



Demand Side Analytics
DATA DRIVEN RESEARCH AND INSIGHTS

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FINAL REPORT

2025 Load Impact Evaluation of GoodLeap's California Demand Response Resources



Prepared for GoodLeap
By Demand Side Analytics, LLC
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ABSTRACT

This report provides an evaluation of GoodLeap's demand response (DR) performance in California for the 2025 program year, covering dispatch events in 2025. GoodLeap is a Demand Response Provider (DRP) that aggregates behind-the-meter battery storage systems, primarily enrolled through power purchase agreements and leases, to provide grid-responsive load reductions. In 2025, GoodLeap managed a rapidly growing portfolio of residential battery systems across the Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E) service territories. Portfolio enrollment expanded substantially over the program year, increasing from approximately 560 sites in May 2025 to more than 3,500 by October 2025, with continued growth to over 7,400 sites by March 2026. These resources were dispatched during system events and test events, with participation occurring primarily through the California Energy Commission's Demand Side Grid Support (DSGS) program.

The purpose of this evaluation is to estimate the actual energy reductions delivered during demand response events in 2025 (known as ex-post impacts), examine how performance varied across utilities, climate regions, and battery manufacturers, and estimate the load reduction potential of GoodLeap's portfolio under resource adequacy planning conditions (referred to as ex-ante impacts). The evaluation also aims to understand how battery behavior differs between event and non-event conditions and to inform expectations for future DR capability under a four-hour dispatch requirement.

In 2025, GoodLeap's portfolio experienced nine primary event days, each consisting of two-hour dispatch windows, with some variation in timing across utilities. Event performance was characterized by strong and consistent battery discharge during event windows, with impacts concentrated in the first hour due to the absence of requirements to distribute output across the event duration. The largest observed event delivered approximately 21 MWh of aggregate load reduction over a two-hour window. Across events, battery state of charge was consistently over 95% prior to dispatch and declined substantially during events, demonstrating reliable availability and response. Additionally, baseline behavior reflected non-event discharging driven by price signals under the Net Billing Tariff, indicating that the observed impacts represent incremental reductions beyond typical operations.

To estimate expected load reduction potential under utility planning scenarios, the study translated the observed two-hour event performance into four-hour resource adequacy impacts using a state of charge-based modeling framework. Under August 1-in-2 worst-day conditions, the GoodLeap portfolio is estimated to deliver approximately 1.15 kW per site per hour, or 4.6 kWh per site across a four-hour event window. Impacts were scaled to the portfolio level using a conservative, flat monthly growth rate based on the historic trend, supporting an estimated Net Qualifying Capacity of approximately 21.9 MW for 2027.

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1 EXECUTIVE SUMMARY

1.1 PROJECT OVERVIEW

GoodLeap, LLC is a Demand Response Provider (DRP) in California, utilizing a portfolio of behind-the-meter (BTM) battery storage systems to participate in Demand Response (DR). GoodLeap provides financing products for customer-sited solar and storage systems. Because GoodLeap maintains ownership and operational control of batteries under its power purchase agreement and lease products and can offer enrollment to the batteries they finance through its loan products, GoodLeap is able to dispatch this portfolio for DR purposes. This evaluation aims to accurately estimate the load reduction capabilities from GoodLeap’s battery portfolio and to support its intent to qualify for Net Qualifying Capacity (NQC) for participation in Resource Adequacy (RA) in 2027.

GoodLeap is seeking 21.9 MW of NQC for 2027, as summarized in Table 1.

Table 1: Ex-Ante Projections for Qualifying Capacity (2027) Under August 1-in-2 Utility Weather Conditions

Utility Name	Number of Customers	MWs
SCE	9,342	10.7
PG&E	8,966	10.4
SDG&E	722	0.8
TOTAL	19,030	21.9

In 2025, GoodLeap participated in the California Energy Commission’s Demand Side Grid Support Program. By October 2025, the GoodLeap California portfolio included over 3,500 customers, with 43 MW of installed battery capacity, capable of sustaining 18.4 MWh of weather-normalized load reductions over a four-hour period, over and above the normal dispatch of the batteries. The 2027 NQC proposal is based on the actual performance of resources in PY 2025 events and the trend of its growing battery fleet.

The key objectives of this evaluation include:

- Determine the ex-post impacts by GoodLeap’s DR resources dispatched during PY2025.
- Assess how impacts vary by key segments including region and battery manufacturer.
- Identify the key drivers of aggregate impacts.

- Assess the full load reduction delivered by the GoodLeap portfolio as a whole.
- Determine the full ex-ante reduction capability of the portfolio under planning conditions.

1.2 KEY FINDINGS

Table 2 summarizes the key findings of this study.

Table 2: Summary of Key Findings

Key Finding	Description
Substantial growth in enrollment and impacts in PY 2025	<ul style="list-style-type: none"> ▪ Program participation grew dramatically over the analysis period, growing from over 560 enrolled sites in May to more than 3,500 by October. ▪ By March 2026, enrollment has more than doubled since October to over 7,400 sites, representing growth of approximately 680 customers. ▪ As enrollment increased, event performance also grew, with the portfolio delivering approximately 21 MWh of load reductions during two-hour events by the end of the summer.
Ex-Ante Analysis supports an NQC value of 21.9 MW	<ul style="list-style-type: none"> ▪ Under August 1-in-2 weather conditions, the portfolio delivers an average, weather-normalized impact of 4.6 kWh per-site across 4-hour events. ▪ Aggregated to the forecasted 2027 enrollment, assuming the same enrollment trend observed in PY2025
Ex-ante results demonstrate reliable four-hour capability	<ul style="list-style-type: none"> ▪ The modeling framework used in this analysis reflects how battery discharge can be shaped across the event window and that the portfolio can consistently sustain load reductions across a four-hour event.
First-hour impacts drove ex-post performance	<ul style="list-style-type: none"> ▪ Event impacts were heavily concentrated in the first hour of dispatch, with substantially smaller reductions in later hours. ▪ This pattern was influenced by manufacturer-specific dispatch strategies and the absence of requirements to spread impacts across the event window, resulting in front-loaded discharge behavior.
Impacts are incremental to NBT-driven dispatch	<ul style="list-style-type: none"> ▪ Batteries consistently delivered additional load reductions during event hours beyond typical non-event behavior, even during months with high Energy Export Credit (EEC) values. ▪ While the NBT incentives drive discharge during peak periods on non-event days, event impacts represent incremental reductions above this behavior.

2 INTRODUCTION

GoodLeap, LLC is a Demand Response Provider (DRP) in California that utilizes a portfolio of behind-the-meter (BTM) battery storage systems to participate in Demand Response (DR). GoodLeap provides financing products for customer-sited solar and storage systems and, through its power purchase agreement and lease offerings, maintains ownership and operational control of enrolled batteries. In addition, GoodLeap can enroll systems financed through its loan products, enabling dispatch of a broad portfolio of distributed battery assets for DR purposes.

This evaluation assesses the load reduction capabilities of GoodLeap’s battery portfolio over the analysis period from October 2024 through October 2025 (PY2025). During PY2025, GoodLeap participated in the Demand Side Grid Support (DSGS) program, which dispatched the fleet of batteries at least once each month. Load impacts from historical events and the growth trend in the GoodLeap battery are used to estimate the portfolio’s performance for Net Qualifying Capacity (NQC). The analysis focuses on summer event performance, as only summer events were called during the study period. In addition to DSGS program events, portfolio-level test events were conducted and are included in the analysis. The results are intended to support GoodLeap’s qualification for NQC and participation in Resource Adequacy (RA) beginning in 2027.

2.1 EVALUATION OBJECTIVES

The focus of this evaluation is to assess the GoodLeap’s battery fleet’s ability to reduce peak demand during DR events. Table 3 summarizes the key research questions explored in this evaluation.

Table 3: Key Research Questions

Research Question	
1	What are the impacts delivered by GoodLeap’s DR resources during PY2025 (ex-post)?
2	How do impacts vary by segment (utility, size, climate zone, battery brand, NEM vintage, etc.)?
3	When and where are load impacts concentrated?
4	What was the full load reduction delivered by the GoodLeap portfolio as a whole?
5	What is the full reduction capability of the portfolio under planning conditions (ex-ante)?

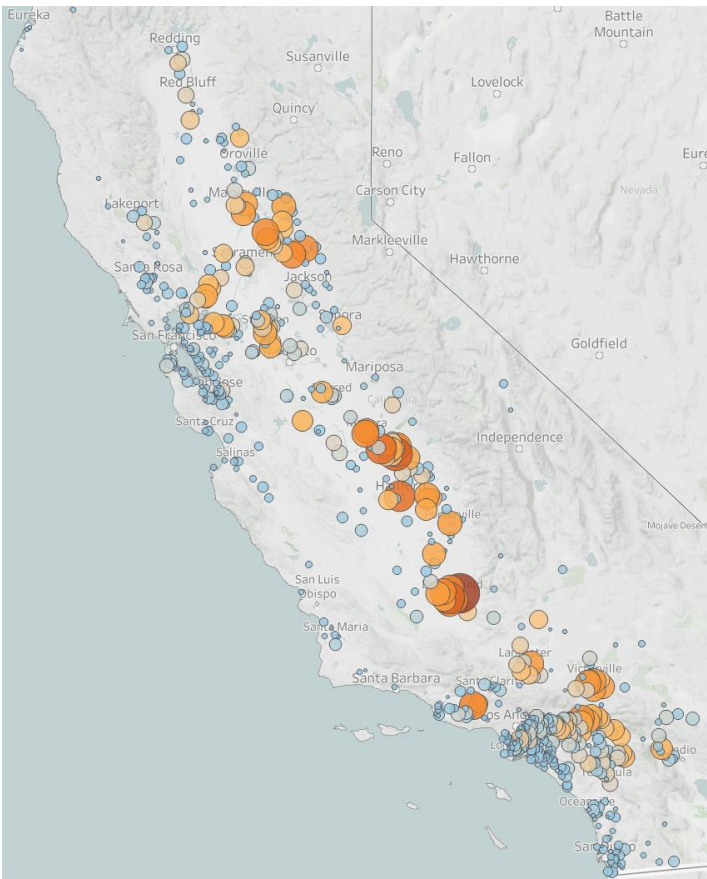
2.2 DESCRIPTION OF GOODLEAP RESOURCES

GoodLeap operates a fleet of BTM battery systems that can be dispatched for demand response events through a combination of power purchase agreements (PPAs) and leasing arrangements with

participating customers. Under these agreements, GoodLeap maintains operational control of the battery systems and can schedule discharges during demand response events while customers continue to benefit from the batteries for backup power and solar self-consumption. The majority of the fleet (more than 98% of participating systems) is enrolled through PPA agreements, with the remaining systems participating through lease arrangements.

The portfolio consists of battery systems from three primary manufacturers: Tesla (58%), SolarEdge (22%), and Enphase (20%). While the technical specifications vary across manufacturers, each system provides dispatchable energy storage that can be coordinated during DR events.

