Applied Energy Group

LOAD IMPACT EVALUATION OF STATEWIDE CRITICAL PEAK PRICING PROGRAMS

PY2020 Evaluation Plan

November 3, 2020 FINAL

Report prepared for:
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CONTENTS

1

INTRODUCTION AND KEY ISSUES

Background

This evaluation plan describes AEG's approach for conducting a load impact evaluation of the Critical Peak Pricing Program[1] (CPP) offered by three investor-owned utilities (IOUs) in California: Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E). The evaluation is being conducted under the guidance of the Demand Response Measurement & Evaluation Committee (DRMEC). The DRMEC consists of representatives from the three IOUs, the California Energy Commission (CEC), and the California Public Utilities Commission (CPUC). SDG&E is managing the contract for this joint study for the three IOUs.

CPP is a statewide price-responsive DR program available at the three IOUs, although the IOUs' programs differ slightly in program features and operation. Participants receive bill credits based upon their peak demand during the summer months (June through September), but incur higher rates during CPP events.

Research Objectives

The key objectives of the PY2020 evaluation are to perform both an ex-post and ex-ante impact evaluation that complies with the California DR Load Impact Protocols.[2]

- PY2020 ex-post impacts will be provided for the average participant and all participants in aggregate for each hour of each event day and the average event day for each IOU's CPP program. These results will be presented at the program level and separately for each size group, each local capacity area (LCA), each industry group, for AutoDR and TA/TI, for dually enrolled DR participants, and for notified vs. non-notified participants.
- Ex-ante impacts will be provided for each year over a 12-year[3] time horizon, based on each IOU's and CAISO's 1-in-2 and 1-in-10 weather conditions for a typical event day and each monthly system peak day. These results will be presented at the program level and separately for each size group, each LCA (as applicable), and each busbar (as applicable). The impacts will be provided for the average participant and all participants in aggregate for all program operating hours and the resource adequacy (RA) window (4 PM to 9 PM). The impacts will also be provided as a portfolio forecast, which excludes load impacts of customers dually enrolled in another DR program.

Key Notes for PY2020 Evaluation

Discussions during the project initiation meeting held on September 4, 2020 brought up the following points to address during the PY2020 analysis:

- All three IOUs confirmed continued interest in impacts by those that were notified vs. those that were not notified of events by subgroup.

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[1] CPP is referred to as Peak Day Pricing (PDP) in PG&E. For consistency, CPP will be used to describe both programs for the remainder of this document.

[2] *Attachment A. Load Impact Estimation for Demand Response: Protocols and Regulatory Guidance*, California Public Utilities Commission, Energy Division, April 2008.

[3] Eleven-year forecast for PG&E and SCE.

- Similarly, all IOUs confirmed interest in incremental impacts due to enrollment in AutoDR and TA/TI.
- PG&E PDP Update:
    - CCA unenrollment was not as significant as in PY2019. No additional defaults were made in PY2020, and no additional defaults are expected through the end of the year.
    - Current PDP customers that request moving into TOU-B before 2021 get unenrolled from PDP. PDP and TOU-B are not compatible until March 2021.
    - As of November 1, 2020, PDP has called 13 events and will likely call more through the rest of the season.
- SCE CPP Update:
    - The CPP window officially changed to 4-9PM in PY2019.
    - More defaulting is scheduled for October 2020, but this will not affect PY2020 ex-post impacts. There was no substantial change in participant counts from PY2019 to PY2020, which remains at around 275k customers.
    - There is some interest in seeing individual regression models for AutoDR participants. AEG will look into this and will likely be doable especially if AutoDR participants are in the large group.
    - SCE CPP is required to call 12 events every year, and all 12 events have been called as of September 4, 2020.
- SDG&E CPP Update:
    - There are no changes to CPP in PY2020.
    - As of September 4, 2020, SDG&E CPP has called 4 events.

Key Changes in PY2020 Approach

In PY2020, AEG is implementing the following key changes to the overall approach to accommodate lessons learned from the PY2019 evaluation and program changes implemented in PY2020:

- Similar to PY2019, AEG will perform preliminary participant and non-participant counts on all segments using monthly billing data through August/September to prepare a sampling (sample v. census) and analysis (within-subjects or matched control) plan for each segment. Under the within-subjects approach, the customer-specific modeling approach will be considered for large customers.
- Along with the sampling and analysis plan, AEG will prepare a secondary data request for interval data, consisting of accounts pulled from the preliminary participant and non-participant counts.
- Specifically, for the ex-ante analysis, AEG will host collaborative meetings in January to discuss and determine the appropriate approach and assumptions related to the Covid-19 situation.

Plan Organization

The remainder of this evaluation plan is organized into the following sections:

- Section 2 describes the study method, including specifics of the data collection and assessment approaches that will be used to complete the evaluation.
- Section 3 lists the types and sources of data necessary for the evaluation.

- Section 4 presents the detailed plan by task and subtask, including identification of deliverables for each task.
- Section 5 shows the schedule for the evaluation activities and deliverables.

2

STUDY METHOD

Overall Method

AEG's overall method will follow the DR Load Impact Protocols and is designed to meet the specific objectives of the project. It will be general enough to apply to all CPP programs offered by each of the IOUs but will be customizable to address any unique program or IOU requirements. We will work closely with the IOU project leads throughout the evaluation to ensure our models appropriately and accurately estimate ex-post and ex-ante impacts.

We will use a combination of techniques that will allow us to fulfill the evaluation's research objectives:

- Subgroup level regression models with customer-specific impacts will be the primary evaluation method for the load impact analysis.
- Customer-specific regression models for large customers with highly variable loads.
- Out-of-sample testing and aggregate regression models will be used as validation tools.

Data Collection Approach

There are three key aspects of our approach to data collection:

- Data Request. We have prepared and delivered an itemized data request for each IOU. The schedule in Section 5 lists due dates for IOUs to deliver key pieces of data. Adhering to the data delivery schedule will help us maintain the overall project schedule.
- Information Security. Since we will be handling confidential customer data, it is essential that we abide by strict information security procedures. All members of AEG's evaluation team will sign an agreement ensuring they will follow AEG's internal information security protocols, as well as project specific protocols set forth by the IOUs, specifically SDG&E's non-disclosure agreement. The information security procedures cover transmitting, storing, handling, controlling access to, and disposing of confidential data.
- Data Validation. We will review the data received from the IOUs to make sure it corresponds to the data request and is complete. We will identify any missing information in a timely manner. We will also validate all interval data using algorithms we developed to detect issues such as zero intervals, missing intervals, peaks, valleys, and erroneous intervals.

