Demand Side Analytics
DATA DRIVEN RESEARCH AND INSIGHTS

REPORT

April 1, 2022

2021 SCE Agricultural & Pumping Interruptible Demand Response Evaluation

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

Prepared for Southern California Edison

By:

Adriana Ciccone
Michael Jehl
Josh Bode
Demand Side Analytics

CALMAC Study ID: SCE0466

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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, a signal is sent to a switch installed on customer pumps and other agricultural loads. Events can be called for CAISO Emergencies, SCE load reduction, 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. 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. Event participation included 964 enrolled customers for the only event of 2021. For this event day, where all participating customers are dispatched, the program provided an average of 28.77 MW (59.6%) of load shed. Including only the full event hours (6 pm to 8 pm), the aggregate impact was 36.12 MW (74.7%).

Table 1: Ex Post Impacts – All Event Hours vs Full Event Hours

Date	Group	# Dispatched	Average Customer (kW)				% Impact	Agg. Impact (MW)
			Reference	Observed	Impact	95% CI		
7/9/2021 (5:50pm to 8:54pm)	All Hours	964	50.09	20.25	29.84	29.46 – 30.22	59.6	28.77
	Full Hours	964	50.15	12.69	37.47	37.09 – 37.85	74.7	36.12

The event in PY2021 was called for system reliability conditions and as such, does not start and end on the top of the hour. To better reflect the program capability, the majority of tables in this report, such as Table 2, shows results for full dispatch hours only; that is, when the program was in place for the full 60 minutes, excluding partial hours.For the full event hours, the majority of impacts came from the Big Creek/Ventura LCA, which delivered 30.55MW of the 36.12MW in the full hours of the event. This was due the large number of customers in the LCA – 825 of the 964 participants. This is in contrast to the Outside LA Basin LCA where customers were larger – with an average reference load of nearly 68kW and per customer impact of 58.04 kW – but due to the small group size, only delivered an aggregate impact of 2.67MW. The participants in the LA Basin provided significantly lower per-customer impacts than the average participant.

Table 2: Ex Post Impacts by LCA – Full Hours

LCA	# Dispatched	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Reference	Observed	Impact	95% CI		
Outside LA Basin	46	67.85	9.81	58.04	55.99 – 60.09	85.5	2.67
LA Basin	93	42.82	11.63	31.19	30.06 – 32.32	72.8	2.90
Big Creek/Ventura	825	49.99	12.96	37.03	36.62 – 37.44	74.1	30.55
All	**964**	**50.15**	**12.69**	**37.47**	**37.09 – 37.85**	**74.7**	**36.12**

As shown in Table 3, AP-I enrollment is projected to decrease from the 964 participants enrolled on the 2021 event day to a constant 934 participants for the next ten years, pending any program changes. SCE recently received approval for proposed program changes, such as temporary exemption from the prohibited resources policy, suspension of the reliability cap, and year-round open enrollment. The current enrollment forecast reflects a similar trend to new enrollments received during the 2020 April window. The proposed changes may impact the number of new enrollments received, however the additional interest has not been quantified and is not factored into this forecast.

Table 3: AP-I Ex Ante Enrollment Forecast

Program/Portfolio	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
Portfolio	934	934	934	934	934	934	934	934	934	934	934
Program	934	934	934	934	934	934	934	934	934	934	934

AP-I impacts are determined by the percent of installed switches being successfully dispatched. Over the ex ante forecast horizon, the switch paging success rate is expected to grow as shown in Table 4, with additional investment in upgrading switches and improving the paging network during this time.

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

Year	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
Switch Success Rate (%)	75.0	75.6	76.3	76.9	77.6	78.2	78.8	79.5	80.1	80.8	81.4

As enrollment stays constant and the switch paging success rate increases over the next ten years, aggregate August Peak Day impacts will increase over time, ranging from 29.94MW in 2022 (SCE 1-in-10) to 32.80MW in 2032 (CAISO 1-in-10). In general, 1-in-10 weather conditions produce nearly the same impacts as 1-in-2. 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 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. Second, nearly 80% of customers enrolled in this program are mapped to SCE's weather station 51. 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.

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

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2022	30.08	29.94	30.13	30.22
2023	30.34	30.19	30.39	30.48
2024	30.59	30.45	30.65	30.74
2025	30.85	30.70	30.90	31.00
2026	31.11	30.96	31.16	31.26
2027	31.36	31.21	31.42	31.51
2028	31.62	31.47	31.67	31.77
2029	31.88	31.72	31.93	32.03
2030	32.13	31.98	32.19	32.29
2031	32.39	32.24	32.44	32.55
2032	32.65	32.49	32.70	32.80

[1] More detail on the weather associated with the ex ante scenarios can be found in Appendix 9

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. A higher-than-average number of customers de-enrolled from the program in PY2021, likely as a response to the frequent dispatch in summer 2020. There were 15 new customers who enrolled on the program this year, but the total number of customers on the program dropped to 964 in 2021, as the number of de-enrollments was higher than the number of new participants. This year, the only event called was on July 9th from 5:50-8:54 PM for reliability reasons. Customers received a monthly bill credit in exchange for their participation.

The 2021 season experienced one AP-I event dispatched territory-wide compared to the 9 distinct events in the 2020 event season dispatched by blocks. The decrease this year is likely due to the lack of extreme weather events. The reliability event of 2021 was also unique in that it took place on July 9, which is earlier in the summer than events called in recent years.

2.1 KEY RESEARCH QUESTIONS

The PY2021 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 2021? 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? Moreover, how well do these reductions align with ex-post results and prior ex-ante forecasts?
- What concrete steps can be undertaken to improve program performance?

2.2 PROGRAM DESCRIPTION

AP-I is a longstanding agricultural demand response program where, in exchange for a monthly bill credit, customers agree to participate in DR events 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. As part of future plans for the AP-I program, SCE will increase the number of available dispatch hours per season and the number of events per month to align with the Baseline Interruptible Program[2].

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. This year was consistent with this format, with one total reliability event, but the timing was unique in that the event took place in July.

2.3 PARTICIPANT CHARACTERISTICS

964 customers participated in the full dispatch event on July 9th. Table 7 summarizes the key characteristics of customers participating in the full dispatch event. Geographically, the majority are in the Ventura LCA, which encompasses the southern end of the agriculturally productive Central Valley. Most customers tend to be moderately sized, with their non-event, summer peak demand falling between 20kW and 200kW.

