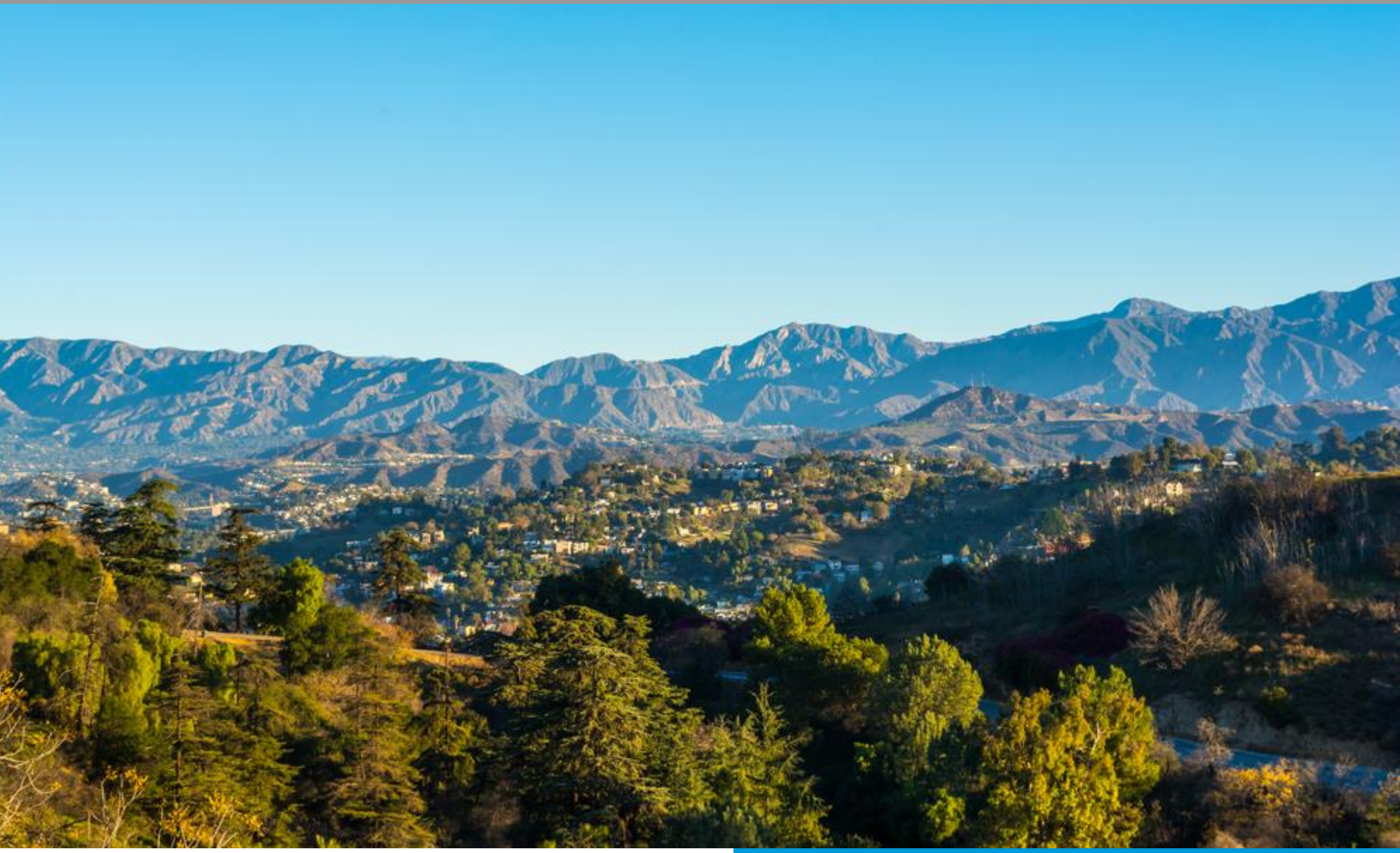
REPORT

CALMAC ID: SCE0454

# 2020 SCE Agricultural & Pumping Interruptible Demand Response Evaluation



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

**April 1, 2021**

**Prepared for Southern California Edison**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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 load. 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 ranged from 986 to 1,010 enrolled accounts for full dispatch events, with an average of 998 customers participating in full dispatch events. For the average full dispatch event day, where all participating customers are dispatched, the program provided an average of 29.44 MW (69.2%) of load shed. Including only the full event hours (6 pm to 8 pm), the aggregate impacts was 33.09 MW (78%).

Table 1: Ex Post Impacts – Average Event Day

| Date | Group | # Dispatched | Average Customer (kW) | | | | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|---|
| | | | Reference | Observed | Impact | 95% CI | | |
| Average Event Day | All Hours | 998 | 42.65 | 13.15 | 29.50 | 28.87 - 30.13 | 69.2 | 29.44 |
| | Full Hours | 998 | 42.53 | 9.38 | 33.16 | 32.52 - 33.79 | 78.0 | 33.09 |

Many events in PY2020 were called for system emergency conditions and as such, do 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 hour excluding partial hours.

Table 2: Ex Post Impacts by Date – Full Event Hours Only

| Date | # Dispatched | Average Customer (kW) | | | | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|
| | | Reference | Observed | Impact | 95% CI | | |
| 8/14/2020 (05:10 - 08:35PM) | 986 | 47.76 | 10.60 | 37.16 | 36.31 - 38.01 | 77.8 | 36.64 |
| 8/15/2020 (03:00 - 07:45PM) | 986 | 46.97 | 11.35 | 35.62 | 34.73 - 36.51 | 75.8 | 35.12 |
| 8/16/2020 (05:40 - 07:25PM) | 986 | 42.86 | 9.47 | 33.40 | 32.48 - 34.32 | 77.9 | 32.93 |
| 8/17/2020 (03:10 - 07:40PM) | 916 | 47.37 | 10.16 | 37.22 | 36.34 - 38.10 | 78.6 | 34.09 |
| 8/18/2020 (01:40 - 07:25PM) | 990 | 49.23 | 10.88 | 38.34 | 37.49 - 39.20 | 77.9 | 37.96 |
| 9/5/2020 (05:30 - 08:25PM) | 1,010 | 37.31 | 8.16 | 29.15 | 28.21 -30.09 | 78.1 | 29.44 |
| 9/6/2020 (04:40 - 08:23PM) | 1,010 | 33.90 | 7.25 | 26.66 | 25.68 -27.64 | 78.6 | 26.92 |
| 9/7/2020 (04:05 - 07:33PM) | 308 | 27.11 | 4.21 | 22.90 | 21.75 - 24.06 | 84.5 | 7.05 |

** On 8/17 there were two separate dispatches, including one from 4:29pm-5:50pm. Because this event did not have a single full hour for dispatch, it is omitted in this table.*

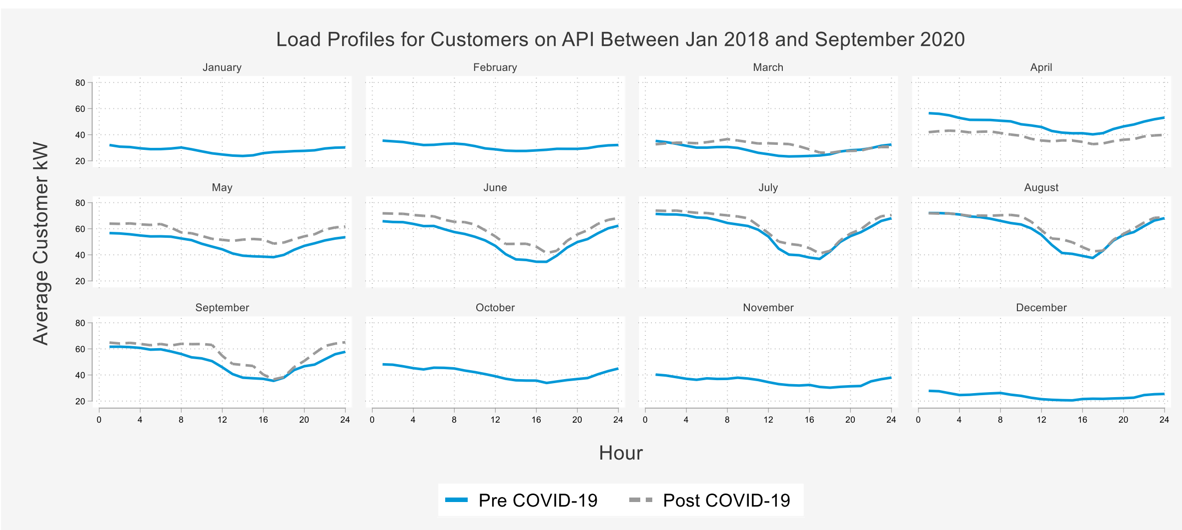
For the full event hours, the majority of impacts came from the Big Creek/Ventura LCA, which delivered 27.21MW of the 33.09MW in the full hours of the event. This was due the large number of customers in the LCA – 865 of the 998 participants. This is in contrast to the Outside LA Basin LCA where customers were larger – with an average reference load of over 77kW and per customer impact of 56.94 kW – but due to the small group size, only delivered an aggregate impact of 2.16MW. The participants in the LA Basin provided slightly higher per-customer impacts than the average participant.

Table 3: Ex Post Impacts by LCA – Full Hours

| LCA | # Dispatched | Average Customer (kW) | | | | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|
| | | Reference | Observed | Impact | 95% CI | | |
| Outside LA Basin | 38 | 77.12 | 20.18 | 56.94 | 53.23 - 60.65 | 73.8 | 2.16 |
| LA Basin | 95 | 47.17 | 8.06 | 39.12 | 36.24 - 42.00 | 82.9 | 3.72 |
| Big Creek/Ventura | 865 | 40.51 | 9.06 | 31.46 | 30.82 - 32.09 | 77.6 | 27.21 |
| **All** | **998** | **42.53** | **9.38** | **33.16** | **32.52 - 33.79** | **78.0** | **33.09** |

The evaluation team also investigated the potential impacts of COVID-19 on program performance during the 2020 event season. Figure 7 shows the pre-COVID and post-COVID load profiles for AP-I customers between January 2018 and September 2020, with the post-COVID period beginning in March 2020. Overall, COVID-19 did not have a significant impact on AP-I customer loads: customer load profiles are marginally higher in the post-COVID period, however given variability in year-to-year pumping needs, this is likely not attributable to the effects of the pandemic. 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.

Figure 1: COVID-19 Impacts on Loads




AP-I enrollment is expected to increase from the 1,010 participants enrolled on September 6th, 2020 to 1,067 in August of 2021 and to 1,152 by August of 2022. This increase is attributable to SCE's efforts to enroll new customers in the program.

Table 4: AP-I Ex Ante Enrollment Forecast

| Program/Portfolio | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | 1,067 | 1,153 | 1,239 | 1,325 | 1,411 | 1,497 | 1,583 | 1,669 | 1,755 | 1,841 | 1,927 |
| Program | 1,067 | 1,153 | 1,239 | 1,325 | 1,411 | 1,497 | 1,583 | 1,669 | 1,755 | 1,841 | 1,927 |

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, with additional investment in upgrading switches and improving the paging network during this time.