To maximize efficiency, some aspects of the data collection and validation will be done in conjunction with the PY2020 Statewide Capacity Bidding Program (CBP) evaluation effort. The data request for each IOU will cover the data requirements for both CBP and CPP evaluations and will indicate which items are specific to one program evaluation and which items are needed in both. Similarly, we will perform joint data validation processes whenever possible (e.g., weather data, hourly usage data, all overlapping data, etc.).

Analysis Methodology

Continuing AEG's approach in PY2019, AEG will develop a matched control group for subgroups where it is feasible and will employ a within-subjects design for subgroups wherein a matched control group is not viable.

The table below presents the counts as of September 2020 and the methodology planned to estimate impacts for each subgroup. It presents the total number of participants, the total eligible non-participant pool, and the ratio of participants to non-participants. We base the chosen methodology on insights from the PY2019 LI evaluation and each IOU's outlook on PY2020 participation. We discuss our rationale on the changes we will employ in PY2020 below.

Analysis Method, Participant and Non-participant Counts, by Subgroup

Utility	Size Group	Participants	Non-Participants	Ratio	Analysis Method
PG&E[4]	< 20 kW	86,863	n/a	n/a	Within-subjects
	20 kW ≤ x < 200 kW	13,924	n/a	n/a	Within-subjects
	≥ 200 kW	868	1,600	approx. 1:2	***Matched control; Customer-specific for top 10%***
SCE[5]	0 to 20 kW	213,969	n/a	n/a	Within-subjects
	20 kW ≤ x < 200 kW	35,015	n/a	n/a	Within-subjects
	≥ 200 kW	1,918	TBD	TBD	***Matched control; Customer-specific for top 10%***
SDG&E	20 kW ≤ x < 200 kW	13,416	n/a	n/a	Within-subjects
	≥ 200 kW	1,448	n/a	n/a	Within-subjects

Recall that the chosen methodology is based on the total non-participant to participant ratio in each group. In general, a non-participant to participant ratio of at least 3 to 1 is required to obtain a good match, therefore for groups with a ratio less than three, we will employ a within-subjects design. The within-subjects design leverages the participant's own load on event-like days to estimate the reference load.

In the interest of efficiency, AEG opted not to request/receive non-participant data for subgroups that utilized a within-subjects design in PY2019. Those subgroups did not have any substantial change in participant populations and have "n/a" under their non-participant information.

Changes to the PY2020 approach are highlighted in the Analysis Method column in the table above are the following:

- PG&E and SCE's Large (≥ 200 kW) subgroups will be utilizing a segmented approach and split into two groups: (1) participants in the top 10% of consumption, and (2) the rest of Large participants.

[4] Excludes 108 customers with no size grouping. We will reconcile these customers in the final population count through the end of October.

[5] Excludes 4 customers with no size grouping. We will reconcile these customers in the final population count through the end of October.

- Large participants in the top 10% group will employ a within-subjects design using customer-specific regression models. This change is motivated by extremely large customers driving unintuitive weather responses in the PY2019 analysis. By isolating these extremely large customers, we can estimate their unique program impacts independently, without driving the entire Large group impact estimates.
- The rest of the Large participants will utilize matched control groups, continuing from PY2019.
  - SCE's Large group saw great success in the PY2019 matched control group development. AEG does not recommend changing the approach in this case and may even see better matches with the exclusion of the top 10% group.
  - PG&E's Large matched control group was not as ideal in PY2019 and PY2020's non-participant to participant ratio is smaller than ideal at 2 to 1. However, AEG still recommends attempting to establish a matched control on the assumption that excluding the top 10% group will increase the chances of producing a successful matched control group.

Sampling Methodology

As mentioned in Section 1, we will be utilizing a sampling approach to limit the amount of data being requested. Since we will be estimating subgroup level models for each IOU, size, and industry, we designed our sampling plan based on this segmentation. If any additional subgrouping is found to be necessary (i.e., notified v. not notified in PY2018), AEG will apply the appropriate weighting on these sampled subgroups.

PG&E and SCE

For PG&E and SCE, we will do the following:

- Pull a sample of 5,000 customers from the subgroup counts highlighted in red.
- Request May through October hourly usage data for all groups, both participants and non-participants.

PG&E Participant and Non-participant Counts by Size and Industry

Industry Type	Participants			Non-participants
	0 to 20 kW	20 to 199.99 kW	200 kW & above	200 kW & above
1. Agriculture, Mining & Construction	5,812	597	261	
2. Manufacturing	3,478	934	147	
3. Wholesale, Transport, other utilities	**14,998**	1,917	180	
4. Retail stores	**7,481**	2,061	42	
5. Offices, Hotels, Finance, Services	**29,591**	4,929	135	
6. Schools	1,415	804	39	
7. Institutional/Government	**18,015**	2,366	56	
8. Other or unknown	**6,073**	316	8	
Total	**86,863**	**13,924**	**868**	**~1,600**

SCE Participant and Non-participant Counts by Size and Industry

Industry Type	Participants			Non-participants
	0 to 20 kW	20 to 199.99 kW	200 kW & above	200 kW & above
1. Agriculture, Mining & Construction	**10,121**	1,033	124	
2. Manufacturing	**7,479**	3,042	509	
3. Wholesale, Transport, other utilities	**11,822**	2,129	284	
4. Retail stores	**27,395**	**5,922**	210	
5. Offices, Hotels, Finance, Services	**96,444**	**14,129**	429	
6. Schools	2,206	678	175	
7. Institutional/Government	**30,245**	2,835	129	
8. Other or unknown	**28,257**	247	58	
Total	**213,969**	**30,015**	**1,918**	**TBD**

SDG&E

SDG&E has a significantly smaller participant population, relative to PG&E and SCE, and will not require a sample.

