



2024 Load Impact Evaluation for Pacific Gas & Electric Company's Automated Response Technology Program

CALMAC Study ID – PGE0509

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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's) Automated Response Technology (ART) program for 2024. The evaluation produces estimates of the ex-post load impacts for each hour of the single event dispatched in 2024, 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 2025 through 2035. 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 (DERs). Customers with smart technologies can enroll through a PG&E-contracted Provider.

ART events will be based on the CAISO market award dispatch or PG&E system emergencies or near-emergencies for distribution service. Total demand response event hours can be up to six 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 resources that did not receive a market award in the given month. ART is available year-round for all hours and seven days a week. By the end of the current program year only one test event was called on October 25, 2024, when all enrolled ART customers were dispatched. All enrolled customers consisted of smart thermostat technologies.¹

If a customer is on a time-varying rate, the Provider must implement a Daily Load-Shifting (DLS) strategy during the hours with time-varying rates using the automated technology. 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. Regardless of whether the customers are in DLS, all customers are included in DR events.

The primary goals of the evaluation include:

1. Estimate ex-post load impacts for the 2024 program year, 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:

¹ Additionally, all enrolled customers in PY2024 were previously enrolled in the Smart Thermostat Control Pilot program.

- 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 2025 to 2035 by sub-LAP and LCA 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., LCA 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 PY2024 all ex-post results are confidential as there was only one third party provider in ART.

Table ES1 summarizes the ex-post load impact estimates (in kWh/customer/hour) for the single event in PY2024². The single event was called as a test event and took place on October 25, 2024, between 4-5 p.m.³ 12,138 customers were dispatched which was all of the enrolled customers at that time. [REDACTED]

[REDACTED] The average temperature during the event was 76.6 degrees Fahrenheit. As all ART customers at that time had smart thermostat technologies, the mild event temperature explains the relatively low impacts.

² PY2024 is defined as September 2023 thru October 2024.

³ The time in the report refers to the prevailing time.

Table ES1: Average Event-Hour Load Impacts by Event

Date	Type of Event	Event Hours (p.m.)	Groups Dispatched	# Dis-patched	Average Event Hour				
					Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Aggregate Impact (MWh/hr)	Avg. Temp (°F)
10/25	Test	4:00-5:00	All Groups Dispatched	12,138					76.6

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 and NEM status) as well as solar panel size.

Table ES2 summarizes the average DLS impacts during the month of October, which is the first and only month in PY2024 that third party providers were required to implement DLS strategies. We summarize average weekday impacts from 4-9 p.m. as that is when most customers on TOU rates are at peak price. There were 13,775 customers enrolled in ART who were on a TOU rate in October.

Table ES2: Average DLS Load Impacts

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)
October Average Weekday	4:00 – 9:00	13,775					71.7
October System Worst Day	4:00 – 9:00	13,775					90.5

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 2025 to 2035 for ART by plotting the average aggregate load impacts for the resource adequacy (RA) window over time by technology type.⁴ 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 type from 2025 to 2035. The trend of increasing aggregate load impacts is driven by both increased enrollments over the forecast window and increased per-customer load impacts. The change in the technological distribution of enrolled customers drives the increase of per-customer load impacts. There is no change in per-customer reference loads as we assume reference loads of all technology type are the same.

⁴ 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.

Figure ES1: Aggregate Load Impacts over RA Window for PG&E 1-in-2 August System Worst Day (2025-2035)

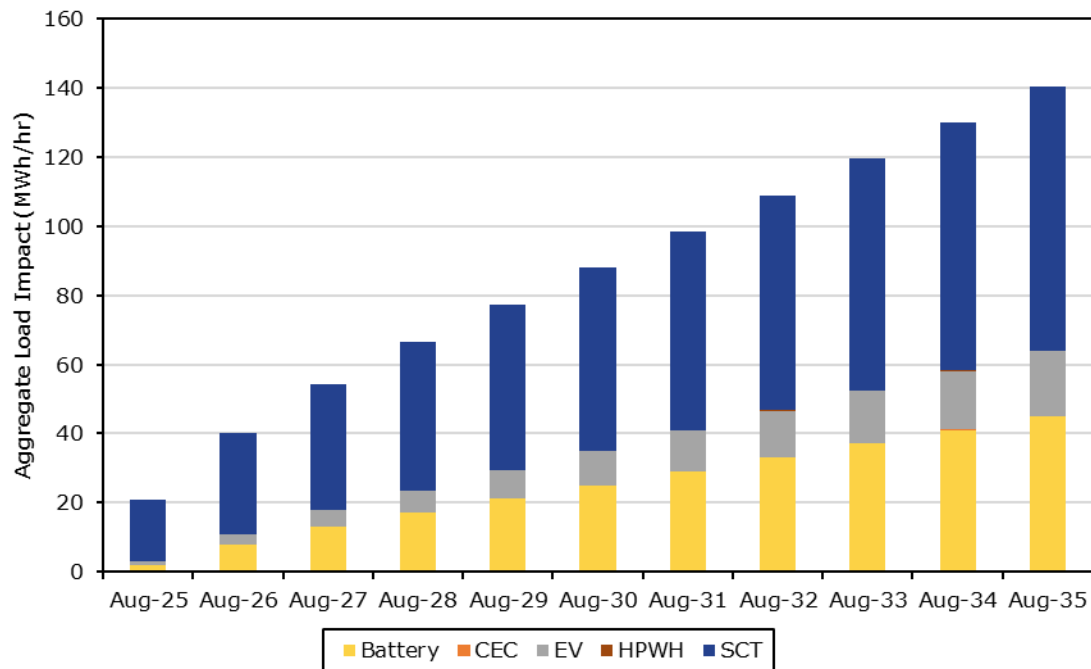


Table ES3: Load Impacts over RA Window for PG&E 1-in-2 August System Worst Day (2025-2035)

Year	# Enrolled	Per-Customer		Aggregate	
		Event Load Impact (kWh/cust/hr)	Event Ref. Load (kWh/cust/hr)	Event Load Impact (MWh/hour)	Event Ref. Load (MWh/hour)
2025	48,597	0.42	1.63	20.64	79.33
2026	87,187	0.46	1.63	40.01	142.29
2027	114,719	0.47	1.63	54.27	187.24
2028	138,870	0.48	1.63	66.37	226.66
2029	160,313	0.48	1.63	77.40	261.63
2030	180,504	0.49	1.63	87.94	294.60
2031	200,726	0.49	1.63	98.50	327.62
2032	220,855	0.49	1.63	109.00	360.45
2033	241,058	0.50	1.63	119.55	393.44
2034	261,211	0.50	1.63	130.07	426.33
2035	281,329	0.50	1.63	140.57	459.15

ES.5 Key Findings and Recommendations

We find small impacts from the single test event in PY2024 as the temperatures were low. DLS strategy produced statistically significant load reductions during peak period for customers on TOU rates. Our ex-ante forecast shows significant growth over the forecast window from 2025-2035 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 to help understand how performance varies by location and weather for each technology type.

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's) Automated Response Technology (ART) program for 2024. The evaluation produces estimates of the ex-post load impacts for each hour of the single event dispatched in 2024, estimates the effects of Daily Load Shifting strategies implemented by third-party providers for customers on time-of-use (TOU) rates, and develops ex-ante load impact forecasts for ART events from 2025 through 2035. 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 program for customers with smart home technologies that officially launched on September 18, 2024. Initial technologies include smart thermostats, heat pump water heaters (HPWH), electric vehicle (EV) chargers, and batteries. Customers with eligible technologies can enroll through a PG&E-contracted third-party provider. Third-party providers receive incentives for participating in Demand Response (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 hours can be up to six 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 receive a market award 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.

Table 1.1 shows the details for the event in program year 2024 (PY2024)⁵. The sole event was a system-wide test event on Friday, October 25, 2024, for all customers enrolled.

⁵ PY2024 is defined as September 2023 thru October 2024.