Table 5: AP-I Ex Ante Switch Paging Success Rate Forecast

| Year | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Switch Success Rate (%) | 76.9 | 77.5 | 78.1 | 78.8 | 79.4 | 80.1 | 80.7 | 81.3 | 82.0 | 82.6 | 83.3 |

As enrollment increases and the switch paging success rate increases over the next ten years, aggregate August Peak Day impacts will range from 34.67MW in 2021 to 68.15MW in 2031. 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 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. Regardless of weather, the aggregate impacts are quite similar across weather scenarios, with the minimal variation across ex ante weather scenarios.

Table 6: 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 |
|---|---|---|---|---|
| 2021 | 35.03 | 34.11 | 34.91 | 36.12 |
| 2022 | 38.16 | 37.17 | 38.04 | 39.36 |
| 2023 | 41.35 | 40.27 | 41.22 | 42.64 |
| 2024 | 44.58 | 43.42 | 44.44 | 45.97 |
| 2025 | 47.86 | 46.61 | 47.71 | 49.36 |
| 2026 | 51.19 | 49.85 | 51.02 | 52.79 |
| 2027 | 54.56 | 53.14 | 54.39 | 56.27 |
| 2028 | 57.98 | 56.47 | 57.80 | 59.79 |
| 2029 | 61.45 | 59.84 | 61.25 | 63.37 |
| 2030 | 64.96 | 63.27 | 64.76 | 66.99 |
| 2031 | 68.52 | 66.73 | 68.31 | 70.66 |

# 2 PROGRAM DESCRIPTION

The Agricultural and Pumping Interruptible (AP-I) program is a longstanding direct load control program for SCE's agricultural and pumping customers. During system emergencies or for measurement and evaluation purposes, SCE sends a signal to radio switches on enrolled customers' pumping and agricultural circuits, shutting them off. At the end of an event, SCE sends another signal to switch load back on, although a subset of pumps and agricultural load must be restarted manually. The program grew in PY2020, with SCE enrolling new customers via a lottery that was held in the late spring. This year, event duration ranged from less than two hours (the 8/17 event (100's blocks only) from 4:29-5:50 PM) to over five hours (the 8/18 event from 1:40-7:25 PM). For events that were dispatched to all blocks, customer participation ranged from 986 to 1,010 customers. Customers receive a monthly bill credit in exchange for their participation.

A key difference between this year's evaluation and previous program years was the number of events that were called. Extreme weather in California during the summer of 2020 resulted in significantly more AP-I events being called than the program has typically experienced. AP-I called 9 distinct events in the 2020 event season, compared to four total events in the previous three program years, from 2017-2019.

AP-I dispatches events by blocks, which correspond to A Bank regions. The 2020 season experienced nine AP-I events: six events were dispatched to all blocks while three events were dispatched to a subset of blocks. The events were also unique in that they occurred in two sets of consecutive days. The first set of event days occurred from August 14$^{th}$ to August 18$^{th}$, and the second set of events followed just over two weeks later, from September 5$^{th}$ to Septembers 7$^{th}$.

## 2.1 KEY RESEARCH QUESTIONS

The PY2020 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 2020 – 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? 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?

Due to the unique nature of the 2020 event season, this year's evaluation also explored some additional questions:

- Did impacts decrease over consecutive dispatch days?
- Did program impacts differ on weekends compared to weekdays?
- How did the ongoing COVID-19 pandemic effect 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 7.

Table 7: 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 marks a departure from this format, with nine total events, all of which were called due to CAISO emergencies.

## 2.3 PARTICIPANT CHARACTERISTICS

By the end of the 2020 event season, 1,010 customers participated in the final full dispatch events on September 5th and September 6th. Table 8 summarizes the key characteristics of customers participating in the final full dispatch event. Geographically, the majority are in the Ventura LCA, which encompasses the southern end of the agriculturally productive Central Valley. Most customers are also on the small end, with their non-event, summer peak demand falling below 200kW.

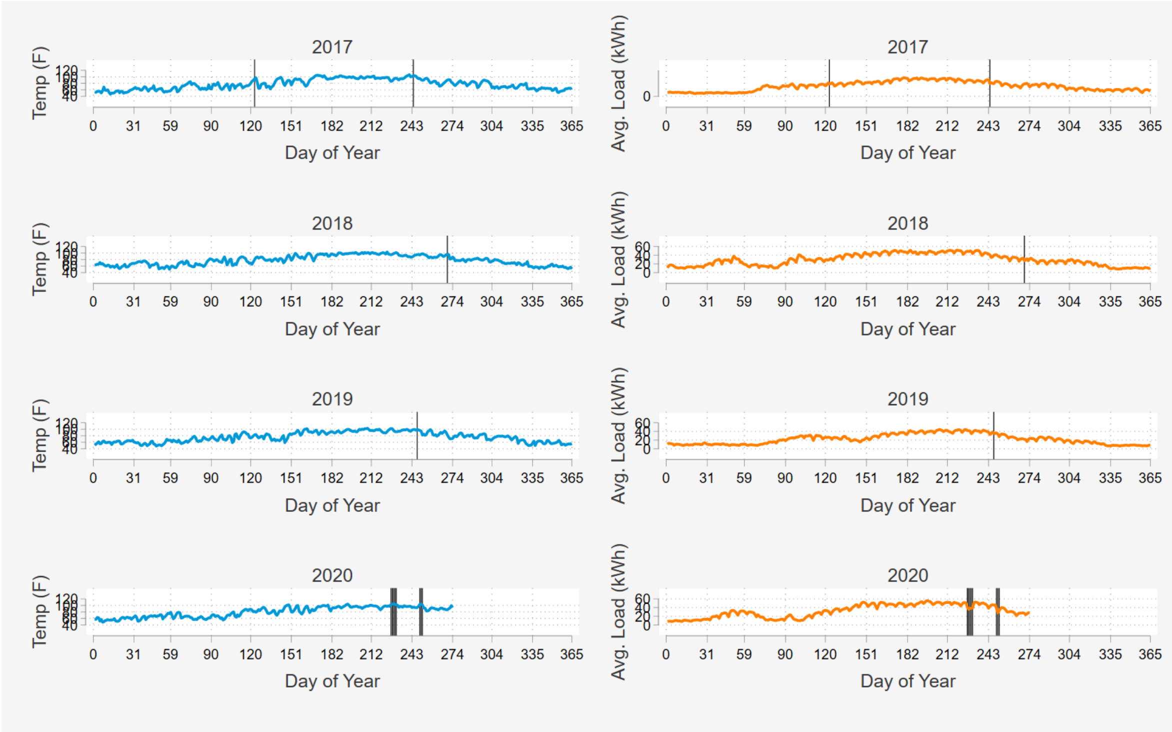
Table 8: Participant Characteristics on 8/18/2020 Event

| Category | Sub Category | Customer Count 8/18 |
|---|---|---|
| All | All | 990 |
| AutoDR | Auto DR | 1 |
| | No Auto DR | 989 |
| LCA | Big Creek/Ventura | 857 |
| | LA Basin | 95 |
| | Outside LA Basin | 38 |
| Size | 20-200kW | 635 |
| | 20kW or Lower | 304 |
| | Greater than 200kW | 51 |
| Zone | Remainder of System | 952 |
| | South Orange County | 13 |
| | South of Lugo | 25 |

## 2.4 2020 EVENT CONDITIONS

Historically, AP-I events have been called in September. In 2019, the only AP-I event was called on the 2019 system peak day on September 4th. This graphic shows participant-weighted daily maximum temperature and average daily pumping loads by year with vertical black lines to denote event days. In 2020, events occurred during periods of extreme, sustained heat. In 2020, maximum daily temperatures during event days ranged from 101.2 to 105.4° F. In the past three program years, the maximum daily temperature during an event was only above 100° F once in four events, on September 1st, 2017. On the right side, the distinct seasonality of agricultural loads is visible with high loads during June, July, and August, and a drop off in September.

Figure 2: Historic Event Day Conditions




## 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 1,017 customers enrolled in the program, which is higher than the 2019 evaluation because of new customer enrollment throughout the 2020 event season. 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 9 and Table 10 summarize our approach for the ex-post and ex-ante analysis, respectively.

Table 9: 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 2020 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. |
| 5. Segmentation of impact results | The results will be segmented by:<br>▪ Local Capacity Area<br>▪ Customer Size<br>▪ Dually enrolled versus non-dually enrolled customers, and<br>▪ Customers with and without enabling technology.<br>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 okW, 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 10: 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:<br>▪ Estimate the relationship between load without DR and weather conditions for each segment using data for current mix of participants.<br>▪ Predict reference loads for 1-in-2 and 1-in-10 ex-ante conditions.<br>▪ Rely on SCE's forecasted switch paging success rate. On circuits with a functional switch, load drops to zero after dispatch.<br>▪ Combine the ex-ante reference loads, switch paging success rate, and enrollment forecasts for each segment.<br>▪ 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

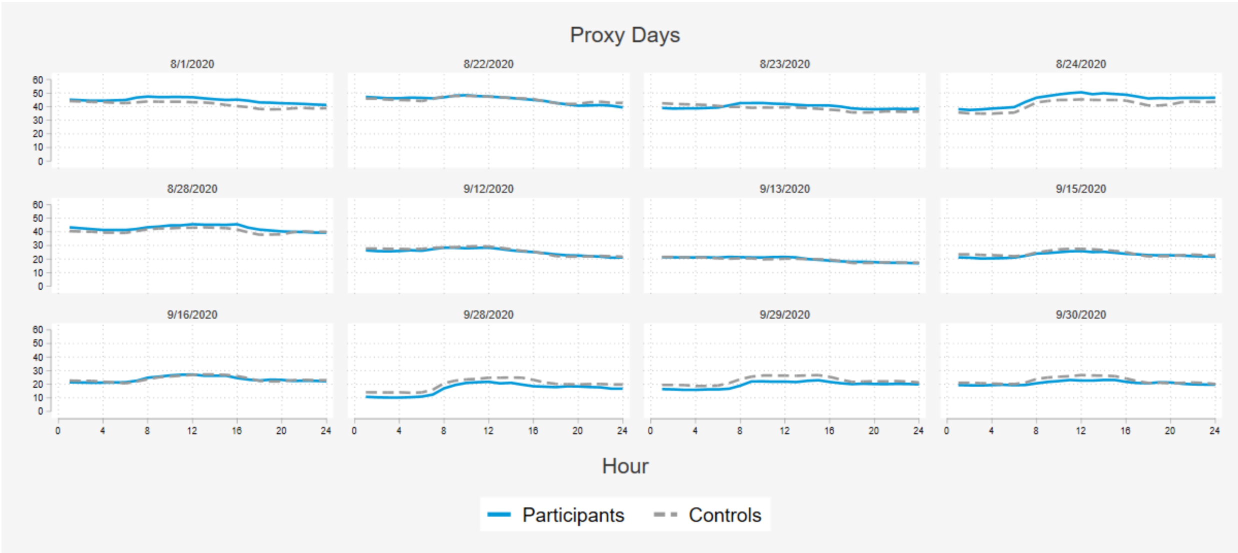
The evaluation team assessed two primary methods of constructing a counterfactual load profile – what participants would have done if they were not dispatched – for AP-I participants: a synthetic control group and individual customer regressions. More detail about these methods, including their tradeoffs, 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 panel model with fixed effects approach, using a matched control group of non-AP-I agricultural customers, and individual customer regressions that included an average profile of the matched control customers on the right hand side of the specification. The panel model performed no better than the individual customer regressions in the out of sample testing. At the same time, the fixed effects modeling 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. For some of the models, information from the matched control group was incorporated by using a variable that captured the average control load by date and hour. The results of the matching are shown in Figure 3 , which compares the average daily loads for AP-I program participants against the matched control group.

