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# DRAFT PROPOSAL

## Demand Response QC Proposal on Alignment of Planning and Operations



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# 1 INTRODUCTION

Demand response resources include a wide range of technologies and customer segments. They can vary in shape, weather sensitivity, and operating limitations such as the maximum event duration, number of consecutive dispatch days, and annual hours of dispatch.

The current Load Impact Protocol (LIP) framework focuses on addressing two main questions:

- **What were the actual demand reductions delivered under the conditions called?** For simplicity, these are called ex-post impacts. The goal is to provide the most accurate estimate of the delivered demand reductions. Most evaluations conduct accuracy tournaments testing different models, and many rely on matched control groups with difference-in-differences using smart meter data.
- **What is the magnitude of program resources available under standard planning conditions?** For simplicity, these are called ex-ante impacts. They rely on developing a predictive model using hourly reductions from historical events, typically the most recent three years. The objective is to model how reductions vary as a function of weather, hour-of-day, hours into the event, and other factors (e.g., cycling strategy, location, etc.). This model is then used to predict demand reduction capability under standardized 1-in-2 and 1-in-10 weather conditions and standardized dispatch hours that align with resource adequacy planning (currently 4-9 PM).

Utilities, CAISO, planners, and program managers need to understand the magnitude of resources available for different hours under various temperature conditions, for different start times, and for different event durations. Because of the format of the outputs, it can be difficult to directly compare the resource capability under planning conditions to bids or to compare them to the performance during actual events. Actual events reflect on-the-ground decisions and do not always align with planning values. The actual weather conditions do not frequently match the 1-in-2 and 1-in-10 weather year planning conditions, and the event start times and durations often differ from the 4-9 PM resource adequacy window. Moreover, DR events are called for multiple reasons –testing or evaluation, economic dispatch, and reliability-related alerts, warnings, and emergencies.

As a result, the current framework does not adequately address two fundamental questions: Do the bids align with the forecasted capability used for planning (ex-ante impacts)? And, how well did actual event performance match the forecasted capability (ex-ante impacts)?

To bridge the gap between and operations, we propose a three-pronged solution:

1. **Create a time-temperature matrix (TTM) for weather-sensitive resources.** A time-temperature matrix should be based on the *same predictive model used to produce the ex-ante planning impacts*. However, it predicts the resource magnitude as a function of temperature conditions, hour-of-day, dispatch start times, and hours into the event. It has multiple uses. It can be used for operations and bidding. Including a time-temperature matrix would better

reflect the range of the resource capabilities for these different conditions that are not captured by a single planning value for each month (or a 24-hour profile for each month). A time-temperature matrix can be used to compare the historical ex-ante forecasts to the bids submitted, and it can be used to compare the historical event forecasts to the actual event performance. In addition, a time-temperature matrix can be used to simulate the resource availability for different weather years, a common application in planning.

2. **Calculate a bid alignment metric (BAM).** The main objective of this metric is to assess if the bids align with the historical forecasted capability, given the conditions actually experienced by operations. By design, the metric is centered on 1.0 and easy to calculate.
3. **Calculate a performance alignment metric (PAM).** The main objective of this metric is to assess if the actual performance during operations aligns with the historical forecasted capability, given the conditions actually experienced by operations. By design, the metric is also centered on 1.0 and is easy to calculate.

