollment and temperature across months as well as the sub-LAPs dispatched. Events during the summer show significant per-customer and aggregate impacts, while event impacts during winter months tend to be insignificant due to low temperatures and the Smart Thermostat technology being limited to cooling-based demand response. While the February 26th and October 29th events have temperatures above 70 degrees, the load impacts are small or insignificant, which indicate customers' AC usage pattern may be different by season. DLS strategy produced statistically significant load reductions during peak period for customers on TOU rates, particularly during summer months. Our ex-ante forecast shows significant growth over the forecast window from 2026-2036 due to increased enrollments and changing technology mix.

Going forward, as customers with new technology types are recruited to the program, we recommend calling events across sub-LAPs and varying weather conditions as well as event length to help understand how performance varies by location and weather for each technology type. This information will help us better forecast future performance for all technologies and can also provide insights on where future customer recruitment or retention is the most cost-effective. We also recommend scheduling shoulder-month events at different points within the month to assess how behavioral responses evolve from early to late month conditions for AC usage. This will inform potential interactions between the time of month and temperature. For example, AC usage may be more prevalent in early October than late October as cooler conditions may lead customers to turn off their AC and not use it again during brief warm periods. By dispatching events at different points throughout the month, we can more accurately identify these shifting patterns.

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") Automated Response Technology ("ART") program for program year 2025 ("PY2025"). The evaluation produces estimates of the ex-post load impacts for each of the fourteen events dispatched in PY2025, estimates the effects of Daily Load Shifting ("DLS") strategies implemented as part of the ART program, and develops ex-ante load impact forecasts for ART events from 2026 through 2036. The evaluation conforms to the Load Impact Protocols adopted by the California Public Utilities Commission (CPUC) in April 2008 (D.08-04-050).

The ART program is a voluntary residential demand response ("DR") program for customers with smart home technologies, and officially launched on September 18, 2024. Customers enrolled in the program can have either smart thermostat technology, electric vehicle chargers, battery storage, the California Energy Commission ("CEC") flex app, heat pumps, or water heaters. Customers with eligible technologies can enroll through a PG&E-contracted third-party "Providers". Third-party Providers receive incentives for participating in DR events when requested by PG&E through the dispatch of smart technologies. The payments are determined on a performance basis as measured at PG&E's meter level and aggregated to the provider's smart technology portfolio.

ART events are based on either CAISO market award dispatch or PG&E system emergencies, or near-emergencies, for distribution service. Total demand response event duration can be up to four hours daily. PG&E has the option to dispatch up to one test event, not exceeding three hours in duration, per month for resources that do not dispatch in the given month for the purpose of calculating incentive payments to the third-party providers. ART events may be called year-round for all hours and seven days a week. In addition to ART events, third party providers are required to implement a Daily Load-Shifting ("DLS") strategy for enrolled customers on a time-varying rate. Customers can choose to opt out of the DLS strategy after the first twelve months of enrollment.[8]

Table 1.1 shows the details of all fourteen events called in PY2025: ten were system-wide events while the other four events were limited to certain sub-LAPs were called. The number of customers called ranged from 1,174 on September 23rd to 41,872 on October 29th, a system-wide event. In PY2025 two events were called as market awards, eleven events were called as test events and one event was called as both a test event and market award.[9]

[8] One of the load impact reporting requirements is to compare customers who have opted out of daily load shifting and who have not. Since the program was launched on September 18, 2024, even for customers that joined at the start, they were only eligible to begin opting out beginning in late September 2025. There was not enough data to conduct an analysis comparing customers who opted out of DLS to customers who did not opt out.

[9] Six of the fourteen sub-LAPs on August 22, 2025 were called for a market award event, while the remaining sub-LAPs were called for a test event during the same hours.

Table 1.1: PY2025 ART Events

Date	Reason	Event Hours	Sub-LAPs Dispatched	# Customers Dispatched
11/22/24	Test	5 - 6	All Groups Dispatched	16,852
12/20/24	Test	5 - 6	All Groups Dispatched	18,705
1/23/25	Test	4 - 5	All Groups Dispatched	18,704
2/26/25	Test	3 - 4	All Groups Dispatched	18,694
3/26/25	Test	6 - 8	All Groups Dispatched	19,001
4/20/25	Test	7 - 8	All Groups Dispatched	20,000
5/21/25	Test	7 - 8	All Groups Dispatched	21,212
6/26/25	Test	6 - 8	All Groups Dispatched	23,326
7/11/25	Market Award	4 - 6	PGEB, PGF1, PGKN, PGNB, PGNP, PGP2, PGSB, PGSI, PGST, PGZP	25,067
7/29/25	Test	4 - 6	PGCC, PGHB, PGFG, PGNC, PGSF	1,750
8/22/25	Test & Market Award	4 - 6	All Groups Dispatched	33,474
9/17/25	Market Award	4 - 6	PGEB, PGF1, PGFG, PGKN, PGNB, PGNP, PGP2, PGSB, PGSI, PGST, PGZP	36,648
9/23/25	Test	4 - 6	PGHB, PGNC, PGSF, PGCC	1,174
10/29/25	Test	4 - 6	All Groups Dispatched	41,872

ART customers are not permitted to be dually enrolled in other DR programs. By the end of the program year (October 2025), there were customers with smart thermostats, electric vehicle chargers, and battery storage enrolled, however only customers with smart thermostats were able to be called to events and impacted by DLS strategy. Many customers enrolled in ART were transitioned from the Smart Thermostat Control Pilot from PY2022-PY2023.

The primary goals of the evaluation include:

1. Estimate ex-post load impacts for PY2025, including:
    a. Hourly and average daily load impacts for each ART event; and
    b. The distribution of hourly and average daily load impacts by customer segment, including Sub-Load Aggregation Point ("sub-LAP"), local capacity area ("LCA"), California Alternate Rates for Energy ("CARE") status, rate type, and smart thermostat device manufacture (e.g., NEST Thermostats).
2. Estimate ex-post load impacts of DLS strategies implemented by Providers, including:
    a. Hourly and average daily load impacts for monthly system worst day and average weekday; and
    b. The distribution of hourly and average daily load impacts by customer segment, including rate type and smart thermostat device manufacture (e.g., NEST Thermostats).
3. Produce ex-ante load impact forecasts of ART events for 2026 to 2036 by sub-LAP, LCA, and technology type on an aggregate and per-customer basis for a typical event day and

the monthly system worst day for January through December. Forecasts are based on the following two sets of weather conditions:

a. PG&E's peaking conditions in a 1-in-2 weather year; and
b. CAISO peaking conditions in a 1-in-2 weather year.

This report is organized as follows:

- Section 2 describes the evaluation methods used in the study.
- Section 3 contains ex-post load impact results for the ART event.
- Section 4 contains DLS results.
- Section 5 contains ex-ante forecasts.
- Section 6 compares ex-post and ex-ante across program years.
- Section 7 provides recommendations.
- Appendices describe the results of our control group matching statistics 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 of the ART event, DLS impacts, and ex-ante forecasts.

2.1 Ex-Post Load Impact Evaluation

We estimated load impacts by comparing ART customer loads to that of a quasi-experimental matched control group of non-ART 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 event-hour or event-day load impact estimates and standard errors (used to develop confidence intervals). The eligible control-group customers consisted of residential customers who were not enrolled in any demand response programs. We selected control-group customers based on the similarity of available customer characteristics (Sub-lap, NEM status, solar installation size, storage size, temperature, and weather sensitivity coefficient[10]) as well as usage patterns on non-event days.

2.1.1 Data

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

- Customer information for ART customers and potential control-group customers (LCA, Sub-LAP, rate schedule, CARE status, NEM status, solar installation size, storage size, and weather station);

[10] We estimated the weather sensitivity coefficient for each treatment and control customer by regressing their daily electricity consumption on temperature.

- Billing-based interval load data (i.e., hourly loads for each treatment and potential control group customer);
- Weather data (i.e., hourly temperatures and other variables for PY2025, by weather station);
- Program event data; and
- Smart thermostat device manufacturer information.

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. We selected control customers from a sample of about 150,000 of PG&E's residential customers.[11] We used propensity score matching to identify a single control customer for each season for each ART customer, conducting the matching separately for the summer, defined as May through September, and winter months. Controls were selected based on similarity in hourly load profiles using a set of non-event, non-holiday days. These non-event days were chosen seasonally and are days with average temperatures closest to the event days in each season. In addition, customers were also matched based on customer characteristics, including solar installation size, battery storage capacity, and weather sensitivity where applicable. ART customers are required to be matched to a control customer residing in the same sub-Lap and with the same NEM status.