Figure 1: GoodLeap's Geographic Footprint*



**Bubbles represent ZIP code centroids with participating systems as of the end of the PY2025 season.*

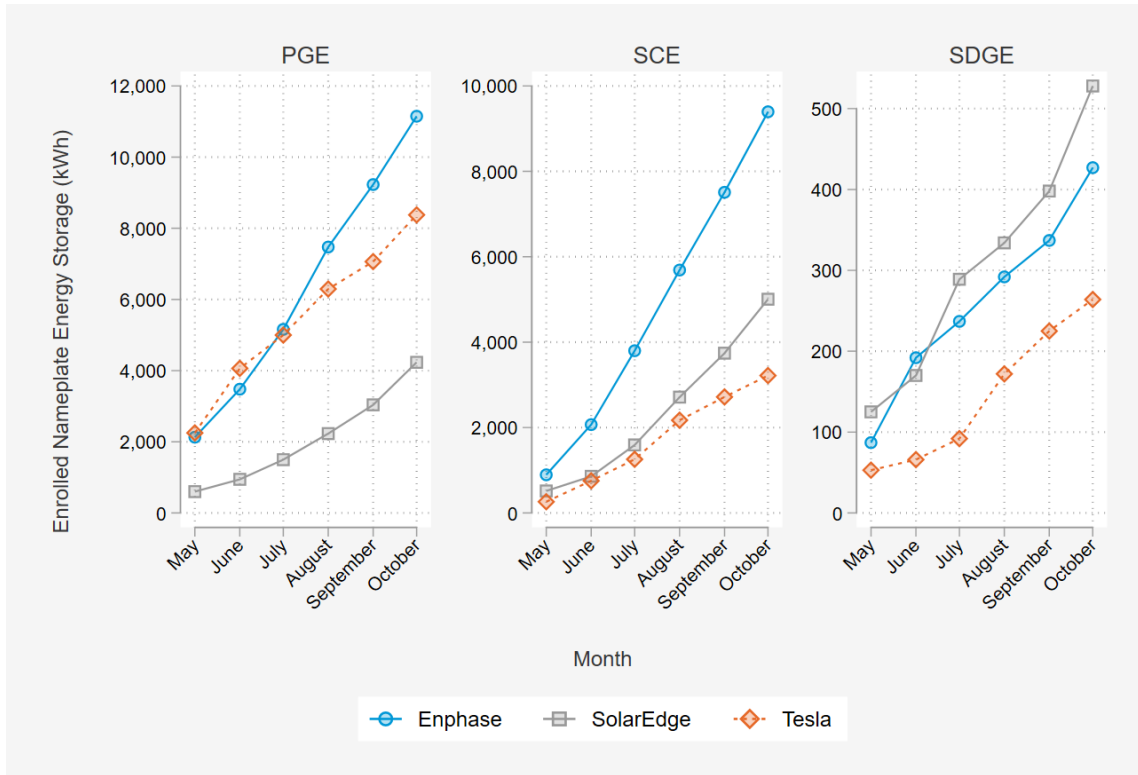
**Bubble size and shading indicate total enrolled nameplate battery storage (kWh), with larger and darker bubbles reflecting higher capacity.*

The battery fleet is geographically distributed across California, with participation spanning the service territories of the three major investor-owned utilities (IOUs). Figure 1 shows the locations of participating systems throughout the state. The largest concentration of sites is located within Pacific Gas and Electric (PG&E) territory, which accounts for just over half of the participating systems. Southern California Edison (SCE) territory represents the second-largest share of the portfolio, while San Diego Gas and Electric (SDG&E) has the fewest sites. It follows that systems are broadly dispersed across many climates and urban areas, creating a geographically diverse portfolio that can contribute to DR across many regions of California.

GoodLeap's customer outreach has increased substantially over time with enrollment expanding from approximately 580 customers in May 2025 to over 3,500 customers by September 30, 2025. Consequently, the

total enrolled nameplate energy capacity has increased significantly over the same period. Figure 2 illustrates the growth in enrolled nameplate battery capacity (kWh) over time by battery manufacturer. Enrollment has nearly doubled after the PY2025 season, passing 7,400 customers in March 2026. This equates to substantial enrollment of 684 customers per month.

Figure 2: Growth in Enrolled Nameplate Energy Storage over the PY2025 Season



2.3 EVENT CONDITIONS

In 2025, GoodLeap’s battery portfolio was dispatched by utility service territory, meaning that all enrolled resources within a given IOU’s territory were dispatched when an event was called. This analysis evaluates the impacts from nine unique event days during which the portfolio was dispatched. For two of these days, the batteries were dispatched during slightly different time windows for two different utilities. All events were two hours in duration.

Table 4 summarizes the system conditions and temperatures during each event. 2025 did not experience extreme conditions or electric grid emergencies, and, thus, event conditions were not severe. Participant weighted temperatures during events ranged from roughly 71°F to 89°F, and day-ahead locational marginal prices (DLAPs) across PG&E, SCE, and SDG&E territories were typically between approximately \$45/MWh and \$65/MWh. CAISO net loads did not exceed 40,000 MW at any point in 2025. The August 22 event stands out as the most extreme event in the sample, with the highest observed temperatures (89°F), the highest CAISO system net load, and substantially elevated market prices exceeding \$100/MWh across all three utility territories. Aside from this event, most dispatches occurred during moderately high system conditions rather than extreme grid stress.

Table 4: 2025 Event Conditions

Event Times	IOUs Dispatched	Temperature (Site Weighted)	CAISO System Net Loads (MW)	Market Price PG&E DLAP	Market Price SCE DLAP	Market Price SDGE DLAP
05/22/2025 7 to 9 PM	All Utilities	70.8	25,352	\$ 50.97	\$ 46.57	\$ 52.13
06/27/2025 7 to 9 PM	All Utilities	82.1	31,172	\$ 62.18	\$ 57.52	\$ 58.10
07/22/2025 7 to 9 PM	All Utilities	72.7	26,469	\$ 47.98	\$ 46.45	\$ 47.35
07/29/2025 7 to 9 PM	All Utilities	78.3	29,037	\$ 59.86	\$ 55.53	\$ 58.05
08/22/2025 6 to 8 PM	All Utilities	89.0	38,967	\$ 107.52	\$ 109.02	\$ 114.60
08/27/2025 6 to 8 PM	SCE and SDGE	82.0	34,130	\$ 60.82	\$ 55.17	\$ 66.30
08/27/2025 7 to 9 PM	PG&E	79.7	34,580	\$ 61.12	\$ 54.80	\$ 65.54
09/25/2025 6 to 8 PM	All Utilities	74.1	27,066	\$ 53.14	\$ 49.64	\$ 54.98
10/21/2025 5 to 7 PM	All Utilities	72.5	26,761	\$ 59.72	\$ 54.41	\$ 54.92
10/29/2025 5 to 7 PM	PGE and SDGE	71.2	29,146	\$ 64.00	\$ 64.08	\$ 69.06
10/29/2025 6 to 8 PM	SCE	74.4	29,583	\$ 63.06	\$ 64.19	\$ 67.65

3 METHODS

The primary challenge of this evaluation is to accurately detect changes in energy consumption while eliminating plausible alternative explanations for those changes. For demand reductions, this involves accurately estimating what demand patterns would have been in the absence of the program – called the counterfactual or reference load. Impacts are estimated as the difference between customers' actual usage and the reference load.

The accuracy of impact estimates is largely driven by five key factors:

1. **The effect or signal size.** In the context of BTM batteries, the effect size corresponds to the amount of discharge provided during a DR event relative to the counterfactual. Larger and more consistent dispatch signals are easier to measure than smaller or more variable ones. For GoodLeap, the discharge profiles can vary by customer segment and battery configuration, which requires careful modeling of the reference load and expected battery behavior.
2. **Data volatility or noise.** Event level impacts are more difficult to detect when underlying load is noisy or when battery charging and discharging patterns vary significantly across days.
3. **The ability to explain variation and filter out noise.** Robust statistical methods are essential for isolating DR impacts from normal consumption patterns. Regression models and comparison groups can help account for predictable variation in load. Because GoodLeap's portfolio spans many geographies and weather conditions, the evaluation incorporated temperature, solar irradiance, and seasonal time-of-day patterns to construct accurate reference loads.
4. **Population size.** Larger participant populations enable more precise impact estimates. Given the number of batteries in the GoodLeap portfolio, the results were highly precise. However, segmentation by climate zone, sub-LAP, or customer type customer counts and the precision of the load impact estimates.
5. **The ability to isolate the intervention in question from other interventions.** When multiple interventions occur simultaneously, they can be difficult to disentangle. In this instance, there is a clear event dispatch and there are no other confounding interventions. The event battery occurs on some days but not on others, creating a distinct ON/OFF pattern.

Figure 3 illustrates the overall workflow used to estimate impacts. The process begins with data collection and validation to ensure completeness and consistency across metered load, battery telemetry, and weather inputs. Following this, event-like days are selected to identify comparable non-event periods that can be used to inform counterfactual estimation. A model tournament framework is then applied at the individual site level. This involves specifying a range of candidate models with varying combinations of control variables, including weather, time-of-day effects, and other relevant predictors. Each model is estimated across all sites, and performance is evaluated using leave-group-out cross-validation to assess out-of-sample accuracy. The best-performing model for each site is selected and applied to generate reference loads. Using the reference loads predicted by the best models, impacts are estimated for each event at each site as the difference between observed load and predicted counterfactual load. These site-level impacts are then aggregated and used to develop predictive models that relate impacts to key drivers such as load type, weather conditions, hour of day, and geographic location. More details about data processing and the ex-post methodology can be found in Appendix A and Appendix B.

Figure 3: Summary of Evaluation Approach

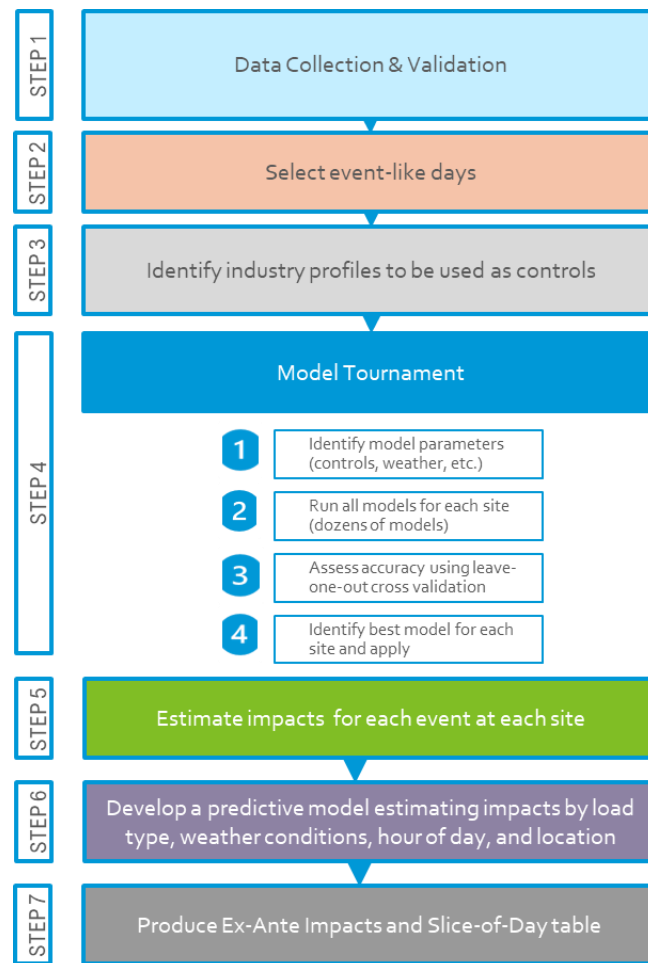
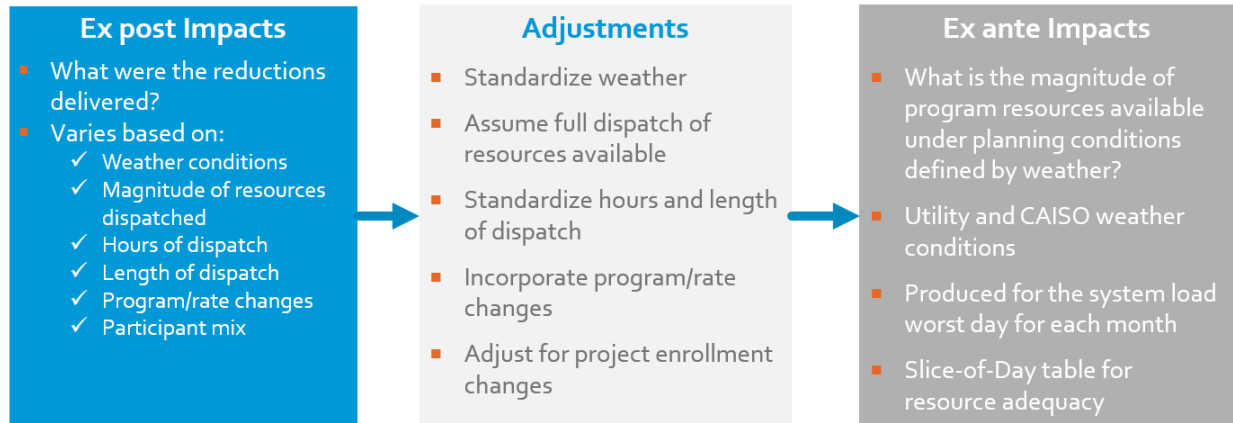


Figure 4 summarizes how ex post impact estimates are translated into ex ante impact projections. The ex-post impacts represent the realized load reductions observed during events and reflect variation in weather conditions, the magnitude of resources dispatched, event timing, event duration, and changes in program conditions or participant composition over time. To develop ex ante estimates suitable for planning and Resource Adequacy applications, impacts are weather normalized and spread across a 4-hour event window. The adjusted impacts are then used to estimate ex ante performance under planning conditions. This involves applying the modeled relationships between impacts and key drivers, such as weather and time-of-day, to utility and CAISO weather conditions. Ex ante impacts are

produced for the highest system load days for each month, and are summarized in Slice-of-Day tables. More information on the ex-ante approach can be found in Appendix C.