[2] Per Decision D21-12-015

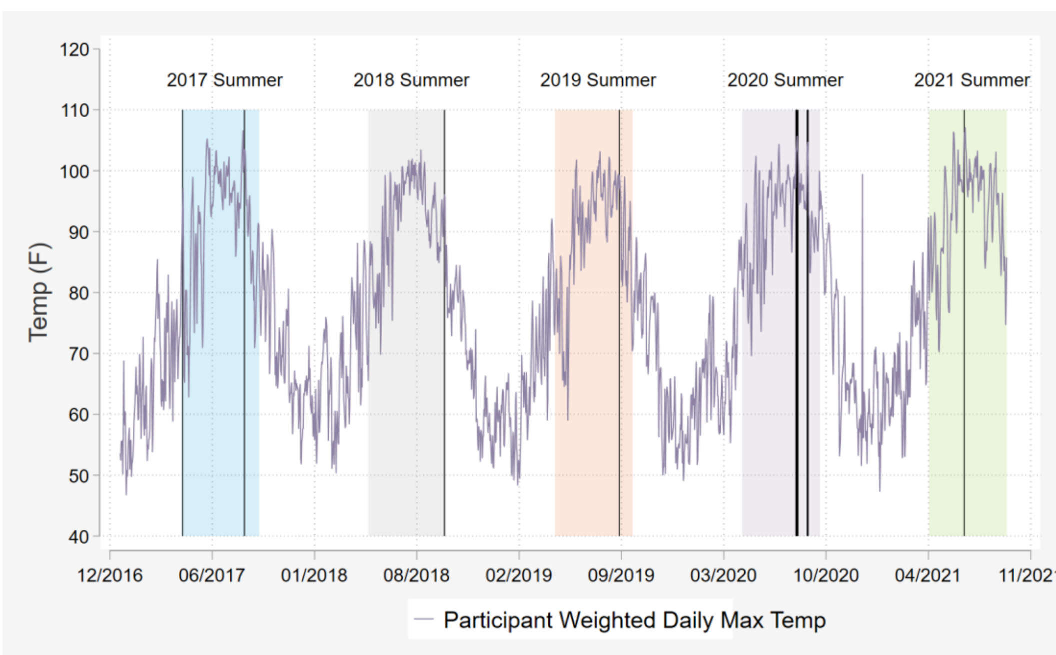
Table 7: Participant Characteristics on 7/9/2021 Event

Category	Sub Category	Customer Count 7/9
All	All	964
AutoDR	Auto DR	1
	No Auto DR	963
LCA	Big Creek/Ventura	825
	LA Basin	93
	Outside LA Basin	46
Size	20-200kW	813
	20kW or Lower	90
	Greater than 200kW	61
Zone	Remainder of System	928
	South Orange County	13
	South of Lugo	23

2.4 2021 EVENT CONDITIONS

Historically, AP-I events have been called in August and September. In 2019, the only AP-I event was called on the 2019 system peak day on September 4th. In 2020, events occurred during periods of extreme, sustained heat, with maximum daily temperatures during event days ranging from 101.2 to 105.4° F. In 2021, the maximum daily temperature on the event day was 105.95° F. Figure 1 below shows participant-weighted daily maximum temperature with shaded areas to mark summer months and vertical black lines to denote event days. The position of the vertical black line on July 9th, 2021, shows this year's event took place much earlier in the summer than in previous years.

Figure 1: Historic AP-I Events and Weather Trends



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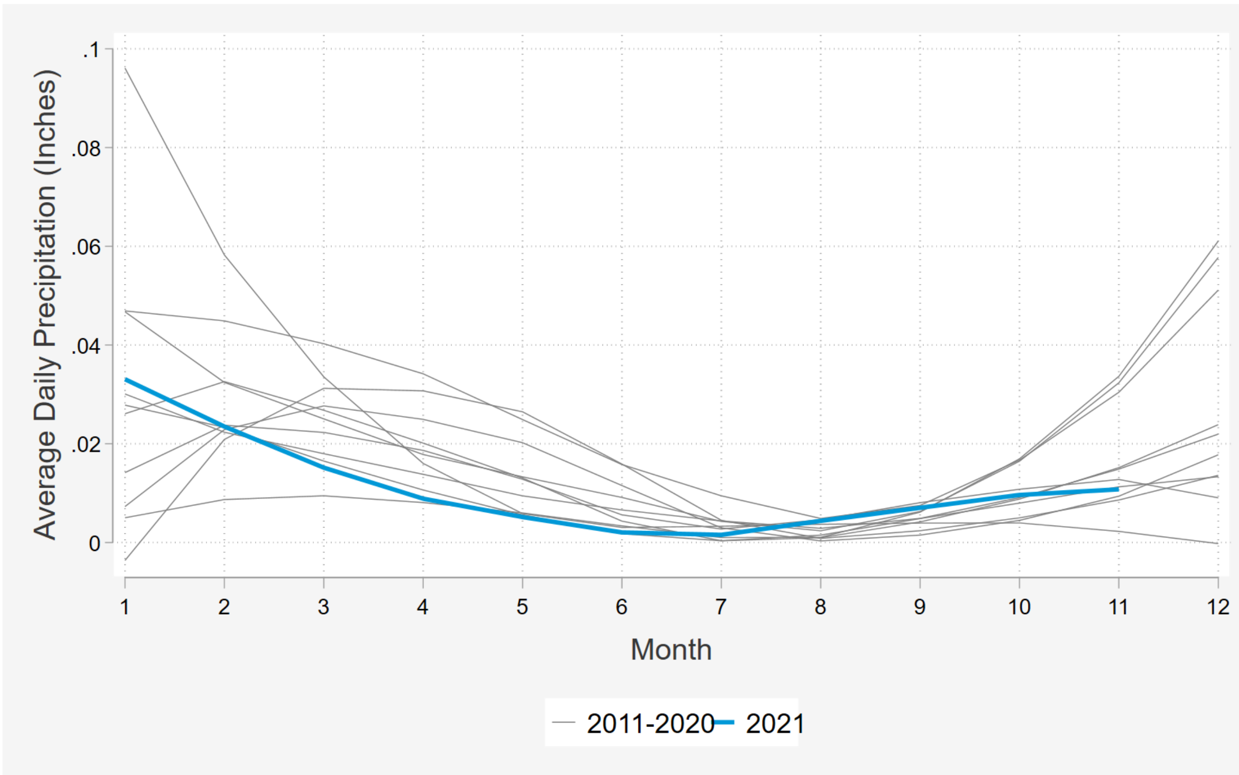
The event in 2021 occurred during a period of extreme drought. Figure 2 below shows historic precipitation trends in Bakersfield for the last ten years. Each grey line represents a single year from 2011 to 2020, while the blue line shows the observed average rainfall for 2021. Overall precipitation in 2021 was lower than most of the previous ten years, and average daily precipitation was lowest on the days leading up the event on July 9.

Figure 2: Historic Precipitation Trends



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.

There are currently 964 customers enrolled in the program, which is lower than in PY2020. A higher-than-average number of customers de-enrolled from the program, likely as a response to the frequent dispatch in summer 2020. Since 2019, the AP-I program has been working to improve switch paging success to customers through the inspection and replacement of legacy switches on participant's pump circuits, which continues to improve program performance. SCE has been replacing switches with new ones that uses the same radio system as the Summer Discount Plan (SDP) Program.

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 – slightly fewer than 1,000 participants.
2. Data included in the analysis	The analysis focuses on PY 2021 load, weather, and precipitation data for all agricultural customers, including approximately slightly fewer than 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. This analysis assessed synthetic control aggregated profiles as well as individual customer regressions for participants to evaluate ex post impacts.
4. Model selection	The final individual customer regression model is identified based on out-of-sample metrics for bias and fit. The process relies on splitting the dataset into training and testing data. The models are developed using the training data and applied, out-of-sample, to the testing data. For each of models specified, we produce standard metrics for bias and goodness of fit. The best model is identified by first narrowing the candidate models to the three with the least bias and then selecting the model with the highest precision.
5. Segmentation of impact results	The results were segmented by: ▪ Local Capacity Area ▪ Customer Size ▪ SCE SubLAP, and ▪ Customers with and without enabling technology. The main segment categories are building blocks. They are designed to ensure segment-level results add up to the total and to enable production of ex-ante impacts, including busbar level results.

