LEAP PY 2024 (FY 2025) LOAD IMPACT PROTOCOL EX POST AND EX ANTE IMPACTS

CALMAC STUDY ID: LPF0003

FINAL REPORT

Submitted to:
Leap and the California Public Utilities Commission

Prepared by:
Verdant Associates, LLC

Verdant Associates, LLC
Berkeley, CA 94707
www.verdantassoc.com

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VERDANT

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1 EXECUTIVE SUMMARY

This report summarizes analysis conducted by Verdant Associates (Verdant) to estimate ex post load impacts of Leap's 2024 California demand response portfolio and forecast ex ante load impacts for the same Leap portfolio for 2026 through 2028. The purpose of these estimated load impacts is to satisfy the California Public Utilities Commission (CPUC) requirements for a Load Impact Protocol (LIP) to determine the contributions to Resource Adequacy (RA) for the Leap programs in RA year 2026.

Table 1-1 provides a summary of the forecasted participant counts and expected aggregate MW contributions for Qualifying Capacity (QC) in 2026 as determined through the LIP. MW contributions are presented under low, medium, and high participant growth scenarios. The underlying per capita impact assumptions are the same for each scenario, with projected participant enrollment growth in Leap's portfolio driving the differences.

TABLE 1-1: TOTAL 2026 RA YEAR PARTICIPANTS UNDER 1-IN-2 UTILITY WEATHER SCENARIO IN THE MONTH OF AUGUST

IOU Service Territory	Low Growth Forecast Scenario		Medium Growth Forecast Scenario		High Growth Forecast Scenario	
	Number of Customers	MW	Number of Customers	MW	Number of Customers	MW
[redacted]						

The LIP filing guide also requests that information related to a third-party Demand Resource Provider's (DRP) participation in other resource programs be presented in the executive summary. However, this information is submitted separately to the CPUC to ensure confidentiality between Leap, Verdant, and other readers.

Leap Participant Summary

During 2024, Leap delivered demand response to [redacted] distinct customer meters across forty load serving entities (LSE) including all three major electric investor-owned utilities[1] throughout the California Independent System Operator's (CAISO) balancing authority area. Table 1-2 presents the number of participants by electric utility.

[1] Major electric investor-owned utilities are defined here as Pacific Gas and Electric Company (PG&E), Southern California Edison Company (SCE), and San Diego Gas and Electric (SDG&E).

TABLE 1-2: PROGRAM ENROLLMENT BY ELECTRIC IOU

IOU	Enrolled Participants
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]

Leap's 2024 portfolio was comprised of 39 partners, each of which contracted with one or more electricity customers to provide load shed during market dispatch. Of these, 29 served non-residential customers and 24 served residential customers, with 14 serving both. For the non-residential partners, the number of meters service ranged from one more than two thousand, [redacted]

TABLE 1-3: NUMBER OF METERS IN THE LEAP RESOURCE, BY PARTNER AND SECTOR

Partner ID	Enrolled Participants		
	Non-Residential	Residential	Total
[redacted]			

Leap 2024 Event Information

During 2024, Leap sold resource adequacy (RA) to LSEs through bilateral agreements. In general, there are three types of events for which Leap participants receive payments for their participation: test events (of which there were 41), market dispatch (totaling 998 events), and combined events (85 events). Test events are called to trigger load reductions regardless of market prices. Market events are called when Leap energy bids clear market prices. Combined events occur when a test event occurs either concurrently or back-to-back with a market event.

2 INTRODUCTION

This report summarizes analysis conducted by Verdant Associates to estimate ex post load impacts of Leap's 2024 California demand response portfolio and forecast ex ante load impacts for the same Leap portfolio for 2026 through 2028. The purpose of these estimated load impacts is to satisfy the CPUC requirements for a LIP to determine the contributions to RA for the Leap programs.

This document describes the characteristics of Leap's DR participants and the methodologies and data used to estimate ex post impacts and produce a forecast of ex ante impacts.

2.1 LEAP DR OFFERINGS AND PARTICIPANT CHARACTERISTICS

During 2024, Leap delivered demand response to [redacted] distinct customer meters across forty load serving entities (LSE) including all three major electric investor-owned utilities[2] throughout the California Independent System Operator's (CAISO) balancing authority area. Table 2-1 presents the number of participants by electric utility.

TABLE 2-1: PROGRAM ENROLLMENT BY ELECTRIC IOU

IOU	Enrolled Participants
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]

Leap's 2024 portfolio was comprised of 39 commercial partners, each of which contracted with one or more electricity customers to provide load shed during market dispatch. Of these, 29 served non-residential customers and 24 served residential customers, with 14 serving both. For the non-residential partners [redacted]

The programs for which Leap aggregates DR resources in California can call events for one or more Sub-Load Aggregation Points (SubLAP) when DR resources are needed in a specific location on the grid. For this reason, it is especially important to identify participants based on their geographic locations,

2 Major electric investor-owned utilities are defined here as Pacific Gas and Electric Company (PG&E), Southern California Edison Company (SCE), and San Diego Gas and Electric (SDG&E).

particularly by SubLAP. Participant enrollment counts by electric IOU and SubLAP are presented in Table 2-2. As requested under LIP guidelines, Verdant estimated ex post and ex ante impacts by these groups.

TABLE 2-2: TOTAL 2024 YEAR PARTICIPANT COUNT BY ELECTRIC IOU AND SUBLAP

PG&E		SCE		SDG&E	
SubLAP	Enrolled Participants	SubLAP	Enrolled Participants	SubLAP	Enrolled Participants
[redacted]					

Leap participants represent 11 distinct load types across residential and commercial sectors. The counts of unique participants by customer sector, load type, and electric IOU are presented in Table 2-3.

TABLE 2-3: ENROLLMENT BY CUSTOMER SECTOR, LOAD TYPE, AND ELECTRIC IOU

Sector	Load Type	Enrollment Count		
		PG&E	SCE	SDG&E
Commercial	Cold Storage	[redacted]	[redacted]	[redacted]
	Electric Vehicle	[redacted]	[redacted]	[redacted]
	HVAC	[redacted]	[redacted]	[redacted]
	Large Battery Storage	[redacted]	[redacted]	[redacted]
	Manufacturing / Process	[redacted]	[redacted]	[redacted]
	Pumping	[redacted]	[redacted]	[redacted]
	Small Battery Storage	[redacted]	[redacted]	[redacted]
Total Commercial		[redacted]	[redacted]	[redacted]
Residential	Electric Vehicle	[redacted]	[redacted]	[redacted]
	HVAC	[redacted]	[redacted]	[redacted]
	Other	[redacted]	[redacted]	[redacted]
	Storage	[redacted]	[redacted]	[redacted]
Total Residential		[redacted]	[redacted]	[redacted]
	Grand Total	[redacted]	[redacted]	[redacted]

2.2 2024 EVENT INFORMATION

Over the course of the 2024 calendar year, Leap resources were called upon 1,151 distinct times across 347 days between January and December. In general, there are three event types for which Leap participants receive payments for their participation: test events (of which there were 41), market dispatch (totaling 998 events), combined events (85 events). Test events are called to trigger load reductions regardless of market prices. Market events are called when Leap energy bids clear market prices. Combined events occur when a test event occurs concurrently with a market event. Table 2-4 and Table 2-5 detail the number of 2024 events by load types (Table 2-4) and timing (Table 2-5).

