Demand Side Analytics
DATA DRIVEN RESEARCH AND INSIGHTS

REPORT

April 1, 2026

PY 2025 SCE Agricultural & Pumping Interruptible Demand Response Evaluation

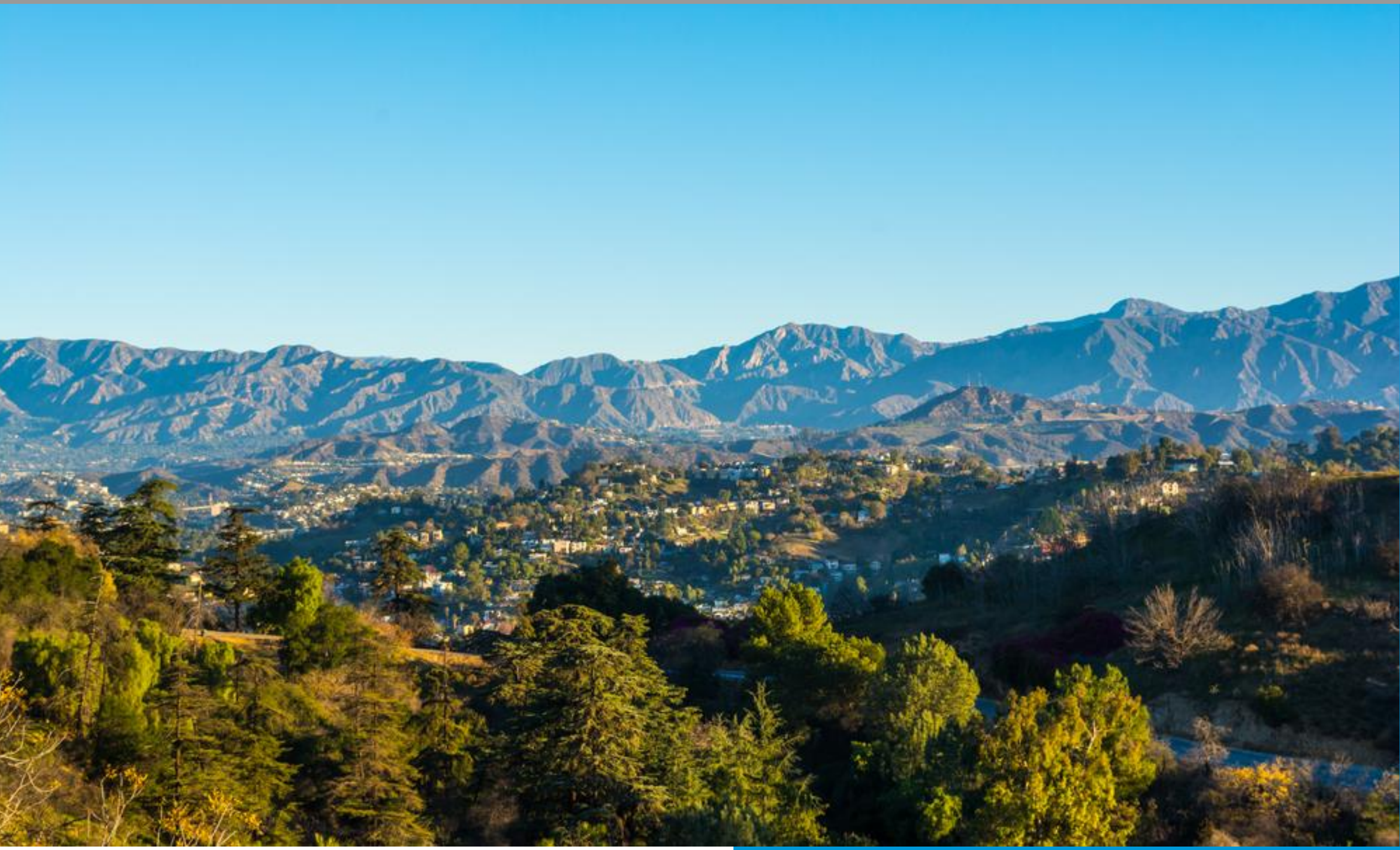

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TABLE OF CONTENTS

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 two events that were called in 2025. 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 2025 consisted of 865 enrolled customers. For the average event day, the program provided an aggregate impact of 16.59 MW (68.3%) of load shed.

Table 1: Ex-Post Impacts – All Event Hours

Event Date	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
8/14/2025 (4:00-5:00)	865	34.09	10.09	24.00	23.80 - 24.20	70.40	20.76
9/16/2025 (4:00-5:00)	865	22.08	7.72	14.36	14.16 - 14.56	65.02	12.42
Average Event Day	**865**	**28.09**	**8.91**	**19.18**	**18.98 - 19.38**	**68.29**	**16.59**

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 13.02 MW of the 16.59 MW reductions during the event. This was due to the large number of customers in the LCA – 732 of the 865 participants. Conversely, the LA Basin LCA has much larger customers – customers have an average reference load of 53.47 kW per customer, and delivered an average of 33.80 kW of impact per customer. However, due to the small group size, this group only delivered an aggregate impact of 2.87 MW.

Table 2: Ex-Post Impacts by LCA – All Hours (Average Event Day)

LCA	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Outside LA Basin	48	21.17	6.68	14.50	13.84 - 15.15	68.46	0.70
LA Basin	85	53.47	19.67	33.80	33.00 - 34.61	63.21	2.87
Big Creek/Ventura	732	25.60	7.80	17.79	17.58 - 18.00	69.51	13.02
All Customers	**865**	**28.09**	**8.91**	**19.18**	**18.98 - 19.38**	**68.29**	**16.59**

AP-I enrollments and assumed percent impact have a large impact on the forecasted load reductions. The enrollment forecast is provided by SCE. While SCE has historically provided switch success rate forecasts for use in estimating future program impacts, in PY2025 SCE decided to move to incorporating a percent impact rather than switch success rate into ex-ante forecasts. Percent impacts reflect the historic average of ex-post percent impacts over the last 4 years (i.e., PY 2022- PY 2025). When estimating impacts under ex-ante weather conditions, impacts are forecasted to be the reference loads for a given set of conditions multiplied by the percent impact. Table 3 shows that AP-I enrollment is projected to increase to 878 in 2026 from the 865 participants in AP-I in PY 2025 and then decrease to 790 participants from 2027 onwards.

Table 3: AP-I Ex-Ante Enrollment Forecast

Program/Portfolio	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036
Portfolio	878	790	790	790	790	790	790	790	790	790	790
Program	878	790	790	790	790	790	790	790	790	790	790

Table 4 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 were associated with SCE system peaks historically, while CAISO conditions are the weather conditions under which the entire CAISO system has peaked historically.

Aggregate August Worst Day impacts increase in the first year of the forecast, reflecting the higher enrollment forecast of 878 participants in 2026. However, ex-ante impacts then fall to roughly 21.4 MW in aggregate in 2027, a result of the lowered expected enrollment during that year and onward. Projected percent impacts stay constant throughout the forecast period, so expected enrollment is the driving force behind changes in ex-ante impacts from year to year. In general, 1-in-10 weather conditions produce nearly the same impacts as 1-in-2, as AP-I is not nearly as weather sensitive as other SCE DR programs like 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 21.4 MW of load reduction on August event days.

Table 4: AP-I Aggregate Portfolio Ex-Ante Impacts (MW) - August Worst Day

Year	SCE 1-in-2	SCE 1-in10	CAISO 1-in-2	CAISO 1-in-10
2026	23.75	23.90	23.73	23.97
2027	21.37	21.50	21.35	21.57
2028	21.37	21.50	21.35	21.57
2029	21.37	21.50	21.35	21.57
2030	21.37	21.50	21.35	21.57
2031	21.37	21.50	21.35	21.57
2032	21.37	21.50	21.35	21.57
2033	21.37	21.50	21.35	21.57
2034	21.37	21.50	21.35	21.57
2035	21.37	21.50	21.35	21.57
2036	21.37	21.50	21.35	21.57

2 PROGRAM DESCRIPTION

The 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 865 in 2025, as the number of de-enrollments was higher than the number of new participants. Mild temperature conditions persisted throughout PY 2025, and two, one hour-long events were dispatched on August 14th and September 16th respectively.

2.1 KEY RESEARCH QUESTIONS

The PY 2025 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 2025? 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?[1]
- 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?

[1] Pursuant to the Load Impact Protocol Process Guide (version 6.1, released by the Energy Division on March 5, 2026), large loads (e.g. data centers, EV fleet charging station load) should be reported as a distinct load type within ex-ante and ex-post table generators. Because the formal definition of "large loads" is still under development, this study does not incorporate large-load effects in either the ex post load impact estimates or the ex ante forecasts.

2.2 PROGRAM DESCRIPTION

AP-I is a longstanding agricultural DR 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 5.

Table 5: AP-I Participant Credit

Size	Rate Block	Bill Credit ($/kW)
Below 200 kW	Summer On Peak	$18.46
	Winter Mid Peak	$9.14
200 kW and Above	Summer On Peak	$18.46
	Winter Mid Peak	$9.14

While AP-I events can be called at any point in the year, they have typically been dispatched once or twice per summer season, usually in August and September. The events this year were consistent with this timing, with one event called in mid-August, and the other in mid-September.

2.3 PARTICIPANT CHARACTERISTICS

865 customers participated in the events on both August 14th and September 16th. Table 6 summarizes the key characteristics of customers participating in the event. Geographically, the majority are in the Big Creek/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 2025. Because there were no enrollment changes between the two events in summer 2025 the distribution of enrollment by category does not change.