The method to evaluate ex ante impacts for the AP-I program is very similar to the ex post analysis: ex ante reference loads use individual customer regression models that incorporate variables for weather and seasonality and apply them to the ex ante 1-in-2 and 1-in-10 weather forecasts. Impacts are related to the overall switch paging success rate – because 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. Because the effects of the COVID-19 pandemic did not influence agricultural loads, using data from 2020 does not affect the results.
2. Process for producing ex-ante impacts	The key steps were: ▪ Estimate the relationship between load without DR and weather conditions for each segment using data for current mix of participants. ▪ Predict reference loads for 1-in-2 and 1-in-10 ex-ante conditions. ▪ Rely on SCE's forecasted switch paging success rate. On circuits with a functional switch, load drops to zero after dispatch. ▪ Combine the ex-ante reference loads, switch paging success rate, and enrollment forecasts for each segment. ▪ Aggregate to produce overall ex-ante load impacts
3. Accounting for changes in the participant mix	Some change is expected in the customer mix over the ex ante forecast horizon. The biggest drivers of change will be the change in switch paging success rate.

3.1 OVERVIEW OF EVALUATION METHOD SELECTED

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

Ex Post Model

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

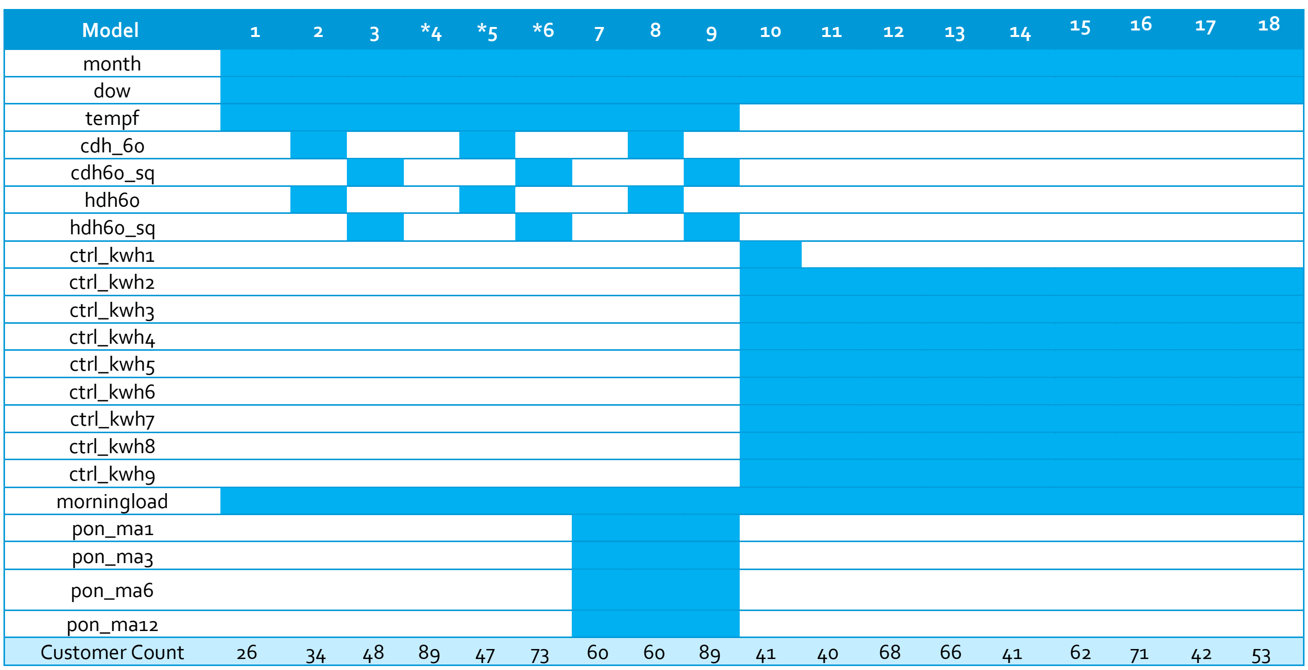
Eighteen models were tested, including last year's preferred model. The best model for each customer was then used to predict ex post loads on the event days. Table 10 shows the definitions of each variable included in at least one model, while Figure 3 summarizes which variables were included in each regression, as well as the number of customers that used each model as their final ex post model. 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*, *dow*, *ctrl_kWh*, and *morningload*. This year, the evaluation team included lagged precipitation variables in some of the models. Specifically, the team used moving average percent of normal levels of precipitation to capture the effects of drought on agricultural loads.

Table 10: Model Variables for Testing

Model Term	Description
month	Month (1-12)
dow	Day of week
tempf	Temperature
cdh_60	Cooling degree hours – base 60
cdh60_sq	CDH squared
hdh60	Heating degree hours – base 60
hdh60_sq	HDH squared
ctrl_kwh	Synthetic controls are aggregated profiles of non-participants that are included in a regression. Nine separate segmentation strategies were tested in this evaluation. The segmentation strategies included customer solar status, industry, SubLAP, and load characteristics, such as bins of annual consumption, load factor, and clusters of hourly load shapes and monthly consumption patterns
morningload	Average electricity consumption during the second half of the morning
pon_ma	Percent of normal moving average precipitation. Different moving averages, including 1-month, 3-month, 6-month and 12-month, were tested

Figure 3 shows which models included each variable listed above, as well as the number of customers for whom a given model was their best model, based on out of sample testing.

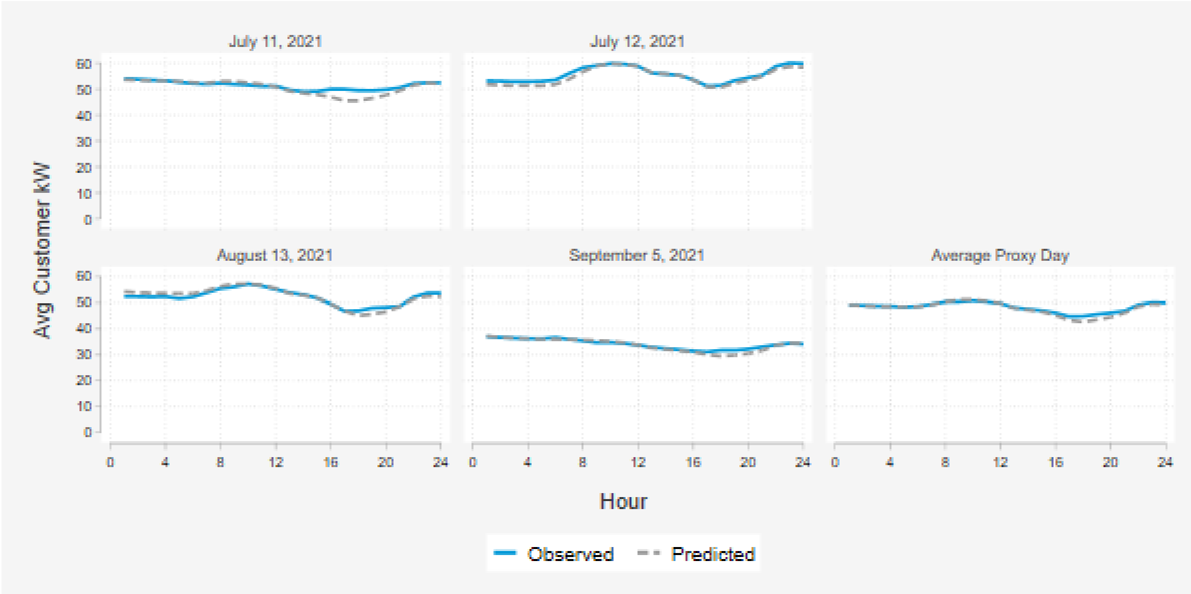
Figure 3: Model Specifications Tested



*These models include interaction terms between month, day of week, etc. on the right hand side of the specification.