TABLE 2-4: EVENT COUNT BY LOAD TYPE AND MONTH

Sector and Load Type		Count of Distinct Events											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Commercial	Cold Storage	[redacted]											
	Electric Vehicle												
	HVAC												
	Large Battery Storage												
	Manufacturing / Process												
	Pumping												
	Small Battery Storage												
Total Commercial													
Residential	Electric Vehicle												
	HVAC												
	Other												
	Storage												
Total Residential													

TABLE 2-5: COUNT OF DISTINCT EVENTS BY LENGTH IN HOURS

Duration (Number of Hours)	1	2	3	4	5
Event Start at 6:00 pm or Earlier	[redacted]				
Event Start After 6:00 pm					
Total					

3 METHODS AND RESULTS

This section describes the methods used for estimating ex post load impacts and the ex ante forecast and summarizes the results of the analysis.

3.1 DATA SOURCES

The analysis conducted for ex ante impact estimation and ex post forecasts relied on data from multiple sources. These are summarized in Table 3-1, followed by a discussion of important details about their use in the analysis.

TABLE 3-1: DATA SOURCE SUMMARY

Data Type	Source	Key Fields	Notes
Interval load data	Leap	Meter ID, date and time stamp, interval energy readings.	
Historical weather data	California Measurement Advisory Council (CALMAC)	Weather station ID, weather station coordinates (latitude and longitude), date and time stamp, temperature, relative humidity, and solar irradiance readings.	https://www.calmac.org/weather.asp
Participant information	Leap	Meter ID, customer load type, location coordinates, sector, SubLAP, and enrollment, and disenrollment dates	
Event data	Leap	Meter ID, event ID, event start and end date and time stamps, program.	
Participant forecast	Leap	Three-year forecast of projected program enrollment by program, load type, and scenario.	Leap's justification for its forecast will be in an Appendix C, which will be delivered with the final report.
Alternate weather scenarios	PG&E, SCE, SDG&E	Monthly series of hourly weather for alternate day types (typical event day vs. system peak/worst day) and weather years (1-2 vs. 1-10) by utility and climate zone.	These data include both utility and CAISO versions of the weather scenarios.

Interval Data

Leap provided the interval data used for the estimation of impacts. The structure of the data was consistent in the individual files, the raw data for each customer meter required assembling the data from hundreds of individual files. Given these characteristics, the preparation of these data for analysis required a careful application of several steps to ensure their consistency and reliability for use in the analysis, including:

- Review of the timestamps to detect any effects of daylight savings time and to ensure the documented time zone was correct.

- Setting timestamps to a consistent local time of Pacific Standard Time and Pacific Daylight time (given the time of year) in a time-zone aware field in R (the software used for data processing and analysis) to ensure correct merging.
- Determining the interval definition associated with the raw data (either interval beginning or interval ending), and then setting all time stamps to a consistent period beginning.
- Aggregation of various interval lengths to a common hourly level.
- Aggregation of individual meters to the facility level and ensuring that each aggregated interval contained the full set of readings from the constituent meters.
- To remove any ambiguity in the model data, Verdant created separate “hour starting” and “hour ending” columns to ensure proper interpretation of the data.

Where applicable, the steps relating to timestamps also applied to several other data sources used for this analysis, including weather and event start and end times.

Historical Weather Data

Historical weather data for 2024 were extracted from the California Measurement Advisory Council (CALMAC), which is a change over the previous evaluations that Verdant has completed for Leap. The 127 stations in the CALMAC data are fewer than the 150 in the previous data extracted from National Oceanic and Atmospheric Administration (NOAA). However, the CALMAC data are far more complete than the NOAA data, which led to substantially more stations available to represent the geographic diversity of Leap’s customers. As with the previous evaluations, the mapping of meters to weather stations was based on using latitude and longitude data to calculate the distances between them.

Participant and Event Data

Leap also provided data to identify and classify the customers in the 2024 participant population and their participation in the various program events. For each meter ID, key information included the load type curtailed, associated SubLAP, enrollment and disenrollment date, and geographic information to map to weather stations. The event information was specific to each meter and included the start and end time, the type of the event (test, market dispatch, or combined), and the program associated with the event (CCA vs. DRAM).

Participant Forecast and Alternate Weather Scenarios

The participant forecasts and alternate weather scenarios are the inputs for the generation of the ex ante impact forecast. The participant forecast provided by Leap represented low and high projections of the total monthly customers for each of the customer load types from 2026 to 2028. For residential, these forecasts were broken out by utility, whereas the non-residential forecasts were for all utilities. For both forecasts, the total forecast was allocated to the different SubLAPs using the proportions from the 2024 customer data. Table 3-2 shows the overall participant forecast by IOU, sector, load type, and year (both high and low cases) as assigned by Verdant. For years beyond 2028, the forecasted customers carry the 2028 values forward without adjustment. To eliminate redundancy, those values have been excluded from the table. Further, the forecasts were provided by month. The values presented in the table below represent a snapshot of annual enrollment forecasts from August of each year. As a result, the enrollment counts found in later sections of this report and in the ex ante table generators may differ from the values presented below.