Table 1.1: PY2024 ART Events

Date	Reason	Event Hours	Sub-LAPs Dispatched	# Customers Dispatched
10/25	Test	4:00-5:00 p.m.	All Sub-LAPs	12,138

ART customers are not permitted to be dually enrolled in other demand response (DR) programs. By the end of the program year (October 2024), the only technology enrolled is smart thermostat, and these customers were transitioned from the Smart Thermostat Control Pilot.

The primary goals of the evaluation include:

1. Estimate ex-post load impacts for the 2024 program year, 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 for 2025 to 2035 by sub-LAP and LCA 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 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 (LCA, NEM status, solar installation size, storage size, temperature, and weather sensitivity coefficient⁶) 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);
- 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 PY2024, by weather station);
- Program event data; and
- Smart thermostat device manufacture 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 200,000 of PG&E's residential customers. We used propensity score matching to find a single control customer for each ART customer with the closest hourly load profile on a selection of non-event, non-holiday, weekdays. We selected non-event days that are closest to the average temperature on the event day. Customers were also matched based on solar installation size and battery storage capacity,

⁶ We estimated the weather sensitivity coefficient for each treatment and control customer by regressing their daily electricity consumption on temperature.

where applicable. We required that ART customers are matched to a control customer residing in the same LCA and have 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 is a logistic function of the following form:

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

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
$\text{avgkW}_{c,h}$	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

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:

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

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., LCA, 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
$\epsilon_{c,d}$	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., house size). In addition, the model includes time variant weather controls such as the mean temperature across the first 17 hours of the day.⁷ 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 using only the event day and then selected non-event days used in selecting the control customers. Since all enrolled customers were dispatched for the event day, we included all customers in the same regression and estimated the distribution of load impacts across different customer subgroups by interacting the event variables with indicator variables for customer subgroups of interest (e.g., different LCAs).⁸

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 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.

⁷ The inclusion of weather variables may improve the effectiveness of the date fixed effects, particularly in models that include customers in different weather regions.

⁸ As shown in Table 3.3, nine out of fifteen sub-LAPs had less than 500 customers during the October 25th event. The low customer counts make the analysis at the sub-LAP level unreliable. We use the LCA-level results to compute the load impacts at the sub-LAP level based on which LCAs the customers in each sub-LAP belong to.

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.⁹ Instead of matching based on daily load profiles, we matched on billing data, particularly total billed consumption during a month. We used nearest neighbor matching with replacement to identify one control customer for each treatment customer.¹⁰

The matching is conducted within the same rate and NEM status (NEM or non-NEM). We calculated the Mahalanobis distance between the treatment and control customer in terms of average monthly billed usage (based on monthly billing data), average cooling degree days, and solar installation size (if applicable). 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 schedule¹¹:

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

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

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

⁹ 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.

¹⁰ We also identified the second and third 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 and third best matches are used.

¹¹ We included May to October data in the analysis as the enrolled ART TOU customers were likely still subject to Daily Load Shifting after the conclusion of the Smart Thermostat Control Pilot and before the official start date of the ART program.

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. The same formula is applied using weather conditions for each monthly system worst day to produce the DLS load impacts for monthly system worst days. 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 2025 through 2035 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 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 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 2024. The regressions account for differences in loads by hour, day-of-week, and month by including various indicator control variables.

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

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

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 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.

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 in ART is Smart Thermostats (SCT). In future years ART is forecasted to have 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. As the ART program is new and there is only a one-hour event occurred with very mild temperature, for smart thermostat customers, we develop ex-ante per-customer load impacts based on the previous ex-ante forecast of the Smart Thermostat Control Pilot. Each technology type is assumed to have the same reference load which is derived from PY2024 ART data. This reference load cannot be pushed into negative values by any technology type. For example, if the reference load is 2 kWh/customer/hour and the customer uses a battery, the maximum load impact would be 2 kWh/customer/hour.

Table 2.5: Ex-Ante Assumptions by Technology Type

Technology	Assumed Impact ¹²	Adjustments ¹³
SCT	Smart Thermostat Control Pilot ex-ante load impacts for the same month and weather scenario	The load impacts were scaled by the ratio of the maximum net daily reference loads estimated using the current ART population to the Smart Thermostat Control Pilot reference loads.
		For April (or October), we apply the percentage load impacts from May (or September).
Battery	2.5 kWh/customer/hour	Load impacts equal to the reference loads if references loads are smaller than 2.5 kWh/customer/hour.
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 the single event called in PY2024. 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 PY2024.

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 the single ART event called in PY2024. Table 3.1 presents a summary of event information, including the sub-LAPs dispatched, the sub-LAP-

¹² SCT is the only technology for which we estimate standard errors, which are calculated based on the ex-ante results of the Smart Thermostat Control Pilot study. For all other technology types, the standard errors are assumed to be zero.

¹³ Since the ex-ante forecast of the Smart Thermostat Control Pilot produced net reference loads and load impacts, we estimated net loads of the current ART population using the same regression as described in section 2.3.1 to scale the load impacts from the Smart Thermostat Control Pilot estimates to account for changes in customer distribution. For April and October, the forecast from the Smart Thermostat Control Pilot produced hourly net load impacts greater than the net reference loads in some sub-LAPs. Since our forecast is based on delivered loads, we made additional adjustments for these months.

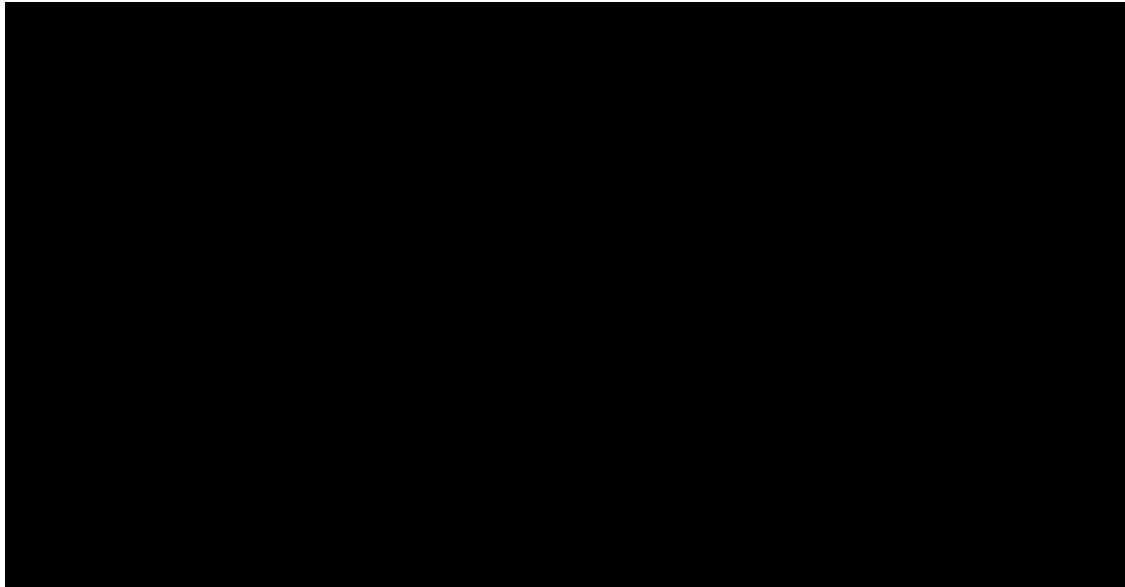
specific event hours, the type of event, and the number of customers dispatched, as well as average load impacts (per-customer and in aggregate), reference loads, and percentage load impacts. 12,138 customers were called to the event which lasted from 4:00-5:00 p.m.

Table 3.1: Average Event-Hour Load Impacts by Event

Date	Type of Event	Event Hours (p.m.)	Groups Dispatched	# Dispatched	Average Event Hour				
					Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Aggregate Impact (MWh/hr)	Avg. Temp (°F)
10/25	Test	4:00-5:00	All Groups and sub-LAPs Dispatched	12,138					76.6

Figure 3.2 illustrates the hourly load impacts for this event. The blue shaded area of the figure represents the event hour. We observe increase of loads before the event hour, similar to the “pre-cooling” observed in the Smart Thermostat Control Pilot study, but loads did not increase after the event, which could be due to the mild temperature.