Figure 4 shows the predicted loads for each selected proxy day. The proxy days closely resemble normal days by month, but there is some variability. The models that perform best on proxy days are weighted on summer weekdays during peak hours. 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 4: Out of Sample Predictions on Proxy Days

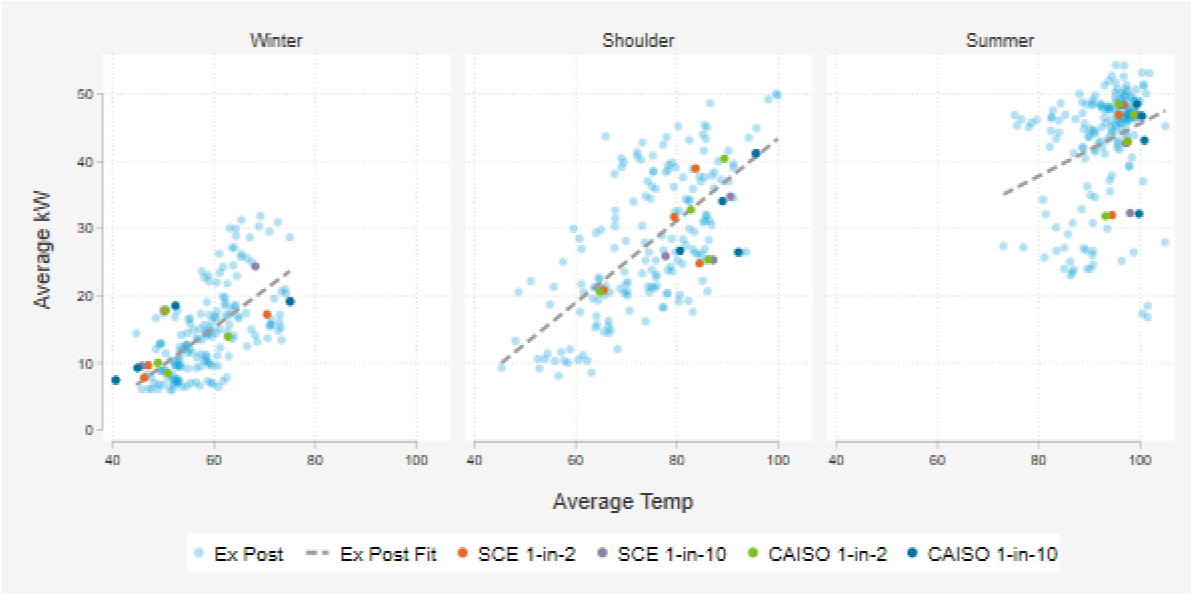


Ex Ante Reference Load Model

For AP-I, the relationship between ex post and ex ante is relatively straightforward. Because impacts are modeled solely as a function of the switch paging success rate forecast – provided by SCE – the focus of ex ante modeling is to estimate unbiased reference loads. To do this, the evaluation team took the best-performing models from ex post and removed any variable that does not have a corresponding metric in ex ante – such as day of week, synthetic control profiles, or lagged precipitation. 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 September 30, 2021 and who were assumed to be representative of future ex ante impacts.

Figure 5 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 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 5: Comparison of Ex Post and Ex Ante Reference Loads



4 EX POST RESULTS

This section summarizes ex post results for the 2021 season event day. Because PY2021 event dispatch does not perfectly align with full hours, we report both the overall results for all event hours and for full event hours in the table below. Table 11 shows the impacts for all event and full event hours on the one event day. To better assess customer response and program performance, we report results for only full event hours in the remaining ex post tables.

4.1 OVERALL RESULTS

The AP-I program delivered 28.77MW of load reduction, or 59.6% of the reference load. Excluding partial hours, the program delivered just over 36MW, or a 75% impact. Per-customer impacts were approximately 29.8kW and were statistically significant.

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

Date	Group	# Dispatched	Average Customer (kW)				% Impact	Agg. Impact (MW)
			Reference	Observed	Impact	95% CI		
7/9/2021 (5:50pm to 8:54pm)	All Hours	964	50.09	20.25	29.84	29.46 – 30.22	59.6	28.77
	Full Hours	964	50.15	12.69	37.47	37.09 – 37.85	74.7	36.12

4.2 RESULTS BY CATEGORY

The majority of impacts came from the Big Creek/Ventura LCA, which delivered 30.55MW of the 36.12MW in the full hours of the event. This was due the large number of customers in the LCA – 825 of the 964 participants. This is in contrast to the Outside LA Basin LCA where customers were larger – with an average reference load of over 67kW and per customer impact of 58.04 kW – but due to the small group size, only delivered an aggregate impact of 2.67MW. The participants in the LA Basin provided lower per-customer impacts than the average participant.

Table 12: Ex Post Impacts by LCA

LCA	# Dispatched	Average Customer (kW)				% Impact	Agg. Impact (MW)
		Reference	Observed	Impact	95% CI		
Outside LA Basin	46	67.85	9.81	58.04	55.99 – 60.09	85.5	2.67
LA Basin	93	42.82	11.63	31.19	30.06 – 32.32	72.8	2.90
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All*	**964**	**50.15**	**12.69**	**37.47**	**37.09 – 37.85**	**74.7**	**36.12**

** 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 [redacted] of load reduction during the full event hours. This represents [redacted] of the total load shed, despite the 36 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 13: Ex Post Impacts by Zone

Zone	# Dispatched	Average Customer (kW) Reference	Observed	Impact	95% CI	% Impact	Agg. Impact (MW)
South Orange County	13	[redacted]					
South of Lugo	23	[redacted]					
Remainder of System	928	50.42	12.60	37.82	37.43 – 38.21	75.0	35.10
All*	**964**	**50.15**	**12.69**	**37.47**	**37.09 - 37.85**	**74.7**	**36.12**

** 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. 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 14: Ex Post Impacts by Customer Size

Size	# Dispatched	Average Customer (kW) Reference	Observed	Impact	95% CI	% Impact	Agg. Impact (MW)
20kW or Lower	90	1.05	0.18	0.87	0.73 - 1.01	82.8	0.08
20-200kW	813	45.25	10.71	34.55	34.17 - 34.92	76.3	28.09
Greater than 200kW	61	187.92	57.53	130.39	127.03 - 133.76	69.4	7.95
All*	**964**	**50.15**	**12.69**	**37.47**	**37.09 - 37.85**	**74.7**	**36.12**

** 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*

[redacted]

Table 15: Ex Post Impacts by AutoDR Status on the Average Event Day

AutoDR Status	# Dispatched	Average Customer (kW) Reference	Observed	Impact	95% CI	% Impact	Agg. Impact (MW)
Auto DR	[redacted]						
No Auto DR	[redacted]						
All*	**964**	**50.15**	**12.69**	**37.47**	**37.09 - 37.85**	**74.7**	**36.12**

** 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

Last year, event participation ranged from 986 to 1,010 enrolled accounts for nine events, all of which were called due to CAISO emergencies. The average reference load was 42.53kW and an impact of 78% yielded 33.09MW, or

33.16kW per customer. Table 16 compares the average event in 2020 to the one event in 2021. In 2021, per-customer and aggregate impacts were higher, although the reference load was higher as well. However, the 2020 results may be a better representation of program capability, since they show program performance over multiple events, rather than in 2021 where there was only one event to represent the entire event season. Percent impacts were actually smaller in 2021, indicating that customers dropped a lower percentage of their load on average than they did in 2020. At the event level, the full dispatch event aggregate impacts in 2021 outperformed the average 2020 event. Differences between the years may also be explained by the timing of the event. In the past, agricultural loads tend to decline starting in September as growing seasons come to an end for particular crops. As there were multiple September events last year, the average PY2020 impact may be depressed as a result of this seasonality. And of course, the effects of incremental years of drought may also explain increases in pumping loads in PY2021 compared to PY2020.