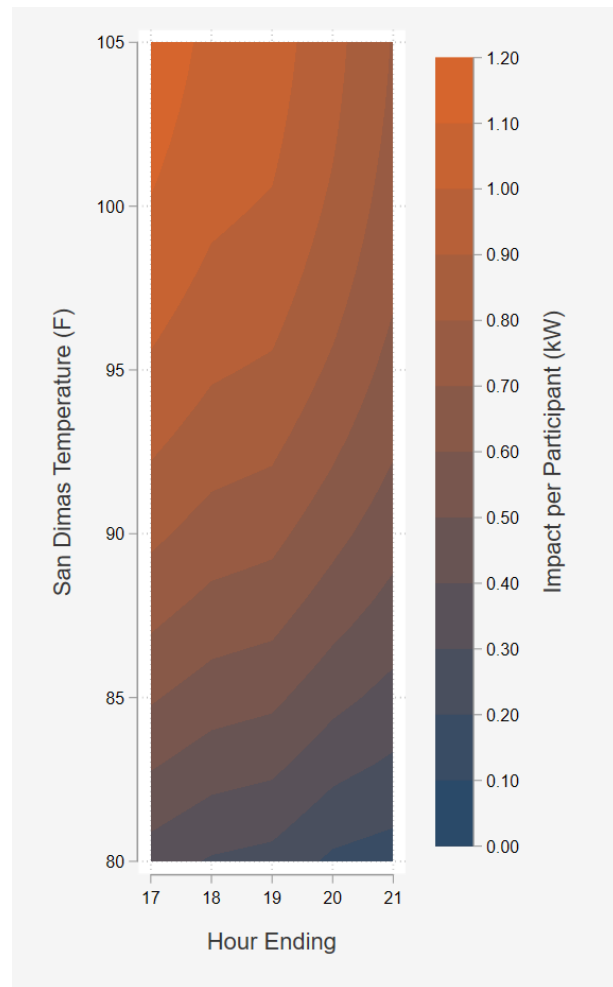
The remainder of the proposal is divided into three main sections. Section 2 describes how to develop a time-temperature matrix. Section 3 illustrates the bidding alignment metric calculation. Section 4 illustrates the performance alignment metric. For each aspect of the proposal, we describe the main concept, outline the calculation steps, and provide an applied example.

## 2 TIME-TEMPERATURE MATRIX

A time-temperature matrix (TTM) quantifies the relationship between demand reductions, temperature conditions, hour of the day, event start times, and hours into an event. Importantly, a TTM is developed using the same predictive model used to produce the ex-ante planning impacts. Figure 2 shows example outputs of a simple TTM developed for SCE's Summer Discount Plan Residential (SDP-R) Program. For this program, the only independent variables used to develop the TTM were temperature (indexed to the San Dimas weather station) and hour of day. Impacts shown in the matrix are static and represent the expected participant-level impact for a territory-wide event for the given hour and temperature.

Figure 1: SDP-R Time-Temperature Matrix

Temp	Hour Ending				
	17	18	19	20	21
105	1.16	1.08	1.05	0.93	0.79
104	1.15	1.07	1.04	0.93	0.79
103	1.14	1.06	1.03	0.92	0.78
102	1.13	1.05	1.02	0.91	0.77
101	1.11	1.04	1.01	0.90	0.76
100	1.09	1.02	0.99	0.88	0.75
99	1.08	1.00	0.97	0.87	0.74
98	1.06	0.98	0.95	0.85	0.72
97	1.03	0.96	0.93	0.83	0.70
96	1.01	0.94	0.91	0.81	0.69
95	0.98	0.91	0.89	0.78	0.66
94	0.96	0.89	0.86	0.76	0.64
93	0.93	0.86	0.83	0.73	0.62
92	0.89	0.82	0.80	0.70	0.59
91	0.86	0.79	0.76	0.67	0.57
90	0.82	0.76	0.73	0.63	0.54
89	0.78	0.72	0.69	0.60	0.51
88	0.74	0.68	0.65	0.56	0.47
87	0.70	0.64	0.61	0.52	0.44
86	0.66	0.59	0.57	0.48	0.40
85	0.61	0.55	0.52	0.43	0.37
84	0.56	0.50	0.48	0.38	0.33
83	0.51	0.45	0.43	0.34	0.29
82	0.46	0.40	0.38	0.29	0.24
81	0.41	0.35	0.32	0.23	0.20
80	0.35	0.29	0.27	0.18	0.15