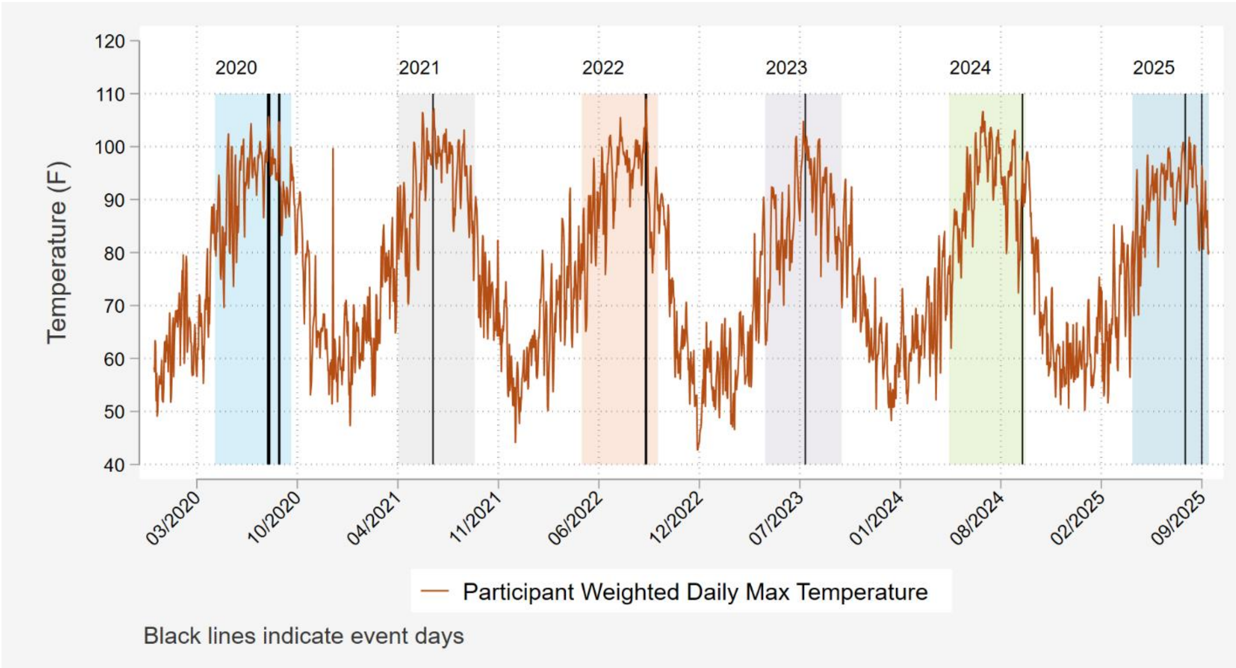
Table 6: Participant Characteristics

Category	Segment	8/14/2025	9/16/2025
All	All Customers	865	865
LCA	Big Creek/Ventura	732	732
	LA Basin	85	85
	Outside LA Basin	48	48
Net Energy Metered Status	NEM Customer	276	276
	Non-NEM Customer	589	589
Prohibited Resource Attestation Status	No	852	852
	Yes and use	6	6
	Yes but don't use	7	7
Size	20-200kW	652	652
	20kW or Lower	152	152
	Greater than 200kW	61	61
SubLAP	SCE Central	56	56
	SCE High Desert	48	48
	SCE North	719	719
	SCE Northwest	13	13
	SCE West	29	29
Zone	Remainder of System	835	835
	South Orange County	12	12
	South of Lugo	18	18

2.4 PY2025 EVENT CONDITIONS

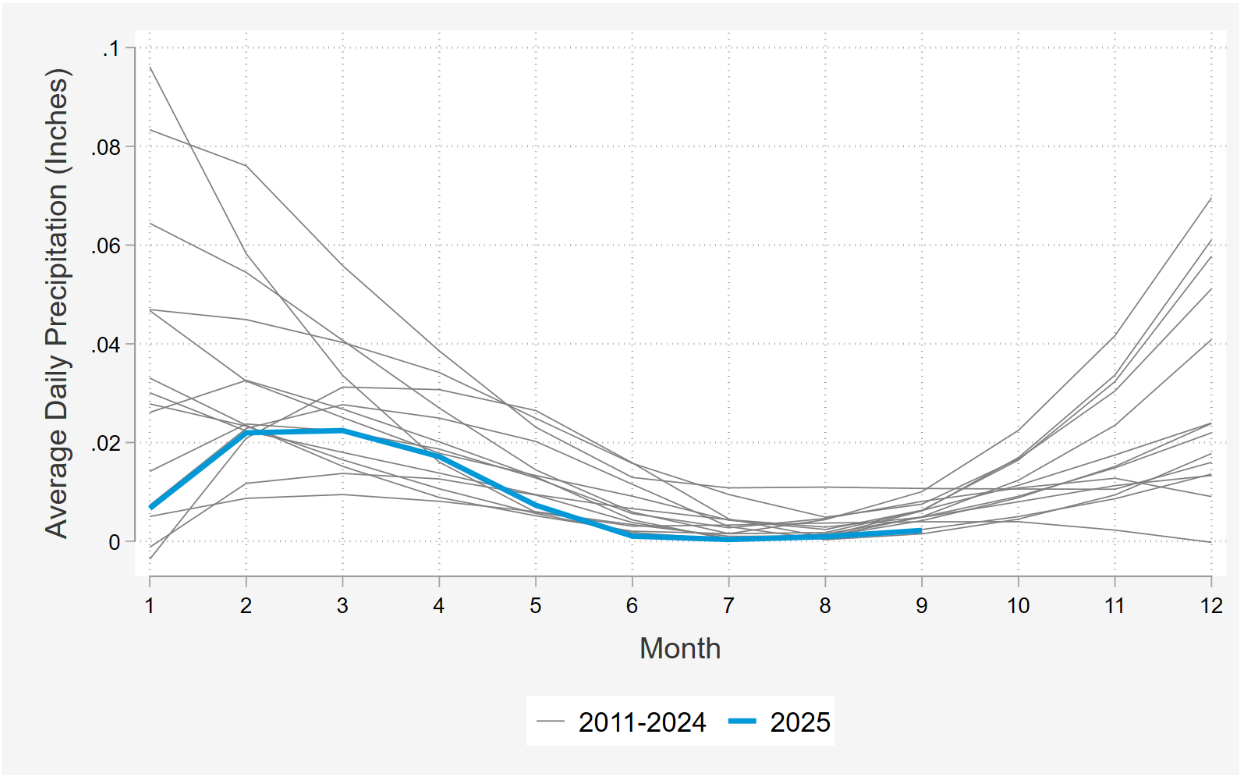
Historically, AP-I events have been dispatched in August and September. In 2025, events were called in mid-August and mid-September, with each event lasting one hour. The events occurred during a period of mild heat, with the average hourly temperature during each event day peaking at 93° F and 96° F for the August and September events, respectively. 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 lines in August and September 2025 show the timing of this year's events.

Figure 1: Historic AP-I Events and Weather Trends



Because this evaluation focuses on estimating impacts from controlling 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 events in 2025 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 2024, while the blue line shows the observed average rainfall for 2025. Precipitation in early 2025 (January through May) was low 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



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, energy use patterns can be observed 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, demand will decrease. In addition, the timing of the change in demand should coincide with the timing of the event. Table 7 and Table 8 summarizes our approach for the ex-post and ex-ante analysis, respectively.

Table 7: 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. 864 participants had full interval data on both event days, so the population analyzed only includes this subset of customers. Final aggregate results will be scaled to include all 865 enrolled customers.
2. Data included in the analysis	The analysis focuses on PY 2025 load, weather, and precipitation data for all agricultural customers.
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 training data and applied, out-of-sample, to the testing data. For each of the 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 ▪ SCE Zone 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. Aggregate impacts are related to the enrollment forecast as well as the assumed percent impact. To estimate total impacts, SCE provided the evaluation team with a customer enrollment forecast for the ex-ante impact forecast, and the percent impact used is based on the historical average percent impact during full event hours from PY 2022 through PY 2025.

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

Methodology Component	Demand Side Analytics Approach
1. Years of historical performance used	Three years (2023-2025) 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 the current mix of participants. ▪ Predict reference loads for 1-in-2 and 1-in-10 ex-ante conditions. ▪ Rely on the average ex-post percent impact for full event hours (2022 –2025). ▪ Combine the ex-ante reference loads, average percent impact, 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 forecasted enrollment changes.

