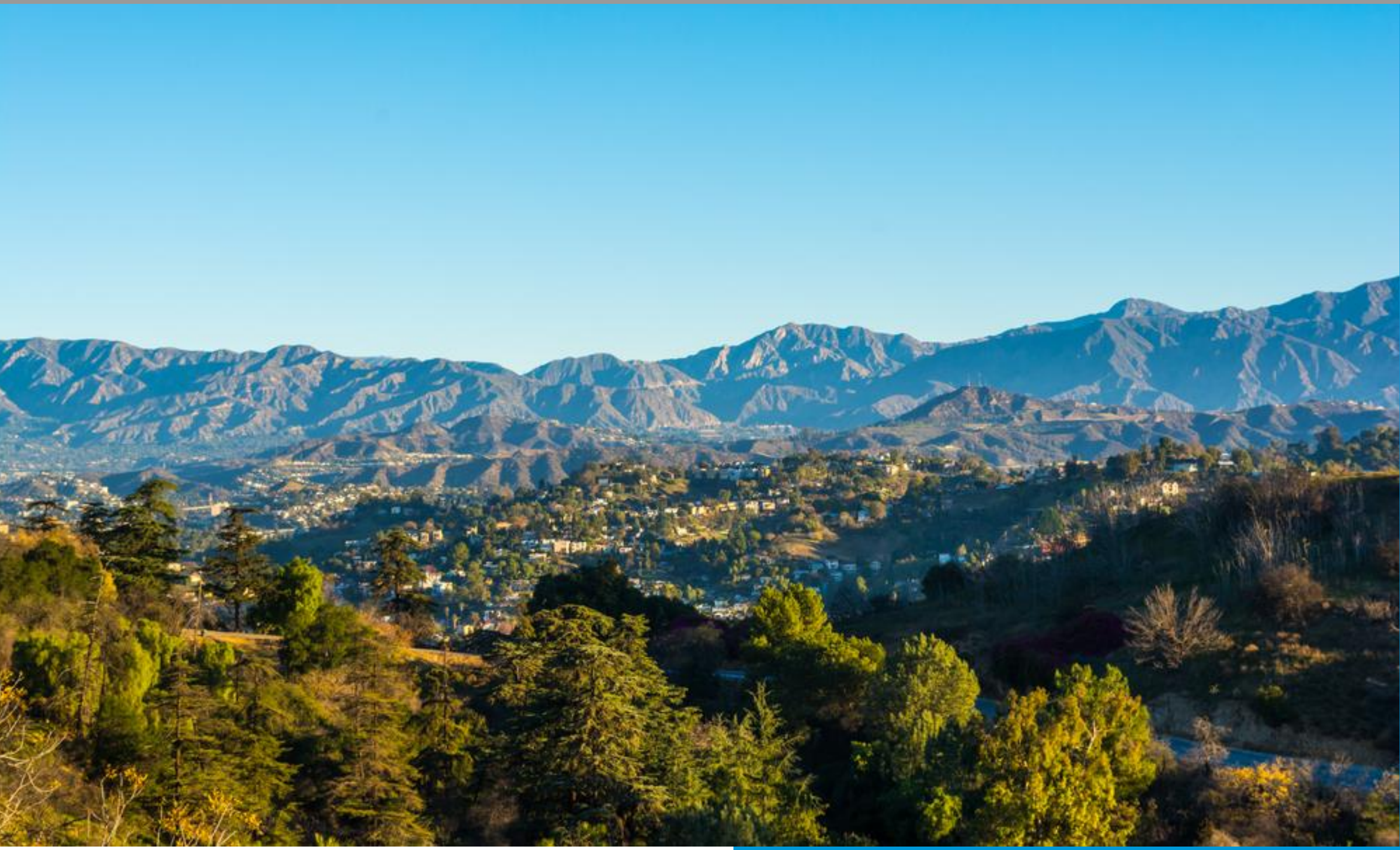
REPORT

April 1, 2025

PY 2024 SCE Agricultural & Pumping Interruptible Demand Response Evaluation



Prepared for Southern California Edison

By:

Adriana Ciccone
Candace Yee
Demand Side Analytics

Confidential information is redacted and denoted with black highlighting: [redacted]

CALMAC ID: SCE0493

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1 EXECUTIVE SUMMARY

The Agricultural & Pumping Interruptible (AP-I) program is a longstanding demand response (DR) program in Southern California Edison (SCE)'s territory. In exchange for a monthly bill credit, customers agree to participate in DR events, and can opt in to receive notifications of the events. During an event, a signal is sent to a switch installed on customer pumps and other agricultural loads. Events can be called for CAISO Emergencies, system contingencies, or program evaluation. At the end of an event, SCE sends another signal to switch load back on, although a subset of circuits must be restarted manually. The number of Periods of Interruption will not exceed one (1) per day and ten (10) per calendar month. The duration of the Periods of Interruption will not exceed 6 hours each and a total of 180 hours per calendar year. Table 1 shows the ex-post results from the one event that was called. The impact, or load reduction, is the difference between the reference and the observed load. The reference load is the estimated load the participants would have had if there was no event, whereas the observed impact is the actual load seen on the event day. Event participation in 2024 consisted of 894 enrolled customers. For the single event day, the program provided an aggregate impact of 12.39 MW (70.0%) of load shed.

Table 1: Ex-Post Impacts – All Event Hours

Date	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
9/24/2024 (4:00pm – 6:18pm)	894	19.79	5.93	13.86	13.47 – 14.25	70.0	12.39
Average Event Day	**894**	**19.79**	**5.93**	**13.86**	**13.47 – 14.25**	**70.0**	**12.39**

Table 2 shows the impacts by Local Capacity Area (LCA) on the average event day. The majority of impacts came from the Big Creek/Ventura LCA, which delivered 8.62 MW of the 12.39 MW reductions during the event. This was due to the large quantity of customers in the LCA – 758 of the 894 participants. Conversely, the AP-I customers in the LA Basin LCA have higher loads – their reference loads averaged 44.99 kW per customer – and these customers delivered an average load reduction of 39.11 kW per customer. However, due to the small group size, this group only delivered an aggregate impact of 3.44 MW.

Table 2: Ex-Post Impacts by LCA – All Hours

LCA	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Outside LA Basin	48	13.83	6.87	6.96	5.80 – 8.11	50.3	0.33
LA Basin	88	44.97	5.88	39.09	37.20 – 40.97	86.9	3.44
Big Creek/Ventura	758	17.24	5.87	11.37	10.97 – 11.77	65.9	8.62
All Customers	**894**	**19.79**	**5.93**	**13.86**	**13.47 – 14.25**	**70.0**	**12.39**

AP-I enrollments and switch paging success rates have a large impact on the forecasted load reductions. Both the enrollment forecast and the forecasted switch paging success rate are provided by SCE. As shown in Table 3, due to recent participant incentive reductions, AP-I enrollment is projected to decrease from the 894 participants enrolled in 2024 to a constant 848 participants for the next ten years, and could change even more depending on future program changes.

Table 3: AP-I Ex-Ante Enrollment Forecast

Program/Portfolio	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Portfolio	848	848	848	848	848	848	848	848	848	848	848
Program	848	848	848	848	848	848	848	848	848	848	848

AP-I impacts are determined by the percent of installed switches being successfully dispatched, or their switch success rate. Customers are flagged as having been successfully dispatched during an AP-I event when their load immediately preceding the first event hour drops by at least 50%, or when their load immediately following the last event hour increases by 100%. Over the ex-ante forecast horizon, the switch paging success rate is expected to grow as shown in Table 4, with additional investment in upgrading switches and improving the paging network during this time.

Table 4: AP-I Ex-Ante Switch Paging Success Rate Forecast

Year	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Switch Success Rate (%)	75.0	75.6	76.3	76.9	77.6	78.2	78.8	79.5	80.1	80.8	81.4

Table 5 shows the aggregate load reduction predictions for the August Monthly Worst Day as well as for SCE and CAISO 1-in-2 and 1-in-10 scenarios. The Monthly Worst Day is the updated language from the CPUC used to refer to the system peak day from the ex-ante weather forecast. 1-in-2 and 1-in-10 indicate average and extreme weather conditions. SCE conditions are the weather conditions that the SCE system has peaked historically, while CAISO conditions are the weather conditions under which the entire CAISO system has peaked historically.

As enrollment stays constant and the switch paging success rate increases over the next ten years, aggregate August Worst Day impacts will increase over time, ranging from 21.12 MW in 2026 (SCE 1-in-2) to 23.05 MW in 2035 (CAISO 1-in-10). In general, 1-in-10 weather conditions produce nearly the same impacts as 1-in-2, as AP-I is not as weather sensitive a program as the Summer Discount Plan or Smart Energy Program. While pumping loads do tend to vary with temperature, seasonality is a bigger driver of loads than hourly temperature. Regardless of weather, the aggregate impacts are quite similar across weather scenarios, with the AP-I program delivering at least 21 MW of load reduction on August event days.

Table 5: AP-I Aggregate Portfolio Ex-Ante Impacts (MW) - August Worst Day

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2025	22.05	22.36	22.07	22.37
2026	21.12	21.42	21.13	21.42
2027	21.30	21.60	21.31	21.60
2028	21.48	21.78	21.49	21.78
2029	21.65	21.96	21.67	21.97
2030	21.83	22.14	21.85	22.15
2031	22.01	22.32	22.03	22.33
2032	22.19	22.50	22.21	22.51
2033	22.37	22.69	22.38	22.69
2034	22.55	22.87	22.56	22.87
2035	22.73	23.05	22.74	23.05

2 PROGRAM DESCRIPTION

The Agricultural and Pumping Interruptible (AP-I) program is a longstanding direct load control program for SCE's agricultural and pumping customers. During system emergencies or for measurement and evaluation purposes, SCE sends a signal to radio switches on enrolled customers' pumping and agricultural circuits, shutting them off. At the end of an event, SCE sends another signal to switch load back on, although a subset of pumps and agricultural load must be restarted manually. The total number of customers on the program dropped to 894 in 2024, as the number of de-enrollments was higher than the number of new participants. Mild temperature conditions persisted throughout PY 2024, and only one event was called on September 24th.

2.1 KEY RESEARCH QUESTIONS

The PY 2024 evaluation of SCE's AP-I program sought to answer the following key research questions:

- What were the demand reductions due to program operations and interventions in 2024? How do these results compare to the ex-post results from the prior year and why?
- How do load impacts differ for customers who have enabling technology, prohibited resources, and/or are dually enrolled in other programs?
- How do weather and event conditions influence the magnitude of demand response?
- How do load impacts vary for different customer sizes, locations, and customer segments?
- What is the ex-ante load reduction capability for 1-in-2 and 1-in-10 weather conditions? Moreover, how well do these reductions align with ex-post results and prior ex-ante forecasts?
- What concrete steps can be undertaken to improve program performance?

2.2 PROGRAM DESCRIPTION

AP-I is a longstanding agricultural demand response program where, in exchange for a monthly bill credit, customers agree to participate in DR events. Customers may opt in to receive notifications in advance of the events. During an event, which can be called for CAISO Emergencies, system contingencies, or program evaluation, a signal is sent to a switch installed on customer pumps and other agricultural load. At the end of an event, SCE sends another signal to switch load back on, although a subset of pumps and agricultural load must be restarted manually. The number of Periods of Interruption will not exceed one (1) per day and ten (10) per calendar month. The duration of the Periods of Interruption will not exceed 6 hours each and a total of 180 hours per calendar year. Participation incentives are dependent on customer size and take the form of monthly credits, as shown in Table 6.

Table 6: AP-I Participant Credit

Size	Rate Block	Bill Credit ($/kW)
Below 200 kW	Summer On Peak	$19.62
	Winter Mid Peak	$10.87
200 kW and Above	Summer On Peak	$19.62
	Winter Mid Peak	$10.87

While AP-I events can be called at any point in the year, they have typically been called once or twice per summer season, especially in August and September. The event this year was consistent with this timing, with the event being called in late September, and the one event called aligns with the historical number of events called per season.