Figure 3: Matching Results of Participants and Synthetic Controls on Proxy Days




Fourteen 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 11 shows the definitions of each variable included in at least one model, while Figure 4 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*, *CDD*, *CDDsquared* and *Ctrl_kWh*.

Table 11: Model Variables for Testing

| Model Term | Description |
|---|---|
| month | Month (1-12) |
| week | Week of the year (1-52) |
| 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 |
| cdh_60 | Cooling degree hours – base 60 |
| cdh60_sq | CDH squared |
| hhd60 | Heating degree hours – base 60 |
| hhd6_sq | HDH squared |
| cdd | Cooling degree days – base 60 |
| cdd_sq | CDD squared |
| ctrl_kwh | Average kWh of the synthetic control customer group by date and hour |

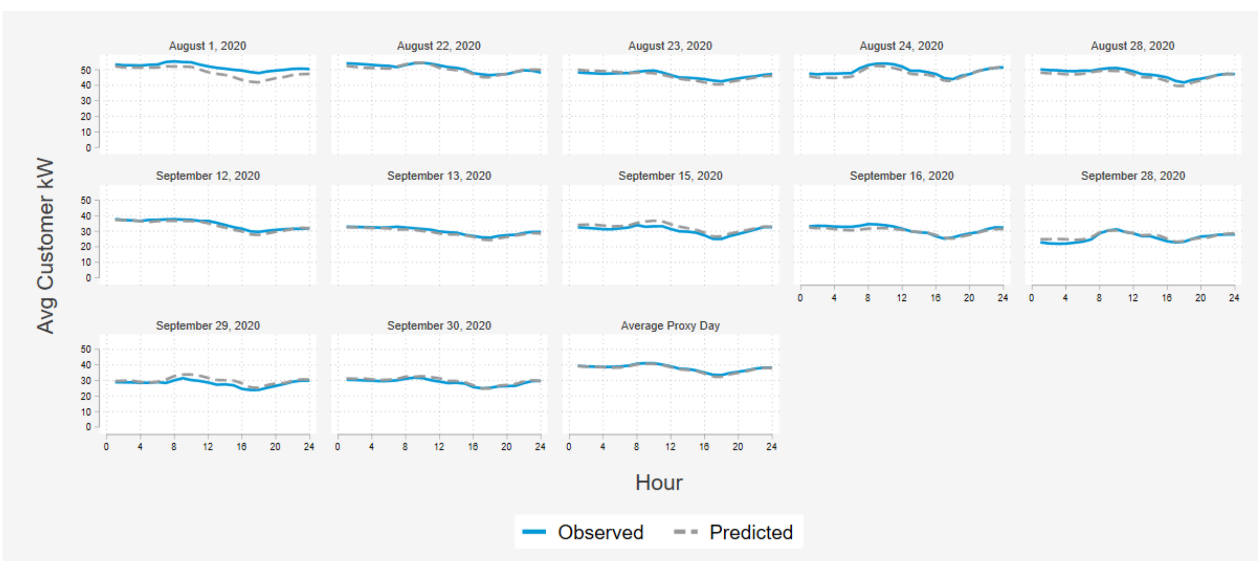
Figure 4 shows which models included each variable listed above, as well as the number of customers for whom a given model was their best model, based on out of sample testing.

Figure 4: Model Specifications Tested

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| month | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ |
| week | | | ■ | | ■ | | | ■ | | ■ | | ■ | | ■ |
| firsthalf | ■ | ■ | ■ | ■ | ■ | | | | | | | | | |
| dow | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | | | | |
| avgtemp | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | | | | |
| tempf | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | | | | |
| cdh_60 | | ■ | ■ | | | | ■ | ■ | | | | ■ | | ■ |
| cdh60_sq | | | | ■ | ■ | | | | ■ | ■ | | ■ | | ■ |
| hdh60 | | ■ | ■ | | | | ■ | ■ | | | | | | |
| hdh6_sq | | | | ■ | ■ | | | | ■ | ■ | | | | |
| cdd | | | | | | | | | | | ■ | | ■ | |
| cdd_sq | | | | | | | | | | | ■ | | ■ | |
| ctrl_kwh | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | | | ■ | ■ |
| Customer Count | 109 | 57 | 85 | 82 | 65 | 79 | 63 | 48 | 70 | 45 | 79 | 46 | 102 | 87 |

Figure 5 shows the predicted loads for each selected proxy day. More detail on the ex post modeling methodology can be found in the appendix.

Figure 5: Out of Sample Predictions on Proxy Days

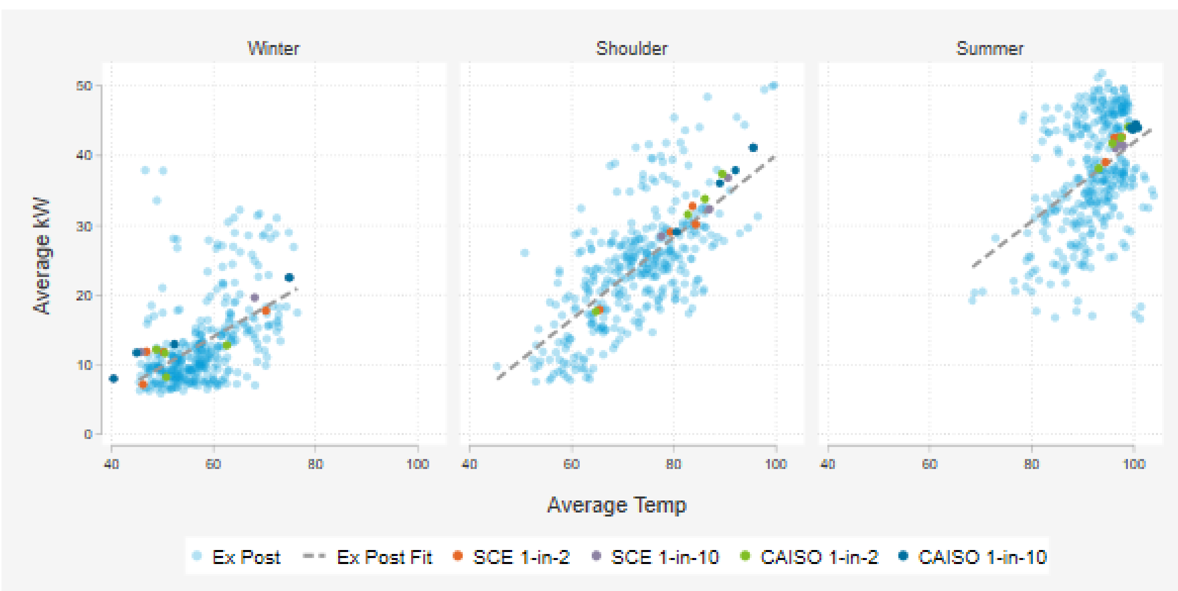


### Ex Ante Reference Load Model

For AP-I, the relationship between ex post and ex ante is relatively straightforward. Because impacts are modeled solely as a function of the switch paging success rate – 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 September 30, 2020 and who were assumed to be representative of future ex ante impacts.

Figure 6 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. While temperature and loads are correlated, this does not necessarily indicate that high temperature 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. While pumping loads are more predictable during the shoulder and summer months, winter pumping may vary more based on the variation of production activities of individual customers during the winter.

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






Demand Side Analytics
DATA DRIVEN RESEARCH AND INSIGHTS

# 4 EX POST RESULTS

This section summarizes ex post results for the 2020 season event days. Because event dispatch generally does not perfectly align with full hours, we report both the overall results for all event hours and for full event hours in the tables below. Table 12 shows the impacts for all event and full event hours on the average event day. Since there were many events during the 2020 season and the events occurred over various hourly windows, the team selected two full dispatch event days with similar event windows and durations to calculate the average event day: August 14th and September 5th. These days provide representation for the both groupings of event days that occurred in mid-August and early September. These days also represent the beginning and end of the 2020 event season, as August 14th was the first event, September 9th was the penultimate, full dispatch event, and both months where events typically occur, since seasonality plays such a large role in the AP-I program. To better assess customer response and program performance, we report results for only full event hours in the remaining ex post tables. Table 13 shows the ex post results for each event across all event hours, while Table 14 shows the results for each event for only full event hours.

## 4.1 OVERALL RESULTS

On average, the AP-I program delivered 29.44MW of load reduction, or 69.2% of the reference load. Excluding partial hours, the program delivered just over 33MW, or a 78% impact. Per-customer impacts were approximately 29.5kW and were statistically significant.

Table 12: Ex Post Impacts – Average Event Day

| Date | Group | # Dispatched | Average Customer (kW) | | | | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|---|
| | | | Reference | Observed | Impact | 95% CI | | |
| Average Event Day | All Hours | 998 | 42.65 | 13.15 | 29.50 | 28.87 - 30.13 | 69.2 | 29.44 |
| | Full Hours | 998 | 42.53 | 9.38 | 33.16 | 32.52 - 33.79 | 78.0 | 33.09 |

Table 13: Ex Post Impacts by Date – All Event Hours

| Date | # Dispatched | Average Customer (kW) | | | | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|
| | | Reference | Observed | Impact | 95% CI | | |
| 8/14/2020 (05:10 - 08:35PM) | 986 | 47.78 | 12.89 | 34.89 | 34.04 - 35.74 | 73.0 | 34.40 |
| 8/15/2020 (03:00 - 07:45PM) | 986 | 47.33 | 11.58 | 35.75 | 34.87 - 36.63 | 75.5 | 35.25 |
| 8/16/2020 (05:40 - 07:25PM) | 986 | 42.60 | 18.76 | 23.84 | 22.92 - 24.77 | 56.0 | 23.51 |
| 8/17/2020 (03:10 - 07:40PM) | 916 | 48.06 | 12.34 | 35.72 | 34.84 - 36.60 | 74.3 | 32.72 |
| 8/17/2020 (04:29 - 05:50PM) | 72 | 35.85 | 11.74 | 24.11 | 21.67 - 26.55 | 67.2 | 1.74 |
| 8/18/2020 (01:40 - 07:25PM) | 990 | 49.87 | 15.97 | 33.90 | 34.84 - 36.60 | 68.0 | 33.56 |
| 9/5/2020 (05:30 - 08:25PM) | 1,010 | 37.52 | 13.41 | 24.11 | 33.04 - 34.75 | 64.3 | 24.35 |
| 9/6/2020 (04:40 - 08:23PM) | 1,010 | 34.03 | 11.44 | 22.59 | 23.17 - 25.05 | 66.4 | 22.82 |
| 9/7/2020 (04:05 - 07:33PM) | 308 | 27.31 | 5.44 | 21.87 | 21.62 - 23.57 | 80.1 | 6.74 |

