Demand Side Analytics
DATA DRIVEN RESEARCH AND INSIGHTS

REPORT

CALMAC ID: SCE0445

2019 SCE Agricultural & Pumping Interruptible Demand Response Evaluation

April 1, 2020

Prepared for Southern California Edison

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

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1 EXECUTIVE SUMMARY

The Agricultural & Pumping Interruptible (AP-I) program is a longstanding demand response program in Southern California Edison (SCE)'s territory. In exchange for a monthly bill credit, customers agree to participate in DR events with no notice. During an event, which can be called for CAISO Emergencies, SCE load reduction, 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 circuits must be restarted manually. Events can be called for up to 6 hours each, up to 40 hours per month, or 150 hours per year. Events cannot be called more than once per day or more than four times in a week. With 941 customers enrolled as of the 2019 system peak and event day – September 4th, 2019 – it provided an average of 18.51MW (55%) of load shed from 3:55pm to 6:44pm. Including only the full event hours (4 pm to 6 pm), the aggregate impact was 23.7MW (72%).

Table 1: Ex Post Impacts by Date

Date	Group	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
			Ref. Load	Obs. Load	Impact	95% CI		
9/4/2019	Full Hours	941	34.91	9.72	25.19	12.90 - 37.47	72.2	23.70
	All Hours	941	35.99	16.32	19.67	6.88 - 32.46	54.6	18.51

For the full event hours, the majority of impacts came from the Big Creek/Ventura LCA, which delivered 20.13MW of the 23.70MW in the full hours of the event. This was due the large number of customers in the LCA – 790 of the 941 participants. This is in contrast to the Outside LCA where customers were larger – with an average reference load of nearly 57kW – but failed to deliver any statistically significant impact. The participants in the LA Basin provided slightly higher per-customer impacts compared to the average participant, but that difference was not statistically significant.

Table 2: Ex Post Impacts by LCA – Full Hours

LCA	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
Outside	38	56.67	51.67	5.00	-5.75 - 15.76	8.8	0.19
LA Basin	113	37.75	7.80	29.95	13.55 - 46.34	79.3	3.38
Big Creek/ Ventura	790	33.45	7.97	25.48	13.83 - 37.13	76.2	20.13
All Customers	941	34.91	9.72	25.19	12.90 - 37.47	72.2	23.70

AP-I enrollment is expected to decline from the 941 participants enrolled on the 2019 event day to 935 in August of 2020 and to 910 by August of 2021. This decline is attributable to customer attrition, which reaches a steady state with a small number of new customer enrollments as SCE manages their portfolio reliability cap.

Table 3: AP-I Ex Ante Enrollment Forecast

Program/Portfolio	2020	2021	2022	2023	2024	2025	2026-2030
Portfolio	935	910	910	910	910	910	910
Program	935	910	910	910	910	910	910

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

Program/Portfolio	2020	2021	2022	2023	2024	2025	2026-2030
Portfolio	76%	86%	90%	90%	90%	90%	90%

Once the AP-I program reaches a steady state in 2022 with constant enrollment and no further changes to the paging success rate, aggregate August Peak Day impacts will range between 31.9MW and 33.2MW. SCE 1-in-10 results are slightly lower than SCE 1-in-2 results for two reasons. First, AP-I is not as weather sensitive a program as something like 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. Second, the majority of customers enrolled in this program are mapped to SCE's weather station 51 (refer to Table 7 for a full breakdown.) That station's ex ante weather forecast is slightly lower for the August Peak Day SCE 1-in-10 than 1-in-2. Regardless of weather, the aggregate impacts are quite similar across weather scenarios, with the AP-I program delivering at least 30MW of load reduction on August event days.

Table 5: AP-I Aggregate Portfolio Ex Ante Impacts - August Peak Day

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2020	28.11	27.70	28.08	28.81
2021	30.96	30.51	30.93	31.73
2022	32.40	31.93	32.37	33.21
2023	32.40	31.93	32.37	33.21
2024	32.40	31.93	32.37	33.21
2025	32.40	31.93	32.37	33.21
2026	32.40	31.93	32.37	33.21
2027	32.40	31.93	32.37	33.21
2028	32.40	31.93	32.37	33.21
2029	32.40	31.93	32.37	33.21
2030	32.40	31.93	32.37	33.21

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. There were 941 customers enrolled in this program on the 2019 event day, which is typically one 2-hour event per summer. This program has been closed to new enrollments since 2017 due to the program being close to SCE's allotted MW associated with CAISO's reliability cap. Customers receive a monthly bill credit in exchange for their participation.

A key difference between this year's evaluation and last year is the decline in enrollment associated with the adoption of D.16-09-056, which prohibited certain types of fossil-fuel based backup generation from operating during demand response events. The prohibition went into effect on January 1, 2019. As a result, enrollment in AP-I decreased from 1,121 participants on the 2018 event day to 941 participants on the 2019 event day. This drop in enrollment has important implications for the ex ante enrollment forecast, as the program historically was expected to remain relatively stable in terms of enrollment.

The 2019 season experienced two AP-I events: the first was called on the system peak day, September 4th, 2019. The second was called on September 8th, but was erroneously dispatched by CAISO. Per SCE guidance, only impacts for the September 4th event day are reported. This event was called for approximately 90 customers from 3:55pm to 6:34pm and from 3:55pm to 6:44pm for the remaining AP-I participants. Because these times only differ by 10 minutes within the same hour period, we do not distinguish between the two dispatch groups in this report.

2.1 KEY RESEARCH QUESTIONS

The PY2019 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 2019 – for each event day and hour and for the average event? 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 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? And 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 with no advance notice. During an event, which can be called for CAISO Emergencies, SCE load reduction, 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. Events can be called for up to 6 hours each, up to 40 hours per month, or 150 hours per year. Events cannot be called more than once per day or more than four times in a week.

Participation incentives are dependent on customer size and take the form of monthly demand charge 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
200kW 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 September and October.

2.3 PARTICIPANT CHARACTERISTICS

941 agricultural customers participated in the September 4th AP-I event in 2019. Table 7 summarizes their key characteristics. As expected, the vast majority of customers have North American Industry Classification System (NAICS) codes associated with agricultural industries. Geographically, the majority are in the Ventura LCA, which is home to California's agriculturally-productive Central Valley. A small subset of customers have onsite generation of which the majority have Solar PV.

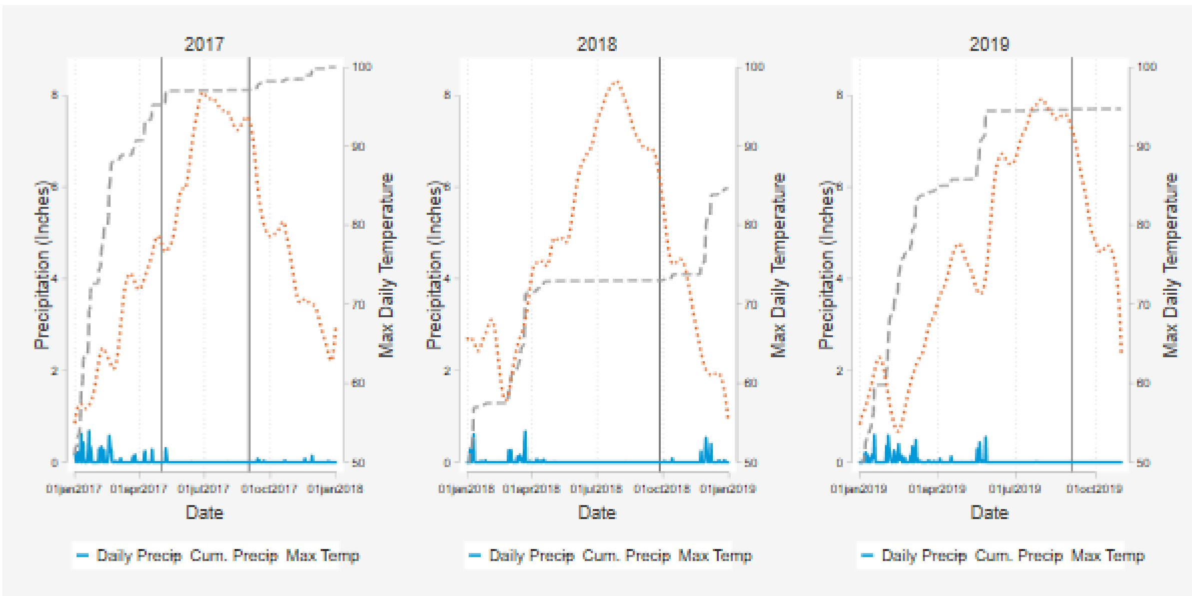
Table 7: Participant Characteristics on 9/4/2019 Event

Category	Sub Category	Customer Count
Industry	Agriculture, Mining, Construction	801
	Wholesale, Transport, Other Utilities	113
	Institutional/Government	20
	Unknown/Other	4
	Offices, Hotels, Finance, Services	3
LCA	Big Creek/Ventura	790
	La Basin	113
	Outside	38
NEM Type	None	902
	Solar	31
	Bio-Gas Aggregated Acct	8
Size	20-200kW	769
	Greater Than 200kW	141
	20kW Or Lower	31
Weather Station	51	698
	193	53
	121	40
	181	27
	141	23
	123	15
	192	15
	173	14
	191	9
	122	8
	111	7
	171	7
	112	6
	131	6
	113	3
	195	3
	151	2
	172	2
	194	2
	132	1
Zone	Remainder Of System	906
	South Of Lugo	22
	South Orange County	13

2.4 2019 EVENT CONDITIONS

The 2019 event occurred in early September, on the 2019 system peak day. Historic AP-I events have also been called in September, as shown in Figure 1. This graphic shows daily average precipitation for Southern California, cumulative average precipitation, and a participant-weighted daily maximum temperature. Event days are denoted by vertical black lines. Similar to the prior two years, and consistent with seasonal precipitation patterns, there had been no rain for several months. While 2019 – through November – did experience more cumulative precipitation than in 2018, it was slightly less than 2017. Both temperature and historic precipitation levels play key roles in the magnitude of pumping loads.

