

FINAL REPORT

CALMAC ID: SDG0371

2024 Load Impact Evaluation for San Diego Gas and Electric's Emergency Load Reduction Pilot



Prepared for SD&GE By Demand Side Analytics, LLC April 1, 2025

ACKNOWLEDGEMENTS

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ABSTRACT

This study quantifies the demand impacts of the Residential and Non-Residential Emergency Load Reduction Program pilot. The study focuses on two primary research questions: What were the 2024 demand reductions due to dispatch operations? What is the magnitude of dispatchable load reduction capability for 1-in-2 weather planning conditions?

The pilot was rolled out in 2021 upon direction by the Commission to expand the state's portfolio of emergency load reduction resources beyond those available in CAISO capacity markets and utility specific emergency resources such as Critical Peak Pricing. Events are triggered by the CAISO in response to extreme grid stress, and event reductions are settled via a \$1/kWh payment for A.6 and a \$2/kWh payment for the other subgroups, determined using baseline settlement rules. Thirteen non-residential ELRP events were called in PY2024, with different subgroups being dispatched for specific events.

Five A.4 residential ELRP events were called in PY 2024, and the average 5 to 8 p.m. event produced 1.97 MW of aggregate load reduction. No A.6 residential events were called.

TABLE OF CONTENTS

1	Exe	cutive Summary	6
2	Intr	oduction	9
	2.1	PROGRAM BACKGROUND	10
	2.2	STUDY RESEARCH QUESTIONS	
	2.3	Overview of Methods	_
3	ELF	RP Event Day Impacts	19
	3.1	EVENT CHARACTERISTICS	19
	3.2	Data Sources and Analysis Method	_
	3.3	Ex Post Load Impacts	
	3.3.	1 ELRP Group A.1 Impacts by Event	22
	3.3.		
	3.3.		
	3.3.	FIRE C. A. I I. F	23
	3.3.	5 ELRP Group A.6 Impacts by Event	. 24
	3.3.		
	3.3.	7 Comparison of Evaluation Load Reductions to Baseline Approach	. 25
	3.4	Ex Ante Load Impacts	. 28
	3.4.	1 Relationship of Customer Loads and Percent Reductions to Weather	28
	3.4.	2 Program Specific and Portfolio Adjusted Impacts	. 30
	3.4.	-	_
	3.4.	·	_
	3.4.	-	_
	3.4.	· · ·	_
	3.4.		
	3.4.	·	
	3.4.		
	3.4.		
	3.4. 3.4.		
,	Э.	nclusions and Recommendations	
4			
^	4.1	ELRP RECOMMENDATIONS	•
Αļ		x	
	Α.	INDIVIDUAL SITE REGRESSIONS WITH SYNTHETIC CONTROLS	.,
	В.	Proxy Day Selection	. 40

Figures

Figure 2-1: Ex Post Methodology Selection Framework	14
Figure 2-2: Out of Sample Process for Control Group Selection	15
Figure 2-3: Difference-in-Differences Calculation Example	16
Figure 2-4: Modeling Parameters Tested and Inclusion in Best Performing Site Specific Models	17
Figure 3-1: ELRP A.1 Average Weekday 5 to 9 p.m. Event Load Impact Compared to Baseline	27
Figure 3-2: ELRP Hourly Percent Reductions and Temperatures	29
Figure 3-3: ELRP A4, A5 Hourly kWh Reductions and Temperatures	29
Figure 3-4: Waterfall Analysis of 2023-2024 Ex Ante Impacts by Key Group	38
Figure A o-1: A.4 Treatment and Control Customers on Event Days	50
Tables	
Table 1-1: Summary of 2024 Average Weekday Ex Post Demand Reductions	7
Table 1-2: Summary of Ex ante Site Enrollments	8
Table 1-3: Summary of Portfolio Adjusted Ex Ante Dispatchable Demand Reductions, August Worst Day, SDG&E 1-in-2 Weather	
Table 1-4: Summary of Program Specific Ex Ante Dispatchable Demand Reductions, August Worst E SDG&E 1-in-2 Weather	
Table 2-1: ELRP Group Eligibility Requirements	10
Table 2-2: Key Research Questions	13
Table 2-3: Evaluation Methodology Used by Subgroup	14
Table 2-4: Evaluation Methods	18
Table 3-1: Participant Populations	19
Table 3-2: ELRP Events in 2024	20
Table 3-3: Dual Enrollment Populations	20
Table 3-4: Non-Residential and Residential ELRP Event Impact Evaluation Data Sources	21
Table 3-5: ELRP A.1 Event Reductions	22
Table 3-6: ELRP A.2 Event Reductions	22
Table 3-7: ELRP A.4 Event Reductions*	23
Table 3-8: ELRP A.5 Event Reductions	24
Table 3-9: ELRP B.2 Event Reductions	25
Table 2-10: Comparison of Settlement Baseline and Load Impact Evaluation Methodologies	26

able 3-11: ELRP Ex post Results vs Baseline Results	. 27
able 3-12: Eligible Dually Enrolled Programs for Ex Ante Considerations	. 30
able 3-13: Participant Enrollment Forecast	. 30
able 3-14: ELRP A.1 Ex Ante Impacts for 1-in-2 August Worst Day (MW)	. 32
able 3-15: ELRP A.2 Ex Ante Impacts for 1-in-2 August Worst Day (MW)	. 32
able 3-16: ELRP A.4 Ex Ante Impacts for 1-in-2 August Worst Day (MW)	33
able 3-17: ELRP A.5 Ex Ante Impacts for 1-in-2 August Worst Day (MW)	. 34
able 3-18: ELRP A.6 Ex Ante Impacts for 1-in-2 August Worst Day (MW)	. 34
able 3-19: ELRP B.2 Ex Ante Impacts for 1-in-2 August Worst Day (MW)	. 35
able 3-20: ELRP A1 Comparison of Ex Post and Ex Ante Load Impacts	. 36
able 3-21: ELRP A4 Battery Comparison of Ex Post and Ex Ante Load Impacts	37
able 3-22: ELRP A6 Residential Comparison of Ex Post and Ex Ante Load Impacts	. 38
able 3-23: ELRP A.1 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impac IW)	-
able 3-24: ELRP A.2 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impac IW)	-
able 3-25: ELRP A.4 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impac IW)	-
able 3-26: ELRP A.5 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impac IW)	-
able 3-27: ELRP A.6 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impac IW)	ts,
able 3-28: ELRP B.2 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impac IW)	-
able A o-1: Ex Post Regression Elements for Non-Residential ELRP	. 48
able A-2: Bias and Fit Measures for Individual Customer Regressions	. 48
able A o-3: Proxy and Event Day Matching: p-Values from t-Tests	. 49

1 EXECUTIVE SUMMARY

The Emergency Load Reduction Program (ELRP) pilot is a demand response program with direct settlements and performance payments to participant sites designed to access additional incremental load reduction during times of high grid stress and emergencies involving inadequate market resources, with the goal of avoiding rotating outages. The pilot was rolled out in 2021 upon direction by the Commission to expand the state's portfolio of emergency reliability resources beyond those available in CAISO capacity markets and utility specific load modifying resources such as Critical Peak Pricing. Two distinct groups of customers are eligible for ELRP participation: (Group A) directly enrolled residential and non-residential customers and aggregators, and (Group B) third-party demand response providers (DRPs) with market-integrated proxy DR (PDR) resources.

Group A: Direct enrolled residential and non-residential customers and aggregators:

- A.1. Non-residential customers.
- A.2. Non-residential aggregators.
- A.3. Rule 21 exporting distributed energy resources.
- A.4. Virtual Power Plant (VPP) aggregators.
- A.5. Electric vehicle and vehicle-grid-integration aggregators.
- A.6. Residential customers.

Group B: Market-integrated PDR resources:

- B.1. Third-party DR providers.
- B.2. IOU Capacity Bidding Program (CBP) aggregators.

ELRP A.6 was rolled out in May of 2022 upon direction by the Commission to capture additional residential emergency load reduction resources. ELRP A.6 is a behavioral demand response program with direct settlements and performance payments to participants, which is currently planned to operate through 2025. All other ELRP subgroups are expected to operate through 2027. All ELRP groups remunerate participant site performance via a \$2/kWh payment, determined using baseline settlement rules specific to each subgroup. However, settlement payments for A.6 decreased in 2024 to \$1/kWh. The eligibility, targeting, and rollout of each subgroup are entirely different.

This study analyzes two primary research questions:

- What were the 2024 demand reductions due to dispatch operations?
- What is the magnitude of dispatchable load reduction capability for 1-in-2 worst day weather planning conditions?

Table 1-1 summarizes the estimated ex post demand reductions for the average weekday ELRP event for each subgroup in which SDG&E customers are enrolled (non-residential and residential). All impacts are incremental to other DR program impacts and statistical significance is noted for each subgroup. Subgroup A.4 produced statistically significant incremental impacts at the 95% confidence interval.

Subgroup A.6 was not dispatched in PY 2024. There were no enrollments in subgroup A.3 in PY 2024, and B.1 is not in the scope of this study.

Table 1-1: Summary of 2024 Average Weekday Ex Post Demand Reductions¹

Group	Sites	Load without DR (MW)	Load reduction (MW)	% Reduction	Significant (90% CI)	Significant (95% CI)
A.1: Non-Res Customers	708					
A.2: Non-Res Customers						
A.4: Virtual Power Plants (VPPs)	632	0.19	1.90	1028.9%	Yes	Yes
A.5: Vehicle-Grid-Integration (VGI) Aggregators						
A.6: Residential Customers	535,621	N/A	N/A	N/A	N/A	N/A
B.2: IOU Capacity Bidding Programs (CBPs)						
Total Customers Dispatched	1,346	225.69	7.39	3.3%	No	No

Table 1-2 summarizes forecasted site enrollments by subgroup, including the A.6 subgroup which is only approved through 2025. Total forecasted enrollments are concentrated in subgroups A.1 (non-residential customers), A.4 (Virtual Power Plants aggregators), and A.5 (Electric vehicle and vehicle-grid-integration aggregators). Subgroup A.6 enrollment is forecasted to decline until 2025 when it will be discontinued.

¹ The average weekday event results incorporate impacts across multiple event windows (e.g. 6 to 9 p.m. and 8 to 9 p.m.) as not all groups and events were dispatched for the same event windows.