Table 14: Ex Post Impacts by Date – Full Event Hours Only

| Date | # Dispatched | Average Customer (kW) Reference | Observed | Impact | 95% CI | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|
| 8/14/2020 (05:10 - 08:35PM) | 986 | 47.76 | 10.60 | 37.16 | 36.31 - 38.01 | 77.8 | 36.64 |
| 8/15/2020 (03:00 - 07:45PM) | 986 | 46.97 | 11.35 | 35.62 | 34.73 - 36.51 | 75.8 | 35.12 |
| 8/16/2020 (05:40 - 07:25PM) | 986 | 42.86 | 9.47 | 33.40 | 32.48 - 34.32 | 77.9 | 32.93 |
| 8/17/2020 (03:10 - 07:40PM) | 916 | 47.37 | 10.16 | 37.22 | 36.34 - 38.10 | 78.6 | 34.09 |
| 8/18/2020 (01:40 - 07:25PM) | 990 | 49.23 | 10.88 | 38.34 | 37.49 - 39.20 | 77.9 | 37.96 |
| 9/5/2020 (05:30 - 08:25PM) | 1,010 | 37.31 | 8.16 | 29.15 | 28.21 - 30.09 | 78.1 | 29.44 |
| 9/6/2020 (04:40 - 08:23PM) | 1,010 | 33.90 | 7.25 | 26.66 | 25.68 - 27.64 | 78.6 | 26.92 |
| 9/7/2020 (04:05 - 07:33PM) | 308 | 27.11 | 4.21 | 22.90 | 21.75 - 24.06 | 84.5 | 7.05 |

** On 8/17 there were two separate dispatches, including one from 4:29pm-5:50pm. Because this event did not have a single full hour for dispatch, it is omitted in this table.*

## 4.2 RESULTS BY CATEGORY

The majority of impacts came from the Big Creek/Ventura LCA, which delivered 27.21MW of the 33.09MW in the full hours of the event. This was due the large number of customers in the LCA – 865 of the 998 participants. This is in contrast to the Outside LA Basin LCA where customers were larger – with an average reference load of over 77kW and per customer impact of 56.94 kW – but due to the small group size, only delivered an aggregate impact of 2.16MW. The participants in the LA Basin provided slightly higher per-customer impacts than the average participant.

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

| LCA | # Dispatched | Average Customer (kW) Reference | Observed | Impact | 95% CI | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|
| Outside LA Basin | 38 | 77.12 | 20.18 | 56.94 | 53.23 - 60.65 | 73.8 | 2.16 |
| LA Basin | 95 | 47.17 | 8.06 | 39.12 | 36.24 - 42.00 | 82.9 | 3.72 |
| Big Creek/Ventura | 865 | 40.51 | 9.06 | 31.46 | 30.82 - 32.09 | 77.6 | 27.21 |
| **All** | **998** | **42.53** | **9.38** | **33.16** | **32.52 - 33.79** | **78.0** | **33.09** |

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 38 enrolled customers in those zones being only 3.8% of the total participants. This was driven primarily by customers in [redacted], who delivered on average [redacted] kW ([redacted]) of load shed per participant.

Table 16: Ex Post Impacts by Zone on the Average Event Day

| Zone | # Dispatched | Average Customer (kW) | | | | | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|
| | | Reference | Observed | Impact | 95% CI | % Impact | |
| South Orange County | 13 | [redacted] | | | | | |
| South of Lugo | 25 | [redacted] | | | | | |
| Remainder of System | 960 | 41.91 | 9.36 | 32.55 | 31.93 - 33.17 | 77.7 | 31.24 |
| **All** | **998** | **42.53** | **9.38** | **33.16** | **32.52 - 33.79** | **78.0** | **33.09** |

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 78% 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 17: Ex Post Impacts by Customer Size on the Average Event Day

| Size | # Dispatched | Average Customer (kW) | | | | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|
| | | Reference | Observed | Impact | 95% CI | | |
| 20kW or Lower | 306 | 7.31 | 2.42 | 4.90 | 4.20 - 5.60 | 67.0 | 1.50 |
| 20-200kW | 642 | 46.58 | 10.01 | 36.57 | 35.84 - 37.30 | 78.5 | 23.46 |
| Greater than 200kW | 51 | 202.61 | 43.14 | 159.48 | 152.27 - 166.69 | 78.7 | 8.13 |
| **All** | **998** | **42.53** | **9.38** | **33.16** | **32.52 - 33.79** | **78.0** | **33.09** |

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

Table 18: Ex Post Impacts by AutoDR Status on the Average Event Day

| AutoDR Status | # Dispatched | Average Customer (kW) | | | | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|
| | | Reference | Observed | Impact | 95% CI | | |
| Auto DR | 1 | [redacted] | | | | | |
| No Auto DR | 997 | [redacted] | | | | | |
| **All** | **998** | **42.53** | **9.38** | **33.16** | **32.52 - 33.79** | **78.0** | **33.09** |

## 4.3 COMPARISON TO PRIOR YEAR

Last year, 941 customers participated in one AP-I event on September 4th, 2019 from 3:55pm to 6:44pm. The average reference load was 34.9kW and an impact of 72% yielded 23.7MW, or 25.2kW per customer. Table 19 compares the 2019 event to the 2020 average event. In 2020, per-customer and aggregate impacts were higher, although the reference load was higher as well. This could be due to switch repairs and improvements performed by SCE. The 2020 results may also be a better representation of program capability, since they show program performance over multiple events, rather than in prior years where there are only one or two events to represent the entire event season. Despite higher reference loads, percent impacts were also larger in 2020, indicating that customers dropped a higher percentage of their load on average than they did in 2019. Note that the event window in 2020 is also later in the day than the event window in 2019. At the event level, all full dispatch event aggregate impacts outperformed the 2019 event, with the lowest 2020 aggregate impact of 26.9MW, on September 6th.

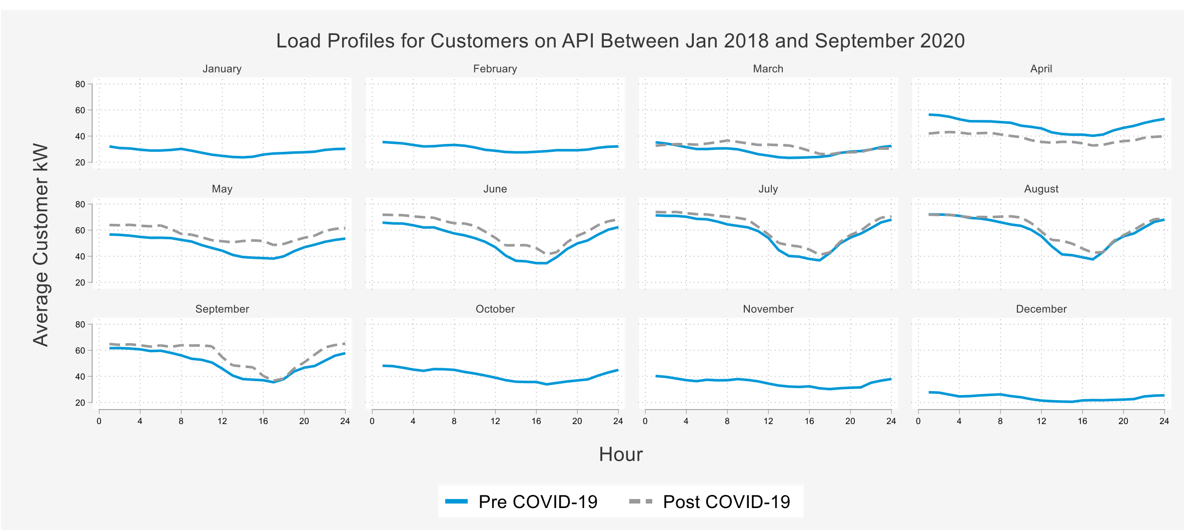
Table 19: Comparison of 2019 and 2020 Ex Post Impacts

| Date | Group | Full Hour Event Window | # Enrolled | Average Customer (kW) | | | | % Impact | Agg. Impact (MW) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Ref. Load | Obs. Load | Impact | 95% CI | | |
| 2019 Event | Full Hours | 4-6 PM | 941 | 34.9 | 9.7 | 25.2 | 12.90 - 37.47 | 72.2 | 23.7 |
| 2020 Average Event | Full Hours | 6-8 PM | 998 | 42.53 | 9.38 | 33.16 | 32.52 - 33.79 | 78.0 | 33.09 |

## 4.4 COVID-19 IMPACTS

The evaluation team also investigated the potential impacts of COVID-19 on program performance during the 2020 event season. Figure 7 shows the pre-COVID and post-COVID load profiles for AP-I customers between January 2018 and September 2020, with the post-COVID period beginning in March 2020. Overall, COVID-19 did not have a significant impact on AP-I customer loads: customer load profiles are marginally higher in the post-COVID period, however given variability in year-to-year pumping needs, this is likely not attributable to the effects of the pandemic. 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.

**Figure 7: COVID-19 Impacts on Loads**



## 4.5 KEY FINDINGS

AP-I delivered over 33MW of load relief on average during the full hours of event dispatch. The largest concentrations of impacts and participants were in the Ventura LCA. Per-customer impacts were consistently higher in 2020 than they were in the singular 2019 event. This could be attributable to several factors:

1. **Improved Switch Success:** the efforts to improve the switch paging system in 2019 and 2020 may have improved the number of customers who received the signal and therefore were able to drop irrigation loads.
2. **Extreme weather:** The extreme weather conditions of 2020 played a large role in program impacts. Low rainfall in PY2020 could have contributed to larger pumping loads that resulted in higher impacts when customers dropped their load.
3. **Event timing:** In 2020, six of the nine total events occurred in mid-August, when pumping loads are higher, compared to prior years where events typically occur in September. Higher pumping loads result in more curtailable load, and therefore larger impacts.
4. **Random chance:** the confidence interval for the 2020 events include the per-customer impact from 2019.

# 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. PY2020 events are highlighted in blue.

Table 20: 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% |
| 14-Aug-20 | 503 | 73.40% |

| Date | # Operating | Paging Success % |
|---|---|---|
| 15-Aug-20 | 533 | 72.20% |
| 16-Aug-20 | 455 | 72.70% |
| 17-Aug-20 | 547 | 73.90% |
| 18-Aug-20 | 557 | 71.50% |
| 5-Sep-20 | 399 | 75.40% |
| 6-Sep-20 | 353 | 70.50% |
| 7-Sep-20 | 111 | 74.80% |

In 2020, switch paging success was higher on average than it was in 2019, ranging from to 70.5% to 75.4%. The switch paging success results are shown in further detail in Table 21. The success rate was consistent throughout the event season. Switch paging success does not appear to be significantly affected by seasonality or weekday vs. weekend events. Additionally, the success rate does not appear to drop off over consecutive event days.

Table 21: 2020 Switch Paging Success By Event

| Date | Not Operating | Did Not Respond | Responded | Paging Success % |
|---|---|---|---|---|
| August 14, 2020 | 481 | 134 | 369 | 73.4 |
| August 15, 2020 | 451 | 148 | 385 | 72.2 |
| August 16, 2020 | 529 | 124 | 331 | 72.7 |
| August 17, 2020 | 439 | 143 | 404 | 73.9 |
| August 18, 2020 | 431 | 159 | 398 | 71.5 |
| September 5, 2020 | 582 | 98 | 301 | 75.4 |
| September 6, 2020 | 628 | 104 | 249 | 70.5 |
| September 7, 2020 | 195 | 28 | 83 | 74.8 |

Paging success was highest in the Big Creek/Ventura LCA, with 74.3% of operating switches responding to the dispatch on average. The switch paging success rate in Big Creek/Ventura was similar to the 2019 success rate, which was 74.1%. This result is a departure from last year, where the highest response rate was in the LA Basin area, at 84%. In 2020, the LA Basin area actually 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 significantly from the previous year, going from 15.8% in 2019 to nearly 64% in the 2020 season.