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 ART customer is then matched to the control customer with the nearest value in terms of their predicted probability, also known as their "propensity score." We assume the probability model for each season is a logistic function of the following form:

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

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

Table 2.1: Propensity Score Model Terms

Symbol	Description
ART_c	Variable indicating whether customer *c* is an ART (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
$\beta_{2,j}$	Estimated coefficient for customer characteristic *j*
ε_c	Error term for customer *c*

[11] This sample is selected from all PG&E customers that are not in any demand response programs and have similar weather pattern, rate, solar and storage sizes, and average billing usage as the ART customers. This initial selection allows for a more tractable matching process using the interval load data.

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

2.1.3 Analysis Methods

To produce estimates of ex-post load impacts, we estimated the following panel model for each hour of the day for each season:

$$kW_{c,d} = \beta_0 + \sum_{i=1}^{n}(\beta_{1,i}ART_{i,c,d} \times Evt_{i,d} \times GROUP_c) + \sum_{i=1}^{n}(\beta_{2,i}Evt_{i,d} \times GROUP_c) + \sum_{all\ j}\beta_{3,j}X_{c,d,j} + C_c + D_d + \varepsilon_{c,d}$$

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

Table 2.2: Ex-post Load Impacts Model Terms

Symbol	Description
$kW_{c,d}$	Load during a given hour for customer *c* on day *d*
$ART_{i,c,d}$	Variable indicating whether customer *c* is an ART (1) or Control (0) customer on the i^{th} event day
$Evt_{i,d}$	Variable indicating that day *d* is the i^{th} event day (1) or not (0)
$Group_c$	Variables indicating which subgroups (i.e., sub-Lap, rate schedule, CARE status, and device manufacturer) each customer belong to
$X_{c,d,j}$	The value of weather variable *j* on day *d* for customer *c*
β_0	Estimated constant coefficient
$\beta_{1,i}$	Estimated load impact for event *i*
$\beta_{2,i}$	Estimated coefficient for event day i
$\beta_{3,j}$	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. In addition, the model includes time variant weather controls such as the cdd60 and hdd60.[12] The $\beta_{1,i}$ coefficients represent the estimated load impacts for each hour of every event day.

We estimated this model separately for each hour of the day and season using only the event day and the selected non-event days identified in Section 2.1.2. Since customers were dispatched differently on certain event days, we include interaction terms between each event indicator and treatment status. In addition, we estimate the distribution of load impacts across customer subgroups by interacting the event indicators with variables identifying subgroups of interest (e.g., different devices).

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 produced *uncertainty-adjusted* program impacts for each event, which show the uncertainty around the estimated

[12] The inclusion of weather variables may improve the effectiveness of the date fixed effects, particularly in models that include customers in different weather regions.

impacts, including the 5th and 95th percentile load changes. These percentiles were generated using the standard errors from the corresponding ex-post regression parameters.

We validated the ex-post load impact estimates against simple D-in-D calculations from load data. Specifically, we compared the average treatment customer hourly loads to the average control-group hourly loads on both the event day and selected non-event days.

2.2 Daily Load Shifting Evaluation

For the DLS analysis, we compared the hourly load data of ART customers on a TOU rate with a matched control group. Since DLS strategies are implemented every day, we cannot match on load profiles in the same way that we do for event-based programs.[13] Instead of matching based on daily load profiles, we matched on the average daily usage by season. We used nearest neighbor matching with replacement to identify one control customer for each treatment customer.[14]

The matching is conducted within the same rate, NEM status (NEM or non-NEM), EV ownership status, and battery ownership status.[15] We calculated the Mahalanobis distance between the treatment and control customer in terms of average daily usage (based on interval load data), average cooling and heating degree days, battery storage size, and solar installation size (if applicable). We match each customer separately for summer (May-October) and winter (all other) months. The Mahalanobis distance adjusts the Euclidean distance for scaling and correlation using the covariance matrix of these characteristics. Each ART customer is then matched to the control customer with the nearest value in terms of the Mahalanobis distance.

To assess the validity of the control-group matching processes, we compared the characteristics of the matched control-group and treatment customers. More details about the evaluation of match quality are provided in Appendix B.

To produce estimates of DLS load impacts, we estimated the following panel model for each hour of the day and rate schedule[16]:

$$kWh_{c,d} = \beta_0 + \beta_1 \times DLS_c + \beta_2 \times Weather_{c,d} + \beta_3 \times DLS_c \times Weather_{c,d} + D_d + \varepsilon_{c,d}$$

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

[13] As many customers were already on Daily Load-Shifting during the Smart Thermostat Control Pilot in 2022 and 2023, we cannot match on their load profile right before the start of the ART program.

[14] We also identified the second best matches for each customer and included these customers as control customers in the regression to verify the estimated load impacts are similar when second best matches are used.

[15] Under TOU rates such as EV2A and E-ELEC, EV charging patterns may confound the detection of load shifts due to DLS if ART customers and control customers differ systematically in EV charging behavior. To mitigate this issue, we identify customers likely to own EVs and exhibit frequent at-home EV charging. By requiring an exact match on this EV ownership status, we reduce the influence of EV charging patterns on estimated smart thermostat-induced load shifts.

[16] The model is estimated separately for summer (May-October) and winter (all other) months using customers' summer and winter matches.

Table 2.3: DLS Load Impacts Model Terms

Symbol	Description
$kWh_{c,d}$	Load in a particular hour for customer *c* on date *d*
DLS_c	Variable indicating whether customer *c* is in Daily Load-Shifting (1) or a Control customer (0)
$Weather_{c,d}$	Weather conditions on day *d* for customer *c*
D_d	Date Fixed Effects
ε_c	Error term for customer *c*

Interactions between the treatment effect and weather allow the load impact to vary based on weather conditions in a given month. The estimated load impact for a given month is obtained by the following formula:

$$Load\ Impact_{month\ m} = \hat{\beta}_1 + \hat{\beta}_3 \times \overline{Weather}_{month\ m}$$

The second term multiplies the average weather conditions during month *m* by the estimated coefficient for the interaction term between the treatment effect and weather. To estimate the load impacts for different device manufactures, we interacted the indicator variable for the customer's smart thermostat device manufacture with the components that include DLS indicators in the regression model.

2.3 Developing Ex-Ante Load Impacts

Ex-ante load impacts represent forecasts of load impacts that are expected to occur when ART program events are dispatched in future years under standardized weather conditions. Ex-ante load impacts are developed for the years 2026 through 2036 for the monthly system worst day under both utility-specific and CAISO 1-in-2 weather scenarios. Furthermore, ex-ante load impacts are developed for the following subgroups of customers:

1. Sub-LAP;
2. LCA; and
3. Technology Type.

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).

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

2.3.1 Reference Loads

The *per-customer reference loads* are simulated based on regression models, which reflect customer load patterns on non-event non-holiday weekdays 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 weather-year conditions provided by PG&E) and month.

The regression model uses the average load profiles created for each sub-LAP using data for treatment customers on all non-holiday weekdays that do not coincide with ART events in PY2025. The regressions account for differences in loads by hour, day-of-week, and month by including various indicator control variables. Two models are estimated to develop reference loads. The first model uses observed loads from Smart Thermostat ART customers to estimate Smart Thermostat reference loads. The second model uses observed loads from ART customers with batteries, along with control customers with batteries[17], to estimate battery reference loads.

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

$$avgkW_{d,h} = \beta_0 + \sum_{h=1}^{24} \beta_{1,h}(CDD60_d \times H_h) + \sum_{h=1}^{24} \beta_{2,h}(HDD60_d \times H_h) + \sum_{h=1}^{24} \beta_{3,h}H_h + \sum_{h=1}^{24} \beta_{4,h}(Mon_d \times H_h) + \sum_{h=1}^{24} \beta_{5,h}(Fri_d \times H_h) + D_d + M_d + \varepsilon_{d,h}$$

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

Table 2.4: Ex-Ante Reference Loads Model Terms

Symbol	Description
$avgkW_{d,h}$	Average load (kWh/customer/hour) on day *d* during hour *h*
$CDD60_d$	The cooling degrees on day *d*
$HDD60_d$	The heating degrees on day *d*
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 heating 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 of the year fixed effects
$\varepsilon_{d,h}$	Error term (robust)

The model includes hour fixed effects to allow loads to vary by hour of the day. Monday and Friday hourly fixed effects allow for differences in load profiles on Mondays and Fridays. Day of

[17] We leverage control customers to increase sample size and enhance the statistical precision of our reference load estimates. Because control customers and battery-equipped treatment customers display similar load profiles on non-event days, pooling these groups for reference load estimation is not expected to bias the results.