2.3 PARTICIPANT CHARACTERISTICS

894 customers participated in the full dispatch event on September 24th. Table 7 summarizes the key characteristics of customers participating in the event. Geographically, the majority are in the Ventura LCA, which encompasses the southern end of the agriculturally productive Central Valley. Most customers tend to be moderately sized, with their non-event, summer peak demand falling between 20 kW and 200 kW. The prohibited resource policy allows participants to use a backup generator during demand response events if they claim it is part of critical infrastructure. Six participants attested to using prohibited resources in PY 2024.

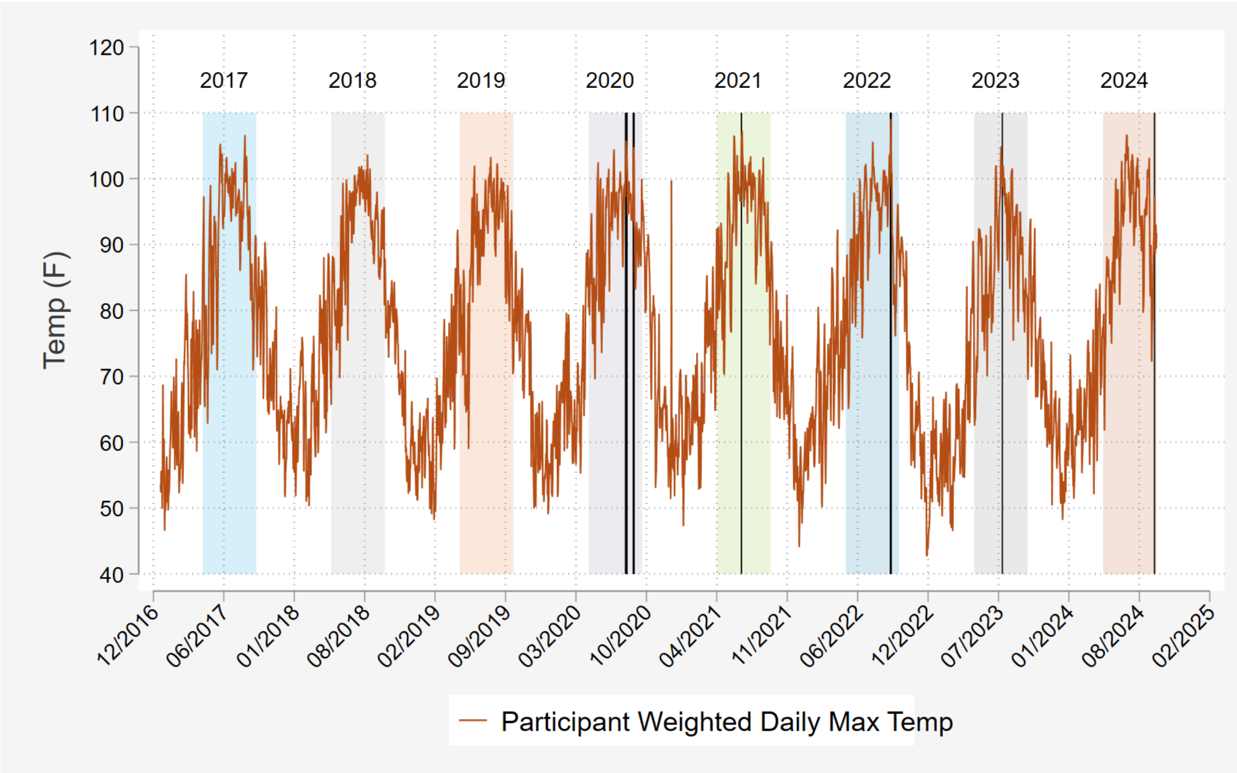
Table 7: Participant Characteristics on 9/24/2024 Event

Category	Segment	Customer Count 9/24
All	All Customers	894
LCA	Big Creek/Ventura	758
	LA Basin	88
	Outside LA Basin	48
Net Energy Metered Status	NEM Customer	265
	Non-NEM Customer	629
Prohibited Resource Attestation Status	No	879
	Yes and use	6
	Yes but don't use	9
Size	20-200kW	686
	20kW or Lower	148
	Greater than 200kW	60
SubLAP	SCE Central	60
	SCE High Desert	48
	SCE North	742
	SCE Northwest	16
	SCE West	28
Zone	Remainder of System	865
	South Orange County	12
	South of Lugo	17

2.4 2024 EVENT CONDITIONS

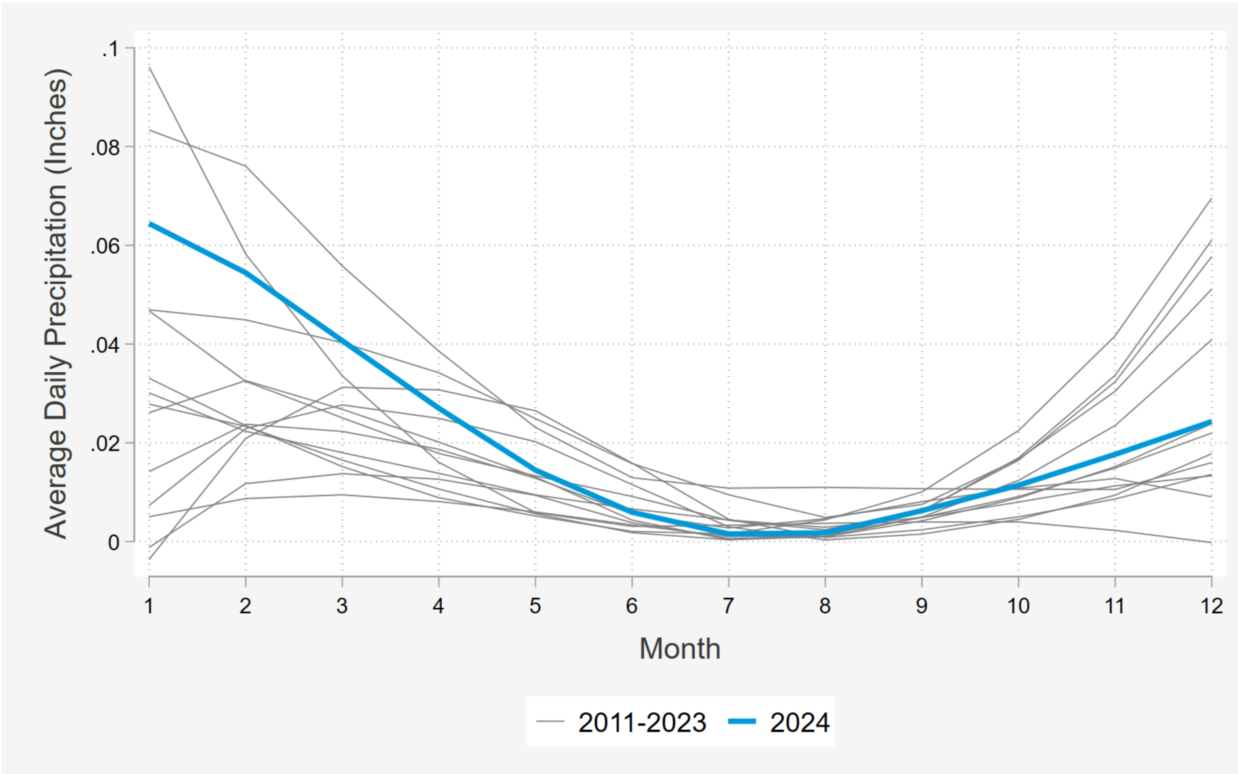
Historically, AP-I events have been called in August and September. In 2024, the only event was called on September 24th for evaluation purposes. The event occurred during a period of mild heat, with the average hourly temperature during the event day peaking at 97° F. Figure 1 shows the participant-weighted daily maximum temperature with shaded areas to mark summer months and vertical black lines to denote event days. The position of the vertical black line in late September 2024 shows the timing of this year's event was much later than the timing of the events in previous years.

Figure 1: Historic AP-I Events and Weather Trends



Because this evaluation focuses on estimating agricultural pumping loads, daily rainfall data from the months preceding the AP-I events is also taken into consideration when estimating reference pumping loads. The event in 2024 occurred during a summer of low precipitation, especially when compared to historical summer precipitation trends. Figure 2 below shows historic precipitation trends in Bakersfield for the last twelve years. Each grey line represents a single year from 2011 to 2023, while the blue line shows the observed average rainfall for 2024. Precipitation in early 2024 (January through May) was moderate to high in comparison to previous years, and precipitation during June through September was lower than the precipitation experienced in the previous 14 years.

Figure 2: Historic Precipitation Trends



Demand Side Analytics
DATA DRIVEN RESEARCH AND INSIGHTS

3 EVALUATION METHODOLOGY

The ex-post evaluation of AP-I impacts is straightforward. Because the events are introduced on some days and not on others, one can observe energy use patterns with and without the program dispatch. This, in turn, enables us to assess whether the outcome – electricity use – rises or falls with the presence or absence of demand response dispatch instructions. If switch paging is successful, one should see a decrease in demand. In addition, the timing of the change in demand should coincide with the timing of the event. Table 8 and Table 9 summarize our approach for the ex-post and ex-ante analysis, respectively.

Table 8: Agricultural & Pumping Interruptible Program Ex-Post Approach

Methodology Component	Demand Side Analytics Approach
1. Population or sample analyzed	The analysis considers the full population of participants active on the event days. 877 participants had full interval data on the event day, so the population analyzed only includes this subset of customers.
2. Data included in the analysis	The analysis focuses on PY 2024 load, weather, and precipitation data for all agricultural customers, including 877 participants.
3. Use of control groups	Agricultural customers have unique schedules and highly seasonal consumption patterns that make finding a suitable control group difficult. To incorporate exogenous information about consumption patterns unrelated to temperature or time of year, synthetic controls were used. The synthetic controls are comprised of matched non-participants that look similar to AP-I participants based on various customer characteristics such as the customer's industry, NEM status, and summer load shape. These profiles are used on the right-hand-side of the regression equation in ex-post model fitting.
4. Model selection	The final individual customer regression model is identified based on out-of-sample metrics for bias and fit. The process relies on splitting the dataset into training and testing data. The models are developed using the training data and applied, out-of-sample, to the testing data. For each of models specified, we produce standard metrics for bias and goodness of fit. The best model is identified by first narrowing the candidate models to the three with the least bias and then selecting the model with the highest precision.
5. Segmentation of impact results	The results were segmented by: ▪ Local Capacity Area ▪ Customer Size ▪ Prohibited Resource Attestation Status ▪ Net Energy Metered Status ▪ SCE SubLAP, and ▪ Customers with and without enabling technology. The main segment categories are building blocks. They are designed to ensure segment-level results add up to the total and to enable production of ex-ante impacts, including busbar level results.

The method to evaluate ex-ante impacts for the AP-I program is very similar to the ex-post analysis: ex-ante reference loads use individual customer regression models that incorporate variables for weather and seasonality and apply them to the ex-ante 1-in-2 and 1-in-10 weather forecasts. Impacts are related to the overall switch paging success rate. Because the AP-I tariffs require participants to curtail all load on the circuit during an event, the percentage of load associated with switches that are successfully triggered is equivalent to the overall ex-ante percentage reduction. To estimate total impacts, SCE provided the evaluation team with a switch paging success rate forecast and a customer enrollment forecast for the ex-ante impact forecast.

Table 9: Agricultural & Pumping Interruptible Program Ex-Ante Approach

Methodology Component	Demand Side Analytics Approach
1. Years of historical performance used	Three years (2022-2024) of historical interval data was used.
2. Process for producing ex-ante impacts	The key steps were: ▪ Estimate the relationship between load without DR and weather conditions for each segment using data for current mix of participants. ▪ Predict reference loads for 1-in-2 and 1-in-10 ex-ante conditions. ▪ Rely on SCE's forecasted switch paging success rate. On circuits with a functional switch, load drops to zero after dispatch. ▪ Combine the ex-ante reference loads, switch paging success rate, and enrollment forecasts for each segment. ▪ Aggregate to produce overall ex-ante load impacts
3. Accounting for changes in the participant mix	Some change is expected in the customer mix over the ex-ante forecast horizon. The biggest drivers of change will be the change in switch paging success rate.