Table 22: Paging Success by LCA for 2020 Event

| LCA | Not Operating | Did Not Respond | Responded | Paging Success % |
|---|---|---|---|---|
| Big Creek/Ventura | 459 | 101 | 294 | 74.3 |
| LA Basin | 35 | 21 | 38 | 63.9 |
| Outside LA Basin | 12 | 7 | 17 | 69.9 |

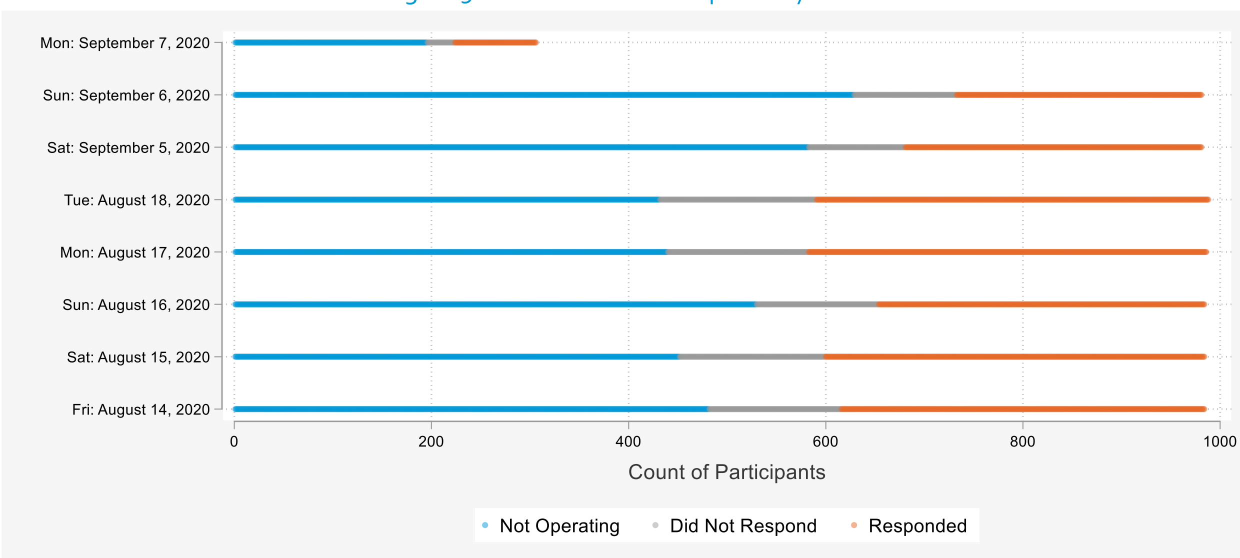
Figure 8 shows the distribution of switch paging success for the first and last full dispatch events of the summer. In this map, [redacted].

Figure 8: Geographic Distribution of Paging Success – 8/18/2020

[Image Redacted]

Figure 9 shows the breakdown of customers' responses to event dispatches by date. The switch paging success rate indicates the percent of AP-I customers who were able to successfully curtail their load upon receipt of the dispatch signal. The rate is calculated by dividing the total number of customers who responded by the total number of operating customers (those who responded and did not respond to a dispatch). Customers are designated as "not operating" if their pre-event load is less than 5% of their daily maximum load.

Figure 9: Customer Event Response by Date




The contribution of each switch paging group to overall program impacts is summarized in Figure 10. 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 10: 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 2021 to 2031 . 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 increase from the 1,010 participants enrolled on final 2020 event day to 1,067 in August of 2021 and to 1,153 by August of 2022. This increase is attributable to SCE's efforts to enroll new customers in the program.

Table 23: AP-I Ex Ante Enrollment Forecast

| Program/Portfolio | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | 1,067 | 1,153 | 1,239 | 1,325 | 1,411 | 1,497 | 1,583 | 1,669 | 1,755 | 1,841 | 1,927 |
| Program | 1,067 | 1,153 | 1,239 | 1,325 | 1,411 | 1,497 | 1,583 | 1,669 | 1,755 | 1,841 | 1,927 |

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

| Year | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Switch Success Rate (%) | 76.9 | 77.5 | 78.1 | 78.8 | 79.4 | 80.1 | 80.7 | 81.3 | 82.0 | 82.6 | 83.3 |

## 6.2 OVERALL RESULTS

As enrollment increases and the switch paging success rate increases over the next ten years, aggregate August Peak Day impacts will range from 34.11MW in 2021 (SCE 1-in-10) to 70.66MW in 2031 (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[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] More detail on the weather associated with the ex ante scenarios can be found in Appendix 9

Table 25: 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 |
|---|---|---|---|---|
| 2021 | 35.03 | 34.11 | 34.91 | 36.12 |
| 2022 | 38.16 | 37.17 | 38.04 | 39.36 |
| 2023 | 41.35 | 40.27 | 41.22 | 42.64 |
| 2024 | 44.58 | 43.42 | 44.44 | 45.97 |
| 2025 | 47.86 | 46.61 | 47.71 | 49.36 |
| 2026 | 51.19 | 49.85 | 51.02 | 52.79 |
| 2027 | 54.56 | 53.14 | 54.39 | 56.27 |
| 2028 | 57.98 | 56.47 | 57.80 | 59.79 |
| 2029 | 61.45 | 59.84 | 61.25 | 63.37 |
| 2030 | 64.96 | 63.27 | 64.76 | 66.99 |
| 2031 | 68.52 | 66.73 | 68.31 | 70.66 |

Load impacts also vary by month, as seasonal changes in farming intensity and precipitation impact pumping requirements. Table 26 shows the average customer impacts for a monthly peak day, assuming an 83.3% switch paging success rate. Impacts are highest in June through September and typically peak in August.

Table 26: AP-I Average Customer Portfolio Ex Ante Impacts (kW) - By Monthly Peak Day in 2031

| Day Type | SCE 1-in-2 | SCE 1-in-10 | CAISO 1-in-2 | CAISO 1-in-10 |
|---|---|---|---|---|
| January Peak Day | 9.90 | 9.85 | 10.15 | 9.77 |
| February Peak Day | 9.86 | 16.36 | 9.74 | 10.77 |
| March Peak Day | 14.92 | 23.67 | 14.71 | 24.21 |
| April Peak Day | 24.20 | 30.70 | 26.30 | 30.02 |
| May Peak Day | 27.29 | 34.26 | 31.16 | 34.26 |
| June Peak Day | 35.43 | 36.68 | 36.78 | 37.12 |
| July Peak Day | 35.50 | 34.18 | 34.79 | 36.68 |
| August Peak Day | 35.56 | 34.63 | 35.45 | 36.67 |
| September Peak Day | 32.56 | 34.49 | 31.83 | 36.41 |
| October Peak Day | 25.12 | 26.92 | 28.14 | 31.59 |
| November Peak Day | 14.81 | 18.77 | 10.66 | 18.77 |
| December Peak Day | 5.97 | 6.69 | 6.88 | 6.69 |

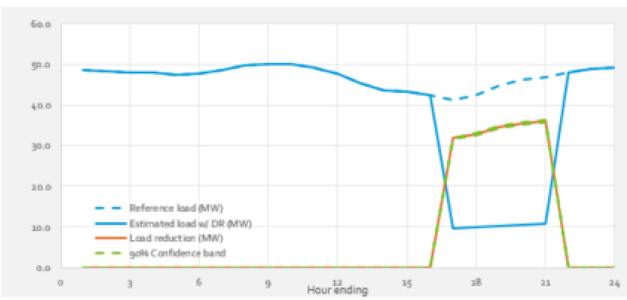
## Figure 11: Aggregate Ex Ante Impacts for SCE 1-in-2 Typical Event Day

**Table 1: Menu options**

| | |
|---|---|
| Program | AP-I |
| Type of result | Aggregate |
| Category | All |
| Subcategory | All Customers |
| Weather Data | SCE |
| Weather Year | 1-in-2 |
| Day Type | Typical Event Day |
| Month | 8 |
| Forecast Year | 2021 |
| Portfolio Level | Program |
| Switch Paging Succes % | Forecast |

**Table 2: Event day information**

| | |
|---|---|
| Event start | 4:00 PM |
| Event end | 9:00 PM |
| Total sites | 1067 |
| Event window temperature (F) | 96.2 |
| Event window load reduction (MW) | 34.1 |
| % Load reduction (Event window) | 76.9% |




| Hour ending | Reference load (MW) | Estimated load w/ DR (MW) | Load reduction (MW) | % Load reduction | Avg temp (F, site weighted) | Uncertainty adjusted impact - Percentiles 5th | 10th | 30th | 50th | 70th | 90th | 95th | Std. error | T-statistic |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 48.42 | 48.42 | 0.00 | 0.0% | 80.83 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 2 | 48.24 | 48.24 | 0.00 | 0.0% | 78.81 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 3 | 48.08 | 48.08 | 0.00 | 0.0% | 76.68 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 4 | 47.82 | 47.82 | 0.00 | 0.0% | 74.52 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 5 | 47.40 | 47.40 | 0.00 | 0.0% | 72.85 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 6 | 47.55 | 47.55 | 0.00 | 0.0% | 71.18 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 7 | 48.52 | 48.52 | 0.00 | 0.0% | 69.51 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 8 | 49.62 | 49.62 | 0.00 | 0.0% | 69.29 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 9 | 50.03 | 50.03 | 0.00 | 0.0% | 72.23 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 10 | 49.93 | 49.93 | 0.00 | 0.0% | 76.83 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 11 | 49.12 | 49.12 | 0.00 | 0.0% | 81.29 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 12 | 47.71 | 47.71 | 0.00 | 0.0% | 85.28 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 13 | 45.23 | 45.23 | 0.00 | 0.0% | 88.68 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 14 | 43.53 | 43.53 | 0.00 | 0.0% | 91.29 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 15 | 43.20 | 43.20 | 0.00 | 0.0% | 93.72 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 16 | 42.48 | 42.48 | 0.00 | 0.0% | 95.86 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 17 | 41.36 | 9.57 | 31.79 | 76.9% | 97.14 | 31.55 | 31.60 | 31.71 | 31.79 | 31.87 | 31.98 | 32.03 | 0.15 | 215.59 |
| 18 | 42.55 | 9.85 | 32.70 | 76.9% | 97.63 | 32.46 | 32.51 | 32.62 | 32.70 | 32.78 | 32.89 | 32.95 | 0.15 | 219.58 |
| 19 | 44.82 | 10.37 | 34.45 | 76.9% | 97.55 | 34.20 | 34.25 | 34.37 | 34.45 | 34.53 | 34.64 | 34.70 | 0.15 | 227.33 |
| 20 | 46.16 | 10.68 | 35.47 | 76.9% | 96.11 | 35.22 | 35.28 | 35.39 | 35.47 | 35.56 | 35.67 | 35.73 | 0.15 | 231.37 |
| 21 | 46.90 | 10.85 | 36.05 | 76.9% | 92.64 | 35.80 | 35.85 | 35.97 | 36.05 | 36.13 | 36.25 | 36.30 | 0.15 | 234.58 |
| 22 | 47.86 | 47.86 | 0.00 | 0.0% | 87.81 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 23 | 48.77 | 48.77 | 0.00 | 0.0% | 84.43 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 24 | 49.24 | 49.24 | 0.00 | 0.0% | 82.24 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |

| Daily | Reference load (MWh) | Estimated load w/ DR (MWh) | Energy savings (MWh) | % Change | Avg. Daily Weighted temp (F) | Uncertainty adjusted impact - Percentiles 5th | 10th | 30th | 50th | 70th | 90th | 95th | Std. error | T-statistic |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1124.53 | 954.06 | 170.46 | 15.2% | 83.93 | 169.22 | 169.50 | 170.07 | 170.46 | 170.86 | 171.43 | 171.70 | 0.75 | 225.80 |