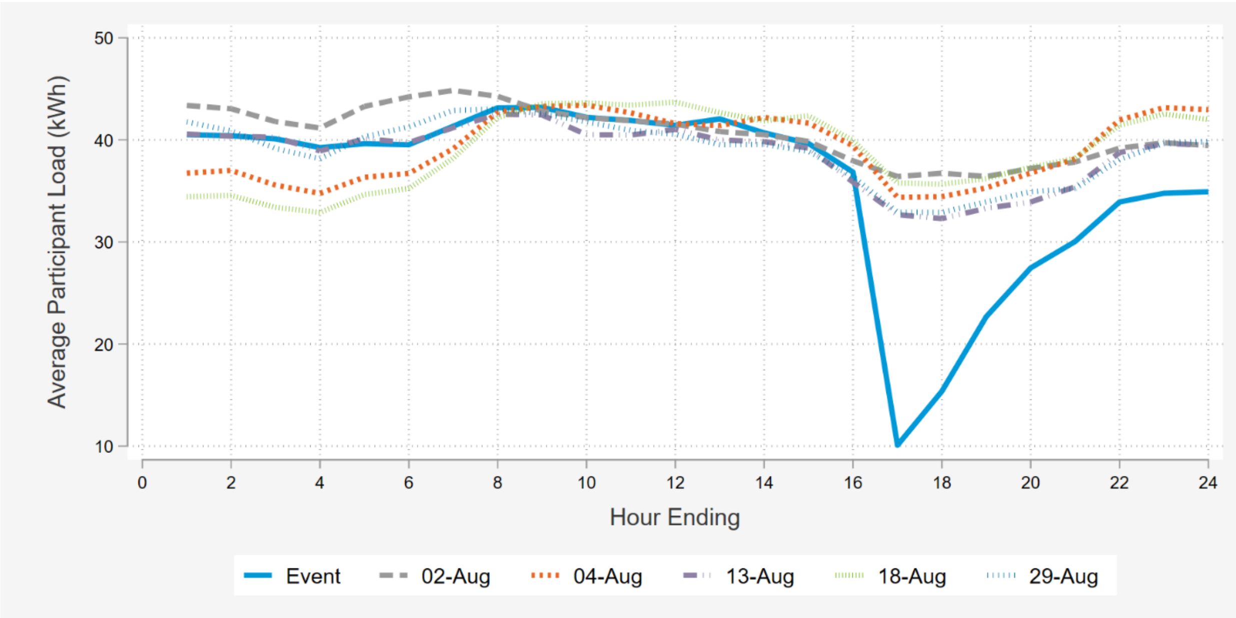
3.1 OVERVIEW OF EVALUATION METHOD SELECTED

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 details 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, days that look similar to the event day, but during which no event was called. Proxy days for both events were picked from weekdays within the same month as the event. For example, for the August event, only days within August were considered as possible proxies. SCE system loads and temperatures were compared between the event days and non-event days to select the five best proxy days. A comparison of the average participant loads for the selected August proxies and the actual event date is shown in Figure 3.

Figure 3: Comparing Proxy Day Loads to the August 14th 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, whose loads can offer useful information about conditions that affect pump loads that are not inherently captured with commonly used temperature and morning load variables. These profiles are aggregated based on features such as size, solar status, total annual usage, total summer usage, rate, and water usage category. A subset of models tested for each participant included different synthetic controls, with the intention of capturing this additional explanatory power.

A total of 15 models were tested for each customer. The models that performed the best on proxy days were then used to predict reference loads on the event days. Table 9 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 as well as statewide reservoir levels to capture the effects of rainfall on agricultural loads but did not include the precipitation variables in the final 15 models. Figure 4 also summarizes the number of customers for whom a given model was their best model based on out of sample testing.

Table 9: Model Variables for Testing

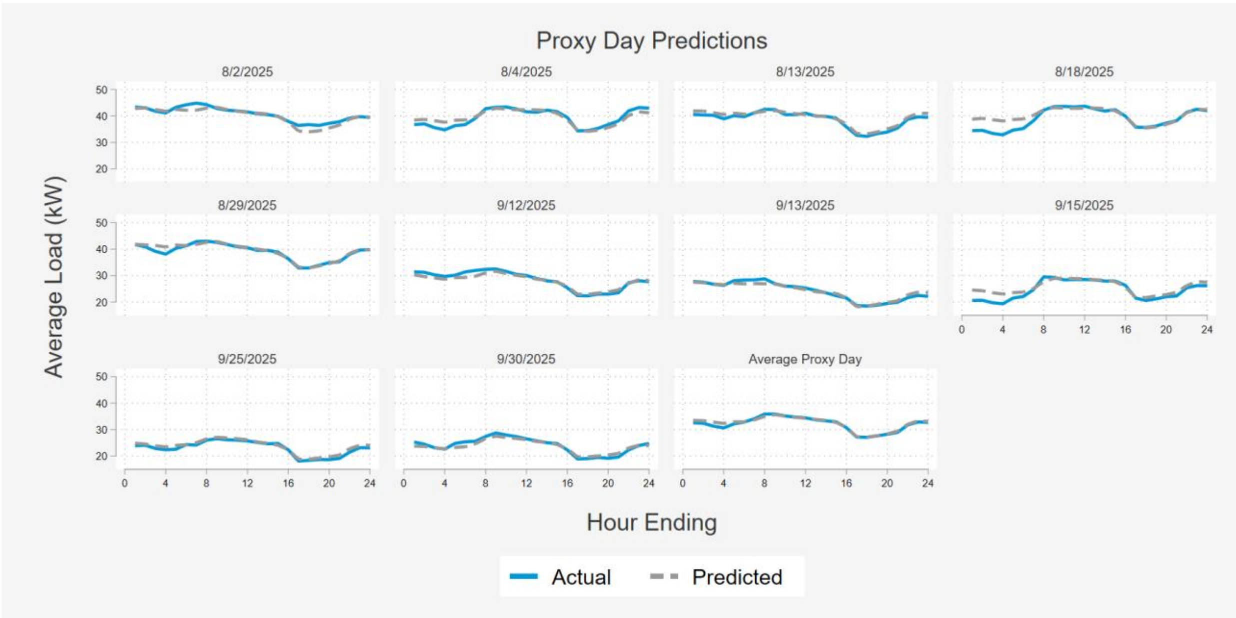
Model Term	Description
month	Month (1-12)
dow	Day of week
biwoy	Bi-week of year (1-26)
weekday	Weekday or weekend (1 or 0)
tempf	Temperature
cdh_60	Cooling degree hours – base 60
cdh60_sq	CDH squared
hdh60	Heating degree hours – base 60
hdh60_sq	HDH squared
ctrl_kwh	Synthetic controls are aggregated 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
morn_load, prvt_load	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

Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
month															
dow															
tempf															
prvt_load															
kwh_24_avg															
kwh_l168															
morn_load															
kwh_f24															
ctrl_kwh11															
ctrl_kwh12															
ctrl_kwh5															
ctrl_kwh8															
ctrl_kwh9															
ctrl_kwh10															
ctrl_kwh13															
ctrl_kwh14															
ctrl_kwh15															
Total Count	52	49	49	80	80	90	90	83	47	43	39	38	39	46	40

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

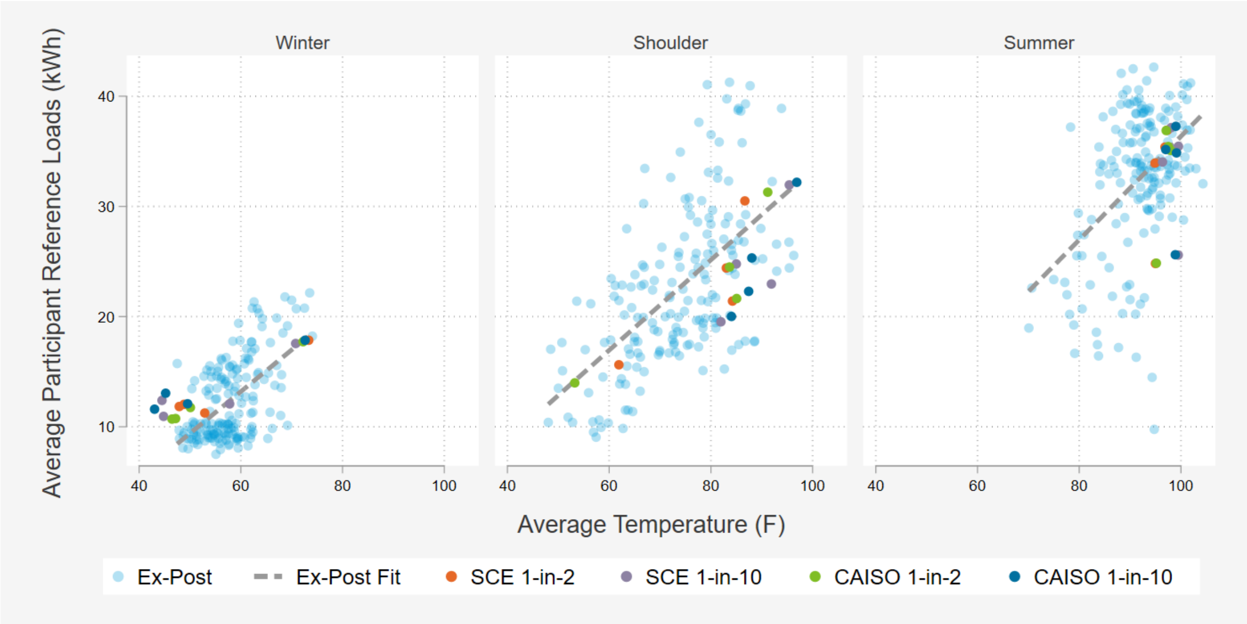


EX-ANTE REFERENCE LOAD MODEL

For AP-I, the relationship between ex-post and ex-ante is relatively straightforward. The focus of ex-ante modeling is to estimate unbiased reference loads, as the average historical percent impact is simply applied to ex-ante reference loads to produce the forecasted impacts. 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 2025 and who were assumed to be representative of future ex-ante impacts. As of PY 2025, a new Availability Assessment Hour (AAH) window is incorporated into the ex-ante modeling process. Per Decision 25-06-048 at the CPUC, the Resource Adequacy (RA) window for November through February was changed to 5 to 10pm in place of the existing 4 to 9pm window that was previously used for those four months. Thus, for PY 2025 ex-ante impacts, an RA window of 5 to 10pm is used for November through May, and 4 to 9pm is used for June through October.