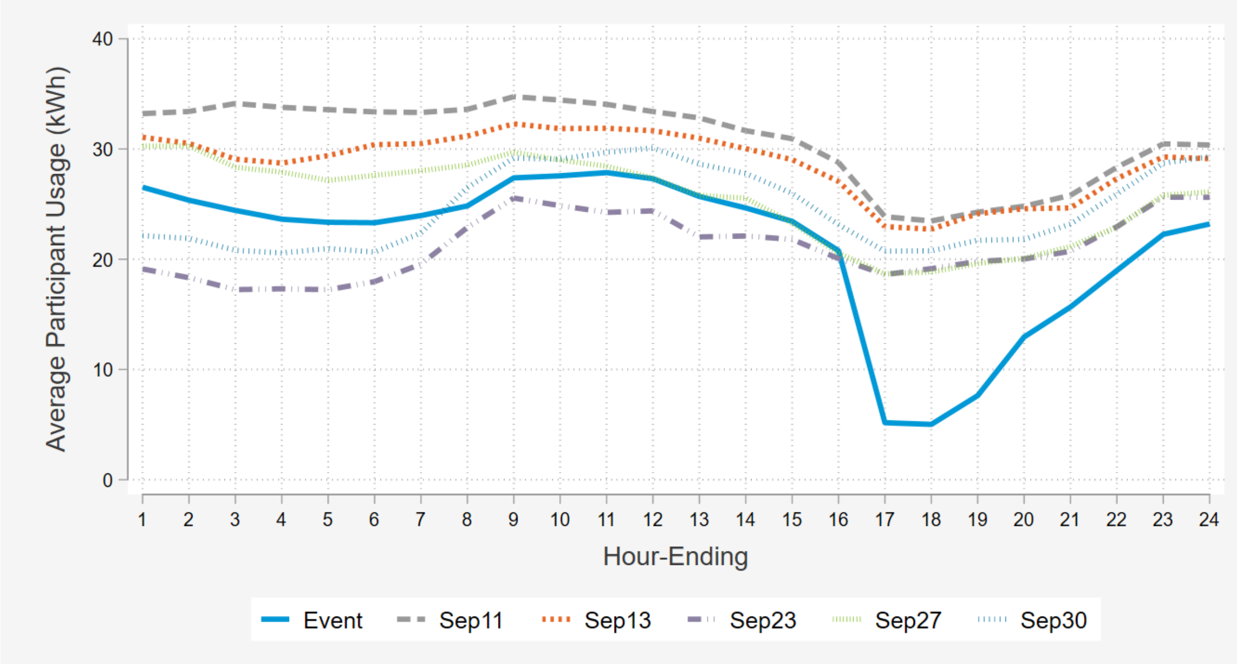
3.1 OVERVIEW OF EVALUATION METHOD SELECTED

The evaluation team assessed two primary methods of constructing a counterfactual load profile – what participants would have done if they were not dispatched – for AP-I participants: individual customer regressions with and without synthetic controls. More detail about these methods, including their tradeoffs, can be found in the appendix. At a high level, however, the goal for both is to produce unbiased estimates of the counterfactual, which is assessed through out-of-sample testing. This process involves selecting event-like days when no event was called and predicting what a customer's load would be. Since no event was called, any difference between the predicted and actual values is modeling error.

EX-POST MODEL

The out-of-sample regression models were tested on five proxy event days. These are days that looked similar to the event day but during which no event was called. Proxy days were picked from other September weekdays and compared to the usage trends of the event day both by investigating temperature and SCE system load. A comparison of these usage trends is shown in Figure 3.

Figure 3: Comparing Proxy Day Loads to the Event Day



The evaluation team tested individual customer regressions with and without an average profile of the synthetic control customers on the right hand side of the specification. Synthetic controls are aggregated profiles of non-participants. The agricultural customers who do not participate in AP-I offer useful information about conditions that affect pump loads. Aggregate profiles of hourly consumption data were included as right-hand side variables in a subset of tested models, with the intention of capturing this additional explanatory power for AP-I models.

Fourteen models were tested, including the preferred model from the PY2023 API evaluation. The best model for each customer was then used to predict ex-post loads on the event days. Table 10 shows the definitions of the variables tested during the exploratory model selection process, while

Figure 4 summarizes which variables were ultimately included in the regressions. In

Figure 4, each column represents a model, and the inclusion of a variable in a given model is denoted with blue highlighting. That is, model 1 includes *month*, *dow*, *preeventload,* and *tempf*. The evaluation team also explored lagged moving averages of precipitation to capture the effects of rainfall on agricultural loads, but did not include the precipitation variables in the final fourteen models.

Figure 4 also summarizes the number of customers for whom a given model was their best model based on out of sample testing.

Because some of the participants were missing interval data on the September 24th event day, ex-post results for the customers who did have complete data were scaled up to account for these customers. Out of the 894 active participants on the event day, 877 had complete interval data.

Table 10: Model Variables for Testing

Model Term	Description
month	Month (1-12)
dow	Day of week
biwoy	Bi-week of year (1-26)
weekday	Weekday or weekend (1 or 0)
tempf	Temperature
cdh_60	Cooling degree hours – base 60
cdh60_sq	CDH squared
hdh60	Heating degree hours – base 60
hdh60_sq	HDH squared
ctrl_kwh	Synthetic controls are aggregated profiles of non-participants that are included in a regression. Nine separate segmentation strategies were tested in this evaluation. The segmentation strategies included customer solar status, industry, SubLAP, and load characteristics, such as bins of annual consumption, load factor, and clusters of hourly load shapes and monthly consumption patterns
morningload, preeventload, eveningload_lag24	Average electricity consumption during early morning, late morning, pre-event and evening hour windows. This value is intended to calibrate reference loads to the morning and pre-event conditions, as well as evening conditions from the previous day. Participants are not given notice of the event, so including a calibration term such as this improves the model fit without biasing reference loads associated with settlement gaming.
pon_ma	Percent of normal moving average precipitation. Different moving averages, including 1-month, 3-month, 6-month and 12-month, were tested
kwh_l24, kwh_l48, kwh_l168, kwh_l1_2_7	Lagged load variables (24 hour, 48 hour, 7 day, and an average of all three)

Figure 4: Model Specifications Tested

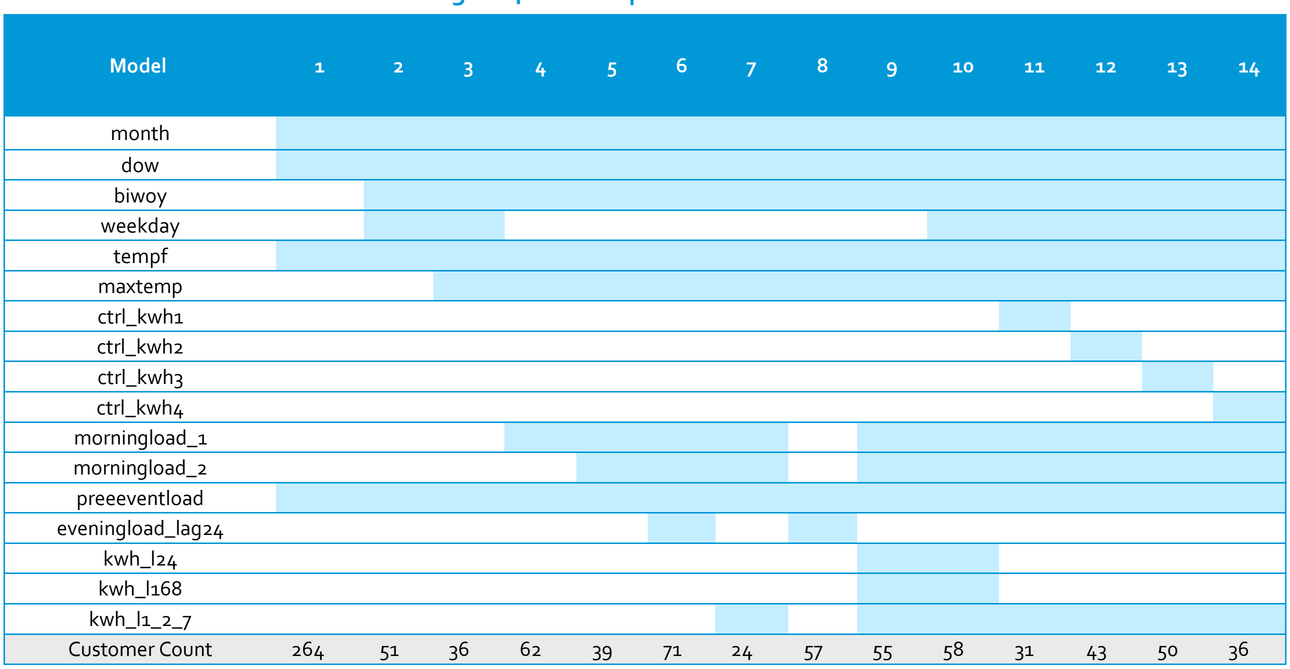
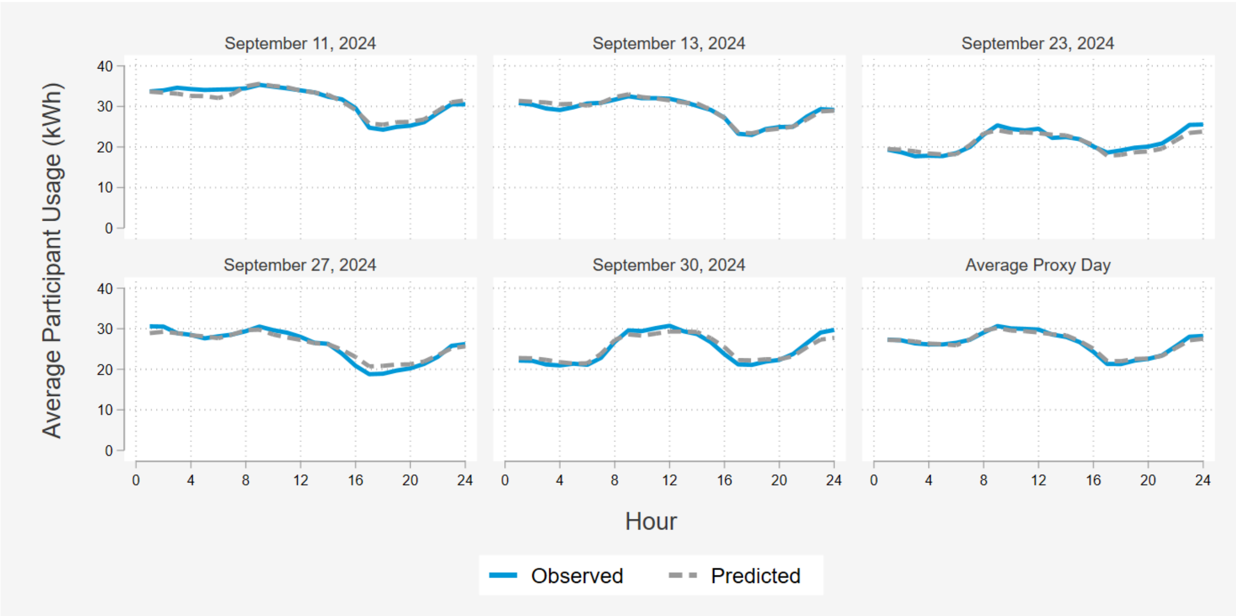


Figure 5 shows the predicted loads for each selected proxy day. The proxy days closely resemble normal days by month, but there is some variability. Models are ranked based on their performance from 4pm to 9pm on proxy days. Any differences between observed and predicted loads are small relative to the measured effect. More detail on the ex-post modeling methodology can be found in the appendix.