Figure 1: Participant Characteristics on 9/4/2019 Event



2.5 PROGRAM CHARACTERISTICS THAT INFLUENCE EVALUATION

The key driver of load impacts for the AP-I program are accurately modeled reference loads and the assessment of switch paging success rate (whether the switch was triggered successfully when the signal was sent). Because agricultural customers have unique load patterns, these accounts have historically been modeled using individual customer regressions. Because of this, out of sample testing and model validation is critical to provide unbiased ex-post estimates of load reduction. For ex-ante, the assumptions about the program's overall switch paging success rate make a substantial difference in the final portfolio value.

AP-I typically calls one event per summer for monitoring purposes. There are currently 941 customers enrolled in the program, which is lower than the 2018 evaluation as a result of customers dropping out of the program due to new rules that ban the use of certain backup generation resources during DR events. One event was called in 2019, on September 4. A second event, triggered by an erroneous dispatch by CAISO, lasted 10 minutes on September 8. Per SCE's guidance, no ex-post impacts will be estimated for this accidental event, and the event will not be included in the ex-ante estimation of future impacts.

A significant departure from prior years is the inspection and replacement of legacy switches on participant's pump circuits. SCE is replacing switches with new ones that uses the same radio system as the Summer Discount Program (SDP).

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 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 day – about 1,000 participants.
2. Data included in the analysis	The analysis focuses on PY 2019 load, weather, and precipitation data for all agricultural customers, including approximately 1,000 participants.
3. Use of control groups	Agricultural customers have unique schedules and highly seasonal consumption patterns that make finding a suitable control group difficult. The analysis considered matching methods (using control groups composed of other agricultural non-participants) as well as individual customer regressions for participants to evaluate ex post impacts.
4. Model selection	The final matching or 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. The analysis will also explicitly test if models that incorporate historical precipitation perform better than historical models that have temperature only.
5. Segmentation of impact results	The results will be segmented by: ▪ Local Capacity Area ▪ Customer Size ▪ Dually enrolled versus non-dually enrolled customers, and ▪ Customers with and without enabling technology.

Methodology Component	Demand Side Analytics Approach
	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 comes from the ex post analysis: ex ante reference loads are constructed by applying the best ex post individual customer regression model to the ex ante 1-in-2 and 1-in-10 weather forecasts. Impacts are related to the overall switch paging success rate – because any paged switch will set the load on that circuit to essentially 0kW, the percentage of load associated with switches that are successfully triggered is 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 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 0 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**	Little 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: a synthetic control group and individual customer regressions. 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.

To keep the connection between ex post and ex ante reference loads clear, the AP-I evaluation uses the same ex post model to make ex ante predictions.

Ex Post Model

The evaluation team tested both a synthetic control approach and individual customer regressions. The synthetic control approach performed no better than the individual customer regressions in the out of sample testing. At the same time, the control group approach has drawbacks in aggregating ex post results by sub-category because impacts for each customer segment are often estimated separately. Because of this, the team proceeded with the individual customer regression approach. Fifteen models were tested, including last year's preferred model. The best model for each customer was then used to predict ex post loads on the event days. Table 10 shows the definitions of each variable included in at least one model, while Figure 2 summarizes which variables were included in each regression. In that table, each column represents a model, and the inclusion of a variable in a given model is denoted with blue highlighting. That is, model 13 includes *month*, *CDD*, and *CDDsquared*.

Table 10: Model Variables for Testing

Model Term	Description
Month	Month
firsthalf	Binary flag for first half or second half of month. Intended to capture intra-month pump-load shifts
dow	Day of week
avgtemp	Daily average temperature
tempf	Temperature
Daily_precip	Daily precipitation in customer's region
Precip_7days	Cumulative precipitation in customer's region in last week
Precip_3months	Cumulative precipitation in customer's region over last three months
CDH_60	Cooling degree hours – base 60
CDH60_sq	CDH squared
HDH60	Heating degree hours – base 60
HDH6_sq	HDH squared
CDD	Cooling degree days – base 60
CDD_sq	CDD squared

Figure 2: Model Specifications Tested

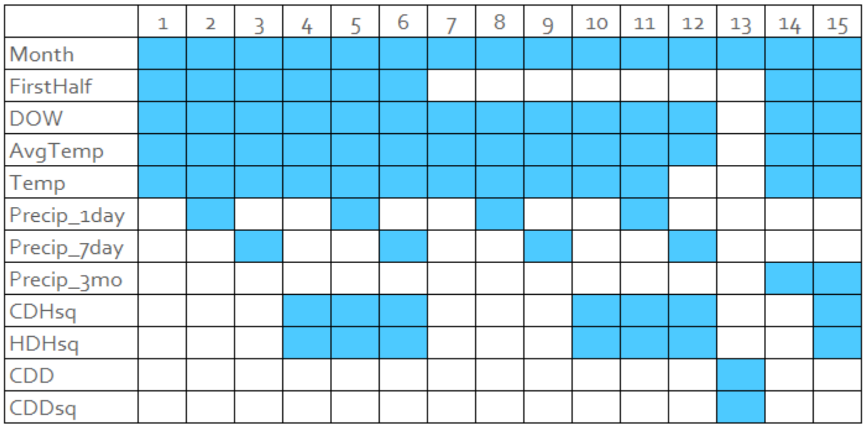


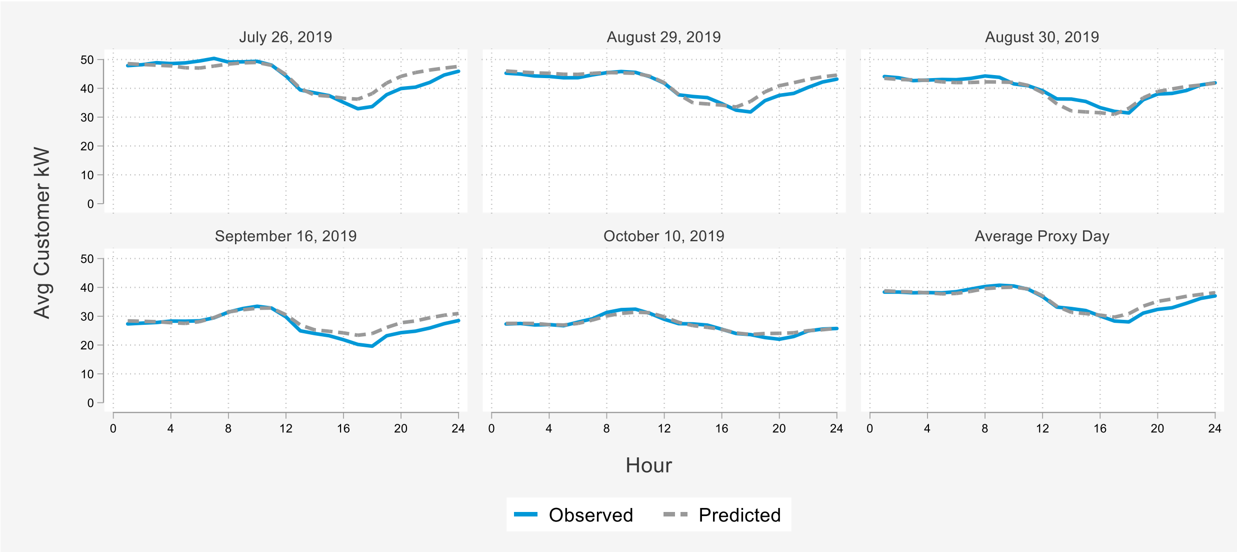
Table 11 shows the number of customers for which each model was selected as the best model.

Table 11: Best Model for Each Customer

Model #	Customer Count
1	33
2	42
3	60
4	41
5	41
6	56
7	59
8	57
9	71
10	52
11	48
12	74
13	178
14	76
15	70

Figure 3 shows the predicted loads for each selected proxy day. More detail, including a summary of model fit statistics can be found in the appendix.