Table 16: Comparison of 2020 and 2021 Ex Post Impacts

Date	Group	Full Hour Event Window	# Enrolled	Average Customer (kW)				% Impact	Agg. Impact (MW)
				Ref. Load	Obs. Load	Impact	95% CI		
2020 Average Event	Full Hours	6-8 PM	998	42.53	9.38	33.16	32.52 - 33.79	78.0	33.09
2021 Event	Full Hours	6-8 PM	964	50.15	12.69	37.47	37.09 - 37.85	74.7	36.12

4.4 COVID-19 IMPACTS

Overall, as in 2020, COVID-19 did not have a significant impact on AP-I customer loads. Since the agricultural businesses that participate in the AP-I program were essential businesses, their operations were likely not as affected by the pandemic as other industries, such as retail or schools.

4.5 KEY FINDINGS

AP-I delivered over 36MW of load relief during the full hours of event dispatch. The largest concentrations of impacts and participants were in the Ventura LCA. Per-customer impacts were higher in 2021 than they were in the 2020 events. This could be attributable to several factors:

1. **Event timing:** The single event in 2021 occurred in July, which is earlier in the season than in previous years, and reference loads were higher than projected. Higher pumping loads result in more curtailable load, and therefore larger impacts.
2. **Drought Conditions:** As summarized in Figure 2, 2021 was a year of substantial drought for AP-I customers. Because AP-I is a pumping program, less rainfall typically means that customers will need to pump from wells to meet their irrigation and other needs. As a result, the program saw higher reference loads and therefore higher impacts when customers dropped their load.
3. **Impact by Size:** More customers from the 20-200kW and Greater than 200kW customer size groups responded in 2021 than in 2020. The number of customers from the 20kW or Lower size group decreased significantly in 2021, resulting in a greater share of curtailable load coming from the larger customers and, in turn, a higher aggregate impact.

5 SWITCH PAGING SUCCESS RATE ANALYSIS

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

Switch paging success is calculated as follows:

1. Determine which customers were operating their pumps in the hour prior to the event start. A customer is assumed to be operating if their load in the hour prior to the event is at least 5% of their 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 low to mid 80% range, but has declined over time. The PY2021 event is highlighted in blue.

Table 17: Reported Historical Switch Paging Success

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

This year, the paging success rate was 70.4%, which is considerably lower than in previous years. According to the AP-I program manager, the 2021 rate likely went down due to maintenance work orders being delayed as a result of personnel changes and resource constraints at the IOU. The 2021 switch paging success results are shown in further detail in Table 18.

Table 18: 2021 Switch Paging Success

Date	Not Operating	Did Not Respond	Responded	Paging Success %
July 9, 2021	382	164	390	70.4

Paging success was highest in the Outside LA Basin LCA, but only slightly higher than in Big Creek/Ventura, with 71.4% and 71.3% of operating switches responding to the dispatches, respectively. The switch paging success rate in Big Creek/Ventura was slightly lower than last year, which was 74.3%. As in 2020, the LA Basin area had the lowest success rate of the three LCAs, although this result should be interpreted with some caution, since the total number of participants in that LCA is low. Although the Outside LA Basin LCA is the smallest of the three, the switch paging success rate in that LCA improved again from the previous year, going from 69.9% in 2020 to 71.4% in the 2021 season.

Table 19: Paging Success by LCA for the 2021 Event

LCA	Not Operating	Did Not Respond	Responded	Paging Success %
Big Creek/Ventura	325	139	346	71.3
LA Basin	41	17	24	58.5
Outside LA Basin	16	8	20	71.4

Figure 6 shows the distribution of switch paging success for the single event in 2021. In this map, [redacted]

Figure 6: Geographic Distribution of Paging Success – 7/9/2021

[IMAGE REDACTED]

The contribution of each switch paging group to overall program impacts is summarized in Figure 7. 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.

Figure 7: Response by Switch Paging Success

[IMAGE REDACTED]

6 EX ANTE RESULTS

This section summarizes the results of the ex ante impact estimation process for AP-I from 2022 to 2032. SCE provided two key drivers of the ex ante impact forecast: the expected number of participants enrolled in the program and the forecast of switch paging success rate.

6.1 ENROLLMENT AND SWITCH PAGING FORECAST

AP-I enrollment is forecasted to decrease from the 964 participants enrolled on the 2021 event day to a constant 934 participants for the next ten years, pending any program changes. SCE's recently accepted program changes, once implemented, may impact the number of new enrollments received. Accepted program changes include a temporary 1% increase in the reliability cap and year-round open enrollment. The additional interest has not been quantified and is not factored into this forecast.

Table 20: AP-I Ex Ante Enrollment Forecast

Program/Portfolio	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
Portfolio	934	934	934	934	934	934	934	934	934	934	934
Program	934	934	934	934	934	934	934	934	934	934	934

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

Year	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
Switch Success Rate (%)	75.0	75.6	76.3	76.9	77.6	78.2	78.8	79.5	80.1	80.8	81.4

6.2 OVERALL RESULTS

As enrollment stays constant and the switch paging success rate increases over the next ten years, aggregate August Peak Day impacts will increase, ranging from 29.94MW in 2022 (SCE 1-in-10) to 32.80MW in 2032 (CAISO 1-in-10). 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 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. Second, nearly 80% of customers enrolled in this program are mapped to SCE's weather station 51. That station's ex ante weather forecast is slightly lower for the August Peak Day SCE 1-in-10 than 1-in-2[3]. 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.

[3] More detail on the weather associated with the ex ante scenarios can be found in Appendix 9

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

Forecast Year	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
2022	30.08	29.94	30.13	30.22
2023	30.34	30.19	30.39	30.48
2024	30.59	30.45	30.65	30.74
2025	30.85	30.70	30.90	31.00
2026	31.11	30.96	31.16	31.26
2027	31.36	31.21	31.42	31.51
2028	31.62	31.47	31.67	31.77
2029	31.88	31.72	31.93	32.03
2030	32.13	31.98	32.19	32.29
2031	32.39	32.24	32.44	32.55
2032	32.65	32.49	32.70	32.80

Load impacts also vary by month, as seasonal changes in farming intensity and precipitation impact pumping requirements. Table 23 shows the average customer impacts for a monthly peak day in 2032, assuming an 81.4% switch paging success rate. Impacts are highest in May through August and typically peak in July.