Figure 5: Out of Sample Predictions on Proxy Days

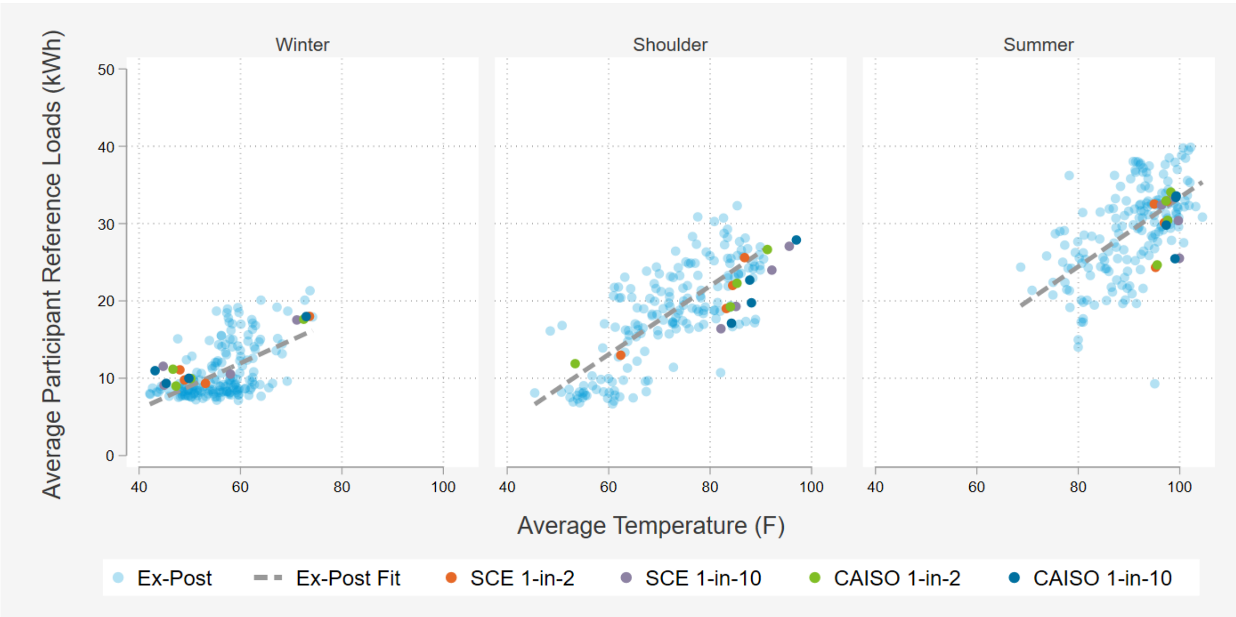


Ex-Ante Reference Load Model

For AP-I, the relationship between ex-post and ex-ante is relatively straightforward. Because impacts are modeled solely as a function of the switch paging success rate forecast – provided by SCE – the focus of ex-ante modeling is to estimate unbiased reference loads. To do this, the evaluation team took the best-performing models from ex-post and removed any variable that does not have a corresponding metric in ex-ante – such as day of week, synthetic control profiles, lagged precipitation, or lagged loads. The ex-ante weather scenarios provided only included temperature data for different event conditions. Variables such as aggregated control group loads and precipitation were removed because they were not part of the ex-ante modeling parameters. No model error is introduced by omitting these variables. These models were then run for the subset of customers who remained on the program as of October 2024 and who were assumed to be representative of future ex-ante impacts. As of PY2022, a new Availability Assessment Hour (AAH) window is incorporated into the ex-ante modeling process. Per Decision 22-06-050 at the CPUC, the Resource Adequacy (RA) window for March and April is changed to 5 to 10pm in place of the existing 4 to 9pm window that will continue to be used for all other months. In PY 2024, this adjusted RA window was extended to May impacts as well.

Figure 6 shows the comparison of daily average temperature and average customer usage for these customers for both their ex-post historical data and predicted ex-ante scenarios for each ex-ante weather year. Each ex-ante point represents a single monthly peak day while all blue ex-post points represent each day in that season. While there is considerable noise around the linear fit for each season, the ex-ante values fit quite closely to the ex-post linear fit, especially in the shoulder and summer seasons. There is some divergence in the predictions for the summer model, which is likely more a reflection of the non-linear relationship between temperature and load, specifically in September when pumping loads start to decrease. While temperature and loads are correlated, this does not necessarily indicate that high temperatures cause higher loads. Both agricultural pumping loads and weather are driven by seasonality. Pumping loads are highest during the summer and drop off during the shoulder months.

Figure 6: Comparison of Ex-Post and Ex-Ante Reference Loads



4 EX-POST RESULTS

This section summarizes ex-post results for the 2024 season event days. Table 11 shows the impacts for the September 24th event.

4.1 OVERALL RESULTS

The AP-I program delivered 12.39 MW of load reduction on the average event day, or 70.0% of the reference load. Per-customer impacts were approximately 13.86 kW and were statistically significant.

Table 11: Ex-Post Impacts – All Event Hours vs Full Event Hours

Date	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
9/24/2024 (4:00pm – 6:18pm)	894	19.79	5.93	13.86	13.47 – 14.25	70.0	12.39

4.2 RESULTS BY CATEGORY

Table 12 shows the impacts by LCA on the average event day. The majority of impacts came from the Big Creek/Ventura LCA, which delivered 8.62 MW of the 12.39 MW reductions during the event. This was due to the large number of customers in the LCA – 758 of the 894 participants. Conversely, the LA Basin LCA has much larger customers – customers have an average reference load of 44.99 kW per customer, and delivered an average of 39.11 kW of impact per customer. However, due to the small group size, this group only delivered an aggregate impact of 3.44 MW.

Table 12: Ex-Post Impacts by LCA

LCA	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Outside LA Basin	48	13.83	6.87	6.96	5.80 – 8.11	50.3	0.33
LA Basin	88	44.97	5.88	39.09	37.20 – 40.97	86.9	3.44
Big Creek/Ventura	758	17.24	5.87	11.37	10.97 – 11.77	65.9	8.62
All Customers	**894**	**19.79**	**5.93**	**13.86**	**13.47 – 14.25**	**70.0**	**12.39**

** Last row indicates results for all customers. The results for the average customer (kW) columns are the weighted average of the different segments, while the result in the aggregate impact (MW) column is the sum across the different segments*

In the two zones affected by the San Onofre Nuclear Generating Station (SONGS) closure, South Orange County and South of Lugo, customers delivered 0.87 MW of load reduction on the average event day. This represents 7% of the total load shed, despite the 29 enrolled customers in those zones being only 3.2% of the total participants. This was driven primarily by customers in [redacted], who delivered on average [redacted] of load shed per participant.

Table 13: Ex-Post Impacts by Zone

Zone	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
South Orange County	12	[redacted]					
South of Lugo	17	[redacted]					
Remainder of System	865	19.34	6.03	13.32	12.95 – 13.68	68.8	11.52
All Customers	**894**	**19.79**	**5.93**	**13.86**	**13.47 – 14.25**	**70.0**	**12.39**

** Last row indicates results for all customers. The results for the average customer (kW) columns are the weighted average of the different segments, while the result in the aggregate impact (MW) column is the sum across the different segments*

AP-I customers were segmented into size categories based on maximum demand over the summer. The results for each category are reported below. Larger customers had higher reference loads with more available load to shed, as expected. [redacted], the majority of impacts came from the medium-demand group (20-200kW) due to the large number of participants in that category.

Table 14: Ex-Post Impacts by Customer Size

Size	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Greater than 200kW	60	[redacted]					
20kW or Lower	148	[redacted]					
20-200kW	686	16.79	5.91	10.88	10.54 – 11.22	64.8	7.46
All Customers	**894**	**19.79**	**5.93**	**13.86**	**13.47 – 14.25**	**70.0**	**12.39**

** Last row indicates results for all customers. The results for the average customer (kW) columns are the weighted average of the different segments, while the result in the aggregate impact (MW) column is the sum across the different segments.*

Six customers were on AP-I with operational prohibited resources during demand response events. These customers had the highest average reference load and percent impact per customer but did not have substantial impacts on the aggregate impacts due to the low number of customers.

Table 15: Ex-Post Impacts by Prohibited Resource Attestation Status

PRA	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Yes and use	6	[redacted]					
Yes but don't use	9	[redacted]					
No	879	19.48	6.10	13.38	12.98 – 13.77	68.7	11.76
All Customers	**894**	**19.79**	**5.93**	**13.86**	**13.47 – 14.25**	**70.0**	**12.39**

** Last row indicates results for all customers. The results for the average customer (kW) columns are the weighted average of the different segments, while the result in the aggregate impact (MW) column is the sum across the different segments.*

4.3 COMPARISON TO PRIOR YEAR

In PY2023, there were 918 enrolled accounts for the only event in July. The average reference load was 37.34 kW and an impact of 67.6% yielded 23.17 MW, or 25.23 kW per-customer. Table 16 compares the event impact in 2023 for the first 30 minutes of the event to the average event impact during full event hours in 2024. In PY 2023, the July event was called from 7:45pm to 8:22 pm, so the first 30 minutes of the event are used here to draw comparisons to the full event hours for PY 2024. In 2023, per-customer and aggregate impacts as well as reference loads were higher than in 2024. Differences between the years may be explained by the event being called later in the year, as the 2024 event occurred in late September whereas the 2023 event occurred in July, when pumping loads are typically at their highest throughout the year. Because reference loads are low due to the timing of the event, there is less load for customers to drop. Table 16 shows that while the percentage impact for this year's event is comparable and slightly higher than the percentage impact from last year, the aggregate impact is much lower.

Table 16: Comparison of 2023 and 2024 Ex-Post Impacts

Date	Full Hour Event Window	# Enrolled	Average Customer (kW)					Agg. Impact (MW)
			Ref. Load	Obs. Load	Impact	95% CI	% Impact	
7/20/2023	7:45-8:15	918	37.34	12.11	25.23	24.87 – 25.60	67.6	23.17
9/24/2024	4:00-6:00	894	19.58	5.09	14.49	14.11 – 14.87	74.0	12.96

Table 17 compares both aggregate percent impact for full event hours between the PY 2024 event and the aggregate percent impact from previous events going back to 2019. The percent load reduction achieved this year is close to the percent load reductions achieved in prior years' AP-I events.

Table 17: AP-I Event Performance for PY 2019-2024

Date	Load Reduction %
4-Sep-2019	72.0%
14-Aug-20	77.8%
15-Aug-20	75.8%

16-Aug-20	77.9%
17-Aug-20	78.6%
18-Aug-20	77.9%
5-Sep-20	78.1%
6-Sep-20	78.6%
7-Sep-20	84.5%
9-Jul-21	74.7 %
5-Sep-22	78.8%
6-Sep-22	77.2%
7-Sep-22	78.2%
20-Jul-23	67.6%
24-Sep-24	**74.0%**

4.4 KEY FINDINGS

AP-I delivered around 13 MW of load relief on average during the event dispatch across all hours, including the partial dispatch hour. The largest concentrations of impacts and participants were in the Ventura LCA. Per-customer impacts were lower in 2024 than they were in the 2023 event. This could be attributable to several factors:

1. **Late event:** The event was called in late September, when pumping loads have drastically decreased in comparison to pumping loads in July, August, and even early September. When reference loads are lower, there is less room for participants to drop a significant amount of load, resulting in smaller aggregate impacts.
2. **High Precipitation:** As summarized in Figure 2, overall precipitation in 2024 was much higher than most of the previous ten years during January through May. Even though rainfall was relatively low during the summer months when pumping would be highest, i.e., June, July, and August, the higher rainfall during the spring may have reduced pumping loads.
3. **Impact by Size:** Fewer customers from the 20-200kW and Greater than 200kW customer size groups responded in 2024 than in 2023. The number of customers from the 20 kW or Lower size group slightly increased in 2024, resulting in a greater share of curtailable load coming from the smaller customers and, in turn, a smaller aggregate impact.