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 a one heating degree day increase. We estimate this model separately for each sub-LAP and season.

Reference loads are simulated by applying the cooling degree days and heating 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 peak load for a Wednesday event.

2.3.2 Load Impacts

The only technology type currently enrolled and deployed during ART events is Smart Thermostats ("SCT"). In future years ART is forecasted to have deployable customers with Battery Storage ("Battery"), Electric Vehicle Chargers ("EV"), Heat Pump Water Heaters ("HPWH"), and the California Energy Commission ("CEC") Flex Application. Table 2.5 shows the assumptions we make to develop the per-customer load impacts for each technology type. We develop ex-ante per-customer load impact estimates for SCT customers based on results from the ex-post impact analysis. For other technologies, impacts are assumption-based. For EVs, HPWHs, and CEC devices, we assume a specified level of load impact per hour per customer. For batteries, however, we take a more data-driven approach by incorporating information on battery capacity and the distribution of battery sizes within the applicable population.

Specifically, we derate each battery's capacity by 25 percent and assume an even dispatch over a four-hour event (i.e., 25 percent of the available battery capacity is dispatched in each hour).[18] We then estimate customer-level impacts by applying these battery capacity constraints to the estimated reference load to produce an ex-ante impact estimate. Given that ex-ante impacts are presented in delivered loads, the customer-level impacts are not allowed to go below zero.

[18] If a customer has a battery that uses less than 25% of it's derated capacity in an event hour to fully offset their load, it is not assumed that the excess capacity is held in reserve for later event hours, rather the excess capacity is exported.

Table 2.5: Ex-Ante Assumptions by Technology Type

Technology	Assumed Impact[19]	Adjustments
SCT	Observed impacts from PY2025 ex-post are used as the basis for ex-ante impacts.	None.
Battery	During the assumed four-hour event, one-fourth of the battery's total derated capacity is discharged in each hour. Battery capacity is assumed to be discharged evenly across all event hours.	Reference loads are based on loads of all battery customers, utilizing both controls and treatments to boost sample size.
		A total derating of 25% is applied to batteries, consisting of a 5% adjustment to usable capacity and a 20% adjustment to reflect the recommended depth of discharge ("DoD").[20]
		The distribution of battery capacities within the population is applied to the reference load to estimate delivered load impacts.
		Load impacts are capped at the estimated reference load.
EV	0.35 kWh/customer/hour	None.
HPWH	0.05 kWh/customer/hour	None.
CEC	0.05 kWh/customer/hour	None.

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 called in PY2025. Our main findings are summarized in this section in various figures and data tables, while detailed results for each hour, event, sub-LAP, rate-category, or LCA are available in electronic form in Protocol table generators provided along with this report. Ex-post results are confidential as there was only one third party provider for ART in PY2025.

As described in Section 2, all results presented in this section are derived from D-in-D regression analyses of hourly data for ART customers and a control group.

3.1 Overall Load Impacts

This section summarizes overall results for all fourteen ART events called in PY2025. Table 3.1 presents a 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. 16,852 customers were called to the first full event on November 22, 2024. 41,872 customers were called to the final event on October 29th, 2025. Impacts are mostly during May through September as only cooling-based demand response is enabled during PY2025. [redacted]

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[19] SCT is the only technology for which we estimate standard errors. For all other technology types, the standard errors are assumed to be zero since load impacts are assumed instead of estimated.

[20] The assumed 20% DoD is based on the industry guidance from Residential Solar Panel. To provide additional context, a recent academic study published in *Nature Energy* analyzed multi-year data from 21 residential battery systems in Germany. The study observed a wide range of DoD values, with a median of approximately 10% and a mean of approximately 35%, suggesting that the 20% assumption falls within the range of real-world residential battery operation.

[redacted].[21] The large range of per-customer impacts is largely due to differences in temperature as average event-hour temperatures ranged from 71.2 degrees to 90.2 degrees during the summer months and the specific sub-LAPs dispatched. [redacted].[22] The large range of aggregate impacts is due to a combination of differences in temperature, sub-LAPs dispatched, aggregate program enrollment over the course of 2025, and the number of customers called on a specific event.

Table 3.1: Average Event-Hour Load Impacts by Event

Date	Type of Event	Event Hours (p.m.)	Sub-LAPs Dispatched	# Dis-patched	Average Event Hour				
					Reference (kWh/ cust/hr)	Impact (kWh/ cust/hr)	% Impact	Aggregate Impact (MWh/hr)	Avg. Temp (°F)
11/22/24	Test	5 - 6	All	16,852	[redacted]	[redacted]	[redacted]	[redacted]	59.7
12/20/24	Test	5 - 6	All	18,705	[redacted]	[redacted]	[redacted]	[redacted]	50.5
1/23/25	Test	4 - 5	All	18,704	[redacted]	[redacted]	[redacted]	[redacted]	65.0
2/26/25	Test	3 - 4	All	18,694	[redacted]	[redacted] [23]	[redacted]	[redacted]	72.6
3/26/25	Test	6 - 8	All	19,001	[redacted]	[redacted]	[redacted]	[redacted]	60.3
4/20/25	Test	7 - 8	All	20,000	[redacted]	[redacted]	[redacted]	[redacted]	65.0
5/21/25	Test	7 - 8	All	21,212	[redacted]	[redacted]	[redacted]	[redacted]	71.3
6/26/25	Test	6 - 8	All	23,326	[redacted]	[redacted]	[redacted]	[redacted]	73.8
7/11/25	Market Award	4 - 6	PGEB, PGF1, PGKN, PGNB, PGNP, PGP2, PGSB, PGSI, PGST, PGZP	25,067	[redacted]	[redacted]	[redacted]	[redacted]	89.2
7/29/25	Test	4 - 6	PGCC, PGHB, PGFG, PGNC, PGSF	1,750	[redacted]	[redacted]	[redacted]	[redacted]	71.2
8/22/25	Test & Market Award	4 - 6	All	33,474	[redacted]	[redacted]	[redacted]	[redacted]	88.8
9/17/25	Market Award	4 - 6	PGEB, PGF1, PGFG, PGKN, PGNB, PGNP, PGP2, PGSB, PGSI, PGST, PGZP	36,648	[redacted]	[redacted]	[redacted]	[redacted]	90.2
9/23/25	Test	4 - 6	PGHB, PGNC, PGSF, PGCC	1,174	[redacted]	[redacted]	[redacted]	[redacted]	83.7
10/29/25	Test	4 - 6	All	41,872	[redacted]	[redacted]	[redacted]	[redacted]	77.7

Figure 3.2 illustrates the hourly load impacts for the August 22nd event, which was the hottest event in which all sub-LAPs were called at the same time. The blue shaded area of the figure represents the event hours. We observe increase of loads before the event hour, similar to the

21 [redacted]

22 [redacted]

23 [redacted]

“pre-cooling” observed in the Smart Thermostat Control Pilot study, as well as some post-event snapback.

Figure 3.1: Overall Load Impacts for August 22nd Event

[redacted]

3.2 Sub-LAP Load Impacts

Table and Figure 3.2 summarize the sub-LAP level ex-post load impacts for the August 22nd event, for which all sub-LAPs were dispatched. The bars on the figure indicate the magnitude of the average per-customer load impacts (in kWh/customer/hour). 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.

For most sub-LAPs, the August 22nd event had relatively high temperatures during this program year. PGF1 and PGKN have temperatures above 100 degrees. Only PGSF, PGCC and PGHB had temperatures below 75 degrees. These three sub-LAPs have three of the four lowest per-customer impacts during the event [redacted]. This result is not surprising given the low event temperature and therefore limited AC load to curtail. The fourth sub-LAP with low per-customer impacts is PGNB, which had 668 customers and an event temp of 79.9 degrees during the event. [redacted]. Figure 3.2 illustrates that there is variation in the size of per-customer impact across sub-LAPs, a big driver for the difference is the temperature variation during the event hours. [redacted]

Table 3.2: Load Impacts by Sub-LAP for August 22nd Event (4-6 p.m.)