Figure 4: Ex-Ante Approach



4 EX-POST RESULTS

4.1 OVERALL

Over the course of the PY2025 season, GoodLeap delivered increasing impacts from its battery portfolio. Figure 5 illustrates the growth in event performance throughout the season. The first event produced approximately 4.5 MWh of estimated energy reductions over two hours, while later season events reached approximately 21 MWh of reductions across the two-hour windows. Table 15 provides additional details underlying the figure, including the impacts for each utility by date and hour into the event.

Figure 5: Total MWh Impacts by Event Day

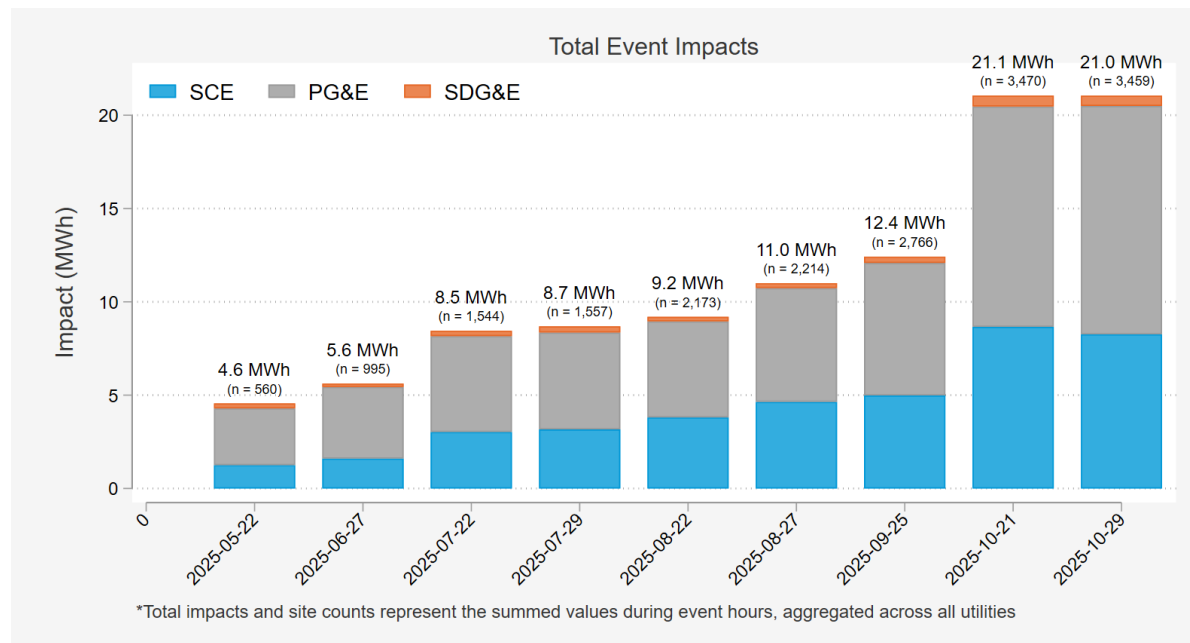


Table 5: Hourly and Total Impacts by Utility, Date, and Event Hour

Event Date	PG&E			SCE			SDGE		
	Impact MW Hour 1	Impact MW Hour 2	Total MWh Impact	Impact MW Hour 1	Impact MW Hour 2	Total MWh Impact	Impact MW Hour 1	Impact MW Hour 2	Total MWh Impact
5/22/2025	1.98	1.06	3.04	0.84	0.41	1.25	0.14	0.13	0.27
6/27/2025	2.85	0.99	3.83	1.36	0.24	1.60	0.14	0.04	0.18
7/22/2025	4.11	1.02	5.14	2.66	0.37	3.03	0.22	0.07	0.29
7/29/2025	4.06	1.14	5.19	2.71	0.46	3.17	0.24	0.09	0.33
8/22/2025	4.72	0.43	5.15	3.27	0.54	3.81	0.17	0.07	0.24
8/27/2025	4.26	1.83	6.10	3.90	0.75	4.64	0.19	0.07	0.26
9/25/2025	6.19	0.91	7.10	4.86	0.13	4.99	0.20	0.13	0.34
10/21/2025	9.18	2.62	11.80	7.47	1.19	8.66	0.42	0.16	0.59
10/29/2025	9.44	2.79	12.23	6.64	1.62	8.26	0.40	0.16	0.55

It is notable that impacts were concentrated in the first event hour with significant decay in the second hour. Figure 6 illustrates this pattern using the event on October 21, 2025, which had the largest participation during a single event window. The figure shows aggregated battery net discharge alongside the estimated reference load and the resulting impacts. During the first hour of the event (hour ending 18), the observed battery discharge diverges sharply from the reference load, producing the majority of the event’s load reduction. Impacts are noticeably smaller in the second hour as available battery energy declines. This concentration reflects the fact that there was no requirement under the DSGS program to distribute discharge evenly across the event window, allowing batteries to concentrate output earlier in the event. This behavior is accounted for in the ex-ante impact estimation, where impacts are adjusted to reflect a four-hour RA dispatch requirement, as described in Appendix C.

Figure 6: Hourly Discharge and Impacts for 10/21/2025 Event – Portfolio Level

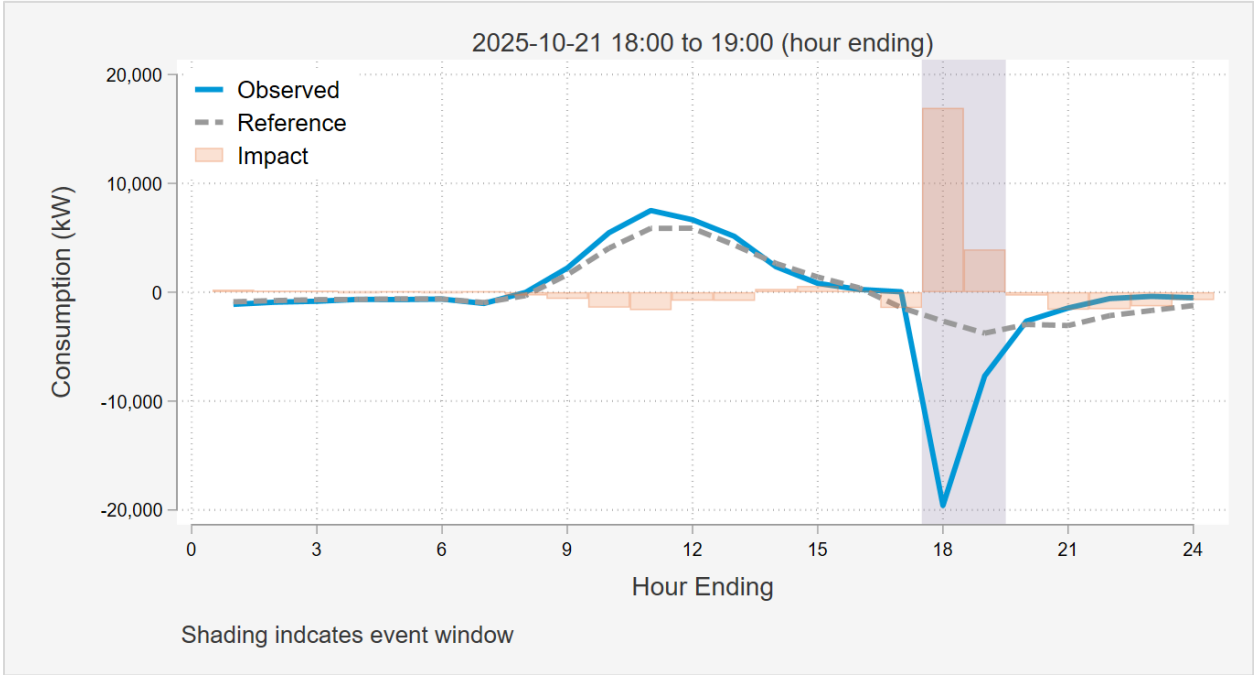


Figure 7 shows how the dispatch behavior varied noticeably across battery manufacturers. Enphase systems tended to concentrate nearly all their discharge in the first event hour, which largely explains the strong concentration of impacts during that period. SolarEdge systems also delivered greater discharge in the first hour, though their output declined only modestly in the second hour, resulting in a more balanced contribution across the event window. Tesla systems exhibited a different pattern, with meaningful discharge occurring in the first hour but with impacts increasing in the second hour.

Figure 7: Average Hourly Discharge by Battery Manufacturer - Site-Level



4.2 SEGMENTED RESULTS

Table 6 summarizes average per-site event performance across several portfolio segments. The values represent simple averages across all events in the PY2025 season and therefore reflect impacts observed across a range of event conditions, months, and temperatures. As such, the results should be interpreted as ex-post averages rather than weather-normalized performance metrics. The table highlights several patterns in how impacts vary across different segments of the portfolio. Event performance differs across battery manufacturers, with Enphase systems concentrating most of their discharge in the first hour of the event window, contributing to the strong first-hour impacts observed across the portfolio. SolarEdge systems exhibit a more balanced dispatch profile, with impacts more evenly distributed across the two-hour event window, while Tesla systems show the opposite pattern, with comparatively greater discharge occurring in the second hour of events. Impacts also scale with battery system size, with larger systems producing greater average reductions during events than smaller systems, reflecting the greater available stored energy available for dispatch. Geographic segmentation shows some variation across Local Capacity Areas (LCAs), with generally higher impacts observed in hotter inland regions such as Sierra and Kern, where higher temperatures likely lead to greater charging and dispatch activity. In contrast, cooler coastal regions tend to exhibit slightly lower average impacts. Impacts are otherwise broadly consistent across utility service territories, indicating that the portfolio performs similarly across PG&E, SCE, and SDG&E dispatch locations.

Table 6: Average Per-Site Impacts by Segment

Category	Subcategory	% of Sites	Average Temperature (Event Hours)	Hour Into Event (Avg.) ^[1]		Event Hour Average ^[2]	
				Hour 1 (kW)	Hour 2 (kW)	Reference Load (Baseline kW)	Impact (kW)
All	All	100%	77.00	4.41	1.19	-1.31	2.80
Battery Count Bin	One	49%	76.43	2.92	1.74	-1.03	2.33
	Two	37%	77.04	5.18	1.02	-1.46	3.10
	Three	10%	78.74	7.10	-0.42	-1.78	3.34
	Four +	4%	79.27	9.20	-0.23	-2.36	4.49
Battery Manufacturer	ENPHASE	60%	77.22	4.90	-0.55	-1.18	2.17
	SOLAREEDGE	19%	77.15	3.93	3.15	-1.35	3.54
	TESLA	21%	76.38	3.49	4.37	-1.63	3.93
Local Capacity Area	Bay Area	8%	65.42	4.49	1.72	-1.20	3.10
	Big Creek/Ventura	9%	78.55	4.49	0.98	-1.28	2.73
	CAISO System	12%	77.04	4.57	1.63	-1.37	3.10
	Greater Fresno	15%	83.74	4.39	0.77	-1.42	2.58
	Kern	7%	84.80	4.38	1.32	-1.52	2.85
	LA Basin	28%	76.38	4.37	0.75	-1.18	2.56
	Other	4%	70.49	4.11	1.62	-1.34	2.87
	San Diego/Imperial Valley	3%	69.81	3.65	1.72	-1.04	2.69
	Sierra	9%	76.37	4.77	1.73	-1.64	3.25
Stockton	5%	74.85	4.25	0.67	-1.33	2.46	
Nameplate Power Bin	1-5 kW	42%	76.55	3.28	0.83	-0.95	2.06
	6-10 kW	31%	77.02	5.21	0.90	-1.42	3.06
	11-15 kW	22%	77.62	5.28	1.45	-1.64	3.36
	15+ kW	5%	77.85	5.69	5.15	-2.39	5.42
Utility	SCE	41%	77.23	4.42	0.90	-1.23	2.66
	PGE	56%	77.28	4.50	1.35	-1.41	2.93
	SDGE	3%	69.81	3.65	1.72	-1.04	2.69

[1] The per-site average reactions for the hour into the event across all dates regardless of start time

[2] The average across all event hours

4.3 MONTHLY VARIATION IN PER-SITE RESULTS

Table 7 presents the average hourly load reductions per-site for each event. It is notable that the impacts are generally lower for the August and September events.