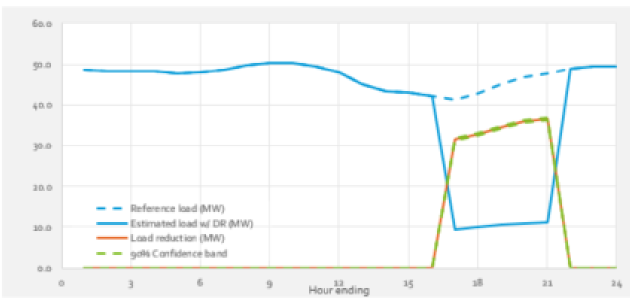
Figure 12: Aggregate Ex Ante Impacts for SCE 1-in-10 Typical Event Day

**Table 1: Menu options**

| | |
|---|---|
| Program | AP-I |
| Type of result | Aggregate |
| Category | All |
| Subcategory | All Customers |
| Weather Data | SCE |
| Weather Year | 1-in-10 |
| Day Type | Typical Event Day |
| Month | 8 |
| Forecast Year | 2021 |
| Portfolio Level | Program |
| Switch Paging Succes % | Forecast |

**Table 2: Event day information**

| | |
|---|---|
| Event start | 4:00 PM |
| Event end | 9:00 PM |
| Total sites | 1067 |
| Event window temperature (F) | 97.7 |
| Event window load reduction (MW) | 34.3 |
| % Load reduction (Event window) | 76.9% |




| Hour ending | Reference load (MW) | Estimated load w/ DR (MW) | Load reduction (MW) | % Load reduction | Avg temp (F, site weighted) | Uncertainty adjusted impact - Percentiles 5th | 10th | 30th | 50th | 70th | 90th | 95th | Std. error | T-statistic |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 48.49 | 48.49 | 0.00 | 0.0% | 80.09 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 2 | 48.39 | 48.39 | 0.00 | 0.0% | 78.37 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 3 | 48.34 | 48.34 | 0.00 | 0.0% | 76.36 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 4 | 48.15 | 48.15 | 0.00 | 0.0% | 74.51 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 5 | 47.78 | 47.78 | 0.00 | 0.0% | 72.72 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 6 | 47.88 | 47.88 | 0.00 | 0.0% | 71.13 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 7 | 48.63 | 48.63 | 0.00 | 0.0% | 70.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 8 | 49.82 | 49.82 | 0.00 | 0.0% | 69.63 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 9 | 50.21 | 50.21 | 0.00 | 0.0% | 72.58 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 10 | 50.20 | 50.20 | 0.00 | 0.0% | 76.95 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 11 | 49.38 | 49.38 | 0.00 | 0.0% | 81.20 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 12 | 47.88 | 47.88 | 0.00 | 0.0% | 85.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 13 | 45.13 | 45.13 | 0.00 | 0.0% | 88.58 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 14 | 43.23 | 43.23 | 0.00 | 0.0% | 92.13 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 15 | 42.92 | 42.92 | 0.00 | 0.0% | 95.14 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 16 | 42.17 | 42.17 | 0.00 | 0.0% | 97.18 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 17 | 41.17 | 9.53 | 31.64 | 76.9% | 98.58 | 31.37 | 31.43 | 31.56 | 31.64 | 31.73 | 31.86 | 31.92 | 0.16 | 192.31 |
| 18 | 42.68 | 9.88 | 32.80 | 76.9% | 99.30 | 32.52 | 32.59 | 32.71 | 32.80 | 32.89 | 33.02 | 33.08 | 0.17 | 194.72 |
| 19 | 45.08 | 10.43 | 34.65 | 76.9% | 98.80 | 34.36 | 34.43 | 34.56 | 34.65 | 34.74 | 34.87 | 34.94 | 0.17 | 198.70 |
| 20 | 46.66 | 10.80 | 35.86 | 76.9% | 97.52 | 35.57 | 35.64 | 35.77 | 35.86 | 35.96 | 36.09 | 36.16 | 0.18 | 202.10 |
| 21 | 47.73 | 11.04 | 36.68 | 76.9% | 94.40 | 36.39 | 36.46 | 36.59 | 36.68 | 36.78 | 36.91 | 36.98 | 0.18 | 205.10 |
| 22 | 48.70 | 48.70 | 0.00 | 0.0% | 90.17 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 23 | 49.33 | 49.33 | 0.00 | 0.0% | 86.60 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 24 | 49.56 | 49.56 | 0.00 | 0.0% | 83.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| Daily | Reference load (MWh) | Estimated load w/ DR (MWh) | Energy savings (MWh) | % Change | Avg. Daily Weighted temp (F) | Uncertainty adjusted impact - Percentiles 5th | 10th | 30th | 50th | 70th | 90th | 95th | Std. error | T-statistic |
| | 1129.52 | 957.87 | 171.64 | 15.2% | 84.58 | 170.22 | 170.54 | 171.19 | 171.64 | 172.10 | 172.75 | 173.06 | 0.86 | 198.73 |

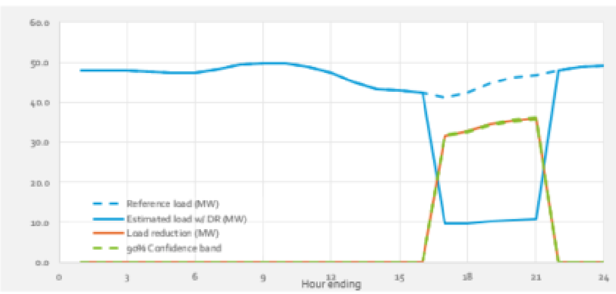
## Figure 13: Aggregate Ex Ante Impacts for CAISO 1-in-2 Typical Event Day

**Table 1: Menu options**

| | |
|---|---|
| **Program** | AP-I |
| **Type of result** | Aggregate |
| **Category** | All |
| **Subcategory** | All Customers |
| **Weather Data** | CAISO |
| **Weather Year** | 1-in-2 |
| **Day Type** | Typical Event Day |
| **Month** | 8 |
| **Forecast Year** | 2021 |
| **Portfolio Level** | Program |
| **Switch Paging Succes %** | Forecast |

**Table 2: Event day information**

| | |
|---|---|
| Event start | 4:00 PM |
| Event end | 9:00 PM |
| Total sites | 1067 |
| Event window temperature (F) | 96.3 |
| Event window load reduction (MW) | 34.0 |
| % Load reduction (Event window) | 76.9% |




| Hour ending | Reference load (MW) | Estimated load w/ DR (MW) | Load reduction (MW) | % Load reduction | Avg temp (F, site weighted) | Uncertainty adjusted impact - Percentiles 5th | 10th | 30th | 50th | 70th | 90th | 95th | Std. error | T-statistic |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 48.09 | 48.09 | 0.00 | 0.0% | 79.65 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 2 | 47.97 | 47.97 | 0.00 | 0.0% | 77.27 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 3 | 47.89 | 47.89 | 0.00 | 0.0% | 75.54 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 4 | 47.68 | 47.68 | 0.00 | 0.0% | 73.61 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 5 | 47.32 | 47.32 | 0.00 | 0.0% | 71.99 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 6 | 47.48 | 47.48 | 0.00 | 0.0% | 70.49 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 7 | 48.37 | 48.37 | 0.00 | 0.0% | 69.08 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 8 | 49.46 | 49.46 | 0.00 | 0.0% | 68.89 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 9 | 49.84 | 49.84 | 0.00 | 0.0% | 71.83 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 10 | 49.73 | 49.73 | 0.00 | 0.0% | 76.36 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 11 | 48.90 | 48.90 | 0.00 | 0.0% | 80.81 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 12 | 47.51 | 47.51 | 0.00 | 0.0% | 85.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 13 | 45.08 | 45.08 | 0.00 | 0.0% | 88.40 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 14 | 43.43 | 43.43 | 0.00 | 0.0% | 91.23 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 15 | 43.08 | 43.08 | 0.00 | 0.0% | 93.61 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 16 | 42.32 | 42.32 | 0.00 | 0.0% | 95.64 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 17 | 41.26 | 9.55 | 31.71 | 76.9% | 97.22 | 31.47 | 31.53 | 31.64 | 31.71 | 31.79 | 31.90 | 31.95 | 0.15 | 218.54 |
| 18 | 42.44 | 9.82 | 32.62 | 76.9% | 97.69 | 32.38 | 32.44 | 32.55 | 32.62 | 32.70 | 32.81 | 32.86 | 0.15 | 222.69 |
| 19 | 44.73 | 10.35 | 34.38 | 76.9% | 97.57 | 34.14 | 34.19 | 34.30 | 34.38 | 34.46 | 34.57 | 34.63 | 0.15 | 229.96 |
| 20 | 46.14 | 10.68 | 35.46 | 76.9% | 96.27 | 35.21 | 35.27 | 35.38 | 35.46 | 35.54 | 35.66 | 35.71 | 0.15 | 234.00 |
| 21 | 46.89 | 10.85 | 36.04 | 76.9% | 92.80 | 35.79 | 35.84 | 35.96 | 36.04 | 36.12 | 36.23 | 36.29 | 0.15 | 238.73 |
| 22 | 47.86 | 47.86 | 0.00 | 0.0% | 88.25 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 23 | 48.74 | 48.74 | 0.00 | 0.0% | 85.38 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 24 | 49.11 | 49.11 | 0.00 | 0.0% | 83.61 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| **Daily** | **Reference load (MWh)** | **Estimated load w/ DR (MWh)** | **Energy savings (MWh)** | **% Change** | **Avg. Daily Weighted temp (F)** | **Uncertainty adjusted impact - Percentiles 5th** | **10th** | **30th** | **50th** | **70th** | **90th** | **95th** | **Std. error** | **T-statistic** |
| | 1121.32 | 951.10 | 170.22 | 15.2% | 83.68 | 169.00 | 169.27 | 169.83 | 170.22 | 170.61 | 171.17 | 171.44 | 0.74 | 228.90 |