## 2.1 CALCULATION

The method for calculating a time-temperature matrix is relatively straightforward. The first step for calculating a time-temperature matrix is to develop a model that predicts impacts for the average customer as a function of temperature. This will be the same model that is used to develop weather-normalized ex-ante impacts as a part of the annual reporting process for demand response. Below is a sample equation for modeling impacts as a function of temperature. This is the equation that was used to predict impacts for the TTM in Figure 2.

$$Impact_i = \beta_0 + \beta_1 * Temp + \beta_2 * Temp^2 + \beta_3 * hour * Temp + \varepsilon_i$$

Model Term	Description
<b>Impact<sub>i</sub></b>	Average impact in kW during interval i
<b>β<sub>0</sub></b>	The model intercept
<b>Temp</b>	Temperature at San Dimas Weather Station
<b>Temp<sup>2</sup></b>	Square of Temperature at San Dimas Weather Station
<b>Hour * Temp</b>	Interaction term between hour and temperature
<b>β<sub>1</sub>-β<sub>3</sub></b>	Regression coefficients
<b>ε<sub>i</sub></b>	Error term

Once the model has been developed, the matrix is created by predicting impacts for the expected temperature range you would expect the program to operate in (in the above example the temperature ranges from 80°F - 105°F) and for the expected operating hours of the program (in the above example the operating hours range from 4-9 PM). For programs where there is event decay the matrix can also include variation in impacts based on the event hour.

## 2.2 STANDARDIZED OUTPUT

The actual model underlying the TTM and ex-ante impacts can vary due to the diversity of programs, but the outputs need to be standardized to include the same columns and use pre-specified weather stations by Sub-LAP. Below is the recommended data structure for the model outputs. The key outputs include the resource, the location, the event start time and duration, the hour of the event, and the average daily temperature. In this output we include the per-unit impact so that the impacts can be scaled if enrollment changes.

Resource Name	Location (Sub-LAP)	Event Hour	Start Time	Avg. Temperature	Event Duration	Forecasted per Unit Impact (kW)
Resource A	SCEC	19	6 pm	90	4	5.00
Resource A	SCEC	20	6 pm	90	4	4.72
Resource A	SCEC	21	6 pm	90	4	7.28
Resource A	SCEC	22	6 pm	90	4	1.11
Resource A	SCEC	20	7 pm	90	4	1.09
Resource A	SCEC	21	7 pm	90	4	2.81
Resource A	SCEC	22	7 pm	90	4	9.76
Resource A	SCEC	23	7 pm	90	4	4.97