Table 7: Average Hourly Per-Site Load Reductions by Event

Event	Total Sites Dispatched	Reference load (kW)	Load w/ DR (kW)	Load reduction (kW)	Avg temp (F, site weighted)	Std. error	t-stat
05/22/2025 20:00 to 21:00	571	-0.94	-5.01	4.07	71	0.112	36.28
06/27/2025 20:00 to 21:00	1,030	-1.34	-4.16	2.82	82	0.076	37.27
07/22/2025 20:00 to 21:00	1,580	-1.28	-4.02	2.74	73	0.052	52.59
07/29/2025 20:00 to 21:00	1,580	-1.35	-4.14	2.79	78	0.051	54.32
08/22/2025 19:00 to 20:00	2,277	-1.74	-3.86	2.12	89	0.022	98.22
08/27/2025 20:00 to 21:00	1,265	-1.79	-4.27	2.48	80	0.032	77.91
08/27/2025 19:00 to 20:00	1,012	-1.45	-3.95	2.49	82	0.034	72.81
09/25/2025 19:00 to 20:00	2,858	-1.83	-4.08	2.25	74	0.019	116.62
10/21/2025 18:00 to 19:00	3,564	-0.93	-3.97	3.03	72	0.016	191.50
10/29/2025 18:00 to 19:00	2,000	-0.76	-4.05	3.29	71	0.019	169.85
10/29/2025 19:00 to 20:00	1,564	-1.03	-3.76	2.73	74	0.026	105.40

Figure 8 provides additional context by showing the average non-event load shapes by month. The figure indicates that during August and September batteries discharge more during the same hours as typical event windows on non-event days. This behavior is consistent with the incentives under California’s Net Billing Tariff (NBT), which encourages customers to export energy during peak periods in exchange for energy export credits (EEC). Figure 9 displays a heatmap of SCE’s EECs over the analysis period as an example, highlighting that these credits spike in August and September. As a result, baseline load appears reduced during these hours, which affects the magnitude of measured event impacts. Because impacts are calculated relative to a modeled baseline, increased non-event dispatch during peak periods leads to lower incremental reductions observed during events. Despite this, event-day load reductions are consistently observed relative to non-event conditions. This indicates that batteries provide additional discharge during events beyond typical non-event behavior, including periods when NBT-driven dispatch is already occurring.

Figure 8: Average Per-Site Load Shapes by Month

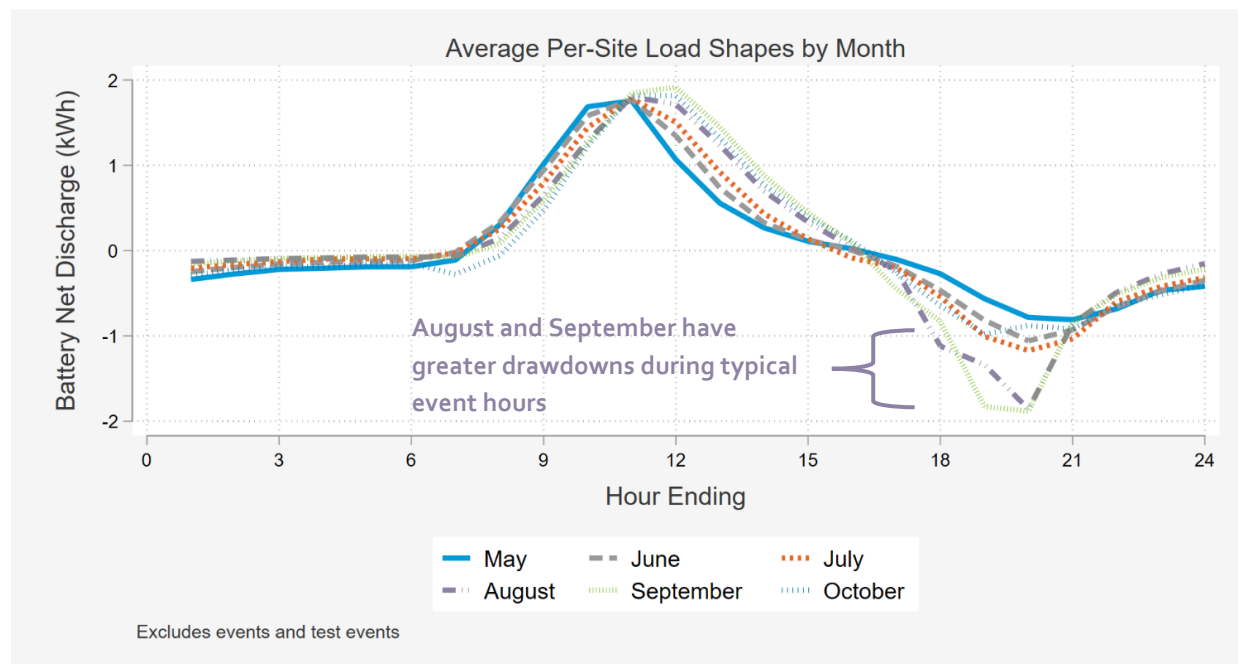
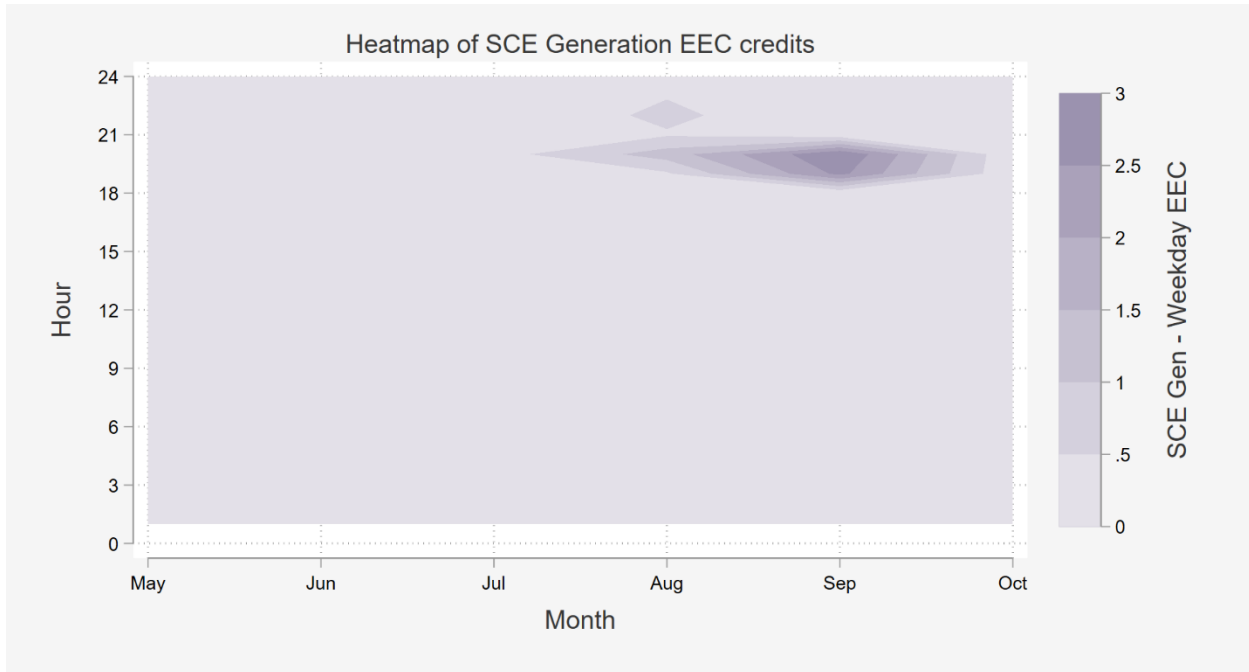


Figure 9: Heatmap of SCE Generation EEC Credits



4.4 STATE-OF-CHARGE BEHAVIOR ON EVENT DAYS

Figure 10 and Table 8 illustrate how the battery's state-of-charge (SOC) changes during event days using the 8/22/2025 event as an example. Batteries are consistently charged to near full capacity prior to dispatch, with observed SOC in the hour preceding events typically exceeding 95%. This indicates how batteries are actively preparing for dispatch by increasing charging earlier in the day. During the event window, the SOC declines rapidly as batteries discharge to deliver load reductions, falling to approximately 15 to 25% by the end of the two-hour event period. These patterns are consistent across events and highlight a coordinated charge and discharge cycle, where energy is accumulated ahead of the event and deployed over a relatively short, two-hour window. This behavior is important for interpreting the concentration of impacts observed in ex-post results and provides a foundation for the ex-ante analysis, where the impacts are extended and reshaped to evaluate performance over a four-hour event.

Figure 10: Hourly Average State-of-Charge for 8/22/2025

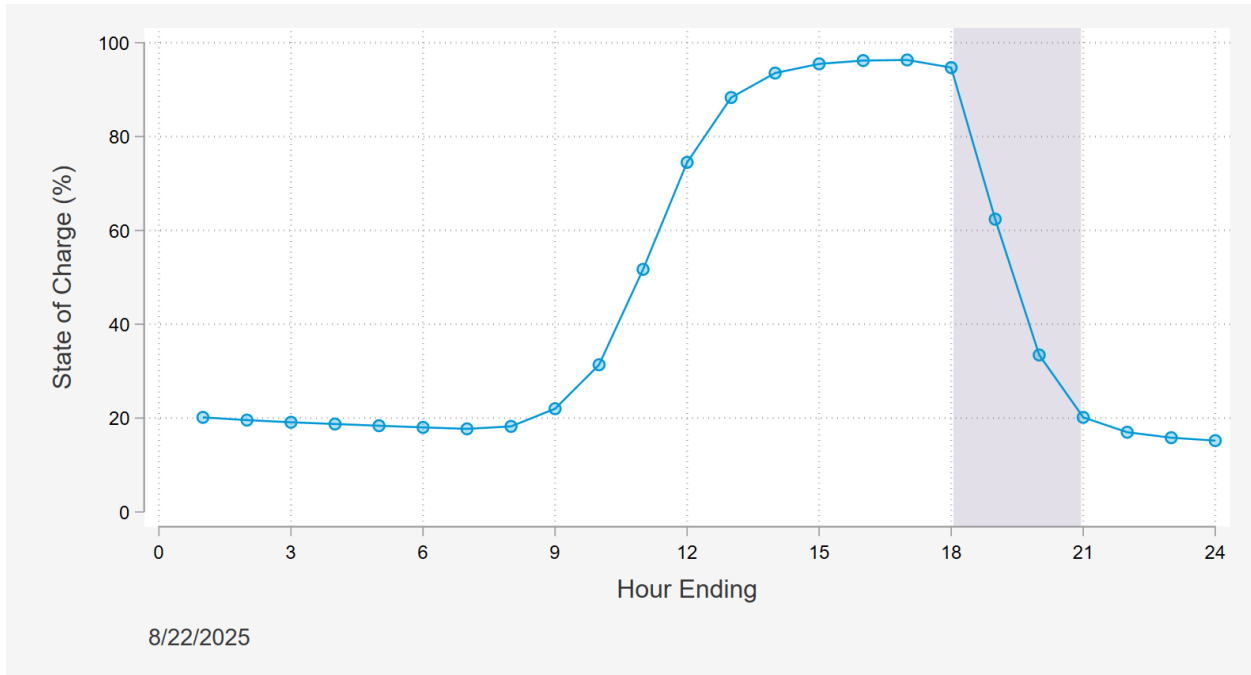


Table 8: Average Observed and Baseline State-of-Charge for Hour Prior and Hour After Events¹

Event	Hour Prior to Event		Hour After Event	
	Observed	Baseline	Observed	Baseline
05/22/2025 7 to 9 PM	97%	80%	19%	52%
06/27/2025 7 to 9 PM	97%	76%	20%	43%
07/22/2025 7 to 9 PM	97%	73%	22%	42%
07/29/2025 7 to 9 PM	96%	71%	19%	40%
08/22/2025 6 to 8 PM	95%	68%	20%	28%
08/27/2025 6 to 8 PM	96%	71%	16%	29%
08/27/2025 7 to 9 PM	96%	63%	19%	26%
09/25/2025 6 to 8 PM	97%	73%	20%	29%
10/21/2025 5 to 7 PM	98%	88%	22%	61%
10/29/2025 5 to 7 PM	98%	90%	24%	65%
10/29/2025 6 to 8 PM	98%	79%	22%	48%

¹ Baseline values represent predicted SOC under extreme non-event conditions for high system load days. These predictions are based on models estimated under the ex-ante framework using non-event days and account for factors such as temperature and time-of-day to reflect typical battery behavior absent dispatch. The full model specification and estimation approach are provided in Appendix C.