5 SWITCH PAGING SUCCESS RATE ANALYSIS

A key driver of ex-ante impacts is the switch paging success rate. AP-I customers are assumed to drop nearly 100% of their load once dispatched using a radio paging communication network. The extent to which that paging attempt is successful dictates the available load shed for the ex-ante impacts.

Switch paging success is calculated as follows:

1. Determine which customers were operating their pumps in the hour prior to the event start. A customer is assumed to be operating if their load in the hour prior to the event is at least 5% of their maximum load on the event day.
2. Calculate the ratio of individual customer's load in the hour prior to the event compared to the first full hour of the event. If that ratio is higher than 50% - that is, if a customer reduces at least 50% of their pre-event load – a customer is deemed to have responded.
3. Calculate the ratio of individual customer's load in the hour immediately following the event compared to the last full hour of the event. If that ratio is higher than 200% - that is, if a customer's load rebounds by at least 200% of their load during the event – a customer is deemed to have responded.
4. Of the customers who were operating on the event day, calculate the ratio of customers who responded to those who were operating.

Table 18 shows the historic switch paging success values reported over the last 16 years. Historical paging success rates reported in prior year's evaluations tended to hover in the low to mid 80% range but have declined over time. The 2024 event is highlighted in blue.

Table 18: Reported Historical Switch Paging Success

Date	# Operating	Paging Success %
7-Nov-08	311	78.00%
29-Jul-10	433	80.80%
27-Sep-10	342	85.40%
21-Sep-11	384	85.40%
26-Sep-12	263	87.50%
19-Sep-13	465	88.00%
6-Feb-14	377	81.70%
24-Sep-15	481	87.90%
19-Oct-16	431	86.10%
Combined 2017 Events	894	78.70%
27-Sep-18	348	83.30%
4-Sep-19	359	72.40%
Combined 2020 Events	432	73.05%
9-Jul-21	554	70.4 %
5-Sep-22	478	73.6%
6-Sep-22	482	71.4%
7-Sep-22	477	70.6%
20-Jul-23	500	64.4%
24-Sep-24	**367**	**59%**

In PY 2024, the paging success rate was 59%, which is considerably lower than previous years. There were fewer customers actively pumping the day of the event, which can be attributed to the late summer timing of the event day. Because there was only one event in 2024, it is unknown whether the non-operating customers would have been dispatched successfully had they been operating on September 24th. The 2024 switch paging success results by category are shown in further detail in Table 19. Switch paging success does not appear to be significantly affected by seasonality or weekday or holiday events.

Table 19: 2024 Switch Paging Success

Date	Not Operating	Did Not Respond	Responded	Paging Success %
September 24, 2024	510	149	218	59

Paging success was considerably higher in the LA Basin and Big Creek/Ventura LCAs the Outside LA Basin LCA, with 75.8%, 57.4%, and 41.4% of operating switches responding to the dispatches, respectively. The switch paging success rates during this year's event were higher in the LA Basin and the Big Creek/Ventura LCAs than during last year's events. However, the switch success rate for the Outside LA Basin LCA dropped significantly from last year, from 50% to 41%.

Table 20: Paging Success by LCA for the 2024 Event Season

LCA	Not Operating	Did Not Respond	Responded	Paging Success %
Big Creek/Ventura	470	117	159	57.4
LA Basin	22	15	47	75.8
Outside LA Basin	18	17	12	41.4

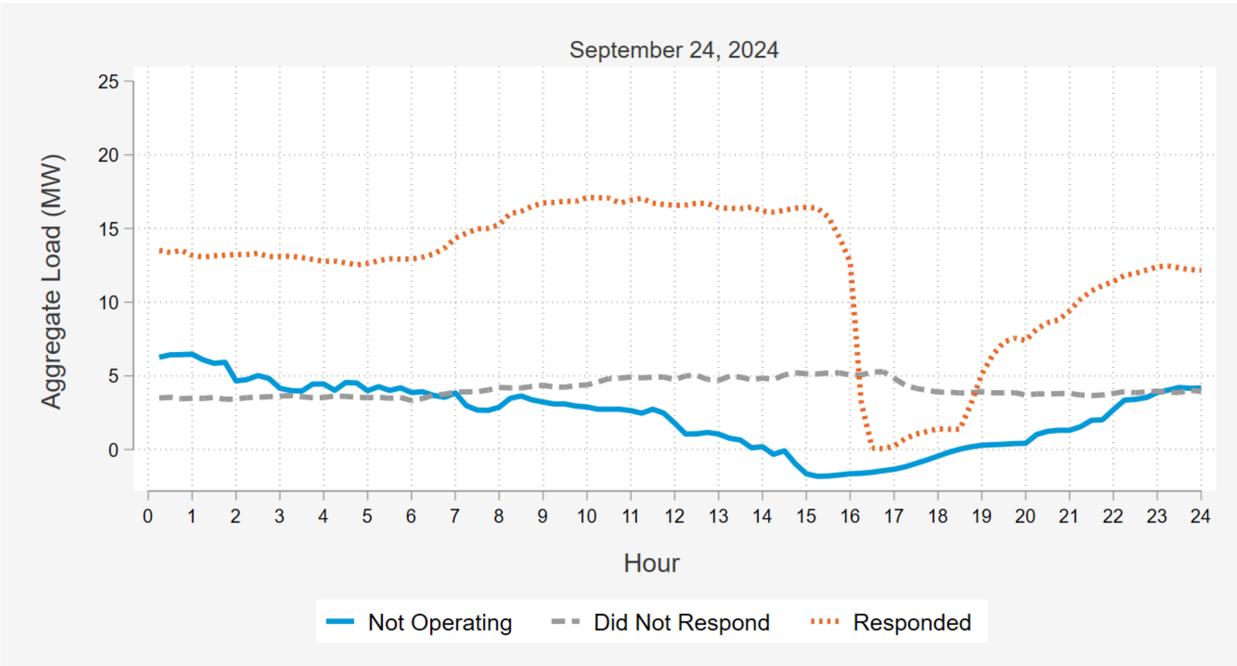
Figure 7 shows the distribution of switch paging success by zip code for the September 24th event. Most of the customers are concentrated in the southern-most region of the CA Central Valley, and the switch success rate averages 50-70% in these zip codes.

Figure 7: Geographic Distribution of Paging Success – 9/24/2024

[redacted]

The contribution of each switch paging group to overall program impacts is summarized in Figure 8. Customers who did get the dispatch notification dropped their load down to essentially 0 kW, while customers who were operating and did not respond showed consistent demand throughout the event. Customers who were not operating in the hour prior to the event were operating on the event day but avoided pumping during the middle of the day in general.

Figure 8: Response by Switch Paging Success



6 EX-ANTE RESULTS

This section summarizes the results of the ex-ante impact estimation process for AP-I from 2025 to 2035. SCE provided two key drivers of the ex-ante impact forecast: the expected number of participants enrolled in the program and the forecast of switch paging success rate.

6.1 ENROLLMENT AND SWITCH PAGING FORECAST

AP-I enrollment is forecasted to decrease from the 894 participants enrolled on the September 24, 2024 event day to a constant 848 participants for the next ten years, pending any program changes. The number of participants at the end of September 2024 (893) is assumed to remain constant through August 2025, after which the new enrollment forecast (848) applies.

Table 21: AP-I Ex-Ante Enrollment Forecast

Program/Portfolio	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Portfolio	848	848	848	848	848	848	848	848	848	848	848
Program	848	848	848	848	848	848	848	848	848	848	848

The switch paging success rate is expected to grow over the course of the forecast horizon with additional investment in upgrading switches and improving the paging network during this time.

Table 22: AP-I Ex-Ante Switch Paging Success Rate Forecast

Year	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Switch Success Rate (%)	75.0	75.6	76.3	76.9	77.6	78.2	78.8	79.5	80.1	80.8	81.4

Going forward, SCE plans to investigate the low switch paging success rate to determine the causes of non-responsive participants and possible solutions. In addition, SCE plans to call multiple events in one program year, and call events earlier in the summer rather than later. Calling multiple events will help SCE understand whether a switch is inoperative, as there will be a pattern of consistent non-response across all the events in a program year. Calling earlier events will provide a more accurate switch paging success rate, as more participants will be operating on the event day, and can be classified as either responsive or non-responsive instead of non-operating.

6.2 OVERALL RESULTS

As enrollment stays constant and the switch paging success rate increases over the next ten years, aggregate August Worst Day impacts will slightly increase over time, ranging from 21.12 MW in 2026 (SCE 1-in-2) to 23.05 in 2035 (CAISO 1-in-10). In general, 1-in-10 weather conditions produce nearly the same impacts as 1-in-2, as AP-I is not as weather sensitive a program as the Summer Discount Plan or Smart Energy Program. While pumping loads do tend to vary with temperature, seasonality is a bigger driver of loads than hourly temperature. Regardless of weather, the aggregate impacts are quite similar across weather scenarios, with the AP-I program delivering at least 21 MW of load reduction on August event days.

Table 23: AP-I Aggregate Portfolio Ex-Ante Impacts (MW) - August Worst Day

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2025	22.05	22.36	22.07	22.37
2026	21.12	21.42	21.13	21.42
2027	21.30	21.60	21.31	21.60
2028	21.48	21.78	21.49	21.78
2029	21.65	21.96	21.67	21.97
2030	21.83	22.14	21.85	22.15
2031	22.01	22.32	22.03	22.33
2032	22.19	22.50	22.21	22.51
2033	22.37	22.69	22.38	22.69
2034	22.55	22.87	22.56	22.87
2035	22.73	23.05	22.74	23.05

Load impacts also vary by month, as seasonal changes in farming intensity and precipitation impact pumping requirements. Table 24 shows the average customer (kW) impacts for a monthly peak day in 2035, assuming an 81.4% switch paging success rate. Impacts are highest during May through August, and typically peak in July.

Table 24: AP-I Average Customer Portfolio Ex-Ante Impacts (kW) - By Monthly Worst Day in 2035

Day Type	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
January Worst Day	7.60	7.41	7.32	7.61
February Worst Day	7.96	8.58	8.11	8.14
March Worst Day	10.72	13.68	9.83	14.21
April Worst Day	15.80	16.11	16.04	16.50
May Worst Day	21.28	22.67	22.17	23.33
June Worst Day	24.51	24.74	24.77	24.27
July Worst Day	26.48	26.38	27.74	27.34
August Worst Day	26.80	27.18	26.82	27.19
September Worst Day	19.82	20.78	20.07	20.73
October Worst Day	17.91	19.53	18.14	18.47
November Worst Day	14.66	14.28	14.36	14.64
December Worst Day	9.03	9.40	9.09	8.94

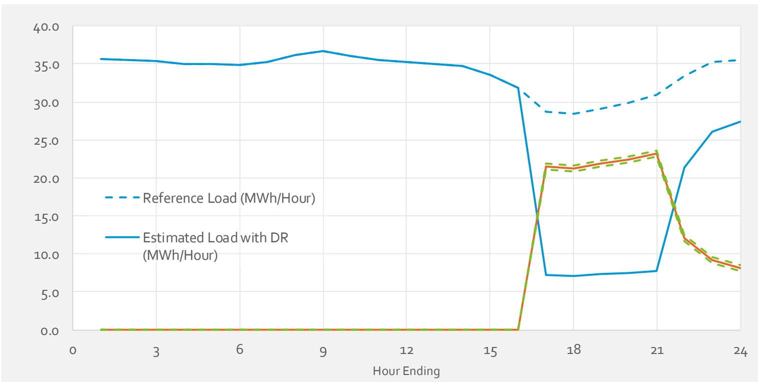
Figure 9: Aggregate Ex-Ante Impacts for 2025 SCE 1-in-2 August Monthly Worst Day

Table 1: Menu options

Type of result	Aggregate
Category	All
Segment	All Customers
Weather Data	SCE
Weather Year	1-in-2
Day Type	August Monthly Worst Day
Forecast Year	2025
Portfolio Level	Portfolio
Switch Paging Success %	Forecast
Switch Paging Success Used	75.0%
Hour Ending View	HE (Prevailing Time)