Figure 3: Out of Sample Predictions on Proxy Days

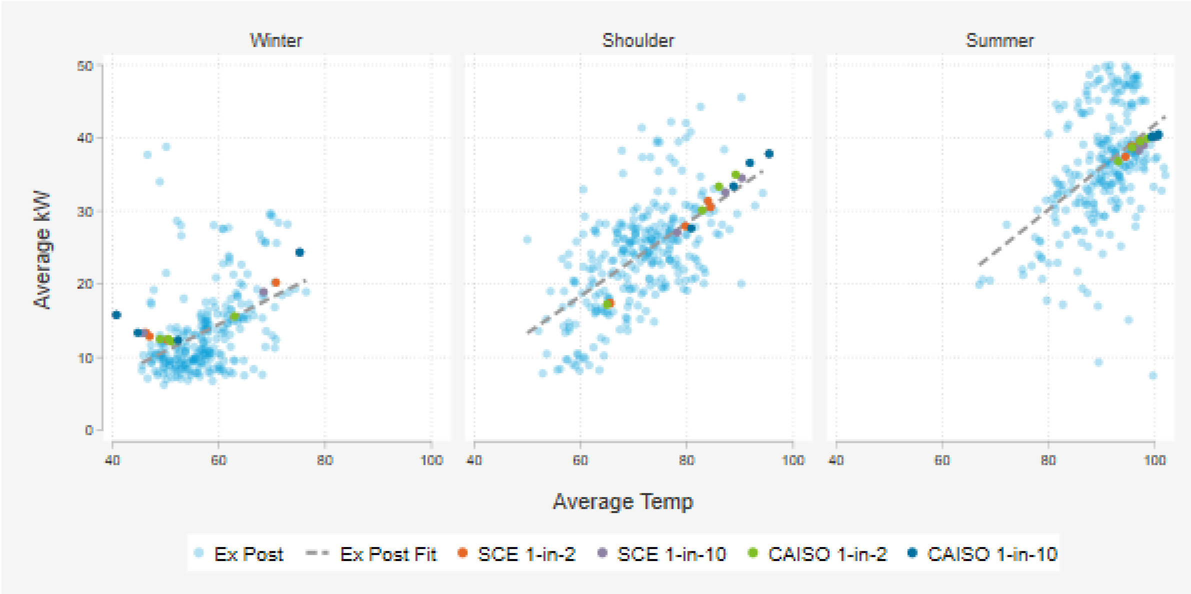


Ex Ante Reference Load Model

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 – provided by SCE – the focus of ex ante modeling is estimating 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 or lagged precipitation. These models were then run for the subset of customers who remained on the program as of October 1, 2019 and who were assumed to be representative of future ex ante impacts.

Figure 4 shows the comparison of daily average temperature and average customer kW for these customers for both their ex post historical data and predicted ex ante scenarios. 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 winter model, which is likely more a reflection of the non-linear relationship between temperature and load. That is, below a certain temperature, agricultural accounts may still have baseline operational requirements that operate continuously. This is reflected in the flattening of the relationship between temperature and load below about 55 degrees Fahrenheit.

Figure 4: Comparison of Ex Post and Ex Ante Reference Loads



4 EX POST RESULTS

This section summarizes ex post results for the September 4th AP-I event day. This event was called from 3:55pm to 6:44pm, with a subset of customers finishing 10 minutes earlier (6:34pm). Because event dispatch did not perfectly align with full hours, we report both the overall results for all event hours and for full event hours in Table 12, below. To better assess customer response and program performance, we report results for only full event hours (4pm-6pm) in the remaining ex post tables.

4.1 OVERALL RESULTS

Over the entire event period, the AP-I program delivered 18.51MW of load reduction, or 55% of the reference load. Excluding partial hours, the program delivered closer to 24MW, or a 72% impact. Per-customer impacts were approximately 19.7kW and were statistically significant.

Table 12: Ex Post Impacts by Date

Date	Group	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
			Ref. Load	Obs. Load	Impact	95% CI		
9/4/2019	Full Hours	941	34.91	9.72	25.19	12.90 - 37.47	72.2	23.70
	All Hours	941	35.99	16.32	19.67	6.88 - 32.46	54.6	18.51

Figure 5: Average Customer Ex Post Impacts on September 4, 2019

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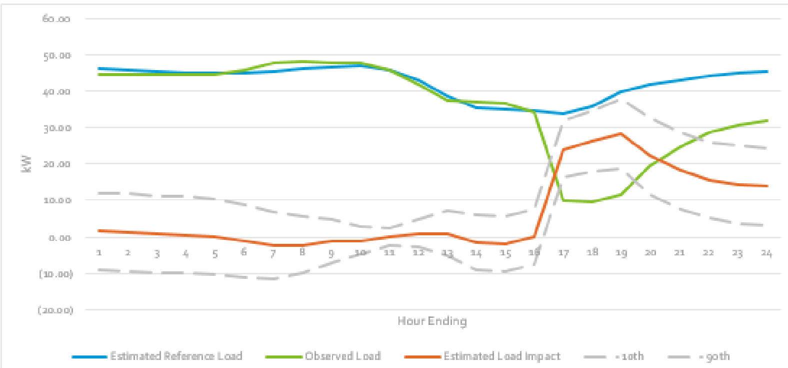
Selection Options	
Reporting Level	Average Customer
Date	September 4, 2019
Customer Segment	All Customers

Event Characteristics	
Event Hours	3:55 pm - 6:44 pm
# Dispatched	941
Daily Max Temp	98.3
Average Impact - kW	19.67
Average Impact - %	54.6%



Hour Ending	Estimated Reference Load	Observed Load	Estimated Load Impact		Temp	Estimated Load Impact Range				
	kW	kW	kW	%	F	10th	30th	50th	70th	90th
1	46.08	44.57	1.50	3%	80	(9.14)	(2.85)	1.50	5.85	12.15
2	45.79	44.63	1.16	3%	79	(9.47)	(3.19)	1.16	5.51	11.80
3	45.34	44.64	0.71	2%	78	(9.88)	(3.62)	0.71	5.04	11.30
4	45.08	44.50	0.59	1%	77	(9.89)	(3.70)	0.59	4.87	11.06
5	44.87	44.75	0.12	0%	74	(10.20)	(4.10)	0.12	4.33	10.44
6	44.87	45.96	(1.10)	-2%	72	(11.06)	(5.17)	(1.10)	2.97	8.86
7	45.38	47.67	(2.29)	-5%	72	(11.50)	(6.06)	(2.29)	1.48	6.92
8	46.13	48.28	(2.14)	-5%	73	(9.77)	(5.26)	(2.14)	0.97	5.49
9	46.67	47.95	(1.28)	-3%	77	(7.24)	(3.72)	(1.28)	1.16	4.68
10	46.80	47.77	(0.96)	-2%	81	(4.91)	(2.57)	(0.96)	0.65	2.98
11	45.80	45.88	(0.08)	0%	86	(2.44)	(1.05)	(0.08)	0.88	2.27
12	42.86	41.90	0.96	2%	89	(2.87)	(0.61)	0.96	2.52	4.79
13	38.45	37.45	1.00	3%	93	(5.25)	(1.55)	1.00	3.56	7.26
14	35.37	36.85	(1.49)	-4%	96	(8.93)	(4.53)	(1.49)	1.56	5.96
15	34.94	36.79	(1.85)	-5%	97	(9.32)	(4.90)	(1.85)	1.21	5.62
16	34.49	34.40	0.09	0%	98	(7.58)	(3.04)	0.09	3.23	7.76
17	33.84	9.89	23.95	71%	98	16.19	20.78	23.95	27.12	31.71
18	35.97	9.55	26.42	73%	97	18.12	23.03	26.42	29.81	34.72
19	39.66	11.45	28.21	71%	96	18.62	24.29	28.21	32.13	37.80
20	41.91	19.72	22.19	53%	94	11.64	17.88	22.19	26.50	32.73
21	43.12	24.90	18.22	42%	89	7.74	13.94	18.22	22.50	28.69
22	44.21	28.71	15.50	35%	86	5.03	11.22	15.50	19.78	25.98
23	44.98	30.52	14.46	32%	85	3.79	10.10	14.46	18.83	25.13
24	45.56	31.67	13.89	30%	83	3.28	9.56	13.89	18.23	24.50
Daily	Daily Energy					Estimated Energy Change				
	kWh	kWh	kWh Δ	%	ΣCDH (75)	10th	30th	50th	70th	90th
	1,018.17	860.39	157.78	15%	260	148.99	154.19	157.78	161.38	166.58

Figure 6: Aggregate Ex Post Impacts on September 4, 2019

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Ex Post - 2019

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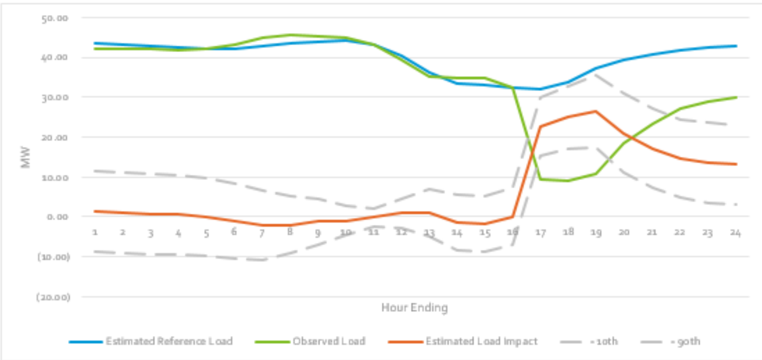
Selection Options	
Reporting Level	Aggregate
Date	September 4, 2019
Customer Segment	All Customers