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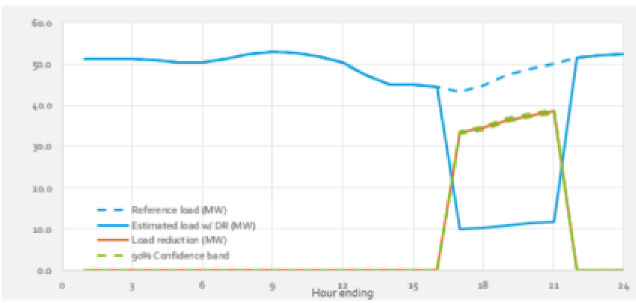
Figure 14: Aggregate Ex Ante Impacts for CAISO 1-in-10 Typical Event Day

**Table 1: Menu options**

| | |
|---|---|
| Program | AP-I |
| Type of result | Aggregate |
| Category | All |
| Subcategory | All Customers |
| Weather Data | CAISO |
| Weather Year | 1-in-10 |
| Day Type | Typical Event Day |
| Month | 8 |
| Forecast Year | 2021 |
| Portfolio Level | Program |
| Switch Paging Succes % | Forecast |

**Table 2: Event day information**

| | |
|---|---|
| Event start | 4:00 PM |
| Event end | 9:00 PM |
| Total sites | 1067 |
| Event window temperature (F) | 100.1 |
| Event window load reduction (MW) | 36.0 |
| % Load reduction (Event window) | 76.9% |




| Hour ending | Reference load (MW) | Estimated load w/ DR (MW) | Load reduction (MW) | % Load reduction | Avg temp (F, site weighted) | Uncertainty adjusted impact - Percentiles 5th | 10th | 30th | 50th | 70th | 90th | 95th | Std. error | T-statistic |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 51.17 | 51.17 | 0.00 | 0.0% | 82.61 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 2 | 51.12 | 51.12 | 0.00 | 0.0% | 81.23 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 3 | 51.03 | 51.03 | 0.00 | 0.0% | 79.36 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 4 | 50.84 | 50.84 | 0.00 | 0.0% | 77.39 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 5 | 50.31 | 50.31 | 0.00 | 0.0% | 75.52 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 6 | 50.20 | 50.20 | 0.00 | 0.0% | 74.33 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 7 | 51.14 | 51.14 | 0.00 | 0.0% | 72.48 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 8 | 52.37 | 52.37 | 0.00 | 0.0% | 71.77 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 9 | 52.83 | 52.83 | 0.00 | 0.0% | 75.10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 10 | 52.77 | 52.77 | 0.00 | 0.0% | 80.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 11 | 51.85 | 51.85 | 0.00 | 0.0% | 84.64 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 12 | 50.16 | 50.16 | 0.00 | 0.0% | 88.92 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 13 | 47.24 | 47.24 | 0.00 | 0.0% | 92.24 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 14 | 45.14 | 45.14 | 0.00 | 0.0% | 95.67 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 15 | 44.91 | 44.91 | 0.00 | 0.0% | 98.32 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 16 | 44.31 | 44.31 | 0.00 | 0.0% | 100.26 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 17 | 43.30 | 10.02 | 33.28 | 76.9% | 101.21 | 32.93 | 33.01 | 33.17 | 33.28 | 33.40 | 33.56 | 33.64 | 0.22 | 154.62 |
| 18 | 44.78 | 10.36 | 34.42 | 76.9% | 101.52 | 34.06 | 34.14 | 34.30 | 34.42 | 34.53 | 34.70 | 34.77 | 0.22 | 158.66 |
| 19 | 47.31 | 10.95 | 36.36 | 76.9% | 101.17 | 36.00 | 36.08 | 36.25 | 36.36 | 36.48 | 36.64 | 36.72 | 0.22 | 164.71 |
| 20 | 48.82 | 11.30 | 37.52 | 76.9% | 99.65 | 37.15 | 37.24 | 37.40 | 37.52 | 37.64 | 37.81 | 37.89 | 0.22 | 168.02 |
| 21 | 50.08 | 11.59 | 38.49 | 76.9% | 96.73 | 38.12 | 38.20 | 38.37 | 38.49 | 38.61 | 38.78 | 38.86 | 0.23 | 170.68 |
| 22 | 51.36 | 51.36 | 0.00 | 0.0% | 92.58 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 23 | 52.14 | 52.14 | 0.00 | 0.0% | 89.08 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 24 | 52.43 | 52.43 | 0.00 | 0.0% | 86.14 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| Daily | Reference load (MWh) | Estimated load w/ DR (MWh) | Energy savings (MWh) | % Change | Avg. Daily Weighted temp (F) | Uncertainty adjusted impact - Percentiles 5th | 10th | 30th | 50th | 70th | 90th | 95th | Std. error | T-statistic |
| | 1187.60 | 1007.52 | 180.08 | 15.2% | 87.42 | 178.26 | 178.66 | 179.50 | 180.08 | 180.65 | 181.49 | 181.89 | 1.10 | 163.44 |

## 6.3 RESULTS BY CATEGORY

Table 27 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 27: AP-I Aggregate Portfolio Ex Ante Impacts - Typical Event Day by LCA (MW)

| LCA | Weather Year | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 | 2031 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Big Creek/Ventura | CAISO 1-in-10 | 31.06 | 33.84 | 36.66 | 39.52 | 42.43 | 45.37 | 48.36 | 51.39 | 54.46 | 57.58 | 60.73 |
| | CAISO 1-in-2 | 29.16 | 31.77 | 34.41 | 37.10 | 39.83 | 42.60 | 45.40 | 48.25 | 51.13 | 54.05 | 57.01 |
| | SCE 1-in-10 | 29.37 | 32.00 | 34.67 | 37.38 | 40.13 | 42.91 | 45.74 | 48.60 | 51.51 | 54.45 | 57.44 |
| | SCE 1-in-2 | 29.21 | 31.82 | 34.47 | 37.17 | 39.90 | 42.67 | 45.48 | 48.33 | 51.22 | 54.14 | 57.11 |
| LA Basin | CAISO 1-in-10 | 3.21 | 3.52 | 3.79 | 4.11 | 4.39 | 4.71 | 5.01 | 5.34 | 5.67 | 5.98 | 6.32 |
| | CAISO 1-in-2 | 3.16 | 3.46 | 3.73 | 4.04 | 4.32 | 4.63 | 4.92 | 5.25 | 5.58 | 5.88 | 6.22 |
| | SCE 1-in-10 | 3.23 | 3.54 | 3.81 | 4.13 | 4.41 | 4.74 | 5.03 | 5.37 | 5.70 | 6.01 | 6.36 |
| | SCE 1-in-2 | 3.16 | 3.46 | 3.74 | 4.04 | 4.32 | 4.64 | 4.93 | 5.26 | 5.59 | 5.89 | 6.23 |
| Outside LA Basin | CAISO 1-in-10 | 1.75 | 1.88 | 2.07 | 2.21 | 2.41 | 2.55 | 2.69 | 2.89 | 3.04 | 3.25 | 3.40 |
| | CAISO 1-in-2 | 1.73 | 1.86 | 2.05 | 2.19 | 2.38 | 2.52 | 2.66 | 2.87 | 3.01 | 3.22 | 3.37 |
| | SCE 1-in-10 | 1.73 | 1.86 | 2.05 | 2.18 | 2.38 | 2.52 | 2.66 | 2.86 | 3.01 | 3.21 | 3.36 |
| | SCE 1-in-2 | 1.72 | 1.85 | 2.04 | 2.18 | 2.37 | 2.51 | 2.65 | 2.86 | 3.00 | 3.21 | 3.36 |

## 6.4 COMPARISON TO PRIOR YEAR

Compared to PY2019, enrollment is projected to increase over the next 10 program years rather than decreasing and then stabilizing. This is due to program efforts to enroll new customers and anticipation of new enrollment in future years. On the other hand, paging success is projected to increase, but at a slower rate than predicted in 2019. This change is reflective of the increase in switch success between 2019 and 2020, which incorporated the program's efforts to improve switch technology for customers as well as the impact of newly enrolled customers.

Table 28: PY2019 Ex Ante Forecast Elements

| Forecast Year | Enrollment | | Paging Success Rate | |
|---|---|---|---|---|
| | 2019 | 2020 | 2019 | 2020 |
| **2020** | 935 | … | 76% | … |
| **2021** | 910 | 1,067 | 86% | 76.9% |
| **2022** | 910 | 1,153 | 90% | 77.5% |
| **2023** | 910 | 1,239 | 90% | 78.1% |
| **2024** | 910 | 1,325 | 90% | 78.8% |
| **2025** | 910 | 1,411 | 90% | 79.4% |
| **2026** | 910 | 1,497 | 90% | 80.1% |
| **2027** | 910 | 1,583 | 90% | 80.7% |
| **2028** | 910 | 1,669 | 90% | 81.3% |
| **2029** | 910 | 1,755 | 90% | 82.0% |
| **2030** | 910 | 1,841 | 90% | 82.6% |
| **2031** | … | 1,927 | … | 83.3% |

## 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 monthly peak day projections for August and September.

Because of the extreme weather that accompanied the events in 2020, the weather projections are consistently higher in the ex post events, and most similar to the 1-in-10 CAISO scenarios. We would expect both per-customer and aggregate impacts to by higher in 2021, due to a projected improvement in the switch success rate and a higher customer count. In August, the ex ante projected impacts are actually in line with ex post impacts, and in some cases slightly lower than impacts achieved in the 2020 event season. Weather in August 2020 was more extreme than previous years, and had significantly higher pumping loads, which likely contributed to larger program impacts. Because the ex ante projection incorporates multiple years of reference loads, the impact of 2020's extreme weather is tempered by previous years of data[2]. In September, the per-customer and aggregate ex ante projections are slightly higher than the ex post results, as we would expect.

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

Table 29: Ex Post Compared to Ex Ante – August 2020 and 2021

| 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: Aug Peak Day CAISO 1-in-10 (4:00 - 9:00PM) | 1,067 | 100.8 | 102.2 | 44.0 | 76.9 | 76.9 | 33.9 | 36.1 |
| Ex Ante: Aug Peak Day CAISO 1-in-2 (4:00 - 9:00PM) | 1,067 | 97.6 | 98.7 | 42.6 | 76.9 | 76.9 | 32.7 | 34.9 |
| Ex Ante: Aug Peak Day SCE 1-in-10 (4:00 - 9:00PM) | 1,067 | 96.9 | 98.5 | 41.6 | 76.9 | 76.9 | 32.0 | 34.1 |
| Ex Ante: Aug Peak Day SCE 1-in-2 (4:00 - 9:00PM) | 1,067 | 97.6 | 98.8 | 42.7 | 76.9 | 76.9 | 32.8 | 35.0 |
| Ex Post: 8/14/2020 (05:10 - 08:35PM) | 986 | 101.8 | 102.6 | 47.8 | 73.4 | 77.8 | 37.2 | 36.6 |
| Ex Post: 8/15/2020 (03:00 - 07:45PM) | 986 | 102.5 | 103.3 | 47.0 | 72.2 | 75.8 | 35.6 | 35.1 |
| Ex Post: 8/16/2020 (05:40 - 07:25PM) | 986 | 103.9 | 104.6 | 42.9 | 72.7 | 77.9 | 33.4 | 32.9 |
| Ex Post: 8/18/2020 (01:40 - 07:25PM) | 990 | 100.4 | 101.6 | 49.2 | 71.5 | 77.9 | 38.3 | 38.0 |

Table 30: Ex Post Compared to Ex Ante – September 2020 and 2021

| 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: Sept Peak Day CAISO 1-in-10 (4:00 - 9:00PM) | 1,067 | 99.8 | 101.7 | 43.7 | 76.9 | 76.9 | 33.6 | 35.9 |
| Ex Ante: Sept Peak Day CAISO 1-in-2 (4:00 - 9:00PM) | 1,067 | 93.1 | 95.3 | 38.2 | 76.9 | 76.9 | 29.4 | 31.4 |
| Ex Ante: Sept Peak Day SCE 1-in-10 (4:00 - 9:00PM) | 1,067 | 97.9 | 100.2 | 41.4 | 76.9 | 76.9 | 31.8 | 34.0 |
| Ex Ante: Sept Peak Day SCE 1-in-2 (4:00 - 9:00PM) | 1,067 | 94.4 | 96.2 | 39.1 | 76.9 | 76.9 | 30.1 | 32.1 |
| Ex Post: 9/5/2020 (05:30 - 08:25PM) | 1,010 | 102.0 | 103.4 | 37.3 | 75.4 | 78.1 | 29.2 | 29.4 |
| Ex Post: 9/6/2020 (04:40 - 08:23PM) | 1,010 | 101.5 | 104.2 | 33.9 | 70.5 | 78.6 | 26.7 | 26.9 |

# 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.

- 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.
- The number of events called in 2020 revealed that program impacts do not fade over consecutive dispatch days and are consistent across weekdays and weekends.
- Increases in paging success and forecasted enrollments will grow the AP-I program over time to produce higher load reductions during periods of grid stress.
- 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.