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



In an attempt to address the differences between switch success rate and ex-post percent impacts, as well as narrow the gap between the ex-ante forecasts and ex-post results, program staff and the evaluation team have opted to use the average historical ex-post percent impacts to estimate ex-ante impacts instead of using the switch success rate forecast for PY 2025. Using a percent impact will be more accurate and help the ex-ante forecast better align with ex-post results because it directly captures the magnitude of load drop seen historically for all customers.

4 EX-POST RESULTS

4.1 OVERALL RESULTS

The AP-I program delivered 16.59 MW of load reduction on the average event day, or 68.3% of the reference load. Per-customer impacts were approximately 19.18 kW and were statistically significant.

Table 10: Ex-Post Impacts

Event Date	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
8/14/2025 (4:00-5:00)	865	34.09	10.09	24.00	23.80 - 24.20	70.40	20.76
9/16/2025 (4:00-5:00)	865	22.08	7.72	14.36	14.16 - 14.56	65.02	12.42
Average Event Day	**865**	**28.09**	**8.91**	**19.18**	**18.98 - 19.38**	**68.29**	**16.59**

4.2 RESULTS BY CATEGORY

Table 11 shows the impacts by LCA on the average event day. The majority of impacts came from the Big Creek/Ventura LCA, which delivered 13.02 MW of the 16.59 MW reductions during the event. This was due to the large number of customers in the LCA – 732 of the 865 participants. Conversely, the LA Basin LCA has much larger customers – customers have an average reference load of 53.47 kW per customer and delivered an average of 33.80 kW of impact per customer. However, due to the small group size, this group only delivered an aggregate impact of 2.87 MW.

Table 11: Ex-Post Impacts by LCA (Average Event Day)

LCA	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Outside LA Basin	48	21.17	6.68	14.50	13.84 - 15.15	68.46	0.70
LA Basin	85	53.47	19.67	33.80	33.00 - 34.61	63.21	2.87
Big Creek/Ventura	732	25.60	7.80	17.79	17.58 - 18.00	69.51	13.02
All Customers	**865**	**28.09**	**8.91**	**19.18**	**18.98 - 19.38**	**68.29**	**16.59**

** 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 0.8 MW of load reduction on the average event day. This represents roughly 5% of the total load shed, despite the 30 enrolled customers in those zones being only 3.5% of the total participants. This was driven primarily by customers in [redacted], who delivered on average [redacted] of load shed per participant.

Table 12: Ex-Post Impacts by Zone (Average Event Day)

Zone	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
South Orange County	12	[redacted]					
South of Lugo	18	[redacted]					
Remainder of System	835	27.66	8.74	18.91	18.72 - 19.11	68.39	15.79
All Customers	**865**	**28.09**	**8.91**	**19.18**	**18.98 - 19.38**	**68.29**	**16.59**

** 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 13: Ex-Post Impacts by Customer Size (Average Event Day)

Size	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Greater than 200kW	61	[redacted]					
20kW or Lower	152	[redacted]					
20-200kW	652	26.35	8.53	17.82	17.61 - 18.02	67.61	11.62
All Customers	**865**	**28.09**	**8.91**	**19.18**	**18.98 - 19.38**	**68.29**	**16.59**

** 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 14: Ex-Post Impacts by Prohibited Resource Attestation Status (Average Event Day)

PRA	# Dispatched	Average Customer (kW)					Agg. Impact (MW)
		Reference	Observed	Impact	95% CI	% Impact	
Yes and use	6	[redacted]					
Yes but don't use	7	[redacted]					
No	852	28.32	9.77	18.55	18.35 - 18.75	65.49	15.80
All Customers	**865**	**28.09**	**8.91**	**19.18**	**18.98 - 19.38**	**68.29**	**16.59**

** 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 PY 2024, there were 894 enrolled accounts for the September event. The average reference load was 19.58 kW and an impact of 74.0% yielded 12.96 MW, or 14.49 kW per-customer. Table 15 compares the full event hours in PY 2024 to the average full event hour impact in PY 2025. In PY 2024, the only event held was called late in the season, on September 24th. During this time, reference loads for agricultural customers are typically low when compared to loads in July and August, leading to lower impacts overall. As expected, the August event yielded higher impacts, as reference loads on August 14th were higher, than the PY 2024 event. The PY 2025 mid-September event yielded comparable aggregate and per-site impacts to last year's late September event, although the percent impacts were lower than those seen in PY 2024.

Table 15: Comparison of 2024 and 2025 Ex-Post Impacts

Date	Full Hour Event Window	# Enrolled	Average Customer (kW)					Agg. Impact (MW)
			Ref. Load	Obs. Load	Impact	95% CI	% Impact	
9/24/2024	4:00-6:00	894	19.58	5.09	14.49	14.11 - 14.87	74.00	12.96
8/14/2025	4:00-5:00	865	34.09	10.09	24.00	23.80 - 24.20	70.40	20.76
9/16/2025	4:00-5:00	865	22.08	7.72	14.36	14.16 - 14.56	65.02	12.42

Table 16 compares both aggregate percent impact for full event hours between the PY 2025 events 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 16: AP-I Event Performance for PY 2019-2025

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%
14-Aug-25	**70.4%**
16-Sep-25	**65.0%**

4.4 KEY FINDINGS

AP-I delivered an average of 16.59 MW of load relief on average during the event dispatch hours. The largest concentrations of impacts and participants were in the Ventura LCA. Per-customer and aggregate impacts were similar between the two September events in PY 2024 and Py 2025. Despite this, it is clear that AP-I impacts have been on a downward trend since 2022, during which AP-I participants delivered up to 27 MW of impact in an early September event. The overall decline in impacts is in large part due to lower reference loads, as there is less room for participants to drop a significant amount of load when reference loads are lower. There are several reasons for lower pumping loads:

1. **Timing:** Pumping loads peak in July and August then decline sharply by late September and even sometimes by mid-September. Because pumping is largely seasonal, as it is dependent on the timing of growing and harvesting various crops, the reference loads modeled in ex-post reflect this.
2. **Precipitation:** Precipitation varies greatly from year to year, and higher levels of precipitation during the spring and summer could influence participants' need for pumping. An additional feature to explore in future evaluations could be the statewide or local reservoir levels in relation to pumping loads, as participants may not need to pump if there is water already available in local reservoirs and aqueducts.
3. **Customer Mix:** The number of customers from the 20 kW or Lower size group slightly increased in 2025, resulting in a greater share of curtailable load coming from the smaller customers and, in turn, a smaller aggregate impacts. One aspect of agricultural pumping that AP-I does not directly capture is how the customer mix has changed with regard to water usage categories. AP-I customers consist of those who pump water for crops, as well as those who pump for non-agricultural purposes, which can include water, aqueduct, oil, and natural gas pumping. It may be worthwhile to understand if customers are more likely to respond if they are primarily agricultural, or have another primary use for the water that they pump.

5 SWITCH PAGING SUCCESS RATE AND PERCENT IMPACTS

A key metric that can help SCE understand which customers and how many are successfully curtailing their pumping load in accordance with the AP-I program tariff 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 can help provide context for ex-ante impacts, and inform program staff of paging device related issues for specific customers.

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 17 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 2025 events are highlighted at the bottom of the table.

Table 17: Reported Historical Switch Paging Success

Date	# Operating	Paging Success %
7-Nov-08	311	78.0%
29-Jul-10	433	80.8%
27-Sep-10	342	85.4%
21-Sep-11	384	85.4%
26-Sep-12	263	87.5%
19-Sep-13	465	88.0%
6-Feb-14	377	81.7%
24-Sep-15	481	87.9%
19-Oct-16	431	86.1%
Combined 2017 Events	894	78.7%
27-Sep-18	348	83.3%
4-Sep-19	359	72.4%
Combined 2020 Events	432	73.1%
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	59.4%
14-Aug-25	**473**	**66.6%**
16-Sep-25	**359**	**61.6%**

In PY 2025, the paging success rate was 67% and 62% for the August and September events. While this is higher than the paging success in PY 2024, it is lower than other, recent years' paging success rates, and continues a downward trend of switch success rate since 2022. The 2025 switch paging success results by category are shown in further detail in Table 18. Switch paging success does not appear to be significantly affected by seasonality or weekday or holiday events.

Table 18: 2025 Switch Paging Success

Date	Not Operating	Did Not Respond	Responded	Paging Response %
8/14/2025	392	158	315	67
9/16/2025	505	138	221	62

For the August event, paging success was highest in the Big Creek/Ventura and Outside LA LCAs (67%) compared to the LA Basin LCA, which saw 62% paging success. During the September event, the LA Basin LCA saw the highest paging success (65%), where the Outside LA Basin saw the lowest paging success (55%).