Table 1-2: Summary of Ex ante Site Enrollments

Year	A.1	A.2	A.4	A.5	A.6	B.2	Total
2024	700		631		531,948		533,285
2025	739		927	606	509,080		511,355
2026	784		1,224	1,211	0		3,222
2027	835		1,518	1,816	0		4,172

Table 1-3 summarizes portfolio adjusted ELRP dispatchable ex ante reductions under August worst day conditions for an SDG&E 1-in-2 weather year. Table 1-4 shows the same for program specific impacts. For most groups, ELRP load reductions are assumed to be a function of curtailment of the weather sensitive load on a percent basis. The results reflect the reduction capability from 4 to 9 p.m., which aligns with resource adequacy requirements. Exporting groups (A.4, A.5) apply a consistent percustomer reduction across all weather specifications, over the first three hours of the 5 to 8 p.m. window to align with the program rules which limit events to three hours. The ex ante load reduction predictions are primarily developed using PY 2024 impacts.

Table 1-3: Summary of Portfolio Adjusted Ex Ante Dispatchable Demand Reductions, August
Worst Day, SDG&E 1-in-2 Weather

Year	A.1	A.2	A.4	A.5	A.6	B.2	Total
2024	6.4		2.0		9.5		17.2
2025	6.7		2.9	1.7	9.2		18.8
2026	7.1		3.9	3.2	0.0		11.4
2027	7.5		4.8	4.8	0.0		13.3

Table 1-4: Summary of Program Specific Ex Ante Dispatchable Demand Reductions, August Worst
Day, SDG&E 1-in-2 Weather

Year	A.1	A.2	A.4	A.5	A.6	B.2	Total
2024	6.4		2.0		9.5		17.2
2025	6.7		2.9	1.7	9.2		18.8
2026	7.1		3.9	3.2	0.0		11.4
2027	7.5		4.8	4.8	0.0		13.3

2 INTRODUCTION

The Emergency Load Reduction Program (ELRP) pilot is a demand response program with direct settlements and performance payments to participant sites designed to access additional incremental load reduction during times of high grid stress and emergencies involving inadequate market resources, with the goal of avoiding rotating outages. The pilot was rolled out in 2021 upon direction by the Commission to expand the state's portfolio of emergency reliability resources beyond those available in CAISO capacity markets and utility specific load modifying resources such as Critical Peak Pricing. Two distinct groups of customers are eligible for ELRP participation: (Group A) directly enrolled residential and non-residential customers and aggregators, and (Group B) third-party demand response providers (DRPs) with market-integrated proxy DR (PDR) resources.

Group A: Direct enrolled residential and non-residential customers and aggregators:

- A.1. Non-residential customers.
- A.2. Non-residential aggregators.
- A.3. Rule 21 exporting distributed energy resources.
- A.4. Virtual Power Plant (VPP) aggregators.
- A.5. Electric vehicle and vehicle-grid-integration aggregators.
- A.6. Residential customers.

Group B: Market-integrated PDR resources:

- B.1. Third-party DR providers.
- B.2. IOU Capacity Bidding Program (CBP) aggregators.

ELRP A.6 was rolled out in May of 2022 upon direction by the Commission to capture additional residential emergency load reduction resources. ELRP A.6 is a behavioral demand response program with direct settlements and performance payments to participants, which is currently planned to operate through 2025. All other ELRP subgroups are expected to operate through 2027. All ELRP groups remunerate participant site performance via a \$2/kWh payment, determined using baseline settlement rules specific to each subgroup. However, settlement payments for A.6 decreased in 2024 to \$1/kWh. The eligibility, targeting, and rollout of each subgroup are entirely different.

2.1 PROGRAM BACKGROUND

ELRP differs from market programs like Base Interruptible Load (BIP) and Capacity Bidding Program (CBP) in its eligibility, trigger, and settlement rules. Namely:

- Deployment Triggers: ELRP is dispatched via emergency triggers, as opposed to economic triggers.
- Payment Rules: ELRP has no penalties or capacity payments.
- Baseline Settlement Rules: ELRP utilizes top 10 of 10 or top 5 of 10 baselines with optional
 asymmetric adjustments and treatment of net exports (option to include for some groups,
 only exports considered for other groups).
- Back Up Generation (BUG) Rules: ELRP allows for BUG operation during events. BUG is generally ineligible for market programs.

The ELRP program dispatch rules are the following for all A and B subgroups:

- **Program availability:** May 1st October 31st; seven days a week; 4 to 9 p.m.
- Event duration: 1-hour minimum; 5-hour maximum
- Annual dispatch limit: Up to 60 hours
- Consecutive day dispatches: No constraints

Group A participants, in general, are not to be enrolled in a supply-side DR program offered by an IOU, third-party DRP, or CCA. This requirement does not apply to the Base Interruptible Program.² Customers or providers which are enrolled in DR programs, specifically CBP, may be eligible for enrollment in Group B. Table 2-1 summarizes the eligibility rules for each subgroup.

Table 2-1: ELRP Group Eligibility Requirements

Eligibility Requirements

Bundled and unbundled non-residential customers that meet all of the following criteria may directly participate in ELRP:

A.1

- Customer's service account is classified as non-residential; and
- Customer's service account must be able to reduce load by a minimum of one kilowatt during an ELRP event; and

² SDG&E asked for and was granted permission via D.2312005 to discontinue its Base Interruptible Program (BIP) in December 2023.

Eligibility Requirements

 Customer is not simultaneously enrolled in another supply-side DR program offered by an IOU³, third-party demand response provider (DRP), or community choice aggregator (CCA).

Aggregators can only add bundled and unbundled non-residential service accounts for ELRP that meet the following criteria:

A.2

Customer's service account is classified as non-residential; and

Customer's service account is not simultaneously enrolled in another DR program offered by an IOU.

Bundled and unbundled non-residential customers that meet all the following criteria may directly participate in ELRP:

A.3

- Customer's service account is not simultaneously enrolled in any market integrated DR program offered by SDG&E, a third-party DRP, or CCA; and
- Customer's service account possesses a behind-the-meter (BTM) Rule 21- interconnected device (including Prohibited Resources/BUG) with an existing Rule 21 export permit; and
- Customer's BTM Rule 21 physical interconnected device has a minimum capacity of 25 kW and
 is able to export a minimum of 25 kW for at least one hour in compliance with Rule 21 and other
 applicable regulations and permits during an ELRP event

An aggregator managing a BTM virtual power plant (VPP) aggregation consisting of storage paired with net energy metering (NEM) solar or stand-alone storage deployed with residential (bundled or unbundled) or non-residential (bundled or unbundled) customers, whose VPP meet the following criteria, is eligible participate in ELRP:

The VPP or any customer site within the aggregation is not simultaneously enrolled in a market-integrated DR program offered by an IOU, third-party DRP, or CCA, unless the ELRP A.4. payments to the aggregator are based on end use data and the customer site is enrolled in AC Saver.

A.4

- All sites within the VPP aggregation are located within the distribution service area of a single IOU, and
- The aggregated BTM storage capacity of the VPP meets the Minimum VPP Size Threshold of 500 kW, where the VPP size is determined by summing the Rule 21 interconnected capacity of the individual storage devices comprising the aggregation, and
- Each site within the VPP aggregation has a Rule 21 permit.
- A customer participating in ELRP A.6 is permitted, at any time, to enroll in ELRP A.4. After SDG&E becomes aware that the Participant's service account has been enrolled in ELRP A.4 SDG&E will de-enroll the service account from ELRP A.6

³ Dual enrollment in Critical Peak Pricing is allowed

Eligibility Requirements

An aggregator managing a Vehicle-Grid-Integration (VGI) aggregation consisting of any combination of electric vehicles and charging stations – including those that are capable of managed one-way charging (V1G) and bi-directional charging and discharging (V2G) deployed with residential (bundled or unbundled) or non-residential (bundled or unbundled) customers that meets the following criteria, is eligible to participate in ELRP:

- The VGI aggregation or any customer site within the aggregation is not simultaneously enrolled in a market-integrated, supply-side DR program offered by an IOU, third-party DRP, or CCA, unless the ELRP A5 payments to the aggregator are based on end use data and the customer site is enrolled in AC Saver
- All sites within the VGI aggregation are located within the distribution service area of a single IOU, and
- The VGI aggregation can contribute Incremental Load Reduction (ILR) of at least 25 kW for a minimum of one hour during an ELRP event.
- Subject to Rule 21 interconnection requirements, any direct current (DC) V2G electric vehicle supply equipment (EVSE) that has UL 1741 certification but not UL 1741 SA certification, any subsequent UL 1741 supplement certification required in Rule 21, or Smart Inverter Working Group-recommended smart inverter functions may interconnect initially, but only for the purpose of participating in the ELRP.
- A customer participating in ELRP A.6 is permitted, at any time, to enroll in ELRP A.5. After SDG&E becomes aware that the Participant's service account has been enrolled in ELRP A.5 SDG&E will de-enroll the service account from ELRP A.6.

SDG&E shall determine it its sole discretion Participant's eligibility which must include:

- Participant receives electric service on a residential rate
- Participant has an active service agreement with SDG&E
- Participant has a SDG&E SmartMeter
- Participant is not simultaneously enrolled in another supply-side demand response program offered by SDG&E, third party DR provider (DRP), Community Choice Aggregator (CCA), or in ELRP sub-groups A.4 or A.5
- Participant is not an electric customer of a Community Choice Aggregator who has opted out of being included in the Pilot
- A third Party DRP with a market-integrated Proxy Demand Resource (PDR) is eligible to participate in the ELRP. This subgroup is not included in this evaluation.
- Third-party aggregators (Aggregators) or self-aggregated customers (Participant sites) enrolled and participating in SDG&E's Capacity Bidding Program are eligible to participate in the ELRP.

A.5

A.6

2.2 STUDY RESEARCH QUESTIONS

Table 2-2 summarizes the key research questions for the ELRP program.

Table 2-2: Key Research Questions

	Research Question
1	What were the demand reductions due to program operations and interventions in 2024 – for each event day and hour?
2	How does weather influence the magnitude of demand response?
3	How do load impacts differ for customers in each subgroup (Group A and Group B subgroups) during PY2024?
4	What are the ex ante load reduction capabilities for 1-in-2 worst day weather conditions? And how well do those align with ex post results?
5	What concrete steps or experimental tests can be undertaken to improve program performance?

2.3 OVERVIEW OF METHODS

The primary challenge of impact evaluation is the need to accurately detect changes in energy consumption while systematically eliminating plausible alternative explanations for those changes, including random chance. When ELRP events are dispatched, was the program the primary cause of a customer's change in energy usage or were there other factors involved? To estimate a change in energy consumption, it is necessary to estimate what that energy consumption would have been in the absence of the intervention—the counterfactual or reference load.