Figure 3.1: Overall Load Impacts for October 25th Event



3.2 Sub-LAP Load Impacts

Next, we examine the results for the sole event at the sub-LAP level. Figure 3.2 summarizes the sub-LAP level ex-post load impacts for the October 25th event, for which all sub-LAPs were dispatched. The bars 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.

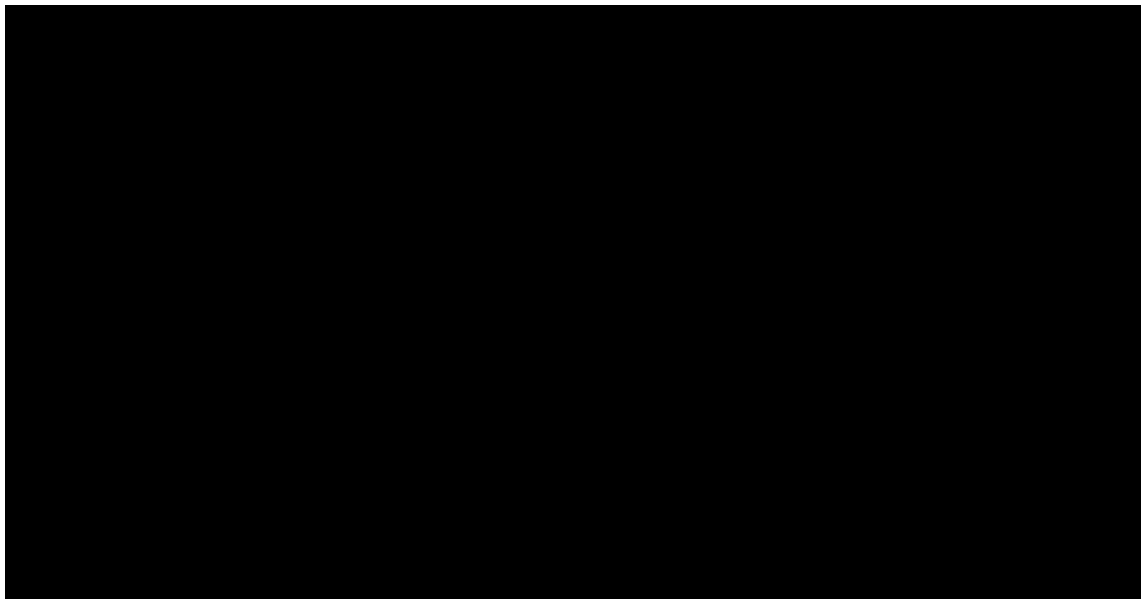
Low Temperatures cause low load impacts across sub-LAPs

For all sub-LAPs, the October 25th event had relatively low temperatures. Customers may not have substantial AC loads to curtail, which explains the low per-customer load impacts.

Figure 3.2 illustrates that there is considerable variation in load impacts across sub-LAPs, but many of the results are not statistically significant as error bars cross zero.

Table 3.2: Load Impacts by Sub-LAP for October 25th Event

Sub-LAP	# Dispatched	Average Event Hour				Avg. Temp (°F)
		Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Agg. Impact (MWh/hr)	
PGCC	144					69.1
PGEB	3,052					77.4
PGF1	942					79.6
PGFG	253					80.0
PGHB	8					69.0
PGKN	390					84.0
PGNB	356					75.1
PGNC	30					79.6
PGNP	815					76.8
PGP2	1,324					75.1
PGSB	2,957					76.0
PGSF	388					70.4
PGSI	878					75.3
PGST	343					77.2
PGZP	258					75.5

Figure 3.2: Load Impacts by Sub-LAP for October 25th Event (4-5 p.m.)

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 95 percent confidence intervals around these estimates. The orange scatter plot represents the average temperatures experienced by customers in each subgroup.

Figure 3.3 shows load impacts vary significantly by subgroup. CARE customers, as well as customers on Rate E1 provide the largest statistically significant per customer impacts. Rate E1 is a non-TOU rate plan with block pricing. The largest share of customers belongs to the E-TOU-C rate group, which has much lower load reduction. Customers on rate E-TOU-B or E-TOU-D have similar load impacts as rate E1 customers, but the load impacts are not statistically significant. 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 for TOU customers.

Figure 3.3: Load Impacts by Subgroup for October 25th Event (4-5 p.m.)

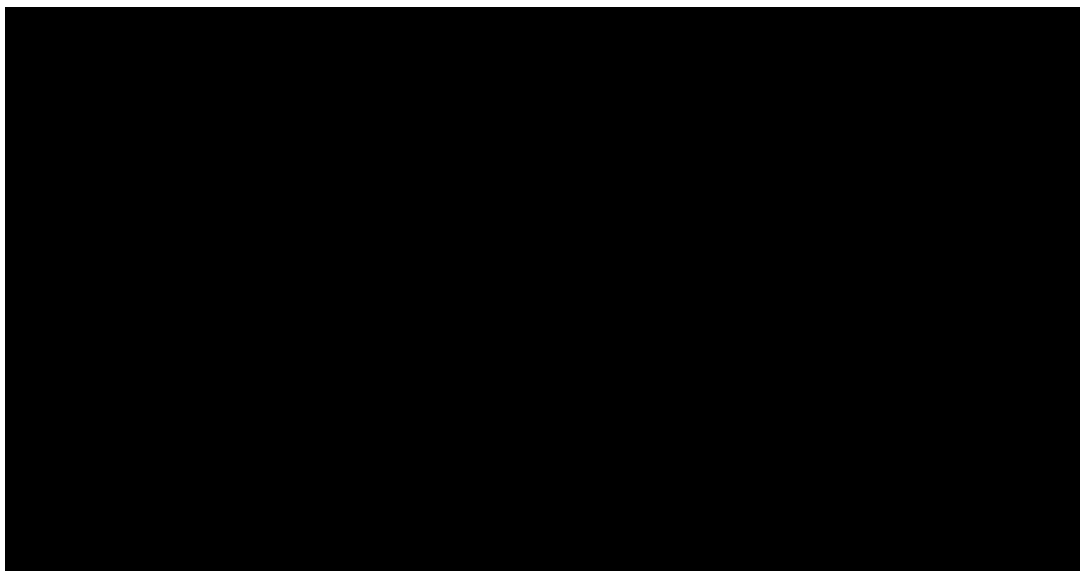


Table 3.3 provides the detailed information underlying Figure 3.3, including the average number of customers dispatched, the total number of enrolled customers in each subgroup, the average load impacts, reference loads, percentage load impacts, and temperatures. Comparisons by percentage load impacts 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 October 25th Event

Subgroup	# Dis-Patched	Average Event Hour				
		Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Agg. Impact (MWh/hr)	Avg. Temp (°F)
All ART Customers	12,138					76.6
CARE	1,922					78.1
Non-CARE	10,216					76.3
Rate E1	2,758					77.2
Rate EELEC	511					76.1
Rate ETOUB	158					77.5
Rate ETOUC	5,530					76.4
Rate ETOUD	1,542					77.0
Rate EV2A	1,614					76.0
Rate EVA	25					76.2
Device Ecobee	3,748					76.8
Device Emerson	285					76.8
Device Honeywell	80					76.7
Device Nest	8,015					76.5

4. DAILY LOAD SHIFTING IMPACTS

This section documents the findings from the Daily Load Shifting (DLS) analysis.

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 experience peak prices (4:00-9:00 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 PY2024.

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 by month. Because DLS officially began after the start of ART program in October 2024, we only present October results. Note that the analysis included May through October 2024 data since we suspected that DLS continued after Smart

Thermostat Control Pilot ended. 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 ex-post load impacts are summarized for peak-period hours in Table 4.2. There were 13,775 ART customers on TOU rates as of October 31, 2024.