Table 2: Event day information

Event start	4:00 PM
Event end	9:00 PM
Total sites	893
Event window temperature (F)	97.5
Event window load reduction (MWh/H	22.05
% Load reduction (Event window)	75.0%
Redaction Information	Public



Hour Ending	Reference Load (MWh/Hour)	Estimated Load with DR (MWh/Hour)	Load Reduction (MWh/Hour)	% Load Reduction	Avg Temp (°F, Site-Weighted)	Uncertainty-Adjusted Impact - 5th	50th	95th	Standard Error	T-Statistic
1	35.63	35.63	0.00	0.00	83.40	0.00	0.00	0.00	0.00	
2	35.52	35.52	0.00	0.00	81.45	0.00	0.00	0.00	0.00	
3	35.35	35.35	0.00	0.00	78.52	0.00	0.00	0.00	0.00	
4	34.93	34.93	0.00	0.00	76.27	0.00	0.00	0.00	0.00	
5	35.02	35.02	0.00	0.00	74.79	0.00	0.00	0.00	0.00	
6	34.81	34.81	0.00	0.00	73.50	0.00	0.00	0.00	0.00	
7	35.28	35.28	0.00	0.00	71.70	0.00	0.00	0.00	0.00	
8	36.10	36.10	0.00	0.00	70.90	0.00	0.00	0.00	0.00	
9	36.72	36.72	0.00	0.00	73.62	0.00	0.00	0.00	0.00	
10	36.08	36.08	0.00	0.00	78.68	0.00	0.00	0.00	0.00	
11	35.56	35.56	0.00	0.00	83.21	0.00	0.00	0.00	0.00	
12	35.24	35.24	0.00	0.00	87.58	0.00	0.00	0.00	0.00	
13	35.01	35.01	0.00	0.00	90.66	0.00	0.00	0.00	0.00	
14	34.76	34.76	0.00	0.00	93.10	0.00	0.00	0.00	0.00	
15	33.60	33.60	0.00	0.00	95.18	0.00	0.00	0.00	0.00	
16	31.83	31.83	0.00	0.00	96.85	0.00	0.00	0.00	0.00	
17	28.63	7.16	21.47	0.75	98.30	21.07	21.47	21.88	0.25	86.45
18	28.37	7.09	21.28	0.75	98.71	20.87	21.28	21.69	0.25	85.72
19	29.14	7.29	21.86	0.75	98.59	21.46	21.86	22.26	0.24	90.19
20	29.89	7.47	22.42	0.75	97.26	22.02	22.42	22.81	0.24	93.44
21	30.97	7.74	23.23	0.75	94.80	22.84	23.23	23.62	0.24	96.82
22	33.42	21.35	12.07	0.36	89.45	11.66	12.07	12.47	0.25	49.09
23	35.24	26.01	9.23	0.26	86.81	8.81	9.23	9.64	0.25	36.90
24	35.45	27.33	8.12	0.23	84.90	7.69	8.12	8.55	0.26	31.30

By Period:	Reference Load (MWh/Hour)	Load with DR (MWh/Hour)	Energy Savings (MWh/Hour)	% Change	Average Temperature (°F)	Uncertainty adjusted impact - Percentiles 5th	50th	95th	Standard Error	T-statistic
Average Event Hour	29.40	7.35	22.05	75.0%	97.53	21.65	22.05	22.45	0.24	90.46
Daily	33.86	28.04	5.82	17.2%	85.76	5.68	5.82	5.95	0.08	70.75

6.3 RESULTS BY CATEGORY

Table 25 shows results of the ex-ante impact forecast by year for each LCA and weather scenario on a typical event day. The majority of impacts, as in the ex-post analysis, come from the Ventura LCA. To determine the number of AP-I customers in each LCA during the ex-ante forecast horizon, the existing ratio of customers in each LCA is applied to the SCE-provided program enrollment forecast.

Table 25: AP-I Aggregate Portfolio Ex-Ante Impacts – August Monthly Worst Day by LCA (MW)

LCA	Weather Year	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Big Creek/Ventura	CAISO 1-in-10	18.20	17.43	17.58	17.73	17.87	18.02	18.17	18.32	18.46	18.61	18.76
	CAISO 1-in-2	17.85	17.09	17.24	17.38	17.53	17.67	17.82	17.96	18.11	18.25	18.40
	SCE 1-in-10	18.20	17.43	17.58	17.73	17.88	18.02	18.17	18.32	18.47	18.61	18.76
	SCE 1-in-2	17.85	17.09	17.24	17.38	17.53	17.67	17.81	17.96	18.10	18.25	18.39
LA Basin	CAISO 1-in-10	3.23	3.09	3.12	3.14	3.17	3.20	3.22	3.25	3.27	3.30	3.33
	CAISO 1-in-2	3.24	3.11	3.13	3.16	3.19	3.21	3.24	3.27	3.29	3.32	3.34
	SCE 1-in-10	3.25	3.11	3.14	3.17	3.19	3.22	3.24	3.27	3.30	3.32	3.35
	SCE 1-in-2	3.23	3.10	3.12	3.15	3.17	3.20	3.23	3.25	3.28	3.31	3.33
Outside LA Basin	CAISO 1-in-10	0.94	0.90	0.91	0.92	0.92	0.93	0.94	0.95	0.95	0.96	0.97
	CAISO 1-in-2	0.97	0.93	0.94	0.95	0.95	0.96	0.97	0.98	0.99	0.99	1.00
	SCE 1-in-10	0.91	0.87	0.88	0.89	0.89	0.90	0.91	0.91	0.92	0.93	0.94
	SCE 1-in-2	0.97	0.93	0.94	0.95	0.95	0.96	0.97	0.98	0.99	0.99	1.00

6.4 ENROLLMENT AND PAGING SUCCESS COMPARISON TO PRIOR YEAR

Effective January 1, 2025, the AP-I tariffs were lowered from $19.62 per kW to $18.46 per kW of summer on-peak demand and from $10.87 to $8.14 per kW of winter mid-peak demand. As a result of this change, SCE expects ex-ante enrollments to decrease to 848 participants starting in 2025. Table 26 below shows the forecasted ex-ante elements used in PY 2024 in comparison with the numbers used in PY2023. Enrollment is projected to remain constant over the next 10 program years, pending any program changes. Paging success is still projected to increase at similar rates as predicted in PY 2023.

Table 26: PY 2024 Ex-Ante Forecast Elements

Forecast Year	Enrollment		Paging Success Rate	
	PY2023	PY 2024	PY2023	PY 2024
2024	910	…	75.6%	…
2025	910	848	76.3%	75.0%
2026	910	848	76.9%	75.6%
2027	910	848	77.6%	76.3%
2028	910	848	78.2%	76.9%
2029	910	848	78.8%	77.6%
2030	910	848	79.5%	78.2%
2031	910	848	80.1%	78.8%
2032	910	848	80.8%	79.5%
2033	910	848	81.4%	80.1%
2034	910	848	82.1%	80.8%
2035	…	848	…	81.4%

6.5 EX-POST TO EX-ANTE COMPARISON

Of particular concern to program staff and evaluators is the process of moving from an ex-post estimate to an ex-ante estimate. To facilitate this, we present a comparison of the ex-post full dispatch event days to the ex-ante September Monthly Peak Day and Typical Event Day projections.

Ex-ante weather projections for September are higher than the weather seen in the ex-post event for 2024, and the ex-post weather more closely matches the SCE 1-in-2 weather scenario. Per customer and aggregate impacts are projected to be slightly larger in 2025 compared to the ex-post impacts of 2024. The gap between ex-post impacts for 2024 and ex-ante September predictions for 2025 can be attributed to the fact that the PY 2024 event was held in late September. Pumping loads for agricultural customers are highly seasonal, and pumping loads can drastically fall off between even early September to late September. However, the ex-ante predictions do not differentiate between an early September and a late September event.

Table 27: Ex-Post Compared to Ex-Ante – September 2024 vs September Monthly Worst Day in 2025

Day Type	# Dispatched	Event Hour Avg Temp	Daily Max Temp	Avg Cust Ref (kW)	Switch Paging Success %	% Impact	Avg Cust Impact (kW)	Agg Impact (MW)
Ex-Ante: September Monthly Worst Day CAISO 1-in-10 (4:00 - 9:00PM)	848	99.07	100.58	25.46	75.0	75.0	19.10	16.19
Ex-Ante: September Monthly Worst Day CAISO 1-in-2 (4:00 - 9:00PM)	848	95.54	98.66	24.66	75.0	75.0	18.50	15.68
Ex-Ante: September Monthly Worst Day SCE 1-in-10 (4:00 - 9:00PM)	848	99.94	103.37	25.53	75.0	75.0	19.14	16.23
Ex-Ante: September Monthly Worst Day SCE 1-in-2 (4:00 - 9:00PM)	848	95.23	97.43	24.34	75.0	75.0	18.26	15.48
Ex-Post: 9/24/2024 (4:00pm to 6:18pm)	894	80.91	97.1	19.79	59.2	70.0	13.86	12.39

6.6 FACTORS INFLUENCING LOWER EX-ANTE REFERENCE LOADS

Average customer reference loads have been declining since PY 2022 even when comparing reference loads within the same months and for similar temperature conditions. Figure 10 compares the PY 2024 ex-post average 4-9pm monthly loads to the PY 2023 and PY 2024 ex-ante average 4-9pm monthly loads. PY 2023 ex-ante average 4-9pm reference loads are much higher than the PY 2024 ex-post and ex-ante 4-9pm average reference load. The PY 2023 ex-ante reference loads are modeled using each participant's historical interval data spanning from October 2021 through September 2023, and the higher reference load reflects the inclusion of one hot and dry year (2022) and one wet and mild year (2023).

On the other hand, the PY 2024 ex-ante reference loads are modeled using each participant's historical interval data spanning from October 2022 through September 2024. The much lower reference loads reflect the inclusion of two years with more mild temperatures and higher precipitation overall when compared to 2022.