SDG&E Participant and Non-participant Counts by Size and Industry

Industry Type	0 to 199.99 kW	200 kW & above
1. Agriculture, Mining & Construction	406	22
2. Manufacturing	928	232
3. Wholesale, Transport, other utilities	729	184
4. Retail stores	1,687	98
5. Offices, Hotels, Finance, Services	6,179	490
6. Schools	495	247
7. Institutional/Government	1,672	162
8. Other or unknown	320	13
Total	**12,416**	**1,448**

3

DATA SOURCES

AEG prepared a comprehensive data request detailing all the data needed to conduct the ex-post and ex-ante load impact evaluation for PY2020. The data request includes the following items:

- Customer characteristics for participants and non-participants
- Monthly billing data for participants and select non-participants
- All DR program participation information for CPP participants
- Local capacity area and local busbar identifier
- All DR program event data
- Hourly usage data for participants and select non-participants
- Outage or PSPS day data
- Actual hourly weather data by weather station
- IOU and CAISO 1-in-2 and 1-in-10 hourly weather scenarios for monthly peak and typical event days
- 2021-2031 enrollment forecast

Appendix A contains the data request file in the form of an embedded link.

4

DETAILED WORK PLAN

Task 1: Schedule and Conduct Project Initiation Meeting

The project began with a project initiation meeting held on September 4, 2020. The meeting kicked-off the project and focused on planning for the PY2020 evaluation. Meeting participants included representatives from the SDG&E, PG&E, SCE, and AEG. This evaluation plan incorporates the results from the meeting.

Prior to the meeting, AEG delivered a meeting agenda and a PowerPoint slide deck to help guide the discussion. AEG then followed up with a memorandum that summarized discussions during the meeting and listed the actions agreed upon by the parties. Appendix B contains these documents in the form of embedded links to the files.

Task 2: Evaluation Plan

This document constitutes the evaluation plan for PY2020.

Task 3: Impact Evaluation

Task 3.1: Data Collection and Validation

Sections 1 and 2 of this evaluation plan discussed the changes in PY2020's evaluation approach, and Section 3 describes the types and sources of data needed to carry out the ex-post and ex-ante evaluation for PY2020. AEG will deliver the initial data request along with the first draft of this document (see Appendix A) and will deliver the secondary data request as soon as the preliminary analysis is done.

To carry out the analysis across all three IOUs, AEG will need to construct a large database of different types of utility information, including hourly usage data. We will validate all usage data using algorithms we developed and used previously for the Statewide Load Impact Evaluations of Aggregator Demand Response Programs (2015-2017) and Capacity Bidding and Critical Peak Pricing Programs (2018-2019).

AEG's current validation process includes carefully checking the interval data for zero intervals, missing intervals, peaks, valleys, and erroneous intervals. AEG's validation process was reevaluated in PY2018 due to concerns of over-omitting data. The validation process was adjusted as necessary, with the key change being to exempt event days from validation rules. Given the nature of the program (having C&I customers), event days are more likely to contain zero intervals and outlier reads.

Task 3.2: Ex-post Impact Analysis

The primary objectives of the ex-post analysis are presented below.

For each of the three IOUs, at both the aggregate and per-participant levels:

- To develop hourly and daily load impact estimates for each CPP event day called in PY2020 for the following:
  - SCE large non-residential customers (≥ 200 kW), and Small-to-Medium Business (SMB) customers (< 200 kW);
  - PG&E large customers (≥ 200 kW) and SMB customers (< 200 kW);

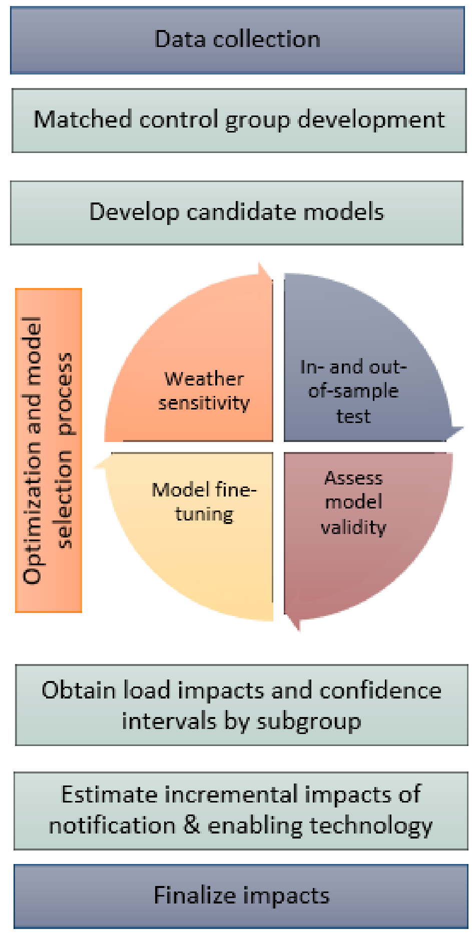
- SDG&E large customers (≥ 200 kW) and medium customers (20 kW ≤ x < 200 kW)

- To provide estimates by various segments: LCA, industry group, dual enrollment in other DR programs, notified status and other industrial classifications such as busbar,
- To provide incremental impact estimates associated with participation in TA/TI and/or AutoDR.

Overview of AEG's Approach

Below we describe AEG's approach to the ex-post analysis. The key points we'd like to highlight in our approach are as follows:

Ex-Post Analysis Approach



- We will utilize a within-subjects approach or a matched control group. We will perform the analysis with or without the matched control groups, depending on each subgroup's defaulting status and available control group pool. We discuss AEG's planned approach for each subgroup in Section 2.
- We will estimate aggregate models on customer subgroups based on size and/or industry type. The purpose of subgrouping is to minimize variation in the models while eliminating the need for customer-specific models, which is also unfeasible given the number of participants in CPP. While the models will be estimated at the subgroup level, impacts will be calculated at the participant level, allowing for ease of aggregation to various segments of interest.
- We will estimate customer-specific models for a small subset of extremely large customers. Based on lessons learned from the PY2019 LI analysis, AEG recommends utilizing customer-specific models for extremely large customers. This approach will also minimize variation in the aggregate models and allow for better impact estimates.
- We will implement the regression models using our well-established model optimization process which employs hourly models and continuous daily data. We prefer using continuous daily data because this approach allows us to perform out-of-sample testing, which is a key feature of our model optimization process. To streamline data processing and to narrow down event day impacts, we can perform the analysis on more defined time periods instead of the entire program year. This will allow us to minimize the amount of data required for processing while capturing usage patterns specific to periods when events are called.

The figure on the right side of the page presents a high-level overview of the approach we will use to develop ex-post impacts for each program year. We will use an approach like what we've used in previous evaluations for the Statewide DR Aggregator, CBP, and CPP programs.

CPP is implemented differently within each IOU's territory. Therefore, the ex-post analysis will be conducted independently to account for those differences during the modeling and analysis. However, AEG will employ the same methodology across all three IOUs which will maintain consistency in the results while allowing for customization of the models. The key differences include frequency of events, event windows, and the season during which events are called.