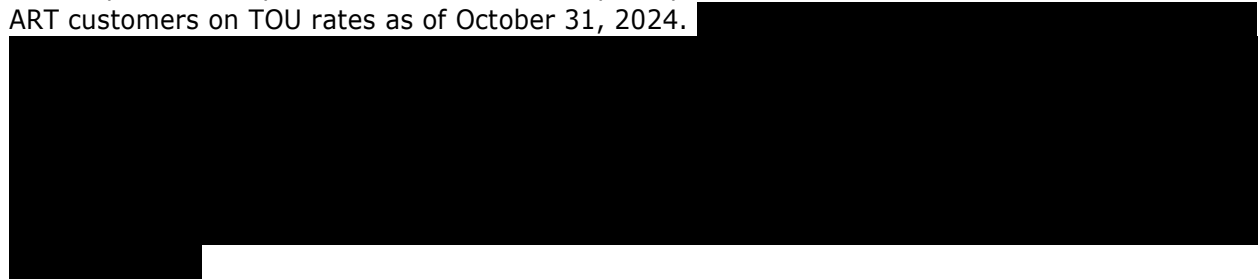
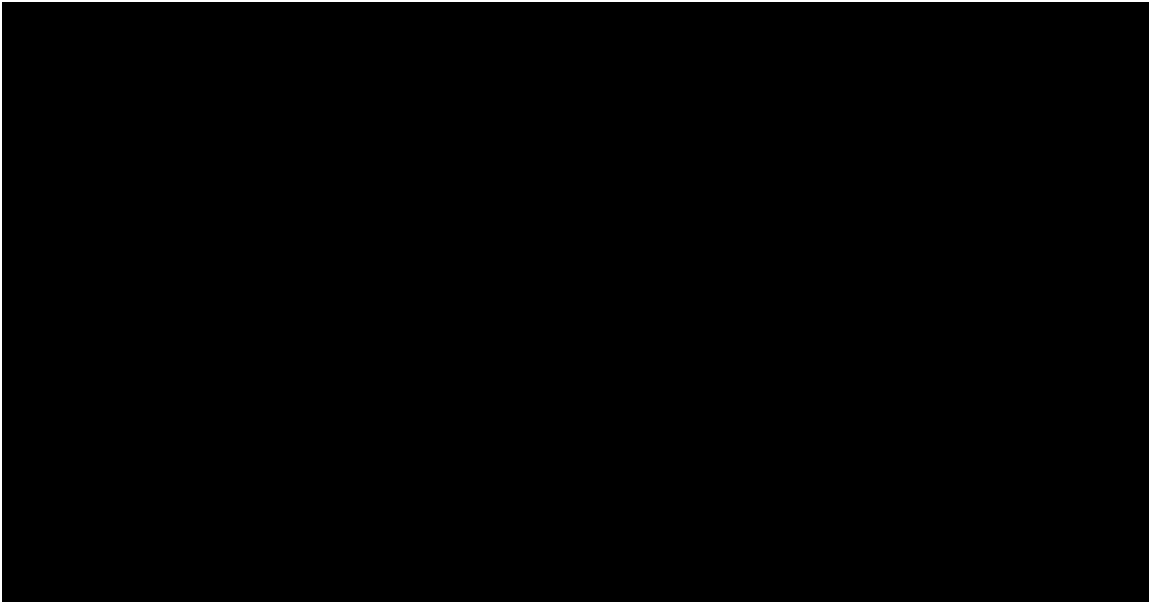


Table 4.1: Average Peak Period Load Impacts by Event

Day Type	Peak Period Hours (p.m.)	# TOU Customers	Average Event Hour				Avg. Temp (°F)
			Reference (kWh/cust/hr)	Impact (kWh/cust/hr)	% Impact	Aggregate Impact (MWh/hr)	
October Average Weekday	4:00 – 9:00	13,775					71.7
October System Worst Day	4:00 – 9:00	13,775					90.54

Figure 4.1 illustrates the DLS load impacts for the PY2024 October average weekday. Light blue shaded hours are when all rates are on peak periods. There are reductions in loads during peak hours and increase of loads during early and late hours of the day.

Figure 4.1: Overall Load Impacts for October Average Weekday



4.2 Subgroup Load Impacts

This section summarizes how DLS load impacts are distributed across subgroups of interest including rate type and device manufacture (e.g., NEST Thermostat).

The average DLS load impacts are summarized for each subgroup in Figure 4.2. 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 95 percent confidence intervals around these estimates. The orange scatter plot represents the average temperatures experienced by customers in each subgroup.

Figure 4.2 shows that there are statistically significant load impacts for almost every subgroup other than customers on rate EVA, which only has 40 customers. Across device manufacturers, the highest load impacts come from Honeywell, and the lowest load impacts come from Emerson. E-TOU-B has the highest load impacts, while EVA has the lowest load impacts across rates. In both cases, the difference between the highest and lowest load impacts are not statistically significant.

Figure 4.2: Average Peak Period Load Impacts by Subgroup

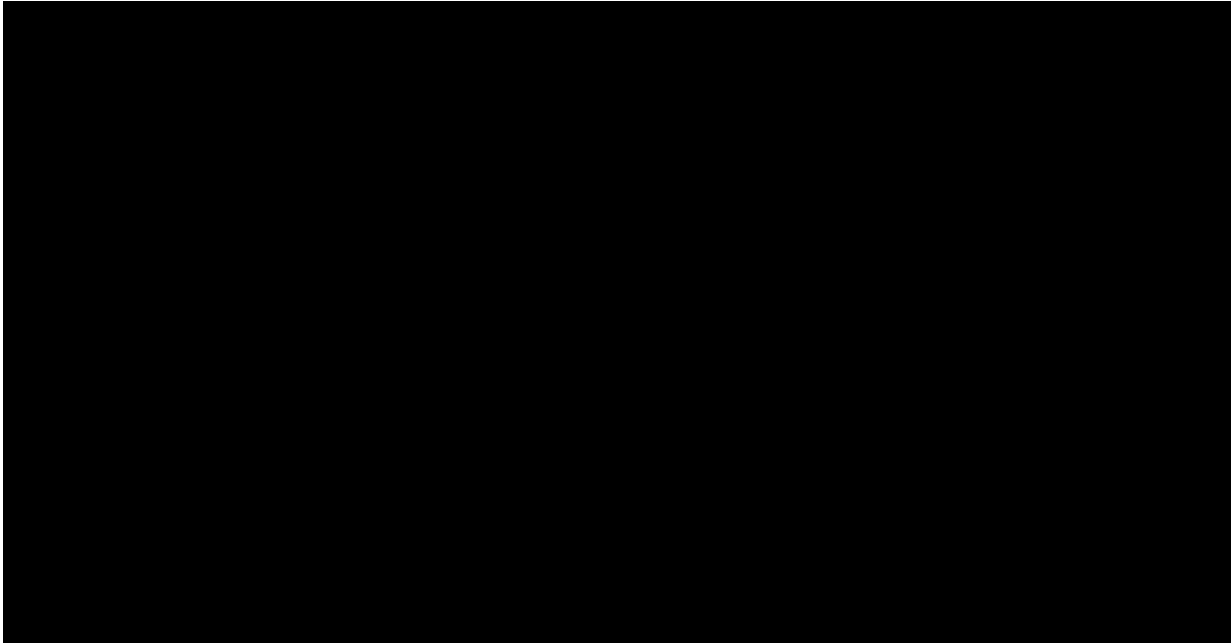


Table 4.2 provides the detailed information underlying Figure 4.2, including the average number of customers dispatched, the total number of enrolled customers in each subgroup, the average load impacts, reference loads, percentage load impacts, and temperatures. Comparisons by percentage load impacts 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 4.2: Average Peak Period Load Impacts by Subgroup

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	13,775					
Ecobee	4,209					
Emerson	309					
Honeywell	91					
Nest	9,136					
E-TOU-B	253					
E-TOU-C	8,148					
E-TOU-D	2,243					
EV2-A	2,330					
EVA	40					
E-ELEC	761					

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 [REDACTED], has much lower load impacts than customers on non-TOU rates. Since TOU customers are subject to DLS, both event day and non-event day loads are expected to have lower during peak hours, resulting in lower estimated load impacts. To help understand the impacts of DLS and event day together we estimated the incremental load impacts from DLS strategies on the October 25th event day. 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 4.3 shows the impacts of the event and DLS on October 25th. 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 4.3: Per Customer Reference Loads with DLS and Event Impacts