Table 19: Paging Success by LCA for the PY 2025 Event Season

LCA	Date	Not Operating	Did Not Respond	Responded	Paging Response %
Big Creek/Ventura	8/14/2025	351	124	257	67
LA Basin	8/14/2025	20	25	40	62
Outside LA Basin	8/14/2025	21	9	18	67
Big Creek/Ventura	9/16/2025	468	101	162	62
LA Basin	9/16/2025	22	22	41	65
Outside LA Basin	9/16/2025	15	15	18	55

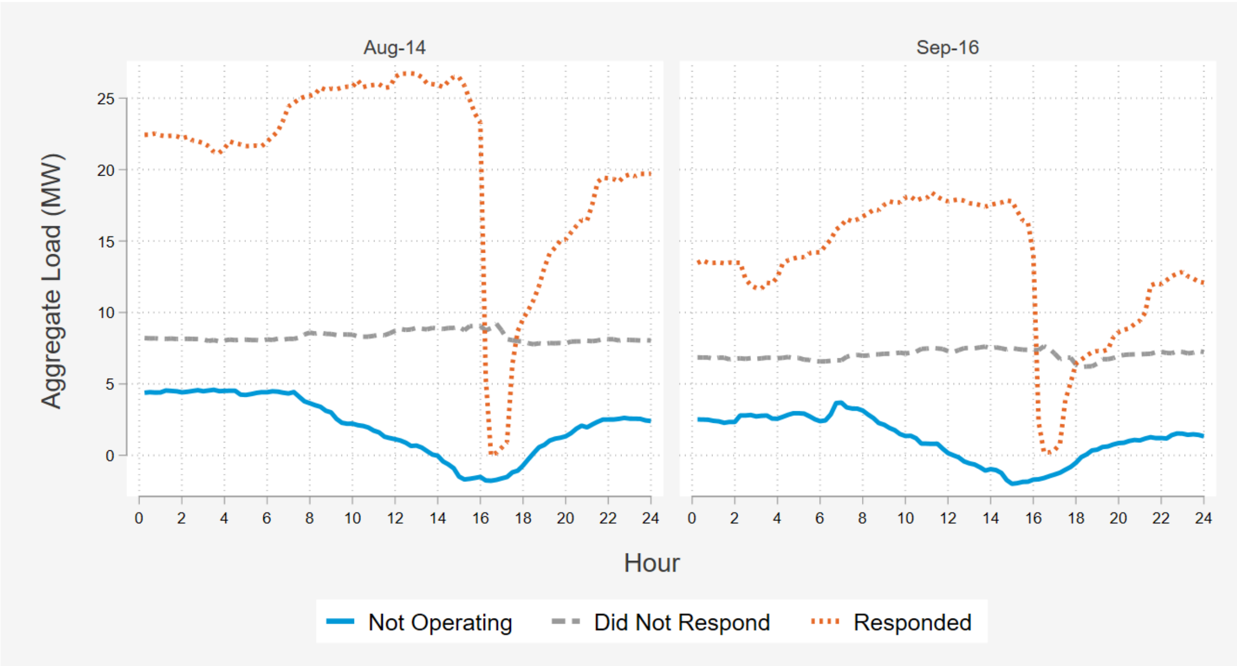
Figure 7 shows the distribution of switch paging success by zip code for the August 14th and September 16th events. Most of the customers are concentrated in the southern-most region of the CA Central Valley, and the switch success rate averages 50-70% in these zip codes.

Figure 7: Geographic Distribution of Paging Success – All Events

[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



One important consideration for program staff is that switch success rate differs from percent impacts. Switch success rate simply captures the percentage of operating customers who dropped their load by at least 50%, whereas the percent impact is the difference between the predicted reference load and the observed load. Thus, customers who dropped load by less than 50% will still have their impacts counted toward the aggregate and percent impacts. In addition, the switch success rate metric assumes that customers who dropped their load by 50% at the start of the event (or increase their load after the event by 100%) dropped the entirety of the reference load during the event, which is not always true. Participants can drop their load substantially but still have residual load on the circuit during events. Typically, percent impacts are higher than the actual switch success rate because of these distinctions, which is shown in Table 20.

Table 20: Historical SSR and Percent Impact Comparison

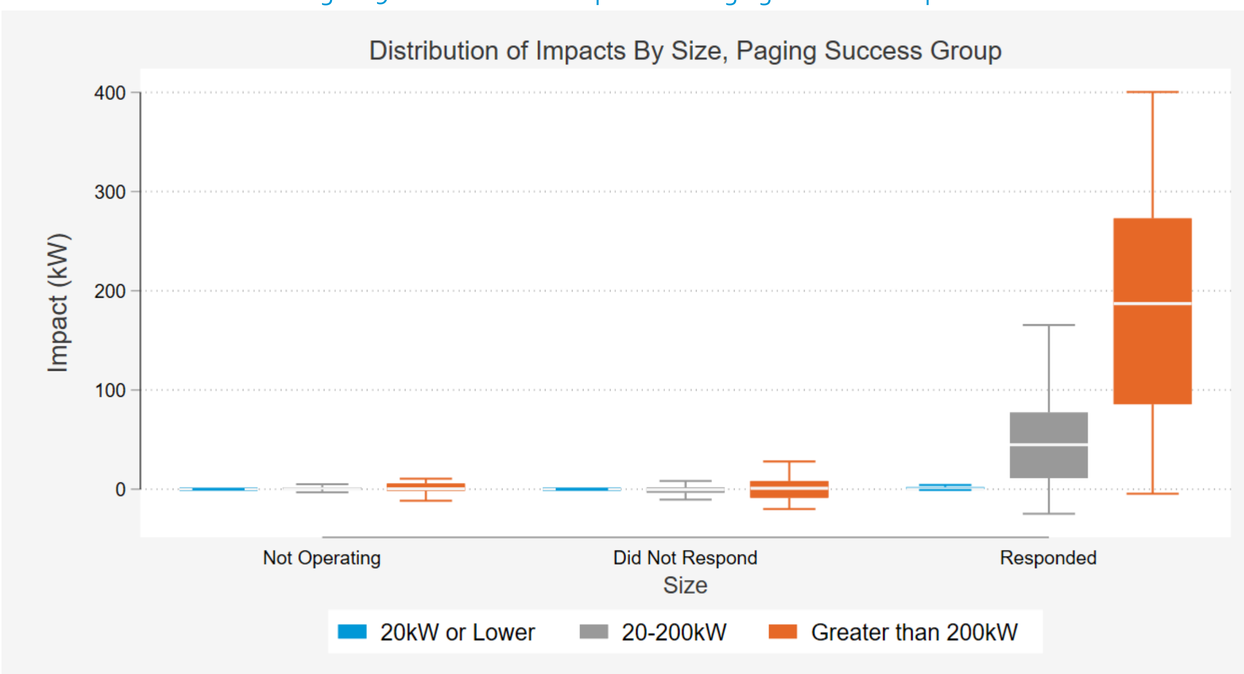
Event Date	Actual SSR	% Impact	Forecasted SSR
9/5/2022	74%	80%	75%
9/6/2022	71%	79%	75%
9/7/2022	71%	79%	75%
7/20/2023	64%	64%	75%
9/24/2024	59%	74%	76%
8/14/2025	67%	70%	75%
9/16/2025	62%	65%	75%

Furthermore, in past evaluations the SCE team has provided the forecasted switch success rate as an input to the ex-ante forecast, which is based on (1) the actual switch success rates seen each year, and (2) improvements and changes SCE plans on making to the paging network. Table 20 shows the forecasted switch success rate in comparison to the actual switch success rate and percent impact. In most years, there is a gap between the forecast and both the actual switch success rate and the percent impact seen by the program.

In an attempt to address the differences between switch success rate and ex-post percent impacts, as well as narrow the gap between the ex-ante forecasts and ex-post results, program staff and the evaluation team have opted to use the average historical ex-post percent impacts to estimate ex-ante impacts instead of using the switch success rate forecast for PY 2025. Using a percent impact will be more accurate and help the ex-ante forecast better align with ex-post results because it directly captures the magnitude of load drop seen historically for all customers, rather than attempting to classify customers into "responded" or "did not respond" bins based on their event-hour behavior.

Nevertheless, switch success rate and percent impacts are correlated. Customers classified as "did not respond" and "not operating" have impacts on average that are closer to 0. Figure 9 shows that the distribution of impacts for these customers is centered around 0, whereas the distribution of impacts for customers classified as "responded" show impacts spanning from 0 to 400 kW, with most customers falling between 0 and 100 kW impact.

Figure 9: Distribution of Impacts for Paging Success Groups



6 EX-ANTE RESULTS

This section summarizes the results of the ex-ante impact estimation process for AP-I from 2026 to 2036. There are two key drivers for the ex-ante impact forecast: the expected number of participants enrolled in the program and the assumed percent impact. SCE provided the enrollment forecast, and the assumed percent impact was derived from an average of the historical percent impact for full event hours using ex-post results from PY 2022 through PY 2025.

6.1 ENROLLMENT FORECAST

AP-I enrollment is forecasted to increase slightly from the 865 participants enrolled during both PY 2025 events to 878 in 2026, and then decrease starting in 2027 to a constant 790 participants through 2036, pending any program changes. The number of participants at the end of September 2025 (865) is assumed to remain constant through July 2026, after which the new enrollment forecast (878) applies.

Table 21: AP-I Ex-Ante Enrollment Forecast

Program/Portfolio	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036
Portfolio	878	790	790	790	790	790	790	790	790	790	790
Program	878	790	790	790	790	790	790	790	790	790	790

6.2 OVERALL RESULTS

Aggregate August Worst Day impacts, detailed in Table 22, increase in the first few years of the forecast, reflecting the higher enrollment forecast of 878 participants in 2026. However, ex-ante impacts then fall to roughly 21.4 MW in aggregate in 2027, a result of the lowered expected enrollment during that year and onward. Projected percent impacts stay constant throughout the forecast period, so expected enrollment is the driving force behind changes in ex-ante impacts from year to year. In general, 1-in-10 weather conditions produce nearly the same impacts as 1-in-2, as AP-I is not nearly as weather sensitive as other SCE DR programs like 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 21.4 MW of load reduction on August event days.