Sub-LAP	# Dispatched	Average Event Hour: Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Agg. Impact (MWh/hr)	Avg. Temp (°F)
PGCC	309	[redacted]				71.3
PGEB	8,494					88.5
PGF1	3,243					104.5
PGFG	720					83.4
PGHB	15					63.0
PGKN	1,182					104.0
PGNB	668					79.9
PGNC	115					96.4
PGNP	2,388					99.0
PGP2	3,527					77.5
PGSB	7,358					81.2
PGSF	695					62.7
PGSI	2,726					99.2
PGST	1,270					97.2
PGZP	764					89.9

Figure 3.2: Load Impacts by Sub-LAP for August 22nd Event (4-6 p.m.)

[redacted]

3.3 Subgroup Load Impacts

This section summarizes how ART load impacts are distributed across subgroups of interest including: CARE/non-CARE customers, rate type, and device manufacture (e.g., NEST Thermostat).

The average ex-post load impacts are summarized for each subgroup in Figure 3.3. The blue 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 scatter plot represents the average temperatures experienced by customers in each subgroup.

Figure 3.3 shows that load impacts are relatively consistent and significant for all subgroups. While Honeywell Devices and customers on Rate E-TOU-B have the highest estimated impacts across device manufacture and rate groups, these groups have low customer counts, so the estimates have higher uncertainty as illustrated by the wider error bands. CARE customers have higher impacts than non-CARE customers with higher average event hour temperature. The largest share of customers belongs to the E-TOU-C rate group, which has lower customer load reduction than customers on E-TOU-D. As shown in Table 3.3, customers on Rate E-TOU-D have higher reference loads and average event hour temperatures. Customers on Rate E1 on average have higher load impacts than customers on a TOU rate. Besides temperature differences, customers on a TOU rate are also subject to DLS, which may already reduce consumption during peak periods. Section 4.3 discusses the combined effect of DLS and event reductions for TOU customers.

Figure 3.3: Load Impacts by Subgroup for August 22nd Event (4-6 p.m.)

[redacted]

Table 3.3 provides the detailed information underlying Figure 3.3, 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. Comparisons by percentage load impacts mostly follow the same patterns as per-customer load impacts. Customers with Honeywell thermostats have the highest percentage load impact, though low customer count makes the estimates less reliable.

Table 3.3: Load Impacts by Subgroup for August 22nd Event (4-6 p.m.)

Subgroup	# Dis-Patched	Average Event Hour				
		Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Agg. Impact (MWh/hr)	Avg. Temp (°F)
All Subgroups	33,474	[redacted]	[redacted]	[redacted]	[redacted]	88.8
CARE	5,252	[redacted]	[redacted]	[redacted]	[redacted]	96.6
Non-CARE	28,222	[redacted]	[redacted]	[redacted]	[redacted]	87.4
Rate E1	7,138	[redacted]	[redacted]	[redacted]	[redacted]	91.7
Rate EELEC	2,378	[redacted]	[redacted]	[redacted]	[redacted]	87.2
Rate EV2A	4,109	[redacted]	[redacted]	[redacted]	[redacted]	84.0
Rate ETOUB	456	[redacted]	[redacted]	[redacted]	[redacted]	91.6
Rate ETOUC	15,181	[redacted]	[redacted]	[redacted]	[redacted]	88.1
Rate ETOUD	4,145	[redacted]	[redacted]	[redacted]	[redacted]	91.3
Rate All TOU	26,269	[redacted]	[redacted]	[redacted]	[redacted]	88.0
Device Ecobee	11,164	[redacted]	[redacted]	[redacted]	[redacted]	91.1
Device Emerson	415	[redacted]	[redacted]	[redacted]	[redacted]	90.5
Device Honeywell	305	[redacted]	[redacted]	[redacted]	[redacted]	89.7
Device Nest	21,590	[redacted]	[redacted]	[redacted]	[redacted]	87.7

4. DAILY LOAD SHIFTING IMPACTS

This section documents the findings from the Daily Load Shifting ("DLS") analysis. [redacted] The primary load impact results include estimates of the aggregate and per-customer load impacts average weekday profiles during peak price hours in which third party providers are required to implement strategies to reduce customer loads. We average the hourly load impacts across full hours during which the largest share of TOU customers experiences peak prices (5-8 p.m.). Our main findings are summarized in this section in various figures and data tables, while detailed results for each hour, sub-LAP, rate-category, device type, or LCA are available in electronic form in Protocol table generators provided along with this report. Results in this section are confidential as there was only one third party provider in PY2025.

As described in Section 2, all results presented in this section are derived from regression analyses of hourly data for ART customers and a control group.

4.1 Overall Load Impacts

This section summarizes overall results for DLS impacts by month. Results are reported based on average weekday and system worst day impacts. In later sections, we focus attention on how these load impacts are distributed across subgroups of interest, including for customers on different rate types.

The DLS impacts are summarized for peak-period hours in Table 4.1 during all months of PY2025. We summarize average weekday impacts from 5-8 p.m. as that is when most customers on TOU rates are at peak prices. Aggregate impacts increase significantly from November 2024 through September 2025 due to increasing temperatures and program enrollments. Impacts decrease in October 2025 due to a decrease in temperatures at the end of the summer. Enrollments ranged from 14,414 customers in November 2024 to 32,810 customers in October 2025.

[redacted]. August and September, which were the hottest months, had the highest per customer impacts [redacted]

Table 4.1: Average Peak Period Load Shift Impacts by Month

Day Type	Peak Period Hours (p.m.)	# TOU Customers	Average Event Hour				
			Reference (kWh/ cust/hr)	Impact (kWh/ cust/hr)	% Impact	Aggregate Impact (MWh/hr)	Avg. Temp (°F)
November	5-8	14,414	[redacted]	[redacted]	[redacted]	[redacted]	56.6
December	5-8	15,794	[redacted]	[redacted]	[redacted]	[redacted]	53.2
January	5-8	15,863	[redacted]	[redacted]	[redacted]	[redacted]	53.2
February	5-8	15,843	[redacted]	[redacted]	[redacted]	[redacted]	56.6
March	5-8	16,494	[redacted]	[redacted]	[redacted]	[redacted]	57.9
April	5-8	17,244	[redacted]	[redacted]	[redacted]	[redacted]	64.1
May	5-8	17,926	[redacted]	[redacted]	[redacted]	[redacted]	71.5
June	5-8	19,699	[redacted]	[redacted]	[redacted]	[redacted]	73.1
July	5-8	23,658	[redacted]	[redacted]	[redacted]	[redacted]	74.3
August	5-8	27,389	[redacted]	[redacted]	[redacted]	[redacted]	78.6
September	5-8	29,689	[redacted]	[redacted]	[redacted]	[redacted]	76.7
October	5-8	32,810	[redacted]	[redacted]	[redacted]	[redacted]	66.6

Figure 4.1 illustrates the data laid out in table 4.1. The yellow line indicates the temperature for each month. Summer impacts (May-October) are significantly higher than winter impacts. This is almost entirely due to weather effects as currently the only technology that is impacted by DLS strategies is AC load which is highest during hot days and nearly nonexistent in the winter.

Figure 4.1: Per-Customer Peak Period Load Shift Impacts by Month

[redacted]

Figure 4.2 illustrates the DLS impacts for the PY2025 August average weekday. Light blue shaded hours are when all rates are classified as peak periods. There are reductions in loads during peak hours and increase in loads during early and late hours of the day.

Figure 4.2: Overall Load Shift Impacts for August Average Weekday

[redacted]

4.2 Subgroup Load Impacts

This section summarizes how DLS impacts are distributed across subgroups of interest including rate type and device manufacturer (e.g., NEST Thermostat) for the average August weekday in PY2025.

The average DLS impacts are summarized for each subgroup in Figure 4.3. The blue 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 scatter plot represents the average temperatures experienced by customers in each subgroup.

Figure 4.3 shows that there are statistically significant DLS impacts for the majority of the subgroups. [redacted].[24] Across device manufacturers, the highest DLS impacts come from Ecobee, and the lowest DLS impacts come from Honeywell and Nest. Rate E-TOU-D had the highest statistically significant DLS impacts. Rate E-TOU-C had the most customers and therefore the largest aggregate DLS impacts.

Figure 4.3: Average Peak Period Load Shift Impacts by Subgroup for Average August Weekday[25]

[redacted]

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[24] [redacted]

[25] For the purpose of this report, we define the peak period as HE 18–20, since all rates are at their peak prices during this time. Figure 4.3 and Table 4.2 reflect the load impacts during HE 18-20 for each subgroup. However, some rates have peak periods that cover a larger span of hours.

Table 4.2 provides the detailed information underlying Figure 4.3, 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. Comparisons by percentage load impacts mostly follow the same patterns as per-customer load impacts. Customers under EVA rate have the highest percentage load impact, though low customer count makes the estimates less reliable.