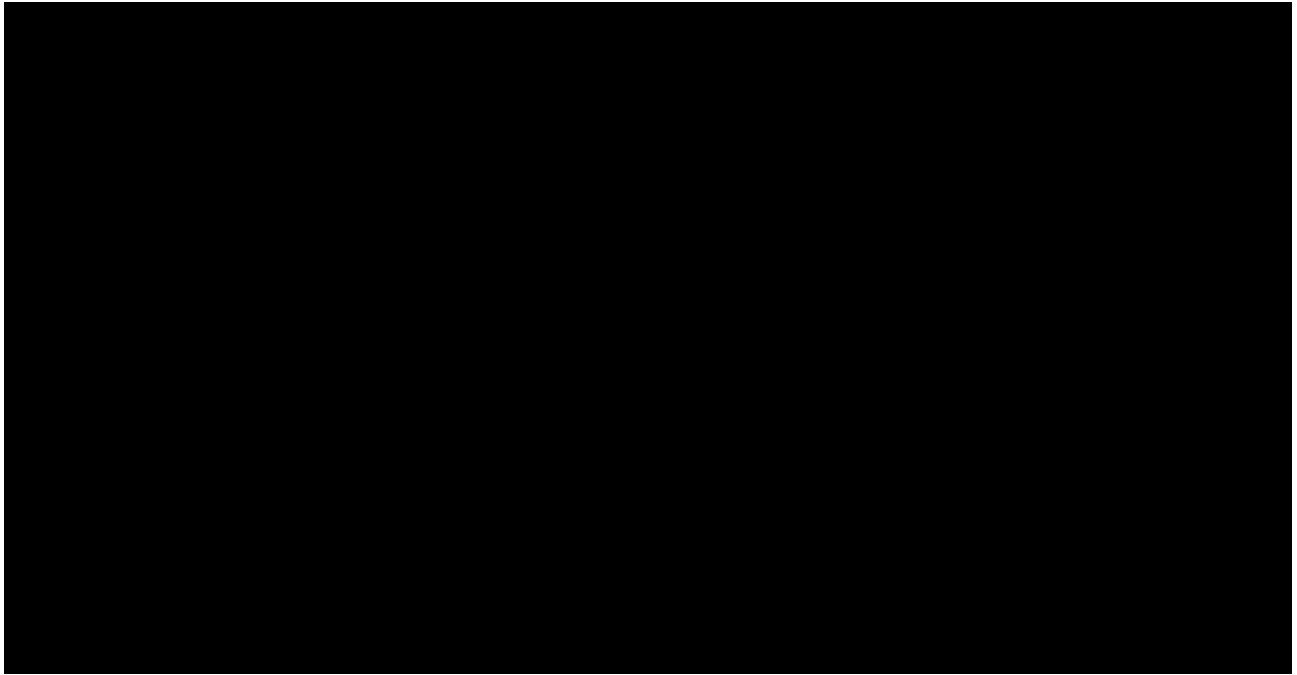


Figure 4.4 illustrates the total load impacts in MWh/hour of the event and DLS strategies on October 25th.

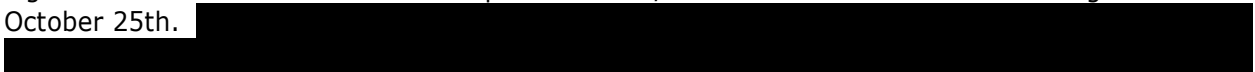
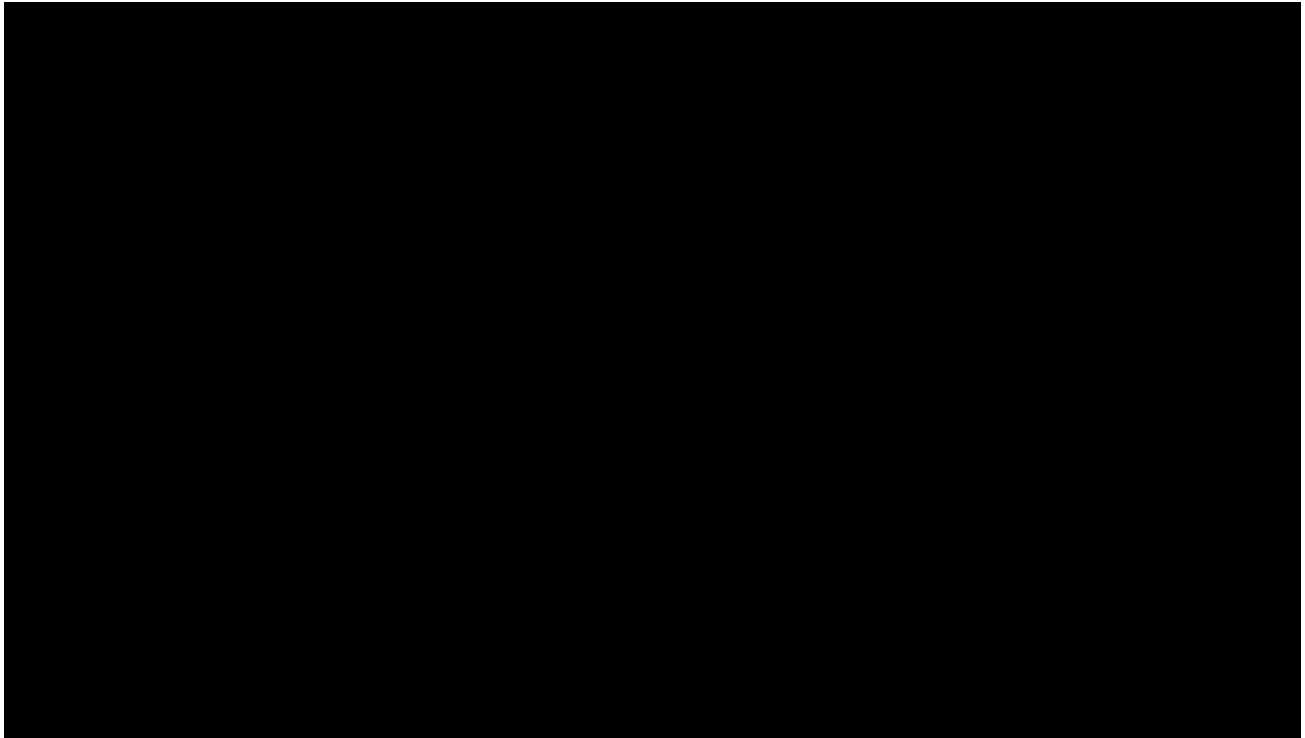


Figure 4.4: Aggregate Combined Load Impacts from Event and DLS



5. EX-ANTE LOAD IMPACTS

This section provides the ART ex-ante load impact forecast for the period from 2025 to 2035. 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 4:00-8:00 p.m. 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.¹⁴ We present yearly, monthly, and geographical variation of ex-ante forecast as well as the hourly reference loads and load impacts for an August system worst day in 2025.

Detailed results for each hour, weather scenario, month, forecast year, and enrollment segment (e.g. by rate 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 2025-2035. Impacts increase substantively over the forecast period. The increase in impacts is largely driven by increasing enrollments, depicted

¹⁴ [LIP Filing Guide 5.1](#), p. 11.

in Figure 5.1. Additionally, increasing per-customer impacts due to changes in the technological distribution of the program contributes to increases in aggregate forecasted load impacts.

Figure 5.1 shows PG&E’s enrollment forecast by technology type from 2025 to 2035 (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:

- After the program’s launch, ART enrolled approximately 17,000 customers with SCTs, comprised of participants that previously participated in PG&E’s Smart Thermostat Control Pilot.
- From 2025 to 2027, the ART program expects to ramp up enrollments through onboarding new providers and supporting marketing, education, and outreach, aiming for approximately 100,000 newly enrolled customers by the end of 2027. Initially, the migrating SCTs will result in those being the majority in 2025, but this proportion will decline as other technologies join. By the end of 2027, it is projected that the ART participation will be comprised of 79% SCTs, 12% EV chargers, 7% batteries, 1.5% HPWHs, and 0.5% CEC Flex App. This trajectory could change if ART opens to non-residential customers during the 2024-2027 program cycle.
- From 2028 to 2035, PG&E projects continued enrollment growth, but with diminishing marginal growth rates, reaching approximately 288,000 customers by the end of 2035, with 68% SCTs, 19% EV chargers, 10% batteries, 2% HPWH, and 1% CEC Flex App.