Event Characteristics	
Event Hours	3:55 pm - 6:44 pm
# Dispatched	941
Daily Max Temp	98.3
Average Impact - MW	18.51
Average Impact - %	54.6%



Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Estimated Load Impact %	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	43.36	41.94	1.42	3%	80	(8.60)	(2.68)	1.42	5.51	11.43
2	43.09	42.00	1.09	3%	79	(8.92)	(3.00)	1.09	5.18	11.10
3	42.67	42.00	0.67	2%	78	(9.30)	(3.41)	0.67	4.74	10.63
4	42.42	41.87	0.55	1%	77	(9.30)	(3.48)	0.55	4.58	10.41
5	42.22	42.11	0.11	0%	74	(9.60)	(3.86)	0.11	4.08	9.82
6	42.22	43.25	(1.03)	-2%	72	(10.40)	(4.86)	(1.03)	2.80	8.34
7	42.71	44.86	(2.16)	-5%	72	(10.82)	(5.70)	(2.16)	1.39	6.51
8	43.41	45.43	(2.02)	-5%	73	(9.20)	(4.95)	(2.02)	0.92	5.16
9	43.92	45.12	(1.21)	-3%	77	(6.82)	(3.50)	(1.21)	1.09	4.41
10	44.04	44.95	(0.91)	-2%	81	(4.62)	(2.42)	(0.91)	0.61	2.81
11	43.09	43.17	(0.08)	0%	86	(2.30)	(0.98)	(0.08)	0.83	2.14
12	40.33	39.43	0.90	2%	89	(2.71)	(0.57)	0.90	2.38	4.51
13	36.18	35.24	0.94	3%	93	(4.94)	(1.46)	0.94	3.35	6.83
14	33.28	34.68	(1.40)	-4%	96	(8.40)	(4.26)	(1.40)	1.46	5.61
15	32.88	34.62	(1.74)	-5%	97	(8.77)	(4.61)	(1.74)	1.14	5.29
16	32.46	32.37	0.09	0%	98	(7.13)	(2.86)	0.09	3.04	7.30
17	31.84	9.31	22.54	71%	98	15.23	19.55	22.54	25.52	29.84
18	33.85	8.99	24.86	73%	97	17.05	21.67	24.86	28.05	32.67
19	37.32	10.77	26.54	71%	96	17.52	22.86	26.54	30.23	35.57
20	39.44	18.56	20.88	53%	94	10.96	16.82	20.88	24.93	30.80
21	40.57	23.43	17.14	42%	89	7.29	13.11	17.14	21.17	27.00
22	41.60	27.01	14.59	35%	86	4.73	10.56	14.59	18.62	24.45
23	42.33	28.72	13.61	32%	85	3.57	9.51	13.61	17.72	23.65
24	42.88	29.80	13.07	30%	83	3.09	8.99	13.07	17.16	23.06
Daily	Daily Energy MWh	MWh	MWh Δ	%	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
	958.10	809.62	148.47	15%	260	(8,125.79)	(3,233.52)	148.47	3,530.47	8,422.74

4.2 RESULTS BY CATEGORY

The majority of impacts came from the Big Creek/Ventura LCA, which delivered 20.13MW of the 23.7MW in the full hours of the event. This was due the large number of customers in the LCA – 790 of the 941 participants. This is in contrast to the Outside LCA where customers were larger – with an average reference load of nearly 57kW – but failed to deliver any statistically significant impact. The participants in the LA Basin provided slightly higher per-customer impacts compared to the average participant, but that difference was not statistically significant.

Table 13: Ex Post Impacts by LCA

LCA	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
Outside	38	56.67	51.67	5.00	-5.75 - 15.76	8.8	0.19
LA Basin	113	37.75	7.80	29.95	13.55 - 46.34	79.3	3.38
Big Creek/ Ventura	790	33.45	7.97	25.48	13.83 - 37.13	76.2	20.13
All Customers	941	34.91	9.72	25.19	12.90 - 37.47	72.2	23.70

In the two zones affected by the San Onofre Nuclear Generating Station (SONGS) closure, South Orange County and South of Lugo, customers delivered [redacted] of load reduction during the full event hours. This represents [redacted] of the total load shed, despite the 35 enrolled customers in those zones being only 3.7% of the total participants. This was driven primarily by customers in [redacted] who delivered on average [redacted] of load shed per participant.

Table 14: Ex Post Impacts by Zone

Zone	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
South Orange County	13	[redacted]					
South of Lugo	22						
Remainder of System	906	34.17	9.61	24.55	12.33 - 36.78	71.9	22.25
All Customers	941	34.91	9.72	25.19	12.90 - 37.47	72.2	23.70

AP-I customers were segmented into size categories based on maximum demand over the prior summer. The results for each category are reported below. Larger customers had higher reference loads with more available load to shed, as expected, and the response rate across customers with peak demand of at least 20kW was relatively similar, with both groups dropping approximately 72% of their reference load. Despite the larger per-customer impacts in the high-demand customer segment, the majority of impacts came from the medium-demand group due to the large number of participants in that category.

Table 15: Ex Post Impacts by Customer Size

Size	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
20kW or Lower	31	1.05	0.01	1.04	0.28 - 1.80	99.2	0.03
20-200kW	769	26.13	7.30	18.83	9.58 - 28.08	72.0	14.48
Greater than 200kW	141	90.02	24.98	65.04	41.81 - 88.26	72.2	9.17
All Customers	941	34.91	9.72	25.19	12.90 - 37.47	72.2	23.70

Only one customer was on AP-I with enabling technology. This customer [redacted].

Table 16: Ex Post Impacts by AutoDR Status

AutoDR Status	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Ref. Load	Obs. Load	Impact	95% CI		
Yes	1	[redacted]					
No	940	[redacted]					
All Customers	941	34.91	9.72	25.19	12.90 - 37.47	72.2	23.70

4.3 COMPARISON TO PRIOR YEAR

Last year, 1,121 customers participated in one AP-I event on September 27th, 2018 from 4pm to 7pm. The average reference load was 37.6kW and an impact of 82% yielded 34.6MW, or 30.9kW per customer. However, 2018 impacts for customers who remained active in AP-I in 2019 were smaller on average, than those who left. The reference load for customers who remained on the program was only 29kW during the 2018 event. Because of this, per-customer impacts were also smaller (22.7kW compared to 30.9kW) despite similar percentage impacts.

Viewed in this context, AP-I performed relatively well in 2019. The customers who provided 22.7kW impacts last year increased their per-customer impact in 2019, to 25.2kW, driven by substantially higher reference loads. Higher reference loads could be driven by hotter temperatures or seasonal variation in pumping. Despite a lower percent impact (72.2% in 2019 vs 79.7% in 2018), the same population of participants delivered 23.7MW of load reduction compared to 21.4MW in the prior year.

Table 17: Comparison of 2019 and 2018 Ex Post Impacts

Date	Group	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
			Ref. Load	Obs. Load	Impact	95% CI		
2018 Event	Full PY 2018 Reported	1,121	37.6	6.8	30.9	Not Reported	82.2	34.6
	Remaining On Program	943	28.5	5.8	22.7	10.69 - 34.79	79.7	21.4
2019 Event	Full Hours	941	34.9	9.7	25.2	12.90 - 37.47	72.2	23.7

** Note that because the event ran from 4pm-7pm, there is no distinction between all hours and full-event hours.*

4.4 KEY FINDINGS

AP-I delivered nearly 24MW of load relief during the full hours of event dispatch. The largest concentrations of impacts and participants were in the Ventura LCA. Despite a smaller participant population than in prior years, per-customer impacts were higher for the same population. This could be attributable to several factors:

1. **Temporal variation:** the 2019 event was called earlier in September compared to last year. As September crops are harvested, there is less pumping required later in the month.
2. **Weather variation:** hotter weather conditions on the 2019 event day relative to the 2018 event day may mean that fields require additional irrigation.
3. **Random chance:** the confidence interval for the 2019 event includes the per-customer impact from 2018.

Because of the ban on the operation of prohibited resources during DR events, many customers appear to have left the program. While the reason for their departure is not clear, the decline in participants is substantially higher than normal customer churn for this program. It is likely that these customers were significantly different than customers who remained on the program; indeed, based on the results summarized in Table 17, they tended to be larger and more responsive to AP-I events than the customers who stayed. This has important implications for the ex ante analysis, as the lower reference loads of remaining customers are a primary determinant of ex ante impacts.

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 annual maximum load.
2. Calculate the ratio of individual customer's load in the hour prior to the event compared to the last 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. Of the customers who were operating on the event day, calculate the ratio of customers who responded to those who were operating.

Historical paging success rates reported in prior year's evaluations tended to hover in the mid to high 80% range. For events that occurred in September – where a similar fraction of pumps is expected to be operating – the weighted average paging success rate was 86.3% for events from 2008 to 2018.

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%
Sept 4, 2019	359	72.4%

In 2019, however, switch paging success dropped to 72.4%. An analysis of the 2019 participants over the last three years, shown in **Table 19** demonstrates that this is likely not 100% attributable to the change in participant population, but rather a distinct change in response rate.