The change in energy use patterns was estimated using a combination of difference-in-differences with matched controls and individual customer regressions. Figure 2-1 summarizes the selection framework used to determine the appropriate method for each site, using subgroup A.1 as an example. Most sites utilize a difference-in-difference model, except in cases where there were not enough sites in a given segment (customer size and climate zone), or for sites with an annual peak above 200 kW and daily usage patterns which exhibited substantial statistical noise (CVRMSE⁴ above 0.25).

⁴ Coefficient of the Variation of the Root Mean Square Error: RMSE is the average distance between modeled and observed usage. CVRMSE reflects the relative size of the errors modeled for each site, normalized for the magnitude of each site's energy usage.

Peak ≤ 200kW (N = 424)

Difference in Differences

N > 70 (N = 540)

Extreme Load (N = 116)

Individual Customer Regressions

Individual Customer Regressions

Individual Customer Regressions

Individual Customer Regressions

Figure 2-1: Ex Post Methodology Selection Framework

Table 2-3 summarizes the approach or approaches used for each subgroup. Note that for some subgroups a combination of methods was used. Additionally, no ex-post evaluation methodologies were applicable to subgroup A.6 since this subgroup was not dispatched in PY2024. However, if events had been called, difference-in-differences would have been used.

Table 2-3: Evaluation Methodology Used by Subgroup

ELI	RP Group	Individual customer regressions	Difference-in-differences
	A.1	✓	✓
	A.2	✓	
	A.4		✓
	A.5	✓	
	B.2	✓	
	A.6	N/A	N/A

Site-specific models for individual customer regressions were selected among dozens of potential specifications, which included synthetic controls using one or more matched control site to help control for factors outside of the ELRP events. Similarly, the difference-in-differences approach used a matched control group to net out changes in energy usage patterns not due to the ELRP events. As such, regardless of evaluation methodology, each participant site was matched to one or more non-

⁵ The functional form of a regression with synthetic controls differs from a panel difference in difference regression in that usage for the control or controls are specified as right hand predictor variables. Additional detailed are available in the Appendix

participant using an out of sample matching tournament where match quality was compared across eight different matching models to identify the best performing model.

Figure 2-2 summarizes the matching tournament process used to select matched controls for the difference-in-difference analyses and synthetic controls for the individual customer regressions. To identify the control pool sites that best matched each participant site's energy use patterns on event-like, proxy days (similar in weather and system conditions to event days) days, as described in the appendix), eight matching methods were tested. These methods included different matching algorithms (e.g. Euclidean and propensity matching) and different site characteristics. Matching methods included different combinations of proxy day load characteristics such as load factor, load shape, and weather sensitivity. Control candidates were also "hard-matched" on climate zone, net metering status, and size bin⁶.

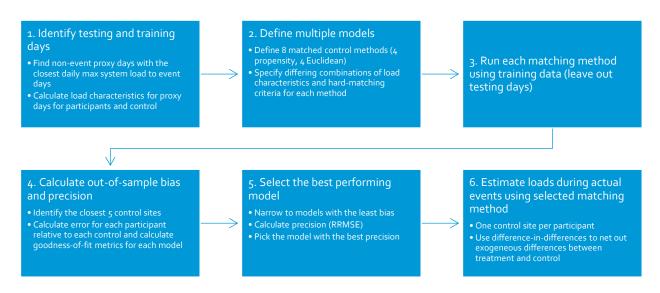


Figure 2-2: Out of Sample Process for Control Group Selection

As described above, difference-in-differences with matched controls was the primary evaluation methodology used, except in cases where there were few sites or large sites with noisy load patterns⁷. Figure 2-3 below demonstrates the mechanics of a difference-in-difference calculation. In the first panel, average observed loads on proxy days are shown for participants and for their matched controls.

⁶ Bins were constructed using average usage on event-like, proxy days. For solar customers, bins were constructed based on system size.

⁷ Out of sample testing was used to calculate RRMSE and other bias and fit metrics to compare across multiple pooled methods (average customer regressions and panel regressions). Based on this testing, difference-in-differences was determined to outperform or at least be comparable in robustness to the other methods. In contrast to the pooled regression-based methods, difference-in-difference has the advantage of enabling segmentation of results (by size, climate zone, industry, solar status, etc.) without the need to run additional regressions while ensuring that segment results add up to group totals.

The difference between these two is the first "difference" and quantifies underlying differences between participants and their controls not attributable to event participation. Note that this first difference is very small, indicative of a high-quality match and sufficient sample size to neutralize the noise inherent in individual customer loads. The second panel shows the average observed participant and matched control loads on event days. The gap between these two is the second "difference" which includes both the difference due to event participation and the underlying first difference observable on non-event days. The third panel shows the average event day loads after netting out the proxy day difference from the event day control load. The result is the difference-in-differences impact.

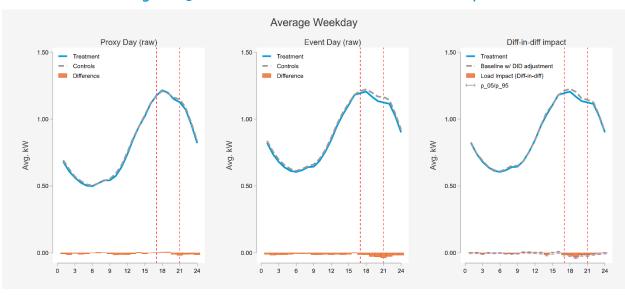


Figure 2-3: Difference-in-Differences Calculation Example⁸

In cases where a difference-in-differences approach was not deemed appropriate due to insufficient sample size or for large sites with noisy loads, site-specific individual customer regression models were selected using another out of sample tournament to select the most accurate regression model specification for each participant site. Synthetic controls were considered in this tournament, including inclusion of an industry profile based on NAICS code and inclusion of solar irradiance. A variety of within subjects lagged loads (1 day, 1 week, 2 weeks) were also considered. To implement out of sample testing, the top 50 system load days, excluding event days, were randomly divided into testing and training datasets. Bias and fit metrics were calculated using the testing dataset and the model with the best fit (lowest Root Mean Squared Error) was selected among models with the least bias (Mean Absolute Error⁹). Site specific load impacts were estimated using the best model for each site.

⁸ This graph is not specific to ELRP but serves as an example of a difference-in-difference calculation.

⁹ MAE was used rather that Mean Average Percent Error (MAPE) to ensure robustness for sites with loads very close to zero, common for sites solar or other generation.

Site specific regression models were selected from 120 different possible specifications across the following parameters:

- Inclusion of an industry profile constructed of loads for other similar large commercial and industrial customers¹⁰
- Inclusion of local solar irradiance data¹¹
- Number of control sites¹²
- Lags of load data¹³

Figure 2-4 shows the different model parameters that were included in the site-specific model tournament and the number of sites¹⁴ for which each parameter was included in the winning model. This is shown for all groups and all sites that were analyzed using an individual customer regression. The widespread across parameters indicates that it was important to allow for individually tailored models to be selected for each participating site.

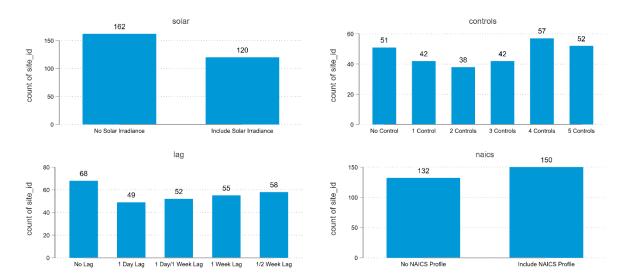


Figure 2-4: Modeling Parameters Tested and Inclusion in Best Performing Site Specific Models

Table 2-4 summarizes the data sources, segmentation, and estimation methods used for each program. The segmentation was defined in advance of the analysis and is of particular importance because the

¹⁰ Selected from granular load profiles within climate zone and industry segment constructed and maintained by Demand Side Analytics for SDG&E for the population NMEC settlement validation purposes for the Summer Reliability Market Access Program.

¹¹ Specific to the weather station nearest to the participant.

¹² Ranges from o to 5, selected using the out of sample match selection process.

¹³ Lags were designed to capture the tendency of large commercial and industrial customers to operate on daily, weekly, or bi-weekly schedules irrespective of weather or time of year.

¹⁴ Shown for the 282 sites across groups for which individual customer regressions were selected.

evaluation used a bottom-up approach to estimate impacts to ensure that aggregate impacts across segments equaled the sum of the parts. Because impacts for each segment were added together, the segmentation was structured to be mutually exclusive and completely exhaustive. In other words, every customer was assigned to exactly one segment. Within each ELRP subgroup, the segmentation differentiated customers who were expected to deliver greater demand reductions—such as customers in the inland climate zone where cooling loads are higher—from customers who were expected to deliver lower demand reductions. For non-residential subgroups, customer size was also used. Additional segments were analyzed, after the fact, as part of exploratory analysis, but the core results presented are based on the segmentation detailed below.

Table 2-4: Evaluation Methods

Evaluation Element	Non-Residential ELRP (A.1, A.2, A.4, A.5, B.2)
Data sources / samples	 All event season data for the past program year for All 714 Non-Residential ELRP participant sites, all 632 A4 participant sites, and a sample of 27,579 A6 participant sites a control pool of 41k commercial non-participants and 15k non-participant residential sites with battery storage
Segmentation	 ELRP Subgroup Dual enrollment Industry Solar Status LCA SubLAP Climate zone
Estimation method (Ex-post)	 Primary method: difference-in-differences with matched controls Secondary method: Site specific regression models with synthetic controls Applied in cases where there were few sites within a segment or large sites with noisy load patterns
Estimation method (Ex-ante)	 Top-down enrollment model based on projections for interconnected capacity and feasible enrollment levels. Load reductions are assumed to be a function of dispatchable generation capacity not weather sensitive load curtailment and therefore the same for all weather specifications

3 ELRP EVENT DAY IMPACTS

Emergency Load Reduction Program (ELRP) participant sites receive day ahead or day-of event notifications via email and phone. The A.4 and A.5 subgroup participants receive dispatch signals sent to the battery storage devices or electric vehicles/charging stations installed on the premises, respectively.

3.1 EVENT CHARACTERISTICS

Event impacts were assessed by site (premise and service point combination). While the modeling was performed individually for each site, results are reported by ELRP subgroup, summarized in Table 3-1. This table also summarizes the number of sample sites used for the ex post event analysis once data cleaning was completed, as well as the total number of sites enrolled during the PY2024 event season (the first event was called on July 10 and the last on October 7). The number of sites in the ex post analysis is slightly smaller than the total number of sites, due to the removal of sites with outages on event days and sites for which an adequate matched control could not be found. The sampled sites for A.6 were designed to be representative of the large program population, although there was no ex post analysis for this group in PY2024.