Figure 5.1: Forecast Enrollment by Technology Type, 2025-2035

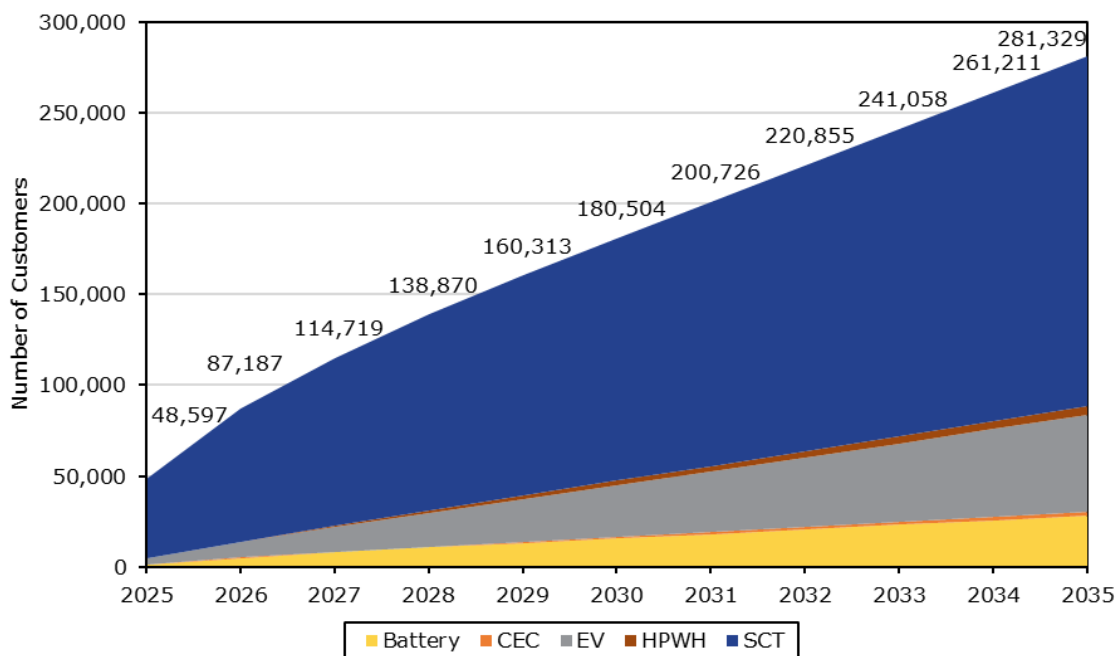


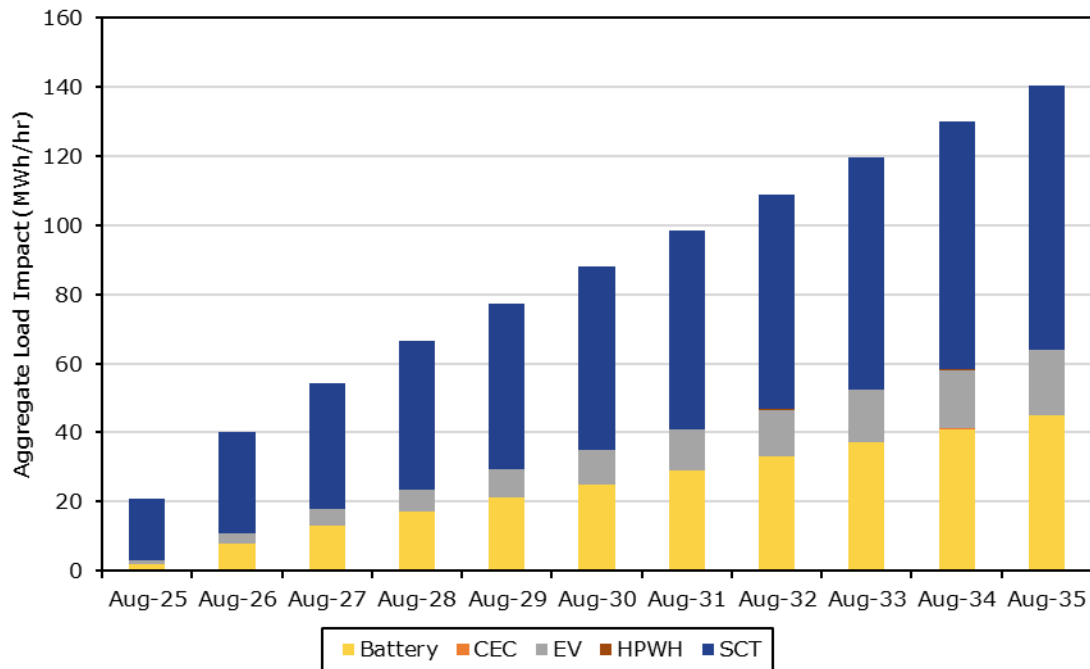
Table 5.1 summarizes per-customer and aggregate load impacts over the 10-year forecast window. The trend of increasing aggregate load impacts is driven by both increased enrollments over the forecast window and increased per-customer load impacts. Per customer load impacts range from 0.42 kwh/customer/hour in 2025 to 0.50 kwh/customer/hour in 2035. Aggregate reference loads increase by between 10 and 20 MWh per year, going from 20.64 MWh/hour in 2025 to 140.57 MWh/hour in 2035. The change in the technological distribution of enrolled customers drives the increase of per-customer load impacts. There is no change in per-customer reference loads as we assume reference loads of all technology type are the same.

**Table 5.1: Load Impacts over RA Window,
PG&E 1-in-2 August System Worst Day, 2025-2035**

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)
2025	48,597	0.42	1.63	20.64	79.33
2026	87,187	0.46	1.63	40.01	142.29
2027	114,719	0.47	1.63	54.27	187.24
2028	138,870	0.48	1.63	66.37	226.66
2029	160,313	0.48	1.63	77.40	261.63
2030	180,504	0.49	1.63	87.94	294.60
2031	200,726	0.49	1.63	98.50	327.62
2032	220,855	0.49	1.63	109.00	360.45
2033	241,058	0.50	1.63	119.55	393.44
2034	261,211	0.50	1.63	130.07	426.33
2035	281,329	0.50	1.63	140.57	459.15

Figure 5.2 illustrates the changes in aggregate load impacts during the Resource Adequacy (RA) window (4 to 9 p.m.) over the forecast period by comparing load impacts for all 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 2025 to 2035. The majority of impacts are from customers with smart thermostats but there are also significant increases in load impacts from battery storage and electric vehicle owners.

Figure 5.2: Aggregate Load Impacts over RA Window by Technology Type, PG&E 1-in-2 August System Worst Day, 2025-2035



5.2 Ex-Ante Impacts Across Months

In this section we compare impacts across months during PY2025. 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 by technology types. SCT technology has impacts that vary by month based on the analysis of the Smart Thermostat Control Pilot program. Other technologies have impacts that are constant across months.

Table 5.2 summarizes the average per-customer load impacts and aggregate impacts by month during 2025. 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 4-9:00 p.m. except for March-April where the RA window is HE 5-10:00 p.m.¹⁵ This later RA window hours leads to lower average RA window load impacts in March, April and May due to cooler temperatures during later hours, which decrease 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.