5 EX-ANTE RESULTS

The electric grid is designed to maintain reliability under peaking conditions when temperatures are typically hottest. Thus, the magnitude and performance of DR resources under peaking conditions used for planning is critical for understanding the degree they can offset other resources, such as peaking gas power plant. Load impacts under planning conditions are referred to as ex-ante impacts and are informed by performance during historical events. They are an estimate of the load reduction capability that aligns with peak day weather, standardized hours, and length of dispatch. In essence, they are weather normalized impact values that are helpful when forecasting a resource's load reduction potential for different forecasts. A key step for residential batteries was adjusting the loads impacts from 2025, which were mostly two or three hour events, to reflect the capability over a four-hour event. This section explores the ex-ante results found by DSA.

5.1 EX-ANTE LOAD IMPACT PROJECTIONS

GoodLeap's ex-ante enrollment forecasts are based on the observed growth during the PY2025 season and current enrollment as of March 2026, with a flat year-over-year growth rate applied over the forecast horizon. From May 2025 to October 2025, the number of sites enrolled grew from approximately 560 enrolled sites to more than 3,500. By March 2026, GoodLeap had more than more than doubled the number of participants to over 7,400 sites. On average, GoodLeap has been adding 684 battery sites per month. Projected to August 2027, enrollments are expected to exceed 24,000 battery sites.

However, the forecast assumes a conservative, steady growth rate and 19,030 by August 2027, providing ample cushion in case the rate of residential battery site growth changes. Dispatch is modeled over an event window of 5:00 PM to 9:00 PM, with resources capable of meeting a four-hour Resource Adequacy requirement. Table 9 presents the 1-in-2 ex-ante impacts during the August Worst Day by utility. Aggregate impacts are expected to grow significantly by 2027.

Table 9: Aggregate Ex-Ante Impacts – August Worst Day – Utility 1-in-2 Weather

Year	PGE			SCE			SDGE			Total		
	Sites	MW	MWh	Sites	MW	MWh	Sites	MW	MWh	Sites	MW	MWh
2025 (Base August)	1,265	1.5	5.9	938	1.1	4.3	74	0.1	0.3	2,277	2.6	10.5
2026	5,150	6.0	23.9	5,262	6.0	24.1	410	0.4	1.8	10,822	12.5	49.8
2027 (NQC Request)	8,966	10.4	41.7	9,342	10.7	42.9	722	0.8	3.1	19,030	21.9	87.6
2028	12,782	14.9	59.4	13,422	15.4	61.6	1,034	1.1	4.4	27,238	31.4	125.4
2029	16,598	19.3	77.1	17,502	20.1	80.3	1,346	1.4	5.7	35,446	40.8	163.2
2030	20,414	23.7	94.9	21,582	24.8	99.0	1,658	1.8	7.1	43,654	50.2	201.0
2031	24,230	28.2	112.6	25,662	29.4	117.8	1,970	2.1	8.4	51,862	59.7	238.8
2032	28,046	32.6	130.3	29,742	34.1	136.5	2,282	2.4	9.7	60,070	69.1	276.6
2033	31,862	37.0	148.1	33,822	38.8	155.2	2,594	2.8	11.1	68,278	78.6	314.4
2034	35,678	41.5	165.8	37,902	43.5	173.9	2,906	3.1	12.4	76,486	88.0	352.1
2035	39,494	45.9	183.5	41,982	48.2	192.7	3,218	3.4	13.7	84,694	97.5	389.9
2036	43,310	50.3	201.3	46,062	52.8	211.4	3,530	3.8	15.1	92,902	106.9	427.7

Table 10 presents the projected monthly impacts for 2027, illustrating the seasonal profile of performance. Impacts grow steadily throughout the year with increased enrollments, with a modest decline observed from August to September, reflecting the influence of EECs on measured impacts.

Table 10: Aggregate 2027 Ex-Ante Impacts by Monthly Worst Day 1-in-2 Utility Weather

Day Type	PGE		SCE		SDGE		Total	
	MW	MWh	MW	MWh	MW	MWh	MW	MWh
January Worst Day	7.8	31.2	7.4	29.7	0.6	2.4	15.8	63.3
February Worst Day	8.1	32.3	7.9	31.6	0.6	2.5	16.6	66.4
March Worst Day	8.4	33.5	8.1	32.4	0.6	2.5	17.1	68.4
April Worst Day	8.1	32.4	8.1	32.5	0.6	2.6	16.9	67.5
May Worst Day	8.1	32.6	8.3	33.2	0.7	2.7	17.1	68.5
June Worst Day	8.4	33.7	8.5	34.0	0.7	2.8	17.6	70.5
July Worst Day	9.5	38.1	9.4	37.7	0.7	2.9	19.7	78.8
August Worst Day	10.4	41.7	10.7	42.9	0.8	3.1	21.9	87.6
September Worst Day	10.3	41.1	10.4	41.5	0.8	3.2	21.5	85.9
October Worst Day	12.7	50.8	12.6	50.5	1.0	3.9	26.3	105.2
November Worst Day	11.3	45.2	10.6	42.5	0.8	3.4	22.8	91.1
December Worst Day	11.9	47.4	11.6	46.4	0.9	3.6	24.4	97.5

5.2 RESOURCE ADEQUACY SLICE-OF-DAY TABLE

Table 11 presents the slice-of-day analysis for forecast year 2027 using utility weather data under 1-in-2 worst day planning conditions. Impacts are flat across the event windows and are their highest in August and October. The figure also shows increased usage in the early hours of the day, reflecting pre-event battery charging behavior. Table 12 shows the same table on a per-site basis.

Table 11: Aggregate Slice-of-Day Table – 2027 Worst Days - Utility 1-in-2 Weather

Units: MW

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	-2.69	-2.69	-2.32	-1.45	-1.22	-0.72	1.29	0.12	0.69	1.10	-2.07	-2.88
2	-2.69	-2.69	-2.32	-1.45	-1.22	-0.72	1.29	0.12	0.69	1.10	-2.07	-2.88
3	0.58	0.57	0.14	-0.88	-1.14	-0.16	0.50	-0.02	0.27	0.94	-0.15	0.79
4	1.24	1.24	0.74	-0.43	-0.74	-0.61	-0.03	0.16	-0.11	0.74	0.41	1.49
5	0.94	0.93	0.50	-0.50	-0.77	-0.13	-0.22	0.07	-0.22	0.59	0.22	1.15
6	0.09	0.09	-0.09	-0.52	-0.63	0.00	-0.60	0.00	0.05	0.66	-0.21	0.19
7	-0.03	-0.03	-0.08	-0.20	-0.24	0.28	0.01	-0.07	-0.03	0.51	-0.12	-0.01
8	0.98	0.98	0.62	-0.23	-0.45	-0.89	0.01	-0.12	-0.88	-5.29	0.38	1.17
9	-4.37	-4.36	-3.38	-1.06	-0.45	0.21	1.97	-0.12	-8.29	10.17	-2.71	-4.86
10	-17.29	-17.27	-13.80	-5.67	-3.52	2.13	0.33	-0.61	-12.77	-9.60	-11.47	-19.04
11	-21.89	-21.87	-17.18	-6.19	-3.29	-2.52	-4.07	-10.80	-14.54	-8.33	-14.04	-24.26
12	-1.53	-1.38	-4.02	-2.93	-1.27	-5.71	-6.54	-16.66	-7.74	0.65	-4.11	-0.23
13	14.61	14.45	11.41	1.85	-0.15	-5.77	-2.51	-6.24	3.92	7.25	8.65	-16.41
14	9.92	9.98	8.23	2.83	0.86	-3.79	0.45	2.29	9.35	7.30	6.63	-10.70
15	2.38	2.06	1.22	-1.05	-1.83	-1.45	-1.72	1.52	5.15	5.07	0.64	2.63
16	-2.32	-2.16	-2.27	-3.68	-4.20	-3.35	-4.78	-2.38	-1.62	1.11	-2.47	-2.24
17	-8.01	-7.96	-6.75	-4.13	-3.48	-6.24	-7.29	-5.24	-11.05	-5.02	-5.97	-8.59
18	21.16	21.16	20.84	19.71	19.19	18.99	20.42	21.91	20.72	24.54	20.55	21.30
19	21.16	21.16	20.84	19.71	19.19	18.99	20.42	21.91	20.72	24.54	20.55	21.30
20	21.16	21.16	20.84	19.71	19.19	18.99	20.42	21.91	20.72	24.54	20.55	21.30
21	21.16	21.16	20.84	19.71	19.19	18.99	20.42	21.91	20.72	24.54	20.55	21.30
22	-8.20	-8.21	-8.57	-9.43	-9.65	-4.58	-5.81	-2.54	-3.45	-7.72	-8.81	-8.02
23	-8.20	-8.21	-8.57	-9.43	-9.65	-4.58	-5.81	-2.54	-3.45	-7.72	-8.81	-8.02
24	-3.71	-3.72	-4.89	-7.65	-8.38	-3.73	-4.72	-1.75	-2.35	-6.25	-5.68	-3.12

Demand reductions are positive (Blue)

Load increases are negative (Orange)