Table 22: AP-I Aggregate Portfolio Ex-Ante Impacts (MW) - August Worst Day

Year	SCE 1-in-2	SCE 1-in10	CAISO 1-in-2	CAISO 1-in-10
2026	23.75	23.90	23.73	23.97
2027	21.37	21.50	21.35	21.57
2028	21.37	21.50	21.35	21.57
2029	21.37	21.50	21.35	21.57
2030	21.37	21.50	21.35	21.57
2031	21.37	21.50	21.35	21.57
2032	21.37	21.50	21.35	21.57
2033	21.37	21.50	21.35	21.57
2034	21.37	21.50	21.35	21.57
2035	21.37	21.50	21.35	21.57
2036	21.37	21.50	21.35	21.57

Load impacts also vary by month, as seasonal changes in farming intensity and precipitation impact pumping requirements. Table 23 shows the average customer (kW) impacts for a monthly peak day in 2036, assuming an 73.3% impact. Impacts are highest during May through August, and typically peak in July and August.

Table 23: AP-I Average Customer Portfolio Ex-Ante Impacts (kW) - By Monthly Worst Day in 2036

Day Type	SCE 1-in-2	SCE 1-in10	CAISO 1-in-2	CAISO 1-in-10
January Worst Day	8.29	8.15	7.98	9.65
February Worst Day	8.88	8.85	8.68	8.97
March Worst Day	11.52	14.55	10.36	14.81
April Worst Day	18.10	18.44	18.26	18.86
May Worst Day	22.72	23.95	23.33	24.13
June Worst Day	25.92	25.97	25.96	25.76
July Worst Day	24.86	24.93	25.70	25.53
August Worst Day	27.05	27.22	27.03	27.30
September Worst Day	18.18	18.75	18.20	18.76
October Worst Day	15.68	16.82	15.85	16.33
November Worst Day	13.11	12.89	12.97	13.12
December Worst Day	8.747	9.187	7.949	8.611

Figure 10 shows the aggregate hourly ex-ante load impact for the August monthly worst day in 2026, which is forecasted to have 878 participants. For the AP-I program, post-event loads do not automatically revert to pre-event loads, as participants need to manually turn their pumps back on, which is why there are typically residual impacts in the hours after an event is held. The percent reduction after event hours is estimated using the historical, post-event load impacts from ex-post events in PY 2021 through PY 2025, and is applied to the reference load to model this effect.

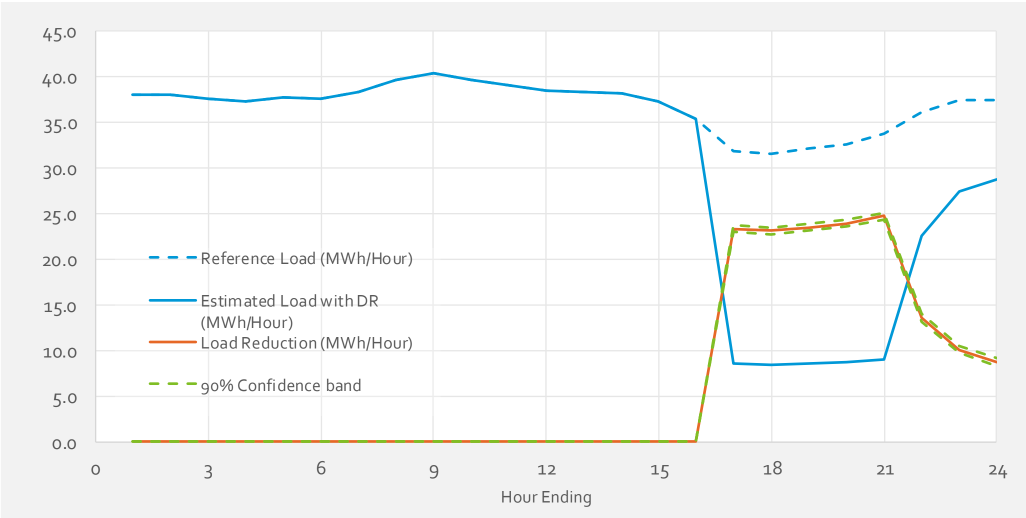
Figure 10: Aggregate Ex-Ante Impacts for 2026 SCE 1-in-2 August Monthly Worst Day

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	2026
Portfolio Level	Portfolio
Impact %	Forecast
Impact % Used	73.3%
Hour Ending View	HE (Prevailing Time)

Table 2: Event day information

Event start	4:00 PM
Event end	9:00 PM
Total sites	878
Event window temperature (F)	97.3
Event window load reduction (MWh/H	23.75
% Load reduction (Event window)	73.3%
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	38.09	38.09	0.00	0%	83.02	0.00	0.00	0.00	0.00	
2	38.04	38.04	0.00	0%	81.09	0.00	0.00	0.00	0.00	
3	37.70	37.70	0.00	0%	78.17	0.00	0.00	0.00	0.00	
4	37.28	37.28	0.00	0%	75.91	0.00	0.00	0.00	0.00	
5	37.84	37.84	0.00	0%	74.40	0.00	0.00	0.00	0.00	
6	37.57	37.57	0.00	0%	73.11	0.00	0.00	0.00	0.00	
7	38.31	38.31	0.00	0%	71.29	0.00	0.00	0.00	0.00	
8	39.67	39.67	0.00	0%	70.48	0.00	0.00	0.00	0.00	
9	40.45	40.45	0.00	0%	73.23	0.00	0.00	0.00	0.00	
10	39.73	39.73	0.00	0%	78.37	0.00	0.00	0.00	0.00	
11	39.07	39.07	0.00	0%	82.95	0.00	0.00	0.00	0.00	
12	38.48	38.48	0.00	0%	87.39	0.00	0.00	0.00	0.00	
13	38.42	38.42	0.00	0%	90.45	0.00	0.00	0.00	0.00	
14	38.28	38.28	0.00	0%	92.93	0.00	0.00	0.00	0.00	
15	37.37	37.37	0.00	0%	95.00	0.00	0.00	0.00	0.00	
16	35.38	35.38	0.00	0%	96.65	0.00	0.00	0.00	0.00	
17	31.91	8.53	23.37	73%	98.17	22.99	23.37	23.76	0.23	99.93
18	31.59	8.45	23.14	73%	98.53	22.76	23.14	23.52	0.23	99.99
19	32.12	8.59	23.53	73%	98.39	23.15	23.53	23.91	0.23	102.97
20	32.68	8.74	23.94	73%	97.05	23.57	23.94	24.32	0.23	104.58
21	33.82	9.05	24.77	73%	94.53	24.39	24.77	25.15	0.23	107.02
22	36.19	22.60	13.58	38%	89.16	13.19	13.58	13.98	0.24	56.03
23	37.55	27.42	10.13	27%	86.53	9.72	10.13	10.54	0.25	40.96
24	37.54	28.83	8.71	23%	84.62	8.30	8.71	9.12	0.25	34.89

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	32.42	8.67	23.75	73.3%	97.33	23.37	23.75	24.13	0.23	102.89
Daily	36.88	30.58	6.30	17.1%	85.47	6.17	6.30	6.43	0.08	79.84

6.3 RESULTS BY CATEGORY

Table 24 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 Big Creek/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 24: AP-I Aggregate Portfolio Ex-Ante Impacts – August Monthly Worst Day by LCA (MW)

LCA	Weather Year	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036
Big Creek/Ventura	CAISO 1-in-10	19.49	17.54	17.54	17.54	17.54	17.54	17.54	17.54	17.54	17.54	17.54
	CAISO 1-in-2	19.31	17.37	17.37	17.37	17.37	17.37	17.37	17.37	17.37	17.37	17.37
	SCE 1-in-10	19.43	17.48	17.48	17.48	17.48	17.48	17.48	17.48	17.48	17.48	17.48
	SCE 1-in-2	19.32	17.38	17.38	17.38	17.38	17.38	17.38	17.38	17.38	17.38	17.38
LA Basin	CAISO 1-in-10	3.37	3.03	3.03	3.03	3.03	3.03	3.03	3.03	3.03	3.03	3.03
	CAISO 1-in-2	3.30	2.97	2.97	2.97	2.97	2.97	2.97	2.97	2.97	2.97	2.97
	SCE 1-in-10	3.32	2.99	2.99	2.99	2.99	2.99	2.99	2.99	2.99	2.99	2.99
	SCE 1-in-2	3.32	2.99	2.99	2.99	2.99	2.99	2.99	2.99	2.99	2.99	2.99
Outside LA Basin	CAISO 1-in-10	1.10	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	CAISO 1-in-2	1.12	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	SCE 1-in-10	1.14	1.03	1.03	1.03	1.03	1.03	1.03	1.03	1.03	1.03	1.03
	SCE 1-in-2	1.11	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

6.4 ENROLLMENT AND PAGING SUCCESS COMPARISON TO PRIOR YEAR

On 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 projected ex-ante enrollments to decrease to 848 participants starting in 2025. Enrollments in PY 2025 exceeded this figure, however, and 865 participants were enrolled during the two PY 2025 events. Table 25 below shows the forecasted ex-ante elements used in PY 2025 in comparison with the numbers used in PY 2024. Enrollment is projected to grow slightly in 2026 to 878, and decrease sharply to 790 from 2027 and onwards.