Sites in **ELRP Group** Sector(s) **Total sites** analysis* Non-Residential 708 A.1 700 Non-Residential A.2 Non-Residential A.4 632 629 & Residential Non-Residential A.5 A.6 Residential 535,621 27,579 Non-Residential B.2 Total 536,967 28,914

Table 3-1: Participant Populations

Table 3-2 shows the thirteen PY2024 ELRP event days and the SDG&E system peak load on each day. While event dispatch dates and hours were the same for most non-residential subgroups and events in July, the August, September, and October events were typically called for a few specific subgroups on specific hours. All but one of the events occurred on a weekday, and none occurred on a holiday. The SDG&E system weekday peak occurred on September 9, which coincided with 5 to 9 p.m. and 6 to 9 p.m. events called for A.5 and A.4, respectively. No events were called for subgroup A.6 in PY2024.

^{*}Excludes a few sites without complete data. For A.6 reflect sites sampled for the analysis

Max SDG&E Event Event date Day of week system load A.1 **A.2 A.4** A.5 A.6 **B.2** window (MW) Wednesday 7/10/2024 3,063 6 to 9 pm Thursday 7/11/2024 6 to 9 pm 3,045 Wednesday **V** 7/24/2024 3,664 5 to 9 pm Wednesday 7/24/2024 3,664 6 to 9 pm 8/20/2024 Tuesday 3,969 5 to 8 pm \checkmark \checkmark Wednesday \checkmark \checkmark 9/4/2024 4,057 5 to 8 pm 9/5/2024 Thursday 4,633 5 to 8 pm \checkmark Thursday 9/5/2024 4,633 5 to 9 pm Friday 4 4 9/6/2024 4,381 5 to 8 pm 9/9/2024 Monday 4,698 5 to 8 pm Monday 4 4,698 6 to 8 pm 9/9/2024 4 10/6/2024 Sunday 2,900 5 to 8 pm Monday 5 to 8 pm 10/7/2024 3,194

Table 3-2: ELRP Events in 2024

Dual enrollment is allowed for some of the ELRP subgroups, which is categorized in Table 3-3. One ELRP subgroup requires dual enrollment; B.2 must be enrolled in the Capacity Bidding Program (CBP). Customers in the A.1 subgroup can also be enrolled in Critical Peak Pricing (CPP). In addition to the dually enrolled populations, Table 3-3 lists the ELRP event days where a dual program was also called. Notably, these participants were not dually dispatched during any of the ELRP events this season.

Table 3-3: Dual Enrollment Populations

ELRP Group	Dual Enrollment Allowed	Sites Dually Enrolled	Days with Dual Event Overlap
A.1	CPP	102	-
B.2	CBP		-

3.2 DATA SOURCES AND ANALYSIS METHOD

Table 3-4 summarizes the five data sources used to conduct the Non-Residential and Residential ELRP event impact analysis. The analysis was performed by site on hourly load data. Various data sources were used to classify sites into the study segments. While different segments were developed for the various analyses in this report, the characteristic definitions used to build segments were consistent across analyses.

^{*} Highlighted rows indicate event days where another program was also dispatched.

Table 3-4: Non-Residential and Residential ELRP Event Impact Evaluation Data Sources

Source	Comments		
Hourly interval data	 Summer 2024 All analysis done by site (premise ID-service point ID pair) 		
Outage PSPS and emergency outage data details which customers and what times impacted by outages			
Customer characteristics	 Non-residential treatment: 708 customer sites Residential treatment: 632 A.4 sites, 27,579 A.6 sites Non-residential controls: 41k non-residential sites A4 controls: 15k residential sites with battery storage Dual enrollment, subLAP used in matched control selection NAICS codes for development of industry profiles 		
SDG&E hourly system loads	Summer 2024Used to identify non-event high system load days		
Ex post weather data by weather station	 Used to derive weather sensitivity for treatment and control pool sites, used as a matching criteria Solar irradiance considered for site specific regression model selection 		

The primary analysis method was difference-in-differences with matched controls. Site-specific individual regression models with synthetic controls were used in cases where there were too few participant sites in a segment or for very large sites (peak load above 200 kW) with noisy daily load patterns (CVRMSE above 0.25). An out of sample tournament was used to select a matching model for each subgroup. Matches were one of multiple controls used in the regression models. A winning distance matching model was selected for each subgroup. These winning models were used to select five matches for each of the ELRP participant sites among the appropriate control candidate pool, which is comprised of sites not enrolled in other DR programs because it may influence energy use and renders a customer ineligible for ELRP¹⁵.

Once the matches were selected for each participant, the difference-in-differences model was used to assess impacts and standard errors for each event and each study segment, using the top match for each site. For sites requiring individual customer regressions, an out of sample tournament was used to select site specific regression models among dozens of possible specifications across 4 parameters:

21

¹⁵ For the B₂ subgroup, which is explicitly designed for dual participation with CBP, controls were pulled from the same pool of non-DR participants.

industry profiles, solar irradiance, up to five synthetic controls (selected in the tournament described above), and lagged participant site loads.

3.3 EX POST LOAD IMPACTS

3.3.1 ELRP GROUP A.1 IMPACTS BY EVENT

Group A.1 is designated for non-residential customers, and it is currently the largest non-residential ELRP subgroup with over 700 participating sites. There was one event called for subgroup A.1 in PY2024 on July 24, 2024. Table 3-5 summarizes the load reductions and participant weighted event temperatures for ELRP A.1 sites each event and for the average weekday event.



Table 3-5: ELRP A.1 Event Reductions

		Avg		Red	ductions (Ex	Post)		
Event Date	Event Window	Event Temp (F)	Sites Enrolled	Aggregate (MW)	% Reduction	Average Site (kW)	Significant (90% CI)	Significant (95% CI)
7/24/2024	5 to 9 pm	73.8	708					
Avg Weekday (any)	5 to 9 pm	73.8	708					

3.3.2 ELRP GROUP A.2 IMPACTS BY EVENT

Group A.2 is designated for non-residential aggregators and included only one participating site in PY2024. There were three events called for subgroup A.2 in PY2024, across a variety of durations and start times. Table 3-6 summarizes the load reductions and participant weighted event temperatures for the ELRP A.2 site on event days or the average event. In the tables, the bars show a visual comparison of the reductions that are numerically labeled on the left of the bars.



Table 3-6: ELRP A.2 Event Reductions

		Avg		Red	Post)			
Event Date	Event Window	Event Temp (F)	Sites Enrolled	Aggregate (MW)	% Reduction	Average Site (kW)	Significant (90% CI)	Significant (95% CI)
7/24/2024	5 to 9 pm	70.5						
8/20/2024	5 to 8 pm	70.0						
9/5/2024	5 to 9 pm	72.3						
Avg Weekday 5-8 pm	5 to 8 pm	70.0						
Avg Weekday (any)	5 to 9 pm	70.8						

3.3.3 ELRP GROUP A.4 IMPACTS BY EVENT

Group A.4 is designated for aggregators managing a behind the meter virtual power plant (VPP) aggregation of residential or non-residential customers. In PY2024, there was one aggregator enrolled, consisting of 632 residential participant sites. There were five events called for subgroup A.4 in PY2024. Four of the events had a three hour duration starting at 5 p.m., and one of the events had a two hour duration starting at 6 p.m. Table 3-7 summarizes the load reductions and participant weighted event temperatures for ELRP A.4 sites during the five events and for the average weekday event. In the tables, the bars show a visual comparison of the reductions that are numerically labeled on the left of the bars.

Aggregate reductions for significant events range from 1.9 MW (September 4th, 5th, and 6th) to 3.1 MW (September 9th). No clear correlation between weather conditions, event window, and load reductions is evident. This makes sense conceptually since A.4 load reductions are typically only dependent on battery capacity.

Additionally, A.4 participants experience significant post-event charging after the conclusion of the event. This is seen prior to the event as typical battery dispatch, used to offset the whole-home load, is halted to preserve the state-of-charge for actual event hours. Similarly, the post-event charging is the result of participant's having depleted their battery over the course of the event, requiring them to draw more from the grid than they would have if their battery still had its typical charge.

	Ava		Reduction	ons (Ex Post)		
Event Window	Event Temp (F)	Sites Enrolled	Aggregate (MW)	Average Site (kW)	Significant (90% CI)	Significant (95% CI)
5 to 8 pm	75.6	631	2.1	3.3	Yes	Yes
5 to 8 pm	74.3	631	1.9	3.1	Yes	Yes
5 to 8 pm	77.7	632	1.9	3.0	Yes	Yes
5 to 8 pm	76.4	632	1.9	3.1	Yes	Yes
6 to 8 pm	79.3	632	3.1	4.9	Yes	Yes
5 to 8 pm	76.o	632	2.0	3.1	Yes	Yes
5 to 8 pm	76.9	632	1.9	3.0	Yes	Yes
	Window 5 to 8 pm 5 to 8 pm 5 to 8 pm 5 to 8 pm 6 to 8 pm 5 to 8 pm 5 to 8 pm	Window Event Temp (F) 5 to 8 pm 75.6 5 to 8 pm 74.3 5 to 8 pm 77.7 5 to 8 pm 76.4 6 to 8 pm 79.3 5 to 8 pm 76.0 5 to 8 pm 76.9	Event Window Event Temp (F) Sites Enrolled 5 to 8 pm 75.6 631 5 to 8 pm 74.3 631 5 to 8 pm 77.7 632 5 to 8 pm 76.4 632 6 to 8 pm 79.3 632 5 to 8 pm 76.0 632 5 to 8 pm 76.9 632	Event Window Avg Event Temp (F) Sites Enrolled Aggregate (MW) 5 to 8 pm 75.6 631 2.1 5 to 8 pm 74.3 631 1.9 5 to 8 pm 77.7 632 1.9 5 to 8 pm 76.4 632 1.9 6 to 8 pm 79.3 632 3.1 5 to 8 pm 76.0 632 2.0 5 to 8 pm 76.9 632 1.9	Event Window Avg Event Temp (F) Sites Enrolled Aggregate (MW) Average Site (kW) 5 to 8 pm 75.6 631 2.1 3.3 5 to 8 pm 74.3 631 1.9 3.1 5 to 8 pm 77.7 632 1.9 3.0 5 to 8 pm 76.4 632 1.9 3.1 6 to 8 pm 79.3 632 3.1 4.9 5 to 8 pm 76.0 632 2.0 3.1	Event Window Avg Event Temp (F) Sites Enrolled Aggregate (MW) Average Site (kW) Significant (90% CI) 5 to 8 pm 75.6 631 2.1 3.3 Yes 5 to 8 pm 74.3 631 1.9 3.1 Yes 5 to 8 pm 77.7 632 1.9 3.0 Yes 5 to 8 pm 76.4 632 1.9 3.1 Yes 6 to 8 pm 79.3 632 3.1 4.9 Yes 5 to 8 pm 76.0 632 2.0 3.1 Yes 5 to 8 pm 76.9 632 1.9 3.0 Yes

Table 3-7: ELRP A.4 Event Reductions*

3.3.4 ELRP GROUP A.5 IMPACTS BY EVENT

Group A.5 is designated for non-residential vehicle-grid integration (VGI) aggregators not participating in DR programs and was comprised of three participating sites in PY2024. There were ten events called for subgroup A.5 in PY2024, across a variety of durations and start times. Table 3-8 summarizes the load reductions and participant weighted event temperatures for ELRP A.5 sites during the ten events and for the average weekday event. In the tables, the bars show a visual comparison of the reductions that are numerically labeled on the left of the bars.