Table 12: Per-Site Slice-of-Day Table – 2027 Worst Days - Utility 1-in-2 Weather

Units: kW

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	-0.14	-0.14	-0.12	-0.08	-0.06	-0.04	0.07	0.01	0.04	0.06	-0.11	-0.15
2	-0.14	-0.14	-0.12	-0.08	-0.06	-0.04	0.07	0.01	0.04	0.06	-0.11	-0.15
3	0.03	0.03	0.01	-0.05	-0.06	-0.01	0.03	0.00	0.01	0.05	-0.01	0.04
4	0.07	0.07	0.04	-0.02	-0.04	-0.03	0.00	0.01	-0.01	0.04	0.02	0.08
5	0.05	0.05	0.03	-0.03	-0.04	-0.01	-0.01	0.00	-0.01	0.03	0.01	0.06
6	0.00	0.00	0.00	-0.03	-0.03	0.00	-0.03	0.00	0.00	0.03	-0.01	0.01
7	0.00	0.00	0.00	-0.01	-0.01	0.01	0.00	0.00	0.00	0.03	-0.01	0.00
8	0.05	0.05	0.03	-0.01	-0.02	-0.05	0.00	-0.01	-0.05	-0.28	0.02	0.06
9	-0.23	-0.23	-0.18	-0.06	-0.02	0.01	0.10	-0.01	-0.44	-0.53	-0.14	-0.26
10	-0.91	-0.91	-0.73	-0.30	-0.19	0.11	0.02	-0.03	-0.67	-0.50	-0.60	-1.00
11	-1.15	-1.15	-0.90	-0.33	-0.17	-0.13	-0.21	-0.57	-0.76	-0.44	-0.74	-1.28
12	-0.08	-0.07	-0.21	-0.15	-0.07	-0.30	-0.34	-0.88	-0.41	0.03	-0.22	-0.01
13	0.77	0.76	0.60	0.10	-0.01	-0.30	-0.13	-0.33	0.21	0.38	0.45	0.86
14	0.52	0.52	0.43	0.15	0.05	-0.20	0.02	0.12	0.49	0.38	0.35	0.56
15	0.13	0.11	0.06	-0.06	-0.10	-0.08	-0.09	0.08	0.27	0.27	0.03	0.14
16	-0.12	-0.11	-0.12	-0.19	-0.22	-0.18	-0.25	-0.13	-0.09	0.06	-0.13	-0.12
17	-0.42	-0.42	-0.35	-0.22	-0.18	-0.33	-0.38	-0.28	-0.58	-0.26	-0.31	-0.45
18	1.11	1.11	1.10	1.04	1.01	1.00	1.07	1.15	1.09	1.29	1.08	1.12
19	1.11	1.11	1.10	1.04	1.01	1.00	1.07	1.15	1.09	1.29	1.08	1.12
20	1.11	1.11	1.10	1.04	1.01	1.00	1.07	1.15	1.09	1.29	1.08	1.12
21	1.11	1.11	1.10	1.04	1.01	1.00	1.07	1.15	1.09	1.29	1.08	1.12
22	-0.43	-0.43	-0.45	-0.50	-0.51	-0.24	-0.31	-0.13	-0.18	-0.41	-0.46	-0.42
23	-0.43	-0.43	-0.45	-0.50	-0.51	-0.24	-0.31	-0.13	-0.18	-0.41	-0.46	-0.42
24	-0.19	-0.20	-0.26	-0.40	-0.44	-0.20	-0.25	-0.09	-0.12	-0.33	-0.30	-0.16

Demand reductions are positive (Blue)
Load increases are negative (Orange)

5.3 COMPARISON TO EX-POST RESULTS

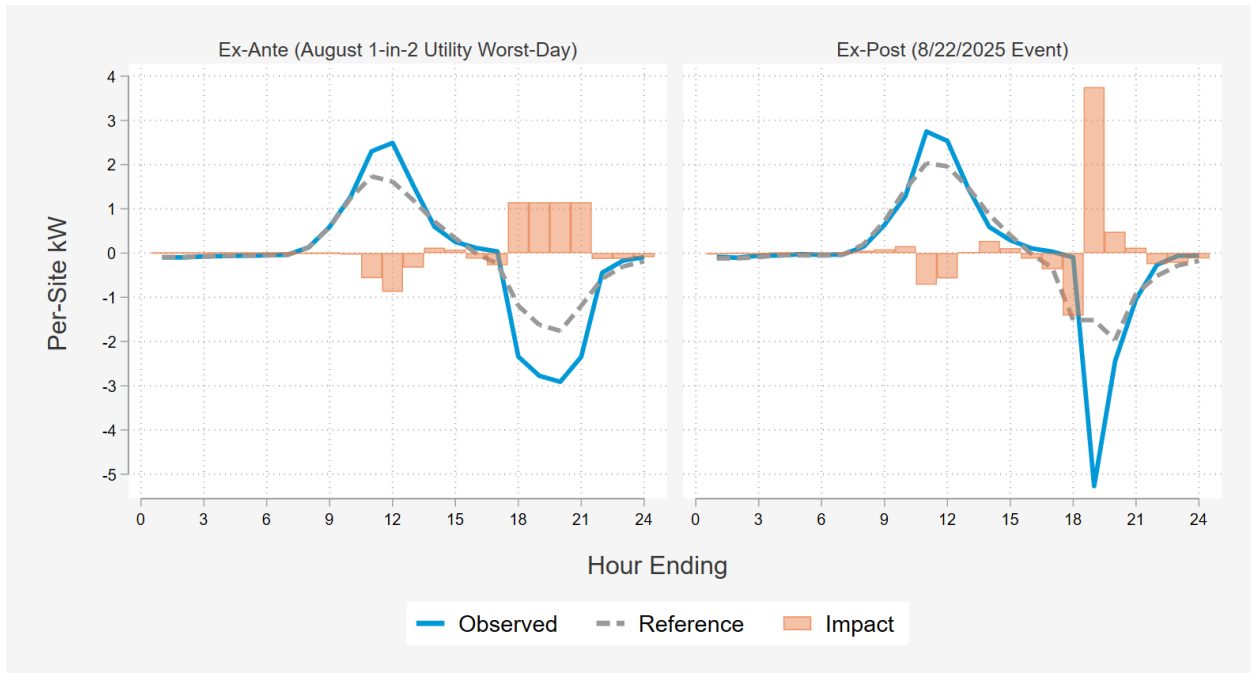
Table 13 compares ex-ante and ex-post impacts for October, as the October 21, 2025 event reflects a full dispatch of the end-of-season population, offering a good basis for comparison. Although the ex-ante case represents more extreme system conditions, the resulting impacts are lower on both a per-customer and aggregate basis than those observed during the October 21 event. This difference is primarily driven by how the battery energy is deployed. The October 21 event produced the highest observed dispatch during a single event window, with impacts concentrated over a two-hour period and a large share of available energy discharged in the first hour. In contrast, the ex-ante framework assumes a four-hour RA event, requiring energy to be distributed across a longer duration, which reduces hourly intensity. As a result, the hourly ex-ante impacts are lower because they reflect sustained, reliability-aligned dispatch rather than short-duration peak performance.

Table 13: Comparison between Ex-Post and Ex-Ante Impacts

Day Type	# Dispatched	Event Hour Avg Temp	Avg Per-Customer Hourly Impact (kW)	Avg Per-Customer Total Impact (kWh)	Agg Total Impact (MWh)
Ex-Ante: 2025 October Worst Day 1-in-2 (4-hour event; 5:00 - 9:00PM)	3,564	78.9	1.29	5.16	18.4
Ex-Post: 10/21/2025 (2-hour event; 5:00-7:00 PM)	3,564	72.5	3.03	6.07	21.1

Figure 11 shows a comparison of the per-site values predicted for ex-ante versus what was observed during the 8/22/2025 event. Both panels illustrate how event impacts are incremental to any existing battery dispatch behavior, with similar patterns in the hours leading up to the event and in the hours after. While the ex-post results show a sharp, concentrated discharge during the two-hour event window, the ex-ante profile spreads these impacts across a four-hour period, resulting in a lower but more sustained per-site reduction. This demonstrates how the more dramatic, front-loaded impacts observed in ex-post results are reshaped to reflect a reliable four-hour RA profile.

Figure 11: Comparison Between August Ex-Ante Predictions and Ex-Post Event Impacts



6 KEY FINDINGS AND RECOMMENDATIONS

The GoodLeap battery portfolio demonstrated effective load reductions during PY2025. Below are DSA’s key findings and recommendations from this analysis.

Table 14: Key Findings

Key Finding	Description
Substantial growth in enrollment and impacts in PY 2025	<ul style="list-style-type: none"> Program participation expanded significantly over the analysis period, growing from 560 enrolled sites in May to more than 3,500 by October. By March 2026, enrollment has more than doubled to over 7,400 sites The growth from May 2025 to March 2026 represents monthly growth of approximately 680 customers. As enrollment increased, event performance also grew, with the portfolio delivering approximately 21 MWh of load reductions during two-hour events by the end of the summer.
Ex-Ante Analysis supports an NOC value of 21.9 MW	<ul style="list-style-type: none"> Under August 1-in-2 weather conditions, the portfolio delivers an average, weather-normalized impact of 4.6 kWh per-site across 4-hour events. Aggregated to the forecasted 2027 enrollment, assuming the same enrollment trend observed in PY2025
Ex-ante results demonstrate reliable four-hour capability	<ul style="list-style-type: none"> The modeling framework used in this analysis reflects how battery discharge can be shaped across the event window and that the portfolio can consistently sustain load reductions across a four-hour event.
First-hour impacts drove ex-post performance	<ul style="list-style-type: none"> Event impacts were heavily concentrated in the first hour of dispatch, with substantially smaller reductions in later hours. This pattern was influenced by manufacturer-specific dispatch strategies and the absence of requirements to spread impacts across the event window, resulting in front-loaded discharge behavior.
Impacts are incremental to NBT-driven dispatch	<ul style="list-style-type: none"> Batteries consistently delivered additional load reductions during event hours beyond typical non-event behavior, even during months with high Energy Export Credit (EEC) values. While the NBT incentives drive discharge during peak periods on non-event days, event impacts represent incremental reductions above this behavior.

We recommend the following for continuing research on the potential of GoodLeap's ability to reduce peak demand:

1. Ensure that all events are internally recorded and that program events and test events are easily discernable
2. Test different battery dispatch strategies to:
 - a. Shape the energy output so impacts are concentrated in hours where RA value is the highest
 - b. Provide flat, consistent MW over events
 - c. Test impacts under a variety of system conditions

7 APPENDIX A – DATA PROCESSING

The data used for this evaluation were sourced either from GoodLeap, or pulled externally to supplement the analysis. The following sections describe the data from each source.

7.1 DATA PROVIDED BY GOODLEAP

Table 15 summarizes the datasets provided by GoodLeap for this evaluation. Three primary data sources were used in the analysis: customer characteristics, event details, and battery end-use interval data. The customer characteristics dataset contained information describing the enrolled battery systems and their geographic locations, which supported segmentation. The event dataset identified the timing of DR events and the utilities for which dispatch occurred. Finally, the interval dataset contained 15-minute consumption data used to estimate event-load impacts and to construct nonevent-day baselines. For each dataset, a series of data quality assurance and cleaning steps was performed prior to analysis, including duplicate checks, missing data reviews, and validation of key fields used in the modeling framework.

Table 15: Summary of Data Provided by GoodLeap

Data source	Purpose	Key variables	Primary cleaning and QA steps
1. Customer Characteristics	Segmentation and identification of enrollment status across relevant time periods	Site ID, utility, battery manufacturer, battery size, inverter size, battery count, latitude, longitude, ZIP code	Duplicate checks (none found); missing data checks (limited missing location fields, <2%); review and validation of record counts
2. Event details	Identification of event timing and utility-specific dispatch locations	Event date, dispatched utility, event hours	Validation that all event hours are correctly matched to the corresponding utility
3. Interval data	Estimation of event load impacts and construction of nonevent baselines using interval load shapes	Site ID, timestamp, battery net discharge, state of charge	Duplicate checks (none found); missing data checks (notable for state of charge); aggregation to hourly totals (sum of battery net discharge, average state of charge); verification of PST time alignment and daylight savings adjustments; load shape visualization and outlier review

7.2 EXTERNALLY SOURCED DATA

Table 16 summarizes the external datasets used to support this evaluation. These datasets provide information on weather conditions, system-level grid conditions, and geographic mappings used to characterize participating sites. Weather data from CALMAC were used to construct temperature and solar irradiance variables for modeling. CAISO system load data, net of renewable generation, were used to characterize grid conditions and to identify comparable event and nonevent days. Additional geographic mapping datasets were used to assign climate zones and grid locations to each participating site.