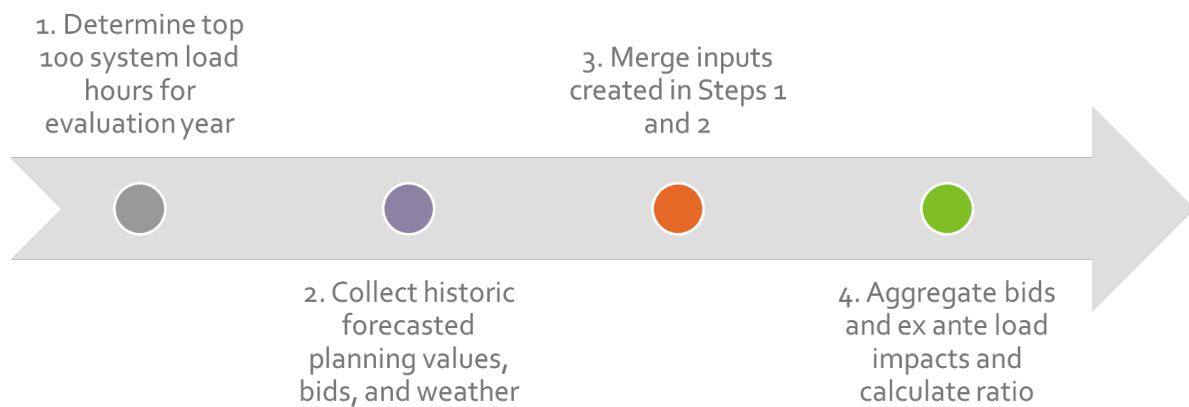
### 3 BID ALIGNMENT METRIC

The bid alignment metric aims to determine whether historic bids align with the forecasted capability used for planning (ex-ante impacts). Our proposed metric is a ratio between the historic bidding values and the capability forecasted by the historic ex-ante model. We propose narrowing the comparison to the top 100 net load hours for each year for simplicity and because these hours are when DR resources are most needed. A ratio of 1.0 indicates full alignment between operations and planning, a value greater than 1.0 means that the bid values were greater than the capability forecasted by the ex-ante model, and a value less than 1.0 would indicate that the bid values are lower than the values indicated by the planning model.

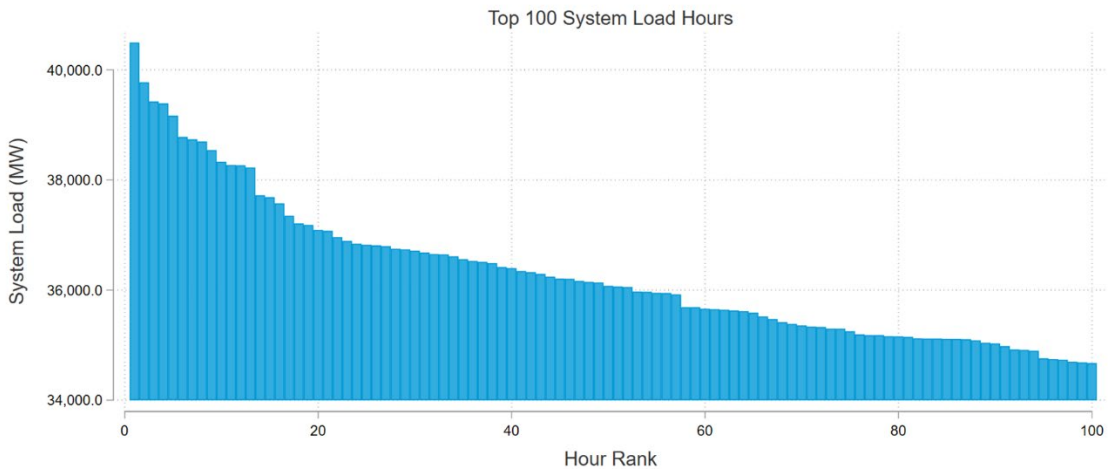
The goal of the bid alignment metric is to use a standardized metric that is easy for all parties to understand and has a transparent calculation method. This metric can let implementers, planners, and CAISO know if there needs to be an adjustment to the planning model or the bidding process to improve alignment.

#### 3.1 KEY STEPS

The figure below illustrates the key steps for developing the comparison between ex-ante values and bid values. The table below details the steps to produce the bid alignment metric.