TABLE 3-2: PARTICIPANT FORECAST BY IOU, SECTOR, LOAD TYPE, AND YEAR (LOW AND HIGH CASES)

	Low Enrollment Growth			Medium Enrollment Growth*			High Enrollment Growth		
	2026	2027	2028+	2026	2027	2028+	2026	2027	2028+
PG&E									
Non-Residential									
EV - C/I	[redacted]								
HVAC - C/I	[redacted]								
Large Commercial Storage	[redacted]								
Pumping	[redacted]								
Small Commercial Storage	[redacted]								
Residential									
EV - Resi	[redacted]								
HVAC - Resi	[redacted]								
Resi Storage	[redacted]								
SCE									
Non-Residential									
EV - C/I	[redacted]								
HVAC - C/I	[redacted]								
Large Commercial Storage	[redacted]								
Pumping	[redacted]								
Small Commercial Storage	[redacted]								
Residential									
EV - Resi	[redacted]								
HVAC - Resi	[redacted]								
Resi Storage	[redacted]								
SDG&E									
Non-Residential									
EV - C/I	[redacted]								
HVAC - C/I	[redacted]								
Large Commercial Storage	[redacted]								
Pumping	[redacted]								
Small Commercial Storage	[redacted]								
Residential									
EV - Resi	[redacted]								
HVAC - Resi	[redacted]								
Resi Storage	[redacted]								

*Note: Medium is only applicable to the non-residential sector. As a result, Medium is the same for the residential sector.

The weather scenarios provided by the utilities represent 24-hour temperature estimates for each month under different system conditions (monthly peak versus typical event day) and weather conditions (1-in-2 versus 1-in-10 years). These days have historically been used to develop estimates of potential portfolio performance under different weather conditions, but for this year the requirements are only for the monthly peak day (worst day) and 1-in-2 weather conditions.

3.2 PARTICIPANT ASSESSMENT

After the initial processing of the data, Verdant conducted a thorough assessment of the data through both summary statistics and visualization to better understand the nature of the participants in the Leap programs. The first part of this analysis was to identify any issues with overall data quality. Verdant and Leap had multiple engagements to better understand the data and address potential data quality issues, which resulted in a high-quality dataset used for modeling. Equally important is to get a sense of the challenges that the analysis is likely to provide. Verdant's experience with evaluating DR programs has been that non-residential participants not only have far more varied and volatile load (compared to residential), but their response to events can be similarly unpredictable. For this reason, a large part of this assessment is the review of a variety of data visualizations to look at participants' load on both event and non-event days. As a rule, if there is not a clearly discernible curtailment when examining a facility's load profile on an event day, it will be challenging or impossible to reliably model its impacts. But even what might seem to be response to an event might be less clear when seen in the context of usage on other days, so it is valuable to have a more complete perspective of usage patterns.

For residential meters, there was additional analysis to validate that meter level data could be appropriately combined into panel models. This included exploring the number of event participants withing a given month and SubLAP, the completeness of interval data to be pooled and that residential loads were sufficiently homogeneous.

Non-Residential Weather Sensitivity Modeling

As discussed previously, the meters in Leap's portfolio represent a wide variety of load types. The loads of industrial meters are frequently found to have no relationship to outdoor air temperatures. To determine participant level weather sensitivity, Verdant applied a simple analysis to assess the relationship between load and outdoor temperature. The results were used to determine whether the candidate models for estimating impacts came from a group with various weather variables or from a group based on variables unassociated with weather.

Using the interval load and weather data for non-winter months (April through October), the analysis estimated regression models of consumption on different thresholds of cooling-degree hours for each facility by day type. If any of these models resulted in a parameter estimate with a probability ("p value") less than .05, the facility was deemed to be weather sensitive for that day type.

Table 3-3, shows the count of meters in each load type category that exhibit summer weather sensitivity.

TABLE 3-3: COUNT OF COMMERCIAL METERS BY LOAD TYPE EXHIBITING SUMMER WEATHER SENSITIVITY

Weather Sensitivity Type	EV	HVAC	Large Battery Storage	Manufacturing / Process	Pumping	Small Battery Storage
Cooling	[redacted]					

For winter events, Verdant conducted a similar analysis using data from January, February, March, April, October November, and December that looked at both heating and cooling weather sensitivity. As shown in Table 3-4, only a small number of facilities appear to have weather sensitive heating load. And while the cooling in these winter months might seem counter-intuitive, for many of the facilities outside of coastal regions, there can be relatively warm temperatures in the winter months.

TABLE 3-4: COUNT OF FACILITIES BY INDUSTRY EXHIBITING WINTER WEATHER SENSITIVITY

Weather Sensitivity Type	EV	HVAC	Large Battery Storage	Manufacturing / Process	Pumping	Small Battery Storage
Cooling	[redacted]					
Heating						

For residential meters, there is always an assumed relationship with temperature. As result, there is always a variable to capture temperature effects in the baseline. No weather sensitivity analysis was conducted for these meters.

Data Attrition

The estimation of load impacts requires having a minimum amount of data to reliably model the relationship between a participant's load and the independent variables used to predict it. Furthermore, these data need to be of sufficient quality for reliable results. In cases where the quantity and/or quality of the data was not sufficient, meters were removed from the analysis. Additionally, non-residential meters that could not be modeled with sufficient reliability were removed based on an adjusted R squared value of less than 0.2. Meters that consistently produced load increase of greater than 15% or produced load increases greater than 1 MW were also removed from the ex post and ex ante results. In total there were 4,259 of the 4,378 non-residential meters had data and were modellable.

Data attrition is a more complicated matter for residential meters. In general, data attrition for residential meters is associated with the same issues as the other groups, such as missing or poor-quality data, but there are several differences for this group that make it difficult to provide a clear accounting. Meters that were sporadically populated with weather were not included in the analysis. Primarily this is because the estimation of impacts used panel data models, which, in contrast to individual customer models, require a relative balance or symmetry in the days of data for each customer. This resulted in the dropping of a small share of customers that for various reasons had data less aligned with the others in the segment.

3.3 EX POST IMPACT ESTIMATION METHODOLOGY

Verdant estimated ex post load impacts using two main regression-based approaches. Beginning with the non-residential segments, the models were based on individual regression models. There were a few key considerations that made this approach more practical for these customers. The first consideration was the sparseness of interval data. Not all sites had the same amount of data available for analysis, therefore aggregate or panel data models would have required excluding a substantial amount of data to ensure that the aggregated load was inclusive of all relevant accounts. The second consideration was the variation in event participation. Unless every participant participates in the same events, aggregate models will require the creation of multiple data sets to account for the various participant-event permutations. Finally, individual models were the most practical way to provide the desired granularity of results. The ability to show impacts at different levels of aggregation including utility, SubLAP, load type, and event type would have made the development of data sets with the correct aggregation of accounts overly complicated.

For the residential load types, the ex post impacts were based on panel data regression models. The large number of customers (except for residential storage, which has far fewer accounts than previous years) allowed for robust estimation of impacts on a subset of customers, so the concerns about data attrition due to sparse data are not as relevant to these groups. But more importantly, individual residential households can have highly volatile load, so panel models are better suited to capture the effects of temperature and other variables to establish the baseline consumption across all participants. This applies to capturing event impacts as well.