We describe each of the activities, excluding data collection, which was described as part of task 3.1, in more detail in the subsections that follow.

Matched Control Group Development

Event-like Days Selection

The selection of comparable non-event days, or event-like days, is essential to several of the evaluation activities. These days will be used in the matched control group development and the out-of-sample testing in model optimization.

The event-like days should include 5 to 15 days which are comparable to called event days in weather, day of the week, and month of the year. We will use these days to establish that control and treatment customers are well matched on days that are similar to event days, and therefore also on event days. We will select the event-like days within the same year, but depending on the number of available non-event days, we may select days from the previous summer. We will work with each IOU to determine if this will be necessary.

We will use a Euclidean distance metric (similar to what we describe below) to select days that are as similar as possible to actual event days using multiple weather-based criteria. [6]

Matched Control Group

To create the matched control group, we will use a Stratified Euclidean Distance Matching (SEDM) technique which we have used successfully with many other utilities in more than a dozen past evaluations. The basic steps are as follows.

Step 1 is to define both the participant and non-participant populations and the treatment and pre-treatment periods for each participant. At this stage, we would generally apply specific exclusions to the participant and non-participant populations. We will work with each IOU to develop these exclusions. Examples of exclusions might include customers without enough event-like day usage data, customers participating in other DR programs, or customers without adequate demographic information. After we determine the participants and the treatment periods, we can also similarly identify non-participants that are potential control group customers. The potential control group will include all customers not identified as participants or being excluded for other reasons.

Once the participant and non-participant populations are identified, both populations can be assigned to strata or filters that are categorical in nature. For CPP participants, we will use size and industry type as key filters. This ensures that customers with similar usage characteristics will be matched to one another, capturing some of the unobservable attributes that affect the way customers use energy. At this stage, it is critical to ensure that there are enough potential control group customers in each stratum. Usually a

[6] We included three weather variables in the Euclidean distance metrics calculation to select similar non-event days: (1) daily maximum temperature; (2) daily minimum temperatures; and (3) average daily temperature. We will work with each IOU to determine which weather variables are best suited for selecting days that are most similar to event days. In PY2019, the Euclidean distance metric used was calculated by the following equation:

$$ED = \sqrt{(MaxTemp_{event} - MaxTemp_{non-event})^2 + (MinTemp_{event} - MinTemp_{non-event})^2 + (MeanTemp_{event} - MeanTemp_{non-event})^2}$$

ratio of 3 control customers to each participant is sufficient; however, larger ratios can yield a better match.[7]

Step 2 is to perform the one-to-one match based on hourly demand data of comparable non-event days. As discussed above, the event-like days will act as pre-treatment data, allowing us to establish that the control customers and participants have similar load shapes on event days. To determine how close each participant is to a potential match, we will use a Euclidean distance metric. The Euclidean distance is defined as the square root of the sum of the squared differences between the matching variables. Any number of relevant variables could be included in the Euclidean distance. For this one-to-one match, we will include three demand variables:

- The average demand on event-like days during the typical event window;
- The demand on event-like days during the typical system peak hour;
- And the average demand on event-like days during the hours outside the typical event window.

We will then weight the variables to reflect the relative importance of the estimates, with typical system peak hour having the most weight and the average demand outside the typical event window having the least weight. The Euclidean distance for this set of variables can be calculated using the equation below. [8]

$$ED = \sqrt{w_1(avgevnt_{Ti} - avgevnt_{Ci})^2 + w_2(peak_{Ti} - peak_{Ci})^2 + w_3(avgnonevnt_{Ti} - avgnonevnt_{Ci})^2}$$

In this example, the Euclidean distance in the equation above would be calculated for participants within each stratum as the distance between each participant and all potential control customers. Using a distance metric allows us to compare participants with potential control customers based on their overall similarity as defined by the demand variables included in the Euclidean distance.

After calculating the distance metric within each group for each possible combination of participant and control customer, the control customer with the smallest distance is matched to each participant without replacement. We can then select the closest matches for each of our participants, creating a one-to-one match of control customers to participants.

Checking the Match

Once the matching process is complete, we will thoroughly check the match using the appropriate t-tests and visual inspection of the event-like day load shapes.

Develop Candidate Regression Models

Since we will be utilizing both subgroup (we anticipate having at least 20 subgroups) and individual customer models, it is not practical to develop models individually given the evaluation timeline. Therefore, we will develop a set of candidate models that can be fit to all subgroups and individual customers and utilize algorithms developed in previous Statewide DR Aggregator evaluations. After each candidate model is fit to each subgroup, the best model is selected through an optimization process. Results will be estimated at the customer level and can then be aggregated to different levels within each utility and various segments of interest. We will validate the models using both statistical and visual methods.

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[7] AEG will assess the approach depending on the number of eligible control customers. If the potential control group is significantly large, AEG may opt for a two-stage matching procedure, performing a pre-match screen using billing data on the eligible control group. The pre-match screen will select the top 5-10 matches for each participant and will pare down the requested amount of hourly interval data for the candidate control group and allow for more efficient data processing.

[8] The Euclidean distance metric for pre-matching on monthly data could be formulated as follows:

$$ED = \sqrt{w_1(jun_{Ti} - jun_{Ci})^2 + w_2(jul_{Ti} - jul_{Ci})^2 + w_3(aug_{Ti} - aug_{Ci})^2 + w_4(sep_{Ti} - sep_{Ci})^2}$$

We can think of regression models as being made up of building blocks, which are in turn made up of one or more explanatory variables. These different sets of variables can be combined in different ways to represent different types of customers. The blocks can be generally categorized into either "baseline" variables, or "impact" variables and could be made up of a single variable (e.g., cooling degree hours, CDH), or a group of variables (e.g., days of the week). The baseline portion of the model explains variation in usage unrelated to demand response events, while the impact portion explains the variation in usage related to a DR event.[9]

The different building blocks will be combined in different ways to create a set of candidate models that will represent a wide variety of customers and their impacts. We will use our judgement and experience, and work closely with each IOU, to develop an initial set of 10 to 20 models to run through our optimization process. Based on experience, we anticipate that the different candidate models will fit into two basic categories:

- Weather sensitive models which include weather effects and calendar effects. These models are less likely to require a morning load adjustment due to much of the variation in load on a day-to-day basis being captured by weather terms.
- Non-weather sensitive models that include the morning load adjustment and calendar effects.