Step	Example												
<div>1</div> <div>Determine the Top 100 hours for the evaluation year.</div> <div>Use the CAISO net system load to determine the top 100 hours for the year.</div>	<div>Below is a graph of the top 100 system load hours for 2021.</div> <div><div>Top 100 System Load Hours</div></div>												
<div>2</div> <div>Collect historic forecasted planning values, bids, enrollments, and weather</div>	<div>At a high level, the inputs are summarized below. The data inputs are intentionally structured so they can merge with the inputs developed in step 1.</div> <table><tr><th>Component</th><th>Weather Sensitive Resources</th><th>Non-Weather Sensitive Resources</th></tr><tr><td>Historic forecasted planning values</td><td>Table by hour-of-day, and average daily temperature bins, event start, and hours into the event (TTM)</td><td>Table by hour-of-day and month (ex-ante load impact tables)</td></tr><tr><td>Historic bids for evaluation</td><td colspan="2">Table that includes date, hour, number of customers, and bid MW for CAISO. The bids should be aggregated across sub-LAPS since the goal is to assess if the capacity is being bid into the market.</td></tr><tr><td>Historic Weather Conditions</td><td colspan="2">Table that includes the date, hour, and temperature.</td></tr></table>	Component	Weather Sensitive Resources	Non-Weather Sensitive Resources	Historic forecasted planning values	Table by hour-of-day, and average daily temperature bins, event start, and hours into the event (TTM)	Table by hour-of-day and month (ex-ante load impact tables)	Historic bids for evaluation	Table that includes date, hour, number of customers, and bid MW for CAISO. The bids should be aggregated across sub-LAPS since the goal is to assess if the capacity is being bid into the market.		Historic Weather Conditions	Table that includes the date, hour, and temperature.	
Component	Weather Sensitive Resources	Non-Weather Sensitive Resources											
Historic forecasted planning values	Table by hour-of-day, and average daily temperature bins, event start, and hours into the event (TTM)	Table by hour-of-day and month (ex-ante load impact tables)											
Historic bids for evaluation	Table that includes date, hour, number of customers, and bid MW for CAISO. The bids should be aggregated across sub-LAPS since the goal is to assess if the capacity is being bid into the market.												
Historic Weather Conditions	Table that includes the date, hour, and temperature.												
<div>3</div> <div>Merge dataset from Steps 1 and 2.</div>	<div>Below is an example of 10 hours of the merged inputs for a weather-sensitive resource.</div>												

Non-weather-sensitive inputs are merged with bids for the top 100 hours based on day type, month, and event hour. Weather-sensitive inputs are merged based on temperature and event hour.

Resource Name	Date	Hour	Start Time	Temp	Event Duration	Bid Value (MW)	Forecasted Planning Value MW (Ex-Ante /TTM )
Resource A	6/15/2021	21	6 pm	90	4	15.03	12.63
Resource A	6/16/2021	20	6 pm	81	4	78.76	88.96
Resource A	6/16/2021	21	6 pm	81	4	26.96	26.56
Resource A	6/17/2021	20	6 pm	81	4	19.74	19.80
Resource A	6/17/2021	21	6 pm	81	4	39.89	42.84
Resource A	6/17/2021	22	6 pm	81	4	7.84	8.52
Resource A	6/18/2021	20	6 pm	75	4	99.25	113.17
Resource A	6/18/2021	21	6 pm	75	4	87.18	79.30
Resource A	7/8/2021	20	6 pm	80	4	54.47	62.25
Resource A	7/8/2021	21	6 pm	80	4	36.61	37.77

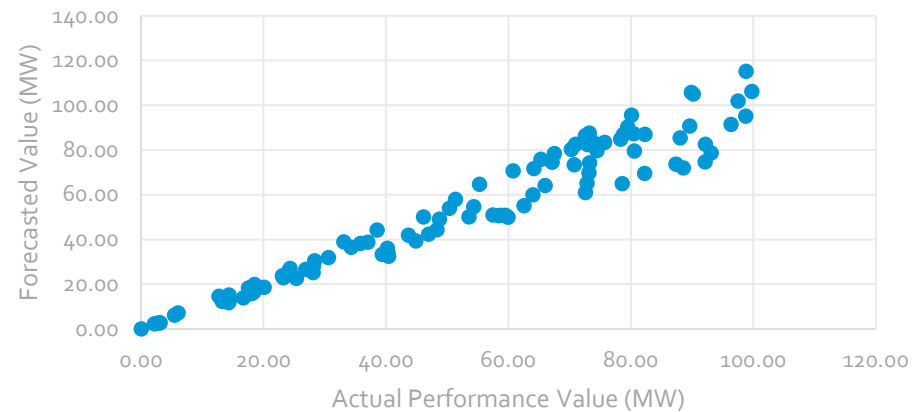
##### 5 Aggregate bids and ex-ante load impacts and calculate the ratio.