The different regression approaches also led to differences in how impacts were estimated for the residential and non-residential load types. With individual regression models, the non-residential impacts could be estimated using whatever data is available, so the estimation of impacts was done seasonally. For residential load types, Verdant segmented customers by SubLAP and by an internally created designation of whether the customer likely had solar panels.

There were multiple motives for this approach. The segmentation by SubLAP allowed for the control of distinct characteristics associated with each SubLAP -- primarily weather, but also potentially home size, fuel mix, etc. Estimation by SubLAP also allows for the estimation of impacts at a level of interest to grid planners and other stakeholders.

For customers with solar – particularly when only delivered load is available – the relationship between temperature and load can be ambiguous. Higher temperatures can also be associated with sunny days, which result in increased solar generation, which can reduce the delivered load. Verdant incorporated solar irradiance into the models for these customers, but even with this variable, the sign of the parameter estimates is not always intuitive. Modeling these groups separately allows for the more precise estimation baselines.

Non-Residential Candidate Model Specifications

Overall, Verdant implemented 34 individual model specifications to estimate ex post impacts. These varied by season and type of weather sensitivity (Table 3-5). Heating sensitive models were only included for winter months. Cooling sensitive and non-weather sensitive specifications were identical between seasons. The selected model specification, however, was allowed to differ between seasons.

TABLE 3-5: COUNT OF MODEL SPECIFICATIONS FOR IMPACT ESTIMATION

Season	Weather-Sensitive Cooling	Weather-Sensitive Heating	Non-Weather Sensitive
Summer and Shoulder Day	14	--	10
Winter Day		10	

Despite the large number of models, they all follow a similar form, with only a few minor differences in the independent variables. This general form is presented in Equation 1.

EQUATION 1: GENERAL NON-RESIDENTIAL MODEL SPECIFICATION

$$kWh_{d,h} = \beta_0 + \beta_{1e,h}EventDay_eHour_h + \beta_2Temp_h + \beta_{4,h}Hour_h + \beta_{5,m}Month_m + \beta_{6,d}Wday_d + \varepsilon$$

Where:

$kWh_{,d,h}$	The Net Load on day d in hour h
β_0	The intercept of the regression model
$EventDay_eHour_h$	The interaction between the event day dummy and hour. Its coefficient, $\beta_{1e,h}$, yields the impact of the event ID on event day *e* during hour *h*
$Temp_h$	A temperature variable in hour *h*.
$Hour_h$	A dummy variable for each hour *h*
$Month_m$	A dummy variable for each month *m*
$Wday_d$	A dummy variable indicating the day of the week *d*
ε	The regression error term

A comprehensive list of the model specifications along with definitions of each variable is provided in Appendix A.

Residential Candidate Model Specifications

Verdant evaluated 16 different model specifications for the panel data models based on different permutations of cooling- and heating-degree days/hours, day type versus weekend dummy variables, and minimum versus maximum daily temperature. These models were based on the same specifications used last year with the additional of some rolling average weather terms. While the specific weather (degree-hour, degree-day, etc.) and calendar variables (day of week, weekend/holiday, etc.) varied, Equation 2 presents the general model specification used to estimate ex post impacts for the residential subgroup.

EQUATION 2: RESIDENTIAL GENERAL MODEL SPECIFICATION

$$kWh_{e,h,i} = \beta_0 + \beta_{1e,h}EventDay_e + \beta_3 Temp_h + \beta_4 Irr_h + \beta_{5,m}Month_m + \beta_{6,d}Wday_d + \ \beta_{7,d} + \alpha_i \ + \varepsilon$$

Where:

$kWh_{e,d,h,i}$	The delivered load on day *d* in hour *h* during event *e* for participant *i*
β_0	The intercept of the regression model
$EventDay_e$	The interaction between the event day dummy and the event ID dummy. Its coefficient, $\beta_{1e,\mathrm{h}}$, yields the event ID's effect on impact of the event day *e* during hour *h*
$Temp_\mathrm{h}$	A temperature variable or variables in hour *h*.
Irr_h	A variable representing the solar irradiance in hour *h.* Only for homes with solar generation.
$Hour_\mathrm{h}$	A dummy variable for each hour *h*
$Month_m$	A dummy variable for each month *m*
$Wday_d$	A dummy variable indicating the day of the week *d* or weekend/holiday
α_i	The fixed effect for participant *i* that captures the participant level heterogeneity.
ε	An error term

Model Selection

The selection of the final model for both sectors was based on an assessment of model performance using a set of non-event days with event-like weather as a holdout sample. While the model R^2 or adjusted R^2 are valuable as a measure of how much variability is explained by the model, they are influenced by model overspecification and can be misleading. The ability of the models to predict load out of sample is a far better way to assess how well a model works at estimating a baseline.

Verdant selected for each weather station a set of days with event-like weather (based on the max temperature) for use as a holdout sample. In the first stage of model estimation, we removed these days from the data and then used the remaining data to estimate the candidate models. Verdant then used the parameter estimates from candidate models to predict load on the holdout days. Based on the predicted and actual load, Verdant calculated a variety of metrics to assess model performance (mean absolute percent error (MAPE), root mean square error (RMSE), etc.) using the daytime hours to determine which models predicted load most accurately during the relevant periods. The model with the best out-of-sample predictions for each meter was set aside as the final model. Verdant then applied these final model specifications to the full set of seasonal or monthly data – with the holdout days restored – to estimate the final set of ex post program impacts.

3.4 EX POST RESULTS

A detailed set of results with impacts by IOU, load types, and event types for all event days is available in the load protocol workbooks submitted with this report. These workbooks provide event-specific results by utility and program as well as more detailed breakdowns by numerous meter characteristics. Given the sheer quantity of results, this section presents only the impact estimates by month and load types for the residential and non-residential impacts.

The average ex post results are presented by day and month in Table 3-6 through Table 3-10 with some or all of the following columns:

- Number of Event Days: The total number of unique days in which events were called. Since there can be more than one event per day and the number of event ids vary across customers, the event days are not an indication of the number of unique Leap events.
- Mean Event Day Meter Count: The average number of meters that were notified for the event on a given event day.
- Mean Reference Load (kWh/h): The average hourly reference load per participant. This is the counterfactual, or the model estimate of what load would have been without the event.
- Mean Meter Impact (kWh/h): The average hourly kWh/h impact resulting from curtailment.
- Percent Load Reduction Average: The impact as a percentage of the reference load.
- Total MWh/h Reduction: The average MWh/h load reduction during the event period calculated as the number of facilities multiplied by mean meter impact.
- Average Event Temperature: The average temperature in degrees Fahrenheit during the event period.