The models will be built and optimized using both the participant and non-participant data, i.e. including the matched control group. Once the models have been optimized, we will then run the models again without the matched control group, using only participants on event and non-event days, to see how this affects the impacts. We will talk more about comparing the impacts in a later subsection.

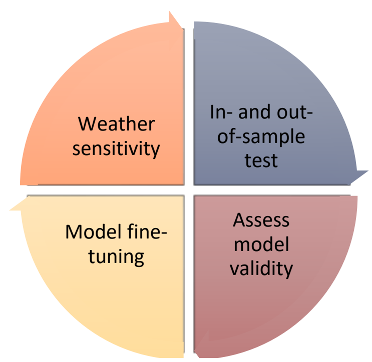
Optimization and Model Selection Process

Our optimization process incorporates the validation of the subgroup regression models. The subgroup models are designed to:

1. Accurately predict the actual participant load on event days, and
2. Accurately predict the reference load, or what participants would have used on event days in absence of an event.

To meet these two specific goals, our proposed optimization process includes a four-part cycle consisting of the following steps: (1) assessing weather sensitivity; (2) in-sample and out-of-sample testing; (3) assessing model validity; and, (4) model fine-tuning.

Optimization Process



Assess Weather Sensitivity

To increase efficiency in the model selection process, we first assess weather sensitivity by performing p-value tests on coefficient estimates on weather variables. We do this on 3 hourly models: a morning, afternoon, and evening model. This test will determine if each customer or subgroup will be tested on weather sensitive or non-weather sensitive models during the optimization process. Performing this first step will shorten the model optimization process, since we will not be running subgroups and customers through all 10-20 candidate models. This is extremely valuable given the number of participants in CPP, across all three IOUs.

[9] Any unexplained variation will end up in the error term.

In-Sample and Out-of-Sample Testing

We use in-sample tests to show how well each model performs on the actual event days; therefore, it helps us understand how well the model is able to match the actual load. We use out-of-sample tests to show how well each of the candidate models could predict a customer's load on non-event days that were as similar as possible to actual event day; this test gives us an estimate of how well each model could predict the reference load.

To perform the in-sample test, we fit each candidate model to the entire data set. The results of these fitted models are used to predict the usage on event days. Then we assess the accuracy and bias of the predictions by calculating the mean absolute percent error (MAPE)[10] and mean percent error (MPE)[11], respectively. We refer to these metrics as the in-sample MAPE and MPE.

To perform the out-of-sample test, we first identify the out-of-sample event-like days as several days that are similar to event days. For efficiency and consistency, we will use the same event-like days used in matched control group development. After identifying the event-like days, event-like days are removed from the analysis dataset and the candidate models are fit to the remaining data. Lastly, we assess the accuracy and bias of the predictions by calculating the MAPE and MPE, respectively. Similarly, we refer to these metrics as the out-of-sample MAPE and MPE.

These two tests result in several in-sample and out-of-sample metrics. Recall that the goal of the tests is to find the best model for each subgroup in terms of its ability to predict the reference load and the actual load for each subgroup. Therefore, for each subgroup, we will combine the two tests into a single metric, giving each candidate model a single metric. The proposed metric is defined in as follows:

$$\boldsymbol{metric_{ic}} = (0.4 * MAPE_{in}) + (0.4 * MAPE_{out}) + (0.1 * MPE_{in}) + (0.1 * MPE_{out})$$

Once we compute a single metric for each subgroup and candidate model combination, we can then select the best model for each subgroup by choosing the model specification with the smallest overall metric.

Assessing Model Validity

After selecting the best model for each subgroup by minimizing the smallest overall metric, AEG will assess model validity at the program level. We do this by calculating the weighted average MAPE and MPE at the program level. For both metrics, we like them to be low or very close to zero to be able to say that all the subgroup best models collectively deliver good levels of accuracy and bias.

Model Fine-Tuning

We also routinely use visual inspection of the results as a simple but highly effective tool. During the inspection, we will look for specific aspects of the segment-level predicted and reference load shapes to determine how well the models perform. We use observations derived from these inspections to make necessary edits to the model specifications obtained from the optimization process. For example:

- We check to make sure that the reference load is closely aligned with the actual and predicted loads during the early morning and late evening hours when there is likely to be little effect from the event. Large differences can indicate that there is a problem with the reference load either over or under estimating usage in absence of the rate.

[10] The mean absolute percent error (MAPE) is defined as: $MAPE = \frac{100\%}{n}\sum_{h=1}^{n}\left|\frac{Actual_h - Estimate_h}{Actual_h}\right|$

[11] The mean percent error (MPE) is defined as: $MPE = \frac{100\%}{n}\sum_{h=1}^{n}\frac{Actual_h - Estimate_h}{Actual_h}$

- We closely examine the reference load for odd increases or decreases in load that could indicate an effect that is not properly being captured in the model.
- We also look for bias both visually and mathematically. Identification of bias and its source often allows us to adjust the models to capture and isolate the bias-inducing effects within the model specification.

Obtain Load Impacts and Confidence Intervals by Segment

The following example illustrates the process of estimating the impacts from the final model for a single subgroup. There will be several subgroups in the actual analysis, each with their own final model specification determined by the optimization process. Nevertheless, the process will be the same in each case.

Let's assume that this subgroup is weather sensitive and that the final model specification includes calendar and weather effects in the baseline portion of the model. In this simple example below, α_t, δ_t, and CDH_t, make up the baseline blocks of the model, and explain variation in kwh_t unrelated to demand response events. The remaining variables, $EVNT$, and the interaction term $(\alpha_t * EVNT)$ are the impact blocks and explain the variation in kwh_t related to a DR event.[12] An hourly model like equation (1) below can be equivalently estimated as one model with hourly dummy variables, or as 24 separate hourly models.

$$kwh_{it} = \beta_0 + \alpha_t + \delta_t + CDH_t + EVNT + (\alpha_t * EVNT) + \varepsilon_{it} \quad (1)$$

Where:

kwh_{it} is the consumption of customer i in hour t

β_0 is the intercept

α_t is a vector of segment indicators, i.e. AutoDR, LCA, etc.

δ_t is a vector of calendar variables, i.e. month, year, and day of week

CDH_t represents the cooling degree hours for hour t

$EVNT$ is a dummy variable indicating that hour t was on a CPP or PDP event day

$(\alpha_t * EVNT)$ is an interaction between the event indicator and the segment indicator variables

ε_{it} is the error for participant i in time t

This type of time-series model is likely to have auto-correlated errors which will be handled either directly through modeling the appropriate autoregressive process or more simply by using the Newey-West error correction.