Table 19: Trends in Historical Switch Paging Success for Participants Active in 2019

Date	Not Operating	Did Not Respond	Responded	Paging Success %
May 3, 2017	655	72	222	75.5
Sept 1, 2017	632	69	245	78.0
Sept 27, 2018	657	48	241	83.4
Sept 4, 2019	582	99	260	72.4

Paging success was highest in the LA Basin, with 84% of operating switches responding to the dispatch. The lowest success rate was in the Outside LA LCA, but this result should be interpreted with some caution, since the total number of participants in that LCA is low.

Table 20: Paging Success by LCA for 2019 Event

LCA	Not Operating	Did Not Respond	Responded	Paging Success %
Big Creek/Ventura	500	75	215	74.1
LA Basin	63	8	42	84.0
Outside	19	16	3	15.8

A map of customers by switch paging success, shown in Figure 7 [redacted].

Figure 7: Geographic Distribution of Paging Success

[Image Redacted To Protect Confidential Information]

The contribution of each switch paging group to overall program impacts is summarized in Figure 8. Customers who did get the dispatch notification dropped load down to essentially 0kW, 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. This non-operating group also included 29 out of the 39 NEM customers enrolled in AP-I.

Of particular interest are the customers who did not respond to the event. In prior years, the aggregate load of non-responder was approximately [redacted] as shown in the graph below. However, in 2019, aggregate load for non-responding customers was approximately [redacted]

Figure 8: Response by Switch Paging Success

[Image Redacted To Protect Confidential Information]

6 EX ANTE RESULTS

This section summarizes the results of the ex ante impact estimation process for AP-I from 2020 to 2030. 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 expected to decline from the 941 participants enrolled on the 2019 event day to 935 in August of 2020 and to 910 by August of 2021. This decline is attributable to customer attrition, which reaches a steady state with a small number of enrollments as SCE manages their portfolio reliability cap.

Table 21: AP-I Ex Ante Enrollment Forecast

Program/Portfolio	2020	2021	2022	2023	2024	2025	2026-2030
Portfolio	935	910	910	910	910	910	910
Program	935	910	910	910	910	910	910

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

Program/Portfolio	2020	2021	2022	2023	2024	2025	2026-2030
Portfolio	76%	86%	90%	90%	90%	90%	90%

6.2 OVERALL RESULTS

Once the AP-I program reaches a steady state in 2022 with constant enrollment and no further changes to the switch paging success rate, aggregate August Peak Day impacts range between 31.9MW and 33.2MW. SCE 1-in-10 results are slightly lower than SCE 1-in-2 results for two reasons. First, AP-I is not as weather sensitive a program as something like Summer Discount Plan or Smart Energy Program. While pumping and agricultural loads do tend to vary with temperature, seasonality is a bigger driver of loads than hourly temperature. Second, the majority of customers enrolled in this program are mapped to SCE's weather station 51 (refer to Table 7 for a full breakdown.) That station's ex ante weather forecast is slightly lower for the August Peak Day SCE 1-in-10 than 1-in-2[1]. Regardless of weather, the aggregate impacts are quite similar across weather scenarios, with the AP-I program delivering at least 30MW of load reduction on August event days.

[1] See the appendix for more details

Table 23: AP-I Aggregate Portfolio Ex Ante Impacts - August Peak Day

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2020	28.11	27.70	28.08	28.81
2021	30.96	30.51	30.93	31.73
2022	32.40	31.93	32.37	33.21
2023	32.40	31.93	32.37	33.21
2024	32.40	31.93	32.37	33.21
2025	32.40	31.93	32.37	33.21
2026	32.40	31.93	32.37	33.21
2027	32.40	31.93	32.37	33.21
2028	32.40	31.93	32.37	33.21
2029	32.40	31.93	32.37	33.21
2030	32.40	31.93	32.37	33.21

Load impacts also vary by month, as seasonal changes in farming intensity and precipitation impact pumping requirements. Table 24 shows the average customer impacts for a monthly peak day, assuming a 90% switch paging success rate. Impacts are highest in June through September and typically peak in August.

Table 24: AP-I Average Customer Portfolio Ex Ante Impacts - By Monthly Peak Day in 2030

Day Type	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
January Peak Day	11.61	12.02	11.27	12.05
February Peak Day	11.16	17.02	11.27	11.15
March Peak Day	15.68	24.36	15.50	24.87
April Peak Day	25.14	31.07	27.10	30.06
May Peak Day	28.24	34.06	31.49	34.06
June Peak Day	35.01	36.06	35.95	36.27
July Peak Day	35.25	34.47	34.82	36.11
August Peak Day	35.60	35.08	35.57	36.49
September Peak Day	33.69	35.13	33.12	36.27
October Peak Day	27.47	29.31	30.03	32.93
November Peak Day	18.18	21.91	14.09	21.91
December Peak Day	12.05	14.25	11.00	14.25

Figure 9: Aggregate Ex Ante Impacts for SCE 1-in-2 Typical Event Day

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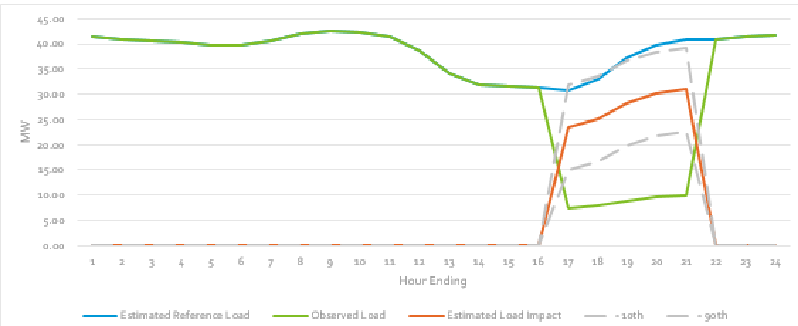
Selection Options	
Reporting Level	Aggregate
Customer Segment	All Customers
Day Type	Typical Event Day
Weather Year	SCE 1-in-2
Forecast Year	2020
Portfolio Level	Portfolio
itch Paging Success	Forecast

Event Characteristics	
Event Hours	4pm-9pm
# Enrolled	935
Daily Max Temp	97.5
MW Impact	27.6
% Impact	76.0%



Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	41.30	41.30	0.00	80.7858	0.00	0.00	0.00	0.00	0.00
2	40.92	40.92	0.00	78.7955	0.00	0.00	0.00	0.00	0.00
3	40.67	40.67	0.00	76.7196	0.00	0.00	0.00	0.00	0.00
4	40.38	40.38	0.00	74.6254	0.00	0.00	0.00	0.00	0.00
5	39.81	39.81	0.00	72.9937	0.00	0.00	0.00	0.00	0.00
6	39.84	39.84	0.00	71.3763	0.00	0.00	0.00	0.00	0.00
7	40.70	40.70	0.00	69.7504	0.00	0.00	0.00	0.00	0.00
8	42.12	42.12	0.00	69.5663	0.00	0.00	0.00	0.00	0.00
9	42.42	42.42	0.00	72.5115	0.00	0.00	0.00	0.00	0.00
10	42.14	42.14	0.00	77.1345	0.00	0.00	0.00	0.00	0.00
11	41.50	41.50	0.00	81.6215	0.00	0.00	0.00	0.00	0.00
12	38.71	38.71	0.00	85.6303	0.00	0.00	0.00	0.00	0.00
13	34.20	34.20	0.00	89.0081	0.00	0.00	0.00	0.00	0.00
14	31.75	31.75	0.00	91.5862	0.00	0.00	0.00	0.00	0.00
15	31.51	31.51	0.00	93.9562	0.00	0.00	0.00	0.00	0.00
16	31.19	31.19	0.00	95.9539	0.00	0.00	0.00	0.00	0.00
17	30.85	7.40	23.45	97.155	15.09	20.03	23.45	26.86	31.80
18	33.01	7.92	25.09	97.5251	16.73	21.67	25.09	28.50	33.44
19	37.10	8.90	28.19	97.3409	19.84	24.78	28.19	31.61	36.55
20	39.61	9.51	30.11	95.8433	21.75	26.69	30.11	33.52	38.46
21	40.72	9.77	30.95	92.3685	22.59	27.53	30.95	34.36	39.30
22	40.92	40.92	0.00	87.6683	0.00	0.00	0.00	0.00	0.00
23	41.31	41.31	0.00	84.3944	0.00	0.00	0.00	0.00	0.00
24	41.76	41.76	0.00	82.2284	0.00	0.00	0.00	0.00	0.00
Daily	Daily Energy MWh	MWh	MWh Δ	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
	924.43	786.64	137.79	235.72	(3,675.61)	(1,420.89)	137.79	1,696.46	3,951.18

Figure 10: Aggregate Ex Ante Impacts for SCE 1-in-10 Typical Event Day

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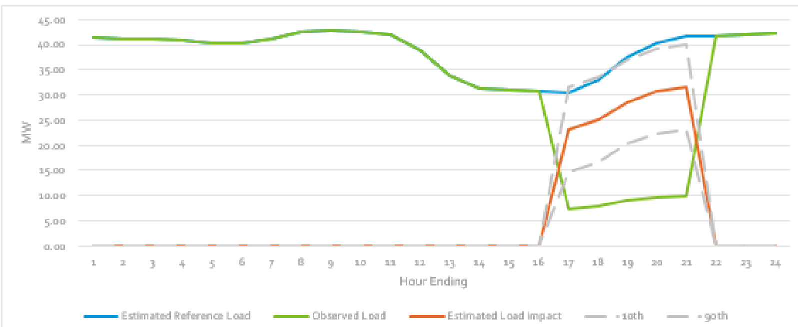
Selection Options	
Reporting Level	Aggregate
Customer Segment	All Customers
Day Type	Typical Event Day
Weather Year	SCE 1-in-10
Forecast Year	2020
Portfolio Level	Portfolio
itch Paging Success	Forecast