Table 3-6 provides the average ex post impact for non-residential meters. The impacts were first estimated for each individual meter event and then were averaged to get the average monthly impact for a given meter. The individual meter level event impacts were removed if the estimated average event impact resulted in a load increase that was above 1 MW or represented a load increase greater than 15% of baseline delivered load. As seen, the monthly average event day load reduction averages between [redacted] The variation in load impacts is highly dependent on the types of resources dispatched and to a lesser extent which participants were dispatched for curtailment. Despite this, the information does demonstrate the ability to reliably dispatch sizable load reductions when only a portion of Leap's non-residential resources are notified for event participation.

TABLE 3-6: MEAN EVENT MONTHLY EX POST IMPACTS FOR NON-RESIDENTIAL METERS BY PROGRAM

Month	Num. of Event Days*	Mean Event Meter Count**	Mean Reference Load (kWh/h)	Mean Impact (kWh/h)	Percent Load Reduction	Mean Aggregate MWh/h Reduction	Average Event Temp.
CCA							
Jan.	[redacted]						
Feb.							
Mar							
April							
May							
June							
July							
Aug.							
Sept.							
Oct.							
Nov.							
Dec.							
DRAM							
Jan.	[redacted]						
Feb.							
Mar							
April							
May							
June							
July							
Aug.							
Sept.							
Oct.							
Nov.							
Dec.							

*More than one event can occur on a given day and event day counts not distinct by utility in this summarization. As a result, event days do not align with event counts.

**Meter counts represent the average dispatch meter counts of modeled meters.

As mentioned above, the average event day load impact varies by load type. Table 3-7 presents the average of the non-residential hourly event day per capita impacts (kW) by month, load type and program. The largest impacts by month were typically seen in the [redacted] load types. The smallest per capita impacts typically belong to the [redacted] load types. Table 3-7.

TABLE 3-7: MEAN MONTHLY PER CAPITA (KW) EX-POST IMPACTS - NON-RESIDENTIAL METERS BY LOAD TYPES AND PROGRAM

Month	Cold Storage	EV – Non Residential	HVAC – Non Residential	Large Battery Storage	Manufacturing / Process	Pumping	Small Battery Storage
CCA							
Jan.	[redacted]						
Feb.							
Mar							
April							
May							
June							
July							
Aug.							
Sept.							
Oct.							
Nov.							
Dec.							
DRAM							
Jan.	[redacted]						
Feb.							
Mar							
April							
May							
June							
July							
Aug.							
Sept.							
Oct.							
Nov.							
Dec.							

Table 3-8 presents the average of the non-residential hourly event day per capita impacts (kW) by month, load type and IOU. These results present the average per meter impact within a given IOU, given that ex ante impacts use both CCA and DRAM participation it is worth presenting average per meter impacts. In this way.

TABLE 3-8: MEAN MONTHLY PER CAPITA (KW) EX-POST IMPACTS - NON-RESIDENTIAL METERS BY LOAD TYPES AND IOU

Month	Cold Storage	EV – Non Residential	HVAC – Non Residential	Large Battery Storage	Manufacturing /Process	Pumping	Small Battery Storage
PG&E							
Jan.	[redacted]						
Feb.	[redacted]						
Mar.	[redacted]						
April	[redacted]						
May	[redacted]						
June	[redacted]						
July	[redacted]						
Aug.	[redacted]						
Sept.	[redacted]						
Oct.	[redacted]						
Nov.	[redacted]						
Dec.	[redacted]						
SCE							
Jan.	[redacted]						
Feb.	[redacted]						
Mar.	[redacted]						
April	[redacted]						
May	[redacted]						
June	[redacted]						
July	[redacted]						
Aug.	[redacted]						
Sept.	[redacted]						
Oct.	[redacted]						
Nov.	[redacted]						
Dec.	[redacted]						
SDG&E							
Jan.	[redacted]						
Feb.	[redacted]						
Mar.	[redacted]						
April	[redacted]						
May	[redacted]						
June	[redacted]						
July	[redacted]						
Aug.	[redacted]						
Sept.	[redacted]						
Oct.	[redacted]						
Nov.	[redacted]						
Dec.	[redacted]						

Table 3-9 provides the average ex post impact for residential meters. As seen, the monthly average event day load reduction averages between [redacted] of delivered load. The variation in load impacts is dependent on the types of resources dispatched and to a lesser extent which participants were dispatched for curtailment.

TABLE 3-9: MEAN MONTHLY EX POST IMPACTS FOR RESIDENTIAL METERS

Month	Num. of Event Days*	Mean Event Day Meter Count	Mean Reference Load (kWh/h)	Mean Observed Load (kWh/h)	Mean Impact (kWh/h)	Percent Load Reduction	Average Total MWh/h Reduction
CCA							
Jan.	[redacted]						
Feb.							
Mar.							
April							
May							
June							
July							
Aug.							
Sept.							
Oct.							
Nov.							
Dec.							
DRAM							
Jan.	[redacted]						
Feb.							
Mar.							
April							
May							
June							
July							
Aug.							
Sept.							
Oct.							
Nov.							
Dec.							

*More than one event can occur on the same day. As a result, event days do not align with event counts.

Table 3-10 presents the average residential hourly event day per capita impacts (kW) by month and load type. The results in Table 3-10 show that [redacted] measures provided consistent average reductions in per capita load during events while [redacted] did not have sufficient events to accurately characterize the load reduction capability in most cases. [redacted] show their strongest curtailment during the summer months, specifically from July to September, which is the intuitive result for the latter, since these months have the highest cooling loads.

TABLE 3-10: MEAN MONTHLY PER CAPITA EX-POST IMPACTS FOR RESIDENTIAL METERS BY LOAD TYPES

Month	HVAC	EV-Residential	Residential Battery Storage
PG&E			
Jan.	[redacted]		
Feb.	[redacted]		
Mar.	[redacted]		
April	[redacted]		
May	[redacted]		
June	[redacted]		
July	[redacted]		
Aug.	[redacted]		
Sept.	[redacted]		
Oct.	[redacted]		
Nov.	[redacted]		
Dec.	[redacted]		
SCE			
Jan.	[redacted]		
Feb.	[redacted]		
Mar.	[redacted]		
April	[redacted]		
May	[redacted]		
June	[redacted]		
July	[redacted]		
Aug.	[redacted]		
Sept.	[redacted]		
Oct.	[redacted]		
Nov.	[redacted]		
Dec.	[redacted]		
SDG&E			
Jan.	[redacted]		
Feb.	[redacted]		
Mar.	[redacted]		
April	[redacted]		
May	[redacted]		
June	[redacted]		
July	[redacted]		
Aug.	[redacted]		
Sept.	[redacted]		
Oct.	[redacted]		
Nov.	[redacted]		
Dec.	[redacted]		