Table 4.2: Average Peak Period Load Shift Impacts by Subgroup for Average August Weekday

Subgroup	# Dis-Patched	Average Load Impacts				
		Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Agg. Impact (MWh/hr)	Avg. Temp (°F)
All DLS Customers	27,389	[redacted]				78.6
Ecobee	8,567	[redacted]				80.8
Emerson	300	[redacted]				79.9
Honeywell	228	[redacted]				79.4
Nest	18,008	[redacted]				77.7
E-TOU-B	477	[redacted]				81.7
E-TOU-C	15,799	[redacted]				78.7
E-TOU-D	4,274	[redacted]				81.5
EV2-A	4,277	[redacted]				74.9
EVA	69	[redacted]				75.0
E-ELEC	2,493	[redacted]				79.0

4.3 Combining Ex-post and DLS Impacts

As discussed in Section 3.3, load impacts for E-TOU-C, which is the largest TOU group in the ART program (approximately 45% of total enrollment), has lower event load impacts than customers on a Rate E1. Since TOU customers are subject to DLS, both event day and non-event day loads are expected to be lower during peak hours, resulting in lower estimated event load impacts. To help understand the impacts of DLS and event day together we estimated the incremental load impacts from DLS strategies on the event days. We use weather patterns and observed usage, along with the results of the DLS and event-based models to create figures that layer impacts together to show total impacts for customers who are enrolled in ART and on TOU rates.

Figure 4.4 shows the impacts of the event and DLS on August 22nd on a per-customer basis. The figure illustrates the customers observed loads (in blue) and the reference loads assuming only an event was called (in yellow) and the reference loads in the presence of an event and DLS strategies combined (in grey). The combination of impacts of DLS and the event are greater than the impacts of the event by itself for TOU customers.

Figure 4.4: Per Customer Reference Loads with DLS and Event Impacts

[redacted]

Figure 4.5 illustrates the total load impacts in MWh/hour of the event and DLS strategies on August 22nd. [redacted] The DLS impacts reflect the program's Daily Load Shifting, which operates independently of event dispatches. While these load shifts can contribute incremental reductions during event hours, the program only claims event-specific impacts for event-day performance.

Figure 4.5: Aggregate Combined Load Impacts from Event and DLS

[redacted]

5. EX-ANTE LOAD IMPACTS

This section provides the ART ex-ante load impact forecast of events for the period from 2026 to 2036. 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. Average load impacts are presented for the four-hour event dispatch window from 4-8 p.m. during June through October and 5-9 p.m. in all other months. 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. For PG&E, the first 4 hours of the RA window are reported for ex-ante.[26] We present yearly, monthly, technology, and geographical variations of the ex-ante forecast as well as the hourly reference loads and load impacts for an August system worst day in 2026.

Detailed results for each hour, weather scenario, month, forecast year, and enrollment segment (e.g. by technology type) are available in electronic form in Protocol table generators provided along with this report.

5.1 Total Ex-Ante Impacts by Year

This section illustrates how impacts change from 2026-2036. Impacts increase substantively over the forecast period. The increase in aggregated impacts is largely driven by increasing enrollments, depicted in Figure 5.1.

Figure 5.1 shows PG&E's enrollment forecast by technology type from 2026 to 2036 (August). Eligible technologies include SCTs, HPWHs, EV chargers, batteries, and the CEC Flex App.

PG&E's enrollment forecast is based on the following assumptions:

- Projected strong growth for 2026 – 2029 in CEC Flex App customers with growth starting to plateau after. Strong percentage growth in HPWH and EV customers and moderate percentage growth in SCT and Battery customers.

- Year-over-year growth is projected to be approximately 21,000 customers. With 86,733 customers by the end of 2026 and 293,021 by the end of 2036.

- The projected composition of customers is 84% SCT, 2% Battery, 8% CEC, 5% EV, and 1% HPWH by the end of 2026 and 69% SCT, 3% Battery, 8% CEC, 19% EV, and 2% HPWH by the end of 2036.

[26] LIP Filing Guide 5.1, p. 11.

Figure 5.1: Forecast Enrollment by Technology Type, 2026-2036

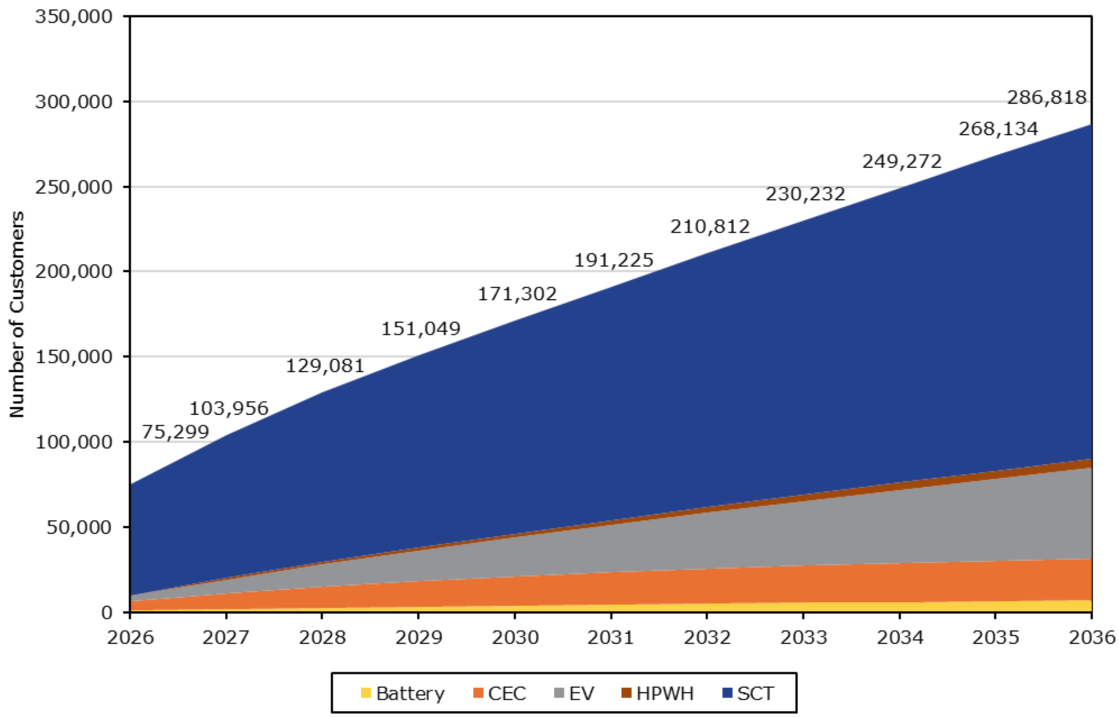


Table 5.1 summarizes per-customer and aggregate load impacts over the 11-year forecast window. The trend of increasing aggregate load impacts is driven by increased enrollments over the forecast window. Per-customer loads impacts are expected to decrease slightly from 0.45 kWh/customer/hour in 2026 to 0.42 kWh/customer/hour in 2029 and there is no material change in load impacts until 2036. The decrease in per-customer load impacts is driven by enrollment shares increasing for technologies with smaller assumed impacts than SCT, such as CEC and HPWH. Aggregate load impacts increase by between 8 and 11 MWh per year, going from 33.67 MWh/hour in 2026 to 119.97 MWh/hour in 2036. The per-customer reference load remains largely consistent throughout the forecast since we assume that per-customer reference loads are the same across all technologies except batteries. For battery customers, we estimate a separate reference load; however, given the relatively small enrollment share of batteries, the resulting difference is not material at the hundredth decimal place in kWh.

Table 5.1: Load Impacts over RA Window,
PG&E 1-in-2 August System Worst Day, 2026-2036

Year	# Enrolled	Per Customer		Aggregate	
		Event Load Impact (kWh/cust/hr)	Event Ref. Load (kWh/cust/hr)	Event Load Impact (MWh/hr)	Event Ref. Load (MWh/hr)
2026	75,299	0.45	1.89	33.67	142.66
2027	103,956	0.43	1.89	44.99	196.98
2028	129,081	0.43	1.89	55.00	244.57
2029	151,049	0.42	1.89	63.72	286.07
2030	171,302	0.42	1.89	71.81	324.39
2031	191,225	0.42	1.89	79.88	362.02
2032	210,812	0.42	1.89	87.91	399.02
2033	230,232	0.42	1.89	95.94	435.70
2034	249,272	0.42	1.89	103.97	471.63
2035	268,134	0.42	1.89	111.97	507.21
2036	286,818	0.42	1.89	119.97	542.48

Figure 5.2 illustrates the changes in aggregate load impacts during the Resource Adequacy (RA) window (4-9 p.m.) over the forecast period by comparing load impacts for all ART customers by technology type for the PG&E 1-in-2 scenario for an August system worst day. Aggregate load impacts increase across all technology types from 2026 to 2036. The majority of impacts are from customers with smart thermostats but there are also significant increases in load impacts from electric vehicle owners.