^{*} The July 10th and July 24th event days were excluded from this evaluation, due to ineffective dispatch.

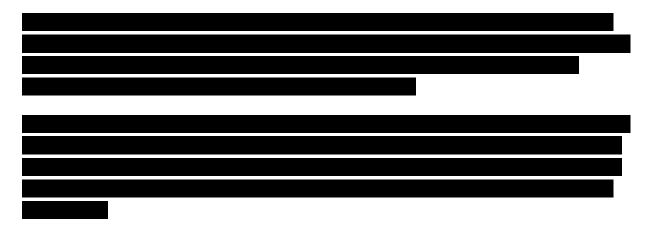


Table 3-8: ELRP A.5 Event Reductions

		Avq		Reduction	ns (Ex Post)		
Event Date	Event Window	Event Temp (F)	Sites Enrolled	Aggregate (MW)	Average Site (kW)	Significant (90% CI)	Significant (95% CI)
7/10/2024	6 to 9 pm	70.4					
7/11/2024	6 to 9 pm	68.7					
7/24/2024	6 to 9 pm	75.8					
8/20/2024	5 to 8 pm	80.2					
9/4/2024	5 to 8 pm	78.7					
9/5/2024	5 to 8 pm	83.2					
9/6/2024	5 to 8 pm	79.7					
9/9/2024	5 to 8 pm	84.3					
10/6/2024	5 to 8 pm	70.2					
10/7/2024	5 to 8 pm	72.6					
Avg Weekday 5-8 pm	5 to 8 pm	79.8					
Avg Weekday 6-9 pm	6 to 9 pm	71.6					
Avg Weekend (any)	5 to 8 pm	70.2					
Avg Weekday (any)	5 to 9 pm	76.7					

3.3.5 ELRP GROUP A.6 IMPACTS BY EVENT

There were no events called for Group A.6 during PY2024, so ex post impacts cannot be evaluated for this group.

3.3.6 ELRP GROUP B.2 IMPACTS BY EVENT

Group B.2 is designated for IOU Capacity Bidding Program (CBP) PDR resources and was comprised of two participating sites in PY2024. There was only one event called for subgroup B.2 in PY2024 on July 24, 2024. Table 3-9 summarizes the load reductions and participant weighted event temperatures for ELRP B.2 sites during the July 24th event.

The population changed drastically relative to PY2023,

Table 3-9: ELRP B.2 Event Reductions

		Avg		Red	ductions (Ex			
Event Date	Event Window	Event Temp (F)	Sites Enrolled	Aggregate (MW)	% Reduction	Average Site (kW)	Significant (90% CI)	Significant (95% CI)
7/24/2024	5 to 9 pm	75.7						
Avg Weekday (any)	5 to 9 pm	75-7						

3.3.7 COMPARISON OF EVALUATION LOAD REDUCTIONS TO BASELINE APPROACH

The ELRP pilot remunerates participant site performance via a \$2/kWh payment, determined using baseline settlement rules specific to each subgroup. However, settlement payments for A.6 decreased in 2024 to \$1/kWh. The baseline rules are mostly applied at the customer account level¹⁶ and differ for weekday and weekend events as follows:

- Group A All Events¹⁷:
 - Calculate the average event hour load for the prior 10 non-event calendar days.
 - Take the average hour loads across these 10 days. This is the baseline for that customer for that event.
 - Calculate a same day adjustment and apply to the average non-event day load: the ratio of the average event day load (first three hours of the four preceding the event) to the same hours on the average non-event day loads¹⁸.
 - o Subtract observed load from the adjusted baseline to calculate the load reduction.
 - To determine the kWh eligible for payment, take the load reduction in each hour during the event window and sum. No payments or penalties apply to totals below zero kWh for an event hour.
- Group B All Events: follows slightly different baseline calculation rules which include steps for netting out CBP event reductions to avoid double counting.

The baseline approach is used to determine settlements for participant sites because it is simple to calculate and simple to explain to customers. Table 3-10 compares the ELRP settlement baseline to the control group based methods used for the load impact evaluation and underscores why the latter is more methodologically robust.

¹⁶ Settlement occurs at the aggregator level for A.4 and B.2

¹⁷ These baseline calculation rules apply for Group A.1, and this section does not include the slight differences in baseline methodology for other subgroups.

¹⁸ Capped at minimum 1.00 and maximum 1.40.

Table 3-10: Comparison of Settlement Baseline and Load Impact Evaluation Methodologies

	Settlement Baseline	Load Impact Evaluation
Approach	Within-subjects baseline	Difference-in-difference with matched controls supplemented by Site specific regression with synthetic controls
Does the approach control for exogenous factors?	No. A pre-post within subjects approach only compares participant site load before and during the event. There is no way to identify changes in loads that may not be due to the event.	Yes. Any changes in load not due to the event will be apparent in the loads of the controls.
Does the approach minimize statistical noise?	No. The calculation occurs at the account level ¹⁹ and individual account loads are inherently noisy from day to day.	Yes. Tournaments are used to select controls and regression models which minimize error and bias. Then results are aggregated across participating sites (hundreds of customers for some subgroups). Noise that is apparent at the individual level is thereby averaged out.
Is the approach symmetrical?	No. The baseline may be adjusted upwards, but not downwards. Also, customers are compensated for positive event reductions (after summing positive and negative event reductions across event hours ²⁰) but there is no penalty for reductions which are negative.	Yes. Load increases are treated no differently than load reductions.

Table 3-11 compares ex post results to baseline results across all event hours. The baseline is within ten percent of the ex post results for A.4, which was the only subgroup to produce significant impacts at 95% confidence in PY2024. For the other subgroups, the baseline and ex post results are simply noise.

¹⁹ Settlement occurs at the aggregator level for A.4 and B.2

²⁰ Negative reductions are set to o before summing across event hours for B.2

Table 3-11: ELRP Ex post Results vs Baseline Results

	Max				Red		Reductions			
Group	Event Window*	Avg Event Temp (F)	Sites Enrolled	Aggregate (MW)		% Reduction	Significant (90% CI)	Significant (95% CI)		Average Site (kW)
A1	5 to 9 pm	73.8	708							
A2	5 to 9 pm	70.8								
A ₄	5 to 8 pm	76.9	632	1.9	3.0	1029%	Yes	Yes	2.0	3.2
A5	5 to 9 pm	76.7								
В2	5 to 9 pm	75.7								

^{*} All event hours fell in this window.

Figure 3-1 compares the settlement baseline (left panel) averaged across the average 5 to 9 p.m. weekday event to the ex post results (right panel) for the average 5 to 9 p.m. weekday event. The baseline loads shown are calculated at the individual customer level and then summed. As described above, the baseline (blue line in the left panel) is the average of the ten previous non-event days for each participant site. These days are individually selected for each participant site and are not necessarily the same days for all participant sites. The load impact counterfactual (blue line in the right panel) is the load modeled using site specific regression models with synthetic controls. The shape of the load impact counterfactual follows the shape of the observed event day participant site load shape relatively closely. The settlement baseline has a similar shape but is essentially pinned to the event day load in pre-event hours (as a result of the baseline adjustment). However, in both cases any impacts estimated are much smaller than the noise inherent in the loads, as indicated by the 90% confidence band in the load impact estimate (right panel).





Incorporating a post event adjustment may somewhat reduce the gap in post event hours but would still not result in an adjusted load shape that follows event day loads in most non-event hours. In addition, the current baseline rules are asymmetrical and only allow for upward adjustments of the baseline. This means that the baseline could not be adjusted downwards to better align with post-event loads. Finally, there is always some amount of payment for noise with baseline settlements. This is

exacerbated with asymmetric settlements and when actual impacts are not substantially higher than the noise inherent in the loads, or near zero as in PY 2024. One possible solution to this issue is implementation of a buffer or minimum percent impact which must be achieved in order for a settlement baseline to qualify for payment. This minimum would ideally be set above the noise observed in loads.

3.4 EX ANTE LOAD IMPACTS

A key objective of the 2024 evaluation is to quantify the relationship between demand reductions, temperature, and hour of day. Ex ante impacts are estimated load reductions as a function of weather conditions, time of day, and forecasted changes in enrollment. By design, they reflect planning conditions defined by normal (1-in-2) peak demand weather conditions. The historical load patterns and performance during actual events are used as the reductions for a standardized set of weather conditions.

3.4.1 RELATIONSHIP OF CUSTOMER LOADS AND PERCENT REDUCTIONS TO WEATHER

When developing the ex ante forecast it is important to ask two questions:

- 1. What are the most event relevant weather conditions for an emergency program such as ELRP?
- 2. How do observed impacts vary under those weather conditions?

The first question is important for determining which historical impacts should be used for developing the ex ante forecast. PY 2024 ex post impacts were largely not significant across the non-residential subgroups. This stands in contrast to ex post results for PY 2022 which yielded positive, significant reductions. The previous year's evaluation relied on these PY 2022 impacts because it was believed that the PY 2023 dispatches, specifically the notifications, were abnormal. This year's events were more similar to PY 2023 than PY 2022. Ideally, ex ante relies on multiple years of data, but the customer mix year-over-year for the majority of ELRP subgroups changes drastically. For this reason, all subgroups rely on PY 2024 impacts. The A.1 impact modelling relies on a solar status segmentation, since it was found that customers with solar produced statistically significant results.

The second question which should be asked when developing an ex ante weather model is how observed impacts vary under those weather conditions. Figure 3-2 shows the hourly percent reductions for historical weekday events as a function of hourly temperatures for sites in each ELRP subgroup²¹. Notably, there is no clear relationship between impacts and temperature despite the relatively wide range of temperatures. Given this lack of a clear relationship, ex ante estimates reflect static average

28

²¹ Impacts that are not statistically significant have been recoded to zero.

percent reductions for each event hour. Therefore, ex ante reductions are assumed to vary only as a function of the reference load.