3.5 EX ANTE FORECAST ESTIMATION METHODOLOGY

The ex ante impact forecasts are largely the product of multiplication and summarization of impacts derived from modeling similar to the ex post models. First, the ex post models are modified to assess multiple events at once, incorporating a weather terms in the impact variable, to capture overall, or typical, effects. Alternative weather scenarios are applied to these parameter estimates to generate monthly impacts for each facility or segment where data were available. In previous studies, the ex ante scenarios covered different day types, weather scenarios, and weather data sources. These impacts are then summarized to the desired level of aggregation and combined with Leap's forecast of participation to generate the forecast of annual impacts. Note that for this year, the requirements call only for the 1-in-2 weather scenarios. Though table generators should have both CAISO and Utility weather, the LIP filing guide requests that the tables use the Utility 1-in-2 results for consistency.

Ex Ante Modeling

Despite the simple description above for generating the ex ante forecasts, the requirement to provide estimates of impacts for the full RA window complicates the process. For California, the RA window is the peak period of 4:00 pm to 9:00 pm in all months except March and April, which is from 5:00pm to 10:00pm. The complication is that there are few or no events that cover the full four hours within the RA window. Events vary in type, length, start time, so it is often not possible to directly estimate what the impacts of such an event would be, and rarely based on more than a single event. An example of this is presented in Figure 3-1, which shows the observed and reference loads in August for one SubLAP. In the figure, the two events are shown in the leftmost line plots. Independently, the events show clear load reductions (average kW and the percent load reduction are in each plot's title) over their respective two- and three-hour event windows. There is some degradation of the impact over the duration of the event, but overall, the participants maintain the load reduction over the event window. However, the conversion of these two events to represent the impacts over the full resource adequacy is not straightforward. As the average of the two events show, the load profile for the observed load distorts the load reduction patterns. The load impacts don't cover the full resource adequacy window - and can even show increases in the first hour due to the pre-cooling – so clearly additional steps are necessary to develop reasonable estimates that cover the entire event period.

FIGURE 3-1: EXAMPLE OF EX POST LOAD REDUCTIONS USED FOR EX ANTE ESTIMATION

This variability in event permutations calls for an approach that will allow for an estimation of the impacts that can be applied to every hour of the RA window. To address these issues, Verdant estimated impacts based on an "hour-of-event" model specification. As stated above, the functional form of the regression equations used to estimate ex ante impacts followed those used to estimate ex post impacts. However, this "hour-of-event" approach employs the following modifications:

- The ex post model $\beta_{1e,h}EventDay_eHour_h$ impact estimator was altered to $\beta_1 EventHour * nth\_HOUR$ for non-weather sensitive customers and to $\beta_1 WeatherVar * EventDay + \beta_1 EventHour * nth\_HOUR$ for summer cooling customers and winter heating sensitive customers. Where the variable $WeatherVar$ is a seasonal weather variable; either CDH65 or HDH60 for summer cooling and winter heating sensitive customers, respectively. Winter cooling weather variables were included in the baseline calculation, but not interacted with the impact estimator. Overall, these weather interactions allow for ex ante impacts to "adjust" accordingly to each weather scenario. The nth_HOUR variable represents the nth hour of an event and is intended to capture the effect of long duration events over the course of five-hour RA window.

- For non-residential, weekday dummy variables ($Wday_d$) were set to 0.2 when producing ex ante estimates of baseline load. This value represents the average weekday dummy value (1 divided by 5) for each weekday (Monday through Friday). For residential, all events were assumed to be weekdays.

- For residential, the results of the ex ante models were used to estimate a percentage load reduction as a function of the hour of the event. These load reductions were calculated across sublaps, to maintain an appropriate season differentiation. In previous years, these models were estimated for separate months. This is still the case, however, instead of only using a single month's events, we also included events from the adjacent months, but giving each a weight of .25, compared to .5 for the month of interest. The motive for this change was to eliminate some of the anomalies that arose from months that had few events and/or events of only short duration. If, for example, July only had one event of one hour, the inclusion of events from June and August, though weighted less, provided more information for the estimation of ex ante impacts.

For non-residential, after individual meter ex ante impacts were estimated, individual estimates were combined based on IOU service territory, SubLAP and load type to establish the average per capita (kw) load reduction and representative event day baseline for a typical Leap participant in a given SubLAP and load type. Residential impacts were already estimated at the IOU, SubLAP. Finally, as with the ex post impacts, ex ante impacts were modeled separately for summer and winter months for the non-residential load types and by month and SubLAP for residential.

Verdant developed estimates of load reductions for the full five-hour window, and these results are presented in the Ex Ante table generators as a more complete and transparent demonstration of capabilities. However, it should be noted the *LIP Filing Guide v4.0* indicates that ex ante must demonstrate a four consecutive dispatch as a result, ex ante modeling assumes a four-hour event between 4:00pm and 8:00pm where snapback occurs between 8:00pm and 9:00pm. For March through May, 5:00pm to 9:00pm are the assumed event hours with snapback occurring between 9:00 and 10:00 pm. As a result, for the calculation of Ex Ante impacts, consistent with the slice-of-day approach, the load reductions are taken from the first four hours of the RA window.

3.6 EX ANTE RESULTS

As with the ex post impacts, a detailed set of results with impacts by IOU, load type, and SubLAP for all weather scenarios is available in the load protocol table generators submitted with this report. Given the different weather sources, weather years, day types, and months, the number of permutations associated with the results are far too many to present here. Consequently, this section presents only a high-level overview of the ex ante impacts associated with Leap's DR portfolio to present demonstrated RA potential.

Table 3-11 below presents the ex ante MW forecasts under the Utility and CAISO August System Peak 1-in-2 weather scenarios for 2026 through 2028. For each weather scenario, the sector total and the portfolio total MW are presented. As seen, the 2026 ex ante impact estimates for Leap's portfolio under the 1-in-2 Utility August System Peak are [redacted] MW in the high growth scenario. By 2028, it is estimated that that Leap's portfolio potential will be [redacted] in aggregate for the high enrollment scenario.