Figure 5.2: Aggregate Load Impacts over RA Window by Technology Type,
PG&E 1-in-2 August System Worst Day, 2026-2036

[redacted]

5.2 Ex-Ante Impacts Across Months

In this section we compare impacts across months during 2026. Differences in monthly impacts are driven by changes in enrollment counts, as well as changing per-customer impacts due to differences in AC usage resulting from changes in temperature. As described in Section 2.3, we make assumptions about impacts for other technology types. Impacts for all non-battery technologies are assumed to be constant across months. In contrast, battery impacts vary depending on the estimated reference loads and how that interacts with the assumptions outlined in Section 2.3.[27]

Table 5.2 summarizes the average per-customer load impacts and aggregate impacts by month during 2026. The per-customer load impacts are the average load impacts for the first four event hours in the Resource Adequacy (RA) window. The RA window is from 4-9 p.m. except for November through May where the RA window is HE 5-10 p.m.[28] This later RA window hours leads to lower average RA window load impacts due to cooler temperatures during later hours, which decreases the load impact potential during ART events. Per-customer load impacts peak in June, which has the highest temperatures. Aggregate impacts peak in September, which has a combination of high temperatures and also higher total enrollment than the rest of the summer months.

Table 5.2: Load Impacts over RA Window for PG&E 1-in-2 Monthly System Worst Day Scenario (2026)

Month	# Enrolled	Avg Temp (°F)	Per Customer		Aggregate	
			Event Load Impact (kWh/hr)	Event Ref. Load (kWh/hr)	Event Load Impact (MWh/hr)	Event Ref. Load (MWh/hr)
January	52,485	48.7	0.02	1.15	1.23	60.39
February	56,984	49.6	0.03	1.10	1.49	62.91
March	60,337	70.6	0.05	0.90	3.05	54.14
April	63,462	82.9	0.16	0.99	10.29	62.95
May	66,504	85.3	0.36	1.62	24.10	107.60
June	69,440	95.4	0.51	2.00	35.50	139.20
July	72,404	93.4	0.48	1.97	34.79	142.51
August	75,299	91.7	0.45	1.89	33.67	142.66
September	78,209	93.3	0.47	1.88	36.89	146.81
October	81,049	82.4	0.18	0.95	14.66	76.79
November	83,917	60.8	0.04	0.88	3.19	74.18
December	86,733	48.1	0.04	1.18	3.79	102.57

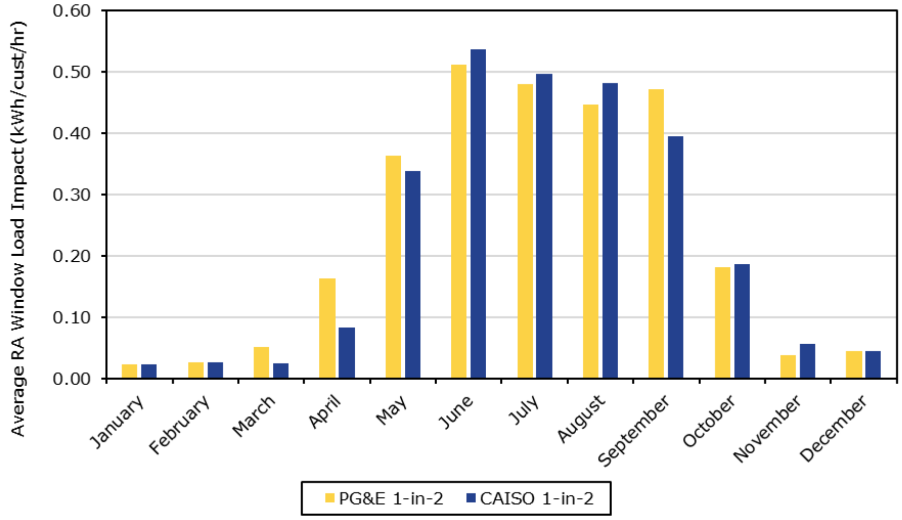
Figure 5.3 illustrates the seasonality and variation by weather scenario. The highest monthly average impact occurs in June for both the PG&E 1-in-2 and CAISO 1-in-2 scenario. In June, the CAISO 1-in-2 scenario has slightly higher load impacts (0.54 kwh/customer/hour) than the PG&E 1-in-2 scenario (0.51 kwh/customer/hour) due to higher temperatures. The second highest

[27] For instance, some battery customers have sufficient derated capacity to fully cover the estimated reference load during event hours, implying that increases in the reference load translate directly into higher estimated battery impacts.

[28] We calculate impacts using the first four hours of the RA Window which means results are presented for 4-8 p.m. for all months except November through May where results are presented from 5-9 p.m.

month is July with 0.50 and 0.48 kwh/customer/hour impacts for the CAISO and PG&E 1-in-2 and scenarios respectively.

Figure 5.3: Average per Customer Load Impacts over RA Window in 2026 by Month and Weather Scenario



5.3 Other Ex-Ante Results

Figure 5.4 illustrates the aggregate reference loads, observed loads, and load impacts for all ART customers on an August system worst day in 2026 for the PG&E 1-in-2 weather scenario. Ex-ante load impacts peak during the first event hour. The average first four-hour August RA window load impact is 33.7 MWh/hour, or 23.6 percent of the average RA window reference loads.

Figure 5.4: Aggregate Hourly Loads and Load Impacts, PG&E 1-in-2 August System Worst Day in 2026

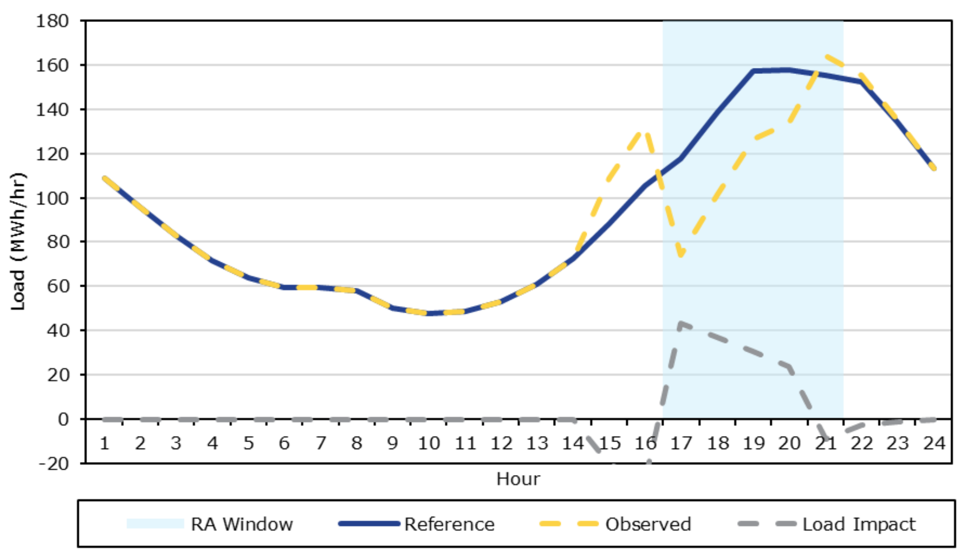
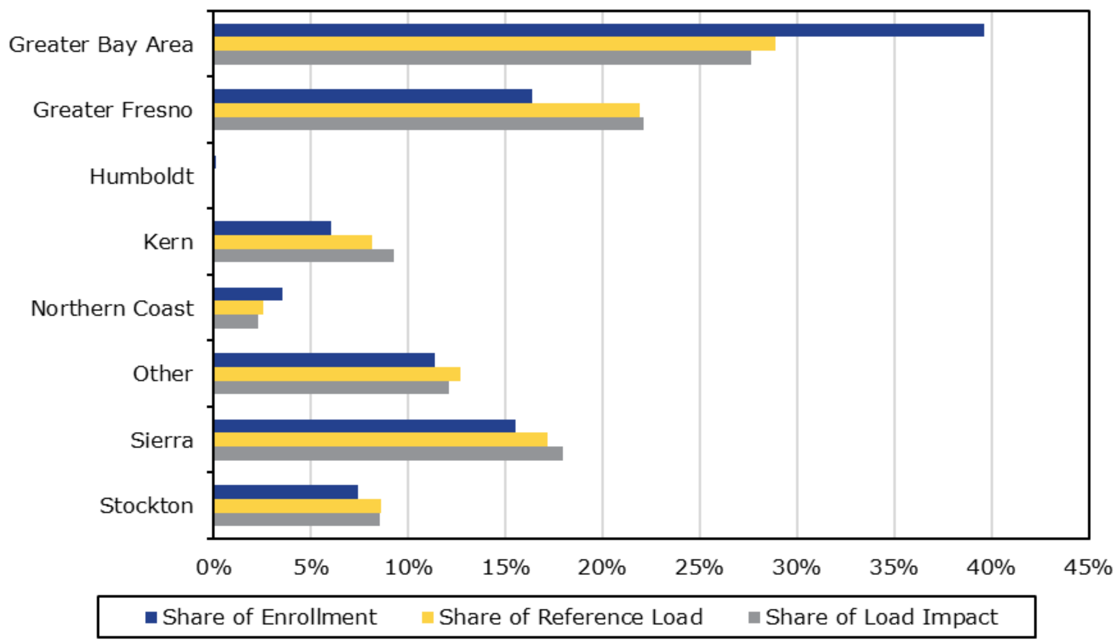