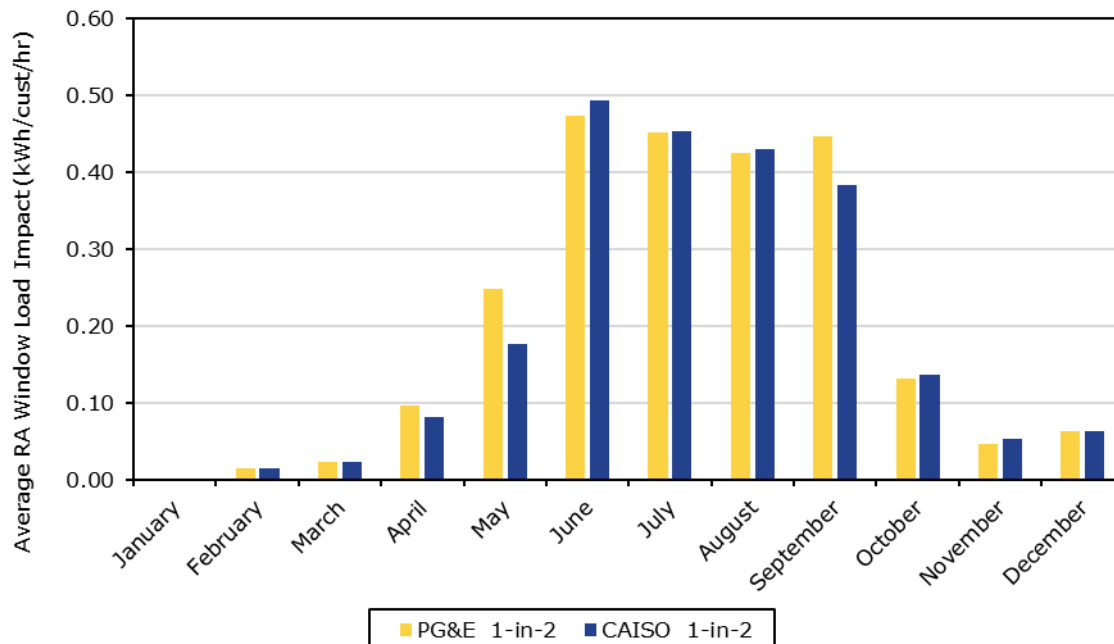
¹⁵ We calculate impacts using the first four hours of the RA Window which means results are presented for HE 4-8 p.m. for all months except March-May where results are presented from 5-9 p.m.

Table 5.2: Load Impacts over RA Window for PG&E 1-in-2 Monthly System Worst Day Scenario (2025)

Month	# Enrolled	Per Customer		Aggregate	
		Event Load Impact (MWh/hr)	Event Ref. Load (MWh/hr)	Event Load Impact (kWh/hr)	Event Ref. Load (kWh/hr)
January	18,794	0.00	1.13	0.00	21.21
February	24,729	0.01	1.03	0.35	25.50
March	28,738	0.02	0.95	0.66	27.25
April	32,718	0.10	1.34	3.14	43.77
May	36,647	0.25	1.45	9.13	53.23
June	40,621	0.47	1.80	19.22	73.02
July	44,628	0.45	1.83	20.19	81.60
August	48,597	0.42	1.63	20.64	79.33
September	52,515	0.45	1.70	23.43	89.02
October	56,471	0.13	1.32	7.44	74.31
November	60,443	0.05	0.67	2.82	40.61
December	64,461	0.06	1.17	4.09	75.37

Figure 5.3 illustrates the seasonality and variation by weather scenario. The highest monthly average impact occurs in June for both the utility 1-in-2 and CAISO 1-in-2 scenario. In June, the CAISO 1-in-2 scenario has slightly higher load impacts (0.49 kwh/customer/hour) than the PG&E 1-in-2 scenario (0.47 kwh/customer/hour) due to higher temperatures. The second highest month is July with 0.45 kwh/customer/hour impacts for both the PG&E and CAISO 1-in-2 scenarios.

Figure 5.3: Average per Customer Load Impacts over RA Window in 2025 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 2025 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 20.6 MWh/hour, or 26 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 2025

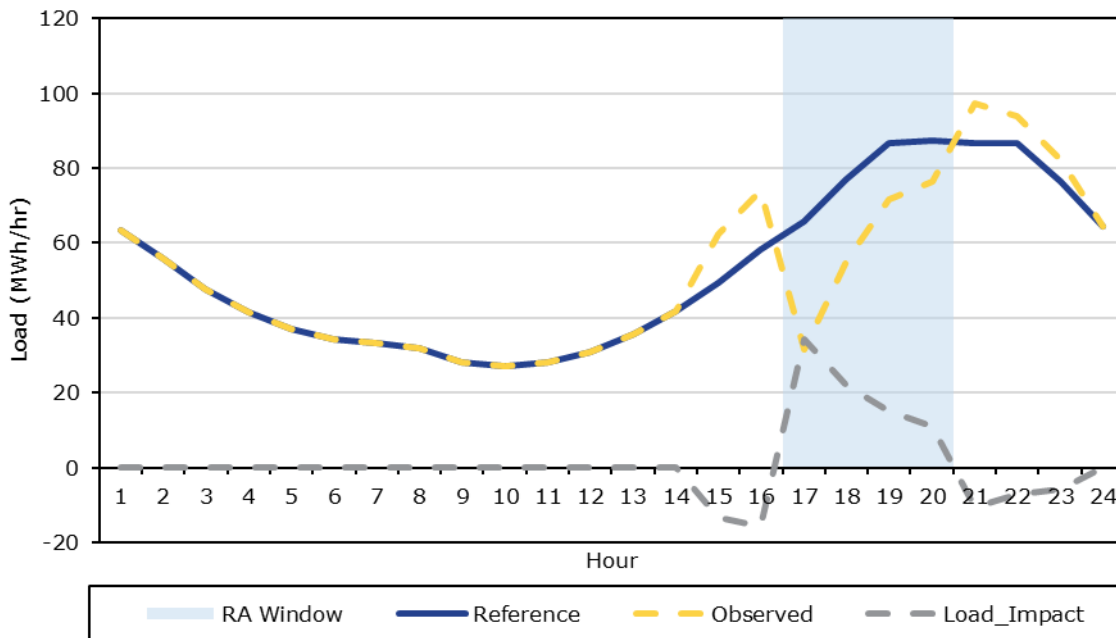
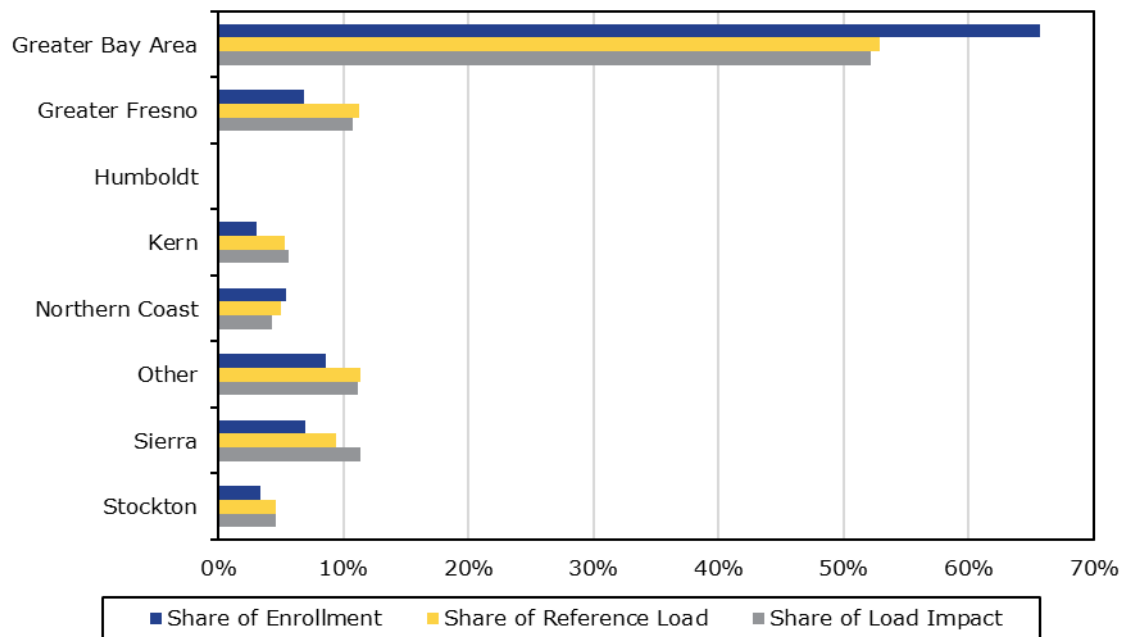


Figure 5.5 compares the LCA shares of average RA window load impacts, reference loads, and enrollments on an August system worst day for the PG&E 1-in-2 scenario in 2025. The load impacts, enrollments and reference loads are all largely concentrated in the Greater Bay Area LCA which is consistent with 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.