TABLE 3-11: 2025 THROUGH 2027 AUGUST SYSTEM PEAK EX ANTE FOR UTILITY 1-IN-2 WEATHER (MW)

	Low Enrollment Growth			Medium Enrollment Growth			High Enrollment Growth		
Sector	**2026**	**2027**	**2028+**	**2026**	**2027**	**2028+**	**2026**	**2027**	**2028+**
Commercial									
CAISO 1-in-2	[redacted]								
Utility 1-in-2									
Residential									
CAISO 1-in-2	[redacted]								
Utility 1-in-2									
Total									
CAISO 1-in-2	[redacted]								
Utility 1-in-2									

TABLE 3-12: EX ANTE MW SLICE OF DAY OVER AAH – UTILITY 1-IN-2, RA YEAR 2026

Sector	Enrollment Type	Availability Assessment Hour (AAH)				
		Hour Ending 17	Hour Ending 18	Hour Ending 19	Hour Ending 20	Hour Ending 21 (Snapback)
Residential	Low	[redacted]				
	Medium					
	High					
Non-Residential	Low					
	Medium					
	High					
Total	Low					
	Medium					
	High					

Table 3-13 presents the August 2026 System Peak MW contributions by load type for the CAISO and Utility weather scenarios. As seen, aggregate MW estimates are concentrated in four main load type groups: [redacted].

TABLE 3-13: UTILITY 1-IN-2 AUGUST SYSTEM PEAK EX ANTE BY LOAD TYPE – RA YEAR 2026

Sector and Load Type	Low Enrollment Growth			Medium Enrollment Growth			High Enrollment Growth		
	Forecast Part. Count	CAISO 1-in-2 (MW)	Utility 1-in-2 (MW)	Forecast Part. Count	CAISO 1-in-2 (MW)	Utility 1-in-2 (MW)	Forecast Part. Count	CAISO 1-in-2 (MW)	Utility 1-in-2 (MW)
Commercial									
EV	[redacted]								
HVAC									
Lg Battery Storage									
Pumping									
Sm Battery Storage									
Residential									
Res EV	[redacted]								
Res HVAC									
Res Battery Storage									
Total									
Total	[redacted]								

Leap has events throughout the year, so Table 3-14 shows the total MW by sector for both low and high enrollment scenarios. There are a couple of important caveats in assessing the monthly ex ante projections. The first is that not every resource had events to allow the estimation of month specific impacts, so in many cases the values are based on impacts from an adjoining month or other SubLAP. The second is that based on 2024 events, the number of customers dispatched in non-summer months are generally fewer. The residential participant forecast reflects this seasonality (last year it did not), but the non-residential participant forecasts do not. As a result, these non-residential ex ante numbers are based on full participation, which is not necessarily representative of actual dispatch tendencies.

TABLE 3-14: EX ANTE MW BY MONTH AND LOAD TYPE – UTILITY 1-IN-2, RA YEAR 2026

Month	Residential			Non-Residential			Total		
	Low Enrollment	Medium Enrollment	High Enrollment	Low Enrollment	Medium Enrollment	High Enrollment	Low Enrollment	Medium Enrollment	High Enrollment
Jan.	[redacted]								
Feb.									
Mar.									
April									
May									
June									
July									
Aug.									
Sept.									
Oct.									
Nov.									
Dec.									

Results Comparisons

Table 3-15 provides a comparison of this year's results with the 2024 filing, with the load types for each sector requiring different discussions. For non-residential, in many cases the comparison of the impacts from 2023 to 2024 has limited value because the underlying population of meters has changed substantially. These customers can vary substantially in size, so even when there are many customers, the addition or loss of just one meter can greatly alter the estimated impacts. Pinpointing any specific cause would take a very detailed analysis to isolate the specific meters that changed and how their estimated load impacts varied from year to year. With respect to the current year ex post and ex ante, there are few if any discrepancies that beckon for a detailed discussion, as most are reasonably similar. The one main exception would be the pumping load type, which has more than double the estimated impacts for ex ante as for ex post in 2024. This is due largely to the estimation of reference loads for this load type, which represent an average profile for loads that are more typically either on or off. To the extent that ex post impacts were derived from low load days, the application of their load reductions to average loads can result in higher estimates of ex ante impacts.

TABLE 3-15: RESULTS COMPARISONS PER CAPITA IMPACTS MONTH OF AUGUST

Sector and Load Type	2023		2024	
	Ex Post	Ex Ante	Ex Post	Ex Ante
Commercial				
Cold Storage	[redacted]			
EV – Non-Residential				
HVAC – Non-Residential				
Large Battery Storage				
Manufacturing/ Process				
Pumping				
Small Battery Storage				
Residential				
Res HVAC	[redacted]			
Res EV				
Res Battery Storage				

*The ex post value for residential storage is from September, as there were not reliably modeled impacts for August.

With respect to the residential results, variability does not present the same challenges when it comes to comparing results. For the current year ex post and ex ante values, the numbers per participant impacts are similar, which is reflective of the similar methods used to estimate those impacts. For the small differences, a typical cause is the difference in the weather used to estimate reference loads, which can be different from conditions on actual events. For any comparisons of the 2023 with 2024 – either ex post or ex ante - the largest factor is simply that the weather in 2024 represented a regression to much more typical weather compared to the cool weather in 2023. This is starkly clear in the ex post values for the two years, with the current average impacts for HVAC more than three times last year's results. For the ex ante results, a key difference is simply the difference in methods. Due to the cooler weather in 2023, the ex ante estimates incorporated 2022 results, though weighted much lower, with the 2023 number. For the current results, all ex ante values are based on models of 2024 events.

4 FINDINGS AND RECOMMENDATIONS

Key findings and recommendations in this study include:

Findings

Based on low and high enrollment forecasts, Leap's DR portfolio is anticipated to be able to provide between [redacted] of incremental curtailment under the August system worst day using the 1-in-2 weather scenario in 2026. These results are the product of standard methods to estimate load type-specific per participant load reductions to forecast the likely participation in Leap's portfolio. Nevertheless, there are some necessary caveats to any interpretation of the results.

One issue is still that there remains a disconnect between the RA window and how load curtailment is dispatched. The hour of the event and the hour of day interact in determining the levels of load curtailment, so the approaches to model events that occurred in many permutations of start time and length can result in impacts that are not always intuitive, although the load impacts remain generally accurate in magnitude. The slice-of-day rules help mitigate some of the challenges of estimating ex ante impacts by allowing for the selection of the first four hours of the event window to determine the load curtailment. Nevertheless, until there is explicit guidance or requirements on an alternative method, this will remain a feature of ex ante impact estimates.