In addition, while SCE has historically provided a switch success rate forecast which has historically been applied to reference loads to estimate impacts, in PY2025 a historic percent impact was used to estimate ex-ante impacts in future years, which remains constant throughout the forecast period. When estimating impacts under ex-ante weather conditions, impacts are forecasted to be the reference loads for a given set of conditions multiplied by the percent impact. Table 25 shows the previous paging success used for forecasting ex-ante impacts to the currently assumed percent impact.

Table 25: PY 2025 Ex-Ante Forecast Elements

Forecast Year	Enrollment		% Impact	
	PY2024	PY2025	SSR	Percent Impact
2025	848		75%	
2026	848	878	76%	73%
2027	848	790	76%	73%
2028	848	790	77%	73%
2029	848	790	78%	73%
2030	848	790	78%	73%
2031	848	790	79%	73%
2032	848	790	79%	73%
2033	848	790	80%	73%
2034	848	790	81%	73%
2035	848	790	81%	73%
2036		790		73%

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 August and September monthly worst day.

Ex-ante weather projections for both August and September are higher than the weather seen in the ex-post events in 2025. Per customer and aggregate impacts are projected to be larger in 2026 compared to the ex-post impacts of 2025. Part of the gap between ex-ante predictions for 2026 and the ex-post impacts for 2025 can be explained by differing weather conditions – while ex-ante predicts impacts under hot weather conditions, the two events in PY 2025 occurred during relatively mild weather conditions. In addition, pumping loads for agricultural customers are highly seasonal, and pumping loads can drastically fall off from early September to late September. Ex-ante predictions do not differentiate between an early September and a late September event.

Table 26: Ex-Post Compared to Ex-Ante – August 2025 vs August Monthly Worst Day in 2026

Day Type	# Dispatched	Event Hour Avg Temp	Daily Max Temp	Avg Cust Ref (kW)	% Impact	Avg Cust Impact (kW)	Agg Impact (MW)
Ex Ante: August Monthly Worst Day CAISO 1-in-10 (4:00 - 9:00PM)	878	98.99	100.82	37.27	73.25	27.30	23.97
Ex Ante: August Monthly Worst Day CAISO 1-in-2 (4:00 - 9:00PM)	878	97.09	99.03	36.90	73.25	27.03	23.73
Ex Ante: August Monthly Worst Day SCE 1-in-10 (4:00 - 9:00PM)	878	98.08	99.73	37.15	73.25	27.22	23.90
Ex Ante: August Monthly Worst Day SCE 1-in-2 (4:00 - 9:00PM)	878	97.33	98.53	36.93	73.25	27.05	23.75
Ex Post: 8/14/2025	865	92.20	93.13	34.09	70.40	24.00	20.76

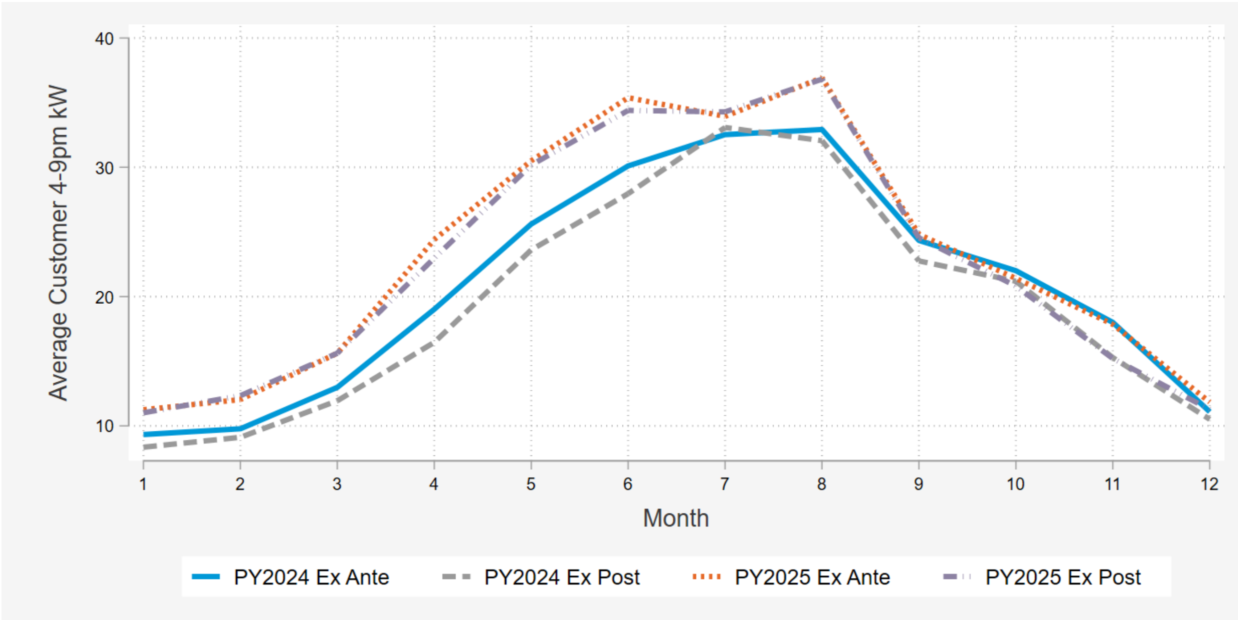
Table 27: Ex-Post Compared to Ex-Ante – September 2025 vs September Monthly Worst Day in 2026

Day Type	# Dispatched	Event Hour Avg Temp	Daily Max Temp	Avg Cust Ref (kW)	% Impact	Avg Cust Impact (kW)	Agg Impact (MW)
Ex Ante: September Monthly Worst Day CAISO 1-in-10 (4:00 - 9:00PM)	878	98.89	100.44	25.62	73.25	18.76	16.47
Ex Ante: September Monthly Worst Day CAISO 1-in-2 (4:00 - 9:00PM)	878	95.16	98.30	24.85	73.25	18.20	15.98
Ex Ante: September Monthly Worst Day SCE 1-in-10 (4:00 - 9:00PM)	878	99.46	102.95	25.59	73.25	18.75	16.46
Ex Ante: September Monthly Worst Day SCE 1-in-2 (4:00 - 9:00PM)	878	94.99	97.23	24.82	73.25	18.18	15.96
Ex Post: 9/16/2025	865	95.38	96.19	22.08	65.02	14.36	12.42

6.6 FACTORS INFLUENCING EX-ANTE REFERENCE LOADS

Ex-ante impacts are dependent on the predicted customer reference loads, which are modeled at the individual site level using three years of each participant's historical interval data. For PY 2025, customer reference loads were modeled using electricity usage data spanning from October 1, 2023 through September 30, 2025. As a result, the ex-ante reference loads modeled will capture some of the weather and rainfall conditions present during the historical time frame. Figure 11 compares the ex-post reference loads and the modeled ex-ante reference loads for PY 2025 and PY 2024. There is an increase between the both the ex-post average loads in PY 2024 and PY 2025, as well as an increase in the ex-ante reference load for both years.

Figure 11: Comparison of Average 4-9pm Load Between Py2024 and Py2025 Ex-Post, Ex-Ante Loads



One reason for this difference that has been tracked and explored is the effect of spring and early summer precipitation on pumping loads. When precipitation during this period is relatively high, pumping loads in late summer, particularly July and August, tend to be lower. Conversely, when precipitation is low during this time frame, pumping loads are high. Figure 12 shows the historic average daily load versus the average daily temperature for AP-I participants in 2022, 2023, 2024, and 2025. Average daily loads were highest in 2022, and lowest in 2023 and 2024 across all temperature conditions. Average daily load in 2025 sits squarely in the middle of this range.

Figure 12: Average Daily Load vs. Average Daily Temperature AP-I Participants (2022-2025)