Table 16: Summary of Externally Sourced Data

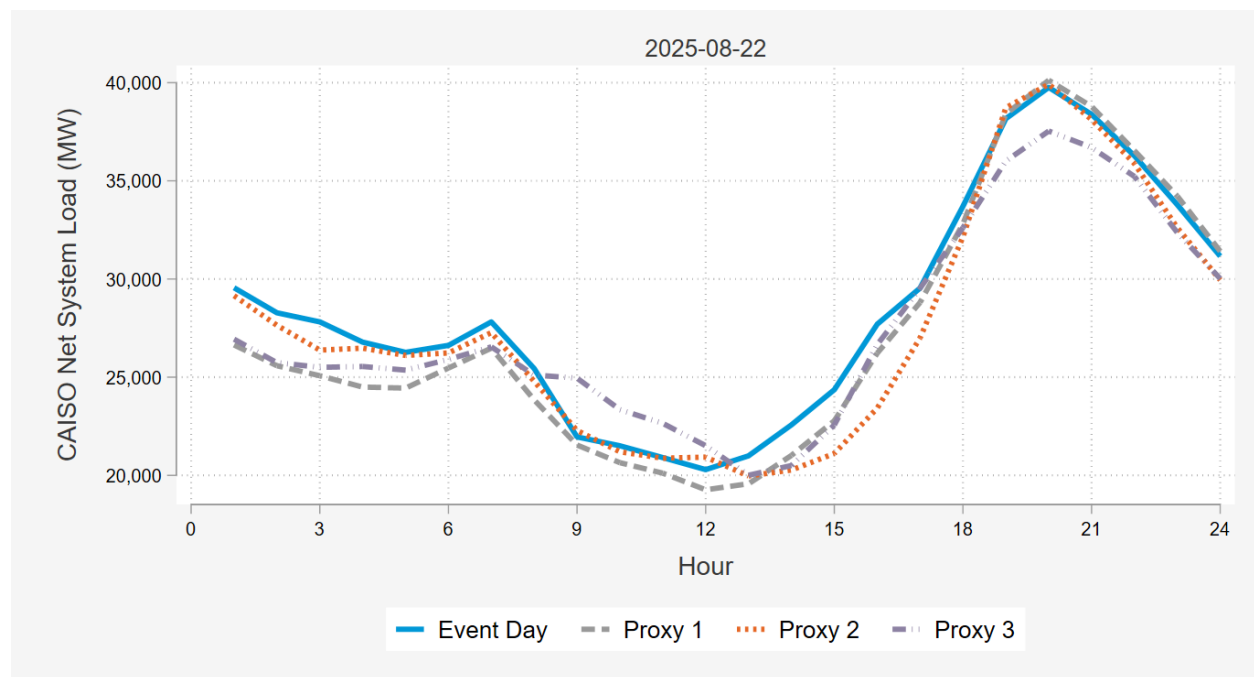
External data source	Key variables and fields	Purpose
1. CALMAC weather data	Air temperature, solar irradiance, station ID, timestamp	CALMAC provides 127 weather stations statewide. Only stations in each utility's ex-ante weather scenarios are used. Sites are matched to eligible stations based on climate zone and distance. Temperature and solar irradiance are used as predictive variables in the models.
2. CAISO system load data (net of renewables)	System load (net of renewables), timestamp	Used to characterize system level conditions and to align event and non-event days with comparable grid conditions.
3. CEC climate zone to ZIP code mapping	ZIP code, CEC climate zone	Used to assign climate zones to sites for weather station matching and segmentation.
4. ZIP code to sub-LAP and LCA mapping (utility provided, non-confidential)	ZIP code, sub-LAP, Load Serving Entity (LCA)	Used to assign grid location for each site and support LIP requirements.
5. Ex-Ante Weather Scenarios (utility provided)	Utility, weather station, weather type, month, temperature	Used to develop ex-ante datasets showing impacts for planning conditions

8 APPENDIX B – EX POST METHODS DETAIL

Ex-post load impacts were estimated using a site-level modeling framework designed to produce accurate counterfactuals during demand response events. To accomplish this, a model tournament approach was implemented in which multiple candidate regression specifications were evaluated for each participating site. The model with the best predictive performance for a given site was then used to estimate its counterfactual during event hours.

The first step in the process involved identifying proxy days for each event day. Proxy days are non-event days that closely resemble the system conditions present during an event. For each event day, three proxy days were selected from non-holiday weekdays based on similarity in CAISO system loads net of renewable generation. Candidate days were scored based on the similarity of hourly system loads to the event day, and the three closest matches were selected. Figure 12 shows the system loads net of renewable generation on proxy days selected for the 8/22/2025 event.

Figure 12: Proxy Day Selections for 8/22/2025 Event



Once the proxy days were selected, a model tournament was then conducted to identify the best-performing regression specification for each site. Eight ordinary least squares (OLS) regression models were tested, each containing different combinations of explanatory variables. For each site, models were trained using a subset of proxy days while withholding a portion of proxy days from the estimation sample. After estimation, each model generated predictions for the withheld proxy days.

Because no demand response event occurred on proxy days, the true impact should be zero. Therefore, the difference between the predicted counterfactual battery discharge and the observed battery behavior represents model prediction error. These errors were used to evaluate model bias and goodness-of-fit across the candidate specifications. The model with the best performance metrics for each site was selected as the preferred specification. Table 17 summarizes the set of variables included across the eight tested models and the general regression specification is as follows:

$$BatteryNet_{i,h} = \alpha_i + X'_{i,h}\beta + \epsilon_{i,h}$$

Where:

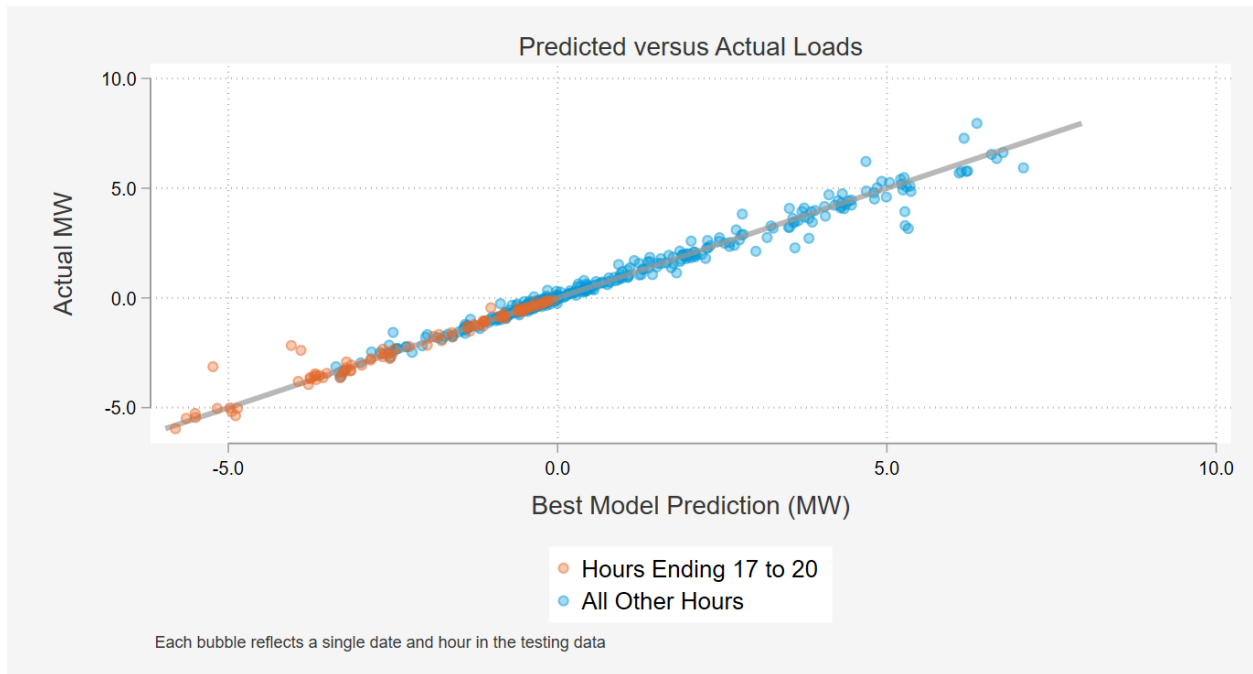
- $BatteryNet_{i,h}$ is the battery net discharge (kWh) for site i in hour h ,
- α_i is a site-specific intercept (for site-level models, this is simply a constant),
- $X'_{i,h}$ is the vector of explanatory variables for site i in hour h ,
- β is the corresponding vector of coefficients, and
- $\epsilon_{i,h}$ is the error term.

Table 17: Model Specifications with Variables Tested in Model Tournament

Model Number	Day-of-Week Factor Variable	Month Factor Variable	Mean 17	SMA Temperature - 4 Hours	Cumulative Solar 8:00AM to 4:00PM	SMA Solar Irradiance - 4 Hours	SMA Solar Irradiance - 24 Hours
1	x	x	x				
2	x	x	x		x		
3	x	x	x			x	
4	x	x	x			x	x
5	x	x		x			
6	x	x		x	x		
7	x	x		x		x	
8	x	x		x		x	x

Figure 13 compares aggregated observed battery net discharge with the corresponding predicted values from the selected models. To construct the figure, observed battery discharge and predicted counterfactual values were summed across all sites for each proxy day and hour. Each point, therefore, represents the portfolio-level battery discharge for a specific proxy day and hour, plotted as actual versus predicted values. Hours corresponding to common event hours (hours ending 17 through 20) are highlighted separately from all other hours. The close alignment of points along the 45-degree line indicates strong alignment between predicted and observed values, demonstrating the ability of the selected models' to accurately reproduce typical battery behavior under event-like conditions.

Figure 13: Aggregated Hourly Loads – Actual versus Predicted



Using the best models for each site, event impacts were calculated as the difference between predicted baseline battery discharge and observed battery discharge during event hours. Positive impacts, therefore, represent additional battery discharge attributable to the demand response event.

Because impacts were estimated at the individual site level, results could be aggregated across multiple dimensions. In this analysis, impacts were segmented and summarized across several characteristics of interest, including battery system size, utility service territory, CAISO sub-LAP, Local Capacity Area (LCA), and battery manufacturer.

9 APPENDIX C – EX ANTE METHODS DETAIL

The ex-ante approach combines observed event performance with modeled battery state of charge (SOC) behavior under high-demand, non-event conditions. By using event and non-event data, the analysis estimates the incremental SOC draw attributable to dispatch and uses this information to construct four-hour equivalent impacts. Table 18 provides an overview of the ex-ante process.

Table 18: Ex-Ante Methods Overview

Methodology Component	Description
Historical Performance Used	PY2025 Ex-Post impacts and State-of-Charge (SOC) data
Process for producing reference loads and event day loads outside of event window	<p>Key steps included:</p> <ul style="list-style-type: none"> Aggregate data by battery manufacturer and utility specific climate groupings Estimate the relationship between hourly non-event SOC and temperature using a time-temperature regression model Predict reference SOC for ex-ante conditions Predict event day SOC outside of event hours for ex-ante conditions
Process for producing ex-ante impacts	<p>Key steps included:</p> <ul style="list-style-type: none"> Predict baseline SOC for each ex-post event day using the reference load model Calculate the SOC change as the difference between SOC at one hour prior to the event (t-1) and four hours after event start (t+4), for both observed and reference conditions Find the SOC impact by subtracting the reference change in SOC from the observed change Model the SOC impact using the same specification as the reference load model, with additional variables for event start hour and pre-event SOC (t-1) Predict event day SOC for ex-ante conditions, spreading the SOC impact over a four hour event window Convert the SOC to kWh by multiplying the hourly SOC change by the nameplate energy storage for each segment
Accounting for enrollment growth	The forecast assumes linear growth for each utility (i.e. the change in sites from 2026 to 2027 is the same for 2027 to 2028)

The analysis began by constructing a dataset of hourly SOC profiles at the site level for both event days and representative non-event peak days. Non-event days were selected as the top five system peak days by utility and month, excluding weekends and event days. These data were then aggregated to the battery manufacturer and climate group level to ensure sufficient sample sizes and stable estimates. Table 19 provides the climate groupings by utility.