The total bid MW available for the top 100 hours is divided by the total ex-ante MW predicted to be available for the top 100 hours. The result produces a ratio that assesses how well the bid values aligned with the values produced by the ex-ante model.

$$\text{Metric} = \frac{\sum \text{Historic Bid MW}}{\sum \text{Forecasted Planning MW}}$$

Below is a comparison of the sample bid values and forecasted values across the top 100 hours. The two are highly correlated in the example, indicating good alignment between the actual bids and the forecasted planning values.

### Correlation between forecasted planning values and actual bids



Below is an example of the summed inputs and ratio calculation. A value of 1.0 indicates perfect alignment. A value greater than 1.0 indicates that the bid values were greater than the forecasted planning values. A value less than 1.0 indicates that the bid values were lower than the forecasted planning values.

	Bid Value (MW)	Ex Ante TTM Value (MW)
TOTAL	4,882	4,629
RATIO	1.05	

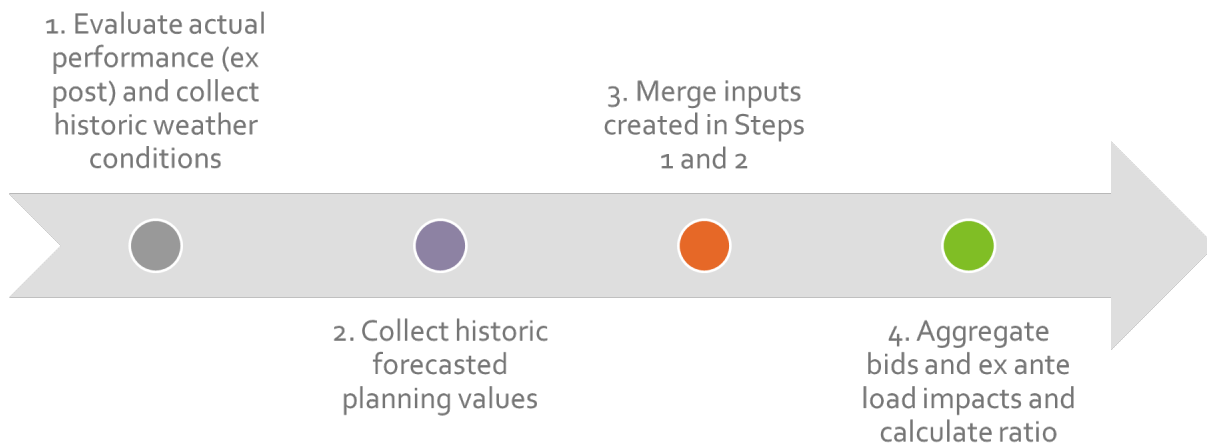
## 4 PERFORMANCE ALIGNMENT METRIC

The performance alignment metric aims to determine whether actual performance during operations aligns with the forecasted capability used for planning (ex-ante impacts). Our proposed metric is a ratio between the historic performance (ex post impacts) and the planning values developed from the historic ex ante model. This comparison would be done for all events called for a given evaluation year. A ratio of 1.0 would indicate perfect alignment between performance and planning, a value greater than 1.0 would indicate that the actual performance during operations is greater than the values indicated by the planning model, and a value less than 1.0 would indicate that the actual performance for operating conditions is lower than the values indicated by the planning model.

The main concept is creating a standardized metric that is easy for all parties to understand and has a transparent calculation method. This metric can let implementers, planners, and CAISO know if there needs to be an adjustment to the planning model in the long term so that there is greater alignment between actual performance and the forecasted performance.

### 4.1 KEY STEPS

The figure below illustrates the key steps for developing the comparison between ex ante values and bid values. We discuss each step in greater detail in the table below.



## Step

- 1 **Evaluate actual program performance (ex post impacts) and collect historic weather conditions.**

Evaluate historic program performance for all events, as is typically done for a DR evaluation. Historic weather conditions are typically collected as a part of this process.

## Example

Below is an example of the outputs from an ex post evaluation. The results need to include the event hour, per unit impact (in kW), and weather conditions for each event.