We can use the model above to estimate the load impacts as follows:

- First, we obtain the actual and predicted load for each participant on each hour and day based on the specification defined in equation (1).
- Next, we can use the estimated coefficients and the baseline portion of the model to predict what this participant would have used on each day and hour, if there had been no events. We call this prediction the reference load.

[12] Any unexplained variation will end up in the error term.

- We calculate the difference between the reference load (the estimate based on the baseline blocks) and the predicted load (the estimate based on the baseline + impact blocks) on each event day. This difference represents our estimated load impact for each participant.

To show the actual observed load (and avoid confusion associated with the predicted load) we re-estimate the reference load as the sum of the observed load and the estimated load impact.

Although we will be fitting models at the subgroup level, we will estimate the impact for each participant and the results for each participant can be easily aggregated to represent impacts for each of the required segments of participants for each of the three IOUs. This includes analysis of impacts for each LCA, industry group, participants dually enrolled in other DR programs, participation in PG&E's in-season support, and other participant segments of interest.

During previous Statewide DR aggregator evaluations, we have developed specific approaches to estimate subgroup and program level load impacts for these programs which deal explicitly with selecting an average event day, and accounting for missing data without "dinging" the overall load impact.

- The average event day can be tricky to define. Historical CPP event calling is significantly simpler than CBP. However, attempting to sum average impacts and participant counts across the multiple combinations of subgroups presented as part of this analysis can prove to be problematic. The approach we will use to determine the averages for each subgroup, and for combinations of groups, involves dividing the aggregate impact for the grouping by the total participant count for the grouping.[13]
- To account for participants with missing or invalid event day data (data omitted during the data validation process), we will apply the average per-participant impacts as a proxy for the "actual" impacts realized by these participants. In these cases, we will determine the aggregate impact for a particular grouping based on the per-participant average of the participants with valid data in the grouping and the total enrolled accounts associated with that grouping for the given event.[14]

Because the impacts are statistical estimates, it is important to establish a range or confidence interval around the estimates resulting in the uncertainty adjusted load impacts required by the Protocols. We will be using a statistical package to output the standard errors of the point estimates. The standard errors can then be used to calculate a confidence interval at various levels (e.g. 50%, 70%, 90%, etc.) for each participant. Then, because we can assume that the customer-specific estimates are independent across participants, the variance of the sum will be the sum of the variances. A similar process can be repeated to obtain confidence intervals for each segment.

Estimate the Incremental Impact of Enabling Technology

Since we will be estimating aggregate regression models, a separate analysis to estimate incremental impacts associated with AutoDR and TA&TI is not necessary. As mentioned in the section above on candidate regression models, we can incorporate estimating the incremental impacts associated with any segment of interest into the subgroup-level models.

Using the example model shown in equation (1), $(\alpha_t * EVNT)$ would contain the estimates of the average incremental impact associated with each segment identified in vector α_t. Let's assume that vector α_t only

[13] Another approach would be to create the averages first at the lowest level of disaggregation, and then sum them to the total level of aggregation desired. Though both approaches are equally valid, they often result in slightly different values. As a result, in the *average* event day impact results, the sum of the subgroup level impacts will not always equal the program level impacts.

[14] It is important to note that the per-participant average may be different depending on the group or subgroup because of the different types and sizes of customers in the grouping. Therefore, during events where average per-participant data will be used as a proxy for one or more participants, the sum of the individual subgroup totals for the event may not exactly add up to the total for the larger segments or participants.

includes an indicator for AutoDR. Similar to the steps discussed in estimating event load impacts, we use the following process to estimate the incremental impact associated with AutoDR:

- First, we obtain the actual and predicted load for each participant on each hour and day based on the specification defined in equation (1).
- Next, we can use the estimated coefficients of the model to predict what this participant would have used on each day and hour if there had been no impact associated with AutoDR (i.e., we set $(\alpha_t * EVNT) = 0$). We call this prediction the impact reference load.
- We calculate the difference between the impact reference and the predicted on each event day. This difference represents our estimated incremental AutoDR load impact for each participant.

Once the incremental impact for each participant is established, we can follow the same procedure in calculating aggregate estimates for each of the required segments of participants for each of the three IOUs.

Task 3.2 Deliverables

- Draft Ex-post Load Impact Estimates — January 15, 2021
- Final Ex-post Load Impact Table Generators — January 31, 2021

Task 3.3: Ex-ante Impact Analysis

The main goal of the ex-ante analysis is to produce an annual twelve-year[15] forecast of the load impacts expected from the CPP programs. Separate forecasts are to be produced for each LCA (as applicable), each busbar (as applicable), and bundled v. direct access (as applicable). We will produce a set of impacts under each of the different weather scenarios required: monthly peak day and typical event day for 1-in-2 weather year and 1-in-10 weather year for each of the IOUs and the CAISO. A portfolio forecast that excludes the forecasted load impacts of dually-enrolled customers will also be provided. An annual twelve-year forecast will be produced for each of the following:

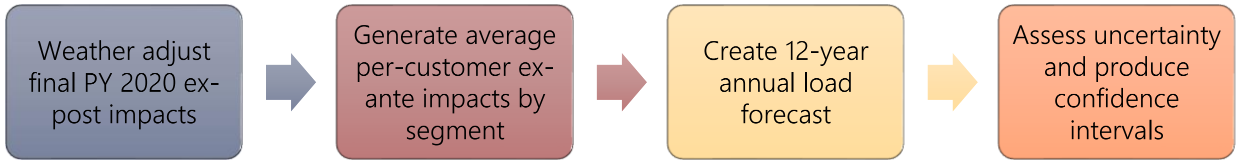
- SCE large non-residential customers (200 kW and above), SMB non-residential customers (less than 200 kW), and residential customers (any size);
- PG&E large customers (200 kW and above) and SMB customers (less than 200 kW); and,
- SDG&E large customers (200 kW and above) and medium customers (20 kW to 199.99 kW) [16].

AEG acknowledges that the uniqueness of 2020 adds to the complexity of developing twelve-year forecasts. In addition to the conventional factors that contribute to ex-ante analysis (i.e., anticipated program changes, enrollment trends, and weather-adjusted ex-post impacts), we will incorporate current and anticipated conditions. Given the uncertainty of current circumstances, AEG understands that program outlook at the time of the PI meeting may change during the actual ex-ante analysis execution (January 2021). AEG will have continuous discussions with each IOU regarding any anticipated changes that may impact the appropriate ex ante assumptions.