Table 19: Climate Groupings by Utility

Utility	Climate Group	CEC Climate Zones
PG&E	Coastal	1, 3, 5, 6, 7
	Warm	2, 4, 8, 9
	Hot	10, 11, 12
	Very Hot	13, 14, 15, 16
SCE	Coastal	1, 3, 5, 6, 7
	Warm	2, 4, 8, 9
	Hot	10, 11, 12
	Very Hot	13, 14, 15, 16
SDG&E	Coastal	1, 3, 5, 6, 7
	Hot	2, 4, 8-16

Hourly SOC was modeled separately for each hour of the day using ordinary least squares regression. Models were estimated on non-event days to capture typical SOC behavior absent dispatch, using temperature, month, and interactions between battery manufacturer and climate group as predictors. These models were then used to generate counterfactual SOC trajectories for event days, representing expected SOC in the absence of dispatch. A parallel set of regressions was estimated using non-event hours on event days to characterize pre- and post-event SOC behavior. For each hour independently ($h \in \{1, \dots, 24\}$), the following regression was run:

Equation 1: Hourly State-of-Charge Model

$$\begin{aligned}
 SOC_{g,t,h} = & \beta_0 + \beta_1 AvgTemp_t + \sum_m \gamma_m Month_{m,t} + \sum_m \sigma_m AvgTemp_t * Month_{m,t} \\
 & + \sum_k \delta_k OEM_k * ClimateGroup_k + \epsilon_{\{g,t,h\}}
 \end{aligned}$$

Where:

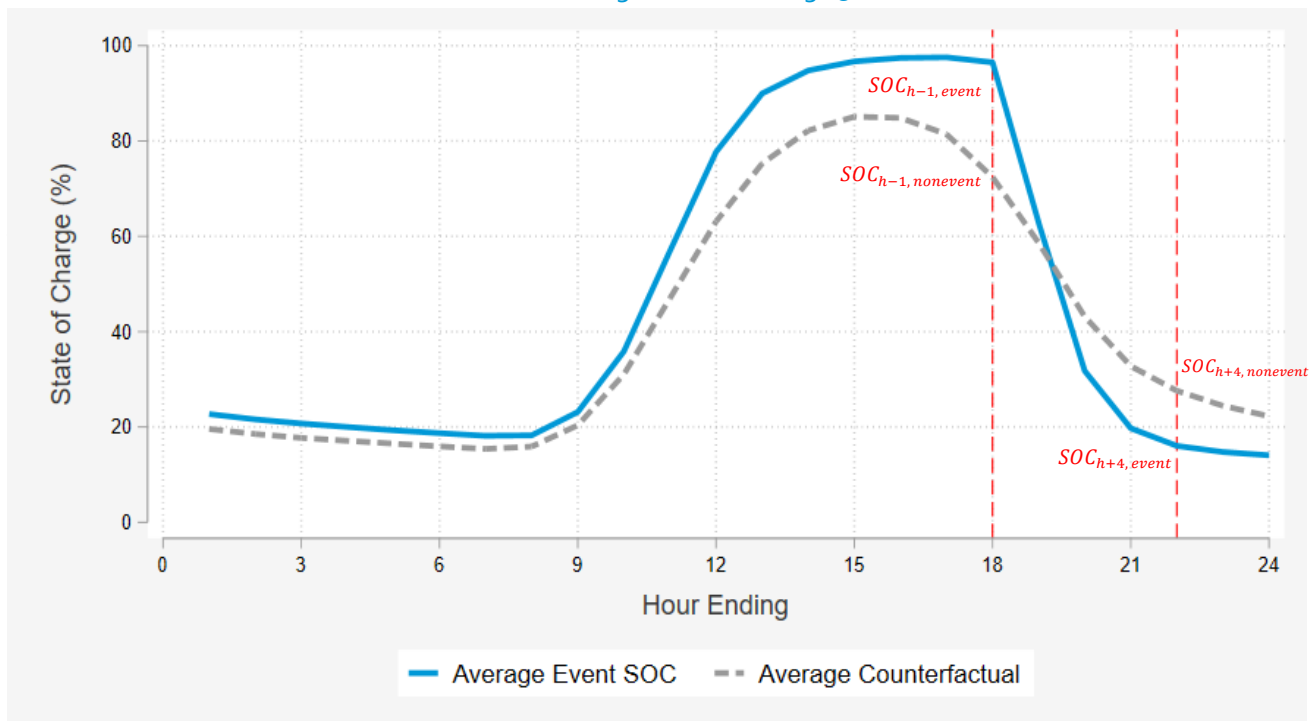
Term	Description
$SOC_{g,t,h}$	Average state of charge (%) for climate group and battery manufacturer segment (g) at hour (h) on day (t)
$AvgTemp_t$	Average temperature build up over the pre-event window (hours 1–9) for day (t)
$Month_{m,t}$	Indicator variables for calendar month
$AvgTemp_t * Month_{m,t}$	Interaction between temperature and month to capture seasonal temperature sensitivity
OEM_k	Battery manufacturer indicator (e.g., Enphase, Tesla, SolarEdge)
$ClimateGroup_k$	Climate grouping based on utility and CEC climate zone
$EM_k * ClimateGroup_k$	Interaction capturing differences in SOC behavior across manufacturer and climate segments
$\beta_1, \gamma_m, \sigma_{m_i}, \delta_k$	Estimated model coefficients
$\epsilon_{\{g,t,h\}}$	Error term

To estimate event-driven impacts, SOC changes were calculated between the hour prior to the event and four hours after the event start. This calculation was performed for both observed SOC and counterfactual SOC, and a difference-in-differences (DiD) approach was used to isolate the SOC change attributable to dispatch. The resulting SOC deltas were then modeled as a function of temperature, month, initial SOC, and portfolio characteristics to normalize impacts across varying system conditions.

Equation 2: Calculation of SOC Impact During Events

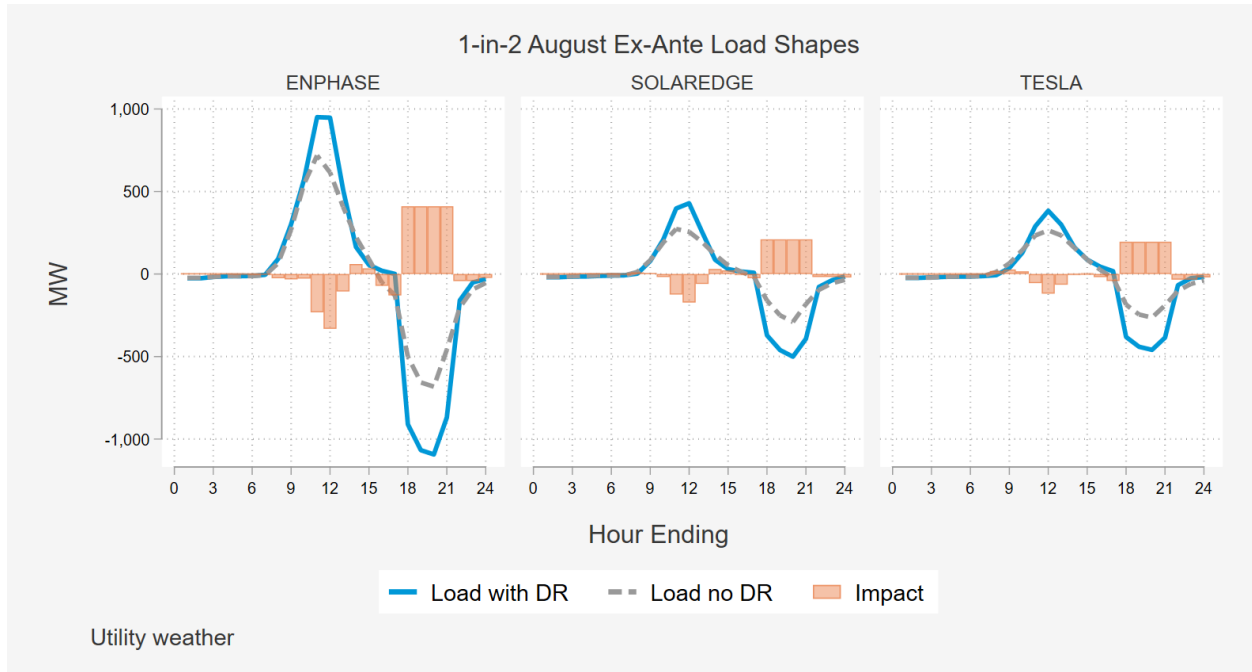
$$SOC \text{ Delta} = (SOC_{h-1, event} - SOC_{h+4, event}) - (SOC_{h-1, nonevent} - SOC_{h+4, nonevent})$$

Figure 14: Average Predicted Versus Average Actual State-of-Charge for Events starting at Hour Ending 19



Finally, impacts were scaled to the portfolio level using enrollment forecasts and observed distributions of battery capacity across utilities, climate groups, and manufacturers. Forecasted site counts were combined with average nameplate capacity to estimate total available energy, which was then applied to the modeled SOC-based load shapes to produce hourly and aggregate ex-ante impacts. The SOC impact was spread over a four hour event window, assuming flat impacts for all event hours. Figure 13 shows an example of the projected load shapes and impacts by battery manufacturer for the August 1-in-2 worst day using utility weather.

Figure 15: Ex-Ante Hourly Load Shapes by Battery Manufacturer



10 APPENDIX D –EVENT DAY BEHAVIOR

The following figures illustrate how battery behavior on event days differs from typical non-event operation. Across all months, event days exhibit a clear and consistent pattern of elevated discharge during the event window relative to non-event days. While batteries often show some level of discharge during peak hours on non-event days, particularly in late summer months, event-day behavior is distinct in both magnitude and timing, with sharper and more pronounced reductions aligned with dispatch periods.

The monthly load shapes demonstrate that event-day discharge stands out clearly from non-event profiles, particularly during evening hours when dispatch occurs. This distinction persists even in months such as August and September, when non-event discharge is elevated due to external incentives. Similarly, the temperature relationship show that event-hour discharge is systematically greater than non-event behavior across a wide range of temperatures and across all utilities.

Figure 16: Per-Site Hourly Load Shapes for Each Day By Month

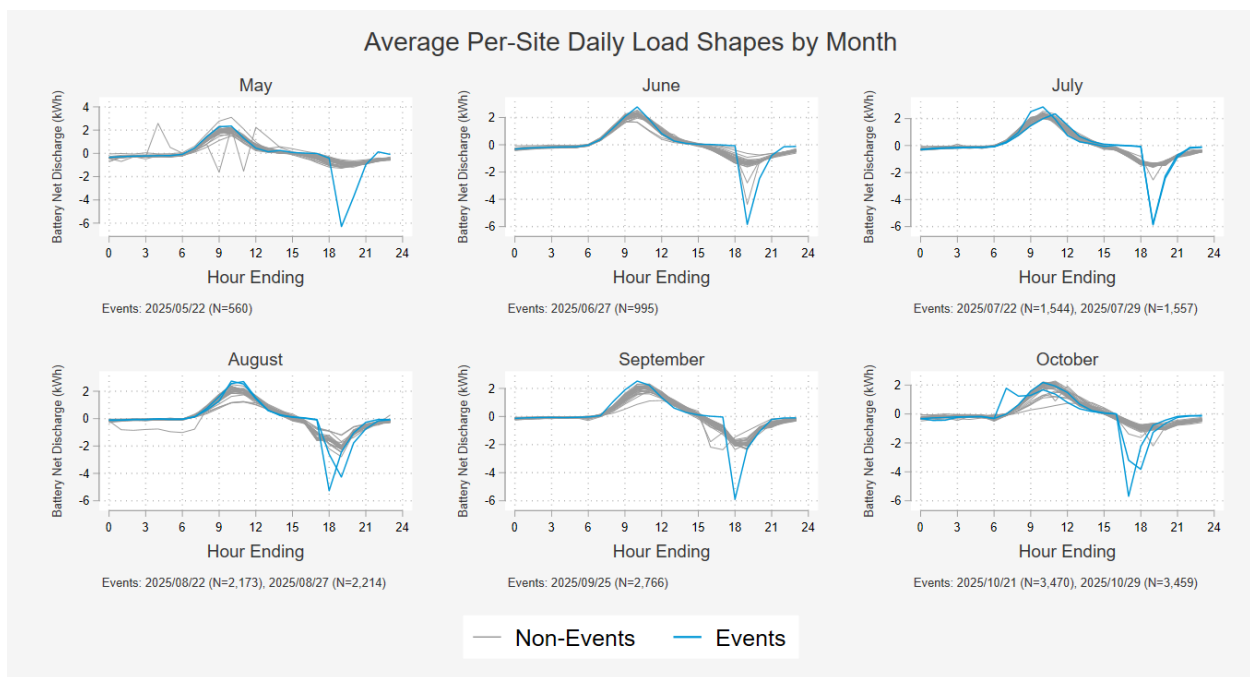


Figure 17: Per-Site Hourly Discharge versus 4-hour Temperature Lag for Hour 7:00PM to 8:00PM by Utility