Figure 10: 2023 Ex-Ante, 2024 Ex-Ante, and 2024 Ex-Post Average 4-9pm Load

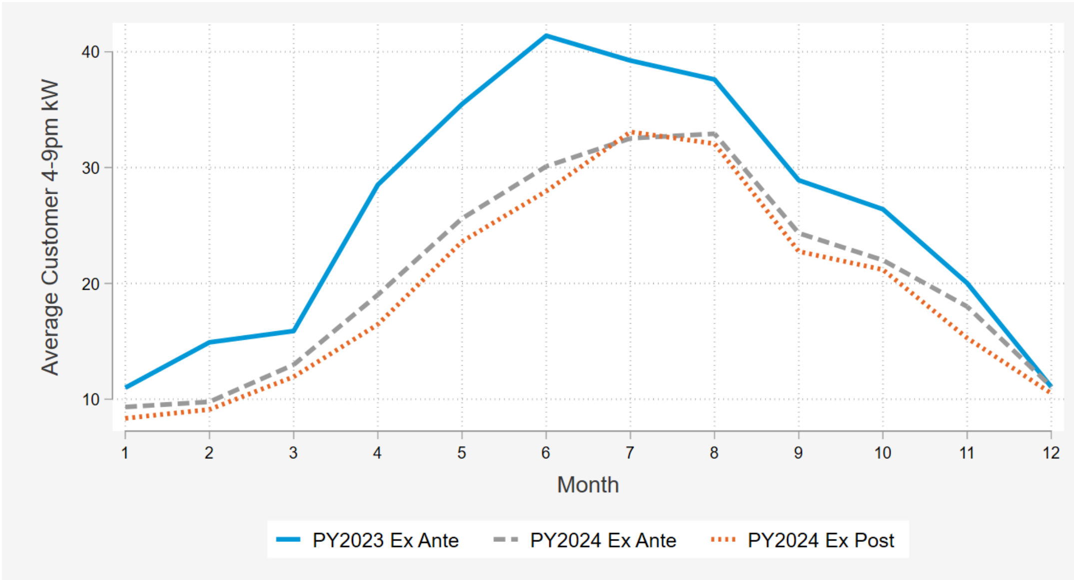
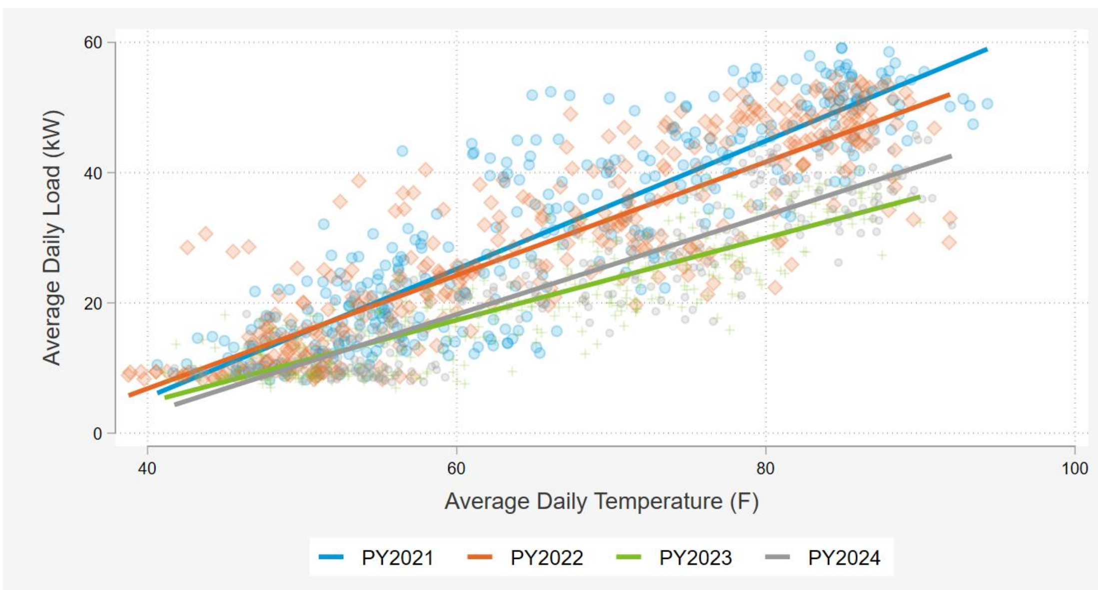


Figure 11 shows the historic average daily load versus the average daily temperature for AP-I participants in 2021, 2022, 2023, and 2024. There is a clear trend — average daily loads among participants have declined since 2021 even under similar temperature conditions. Naturally, the ex-ante reference load predictions have a large impact on the aggregate reduction predictions. If the AP-I participants' reference loads are low, there will be less load the participants can shed in aggregate and on a per customer basis.

Figure 11: Average Daily Load vs. Average Daily Temperature for 2021-2024 AP-I Participants



There are two possible reasons for this decline:

(1) Changing customer mix
(2) Precipitation trends

Since 2021, AP-I has historically lost more participants than it has gained, leading to overall declining enrollments. In addition, in both PY 2023 and PY 2024, while the number of large customers has decreased (> 200 kW), the number of smaller customers (< 20 kW) has increased, albeit marginally. This customer turnover could be causing the lower reference loads.

Figure 12 and Figure 13 shows the historical monthly average 4-9pm loads used in the PY 2024 and PY 2023 ex-post analysis for both continuing customers and all customers during both program years. The blue line shows the customers who were AP-I participants during both program years. The gray line represents all customers. For PY 2024, the gray line includes continuing customers and customers who only participated in 2024. For PY 2023, the gray line includes continuing customers and customers who only participated in 2023. Any differences between the blue and gray lines would indicate that the removal of customers after the 2023 event, or the addition of new customers in time for the 2024 event, had an effect on the average 4-9pm loads. However, both figures show very little difference between these groups. While the changing customer mix may have an impact on declining reference loads, it is unlikely that the customer mix is solely responsible for the large decline year over year in reference loads.

Figure 12: Average Monthly 4-9pm Load — PY 2024 AP-I Participants

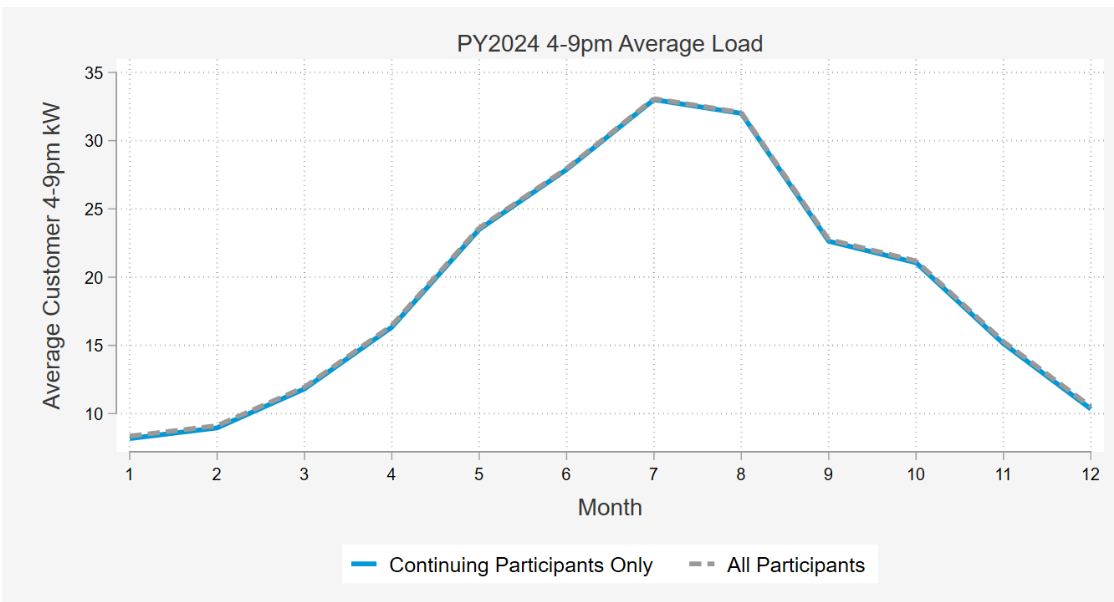


Figure 13: Average Monthly 4-9pm Load — PY 2023 AP-I Participants

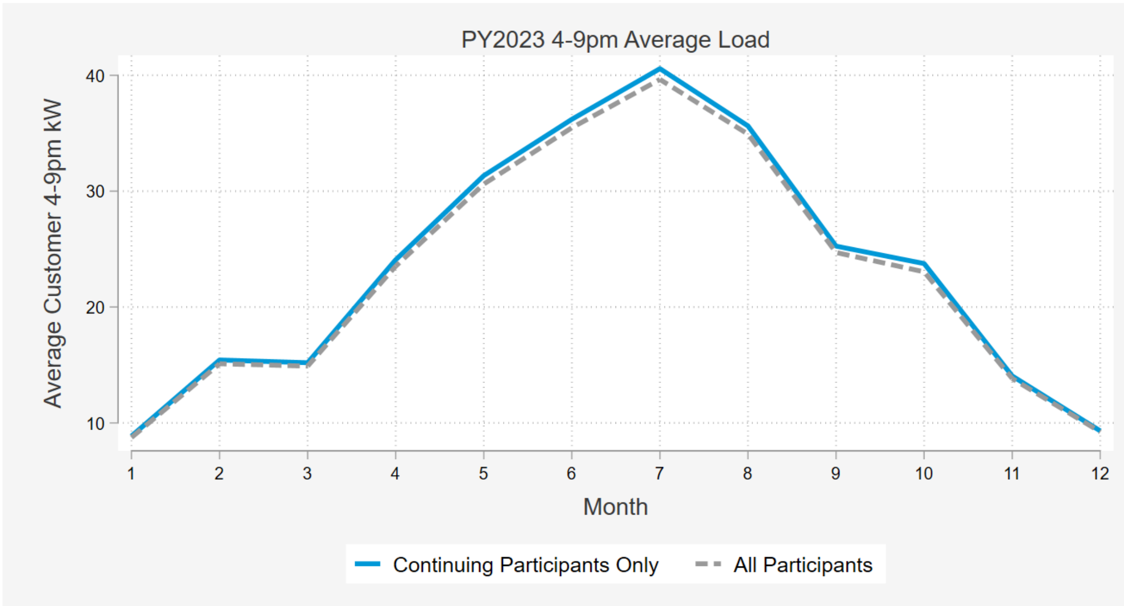
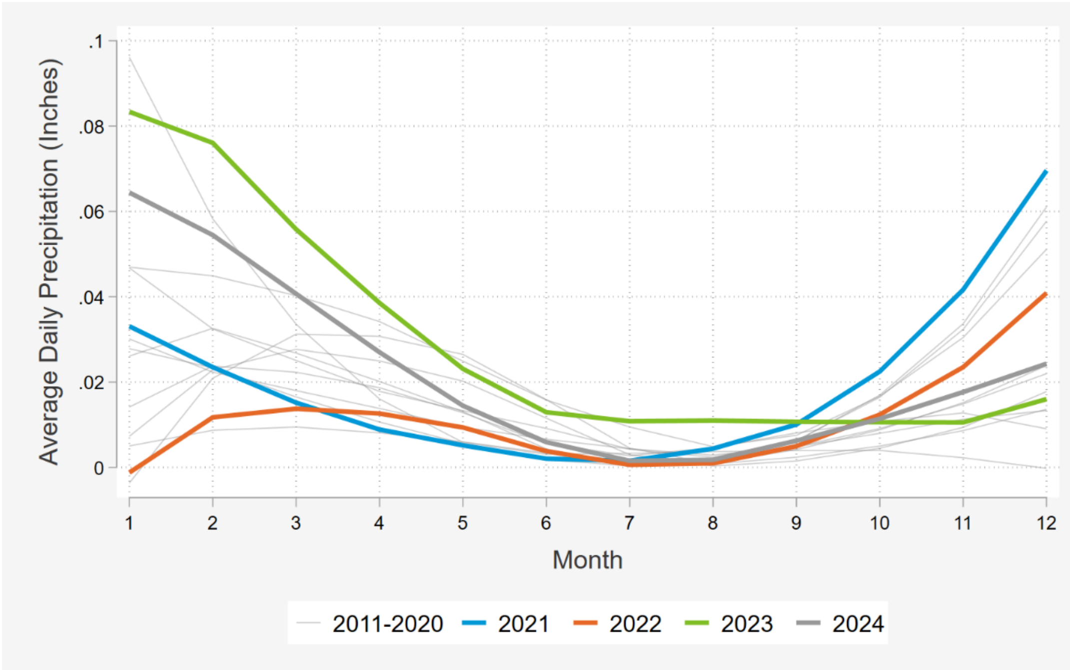


Figure 14 shows the average daily precipitation (inches) from 2011 onwards, and highlights the monthly precipitation trends from 2021 through 2024. During 2024, the summer months leading up to the late September event were dry, and in fact, when compared to the summer rainfall of previous years, experienced relatively low levels of precipitation. Despite this, average daily loads in 2024 were second-lowest when compared to years 2021 through 2023 across almost all temperature conditions. As shown in Figure 14, 2024 did experience heavier rainfall than previous years in the winter and spring months. It is possible that rainfall in the April through June window has a large influence on pumping loads.

In 2023, higher amounts of rainfall persisted throughout the year, and loads were lowest overall in 2023. Likewise, in both 2021 and 2022, rainfall in the springtime ranged from moderate to low, and those same two years experienced high pumping loads throughout all temperature conditions.

Figure 14: Historic average daily precipitation from 2011-2024



Because the ex-ante analysis only predicts pumping loads under 1-in-2 and 1-in-10 weather conditions, the effect of rainfall on pumping loads is not directly accounted for in the ex-ante reference load models. However, it may be worthwhile to study the effects of the magnitude and timing rainfall on pumping loads, as rainfall seems to have a more direct effect on load than temperature does.