Our approach achieves these goals by first determining the appropriate weather-adjusted, per-customer impact for each of the segments of interest, and then multiplying that impact by the number of participants for each year specified by the enrollment forecast. First, we describe the various steps involved in implementing this approach in detail. Then we address uncertainty in the forecast and the calculation of confidence intervals. The figure below provides an overview of the ex-ante analysis approach.

[15] Eleven-year forecasts for SCE and PG&E companies.

[16] SDG&E also requires results for customers less than 500 kW v. greater than 500 kW.



Weather-Adjusted Impacts

The first step in the ex-ante analysis is to use the ex-post regression models to predict weather-adjusted impacts for each segment of interest. This will produce a set of impacts under each of the required weather scenarios. To do this, we will carry out the following steps:

- For each program, we will begin with the coefficients estimated in the subgroup regression models developed for the ex-post analysis.
- Then, we will replace the actual weather from the program year with the 1-in-2 and 1-in-10 weather data to predict a customer's load for each of these scenarios assuming no events are called. The result will be a weather-adjusted reference load for each customer for each weather scenario required.
- Next, we will predict the weather-adjusted event day load by again applying the coefficients from the ex-post models to both the 1-in-2 and 1-in-10 weather data. However, this time we will assume that events were called by changing the event indicator variables from zero to one.
- We will calculate the load impact for each customer by subtracting the weather-adjusted event-day load from the weather-adjusted reference load or calculate it directly from the coefficients involved.

Generation of Per-Customer Average Impacts by Segment

Once weather-adjusted impacts have been predicted for each customer, for each of the desired weather scenarios, it becomes a relatively simple exercise to average the individual impacts and generate per-customer average impacts by segment of interest. For example, the average impact for a particular LCA will be the average of the impacts predicted for each customer in that LCA.

Creation of 12-Year[17] Annual Load Impact Forecasts

The next step in the analysis will be to use the set of per-customer average impacts to create an annual forecast of load impacts over the next 12 years. The exact approach used to complete the forecast will be determined jointly by each IOU and AEG and will depend on the customer class, the stability of the participant population, and any proposed or potential changes to the CPP programs. As stated in the RFP, it will be important that any changes in the customer mix can be accounted for over the forecast horizon.

We will work diligently with the three IOUs and the DRMEC to determine if there are any instances where the impacts used in the ex-ante analysis should be based on a combination of historical ex-post estimates rather than the estimates from the current evaluation.

Uncertainty Estimates and Confidence Intervals

While we are confident we have a sound approach to developing the annual forecasts, the analysis also needs to be completed within context and the assumptions of the enrollment forecasts, especially when making adjustments on the average per-customer weather-adjusted impacts. We will work closely with the SDG&E project manager to ensure that we are aware of all the relevant information and data that

[17] Eleven-year forecasts for SCE and PG&E companies.

might affect how we estimate the forecasts. It may also be appropriate to conduct some sensitivity analyses to see how much the forecasts change when we vary the different inputs.

It is our practice to provide confidence intervals for estimates because it allows those looking at the results to have a good sense of the accuracy of the estimates. Uncertainty in the ex-ante forecasts will come from two separate sources:

- The first will be the modeling error from our models, both the regressions and the weather adjustment to the 1-in-2 and 1-in-10 weather years.
- There will also be error in the enrollment forecast. Assuming that the three IOUs can provide the necessary uncertainty information from the enrollment models, we will incorporate the enrollment error into the estimate and provide confidence intervals for the ex-ante forecasts by segment.

Task 3.3 Deliverables

- Draft Ex-ante Load Impact Estimates — February 15, 2021
- Final Ex-ante Load Impact Table Generators — February 28, 2021

Task 4: Prepare Reports

The report will include two components:

- The program load impact evaluation; and
- Table generator workbooks for ex-post and ex-ante impacts for each customer class within the three IOUs.

We will first update the load impact table generators for each IOU to be filed with the report using the standardized input selection fields presented in the RFP. We will work with the SDG&E project manager and review the appropriate tariff requirement, program specifications, regulatory decisions and any additional material necessary to determine the appropriate options to include in each field.

Next, we will create and deliver a draft report that describes the results of the ex-post and ex-ante load impact estimation and, via a conference call, we will present the draft results to all three IOUs. We will incorporate any comments received during the presentation or directly in the draft report into a Project Final Report. We understand that the draft-review process may require more than one iteration.

We anticipate that the final report will include, at a minimum, the following sections:

- An Abstract containing a short, non-technical overview of the report, which can also be used in CALMAC.org's searchable database.
- An Executive Summary presenting an overview of the findings.
- An Introduction summarizing the objective of the project and presenting an overview of the CPP program.
- A Methods section that will present the analysis techniques employed in the evaluation and a complete assessment and discussion of each of the project tasks.
- An *Ex-post* Results section that will include the presentation of program-level load impacts for each combination of rate, technology and customer class, on each event day, and average impacts over the entire summer for each IOU. We will also present the load impacts by the more granular subgroups specified in the RFP including LCA, industry segment (NAICS Code), kW size, and notice type.

- An *Ex-ante* Results section that will include the 12-year[18] annual load impact forecast for both a 1-in-2 weather year and a 1-in-10 weather year for the same subgroups identified in the *ex-post* analysis.
- A Validity section which will include a discussion of the methods employed to ensure robust and unbiased estimates from the regression models. We will also present graphs that compare the estimated load with actual load for similar non-event days in each evaluation year.
- A Key Findings and Recommendations section summarizing our findings and recommendations.

We will also create two-page summaries of each program for each IOU. The summaries will describe the programs, evaluation methods, and ex-post and ex-ante impact results.

For this evaluation, it will also be important to develop confidential and public versions of reports and summary tables. Therefore, our reporting quality control process will include steps to check that we clearly identify confidential data in confidential reports by using grey highlighting and that we redact confidential data from public versions of the reports.

Task 4 Deliverables

- Draft Report for PY2020 Evaluation — February 20, 2021
- Executive Summary write-up for report — March 1, 2021
- Pre-final Public Evaluation Report — March 1, 2021
- Final Public and Confidential Reports — March 31, 2021
- Non-technical Abstract for CALMAC Website — April 10, 2021

Task 5: Presentation of Results

AEG will attend the annual load impact workshop and present the results of the ex-post and ex-ante analysis.