Event Characteristics	
Event Hours	4pm-9pm
# Enrolled	935
Daily Max Temp	99.6
MW Impact	27.8
% Impact	76.0%



Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	41.48	41.48	0.00	80.3176	0.00	0.00	0.00	0.00	0.00
2	41.19	41.19	0.00	78.5965	0.00	0.00	0.00	0.00	0.00
3	41.03	41.03	0.00	76.6111	0.00	0.00	0.00	0.00	0.00
4	40.83	40.83	0.00	74.7811	0.00	0.00	0.00	0.00	0.00
5	40.30	40.30	0.00	73.0181	0.00	0.00	0.00	0.00	0.00
6	40.28	40.28	0.00	71.462	0.00	0.00	0.00	0.00	0.00
7	41.00	41.00	0.00	70.3433	0.00	0.00	0.00	0.00	0.00
8	42.48	42.48	0.00	70.0215	0.00	0.00	0.00	0.00	0.00
9	42.82	42.82	0.00	73.0113	0.00	0.00	0.00	0.00	0.00
10	42.62	42.62	0.00	77.4948	0.00	0.00	0.00	0.00	0.00
11	41.92	41.92	0.00	81.8491	0.00	0.00	0.00	0.00	0.00
12	38.85	38.85	0.00	85.7671	0.00	0.00	0.00	0.00	0.00
13	33.81	33.81	0.00	89.2976	0.00	0.00	0.00	0.00	0.00
14	31.20	31.20	0.00	92.7795	0.00	0.00	0.00	0.00	0.00
15	31.07	31.07	0.00	95.694	0.00	0.00	0.00	0.00	0.00
16	30.67	30.67	0.00	97.6642	0.00	0.00	0.00	0.00	0.00
17	30.41	7.30	23.11	98.9536	14.76	19.70	23.11	26.53	31.47
18	32.98	7.91	25.06	99.5832	16.71	21.65	25.06	28.48	33.42
19	37.57	9.02	28.55	99.0204	20.20	25.14	28.55	31.97	36.91
20	40.37	9.69	30.68	97.6324	22.33	27.27	30.68	34.10	39.03
21	41.59	9.98	31.61	94.4564	23.25	28.19	31.61	35.02	39.96
22	41.70	41.70	0.00	90.2752	0.00	0.00	0.00	0.00	0.00
23	42.03	42.03	0.00	86.7375	0.00	0.00	0.00	0.00	0.00
24	42.32	42.32	0.00	83.2613	0.00	0.00	0.00	0.00	0.00
Daily	Daily Energy MWh	MWh	MWh Δ	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
	930.52	791.50	139.01	255.99	(3,674.38)	(1,419.66)	139.01	1,697.69	3,952.41

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Figure 11: Aggregate Ex Ante Impacts for CAISO 1-in-2 Typical Event Day

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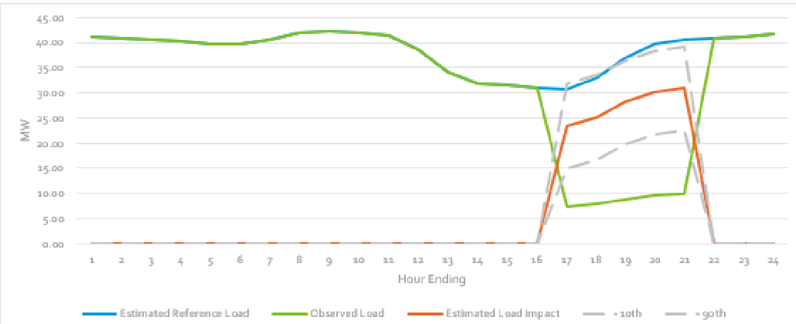
Selection Options	
Reporting Level	Aggregate
Customer Segment	All Customers
Day Type	Typical Event Day
Weather Year	CAISO 1-in-2
Forecast Year	2020
Portfolio Level	Portfolio
itch Paging Success	Forecast

Event Characteristics	
Event Hours	4pm-9pm
# Enrolled	935
Daily Max Temp	97.5
MW Impact	27.5
% Impact	76.0%



Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	41.06	41.06	0.00	79.6606	0.00	0.00	0.00	0.00	0.00
2	40.73	40.73	0.00	77.3472	0.00	0.00	0.00	0.00	0.00
3	40.53	40.53	0.00	75.6415	0.00	0.00	0.00	0.00	0.00
4	40.29	40.29	0.00	73.7459	0.00	0.00	0.00	0.00	0.00
5	39.76	39.76	0.00	72.1583	0.00	0.00	0.00	0.00	0.00
6	39.78	39.78	0.00	70.665	0.00	0.00	0.00	0.00	0.00
7	40.61	40.61	0.00	69.2843	0.00	0.00	0.00	0.00	0.00
8	41.96	41.96	0.00	69.1204	0.00	0.00	0.00	0.00	0.00
9	42.26	42.26	0.00	72.0805	0.00	0.00	0.00	0.00	0.00
10	41.96	41.96	0.00	76.6377	0.00	0.00	0.00	0.00	0.00
11	41.32	41.32	0.00	81.1213	0.00	0.00	0.00	0.00	0.00
12	38.58	38.58	0.00	85.3624	0.00	0.00	0.00	0.00	0.00
13	34.16	34.16	0.00	88.7107	0.00	0.00	0.00	0.00	0.00
14	31.76	31.76	0.00	91.5298	0.00	0.00	0.00	0.00	0.00
15	31.50	31.50	0.00	93.8607	0.00	0.00	0.00	0.00	0.00
16	31.14	31.14	0.00	95.7593	0.00	0.00	0.00	0.00	0.00
17	30.85	7.40	23.45	97.2206	15.09	20.03	23.45	26.86	31.80
18	32.99	7.92	25.07	97.5401	16.72	21.66	25.07	28.49	33.43
19	37.03	8.89	28.14	97.3108	19.78	24.72	28.14	31.55	36.49
20	39.60	9.50	30.09	95.9312	21.74	26.68	30.09	33.51	38.45
21	40.70	9.77	30.94	92.4678	22.58	27.52	30.94	34.35	39.29
22	40.89	40.89	0.00	88.0455	0.00	0.00	0.00	0.00	0.00
23	41.23	41.23	0.00	85.2466	0.00	0.00	0.00	0.00	0.00
24	41.56	41.56	0.00	83.4936	0.00	0.00	0.00	0.00	0.00
Daily	Daily Energy MWh	MWh	MWh Δ	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
	922.25	784.56	137.69	232.89	(3,675.71)	(1,420.98)	137.69	1,696.36	3,951.08

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Figure 12: Aggregate Ex Ante Impacts for CAISO 1-in-10 Typical Event Day

SOUTHERN CALIFORNIA EDISON
Energy for What's Ahead℠

Agricultural & Pumping Interruptible

Ex Ante - 2019

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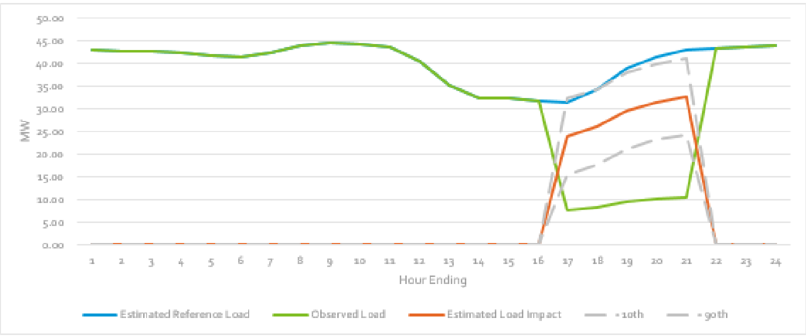
Selection Options	
Reporting Level	Aggregate
Customer Segment	All Customers
Day Type	Typical Event Day
Weather Year	CAISO 1-in-10
Forecast Year	2020
Portfolio Level	Portfolio
itch Paging Success	Forecast

Event Characteristics	
Event Hours	4pm-9pm
# Enrolled	935
Daily Max Temp	101.5
MW Impact	28.7
% Impact	76.0%