Table 23: AP-I Average Customer Portfolio Ex Ante Impacts (kW) - By Monthly Peak Day in 2032

Day Type	SCE 1-in-2	SCE 1-in-10	CAISO 1-in-2	CAISO 1-in-10
January Peak Day	7.86	7.81	8.19	7.57
February Peak Day	14.50	19.87	14.56	15.11
March Peak Day	17.00	21.11	16.76	21.78
April Peak Day	25.86	28.32	26.73	27.77
May Peak Day	31.73	33.55	32.92	33.55
June Peak Day	38.23	38.13	38.28	38.07
July Peak Day	39.43	39.40	39.53	39.49
August Peak Day	34.95	34.79	35.01	35.12
September Peak Day	26.07	26.33	25.96	26.24
October Peak Day	20.24	20.63	20.71	21.57
November Peak Day	14.03	15.63	11.35	15.63
December Peak Day	6.39	6.09	6.95	6.09

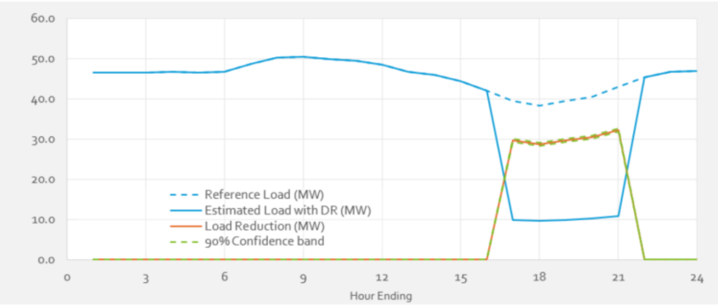
Figure 8: Aggregate Ex Ante Impacts for SCE 1-in-2 Typical Event Day

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 Peak Day
Forecast Year	2022
Portfolio Level	Program
Switch Paging Success %	Forecast
Switch Paging Success Used	75%

Table 2: Event day information

Event start	4:00 PM
Event end	9:00 PM
Total sites	934
Event window temperature (F)	97.6
Event window load reduction (MW)	30.1
% Load reduction (Event window)	75.0%
Redaction Information	Public



Hour Ending	Reference Load (MW)	Estimated Load with	Load Reduction (MW)	% Load Reduction	Avg Temp (°F, Site-Weighted)	Uncertainty-Adjusted Impact - Percentiles 5th	10th	30th	50th	70th	90th	95th	Standard Error	T-Statistic
1	46.56	46.56	0.00	0.00	83.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
2	46.44	46.44	0.00	0.00	81.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
3	46.46	46.46	0.00	0.00	78.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
4	46.61	46.61	0.00	0.00	76.30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
5	46.43	46.43	0.00	0.00	74.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
6	46.70	46.70	0.00	0.00	73.52	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
7	48.58	48.58	0.00	0.00	71.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
8	50.15	50.15	0.00	0.00	70.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
9	50.41	50.41	0.00	0.00	73.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
10	49.88	49.88	0.00	0.00	78.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
11	49.43	49.43	0.00	0.00	83.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
12	48.56	48.56	0.00	0.00	87.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
13	46.74	46.74	0.00	0.00	90.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
14	45.90	45.90	0.00	0.00	93.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
15	44.43	44.43	0.00	0.00	95.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
16	41.99	41.99	0.00	0.00	96.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
17	39.46	9.87	29.60	0.75	98.33	29.21	29.30	29.48	29.60	29.72	29.90	29.98	0.23	126.17
18	38.24	9.56	28.68	0.75	98.75	28.29	28.38	28.56	28.68	28.81	28.99	29.08	0.24	120.30
19	39.42	9.85	29.56	0.75	98.64	29.16	29.25	29.43	29.56	29.69	29.88	29.97	0.25	119.78
20	40.44	10.11	30.33	0.75	97.29	29.93	30.02	30.20	30.33	30.46	30.65	30.74	0.25	123.17
21	42.95	10.74	32.22	0.75	94.84	31.82	31.90	32.09	32.22	32.34	32.53	32.62	0.24	132.17
22	45.29	45.29	0.00	0.00	89.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
23	46.71	46.71	0.00	0.00	86.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
24	46.92	46.92	0.00	0.00	84.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Daily	**Reference Load (MWh)**	**Load with DR (MWh)**	**Energy Savings (MWh)**	**% Change**	**Daily Avg Temp (°F)**	**Uncertainty adjusted impact - Percentiles 5th**	**10th**	**30th**	**50th**	**70th**	**90th**	**95th**	**Standard Error**	**T-statistic**
	1094.69	944.30	150.39	13.7%	85.79	148.40	148.84	149.76	150.39	151.03	151.94	152.38	1.21	124.31

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 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 Peak Day by LCA (MW)

LCA	Weather Year	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
Big Creek/Ventura	CAISO 1-in-10	25.23	25.44	25.66	25.87	26.09	26.30	26.52	26.73	26.95	27.16	27.38
	CAISO 1-in-2	25.14	25.36	25.57	25.78	26.00	26.21	26.43	26.64	26.86	27.07	27.29
	SCE 1-in-10	24.96	25.17	25.38	25.60	25.81	26.02	26.23	26.45	26.66	26.87	27.09
	SCE 1-in-2	25.08	25.30	25.51	25.73	25.94	26.16	26.37	26.58	26.80	27.01	27.23
LA Basin	CAISO 1-in-10	2.98	3.01	3.04	3.06	3.09	3.11	3.14	3.16	3.19	3.21	3.24
	CAISO 1-in-2	2.95	2.97	3.00	3.02	3.05	3.07	3.10	3.12	3.15	3.18	3.20
	SCE 1-in-10	2.99	3.02	3.04	3.07	3.09	3.12	3.14	3.17	3.20	3.22	3.25
	SCE 1-in-2	2.97	2.99	3.02	3.04	3.07	3.09	3.12	3.14	3.17	3.20	3.22
Outside LA Basin	CAISO 1-in-10	2.01	2.03	2.05	2.07	2.08	2.10	2.12	2.13	2.15	2.17	2.19
	CAISO 1-in-2	2.04	2.06	2.08	2.09	2.11	2.13	2.15	2.16	2.18	2.20	2.22
	SCE 1-in-10	1.99	2.01	2.02	2.04	2.06	2.07	2.09	2.11	2.12	2.14	2.16
	SCE 1-in-2	2.03	2.04	2.06	2.08	2.10	2.11	2.13	2.15	2.16	2.18	2.20

6.4 COMPARISON TO PRIOR YEAR

Compared to PY2020, enrollment is projected to stabilize over the next 10 program years rather than increase, pending any program changes. Paging success is still projected to increase, but at a slower rate than predicted in 2020. This change is reflective of the decrease in switch success between 2020 and 2021, which considers the program's continued efforts to improve switch technology for customers while understanding the impact of de-enrolled customers.

Table 25: PY2021 Ex Ante Forecast Elements

Forecast Year	Enrollment		Paging Success Rate	
	PY2020	PY2021	PY2020	PY2021
2021	1,067	…	76.9%	…
2022	1,153	934	77.5%	75.0%
2023	1,239	934	78.1%	75.6%
2024	1,325	934	78.8%	76.3%
2025	1,411	934	79.4%	76.9%
2026	1,497	934	80.1%	77.6%
2027	1,583	934	80.7%	78.2%
2028	1,669	934	81.3%	78.8%
2029	1,755	934	82.0%	79.5%
2030	1,841	934	82.6%	80.1%
2031	1,927	934	83.3%	80.8%
2032	…	934	…	81.4%

6.5 EX POST TO EX ANTE COMPARISON

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

The weather projections are consistently higher in the ex post events than our ex ante forecast for July, and most similar to the 1-in-10 CAISO scenarios. Despite the projected improvement in the switch success rate, both per-customer and aggregate impacts are forecast to be lower in 2022 due to the forecasted enrollment decreases. On July Monthly Peak Days, the ex ante projected impacts are more in line with ex post impacts, but in most cases slightly lower than the impact achieved in the 2021 event season. Because the ex ante projection incorporates multiple years of reference loads, the impact of drought on the 2021 event day is tempered by previous years of data[4]. On Typical Event Days, the per-customer and aggregate ex ante projections are considerably lower than the ex post results, as we would expect.