As with previous years, the estimation of impacts using only the delivered channel of interval data is likely resulting in load reductions that are smaller than what is occurring on the grid. This is particularly the case for residential EV charging and storage, which have participating household with a high saturation of installed solar, leading to large amounts of export that 1) make it more difficult to estimate a baseline, and 2) can obscure actual load curtailment. Verdant previously mitigated this limitation by applying its own segmentation of customers into solar and non-solar groups, which did result in better modeling results for the non-solar group. This year, we also leveraged solar irradiance observations in the CALMAC weather data and included those in the model specifications. Nevertheless, the estimation of impacts using net load would result in better models and provide a more accurate reflection of the actual grid impacts of these programs.

APPENDIX A LIST OF MODEL SPECIFICATIONS

This appendix lists the base model specifications for the full set of models that were estimated as candidate models for the estimation of ex post impacts and ex ante analysis. The appropriate event day, event hour and weather interactions were attached to each respective base model as detailed in the main body of the report. The models are presented in Table A-1 and Table A-2 using R syntax, which is the software used for the analysis. The definitions for the unique list of variables referenced in the formulas are provided below the model specifications.

TABLE A-1: NON RESIDENTIAL GENERAL FORM MODEL SPECIFICATIONS BY SEASON/DAY TYPE AND WEATHER SENSITIVITY TYPE

Weather Sensitivity Type	Model Number	R Code Specification
Weather-Sensitive Cooling	1	kwh ~ cdh65:factor(hour) + factor(month) * factor(hour)
	2	kwh ~ cdh60:factor(hour) + factor(month) * factor(hour)
	3	kwh ~ cdh65:factor(hour) + factor(month) * factor(hour) + dtype
	4	kwh ~ cdh60:factor(hour) + factor(month) * factor(hour) + dtype
	5	kwh ~ cdd65:factor(hour) + factor(month) * factor(hour)
	6	kwh ~ cdd60:factor(hour) + factor(month) * factor(hour)
	7	kwh ~ cdh65:factor(hour) + cdd65 + factor(month) * factor(hour)
	8	kwh ~ cdh65:factor(hour) + cdd65 + factor(month) * factor(hour)
	9	kwh ~ cdh65:factor(hour) + factor(month) * factor(hour) + factor(hour):morning_load
	10	kwh ~ cdh65:factor(hour) + factor(month) * factor(hour) + factor(hour):afternoon_load
	11	kwh ~ I(cdh65^2):factor(hour) + factor(month) * factor(hour) + dtype
	12	kwh ~ I(cdh60^2):factor(hour) + factor(month) * factor(hour) + dtype
	13	kwh ~ cdh65:factor(hour) + I(cdh65^2) + factor(month) * factor(hour) + dtype
	14	kwh ~ cdh60:factor(hour) + factor(month) * factor(hour) + I(cdh60^2) + dtype
Non-Weather Sensitive	1	kwh ~ factor(month) * factor(hour) + factor(dtype)
	2	kwh ~ factor(month) * factor(hour) + factor(dtype) + morning_load:factor(hour)
	3	kwh ~ factor(month) * factor(hour) + factor(dtype) + morning_load:factor(hour) + evening_load:factor(hour)
	4	kwh ~ factor(month) * factor(hour) + factor(dtype) + afternoon_load:factor(hour)
	5	kwh ~ factor(month) * factor(hour) + factor(dtype) + morning_load:factor(hour) + afternoon_load:factor(hour)
	6	kwh ~ factor(month) * factor(hour) + factor(dtype) + morning_load:factor(hour) + afternoon_load:factor(hour) + evening_load:factor(hour)
	7	kwh ~ factor(month) * factor(hour) + factor(dtype) + monday:as.factor(hour) + friday:as.factor(hour)
	8	kwh ~ factor(month) * factor(hour) + factor(dtype) + monday:as.factor(hour) + friday:as.factor(hour) + morning_load:factor(hour)
	9	kwh ~ factor(month) * factor(hour) + factor(dtype) + monday:as.factor(hour) + friday:as.factor(hour) + afternoon_load:factor(hour)
	10	kwh ~ factor(month) * factor(hour) + factor(dtype) + monday:as.factor(hour) + friday:as.factor(hour) + morning_load:factor(hour) + evening_load:factor(hour)
	11	kwh ~ factor(month) * factor(hour) + factor(dtype) + monday:as.factor(hour) + friday:as.factor(hour) + afternoon_load:factor(hour) + evening_load:factor(hour)

TABLE A-2: DEFINITION OF VARIABLES IN MODEL SPECIFICATIONS

Variables	Definition
Morning_load:as.factor(hour)	Morning load interacted with the hour of the day.
Afternoon_load:as.factor(hour)	Afternoon load interacted with the hour of the day.
Evening_load:as.factor(hour)	Evening load interacted with the hour of the day.
cdd65	Cooling degree days using as base of 65 degrees
cdd65:as.factor(hour)	CDD65 interacted with the hour of the day.
Evening_load:as.factor(hour)	Evening load interacted with the hour of day.
Friday:as.factor(hour)	Binary variable indicating Friday interacted with the hour of the day.
Monday:as.factor(hour)	Binary variable indicating Monday interacted with the hour of the day
dtype	Categorical variable indicating the day of the week (Monday through Friday)
ProgramEventHour	Binary variable indicating a program event hour.
as.factor(hour)	Series of binary indicators for the hours of the day
as.factor(hour):CDD65	CDD65 interacted with the hour of the day
as.factor(hour):CDH65	CDH65 interacted with the hour of the day
as.factor(hour):HDD60	HDD60 interacted with the hour of the day
as.factor(hour):HDH60	HDH60 interacted with the hour of the day
as.factor(month)	Series of binary indicators for the months in the model estimation data.
as.factor(month):as.factor(hour)	Month interacted with the hour of the day

APPENDIX B EX ANTE AND EX POST TABLE GENERATORS

Ex ante and Ex Post works are presented in documents outside of this report. The files are entitled:

- CONFIDENTIAL_Leap_2024_LIP_Ex_Post_Tables_FINAL_NonResidential.xlsx and
- CONFIDENTIAL_Leap_2024_LIP_Ex_Post_Tables_FINAL_Residential.xlsx and
- CONFIDENTIAL_Leap_2024_LIP_Ex_Ante_Tables_FINAL_NonResidential.xlsx and
- CONFIDENTIAL_Leap_2024_LIP_Ex_Ante_Tables_FINAL_Residential.xls

APPENDIX C LEAP ENROLLMENT FORECAST RATIONALE [REMOVED FROM PUBLIC VERSION]

Verdant notes: The content in this section is provided for context on the resource being evaluated. Leap wrote it all and Verdant has not evaluated any claims made or altered it in any way.

Click on the icon below to open the Leap Enrollment Forecast Rationale file: