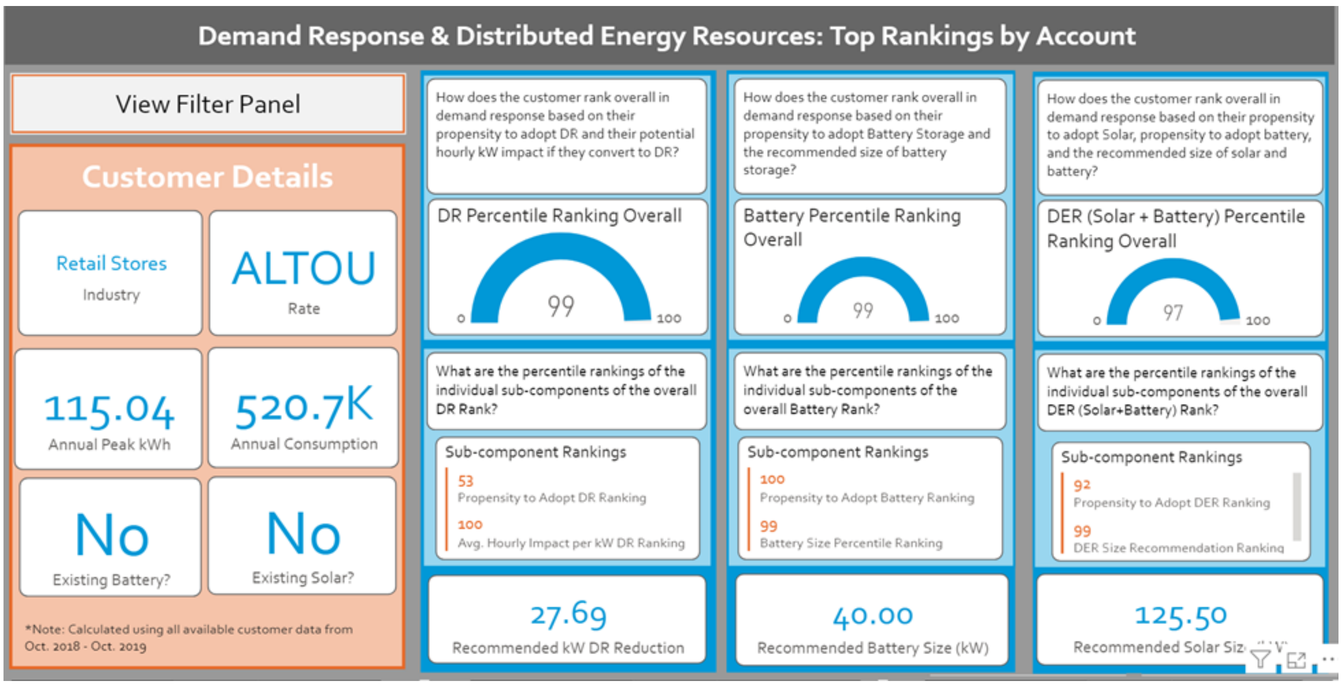
Using Data Analytics to Maximize Demand Response Enrollment and Participation

ETDR19SDG0004 Report



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San Diego Gas & Electric Company

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Disclaimer

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EXECUTIVE SUMMARY

San Diego Gas and Electric (SDG&E) contracted with Demand Side Analytics (DSA) to conduct analysis and develop tools to target Demand Response (DR) programs, behind-the-meter (BTM) battery storage, and distributed solar. The team designed the research tool to inform customer targeting and design of non-residential DR programs. A key objective was to assess SDG&E's ability to incorporate customers with and without battery storage and solar into these programs. Another objective of the study was to make interactive analysis accessible to utility program managers and account representatives via dashboards. The dashboard allows users to identify sites that are likely to enroll, deliver load changes, and experience bill reductions from various combinations of demand response, solar, battery storage, and rates. They also produce granular site-level recommendations and bill impacts for customers.

As part of the study, DSA looked at whether battery storage can be integrated into existing demand response programs. Well-designed demand response (DR) programs can allow utilities to tap into behind-the-meter battery storage by sharing some of the grid benefits with customers who agree to deliver resources when needed. One of the most unique attributes of battery storage is that it affects multiple aspects of the electricity grid's infrastructure and delivers benefits to both customers and utilities. Energy storage provides concrete benefits to customers in the form of reliability improvements and the ability to manage their electric bills. It also can deliver tangible benefits to the electric grid, including reductions in the need to build additional generation, transmission, and distribution infrastructure and the ability to store cheaper electricity generated during off-peak for use during higher cost periods. However, because customers face retail pricing (versus wholesale prices), the grid benefits of behind-the-meter resources are not fully realized without programs to incorporate behind-the-meter battery storage and dispatch mechanisms.

PURPOSE AND OBJECTIVES

The purpose of the project was to conduct an analysis and develop tools for incorporating battery storage into DR programs. The two main objectives were to:

1. Analyze the full population of SDG&E non-residential customers to identify the benefits and optimal combinations of demand response, distributed energy resources (with a focus on batteries), and rates for each individual customer.
2. To use this analysis to develop a tool that provides unique savings estimates and recommendations for each customer based on their characteristics. This tool can be used to identify the product mix that maximizes benefits for both SDG&E and the customer.

MAIN TASKS

The project was conducted across five main tasks:

1. **Develop a prototype of the tool** – This was a preliminary step that helped identify the inputs, user options, and outputs that would be included in the final version of the tool.
2. **Conduct load simulation and billing analysis on the full population of non-residential SDG&E customers** – The results of this analysis were bill savings estimates for various DR options, rates, distributed energy resources (DER) installations, and operation strategies which informed the subsequent target analysis and final tool development.
3. **Model adoption propensity to identify characteristics of customers that were likeliest to participate in Base Interruptible Program (BIP) and Capacity Bidding Program (CBP)** – The goal of this step was to understand who benefits most and to enable SDG&E to direct aggregators and developers towards these customers.
4. **Write a report and conduct training** – This step includes bi-weekly progress meetings, this report, and a workshop to present the results and train users to work with tool.
5. **Develop a tool to allow SDG&E program managers to view site-specific analysis and target recruitment efforts** – The final tool is hosted through Power BI and allows SDG&E staff and account representatives to target customers, view recommendations and energy and bill savings under multiple scenarios, and produce personalized recommendations.

RESULTS

DSA conducted an enrollment propensity analysis to determine the characteristics of customers that were more likely to enroll in demand response or to install solar photovoltaic (PV) or storage systems. The results of that analysis are summarized in Table 1.

TABLE 1: CHARACTERISTICS THAT INFLUENCE ADOPTION OF DR AND DERS

RESOURCE	CHARACTERISTICS ASSOCIATED WITH LOW LIKELIHOOD	CHARACTERISTICS ASSOCIATED WITH HIGH LIKELIHOOD
Demand Response	• Small rate • Higher variability in loads • Agricultural, Mining, & Forestry customers • More premises associated with an account	• Larger loads • More weather sensitive loads • Retail, Education, & Lodging customers • Certain zip codes
Battery Storage	• Small rate • Public Administration, Professional Services, Mining, Utility, and Construction customers	• Larger peak loads • Higher overall consumption • Manufacturing customers

Resource	Characteristics Associated with Low Likelihood	Characteristics Associated with High Likelihood
Solar PV	• Small rate • More weather sensitive loads • Retail, Professional Services customers	• Higher overall consumption • Warehouse, Storage, Postal, and Education customers

Customers have various ways to save money by enrolling in DR, with or without additional DER installations. In general, customers can reduce their total consumption. They can also shift consumption away from peak periods to manage coincident and non-coincident demand charges. Finally, they can claim a participation incentive after enrolling in demand response. These incentives often include a fixed monthly capacity credit and a performance credit for each event, measured by a settlement baseline. As summarized in Table 2, the interaction of DR, Battery, and Solar installation and operations strategies can have varying effects on a customer's bill. Of course, these results depend heavily on the DR program elected, battery and solar sizes, and the customer's operational characteristics. Volumetric charges are electricity charges that vary based on the amount of energy used (in kilowatt-hours) within a time period, demand charges are charges based on the customer's peak demand (in kilowatts) within a time frame, and demand response incentives are bill credits that a customer receives for participating in a demand response program.

Table 2: DR and DER Strategy Impacts on Customer Bills

	Volumetric Charges	Demand Charges	DR Incentives
DR Only	↔ no significant change	↔ no significant change	↑ participation incentive
DR + Battery Peak	↓ slight decrease due to battery charge/discharge roundtrip efficiency	↑↑ shift away from peak periods, reduce peak demand charges	↑ participation incentive
DR + Battery Shift	↓ slight decrease due to battery charge/discharge roundtrip efficiency	↑ reduce peak demand charges, but may increase non-coincident demand due to overnight charging	↔ participation incentive offset by permanent shifting away from peak in baseline period
DR + Battery Peak + Solar	↑↑ solar reduces energy consumption from grid	↑↑ shift away from peak periods, reduce peak demand charges	↓↓ participation incentive offset by lower net demand able to be shed
DR + Battery Shift + Solar	↑↑ solar reduces energy consumption from grid	↑ reduce peak demand charges, but may increase non-coincident demand due to overnight charging	↓↓ participation incentive offset by permanent shift away from peak in baseline period and lower net demand able to be shed

ABBREVIATIONS AND ACRONYMS

AUC	Area under the Curve
BTM	Behind-the-meter
DER	Distributed Energy Resource
DR	Demand Response
DSA	Demand Side Analytics
kW/kWh	Kilowatts/Kilowatt-Hours
MW/MWh	Megawatts/Megawatt-Hours
NAICS	North American Industry Classification System
ROC	Receiver Operating Characteristic
SDG&E	San Diego Gas & Electric
TOU	Time-of-Use
PV	Photovoltaic

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INTRODUCTION

San Diego Gas and Electric (SDG&E) contracted with Demand Side Analytics (DSA) to conduct analysis and develop tools to target Demand Response (DR) programs, behind-the-meter (BTM) battery storage, and distributed solar. The team designed the research and tool to inform customer targeting and design of non-residential DR programs. A key objective was to assess SDG&E's ability to incorporate customers with and without battery storage and solar into these programs. Another objective of the study was to make interactive analysis accessible to utility program managers and account representatives via dashboards. The dashboard allows users to identify sites that are likely to enroll, deliver load changes, and experience bill reductions from various combinations of demand response, solar, battery storage, and rates. They also produce granular site-level recommendations and bill impacts for customers.

As part of the study, DSA whether battery storage can be integrated into existing demand response programs. Well-designed demand response (DR) programs can allow utilities to tap into behind-the-meter battery storage by sharing some of the grid benefits with customers who agree to deliver resources when needed. One of the most unique attributes of battery storage is that it affects multiple aspects of the electricity grid's infrastructure and delivers benefits to both customers and utilities. Energy storage provides concrete benefits to customers in the form of reliability improvements and the ability to manage their electric bills. It also can deliver tangible benefits to the electric grid, including reductions in the need to build additional generation, transmission, and distribution infrastructure and the ability to store cheaper electricity generated during off-peak for use during higher cost periods. However, because customers face retail pricing (versus wholesale prices), the grid benefits of behind-the-meter resources are not fully realized without programs to incorporate behind-the-meter battery storage and dispatch mechanisms.

PURPOSE

The two main objectives of the project were to analyze the full population of SDG&E non-residential customers to identify the benefits and optimal combinations of demand response, distributed energy resources (with a focus on batteries), and rates for each individual customer, and to use this analysis to develop a tool that provides unique savings estimates and recommendations for each customer based on their characteristics. This tool can be used to identify the combination of DR participation and distributed energy resource (DER) operation strategies that maximizes benefits for both SDG&E and the customer.

The project was conducted across five main tasks:

1. **Develop a prototype of the tool** – This was a preliminary step that helped identify the inputs, user options, and outputs that would be included in the final version of the tool.
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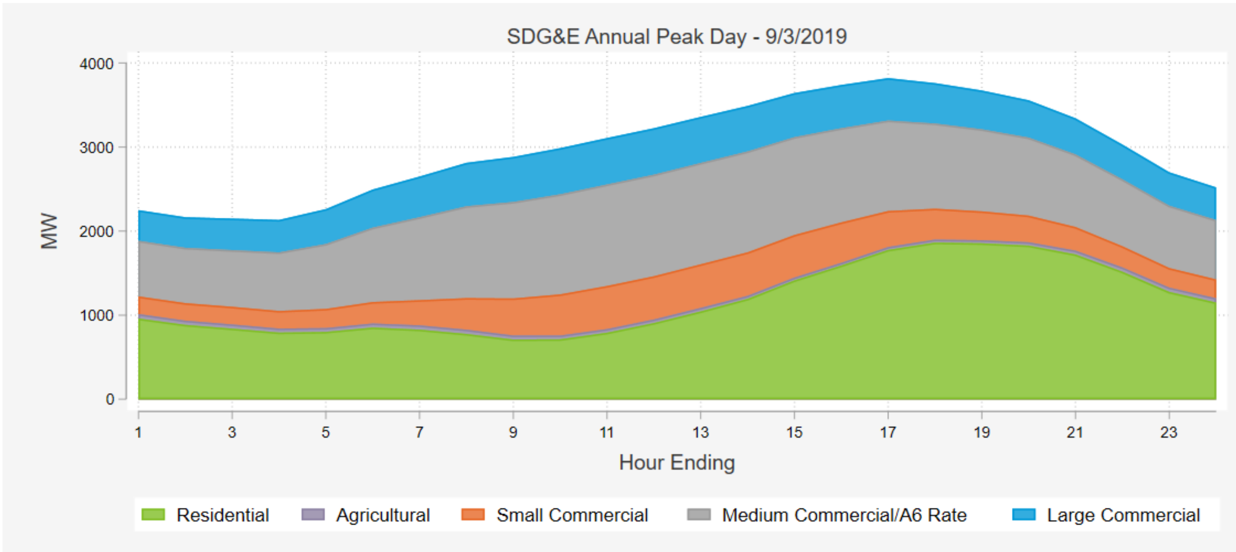
BACKGROUND

SDG&E is an investor-owned public utility in the state of California that serves a population of 3.6 million people in 4,100 square miles, spanning San Diego and the southern Orange counties. SDG&E provides gas and electric service to over 1.4 million electric customers across residential, commercial, and industrial sectors across 1,052 distribution circuits. Figure 1 shows the service area of SDG&E.

FIGURE 1: SDG&E SERVICE TERRITORY

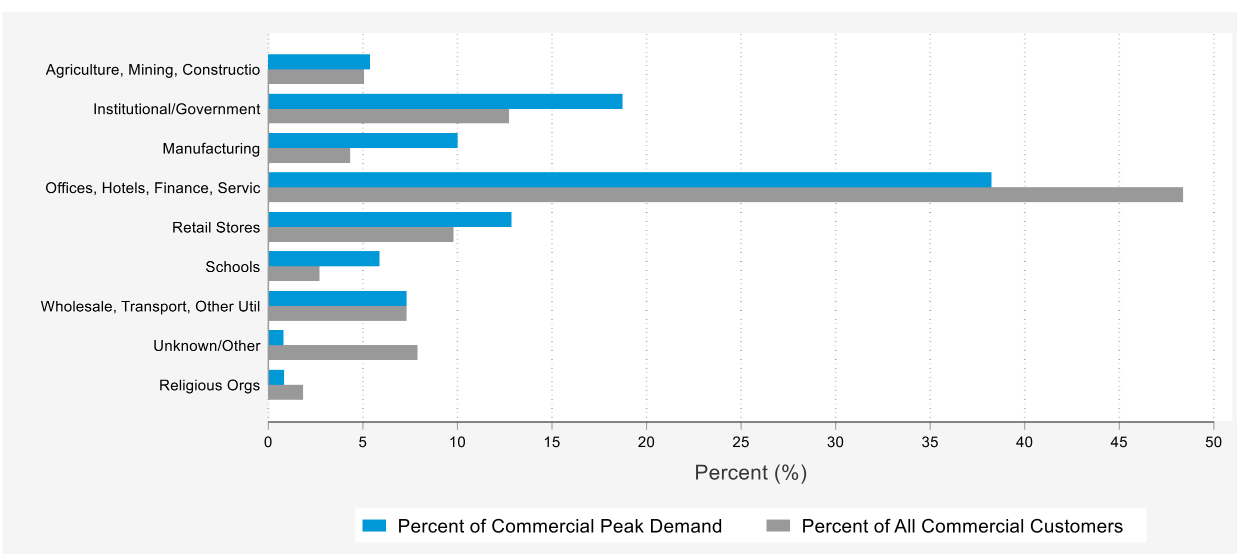
Figure 2 shows the demand for each SDG&E customer group on the 2019 peak demand day. Because 2020 was impacted by the COVID-19 pandemic, the 2019 year is more indicative of typical customer loads. In 2019, the annual peak demand was 3,822 megawatts (MW). SDG&E serves nearly 150,000 non-residential customers. Although this is only about 10% of the customer base, the commercial sector accounted for 53% of the 2019 peak, with 2,010 MW of electricity demand on the peak hour.

Figure 2: Consumption by Customer Type on Peak Demand Day



The contribution of commercial customers to system peak demand varies by industry. Figure 3 compares each industry's (by North America Industry Classification System (NAICS) code) percent of commercial peak demand to their percent of total commercial customers. Offices, Hotels, Finance, and Other Services is the largest industry and has the highest percentage of peak demand. However, their contribution to peak demand is relatively small compared to the size of the industry. The Institutional/Governmental, Manufacturing, Education, and Retail industries all have higher proportions of peak demand than their share of the customer base. These four industries make up only 30% of commercial customers, but account for 48% of peak demand.

Figure 3: Industry Comparison of Peak Demand and Total Customers (2019)



Current Demand Response Programs

One of the purposes of the study was to analyze SDG&E's current demand response offerings and their potential to lead to tangible bill savings when a customer participates in conjunction with distributed energy resources (DER). In 2020, there were approximately 30,000 demand response customers enrolled in a non rate-based (dispatchable) program in SDG&E's territory, with 5,364 non-residential customers, which is a little over 3% of the non-residential customer base. Across all programs, demand response customers are able to provide approximately 22.41 MW of load reduction on average. This represents approximately 0.58% of peak load. Non-residential programs made up 36% of these reductions with 7.75 MW of reduction on average, or 0.21% of peak load.

Industries with relatively high demand compared to their size historically have been more likely to participate in demand response, battery storage and solar. Figure 4 shows the demand response participation rate for each industry, or the percent of customers in each industry that are enrolled in at least one of SDG&E's commercial demand response programs. Religious organizations and schools have the highest percentage of customers participating in demand response, followed by retail and manufacturing customers.

Figure 4: Demand Response Participation Rate by Industry (2019)

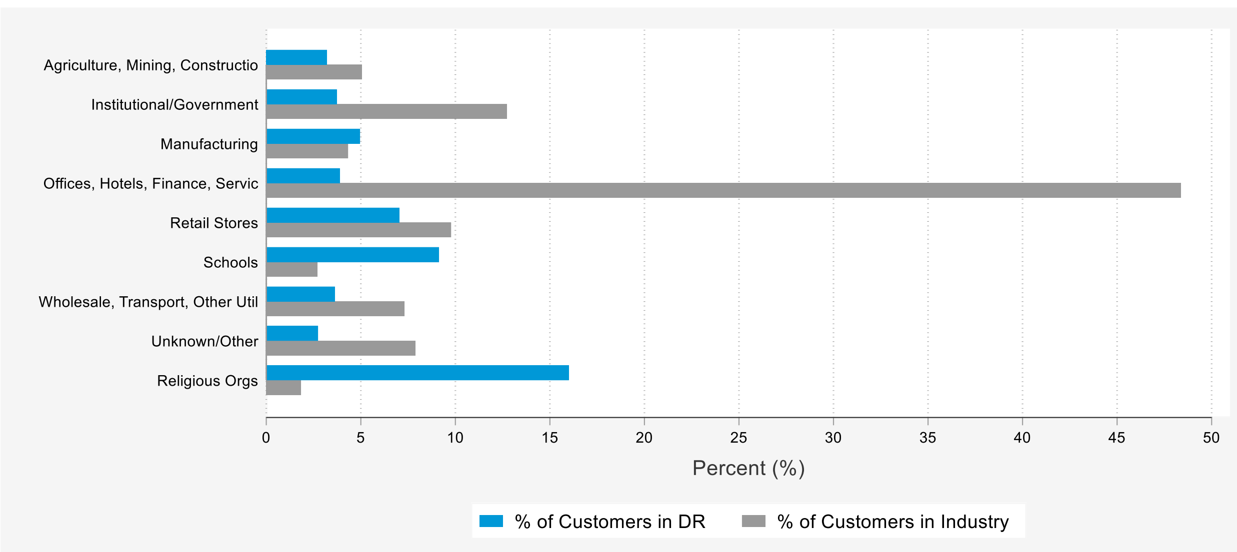


Table 3 provides some statistics on three of SDG&E's demand response programs for summer (May-October) of 2019. The AC Saver program is the most popular, with over 5,000 participating non-residential customers. AC Saver participants get a controller device installed on their A/C unit, that SDG&E can activate to cycle air and reduce cooling load. In BIP and CBP, participants can be called upon to reduce their energy usage on certain days and have the flexibility to decide how to reduce their load. Although these programs have a smaller enrollment, the impact per customer in both of these programs is significantly higher than the AC Saver program. These programs tend to attract large commercial customers; for example, the CBP program accounted for nearly 0.1% of the 2019 SDG&E system peak demand (3,822 MW) with under 200 customers, while the 5,000 customers in the AC Saver program only made up 0.03% of the demand. In recent years, both CBP and BIP rules have been modified so smaller non-residential customers can participate via aggregation.

TABLE 3: SDG&E DEMAND RESPONSE PROGRAMS (2019)

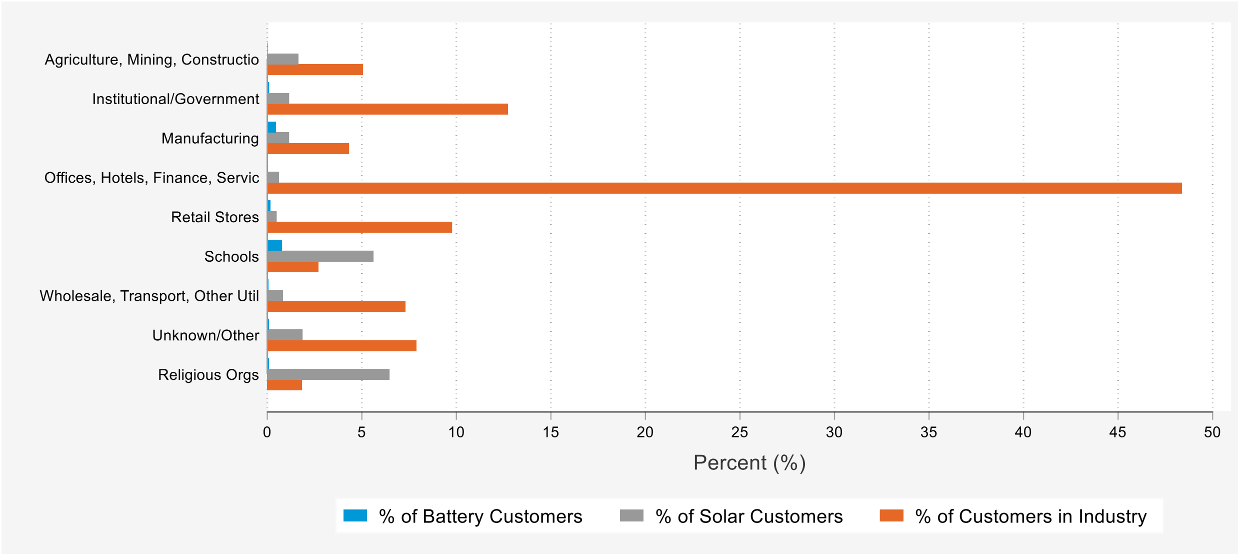
Demand Response Program	Participants	Total Events Called	Average Load Impact Per Customer (kWh)	% Load Reduction	Average Event Impact (MW)	Percent of SDG&E System Peak
AC Saver	5,159	20	0.16	1.90%	1.31	0.03%
BIP	5	1	573	84.80%	0.79	0.02%
CBP	200	23	20.1	14.00%	3.34	0.09%

INTEGRATION OF DISTRIBUTED ENERGY RESOURCES

In California, the single largest change in the electric sector has been the rapid increase of renewables in electricity generation, which have fundamentally changed grid operations and grid planning. The shift is driven by large utility-scale solar generation and customer adoption of smaller, onsite solar. The change in the supply mix has shifted the focus of planning and operations to net loads (i.e. total load minus intermittent renewables), led to large ramps in net loads in evening (when solar production dwindles and loads increase), increased the need for fast response resources, and changed the economics of using electricity in the middle of the day when renewable resources peak. Battery storage is well suited to complement high penetration of renewables. It can charge when solar output is high (reducing the potential for over-generation), discharge energy when it is needed most, provide ramping capacity, and can also deliver fast response services to stabilize the grid.

Larger commercial and industrial customers in California have been adopting behind-the-meter battery storage primarily to manage bills by reducing peak demand charges. In the early years of the energy transition, battery storage was too expensive to be feasible for most sites. As costs come down due to improvements in technology and the market structure develops to better accommodate distributed energy sources, behind-the-meter battery energy storage systems are becoming more common. Behind-the-meter battery storage systems are frequently paired with on-site solar installations. Of the 142 large SDG&E customers who currently have battery storage, over 40% also have on-site solar. However, most of these sites are participating in the wholesale markets and do not have a path to monetized grid services. Currently, just 17% of customers with behind-the-meter storage are participating in DR programs. Battery installations are concentrated in the education and manufacturing sectors, where they are often paired with solar installations as shown in Figure 5.

FIGURE 5: BATTERY AND SOLAR INSTALLATIONS BY INDUSTRY (2019)



SDG&E recognizes the potential of tapping into this behind-the-meter battery storage as a resource to provide flexibility, deliver resources when they are needed most, and store renewable generation. Demand Response (DR) programs are a natural fit for this role, as demand response programs are already a commonly used tool for controlling peak loads and are triggered when wholesale prices are high or resources are in short supply. In demand response programs, participants receive incentives from utility companies to reduce or remove their energy usage from the grid during peak demand periods. This benefits utilities by allowing them to mitigate demand during peak periods and ensure reliable electricity service for their customers. The ability to reduce peak demand can also help utilities control costs, such as lowering transmissions costs or avoiding infrastructure investments that depend on peak demand levels. Demand response can be applied through a wide variety of program designs and mediums, particularly as the electricity industry becomes more reliant on distributed and smart energy resources. One of the potential benefits of using batteries with demand response is that they enable customers to shift their energy usage away from the grid without causing major disruptions or inconveniences to their activities, since they are still receiving electricity, just temporarily shifting the source of that electricity. This could open up demand response opportunities for customers who previously would not be able to reduce their energy usage during the workday. Since batteries are frequently installed alongside solar, it is important to consider relationships between demand response, batteries, and solar.

ASSESSMENT OBJECTIVES

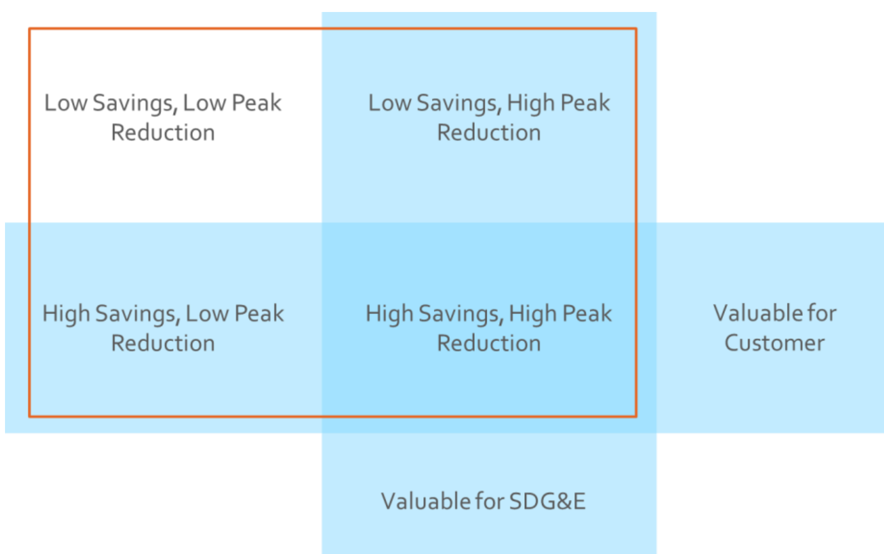
The following section details the key assessment objectives of the analysis. At a high level, the objectives include:

1. Developing recommendations for customer-specific DER sizes
2. Estimate the likelihood of customers to enroll in DR
3. Estimate changes in loads due to DR participation and DER operations
4. Estimate the bill impacts of these changes

OPTIMIZATION FRAMEWORK

All of the objectives and outputs of the project depend on an optimization framework. The optimization framework takes in three factors: the likelihood of demand response enrollment or DER adoption, the expected peak load reduction, and the bill savings associated with the DR and DER adoption. In the analysis, these three elements are calculated for all potential combinations of programs and distributed energy resources for each commercial customer. The outputs can then be used to identify the customers that will benefit most from demand response and DERs, the optimal combination of DR programs and DERs for each customer, and the expected potential demand reduction resulting from each combination. The latter two outputs are key inputs for the online tool. Figure 6 visualizes this framework in two dimensions – peak load reductions and bill savings. The likelihood of adoption adds a third dimension to the analysis, whereby customers who are likely to enroll in DR based on their characteristics are targeted first.

FIGURE 6: OPTIMIZATION FRAMEWORK OVERVIEW



ENROLLMENT LIKELIHOOD

The likelihood of each customer to participate in a demand response program or to adopt distributed energy resources is a critical component in identifying which customers will benefit most from demand response and DER, and which customers SDG&E should focus on for marketing and promotions. The propensities are calculated by identifying customers who have similar characteristics to those who already participate in demand response or have adopted battery or solar technology.

PEAK DEMAND REDUCTION POTENTIAL

Even if a customer has a very high likelihood of participating in demand response or adopting a particular resource, they may not benefit if they have very low or non-coincident peak loads as they do not experience high peak demand charges. Therefore, it is very important to estimate each customer's expected peak load contribution and potential for peak demand reduction under each scenario. Historical load data can be used to forecast peak loads for each customer and how their loads would respond to each program type.

BILL SAVINGS

The ability to modify one's load profile with the adoption of solar and/or battery technologies is significant for a subset of customers. Installed solar can provide low-cost energy to a customer directly, avoiding paying retail rates for electricity from the utility, while batteries can shift load from peak periods to off-peak periods, mitigating peak period and even daily demand charges.

Enrollment in demand response can also provide customers a way to save money by offering an incentive in the form of a capacity credit to reduce load during periods of peak system demand. The exact way in which customers are compensated for their demand response varies by program, but can offer a significant incentive if the customer is able to shift load during peak hours and with relatively little notice.

METHODOLOGY

The following sections describes the data sources used in the assessment and the key analysis steps to meet each assessment objective.

DATA SOURCES

Table 4 describes the data sources used at each step in the analysis. Each data source was provided by SDG&E unless otherwise indicated.

TABLE 4: DATA SOURCES SUMMARY

ANALYSIS TYPE	DATA SOURCES
Propensity Scores	• 2019-2020 hourly interval data for all 150,000 non-residential used to develop to summary statistics • Customer characteristics data for all non-residential customers • Program participation and solar/battery interconnections data for all non-residential customers
DER Size Recommendations	• 2019-2020 hourly interval data for all 150,000 non-residential used to develop to summary statistics • Customer characteristics data for all non-residential customers • Program participation and solar/battery interconnections data for all non-residential customers
Expected Load Impacts	• 2019-2020 hourly interval data for all 150,000 non-residential customers • Customer characteristics data for all non-residential customers • Program participation and solar/battery interconnections data for all non-residential customers • Historical DR events 2017-2020 • DR load reduction estimate by industry (DSA) • DER system size recommendations (DSA)
Expected Bill Impacts	• 2019-2020 hourly interval data for all 150,000 non-residential customers • Customer characteristics data for all non-residential customers • Program participation and solar/battery interconnections data for all non-residential customers • Historical DR events 2017-2020 • Simulated load profiles for each customer and scenario (DSA) • DR load reduction estimate by industry (DSA) • DR program incentives & penalties (SDG&E website) • Rate data for AL-TOU, TOU-A, and DG-R (SDG&E website)

In general, DSA endeavored to use a full year of data for every customer while conducting the analysis. Because of the impacts of the COVID-19 pandemic on commercial and industrial sites across SDG&E's territory, data from prior to March 2020 was used for customers that were active during 2019. In cases where a new account was opened after March 2020, their data from the spring and summer of 2020 was used in the absence of other available data.

KEY ANALYSIS STEPS

DEVELOP DER SIZE RECOMMENDATIONS

The first building block in the analysis was to develop assumptions for the optimal size of solar and battery systems for each non-residential customer. Assumptions were created based on what similar customers have installed, using solar and battery interconnections data.

The first step of the recommendation estimation was to explore potential relationships between the dependent variable (solar and battery system size) and the customer load and characteristics data. The second step was to develop and evaluate multiple models using an out-of-sample testing method. The final step was to apply the best model to the population to predict the recommended system size for each customer. Figure 7 provides additional detail on these three steps.

FIGURE 7: DER SYSTEM SIZE ANALYSIS – METHODOLOGY OVERVIEW

STEP 1: EXPLORATORY DATA ANALYSIS

- Investigate available data, feature engineering, selection & test
- Use one year of data from active customers (pre-interconnection load data)
- Explore relationship of all possible predictive variables to dependent variable (solar and battery system size)

STEP 2: OUT-OF-SAMPLE TESTING

- Train Linear Regression Model on predictive variables
- Narrow down to most predictive variables and train model on customers with battery storage to estimate battery system sizes, and customers with solar for solar system size recommendations

STEP 3: IDENTIFY THE BEST PERFORMING MODEL

- Review results and assess R^2 and RMSE for quality of model fit, identify any need for more features/feature engineering
- Run final model on entire dataset and generate recommended solar and storage system sizes for all customers

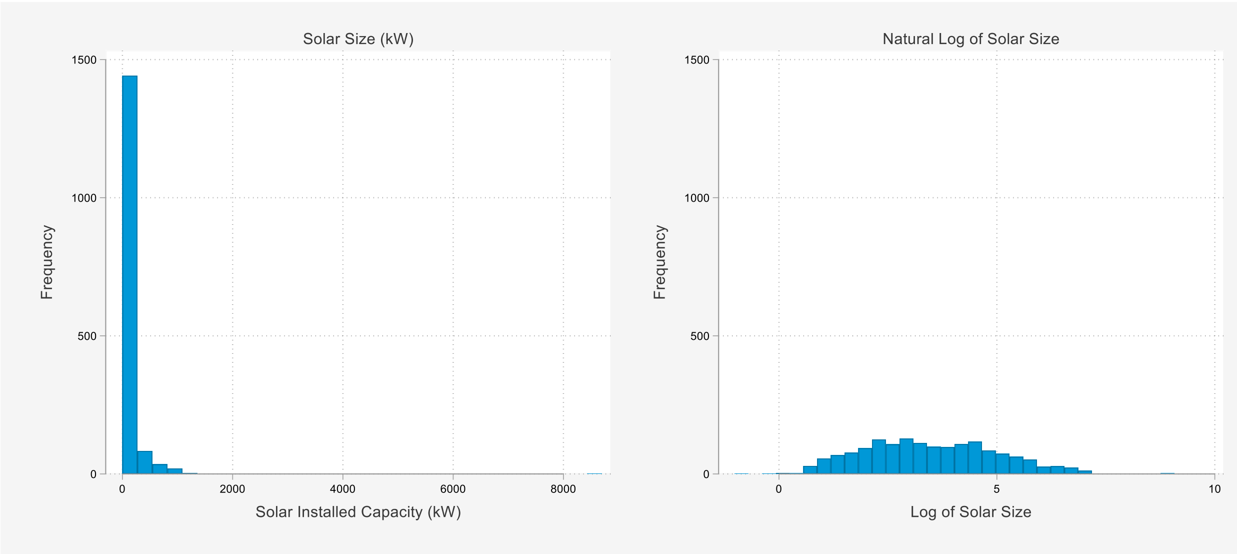
DATA SOURCES AND METHODOLOGY

The primary data sources used in this analysis were pre-treatment load data, interconnections data, and customer characteristics data provided by SDG&E for approximately 150,000 non-residential customers. The interconnections data includes the system size, first install (interconnection) date, and most recent interconnection date on the installations for each solar and battery customer. The load data was further subset to only pre-interconnection data for solar and battery customers.

Exploratory Analysis

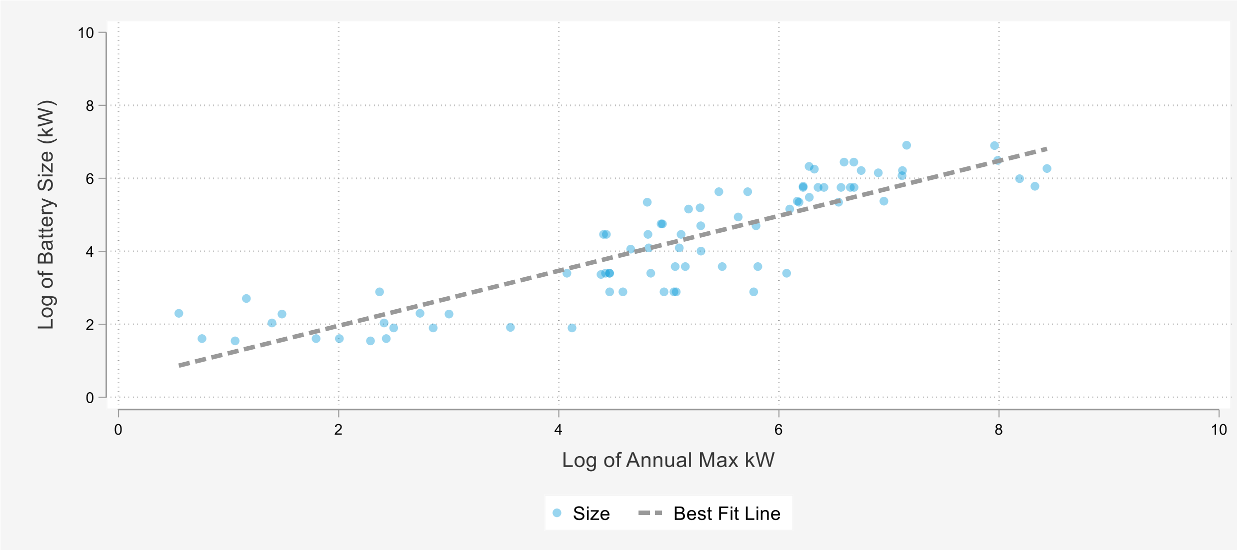
Before the exploratory analysis phase began, DSA cleaned the data and created a dataset of load, interconnections, and characteristics for each non-residential customer. System size is the dependent variable; however, solar and battery size distributions were highly skewed by large customers. DSA used the natural log transformation to normalize these variables, and other similar variables in the dataset. Figure 8 shows the distribution of the solar size variable compared to its natural log transformation.

Figure 8: Natural Log Transformation of Solar Size



Once the data was prepped for analysis, the exploratory analysis began. In the investigative phases, visualizations and bivariate analyses were used to identify the variables that appeared to be the most predictive of system size. Bar graphs and scatter plots to visualize relationships between DER system size and each potential predictive variable. Figure 9 provides an example of a visual used during the exploratory analysis. In this case, the scatter plot shows a distinct, linear relationships between the log of battery system size and the log of annual max consumption.

FIGURE 9: EXPLORATORY SCATTER PLOT EXAMPLE



The bivariate analysis produces performance metrics for classification models that quantify the predictive power of each variable on the dependent variable. These metrics included specificity, sensitivity, and the area under the receiver operating characteristics (ROC) curve[i]. The ROC curve measures a classification model's performance compared to producing a guess at random. The higher the area under the ROC curve (between -1 and 1), the more accurate the model is at predicting true positives and true negatives.

REGRESSION ANALYSIS

Once the dataset was narrowed down to the variables that appeared to be most predictive of system size, DSA created multiple model specifications with varying combinations of these predictors. DSA trained a linear regression model for both battery system size and solar system size individually. DSA tested six models for battery system size and 14 models for solar system size.

ASSESS PERFORMANCE AND IDENTIFY THE BEST MODEL

The regression results for each model specification were evaluated on R2 and RMSE for the quality of the model fit. DSA used these results to refine and test additional model specifications. Once the best performing model was identified, the model was applied to the full population to generate recommendations for solar and battery system sizes for each non-residential customer.

ESTIMATE ADOPTION/PARTICIPATION PROPENSITIES

One of the key research objectives of the SDG&E DER and DR Tool and Analysis project is to identify the non-residential customers who would benefit most from the combination of behind-the-meter battery storage and demand response. The customers will be given scores that can be used by SDG&E for marketing and planning activities. One component of this analysis is to identify which customers are more likely to enroll in demand response programs or adopt battery or solar and to define the characteristics of these customers. In general, this process is composed of three steps; (1) exploratory data analysis, (2) out-of-sample testing, and (3) optimal model selection and application.

Data Sources and Methodology

The primary data sources used in this analysis were pre-treatment load data and customer characteristics data provided by SDG&E for approximately 150,000 non-residential customers. For the battery and solar adoption propensity models, interconnection data was also used. For battery and solar adoption propensities, the parameter of interest was an indicator for having a battery or solar installation. For demand response, the parameter of interest was an indicator for participation in at least one of SDG&E's commercial demand response programs. Demand response was defined broadly and included the following programs:

- Base Interruptible Program
- Capacity Bidding Program
- AC Summer Saver Program (new and old)
- Smart Thermostat Program (new and old)
- Reduce Your Use

The first step of the analysis was to identify potential relationships between the parameters of interest (DR participation, battery adoption, or solar adoption) and the customer load and characteristics data through exploratory analysis. The second step was to develop and evaluate multiple models using an out-of-sample testing method. The final step was to apply the best model to the population to predict the likelihood of demand response participation for each customer. Figure 10 provides additional detail on these three steps.

Figure 10: Propensity Analysis - Methodology Overview

Step 1: Exploratory Data Analysis

- Investigate available data, feature engineering, selection & test
- Use one year of data from active customers (pre-interconnection load data)
- Explore relationship of all possible predictive variables to dependent variable (Solar/No Solar, Battery/No Battery, DR/No DR)

Step 2: Out-of-Sample Testing

- Split data into training/testing data
- Define multiple models (iterative process)
- Train Probit Model on predictive models
- Assess quality of prediction by using model to predict (out-of-sample) for testing dataset

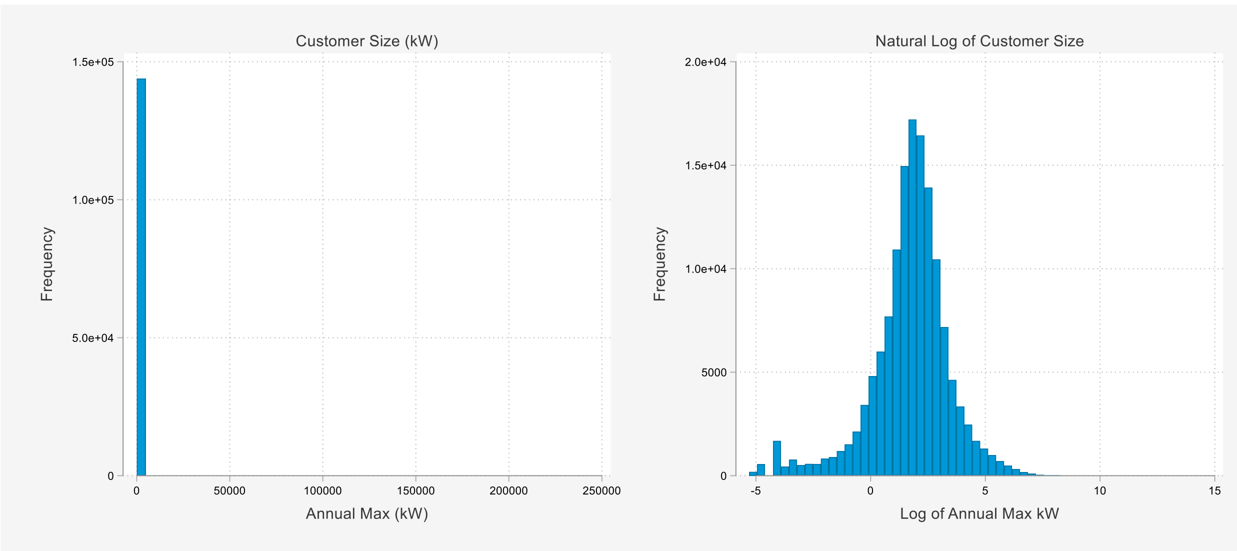
Step 3: Identify the Best Performing Model