Figure 5.5: RA Window Load Impacts by LCA in 2025, PG&E 1-in-2 August System Worst Day



6. LOAD IMPACT RECONCILIATIONS

This section compares estimated load impacts for ART. Because ART is a new program, we have no previous reports or analyses for comparison. Therefore, we present the comparison only the current ex-post and ex-ante load impacts.

6.1 Current Ex-Post vs. Current Ex-Ante

In this section, we compare the program level ex-post findings to the ex-ante forecast for 2025 contained in the current study. Our ex-post results are reported for the one event hour (4-5:00 p.m.), so we use the same hour in our ex-ante results.

Table 6.1 compares the ex-post load impacts from the October 25th event in PY2024 to the ex-ante load impact forecast for an October system worst day with PG&E 1-in-2 weather conditions in 2025. Per-customer load impacts and reference loads are higher in the forecast compared to ex-post analysis. Aggregate reference loads and load impacts are expected to drastically increase due to a forecasted enrollment increase of over 44,000. Percentage load impacts are also higher in the ex-ante forecast.

Table 6.1: Current Ex-Post vs. Ex-Ante Load Impacts

Level	Outcome	PY2024 Ex-Post	PY2024 Ex-Ante for October 2025
Total	Enrollments		56,471
	Reference (MWh/hr)		74.3
	Load Impact (MWh/hr)		7.4
	Avg. Evt Hour Temp (°F)		82.2
	Avg. Daily Temp (°F)		71.7
	% Load Impact		10.0%
Per Participant	Reference (kWh/cust/hr)		1.316
	Load Impact (kWh/cust/hr)		0.132

Table 6.2 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 ex-ante forecast is the higher temperatures that lead to higher response from AC usage and the prevalence of new technologies such as battery and EV charging entering the ART program. The main reason for higher aggregate load impacts is significantly increased enrollment both in terms of smart thermostat customers and in other technology types.

Table 6.2: Comparison of Ex-Post and Ex-Ante Factors

Factor	Ex-Post	Ex-Ante	Expected Impact
Weather	Average event-hour temperature of 76.6°F and average daily temperature of 63.0°F.	Average event-hour temperature of 82.2°F and average daily temperature of 71.7°F.	Significantly higher daily temperature and event hour temperature should lead to higher load impacts.
Technology Distribution	All devices are smart thermostats.	About 90% of devices are smart thermostats. The rest of the program is made up of battery storage, EV chargers, etc.	New technologies, including battery storage and EV charging drives up both aggregate load impact and per customer load impacts.
Enrollment	12,138	56,471	Significantly higher ex-ante enrollment leads to significantly higher impacts.
Methodology	Difference-in-Differences with matched control group.	Smart Thermostat results are derived from PY2023 Smart Thermostat Control Pilot ex-ante results. Load impacts of other technologies are derived from prior studies and assumptions.	Battery and EV charger technologies are assumed to have higher per customer impacts and reference loads than smart thermostats in October which drives up aggregate and per customer impacts.

6. RECOMMENDATIONS

As ART is a new program, we recommend calling events across sub-LAPs and varying weather conditions 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.

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_2024_ART_Ex_Post_CONFIDENTIAL.xlsx

Appendix D Ex-Ante Load Impact Tables:

- 8b. PGE_2024_ART_Ex_Ante_CONFIDENTIAL.xlsx
- 8b. PGE_2024_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.¹⁶

Table A.1 provides the mean percentage error (MPE) and mean absolute percentage error (MAPE) calculated across the average 24-hour load profile as well over the RA window. 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.

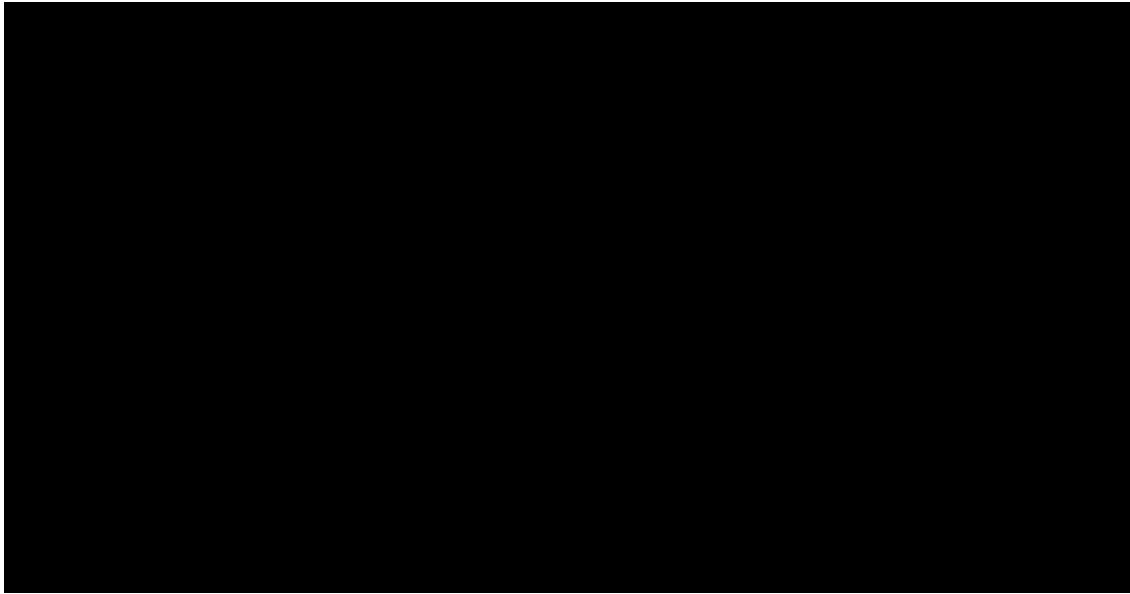
Table A.1: Match Quality Statistics

Comparison Days	MPE	MAPE	MPE RA Window	MAPE RA Window
Matching Days	-2.2%	2.3%	-1.1%	1.2%

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 event hour (4-5 p.m.).

¹⁶ 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.

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



For our event-based analysis we match customers by LCA. Table A2, presents match quality statistics for all LCAs. All MPE and MAPE values are less than 5% except for Humboldt, which only has eight customers.

Table A.2: MPE and MAPE on Matching Days

Comparison Days	MPE	MAPE	MPE RA Window	MAPE RA Window	Number of Customers
Greater Bay Area	-2.6%	2.6%	-1.3%	1.3%	7660
Greater Fresno Area	-2.0%	2.4%	-2.4%	2.6%	821
Humboldt	-43.6%	43.6%	-47.3%	47.3%	8
Kern	-4.1%	4.2%	-4.2%	4.2%	379
North Coast and North Bay	-1.2%	1.9%	-2.8%	2.8%	617
Other	1.4%	2.4%	2.2%	2.2%	1023
Sierra	-2.2%	2.7%	0.7%	1.2%	850
Stockton	-3.9%	4.2%	-0.7%	1.4%	397

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 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.

Table A.3 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 billed consumption by month and the size of customers solar installations (for NEM customers) along with weather station profiles. We evaluate match quality by comparing the average consumption and solar size for ART and control customers.

Table A.3: Match Quality Statistics

NEM	Rate Category	Control			Treatment		
		Billed Consumption (kWh/month)	Solar Size (kWh)	# Cust	Billed Consumption (kWh/month)	Solar Size (kWh)	# Cust
Non-NEM	E-TOU-B			252			93
	E-TOU-C			9889			4373
	E-TOU-D			2379			1027
	E-ELEC			617			355
	EV2A			2234			1246
NEM	E-TOU-B			435			161
	E-TOU-C			8953			3709
	E-TOU-D			2713			1211
	E-ELEC			566			270
	EV2A			1973			1019
	EVA			87			40