Hour Ending	Estimated Reference Load MW	Observed Load MW	Estimated Load Impact MW	Temp F	Estimated Load Impact Range 10th	30th	50th	70th	90th
1	42.99	42.99	0.00	82.621	0.00	0.00	0.00	0.00	0.00
2	42.70	42.70	0.00	81.235	0.00	0.00	0.00	0.00	0.00
3	42.52	42.52	0.00	79.4131	0.00	0.00	0.00	0.00	0.00
4	42.17	42.17	0.00	77.4848	0.00	0.00	0.00	0.00	0.00
5	41.51	41.51	0.00	75.6726	0.00	0.00	0.00	0.00	0.00
6	41.36	41.36	0.00	74.4987	0.00	0.00	0.00	0.00	0.00
7	42.21	42.21	0.00	72.7355	0.00	0.00	0.00	0.00	0.00
8	43.88	43.88	0.00	72.0763	0.00	0.00	0.00	0.00	0.00
9	44.32	44.32	0.00	75.3892	0.00	0.00	0.00	0.00	0.00
10	44.12	44.12	0.00	80.3298	0.00	0.00	0.00	0.00	0.00
11	43.38	43.38	0.00	84.9529	0.00	0.00	0.00	0.00	0.00
12	40.27	40.27	0.00	89.2552	0.00	0.00	0.00	0.00	0.00
13	35.12	35.12	0.00	92.6096	0.00	0.00	0.00	0.00	0.00
14	32.26	32.26	0.00	95.9838	0.00	0.00	0.00	0.00	0.00
15	32.14	32.14	0.00	98.5527	0.00	0.00	0.00	0.00	0.00
16	31.76	31.76	0.00	100.407	0.00	0.00	0.00	0.00	0.00
17	31.44	7.55	23.89	101.313	15.54	20.48	23.89	27.31	32.25
18	34.12	8.19	25.93	101.538	17.57	22.51	25.93	29.34	34.28
19	38.71	9.29	29.42	101.121	21.07	26.01	29.42	32.83	37.77
20	41.42	9.94	31.48	99.5182	23.13	28.07	31.48	34.90	39.84
21	42.85	10.28	32.57	96.541	24.21	29.15	32.57	35.98	40.92
22	43.14	43.14	0.00	92.4406	0.00	0.00	0.00	0.00	0.00
23	43.48	43.48	0.00	88.9914	0.00	0.00	0.00	0.00	0.00
24	43.80	43.80	0.00	86.1089	0.00	0.00	0.00	0.00	0.00
Daily	Daily Energy MWh	MWh	MWh Δ	ΣCDH (75)	Estimated Energy Change 10th	30th	50th	70th	90th
	961.66	818.38	143.29	306.48	(3,670.11)	(1,415.38)	143.29	1,701.96	3,956.68

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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. There is no ex ante enrollment forecast split by LCA, so the participant counts are expected to scale according to proportion of existing customers in each LCA.

Table 25: AP-I Aggregate Portfolio Ex Ante Impacts - Typical Event Day by LCA

LCA	Weather Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Big Creek/ Ventura	CAISO 1-in-10	22.57	24.85	26.01	26.01	26.01	26.01	26.01	26.01	26.01	26.01	26.01
	CAISO 1-in-2	21.54	23.72	24.83	24.83	24.83	24.83	24.83	24.83	24.83	24.83	24.83
	SCE 1-in-10	21.70	23.89	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00
	SCE 1-in-2	21.54	23.72	24.82	24.82	24.82	24.82	24.82	24.82	24.82	24.82	24.82
LA Basin	CAISO 1-in-10	4.34	4.78	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
	CAISO 1-in-2	4.24	4.68	4.89	4.89	4.89	4.89	4.89	4.89	4.89	4.89	4.89
	SCE 1-in-10	4.36	4.80	5.03	5.03	5.03	5.03	5.03	5.03	5.03	5.03	5.03
	SCE 1-in-2	4.27	4.70	4.92	4.92	4.92	4.92	4.92	4.92	4.92	4.92	4.92
Outside	CAISO 1-in-10	1.75	1.92	2.01	2.01	2.01	2.01	2.01	2.01	2.01	2.01	2.01
	CAISO 1-in-2	1.74	1.92	2.01	2.01	2.01	2.01	2.01	2.01	2.01	2.01	2.01
	SCE 1-in-10	1.74	1.91	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
	SCE 1-in-2	1.74	1.92	2.01	2.01	2.01	2.01	2.01	2.01	2.01	2.01	2.01

6.4 COMPARISON TO PRIOR YEAR

Compared to PY2018, both customer enrollments and paging success rates were lower in the first years of the forecast. In 2022 and beyond, the forecasts stabilize, with PY2018's paging success rate higher than that of PY2019 but PY2019's enrollment rate higher than that of PY2018. These effects do not entirely cancel each other out; higher ex ante impacts were reported in PY2018 than PY2019 because the PY2018 evaluation had higher per-customer reference loads for each month.[2]

Table 26: PY2018 Ex Ante Forecast Elements

Evaluation Year	Forecast Element	2019	2020	2021	2022	2023	2024	2025	2026-2030
2018	Enrollment	969	944	919	894	894	894	894	894
	Paging Success Rate	87%	90%	93%	93%	93%	93%	93%	93%
2019	Enrollment		935	910	910	910	910	910	910
	Paging Success Rate		76%	86%	90%	90%	90%	90%	90%

[2] See the appendix for a full comparison.

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 event day to the 2020 September Monthly Peak Day. The ex post day was most similar in temperature to the SCE 1-in-10 weather scenario. Reference loads for the average customer on the ex post day were slightly lower than that of the SCE 1-in-10 day which is attributable to the change in event window: the full event hours for ex post were hours ending 17 and 18, while the ex ante RA window is during hours ending 17 to 21. AP-I customers have a slight U-shape to their loads as some agricultural customers either rely on onsite-generation or avoid irrigating during the middle of the day. Because of this, hours closer to the middle of the day show lower reference loads than the evening. Despite ex ante having lower enrollments, the forecasted switch paging success rate is higher than in ex post. That difference (a 5.2% increase in impact %) more than offsets the 1.3% decline in enrollment.

Table 27: Ex Post Compared to Ex Ante

Day Type	# Enrolled	Event Hour Avg Temp	Daily Max Temp	Avg Cust Ref (kW)	Switch Paging Success %	% Impact	Avg Cust Impact (kW)	Agg Impact (MW)
CAISO 1-in-10	933	99.50	101.49	40.30	76.0	76.0	30.63	28.58
CAISO 1-in-2	933	93.04	95.19	36.80	76.0	76.0	27.97	26.09
SCE 1-in-10	933	97.86	100.19	39.04	76.0	76.0	29.67	27.68
SCE 1-in-2	933	94.40	96.25	37.44	76.0	76.0	28.45	26.55
Sept 4, 2019	941	97.67	98.33	34.91	72.4	72.2	25.19	23.70

7 DISCUSSION

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

- Customers have left the program as a result of the ban on using certain prohibited generating resources during demand response events.
  - ✓ Evidence from the comparison of last year's evaluation to this year indicate that customers who left were larger and possibly more likely to respond to events.
- SCE is in the process of replacing legacy switches at participant sites.
  - ✓ This should improve the switch paging success rate as old equipment is replaced, and is reflected in the switch paging success rate forecast.
- Mapping customer event response across SCE's territory may highlight locations where network reception should be assessed.
  - ✓ This can provide additional insight into the root causes of a given year's result and should be continued.
- Pumping and agricultural loads are driven by on/off operation and not by temperature. Pump operating is highly seasonal.
  - ✓ This fundamentally limits the available load shed in winter months as fewer pumps are in operation.
  - ✓ Conversely, the program is more valuable in July through August when the percentage of customers pumping is higher.
- Estimating switch paging success based on one event per summer is subject to high volatility, as paging success, pump operation, or customer response is ultimately somewhat stochastic in nature.
  - ✓ Calling more events per summer will provide a more robust picture of how customers operate
  - ✓ With 15-minute interval data available, these events do not have to be as long as they have been historically. Quick paging tests can provide valuable information about customer response.

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 rAP-Idly 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 % 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 13 illustrates the process.

Figure 13: Model Selection and Validation

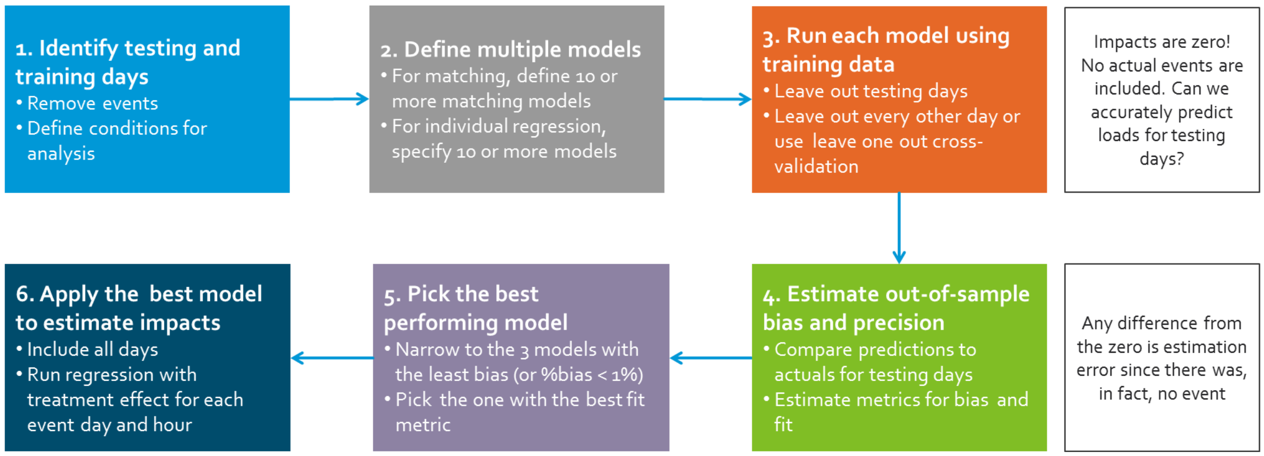

Table 29 summarizes the metrics for bias and precision we employ. Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error describes the relative magnitude and direction of the bias. A negative value indicates a tendency 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	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$
	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 14 and Figure 15. In both figures, bias decreases with the selection of the best model. The average event hour error is centered around 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 14: Model Bias and Error on Proxy Events