Figure 5.5 compares the LCA shares of average RA window load impacts, reference loads, and enrollments on an August system worst day for the PG&E 1-in-2 scenario in 2026. The load impacts, enrollments and reference loads are all largely concentrated in the Greater Bay Area LCA which is consistent with where the large majority of enrolled customers live. Greater Bay Area has a smaller share of load impacts than its share of enrollment and reference loads. This is largely explained by the Greater Bay area having colder temperatures, on average, than LCA's such as Greater Fresno or Kern which have a disproportionately large share of the load impact.

Figure 5.5: RA Window Load Impacts by LCA in 2026, PG&E 1-in-2 August System Worst Day



6. LOAD IMPACT RECONCILIATIONS

To illustrate the relationship between ex-post and ex-ante results this section compares several sets of estimated load impacts for ART events including;

- 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.

6.1 Current Ex-Post vs. Previous Ex-Post

In this section, we compare the previous ex-post findings to the ex-post findings of our current study. In PY2024 there was only one ex-post event in October which restricts the comparisons we can make. Below we present two comparisons, the first between the October 2024 event and the October 2025 event. The second is between the October 2024 event and the August 2025 event.

Table 6.1 compares the October 25, 2024, ex-post event to the October 29, 2025, ex-post event. In PY2025, there were significantly more customers enrolled so aggregate event impacts are much larger. Per customer impacts are slightly higher due in part to slightly higher average temperatures during the October 2025 event.

Table 6.1: Current Ex-Post (October) vs. Previous Ex-Post (October) Load Impacts

Level	Outcome	PY2024 Ex-Post (October 25th event)	PY2025 Ex-Post (October 29th event)
Total	Enrollments	[redacted]	[redacted]
	Reference (MWh/hr)	[redacted]	[redacted]
	Load Impact (MWh/hr)	[redacted]	[redacted]
	Avg. Evt Hour Temp (°F)	[redacted]	[redacted]
	Avg. Daily Temp (°F)	[redacted]	[redacted]
	% Load Impact	[redacted]	[redacted]
Per Participant	Reference (kWh/cust/hr)	[redacted]	[redacted]
	Load Impact (kWh/cust/hr)	[redacted]	[redacted]

Table 6.2 compares the only event in PY2024, October 25th, to the August 22nd event in PY2025. Both per customer and aggregate impacts are larger due to hotter temperatures and larger program enrollments, respectively.

Table 6.2: Current Ex-Post (August) vs. Previous Ex-Post (October) Load Impacts

Level	Outcome	PY2024 Ex-Post (October 25th event)	PY2025 Ex-Post (August 22nd event)
Total	Enrollments	[redacted]	[redacted]
	Reference (MWh/hr)	[redacted]	[redacted]
	Load Impact (MWh/hr)	[redacted]	[redacted]
	Avg. Evt Hour Temp (°F)	[redacted]	[redacted]
	Avg. Daily Temp (°F)	[redacted]	[redacted]
	% Load Impact	[redacted]	[redacted]
Per Participant	Reference (kWh/cust/hr)	[redacted]	[redacted]
	Load Impact (kWh/cust/hr)	[redacted]	[redacted]

6.2 Current Ex-Ante vs. Previous 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 6.3 compares the ex-ante forecast for August 2026 from the PY2024 study to the ex-ante forecast for August 2026 from the PY2025 study. The PY2025 ex-ante forecast contains approximately 12,000 less customers which results in a smaller aggregate impact (40.0 MWh/hour in PY2024 compared to 33.7 MWh/hour in PY2025). However, per participant impacts are roughly the same in both years (0.46 kwh/cust/hr in PY 2024 compared to 0.45 kwh/cust/hr in PY2025). Percentage load impacts have decreased in the current ex-ante forecast even with similar level load impacts due to the increase in the estimated reference load.

Table 6.3: Current Ex-Ante vs. Previous Ex-Ante Load Impacts

Level	Outcome	PY2024 Ex-Ante (August 2026 Event)	PY2025 Ex-Ante (August 2026 Event)
Total	Enrollments	87,187	75,299
	Reference (MWh/hr)	142.3	142.7
	Load Impact (MWh/hr)	40.0	33.7
	Avg. Evt Hour Temp (°F)	90.5	91.7
	Avg. Daily Temp (°F)	78.3	79.1
	% Load Impact	28.1%	23.6%
Per Participant	Reference (kWh/cust/hr)	1.63	1.89
	Load Impact (kWh/cust/hr)	0.46	0.45

6.3 Current Ex-Post vs. Previous Ex-Ante

In this section we compare the ex-ante forecast from the PY 2024 study to the ex-post results from the current study. We use the PY 2024 ex-ante forecast for August compared to the event that occurred on August 22, 2025. To provide a more direct comparison between ex-ante and ex-post, we use the first two hours of the ex-ante event window which corresponds directly to the ex-post event hours.

Table 6.4 compares the previous year's ex-ante forecast with the current ex-post forecast. The previous ex-ante forecast assumed 15,000 more customers leading to higher aggregate reference loads and load impacts. The ex-post event on August 22nd had higher per-customer reference loads [redacted]. Although the ex-post event on August 22nd took place under lower temperature conditions than those assumed in the ex-ante PY2024 forecast, customers still had substantial load reduction [redacted]. This demonstrates that program performance remained strong even with milder temperature.

Table 6.4: Current Ex-Post vs. Previous Ex-Ante Load Impacts

Level	Outcome	PY2024 Ex-Ante (August 2025 Event)	PY2025 Ex-Post (August 22nd Event)
Total	Enrollments	48,597	[redacted]
	Reference (MWh/hr)	71.5	
	Load Impact (MWh/hr)	28.1	[redacted]
	Avg. Evt Hour Temp (°F)	93.3	
	Avg. Daily Temp (°F)	78.3	
	% Load Impact	39.3%	
Per Participant	Reference (kWh/cust/hr)	1.47	
	Load Impact (kWh/cust/hr)	0.58	

6.4 Current Ex-Post vs. Current Ex-Ante

In this section, we compare the program level ex-post findings to the ex-ante forecast for 2026 contained in the current study. To provide a more direct comparison between ex-ante and ex-post, the ex-ante results that are presented are the first two hours of the event window which correspond directly to the ex-post event hours.

Table 6.5 compares the ex-post load impacts from the August 22nd event in PY2025 to the ex-ante load impact forecast for an August system worst day with PG&E 1-in-2 weather conditions in 2026. Aggregate reference loads and load impacts are expected to drastically increase due to a forecasted enrollment increase of over 41,000. [redacted]

Table 6.5: Current Ex-Post vs. Ex-Ante Load Impacts

Level	Outcome	PY2025 Ex-Post (August 22nd Event)	PY2025 Ex-Ante (August 2026 Event)
Total	Enrollments	[redacted]	75,299
	Reference (MWh/hr)		128.0
	Load Impact (MWh/hr)		40.2
	Avg. Evt Hour Temp (°F)		94.4
	Avg. Daily Temp (°F)		79.1
	% Load Impact		31.4%
Per Participant	Reference (kWh/cust/hr)		1.70
	Load Impact (kWh/cust/hr)		0.53

Table 6.6 documents the various potential reasons for differences between the ex-post and ex-ante load impacts. [redacted]. The main reason for higher aggregate load impacts is

increased enrollment both in terms of smart thermostat customers and in other technology types.