# 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 31. 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 31: Methods for Demand Response Evaluation

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

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

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

### Model Selection

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

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

Figure 15: Model Selection and Validation

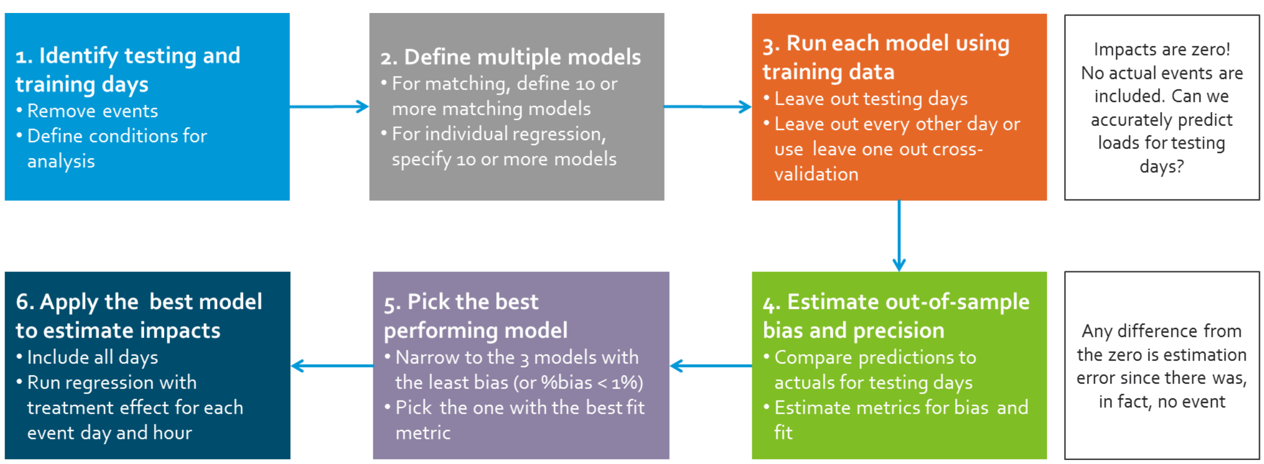



Table 32 summarizes the metrics for bias and precision we employ. Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error describes the relative magnitude and direction of the bias. A negative value indicates a tendency 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 32: Definition of Bias and Precision Metrics

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

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

Figure 16: Model Bias and Error on Proxy Events

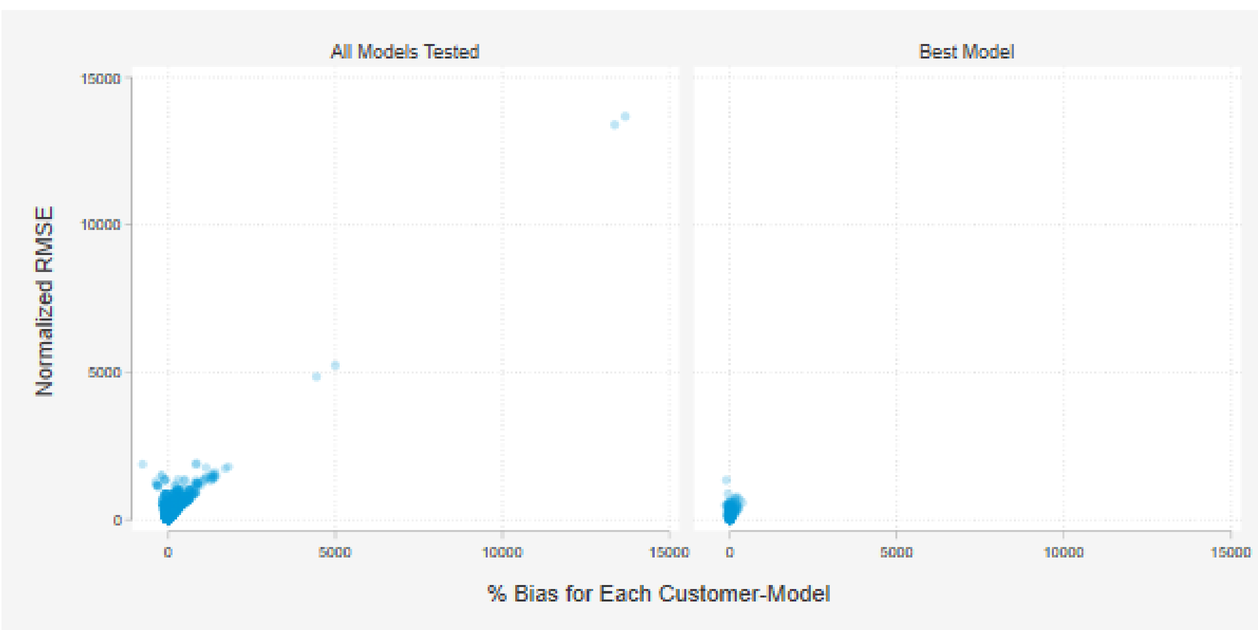
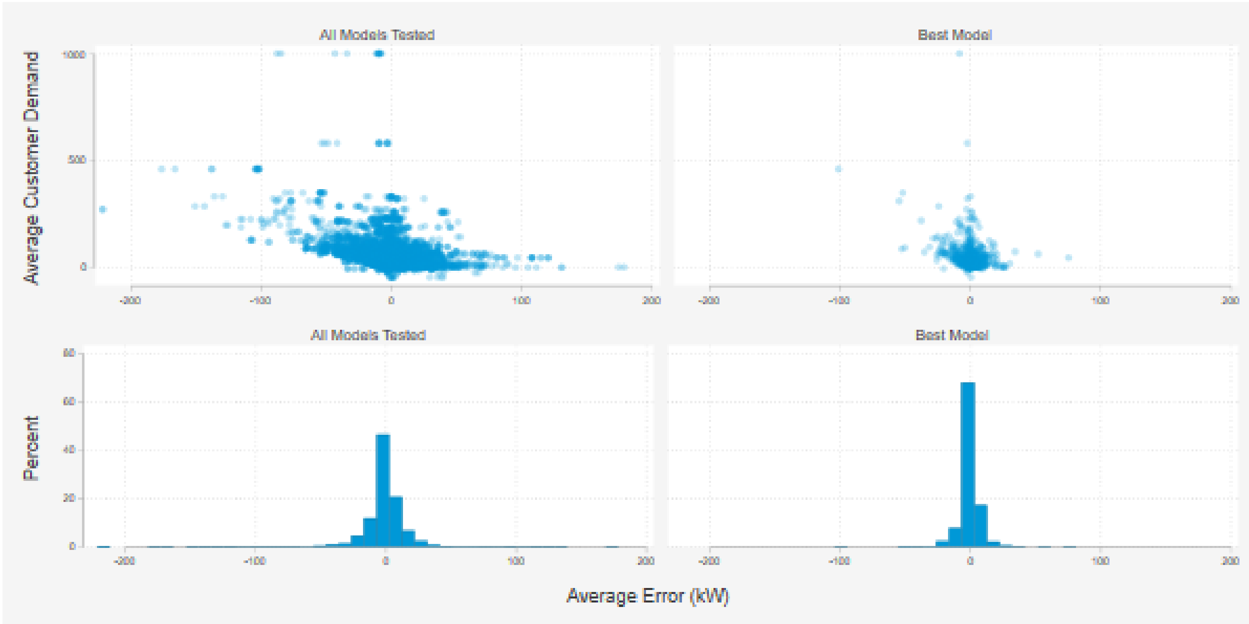


Figure 17: Model Average Error by Customer Size



# 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 API 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.

| 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 2019 and PY 2020 Ex Ante Average Reference Load Predictions

The following table compares the per-customer reference loads by weather scenario and monthly peak day for 2019 and 2020. Reference loads are consistently higher in the 2020 forecast.

| Day Type | SCE 1-in-2 | | SCE 1-in-10 | | CAISO 1-in-2 | | CAISO 1-in-10 | |
|---|---|---|---|---|---|---|---|---|
| | PY19 | PY20 | PY19 | PY20 | PY19 | PY20 | PY19 | PY20 |
| January Peak Day | 11.6 | 13.0 | 12.0 | 12.5 | 11.3 | 13.5 | 12.1 | 12.4 |
| February Peak Day | 11.2 | 14.1 | 17.0 | 19.0 | 11.3 | 14.0 | 11.2 | 13.9 |
| March Peak Day | 15.7 | 19.0 | 24.4 | 26.0 | 15.5 | 18.6 | 24.9 | 26.0 |
| April Peak Day | 25.1 | 27.0 | 31.1 | 32.1 | 27.1 | 28.7 | 30.1 | 32.3 |
| May Peak Day | 28.2 | 33.5 | 34.1 | 38.0 | 31.5 | 35.8 | 34.1 | 38.0 |
| June Peak Day | 35.0 | 41.5 | 36.1 | 43.9 | 36.0 | 42.3 | 36.3 | 44.3 |
| July Peak Day | 35.3 | 43.9 | 34.5 | 44.2 | 34.8 | 43.4 | 36.1 | 45.9 |
| August Peak Day | 35.6 | 43.3 | 35.1 | 43.4 | 35.6 | 43.2 | 36.5 | 45.1 |
| September Peak Day | 33.7 | 38.8 | 35.1 | 40.1 | 33.1 | 39.0 | 36.3 | 41.4 |
| October Peak Day | 27.5 | 28.8 | 29.3 | 30.8 | 30.0 | 30.9 | 32.9 | 34.0 |
| November Peak Day | 18.2 | 17.6 | 21.9 | 19.8 | 14.1 | 14.5 | 21.9 | 19.8 |
| December Peak Day | 12.1 | 8.9 | 14.3 | 8.1 | 11.0 | 9.4 | 14.3 | 8.7 |