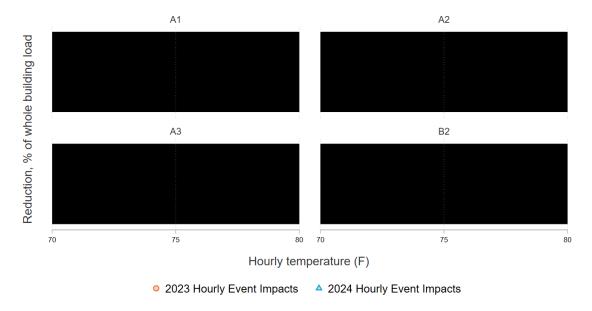


Figure 3-2: ELRP Hourly Percent Reductions and Temperatures

For the A.4 and A.5 subgroups, which is comprised of technology responding to dispatch signals, impacts can be assumed to be a function of the battery capacity made available by participants. Figure 3-3 shows the average kWh per-customer reduction for the A.4 and A.5 events. Assessment of these PY 2024 events show no clear correlation between kWh reductions and weather.

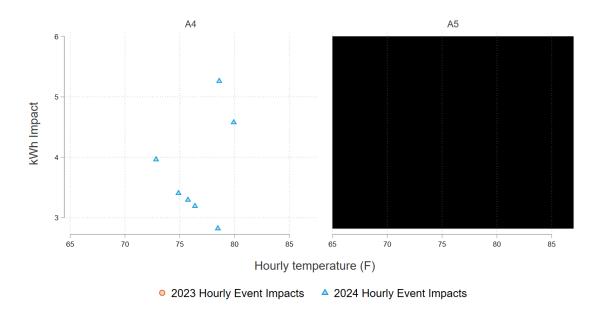


Figure 3-3: ELRP A4, A5 Hourly kWh Reductions and Temperatures

3.4.2 PROGRAM SPECIFIC AND PORTFOLIO ADJUSTED IMPACTS

Program specific and portfolio adjusted impacts are developed for each subgroup. The fundamental difference that necessitates having these two sets of results is grounded in the ability of customers to participate in more than one energy saving program. Dual enrollments make proper attribution of savings estimates essential, to avoid double-counting. Ex post results are properly attributed by calculating the incremental impacts, or the load reduction beyond what was predicted or committed on dually called event hours.

Program specific ex ante estimates, which are the unadjusted impacts of the program, are calculated by using ELRP-only and dually enrolled customers on all ELRP event days. Summing up program specific aggregate ex-ante estimates across all evaluation reports could generate double counting of impacts. Portfolio adjusted ex ante estimates are the population's incremental savings generated by ELRP dispatch. These impacts avoid double counting across evaluation reports, which allows for summing up aggregate ex-ante estimates across all evaluation reports to get an estimate of SDG&E's portfolio of DR programs. Table 3-12 defines the dual enrolled programs for consideration in each subgroup.

Table 3-12: Eligible Dually Enrolled Programs for Ex Ante Considerations

Dual Group	Study	Ex-post		
	ELRP	Full Impacts reported		
ELRP A1 + CPP	CPP	Impacts removed from program average; duals' impacts on dual events not in report		
ELRP B2 + CBP	ELRP	Any impacts beyond nomination		
ELRP B2 + CBP	CBP	Impacts are capped at nomination		

If there are no dual enrollments allowed or there were no dual events in a given season, the program impacts are equal to the portfolio impacts.

3.4.3 EX ANTE ENROLLMENT FORECAST

To derive the aggregate forecast and reference loads, percent impacts per customer are scaled to the site population expected to be enrolled in each planning year. Table 3-13 summarizes the annual enrollments forecast for each subgroup through the approval year for each subgroup, e.g. 2025 for subgroup A.6 and 2027 for all other subgroups. Assumptions for the derivation of these forecasts are described below.

Table 3-13: Participant Enrollment Forecast

Year	A1	A2	A5	A4	A6	B2	Total
2024	700			631	531,948		533,285
2025	739		606	927	509,080		511,355
2026	784		1,211	1,224	0		3,222
2027	835		1,816	1,518	0		4,172

Enrollments in PY2024 were similar to PY2023, with the exception of B.2. Enrollment in B.2 dropped dramatically from 145 sites to just 2 sites in PY2024. Given the small populations and short timeframe for which ELRP has been an active program, A.2 and B.2 enrollments were assumed to stay constant for future years through 2027. The A.1 and A.6 forecasted enrollments are reflective of the net growth for these subgroups, where net growth is equal to total growth less attrition, based on the enrollments at the end of the 2024 season versus the end of the 2023 season. For A.6, these growth and attrition rates are specific to each eligibility group.

The A.4 and A.5 subgroups, which both cover technology-enabled program participation, require more refined assumptions for the enrollment forecast. For A.4, this change in growth is due to an additional aggregator joining the program. Their growth is assumed to follow a similar trajectory as the original aggregator, which is roughly a net growth of 300 enrollments per year. Similarly, A.5 is projecting an additional set of aggregators joining the program. Given that the current enrollment includes only a handful of sites, there is assumed to be a large uptick as these aggregators recruit from the pool of eligible customers, which is roughly a net growth of 600 enrollments per year.

3.4.4 ELRP GROUP A.1 EX ANTE LOAD IMPACTS

Group A.1 is designated for non-residential customers not participating in DR programs and is currently the largest ELRP subgroup by far with over 700 participating sites. Table 3-14 summarizes the program and portfolio adjusted ex ante demand reduction capability by forecast year for different planning conditions. The tables reflect dispatchable demand reductions available from 4 to 9 p.m. under August worst day conditions for 1-in-2 weather conditions, which align with the planning conditions used for resource adequacy attribution. The ex post analysis showed no clear trend in percent load reductions relative to weather patterns so ex ante reductions are assumed to vary only as a function of the reference load. The static average percent reduction in each event hour is applied to this reference load.

The static average percent reduction in each event hour is applied to this reference load. This load impact forecast reflects reductions observed during PY2024 conditions. Enrollments are assumed to stay flat until the last year of ELRP approval in 2027, based on the enrollment forecast described above.

Table 3-14: ELRP A.1 Ex Ante Impacts for 1-in-2 August Worst Day (MW)

		C	AISO	SDG&E		
Year	Sites	Program	Portfolio	Program	Portfolio	
2024	700	6.24	6.24	6.42	6.42	
2025	739	6.56	6.56	6.75	6.75	
2026	784	6.89	6.89	7.09	7.09	
2027	835	7.27	7.27	7.49	7.49	

3.4.5 ELRP GROUP A.2 EX ANTE LOAD IMPACTS

Group A.2 is designated for non-residential aggregators and was comprised of one participating site in PY2024. Table 3-15 summarizes the program and portfolio adjusted ex ante demand reduction capability by forecast year for different planning conditions. The tables reflect dispatchable demand reductions available from 4 to 9 p.m. under August worst day conditions for 1-in-2 weather conditions, which align with the planning conditions used for resource adequacy attribution.

The ex post analysis showed no clear trend in percent load reductions relative to weather patterns so ex ante reductions are assumed to vary only as a function of the reference load. The static average percent reduction in each event hour is applied to this reference load. This load impact forecast reflects reductions observed during PY2024 conditions. Enrollments are assumed to stay flat until the last year of ELRP approval in 2027, based on the enrollment forecast described above.

Table 3-15: ELRP A.2 Ex Ante Impacts for 1-in-2 August Worst Day (MW)

, ,	al.	C	AISO	SDG&E		
Year	Sites	Program	Portfolio	Program	Portfolio	
2024						
2025						
2026						
2027						

3.4.6 ELRP GROUP A.4 EX ANTE LOAD IMPACTS

Group A.4 is designated for Virtual Power Plant (VPP) aggregators of non-residential and residential battery storage. PY2024 enrollment consisted of one aggregator and 632 residential sites. Table 3-16 summarizes the program and portfolio adjusted ex ante demand reduction capability by forecast year for different planning conditions. The tables reflect dispatchable demand reductions available from 5 to 8 p.m. under August worst conditions for 1-in-2 weather conditions, which align with the planning conditions used for resource adequacy attribution.

The ex post analysis showed no trend in reductions by weather patterns and are therefore assumed to not be not weather sensitive. Load reductions are instead assumed to be a function of the total kWh reduction delivered by the average site for the average event, not reductions in weather sensitive loads. To derive expected impacts average kWh delivered during the PY 2024 events is then divided by 3, to take into account the resource availability rules set to go into effect for PY2024. Essentially, A.4 resources are required to provide three hours of reductions, so it is assumed that the kWh reductions will be spread evenly across the three hours of the 5 to 8 p.m. availability window.

Outside of the availability window, there is one hour of pre-event and two hours of post-event load impacts modelled. These are not factored into the impacts reported below but are included in the table generators to accurately reflect battery operation immediately preceding and following an event dispatch.

Table 3-16: ELRP A.4 Ex Ante Impacts for 1-in-2 August Worst Day (MW)

		C	AISO	SDG&E		
Year	Year Sites	Program	Portfolio	Program	Portfolio	
2024	631	1.99	1.99	1.99	1.99	
2025	927	2.92	2.92	2.92	2.92	
2026	1,224	3.86	3.86	3.86	3.86	
2027	1,518	4.78	4.78	4.78	4.78	

3.4.7 ELRP GROUP A.5 EX ANTE LOAD IMPACTS

Group A.5 is designated for vehicle-grid integration (VGI) aggregators of non-residential electric vehicles or charging stations and was comprised of three participating sites in PY2024. Table 3-17 summarizes the program and portfolio adjusted ex ante demand reduction capability by forecast year for different planning conditions. The tables reflect dispatchable demand reductions available from 5 to 8 p.m. under August worst conditions for 1-in-2 weather conditions, which align with the planning conditions used for resource adequacy attribution.

The ex post analysis showed no trend in reductions by weather patterns and are therefore assumed to not be not weather sensitive. Load reductions are instead assumed to be a function of the total kWh reduction delivered by the average site for the average event, not reductions in weather sensitive loads. To derive expected impacts average kWh delivered during the PY 2024 events is then divided by 3, to take into account the resource availability rules set to go into effect for PY2024.²³ Essentially, A.5

²² D.22-06-050 (488540633.PDF (ca.gov))

²³ D.22-06-050 (488540633.PDF (ca.gov))

resources are required to provide three hours of reductions, so it is assumed that the kWh reductions will be spread evenly across the three hours of the 5 to 8 p.m. availability window.

Outside of the availability window, there are two hours of post-event load impacts modelled. These are not factored into the impacts reported below but are included in the table generators to accurately reflect charging operations immediately following an event dispatch.