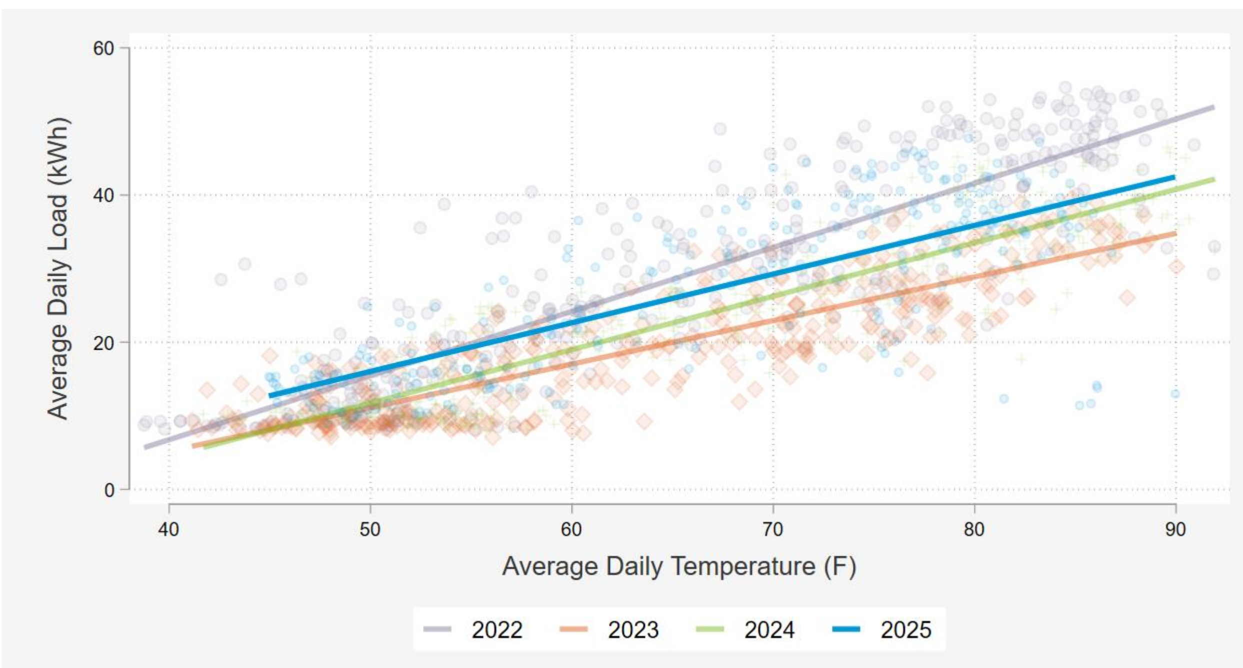
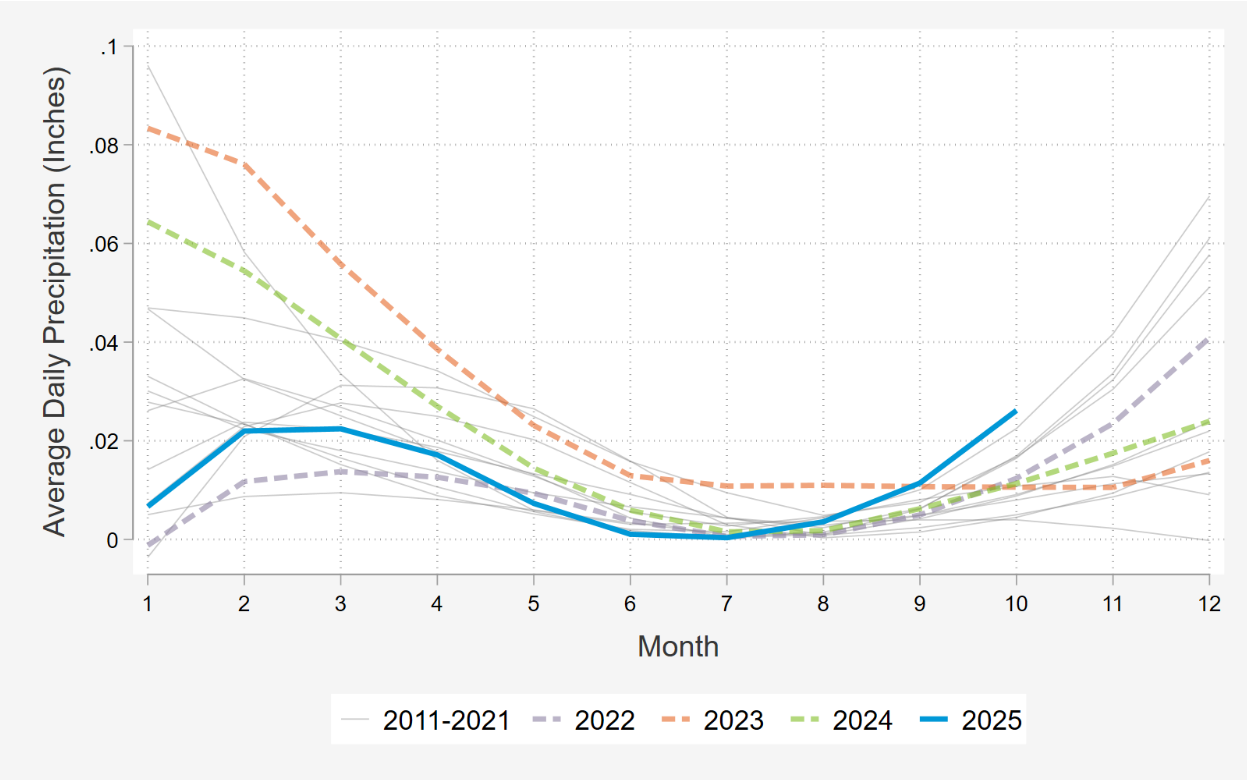


Figure 13 shows the average daily precipitation (inches) from 2011 onwards and highlights the monthly precipitation trends from 2022 through 2025. In 2022 and 2025, the spring and early summer months were relatively dry when compared the last 14 years of rainfall data, and experienced higher average daily pumping loads. In 2023 and 2024, spring and early summer rainfall was quite high, and pumping loads during these two years were low.

Figure 13: Historic Average Daily Precipitation from 2011-2025



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. In addition, utilities such as the California State Water Project and the Central Valley Project distribute water from northern CA rivers to reservoirs in water-scarce areas in central and southern CA. If agricultural customers are getting their water from these aqueducts, pumping loads could be dependent on aqueduct and reservoir levels.

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 both lower ex-post and a lower ex-ante load forecast. If SCE invests in paging switches and network improvements, the AP-I program can grow over time to produce higher load reductions during periods of grid stress.
- Paging success has declined since 2022.
  - ✓ 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 events in PY 2025.
- 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 September event compared to the August 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 continue to call multiple events in one program year. Calling multiple events in one program year helps 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 14 illustrates the process.

Figure 14: Model Selection and Validation

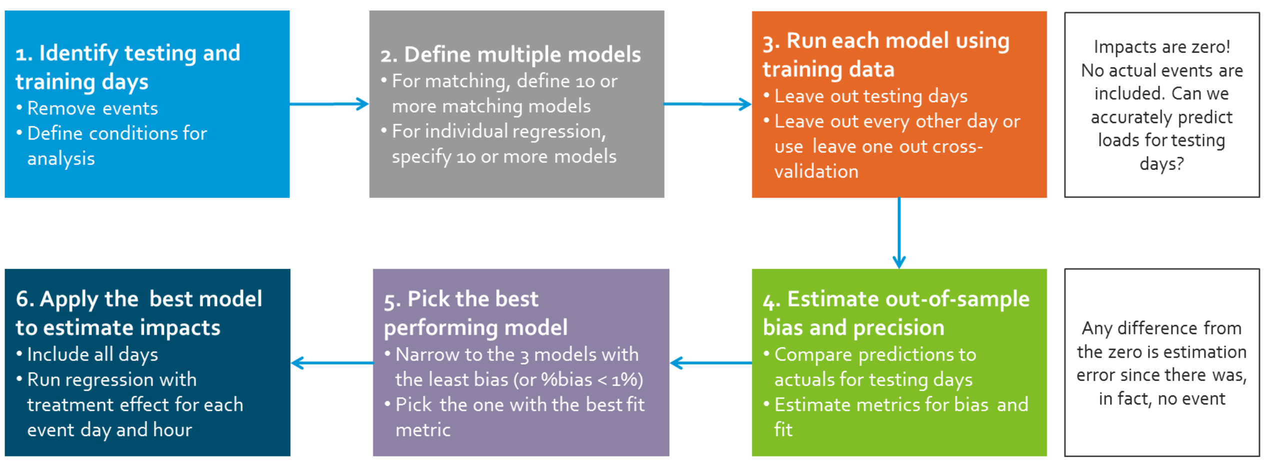


Table 29 summarizes the metrics for bias and precision we employ. Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error describes the relative magnitude and direction of the bias. A negative value indicates a tendency 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 thought of 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 15 and Figure 16. 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 15: Model Bias and Error on Proxy Events

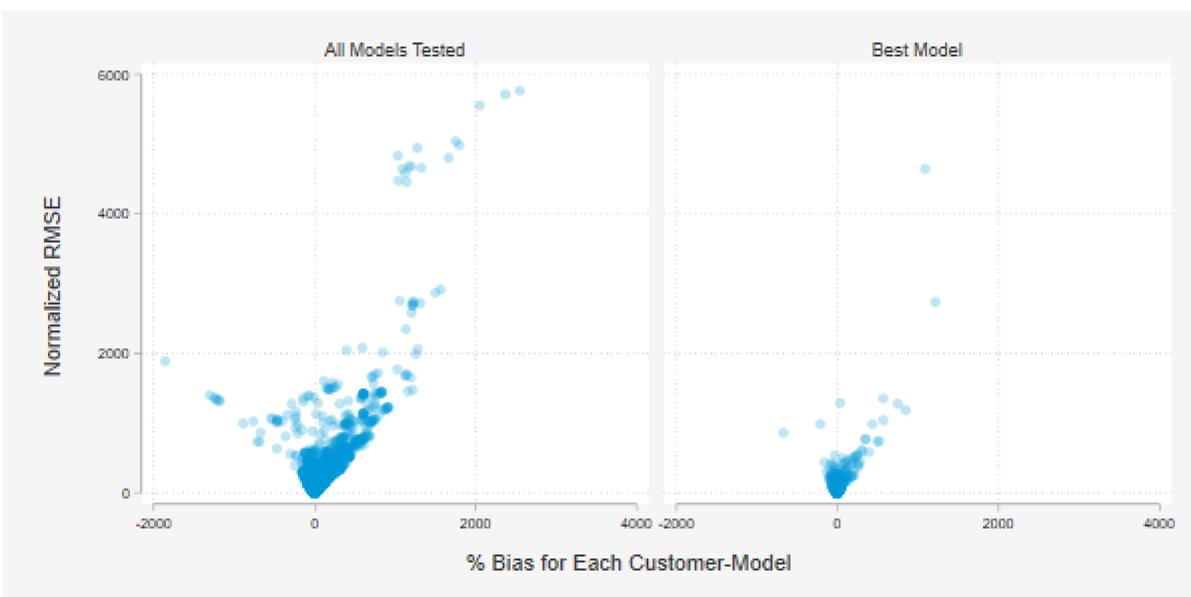


Figure 16: Model Average Error by Customer Size