Table 26: Ex Post Compared to Ex Ante – July 2021 vs July Monthly Peak Day and Typical Event Day in 2022

Day Type	# Dispatched	Event Hour Avg Temp	Daily Max Temp	Avg Cust Ref (kW)	Switch Paging Success %	% Impact	Avg Cust Impact (kW)	Agg Impact (MW)
Ex Ante: July Monthly Peak Day CAISO 1-in-10 (4:00 - 9:00PM)	934	99.34	100.66	48.51	75.0	75.0	36.38	33.98
Ex Ante: July Monthly Peak Day CAISO 1-in-2 (4:00 - 9:00PM)	934	95.70	97.04	48.56	75.0	75.0	36.42	34.02
Ex Ante: July Monthly Peak Day SCE 1-in-10 (4:00 - 9:00PM)	934	96.36	97.49	48.40	75.0	75.0	36.30	33.90
Ex Ante: July Monthly Peak Day SCE 1-in-2 (4:00 - 9:00PM)	934	96.79	97.89	48.44	75.0	75.0	36.33	33.93
Ex Ante: Typical Event Day CAISO 1-in-10 (4:00 - 9:00PM)	934	100.10	101.57	42.97	75.0	75.0	32.23	30.10
Ex Ante: Typical Event Day CAISO 1-in-2 (4:00 - 9:00PM)	934	96.27	97.67	42.98	75.0	75.0	32.24	30.11
Ex Ante: Typical Event Day SCE 1-in-10 (4:00 - 9:00PM)	934	97.82	99.39	42.89	75.0	75.0	32.17	30.05
Ex Ante: Typical Event Day SCE 1-in-2 (4:00 - 9:00PM)	934	96.16	97.59	42.92	75.0	75.0	32.19	30.07
Ex Post: 7/9/2021 (5:50pm to 8:54pm)	964	105.60	105.95	50.15	70.2	74.7	37.47	36.12

[4] More detail on ex ante reference loads can be found in Appendix 9

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 and a decrease in paging success results in a lower ex ante load forecast. With continued investment in paging switches and network improvements, the AP-I program will grow over time to produce higher load reductions during periods of grid stress.
- Paging success declined year-over-year, driven by delays associated with staffing and other constraints related to the COVID-19 pandemic.
  - ✓ As was discussed in more detail last year, paging success for a single event represents a combination of multiple types of failures – signal receipt failures and equipment failures – both of which can be either permanent or temporary. While permanent failures, such as equipment exceeding its operating lifespan, should be corrected, temporary failures, such as a signal not being received for a single event, may never be eradicated.
  - ✓ In DSA's analysis of the multiple PY2020 AP-I events, both temporary and pervasive paging failures were evident. As only one event occurred in PY2021, it is impossible to determine whether the decline in paging success rate was driven more by one failure type or the other.
- 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 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.
- The COVID-19 pandemic did not cause significant impacts to program performance.
  - ✓ Agricultural business were deemed to be essential and their operations were likely not as affected by the pandemic as other industries such as retail or education.

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 27. 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 27: 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 9 illustrates the process.

Figure 9: Model Selection and Validation

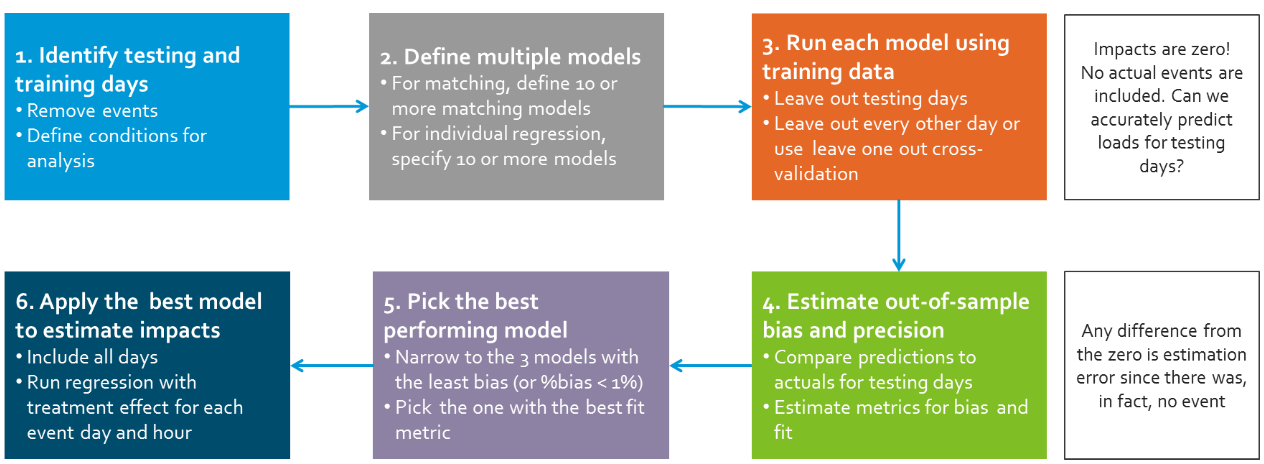


Table 28 summarizes the metrics for bias and precision we employ. Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error describes the relative magnitude and direction of the bias. A negative value indicates a tendency 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 28: Definition of Bias and Precision Metrics

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

The results for AP-I out of sample testing are shown in Figure 10 and Figure 11. 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 10: Model Bias and Error on Proxy Events