Southern California Edison  
2020 Ex Post Load Impacts - SDPR

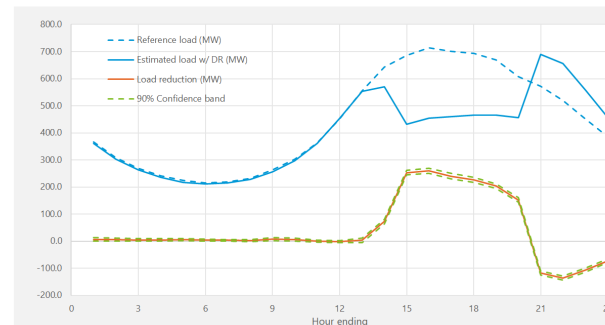


Table 1: Menu options

Program	SDP-R
Type of result	Aggregate
Category	ALL
Subcategory	All
Event date and hours	2020-08-18 (13:40-19:48 PM)

Table 2: Event day information

Event start	1:40 PM
Event end	7:48 PM
Total sites	199,557
Total devices	232,734
Total AC tonnage	846,367
Event window temperature (F)	100.6
Full event hours load reduction (MW)	236.82
Full event hours % load reduction	36.29%
All event hours load reduction (MW)	201.29
All event hours % load reduction	29.9%



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	95th	Std. error	T-statistic
1	367.43	360.50	6.93	1.9%	82.03	0.87	12.99	3.68	1.88
2	309.42	304.00	5.42	1.8%	80.85	-0.09	10.92	3.35	1.62
3	268.75	263.89	4.85	1.8%	79.91	-0.06	9.77	2.99	1.62
4	241.34	236.43	4.90	2.0%	78.86	0.51	9.30	2.67	1.84
5	224.46	217.72	6.74	3.0%	77.74	3.08	10.41	2.23	3.03
6	214.65	210.65	4.00	1.9%	75.93	0.55	7.45	2.10	1.91
7	218.21	216.71	1.50	1.6%	75.54	0.09	6.91	2.07	1.69
8	231.63	228.79	2.83	1.2%	75.36	-1.11	6.78	2.40	1.18
9	264.30	256.54	7.77	2.9%	76.27	2.84	11.69	2.99	2.59
10	302.48	296.85	5.63	1.9%	78.31	0.23	11.02	3.28	1.72
11	362.18	361.54	0.64	0.2%	83.13	-3.27	4.55	2.38	0.27
12	451.59	452.23	-0.64	-0.1%	88.85	-4.55	3.27	2.38	-0.27
13	556.08	552.48	3.60	0.6%	93.73	-4.31	11.51	4.81	0.75
14	643.39	570.51	72.89	11.3%	97.47	64.47	81.30	5.11	14.25
15	685.85	432.43	253.43	37.0%	101.13	244.52	262.34	5.42	46.78
16	713.48	453.87	259.61	36.4%	101.79	250.37	268.85	5.62	46.21
17	700.20	459.69	240.50	34.3%	102.56	230.83	250.18	5.88	40.89
18	692.66	465.69	226.97	32.8%	100.00	217.89	236.06	5.52	41.09
19	669.46	465.87	203.59	30.4%	97.36	195.43	211.75	4.96	41.06
20	608.10	456.08	152.02	25.0%	94.97	143.84	160.19	4.97	30.59
21	572.36	689.30	-116.94	-20.4%	91.93	-124.62	-109.26	4.67	-25.04
22	519.66	655.21	-135.55	-26.1%	87.98	-143.28	-127.82	4.70	-28.83
23	451.22	557.60	-106.37	-23.6%	85.33	-113.81	-98.93	4.52	-23.53
24	385.11	457.05	-71.94	-18.7%	83.61	-78.32	-65.56	3.88	-18.55
Daily	Reference load (MWh)	Estimated load w/ DR (MWh)	Energy savings (MWh)	% Change	Avg. Daily Weighted temp (F)	Uncertainty adjusted impact - Percentiles			
Daily kWh	10654.01	9619.63	1034.38	10.8%	87.24	1001.68	1067.08	19.88	52.03

- 2 **Collect historic forecasted planning values**

At a high level, the inputs are summarized below. The data inputs are intentionally structured so they can merge with the inputs developed in step 1.