CAISO SDG&E Year Sites **Program Portfolio Program Portfolio** 2024 606 1.68 1.68 1.68 1.68 2025 2026 1,211 3.19 3.19 3.19 3.19 1,816 2027 4.79 4.79 4.79 4.79

Table 3-17: ELRP A.5 Ex Ante Impacts for 1-in-2 August Worst Day (MW)

3.4.8 ELRP GROUP A.6 EX ANTE LOAD IMPACTS

Group A.6 is designated for residential customers and was comprised of 531,948 participating sites in PY2024. Table 3-18 summarizes the program and portfolio adjusted ex ante demand reduction capability by forecast year for different planning conditions. The tables reflect dispatchable demand reductions available from 4 to 9 p.m. under August worst conditions for 1-in-2 weather conditions, which align with the planning conditions used for resource adequacy attribution. Since there were no A.6 events in PY 2024, impacts from PY 2022 were used to build the ex ante impact model. The ex post analysis showed no clear trend in percent load reductions relative to weather patterns so ex ante reductions are assumed to vary only as a function of the reference load. The static average percent reduction in each event hour is applied to this reference load. This calculation is performed for each eligibility group, since the reductions, reference loads, and forecasted enrollments all vary by eligibility group.

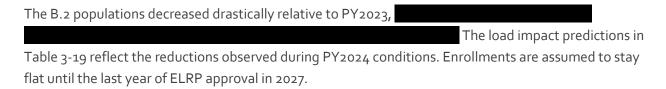
This load impact forecast reflects reductions observed during PY 2022 emergency conditions. Enrollments are assumed to stay flat until the last year of A.6 ELRP approval in 2025.

Year	Sites	CAISO		SDG&E		
		Program	Portfolio	Program	Portfolio	
2024	531,948	9.04	9.04	9.50	9.50	
2025	509,080	8.74	8.74	9.19	9.19	
2026	0	0.00	0.00	0.00	0.00	
2027	0	0.00	0.00	0.00	0.00	

Table 3-18: ELRP A.6 Ex Ante Impacts for 1-in-2 August Worst Day (MW)

ELRP GROUP B.2 EX ANTE LOAD IMPACTS

Group B.2 is designated for IOU capacity bidding (CBP) PDR resources. Table 3-19 summarizes the program and portfolio adjusted ex ante demand reduction capability by forecast year for different planning conditions. The tables reflect dispatchable demand reductions available from 4 to 9 p.m. under August worst conditions for 1-in-2 weather conditions, which align with the planning conditions used for resource adequacy attribution. The ex post analysis showed no clear trend in percent load reductions relative to weather patterns so ex ante reductions are assumed to vary only as a function of the reference load. The static average percent reduction in each event hour is applied to this reference load.



CAISO SDG&E Year Sites **Portfolio Program Portfolio Program**

Table 3-19: ELRP B.2 Ex Ante Impacts for 1-in-2 August Worst Day (MW)

2024 2025 2026 2027

3.4.10 COMPARISON OF EX POST AND EX ANTE LOAD IMPACTS

Table 3-20 compares the demand reductions from 2024 A.1 events. Results are shown for the 4 to 9 p.m. resource adequacy window and compared to the average of the weekday events used in modeling ex-ante. In 2024, A.1 ELRP customers delivered Differences in ex ante and ex post counterfactual loads (Load without

DR) are largely explained by the change in the enrollment population from PY 2024 ex post enrollment as compared to PY 2025 ex ante. Essentially, the average customer load was lower in PY 2024 relative to the average across the three prior years. The SDG&E and CAISO weather ex ante predictions are slightly different because ex ante reference loads are assumed to be weather sensitive. Percent impacts are equal across the two ex ante weather specifications because no weather trend was established for impacts.

Table 3-20: ELRP A1 Comparison of Ex Post and Ex Ante Load Impacts

Result Type	Day Type	Period	Load without DR (avg site kWh/h)	Load Reduction (avg site kWh/h)	% Reduction	Event Avg Temp (F)
Ex Post	Avg Weekday Event	All Hours with Event Dispatch				
Ex Post	Avg Weekday Event	4 to 9 p.m.				
Ex Ante (CAISO)	Aug Worst Day, 1-in-2	Resource Adequacy: 4 to 9 p.m.	47 ⁸ ·57	8.91	1.9%	81.1
Ex Ante (SDG&E)	Aug Worst Day, 1-in-2	Resource Adequacy: 4 to 9 p.m.	495.00	9.18	1.9%	84.0

Ex Post impacts reflect significant, incremental impacts, e.g. those used for ex ante impact model.

Historical impacts weighted by number of current participants in a given event.

Ex Ante impacts reflect portfolio impacts.

Table 3-21 compares the demand reductions from 2024 A.4 events. Results are shown for the 5 to 8 p.m. resource adequacy window and compared to the average of the weekday events used in modeling ex-ante. Technology-enabled subgroups rely on a four-hour window, which is why the resource adequacy window spans from 5 to 8 p.m. instead of 4 to 9 p.m. Essentially, A.4 resources are required to be to provide three hours of reductions, so it is assumed that the kWh reductions will be spread evenly across three hours. The resulting ex ante impact in the three hour window is 3.15 kW per hour.

Table 3-21: ELRP A4 Battery Comparison of Ex Post and Ex Ante Load Impacts

Result Type	Day Type	Period	Load without DR (avg site kWh/h)	Load Reduction (avg site kWh/h)	% Reduction	Event Avg Temp (F)
Ex Post	Avg Weekday Event	All Hours with Event Dispatch	0.00	3.15	N/A	76.7
Ex Post	Avg Weekday Event	4 to 9 p.m.	0.00	3.15	N/A	76.7
Ex Ante (CAISO)	Aug Worst Day, 1-in-2	Resource Adequacy: 4 to 8 p.m.	N/A	3.15	N/A	81.2
Ex Ante (SDG&E)	Aug Worst Day, 1-in-2	Resource Adequacy: 4 to 8 p.m.	N/A	3.15	N/A	83.7

Ex Post impacts reflect significant, incremental impacts, e.g. those used for ex ante impact model.

Historical impacts weighted by number of current participants in a given event.

Ex Ante impacts reflect portfolio impacts.

Table 3-22 compares the demand reductions from 2022 A.6 events, since no events were called in PY 2024. Ex ante results are shown for the 4 to 9 p.m. resource adequacy window and compared to the loads and impacts for the average PY 2022 weekday event day, during the 4 to 9 p.m. window which also corresponded to the event window. Loads, percent impacts, and enrollments are very similar between PY 2022 ex post and PY 2024 ex ante, with moderate differences due to a slight decrease in enrollments in 2024.

Table 3-22: ELRP A6 Residential Comparison of Ex Post and Ex Ante Load Impacts

Result Type	Day Type	Period	Load without DR (avg site kWh/h)	Load Reduction (avg site kWh/h)	% Reduction	Event Avg Temp (F)
Ex Post	Avg Weekday Event	All Hours with Event Dispatch	0.91	0.01	0.8%	79.2
Ex Post	Avg Weekday Event	4 to 9 p.m.	1.20	0.02	1.7%	78.6
Ex Ante (CAISO)	Aug Worst Day, 1-in-2	Resource Adequacy: 4 to 9 p.m.	1.14	0.02	1.5%	80.5
Ex Ante (SDG&E)	Aug Worst Day, 1-in-2	Resource Adequacy: 4 to 9 p.m.	1.20	0.02	1.5%	82.6

Ex Post impacts reflect significant, incremental impacts, e.g. those used for ex ante impact model.

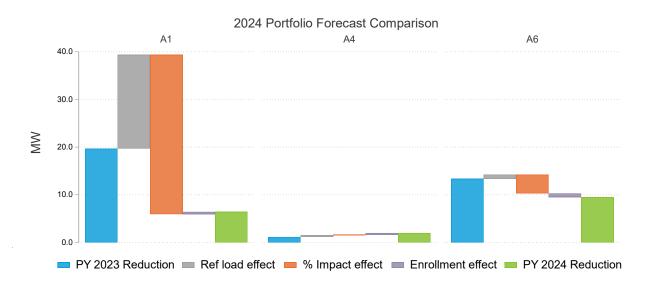
Historical impacts weighted by number of current participants in a given event.

Ex Ante impacts reflect portfolio impacts.

3.4.11 COMPARISON TO 2023 EX ANTE IMPACT ESTIMATES

The following figure gives a breakdown of the difference in ex ante impact estimates from PY2023 and those generated in in PY2024. The graphs can be interpreted as the individual factors (changes in reference load, percent impacts, or enrollments) that explain the change in the estimated ex ante MW impacts in PY2023 (in blue) and PY2024 (in green).

Figure 3-4: Waterfall Analysis of 2023-2024 Ex Ante Impacts by Key Group



The A.1 group estimates primarily changed due to the lower reference load, which is attributable to a smaller average participant, and an update in impact modeling. Last year, the PY 2022 impacts were leveraged to construct the A.1 ex ante estimates, but this year we used impacts from PY 2024 segmented by solar status. For both A.4 and A.6, the reference loads increased slightly, and the impacts decreased. The decrease in impacts for A.4 is due to the change in the resource adequacy event duration, while the A.6 reduction was a result of the updated definition in program specific and portfolio adjusted impacts.

3.4.12 EX ANTE LOAD IMPACT SLICE-OF-DAY TABLES

Table 3-23, Table 3-24, Table 3-25, Table 3-26, Table 3-27, and Table 3-28 show the 2024 ex ante aggregate hourly impacts by ELRP Group for each month under SDG&E 1-in-2 monthly worst day conditions. The tables are designed to enable the CPUC's Slice-of-Day Resource Adequacy requirements. Currently the ELRP pilot does not qualify for Resource Adequacy, but these tables reflect what the slice of day load impacts would look like if ELRP did qualify for Resource Adequacy. The estimated reductions are typically larger in the hotter summer months and smaller in the cooler shoulder months. Reductions are only included for May through October, corresponding to the months in which ELRP events can be called. For Group A.4 and A.5, response to an event is flat across the three-hour Resource Adequacy window to reflect consistent discharge. The pre- and post-event charging are also modelled, but these are not factored into the resource adequacy window. For other groups, however, event response varies by hour.

Table 3-23: ELRP A.1 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impacts, MW)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00	5.47	6.28	6.73	7.15	6.44	0.00	0.00
18	0.00	0.00	0.00	0.00	5.22	5.47	6.11	6.54	6.86	6.28	0.00	0.00
19	0.00	0.00	0.00	0.00	5.08	5.32	5.93	6.33	6.62	6.08	0.00	0.00
20	0.00	0.00	0.00	0.00	5.01	5.26	5.85	6.23	6.50	5.97	0.00	0.00
21	0.00	0.00	0.00	0.00	4.99	5.25	5.90	6.29	6.59	6.00	0.00	0.00
22	0.00	0.00	0.00	0.00	5.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3-24: ELRP A.2 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impacts, MW)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1												
2												
3												
4												
5												
6												
7												
8												
9												
10												
11												
12												
13												
14												
15												
16												
17												
18												
19												
20												
21												
22												
23												
24												

Table 3-25: ELRP A.4 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impacts, MW)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	-1.16	-1.16	-1.17	-1.17	-1.16	-1.17	0.00	0.00
18	0.00	0.00	0.00	0.00	1.98	1.99	1.99	1.99	1.99	1.99	0.00	0.00
19	0.00	0.00	0.00	0.00	1.98	1.99	1.99	1.99	1.99	1.99	0.00	0.00
20	0.00	0.00	0.00	0.00	1.98	1.99	1.99	1.99	1.99	1.99	0.00	0.00
21	0.00	0.00	0.00	0.00	-0.46	-0.46	-0.46	-0.46	-0.46	-0.46	0.00	0.00
22	0.00	0.00	0.00	0.00	-0.26	-0.26	-0.26	-0.26	-0.26	-0.26	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3-26: ELRP A.5 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impacts, MW)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1												
2												
3												
4												
5												
6												
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22												
23												
24												

Table 3-27: ELRP A.6 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impacts, MW)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00	5.61	8.11	8.87	10.29	7.66	0.00	0.00
18	0.00	0.00	0.00	0.00	6.03	6.73	9.21	9.94	11.36	8.80	0.00	0.00
19	0.00	0.00	0.00	0.00	6.64	7.26	9.48	10.11	11.41	9.17	0.00	0.00
20	0.00	0.00	0.00	0.00	6.69	7.19	9.01	9.49	10.57	8.79	0.00	0.00
21	0.00	0.00	0.00	0.00	6.63	7.06	8.67	9.07	10.03	8.51	0.00	0.00
22	0.00	0.00	0.00	0.00	6.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3-28: ELRP B.2 Slice of Day Table for Monthly Worst Day (Portfolio-Adjusted Aggregate Impacts, MW)

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1												
2												
3												
4												
5												
6												
7												
8												
9												
10												
11												
12												
13												
14												
15												
16												
17												
18												
19												
20												
21												
22												
23												
24												

4 CONCLUSIONS AND RECOMMENDATIONS

The non-residential ELRP pilots largely did not deliver statistically significant demand reductions in PY2024 while the A.4 residential battery storage pilot did deliver substantial significant savings. For other pilots there is room for improvement. The recommendations below may not be currently funded and may not be within SDG&E's control, and costs and feasibility need to be considered alongside other research and program priorities.

4.1 ELRP RECOMMENDATIONS

- Reserve ELRP dispatch for clear emergency conditions. Significant load reductions were observed for PY 2022 and largely not for PY 2023 or PY 2024 events. PY 2022 events were also dispatched under more extreme conditions and may be more a function of the emergency conditions under which the event is called. Reserving dispatch to clear emergency conditions which are clearly communicated to participants may be more in line with participant expectations and understanding of the program and may deliver greater impacts when it is called. This may include not calling event in years where extreme weather conditions are not experienced.
- Improve dispatch advance notice. PY 2022 events were also with day-ahead notice, compared to day-of and even hour-ahead notice in PY 2023 and PY 2024. Even for technology enabled dispatch such as A4, reductions were lower in PY 2023 and PY 2024 on one event when notifications were sent after the beginning of the event. The advance notice received by participants, which is a function of when CAISO Emergency Energy Alerts are triggered may also indirectly be a function of extremity of emergency conditions at the time of the alert. To the extent possible, earlier advance notice, ideally day ahead, is likely to improve response to ELRP event notifications.

APPENDIX

A. INDIVIDUAL SITE REGRESSIONS WITH SYNTHETIC CONTROLS

Individual site regressions with synthetic controls and site-specific specifications were used as a supplementary method for estimating load impacts for PY 2023 impacts for Non-Residential ELRP. The approach is implemented on hourly participant site loads. It relies on control sites that did not experience the intervention (up to five matched to each participant site), lagged participant site usage, an industry usage profile, solar irradiance, plus weather and time characteristics, to estimate the counterfactual. The model estimates a counterfactual load using weather and these various synthetic controls and predictors. A separate model is estimated for each hour of day and all modeling excludes event days. Reductions are the difference between the observed participant site and predicted counterfactual loads. With a regression model with synthetic controls, one should observe:

- Very similar energy use patterns for participant site and counterfactual loads when the intervention is not in place.
- A change in demand patterns for customers who are dispatched or subject to time varying prices, but no similar change for the counterfactual load.
- The timing of the change should coincide with the introduction of intervention.

The use of individually specified site-specific regression models allows for incorporation of a subset of possible parameters that best predict out of sample loads for each site and does not rely on finding a single ideal match. The functional form of the regression with synthetic controls differs from a panel difference in difference regression in that usage for the control or controls are specified as right hand predictor variables. This enables the incorporation of multiple controls and the magnitude of coefficients for each control essentially weights the effect of each control in the regression which directly estimates the counterfactual load. In a difference in difference regression, usage for the single matched control is structured on a separate record from the treatment site and a treatment effect is instead estimated. The counterfactual load is then derived by adding back the treatment effect to the observed load. The model equation including the full set up possible parameters is presented below in Equation A o-1 and Table A o-1. In practice the model used for each site and included a varying subset of these parameters. A separate model was estimated for each hour of the day.

Equation A 0-1: Ex Post Regression Model for Non-Residential ELRP

$$\begin{array}{l} kW_t = \ \mathbf{a} + \sum_{n=1}^{max} \mathbf{b} \cdot kW_- \mathbf{0}_{n,t} \ + \sum_{n=1}^{max} \mathbf{c}_n \cdot kW_- \mathbf{1}_{t-n} \ + \sum_{n=1}^{max} \mathbf{d}_n \cdot month_n \ + \\ \sum_{n=1}^{max} \mathbf{e}_n \cdot dow_n \ + \ \mathbf{f} \cdot \ solar_t \ + \ \mathbf{g} \cdot \ industry_t \ + \sum_{n=1}^{max} \mathbf{h}_{n,t} \cdot spline_{n,t} \ + \ \delta_t \ + \ \varepsilon_{i,t} \end{array}$$

Where:

Table A 0-1: Ex Post Regression Elements for Non-Residential ELRP

kW _t	Is the site usage for each time period.
kW_0 _t	Is the synthetic control usage for up to 5 matched controls for each time period. The specific number of controls used varied by site. These synthetic controls were selected based on Euclidean distance matching (the winning matching method in a tournament of 8 methods). They did not experience the treatment.
kW_1 _{t-n}	Is the lagged participant site usage and could by one of: no lags, 1 day, 1 week, 2 weeks, 1 day and 1 week, and 1 and 2 weeks. The specific lags used varied by site.
а	Is the model intercept.
b	Coefficients for the synthetic control loads. The specific number of controls used varied by site and ranged from 0 to 5.
С	Coefficients for the participant site usage lags. The specific lags used varied by site.
d	Coefficients for each month.
е	Coefficients for each day of week.
f	Coefficient for solar irradiance across for each time period. Inclusion of this parameter varied by site.
g	Coefficient for industry load profile: normalized hourly loads (scaled from 0 to 1) for control sites in the same industry as the participant site. Industry grouping developed using NAICS code and customer names indicative of industry activity. Inclusion of this parameter varied by site.
h	Coefficients for weather sensitivity of loads, based on a 2 knot spline of 24 hour moving average of temperature, averaged across participant sites for each time period.
δ_{t}	Represents time effects for each time period. This accounts for observed and unobserved factors that vary by time but affect all customers equally.
$\epsilon_{i,t}$	Represents the error term for each individual customer and time period.

Most sites did not require individual site regressions, as a comparable control group was available to estimate event-day counterfactuals. Among sites that did require the individual regressions, loads were often variable or the sites were located in areas with few similar sites. The tables below report the bias and fit metrics for the models used by subgroup. Mean absolute percent error (MAPE) indicates the percent difference between predicted values and actual kWh on non-event days in summer 2024. The average percent bias is the mean of the percent errors – without taking an absolute value, this becomes the mean of both positive and negative values, with strong models calibrated to achieve a bias close to zero.

Table A-2: Bias and Fit Measures for Individual Customer Regressions

Subgroup	Sites in Sample	Sites w/ Indiv. Regressions	Avg. kW	Mean Absolute Percent Error (MAPE)	Avg. Percent Bias
A.1	700	271			
A.2					
A.5					
B.2					

B. PROXY DAY SELECTION

For the differences-in-differences estimates, participants are compared both over time (event days vs. non-event days) and with a pool of similar, non-participant customers (the matched control group). Proxy days, the non-event days used for comparison, are selected to be as similar as possible to actual event days. In general, these are often the hottest non-holiday weekdays of the summer (e.g. ELRP events are often called on days with extreme weather).

Proxy days are selecting by matching participants pre-event loads on event days (through 2 p.m.) to loads for the same hours on non-event days. Matches are tested and selected as the group that minimizes bias between the event day and non-event day loads.

A t-test can show the likelihood that two data series in fact different from each other. For proxy day selection, better matches should produce results with a higher probability that the two series are not different from each other.

The following tables report the p-values from t-tests of the hypothesis that pre-event hour loads on event days and proxy days are the same. Values are generally very close to one, meaning the hypothesis of similar loads cannot be rejected and the series are in fact very similar.

Table A 0-3: Proxy and Event Day Matching: p-Values from t-Tests

Event date	A.1	A.4
7/24/2024	0.556	-
8/20/2024	-	0.814
9/4/2024	-	0.564
9/5/2024	-	0.077
9/6/2024	-	0.022
9/9/2024	-	0.025

Some smaller values are found in some of the September events for A.4. These event days were more extreme, so some difference with the best proxy days can be expected. At certain levels, the -tests in fact imply the hypothesis of similar loads can be rejected (e.g. September 6th and 9th have significant differences at the 5% level).

Even if very closely matching proxy days cannot be found, differences-in-differences can still be the best estimation method for a DR evaluation. In such cases, dissimilarities between event days and proxy days may simply mean that the event days are very different from other summer days. Differences-in-differences then would still allow for comparison to a control group on these very hot days, with the control group serving as a proxy for the types of loads seen on those extreme days. This is evidenced by Figure A o-1, where the control sites closely mirror the participant sites prior to event dispatch.