Table 6.6: Comparison of Ex-Post and Ex-Ante Factors

Factor	Ex-Post	Ex-Ante	Expected Impact
Weather	Average event-hour temperature of 88.8°F and average daily temperature of 75.8°F.	Average event-hour temperature of 94.4°F and average daily temperature of 79.1°F.	Higher daily temperature and event hour temperature should lead to higher load impacts for battery and SCT customers with no change for the other technologies.
Technology Distribution	All deployed devices are smart thermostats.	About 87% of devices are smart thermostats. The rest of the program is made up of battery storage, EV chargers, etc.	As the share of enrolled technologies with a smaller assumed impact grows, per customer load impacts will shrink while aggregate impacts will grow.
Enrollment	33,474	75,299	Significantly higher ex-ante enrollment leads to significantly higher aggregate impacts.
Methodology	Difference-in-Differences with matched control group.	Smart Thermostat results are derived from PY2025 ex-post results. Load impacts of other technologies are derived from impact assumptions.	As the enrollment share of technologies changes, per-customer impacts adjust according to reflect the evolving technology mix.

6. RECOMMENDATIONS

Going forward, as customers with new technology types are recruited to the program, we recommend calling events across sub-LAPs and varying weather conditions as well as event length to help understand how performance varies by location and weather for each technology type. This information will help us better forecast future performance for all technologies and can also provide insights on where future customer recruitment or retention is the most cost-effective. We also recommend scheduling shoulder-month events at different points within the month to assess how behavioral responses evolve from early to late month conditions for AC usage. This will inform potential interactions between the time of month and temperature. For example, AC usage may be more prevalent in early October than late October as cooler conditions may lead customers to turn off their AC and not use it again during brief warm periods. By dispatching events at different points throughout the month, we can more accurately identify these shifting patterns.

7. APPENDICES

The following Appendices accompany this report. Appendices A and B present information about the match quality in our ex-post analysis. Appendices C and D include ex-post and ex-ante Excel-based table generators:

Appendix C Ex-post Load Impact Tables:
- 8a. PGE_2025_ART_Ex_Post_CONFIDENTIAL.xlsx

Appendix D Ex-ante Load Impact Tables:
- 8b. PGE_2025_ART_Ex_Ante_CONFIDENTIAL.xlsx
- 8b. PGE_2025_ART_Ex_Ante_PUBLIC.xlsx

Appendix A: Ex-Post Matching Results

Below we present summaries of our control group matching process for the ex-post event. Our validity assessment focuses on comparisons of treatment and control-group loads for selected event-like non-event days. We also report statistics such as the mean absolute percentage error (MAPE) and mean percent error (MPE), which provide measures of accuracy and bias in the matches, respectively.[29]

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. We evaluate match quality based on the 24-hour load profiles that we use in matching, which are days with similar temperatures as the event day.

Table A.1: Match Quality Statistics

Comparison Days	MPE	MAPE	MPE RA Window	MAPE RA Window
Matching Days Summer	4.9%	5.0%	5.1%	5.2%
Matching Days Winter	2.0%	2.6%	1.5%	2.0%

Figure A.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. The dashed line represents the average usage of treatment customers, and the solid line represents the average usage of the matched control customers. The average load profiles are nearly identical between treatment and control customers around the period where events are typically called (4-6 p.m.).

[29] 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 on non-event days.

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

[redacted]

For our event-based analysis we match customers by sub-LAP. Tables A.2 and A.3 present match quality statistics for all LCAs. All MPE and MAPE values are less than 10% except for PGHB and PGNC which each have less than 150 customers.

Table A.2: MPE and MAPE on Matching Days Summer

Comparison Days	MPE	MAPE	MPE RA Window	MAPE RA Window	Number of Customers
PGCC	-1.2%	3.8%	2.2%	2.6%	340
PGEB	4.2%	4.2%	4.6%	4.6%	10,494
PGF1	6.3%	6.3%	5.4%	5.4%	3,839
PGFG	1.1%	2.3%	3.0%	3.0%	870
PGHB	22.1%	42.6%	-9.3%	23.2%	24
PGKN	6.4%	6.4%	5.1%	5.1%	1,344
PGNB	5.3%	5.9%	8.5%	8.5%	674
PGNC	13.2%	13.2%	9.6%	9.6%	149
PGNP	6.0%	6.0%	6.0%	6.0%	2,897
PGP2	8.0%	8.0%	9.2%	9.2%	4,240
PGSB	3.2%	3.2%	4.5%	4.5%	8,702
PGSF	4.6%	4.6%	3.9%	3.9%	727
PGSI	6.3%	6.3%	5.4%	5.4%	3,242
PGST	3.6%	3.7%	0.4%	0.6%	1,521
PGZP	3.9%	4.7%	3.9%	3.9%	919

Table A.3: MPE and MAPE on Matching Days Winter

Comparison Days	MPE	MAPE	MPE RA Window	MAPE RA Window	Number of Customers
PGCC	1.5%	4.2%	2.2%	2.7%	347
PGEB	2.6%	2.6%	2.4%	2.4%	10,951
PGF1	5.9%	5.9%	3.8%	3.8%	4,012
PGFG	2.7%	2.9%	5.0%	5.0%	934
PGHB	33.5%	48.1%	25.7%	25.7%	11
PGKN	-0.1%	2.0%	-0.9%	1.1%	1,408
PGNB	0.9%	2.8%	-0.2%	1.4%	726
PGNC	0.9%	4.9%	5.3%	5.3%	152
PGNP	3.7%	3.7%	1.9%	1.9%	3,010
PGP2	2.2%	2.2%	1.8%	1.8%	4,391
PGSB	0.6%	1.2%	0.2%	0.4%	9,074
PGSF	-3.4%	3.8%	-1.9%	2.4%	731
PGSI	1.5%	2.0%	2.6%	2.6%	3,433
PGST	-0.7%	1.7%	-0.7%	1.1%	1,584
PGZP	1.9%	2.6%	3.1%	3.1%	959

Appendix B: Daily Load Shifting Matching Results

In this section, we present summaries of our control group matching process for our analysis of DLS strategies. Our validity assessment focuses on comparisons of treatment and control-group average usage and solar and storage sizes.

Table A.4 provides the average kW consumption and average solar installation size for TOU customers enrolled in ART and their matched counterparts. As described in Section 2 we are attempting to identify the effect of DLS strategies on load shape, therefore we cannot use load profile as a matching criterion. We instead match on average daily net consumption[30] by season and the size of customers' solar and battery installations (for NEM customers) along with weather profiles. We evaluate match quality by comparing the average net consumption, battery storage size and solar size for ART and control customers.

[30] Measured as delivered kWh – received kWh.

Table A.4: Match Quality Statistics

NEM	Rate Category	Treatment				Control			
		# Cust	Avg. Daily Consumption (kWh/cust/day)	Solar Size (kWh)	Battery Size	# Cust	Avg. Daily Consumption (kWh/cust/day)	Solar Size (kWh)	Battery Size
Summer	E-TOU-B	548	[redacted]	[redacted]	[redacted]	830	[redacted]	[redacted]	[redacted]
	E-TOU-C	17740	[redacted]	[redacted]	[redacted]	24736	[redacted]	[redacted]	[redacted]
	E-TOU-D	4761	[redacted]	[redacted]	[redacted]	6972	[redacted]	[redacted]	[redacted]
	E-ELEC	1622	[redacted]	[redacted]	[redacted]	2254	[redacted]	[redacted]	[redacted]
	EV2A	4196	[redacted]	[redacted]	[redacted]	5924	[redacted]	[redacted]	[redacted]
	EVA	73	[redacted]	[redacted]	[redacted]	92	[redacted]	[redacted]	[redacted]
Winter	E-TOU-B	548	[redacted]	[redacted]	[redacted]	836	[redacted]	[redacted]	[redacted]
	E-TOU-C	17740	[redacted]	[redacted]	[redacted]	23797	[redacted]	[redacted]	[redacted]
	E-TOU-D	4761	[redacted]	[redacted]	[redacted]	6744	[redacted]	[redacted]	[redacted]
	E-ELEC	1622	[redacted]	[redacted]	[redacted]	2088	[redacted]	[redacted]	[redacted]
	EV2A	2600	[redacted]	[redacted]	[redacted]	952	[redacted]	[redacted]	[redacted]
	EVA	73	[redacted]	[redacted]	[redacted]	104	[redacted]	[redacted]	[redacted]