Component	Weather Sensitive Resources	Non-Weather Sensitive Resources
Forecasted per unit load reduction capability (kW)	Table by hour of day and average daily temperature bins (TTM)	Table by hour of day and month (ex ante load impact tables)

- 3 **Merge dataset from Steps 1 and 2.**

Below is an example for 10 hours of the merged inputs for a weather-sensitive resource.

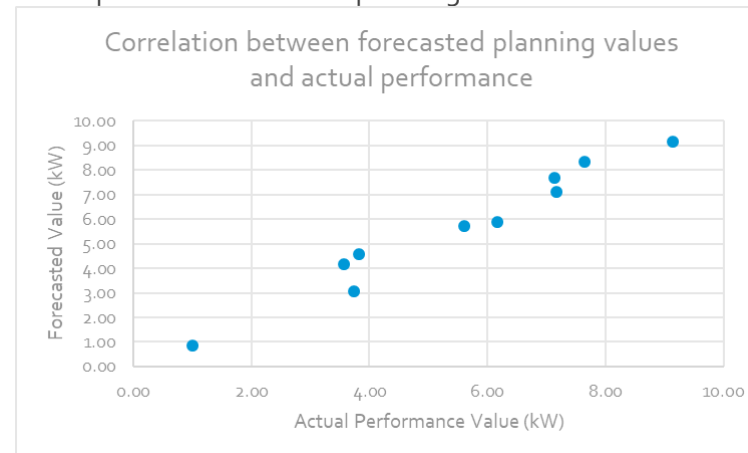
Non-weather-sensitive inputs are merged with bids for top 100 hours based on day type, month, and event hour. Weather-sensitive inputs are merged based on temperature and event hour.

Resource Name	Date	Hour	Start Time	Temp	Event Duration	Actual per Unit Performance (kW)	Forecasted Planning per Unit Value (kW)
Resource A	6/15/2021	21	6 pm	90	4	13.06	12.41
Resource A	6/16/2021	20	6 pm	81	4	88.16	74.65
Resource A	6/16/2021	21	6 pm	81	4	67.91	76.65
Resource A	6/17/2021	20	6 pm	81	4	26.19	28.83
Resource A	6/17/2021	21	6 pm	81	4	45.51	46.91
Resource A	6/17/2021	22	6 pm	81	4	37.78	37.05
Resource A	6/18/2021	20	6 pm	75	4	83.90	72.99
Resource A	6/18/2021	21	6 pm	75	4	15.65	13.78
Resource A	7/8/2021	20	6 pm	80	4	28.10	29.85
Resource A	7/8/2021	21	6 pm	80	4	91.51	93.64

5 **Aggregate bids and ex ante load impacts and calculate ratio.**

The average actual performance kW is divided by the total ex ante kW predicted to be available for all events. We use average impacts instead of aggregate MW as often the entire DR resource is not dispatched during operations. The result produces a ratio that assesses how well the actual performance aligned with the values produced by the ex-ante model.

Below is a comparison of the sample actual performance and forecasted values across all event hours for the DR season. As expected, the two are highly correlated, which indicates good alignment between the actual performance and the planning values.



$$\text{Metric} = \frac{\sum \text{Actual Performance kW}}{\sum \text{Forecasted Ex Ante kW}}$$

Below is an example of the summed inputs and ratio calculation. A value of 1.0 indicates perfect alignment. A value greater than 1.0 indicates that the actual performance is greater than the values in the planning model. A value less than 1.0 indicates that the actual performance is lower than the values in the planning model.

	Average Actual Performance (kW)	Average Forecasted Planning TTM Value (kW)
<b>TOTAL</b>	4.68	4.49
<b>RATIO</b>	1.04	