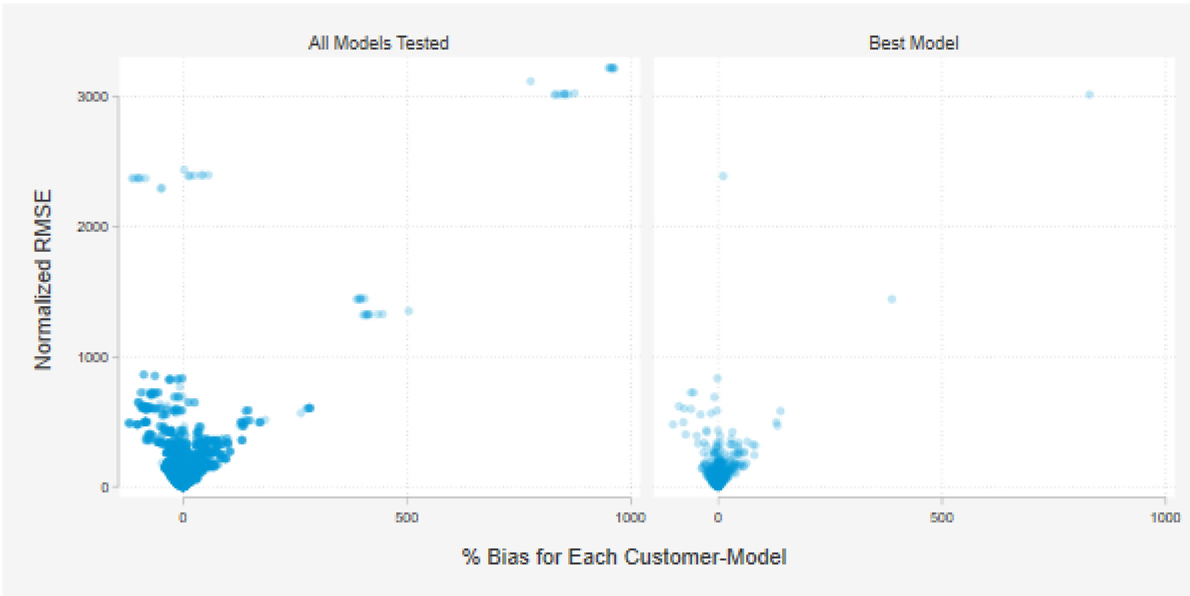

Figure 15: Model Average Error by Customer Size

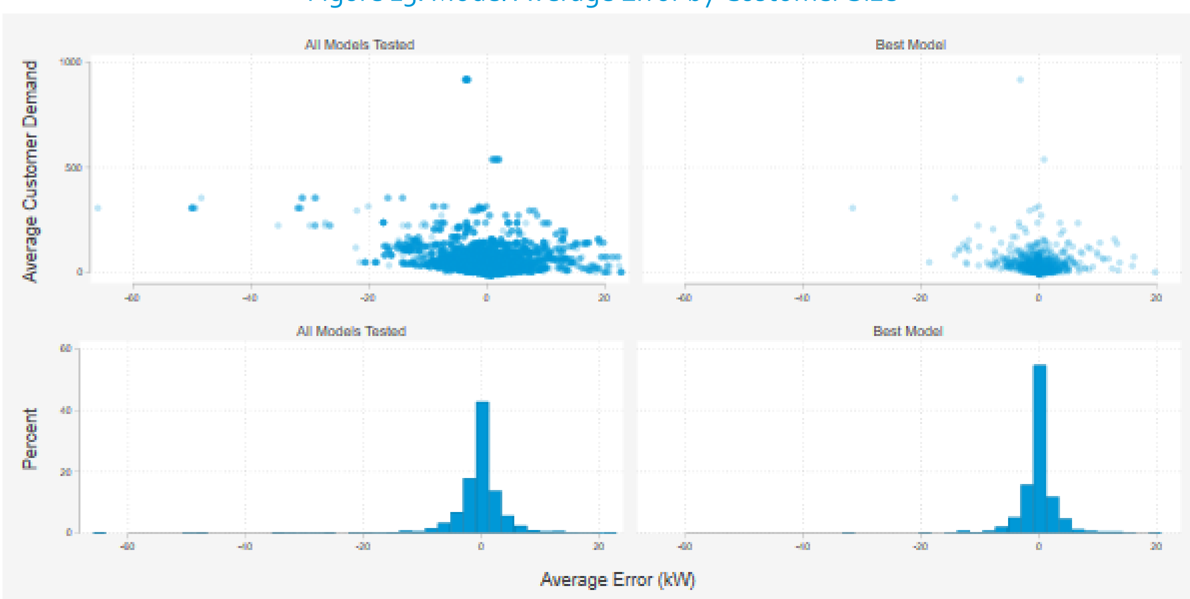

Table 30: Overall Summary Statistics for Each Model

Model	Observed kWh	Avg Error	MSE	MAPE	% Bias	Norm RMSE	R2
1	37.2	-0.2	870.9	199.0	0.0	0.8	0.8
2	37.2	-0.2	870.7	199.1	0.0	0.8	0.8
3	37.2	-0.2	871.0	199.4	0.0	0.8	0.8
4	37.2	-0.3	870.9	198.8	0.0	0.8	0.8
5	37.2	-0.2	870.8	198.9	0.0	0.8	0.8
6	37.2	-0.2	871.0	199.2	0.0	0.8	0.8
7	37.2	0.0	886.9	223.6	0.0	0.8	0.8
8	37.2	0.0	886.8	223.7	0.0	0.8	0.8
9	37.2	0.0	887.1	223.9	0.0	0.8	0.8
10	37.2	-0.1	886.2	222.7	0.0	0.8	0.8
11	37.2	-0.1	886.1	222.8	0.0	0.8	0.8
12	37.2	-0.1	886.4	223.1	0.0	0.8	0.8
13	37.2	-0.6	900.9	184.7	0.0	0.8	0.8
14	37.2	-0.2	870.1	200.1	0.0	0.8	0.8
15	37.2	-0.2	870.2	200.1	0.0	0.8	0.8

9 APPENDIX: EX ANTE SUPPORTING TABLES

EX ANTE WEATHER COMPARISON BY WEATHER STATION – AUGUST PEAK DAY

Weather Station	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
51	85.9	83.9	85.3	87.3
111	85.1	87.1	85.2	84.8
112	81.2	83.0	82.9	81.2
113	70.9	73.8	73.4	71.8
121	86.4	89.8	85.4	88.0
122	89.1	95.6	88.4	93.0
123	75.4	78.1	77.4	75.7
131	73.0	79.2	72.5	77.3
132	84.6	89.1	85.4	85.6
141	80.0	78.0	80.9	80.6
151	68.9	72.0	69.4	71.9
171	77.2	78.1	79.0	77.5
172	76.3	76.5	77.5	76.1
173	79.3	79.5	80.3	78.2
181	96.1	99.0	94.3	97.3
191	90.6	92.5	91.0	94.4
192	89.1	91.9	88.2	92.3
193	87.4	89.1	87.6	90.2
194	85.0	88.1	84.3	88.3
195	84.2	87.5	82.4	88.9

COMPARISON OF PY 2018 AND PY 2019 EX ANTE AVERAGE REFERENCE LOAD PREDICTIONS

Day Type	SCE 1-in-2		SCE 1-in-10		CAISO 1-in-2		CAISO 1-in-10	
	PY19	PY18	PY19	PY18	PY19	PY18	PY19	PY18
January Peak Day	11.6	13.2	12.0	13.2	11.3	13.2	12.1	13.2
February Peak Day	11.2	25.0	17.0	25.0	11.3	25.0	11.2	25.0
March Peak Day	15.7	15.1	24.4	15.3	15.5	15.1	24.9	15.3
April Peak Day	25.1	30.4	31.1	31.7	27.1	30.4	30.1	31.7
May Peak Day	28.2	37.0	34.1	39.0	31.5	38.9	34.1	39.8
June Peak Day	35.0	44.7	36.1	46.9	36.0	46.3	36.3	47.1
July Peak Day	35.3	44.2	34.5	46.2	34.8	45.6	36.1	46.3
August Peak Day	35.6	45.5	35.1	47.7	35.6	46.1	36.5	48.5
September Peak Day	33.7	32.6	35.1	34.5	33.1	34.4	36.3	34.7
October Peak Day	27.5	25.8	29.3	27.2	30.0	25.6	32.9	28.2
November Peak Day	18.2	16.3	21.9	17.2	14.1	16.2	21.9	16.3
December Peak Day	12.1	13.9	14.3	13.9	11.0	13.9	14.3	13.9