Task 5 Deliverables

- Presentation for PY2020 Load Impact Workshop — TBD

Task 6: Project Management and Progress Reporting

AEG is committed to completing all tasks in an excellent and timely manner. Below we have outlined several project management activities that are critical to meeting this commitment.

Communications and Progress Reporting. In addition to the kick-off meeting described in Task 1, we will use several methods to communicate with SDG&E:

- Scheduled conference calls: AEG's project manager will provide a brief phone update with SDG&E's project manager and each IOU project lead every two weeks, or more often, if needed. AEG will use these calls as opportunities to discuss issues that arise during the project and to discuss potential solutions. We will provide an agenda prior to each call and a written summary with decisions reached and action items within two days following each call.
- Monthly progress reports: By the first day of each month, AEG's project manager will deliver a written progress report that describes the tasks performed in the past month, tasks expected to be performed in the next month, information or other action needed from any of the IOUs in order to

[18] Eleven-year forecasts for SCE and PG&E companies.

complete those tasks, and the timeline including any deviations from the evaluation plan. The project report will be timed to coincide with monthly invoices.

- Ad hoc phone calls and emails: At times, we will need to contact the SDG&E project manager or project leads from the other IOUs at unscheduled times. We will do so with ad hoc phone calls and emails as appropriate.

Scheduling tasks, staff assignments and cost control. Staff will be assigned to their relevant tasks to ensure that the timing of the data collection and subsequent analysis match the required timeline and to maintain cost control on the project. The proposed schedule reflects thoughtful consideration of the time needed to procure data, conduct the analyses, and submit all deliverables by dates indicated in the RFP. We outline the proposed schedule of deliverables in Section 5.

Management of the AEG Team. The project management team and lead analysts have direct and hands-on experience in performing similar impact evaluations. We will conduct all analysis with our own staff, using a team that has extensive experience working together. Regular internal team meetings will be held to monitor not just progress but complete understanding of schedules and responsibilities.

Project Quality Control. AEG ensures the quality of our work by close teamwork and monitoring. The senior analysts, project manager and project director review all reports and other written work prior to sending deliverables to SDG&E.

Task 6 Deliverables

• Monthly or bi-weekly conference calls	Schedule TBD with each IOU

Task 7: Database Documentation

Specific to each IOU's request and formatting requirements, AEG will deliver database and analysis documentation for the CPP LI analysis.

Task 7 Deliverables

• 2020 Integrate project database	March 2, 2021
• 2020 Database specifications and documentation	March 2, 2021

5

DELIVERABLES SCHEDULE AND DUE DATES

The table below shows the AEG project timeline.

Task	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
Task 1: Project Initiation Meeting	Agenda, Memo								
Task 2: Evaluation Plan	Draft Plan	Final Plan							
Task 3.1: Data Collection & Validation	Data Request	Interval Data Request							
IOU Deliverables		*Billing, Demo-graphic Data*	*Majority of Data, Interval Data*		*Enroll-ment Forecast*				
Task 3.2: Ex-post Analysis				Draft Ex-post	Pre-Final Ex-post	Final Tables			
Task 3.3: Ex-ante Analysis						Draft, Pre-Final Ex-ante	Final Tables		
Task 4: Prepare Reports						Draft Reports	Final Reports		
Task 5: Presentation of Results									TBD
Task 6: Project Management									
Task 9: Database Documentation							SDG&E Data-base	PG&E & SCE Data-base	

The table below summarizes the PY2020 deliverables and due dates.

Deliverable	Due Date
Task 1: Project Initiation Meeting	
Annual Planning Meeting Agenda	September 4, 2020 (Completed)
Annual Planning Meeting	September 4, 2020 (Completed)
Annual Planning Meeting Memo	September 4, 2020 (Completed)
Task 2: Evaluation Plan	
Draft Plan	September 18, 2020 (Completed)
Final Plan	5 workdays after receiving comments
Task 3: Impact Evaluation	
Task 3.1: Data Collection and Validation	
Data Request	September 18, 2020 (Completed)
IOU Data Delivery	*Customer demographic and billing data by Oct. 15, 2020*
Hourly Interval Data Request	October 31, 2020
IOU Data Delivery	***All Other Data by Nov. 15, 2020***
Task 3.2: Ex-post Analysis	
Draft Ex-post Load Impact Estimates	January 15, 2021
Final Ex-post Load Impact Table Generators	January 31, 2021
Task 3.3: Ex-ante Analysis	
IOU Data Delivery	*Enrollment Forecasts by January 31, 2021*
Draft Ex-ante Load Impact Estimates	February 15, 2021
Final Ex-ante Load Impact Table Generators	February 28, 2021
Task 4: Prepare Reports	
Draft Evaluation Report	February 20, 2021
Executive Summary write-up for report	March 1, 2021
Pre-Final Public Evaluation Report	March 1, 2021
Final Public and Confidential Evaluation Reports	March 26, 2021
Non-technical Abstract for CALMAC Website	April 10, 2021
Task 5: Presentation of Results	
Presentation	TBD
Task 6: Project Management	
Monthly or bi-weekly conference calls	TBD with each IOU
Task 7: Database Documentation	
2020 Integrate project database	March 2, 2021
2020 Database specifications and documentation	March 2, 2021

Below, we outline the PY2020 deliverables specific to each IOU. A more comprehensive list[19] detailing the contents of each deliverable is in Appendix B in the form of embedded links to the files.

For all IOUs

- Ex-post table generators
- Ex-ante table generators
- LTPP Part C requirement

PG&E Deliverables

- DR Impact Tables
- Return of Load
- Ex-ante impacts for each customer

SCE Deliverables

- DR MV Forecasting templates
- LTPP Part B requirement
- DR Executive Summary
- Reliability Cap Data

SDG&E Deliverables

- Executive Summary tables
- Hourly Ex-post and Ex-ante database

[19] This is a document covering both CBP and CPP evaluations.

A

DATA REQUEST

PY2020 Data
Request_09182020.x

B

ANNUAL PLANNING MEETING DELIVERABLES

Meeting Agenda and Slide Deck

CPP_PY2020_Pl
Meeting Slides_0904

Meeting Memorandum

CPP_PY2020_Pl
Meeting Memo_091

Comprehensive List of Deliverables

Statewide
Deliverables Outline

Applied Energy Group, Inc.
500 Ygnacio Valley Road, Suite 250
Walnut Creek, CA 94596
P: 510.982.3525