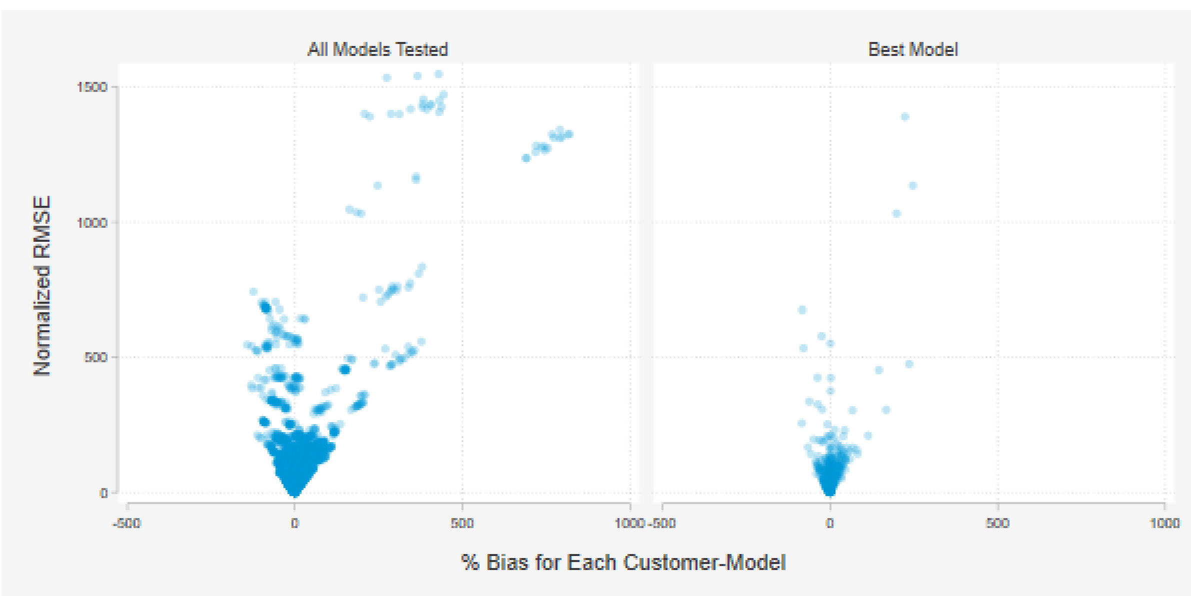


Figure 11: Model Average Error by Customer Size

9 APPENDIX: EX ANTE SUPPORTING TABLES

EX ANTE WEATHER COMPARISON BY WEATHER STATION – AUGUST PEAK DAY

The following table shows the ex ante weather forecast for the August Peak Day by scenario and weather station. Nearly 80% of AP-I customers are mapped to weather station 51. The highest temperatures are projected to occur around weather station 181, in the LA Basin LCA, while the lowest temperatures are anticipated in weather station 113 and 151, which are both in the Big Creek/Ventura LCA.

Table 29: August Monthly Peak Day Ex Ante Weather by SCE Weather Station

Weather Station	SCE		CAISO	
	1-in-2	1-in-10	1-in-2	1-in-10
51	85.9	83.9	85.3	87.3
111	85.0	87.0	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
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	92.4	91.0	94.4
192	89.1	91.9	88.2	92.3
193	87.4	89.1	87.5	90.2
195	84.2	87.5	82.4	88.9

COMPARISON OF PY 2020 AND PY 2021 EX ANTE AVERAGE REFERENCE LOAD PREDICTIONS

The following table compares the per-customer reference loads by weather scenario and monthly peak day for 2020 and 2021. Reference loads are consistently lower in the 2021 forecast.

Table 30: Per-Customer Ex Ante Reference Load Comparison

Day Type	SCE 1-in-2		SCE 1-in-10		CAISO 1-in-2		CAISO 1-in-10	
	PY20	PY21	PY20	PY21	PY20	PY21	PY20	PY21
January Peak Day	13.0	7.86	12.5	7.81	13.5	8.19	12.4	7.57
February Peak Day	14.1	14.50	19.0	19.87	14.0	14.56	13.9	15.11
March Peak Day	19.0	17.00	26.0	21.11	18.6	16.76	26.0	21.78
April Peak Day	27.0	25.86	32.1	28.32	28.7	26.73	32.3	27.77
May Peak Day	33.5	31.73	38.0	33.55	35.8	32.92	38.0	33.55
June Peak Day	41.5	38.23	43.9	38.13	42.3	38.28	44.3	38.07
July Peak Day	43.9	39.43	44.2	39.40	43.4	39.53	45.9	39.49
August Peak Day	43.3	34.95	43.4	34.79	43.2	35.01	45.1	35.12
September Peak Day	38.8	26.07	40.1	26.33	39.0	25.96	41.4	26.24
October Peak Day	28.8	20.24	30.8	20.63	30.9	20.71	34.0	21.57
November Peak Day	17.6	14.03	19.8	15.63	14.5	11.35	19.8	15.63
December Peak Day	8.9	6.39	8.1	6.09	9.4	6.95	8.7	6.09

10 APPENDIX: NET VERSUS DELIVERED LOADS

Comparison of Ex Post Impacts per NEM Customer using Net vs. Delivered Loads

In PY2021, there were 27 customers using net energy metering (NEM) out of the 964 dispatched participants. The following tables show the ex post impacts using net and delivered loads. The observed loads dip into the negative using net loads because the customer's solar system is producing more energy than it uses and the excess is sent back to the electrical grid. Net loads more accurately represent the load per NEM customer and result in a +0.14MW difference in aggregated impacts across the 27 NEM customers. The following graphs compare the average impact per Net Energy Metered (NEM) customer using net versus delivered loads.

Table 31: Average Impact per Customer, Net vs. Delivered Loads (Full Hours)

Date	Group	# Dispatched	Average Customer (kW) Reference	Observed	Impact	95% CI	% Impact	Agg. Impact (MW)
7/9/2021 (5:50pm to 8:54pm)	NEM Customer: Net Loads	27	40.47	-1.36	41.83	39.42 – 44.25	105.0	1.13
	All Customers: Net Loads	964	50.15	12.69	37.47	37.15 – 37.78	75.0	36.12
	NEM Customer: Delivered Loads	27	41.78	4.97	36.81	34.42 – 39.21	88.0	0.99
	All Customers: Delivered Loads	964	50.10	12.86	37.24	36.92 – 37.56	74.0	35.90

Figure 18: Average Impact per Customer using Net Loads

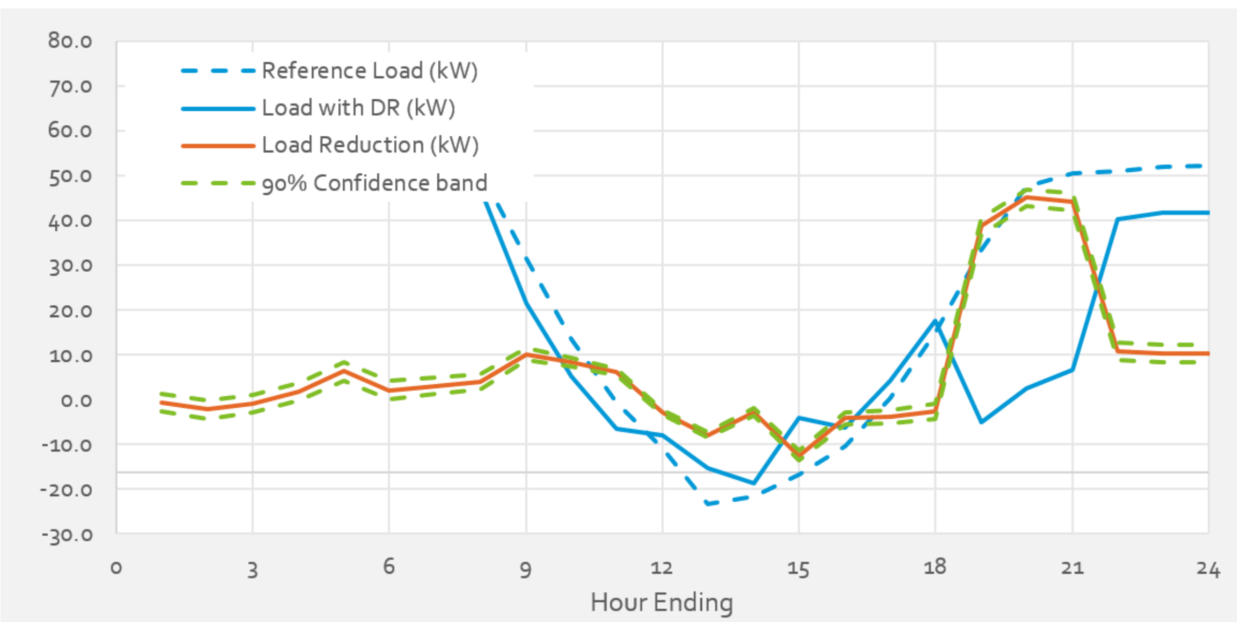


Figure 19: Average Impact per Customer using Delivered Loads