7 DISCUSSION

The AP-I program has consistently delivered load reductions during periods of peak demand. This year, the program experienced a few changes that have important implications for how the program will operate going forward.

- Fewer enrollments, the effects of higher precipitation in the previous year, and a decrease in paging success results in a lower ex-ante load forecast. With continued investment in paging switches and network improvements, the AP-I program will grow over time to produce higher load reductions during periods of grid stress.
- Paging success shows variation year-over-year.
  - ✓ Paging success for a single event represents a combination of multiple types of failures – signal receipt failures and equipment failures – both of which can be either permanent or temporary. While permanent failures, such as equipment exceeding its operating lifespan, should be corrected, temporary failures, such as a signal not being received for a single event, may never be fully eradicated.
  - ✓ Both temporary and pervasive paging failures are likely contributors to low paging success rate during the event in PY 2024. With only one event, it is not possible to determine whether paging failures are temporary signal issues or inoperative switches.
- Pumping and agricultural loads are driven by on/off operation and not by temperature. Pump operation is highly seasonal.
  - ✓ This fundamentally limits the available load shed in late summer and winter months as fewer pumps are in operation. Far more sites were not operating this year during the event compared to last year, which can be explained by the timing of the late September event.
  - ✓ Conversely, the program is more valuable in July through August when the percentage of customers pumping is higher.

There are two recommendations for improving this program going forward:

- Call events earlier in the season and call multiple events in one program year. Calling multiple events in one program year will help SCE understand which customers are consistently not responding to the event, which may indicate an inoperative switch. In addition, earlier events (e.g., a July or August event) will help SCE get a true understanding of what the switch paging success rate is, as more participants will be operating during those times. Load reductions will also be impacted by the timing of the AP-I event, as there will be more load to shed in the July and August months than in September.
- Perform in-house investigations to determine the cause of the low switch paging success rate. The switch paging success rate has been declining over the last few program years, which directly impacts the aggregate load reduction the AP-I program can provide. Investigating locations where a participant has been flagged as non-responsive (and operating on the event day) and determining if the switch is functioning properly, or if the ratio signal is being properly transmitted to the switches, will help SCE in identifying the cause of and improving the low switch success rate.

8 APPENDIX: EVALUATION METHODOLOGY

Demand Response Evaluation 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. Did the dispatch of demand response resources cause a decrease in hourly demand? Or can the differences be explained by other factors? To estimate demand reductions, it is necessary to estimate what demand patterns would have been in the absence of dispatch – this is called the counterfactual or reference load. At a fundamental level, the ability to measure demand reductions accurately depends on four key components:

- The effect or signal size – The effect size is most easily understood as the percent change. It is easier to detect large changes than it is to detect small ones. For most DR programs, the percentage change in demand is relatively large.
- Inherent data volatility or background noise – The more volatile the load, the more difficult it is to detect small changes. Energy use patterns of homes with air conditioners tend to be more predictable than industrial or agricultural load patterns.
- The ability to filter out noise or control for volatility – At a fundamental level, statistical models, baseline techniques, and control groups – no matter how simple or complex – are tools to filter out noise (or explain variation) and allow the effect or impact to be more easily detected.
- Sample/population size – For most of the programs in question, sample sizes are irrelevant because we analyzed data for the full population of participants either using AMI data or thermostat runtime. Sample size considerations aside, it is easier to precisely estimate average impacts for a large population than for a small population because individual customer behavior patterns smooth out and offset across large populations.

A key factor for the AP-I program is the ability to dispatch the resource. The primary intervention – demand response dispatch – is introduced on some days and not on others, making it possible to observe energy use patterns with and without demand reductions. This, in turn, enables us to assess whether the outcome – electricity use – rises or falls with the presence or absence of demand response dispatch instructions.

In general, there are seven main methods for estimating demand reductions, as summarized in Table 28. The first four only make use of use patterns during days when DR is not dispatched to calculate the baseline. The latter three methods incorporate non-event data but also use an external control group to establish the baseline. The control group consists of customers who are similar to participants, experienced the same event day conditions, but are not dispatched during events (or were not transitioned to time-varying pricing). Control and participant groups should have similar energy usage patterns when the intervention is not in place and diverge when the intervention is in effect. The only systematic difference between the two groups should be that one is dispatched for events (or transitioned to time-varying prices) while the other group is not.

Table 28: Methods for Demand Response Evaluation

General Approach		Method	Method Description
Use non-event days only to establish the baseline	1	Day matching baseline	This approach relies on electricity use in the days leading up to the event to establish the baseline. A subset of non-event days in close proximity to the event day are identified (e.g., Top 3 of 10 prior days). The electricity use in each hour of the identified days is averaged to produce a baseline. Day matching baselines are often supplemented with corrections to calibrate the baseline to usage patterns in the hours preceding an event – usually referred to as in-day or same-day adjustments.
	2	Weather matching baseline	The process for weather matching baselines is similar to day-matching except that the baseline load profile is selected from non-event days with similar temperature conditions and then calibrated with an in-day adjustment.
	3	Regression models (interrupted time series)	Regression models quantify how different observable factors such as weather, hour of day, day of week, and location influence energy use patterns. Regression models can be informed by electricity use patterns in the day prior (day lags) and in the hours before or after an event (lags or leads) and can replicate many of the elements of day and weather matching baselines.
	4	Machine learning (w/o external controls)	Most machine learning approaches (e.g., random forest, neural networks, etc.) rely exclusively on non-event day data to establish the baselines. The algorithms test different model specifications and rely on a training and testing datasets (out-of-sample testing) to identify the best model and avoid overfitting.
Use non-event days plus a control group to establish the baseline	5	Matched control groups	Matching is a method used to create a control group out of a pool of nonparticipant customers. This approach relies on choosing customers who have very similar energy use patterns on non-event days and a similar demographic and geographic footprint. The non-event day data is incorporated by either analyzing the data using a regression model, a difference-in-differences model, or both.
	6	Synthetic control groups	This approach is similar to matching except that multiple controls are used and weighted according to their predictive power during a training period. A key advantage of this approach is that it can be used to produce results for individual customers.
	7	Randomized control trials	Participants are randomly assigned to different groups, and one group (the "control" group) is withheld from dispatch to establish the baseline. The control group provides information about what electricity use would have been in the absence of DR dispatch – the baseline. The estimate is refined by netting out any differences between the two groups on hot non-event days (difference-in-differences).

Approaches that use an external control group typically provide more accurate and precise results on an aggregate level when there are many customers (i.e., several hundred). They also make use of non-event days to establish the baseline but have the advantage of also being informed by the behavior of the external control group during both event and non-event days. Except for synthetic controls, the two fundamental limitations to control groups have been the limited ability to disaggregate results, and the inability to use control groups for large, unique customers. The precision of results for control group methods rapidly decrease when results are disaggregated, and a control group cannot be used to estimate outcomes for individual customers (except for synthetic controls).

Methods that rely only on non-event days to establish the baseline – such as individual customer regressions – are typically more useful for more granular segmentation. Individual customer regressions have the benefit of easily producing impact estimates for any number of customer segments. Because they are aggregated from the bottom up, the results from segments add up to the totals. However, the success of individual customer regression hinges on having non-event days comparable to event days. When most of the hottest days are event days, as has been the case historically, estimating the counterfactual requires extrapolating trends to temperature ranges that were not experienced during non-event days. This produces less accurate and less reliable demand reduction estimates for the hottest days when resources are needed most.

Model Selection

A key question every evaluator must address is how to decide which model produces the most accurate and precise counterfactual. In many instances, multiple counterfactuals are plausible but provide different estimated demand reductions. Model selection plays a role both in developing matching models and for individual customer regressions.

Our process for model selection relies on splitting the data into testing and training days and implementing an out-of-sample testing process. First, we define testing and training days. Days with actual events are not included in either the training or testing days. Next, ten or more model specifications are defined. Because the treatment is not activated during either the training or testing days, the impacts are by definition zero. Any estimated impact by models is in fact due to model error. Third, we run each of the models using the training data and predict out-of-sample loads for the testing days. Fourth, the testing data out-of-sample predictions are compared to actual electricity use and used to calculate metrics for bias and fit. Next, the best model is identified by first narrowing the candidate models to the three with least bias (or with percentage bias less than 1%) and then selecting the model with the best fit. Finally, the best performing model is applied to all days and used to estimate the counterfactual for actual event days. The final model is designed to produce load impacts (treatment effects) for each event day and hour. Figure 15 illustrates the process.

Figure 15: Model Selection and Validation

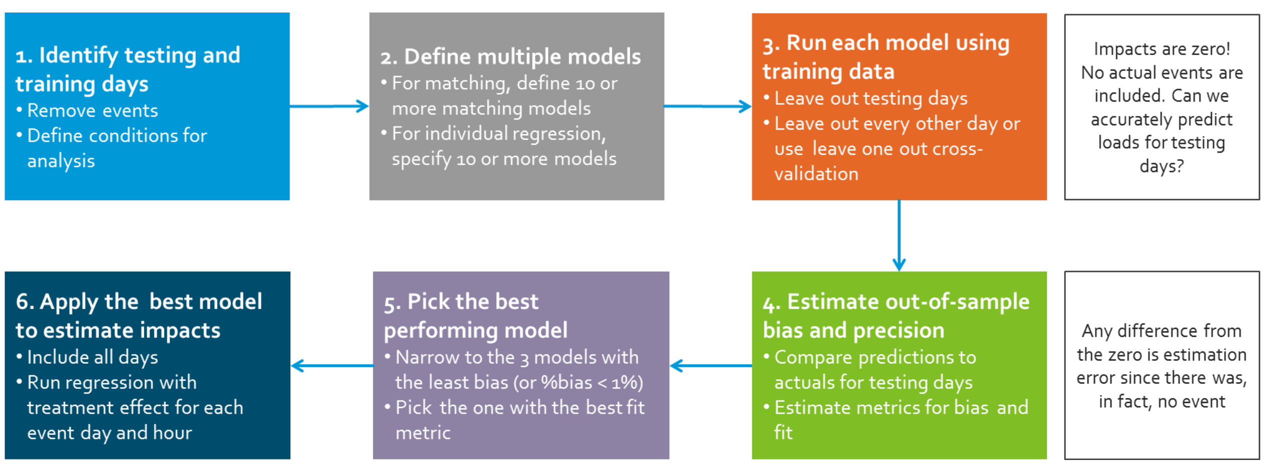


Table 29 summarizes the metrics for bias and precision we employ. Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error describes the relative magnitude and direction of the bias. A negative value indicates a tendency to under predict, and a positive value indicates a tendency to over predict. This tendency is best measured using multiple days and hours. The precision metrics describe the magnitude of errors for individual events days and are always positive. The closer they are to zero, the more precise the results. The mean percentage error is used to narrow down to the three models with the least bias. The Relative RMSE metric is used to identify the most precise and final model among the remaining candidates.

Table 29: Definition of Bias and Precision Metrics

Type of Metric	Metric	Description	Mathematical Expression
Bias	Average Error	Absolute error, on average	$AE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$
	% Bias	Indicates the percentage by which the measurement, on average, over or underestimates the true demand reduction.	$\% \, Bias = \frac{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)}{\bar{y}}$
Precision	Root mean squared error (RMSE)	Measures how close the results are to the actual answer in absolute terms, penalizes large errors more heavily	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$
	Relative RMSE	Measures the relative magnitude of errors across event days, regardless of positive or negative direction. It can be though us as the typical percent error, but with heavy penalties for large errors.	$CV(RMSE) = \frac{RMSE}{\bar{y}}$

The results for AP-I out of sample testing are shown in Figure 16 and Figure 17. In both figures, bias decreases with the selection of the best model. The average event hour error is centered on zero, and tends toward zero, as customers get larger. This is important, as small errors for small customers do not have as big an influence on the accuracy of the overall model as small errors for large customers.

Figure 16: Model Bias and Error on Proxy Events

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Figure 17: Model Average Error by Customer Size