- Model selection based on out-of-sample AUC metric (tradeoff between true positive and false positives)
- Run final model on entire dataset and generate recommended adoption propensities for all customers

Exploratory Analysis

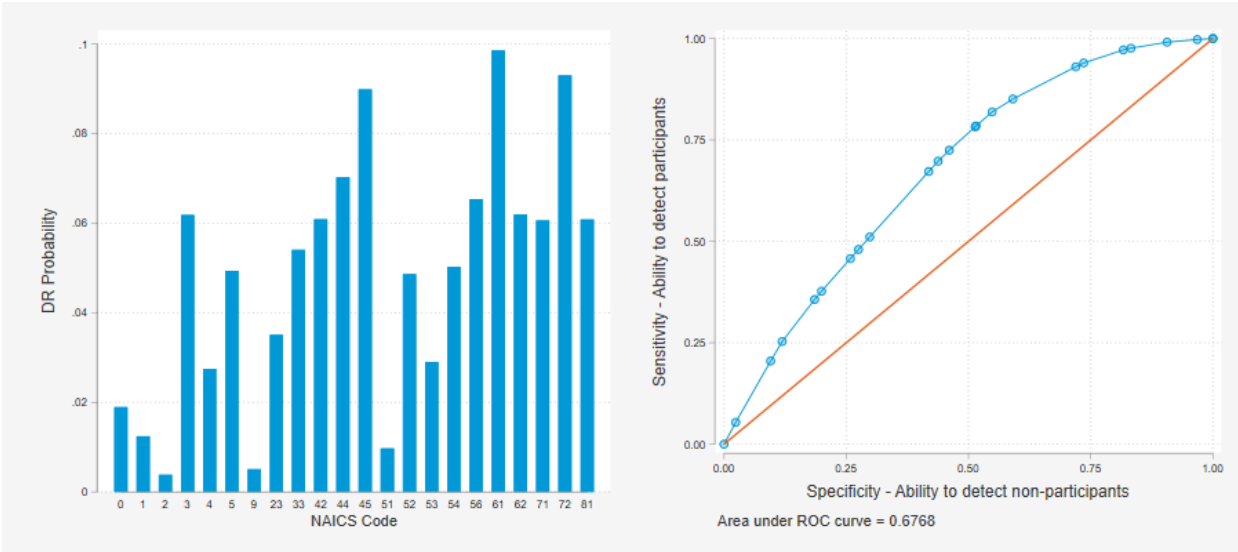
DSA performed additional data cleaning and variable generation to prepare the dataset for analysis. Because the distributions of customer characteristics can tend to be dominated by extremely large customers, DSA created normalized versions of key load and characteristics variables that exhibited skewness by taking the natural log. The natural log transformation preserves the relationships between demand response and the variable, while reducing the potential for bias in the model. DSA evaluated both the regular and transformed versions of these variables. Figure 11 shows a comparison between the distributions of annual max kilowatts and its natural log transformation.

Figure 11: Distribution of Annual Max kW and the Natural Log Transformation of Annual Max kW (2019)



The exploratory analysis consisted of visualization and bivariate analysis of each of the customer load data and characteristics variables with demand response to identify the variables that appeared to be the most predictive. The visual analysis used bar graphs to detect strong relationships between DR and different levels or categories of a given variable. The bivariate analysis used several common performance metrics for classification models to evaluate how accurately a given variable could predict demand response participation. These metrics included specificity, sensitivity, and the area under the ROC curve. Specificity and sensitivity quantify the ability of a predictive variable or model to accurately identify demand response participants and non-participants. Specifically, sensitivity is the ability to correctly identify demand response participants and specificity is the ability to correctly identify non-participants. The area under ROC curve combines sensitivity and specificity to provide an overall assessment of a variable's ability to distinguish the two groups. Figure 12 demonstrates these two types of analysis for the first two digits of a customer's NAICS Code and demand response participation.

FIGURE 12: EXPLORATORY ANALYSIS EXAMPLE



OUT OF SAMPLE TESTING

After identifying the customer characteristics that appeared to be most predictive, DSA defined multiple models using different combinations of these predictors. DSA employed a probit model, which is a type of regression that predicts for the classification of an observation based on its characteristics. In this case, the model outcome is the probability that each customer participates in demand response or to adopt battery or solar. To test each model, DSA performed out-of-sample testing, meaning that the data is split into two groups, training and testing data. The models are run on the training data and then applied to the testing data to assess each model’s ability to predict demand response participation. The same classification model performance metrics can be used for model evaluation that were used for the bivariate analysis; area under ROC curve, sensitivity, and specificity. DSA tested 49 distinct models for demand response, 43 models for battery adoption, and 45 for solar adoption.

IDENTIFY AND APPLY THE BEST PERFORMING MODEL

The final models were chosen based on the highest area under ROC curve value. Once the best performing model was identified, the model was applied to the full population to generate demand response participation, battery adoption, and solar adoption propensities for each non-residential customer.

ESTIMATE CHANGES IN LOADS DUE TO DR, BATTERY STORAGE, AND/OR SOLAR

Once propensity scores and DER system size recommendations were calculated for each customer, loads were simulated for each customer using various combinations of DR and DER adoption. This process involved four general steps:

1. Preparing analysis dataset
2. Estimating demand response impacts

3. Estimating battery and solar impacts
4. Constructing new load profiles under each scenario

Data Sources and Methodology

The load simulations used much of the same data used in the propensity and size recommendations analysis; hourly load data, interconnections data, and customer characteristics data, along with additional data on historical SDG&E demand response events from 2017-2020 and estimated DR load reductions for each program and industry (described in the following section). It also included the system size recommendations estimated in the previous step in the analysis.

The first step of the analysis was to combine the various data sources into an analysis dataset. The second step estimate demand response impacts for customers who are not currently enrolled in CBP or BIP. The third step was to estimate solar and battery impacts under different operations strategies. The final step was to combine the estimated DR, solar, and battery components to construct new load profiles for each customer and scenario. Figure 13 provides additional detail on these four steps.

Figure 13: Load Simulations Analysis – Methodology Overview

Step 1: Prepare Analysis Dataset	Step 2: Estimate Customer DR Impacts	Step 3: Estimate DER Impacts	Step 4: Construct New Load Profiles

▪ Combine hourly interval data, characteristics data, historical DR data, and recommended battery and solar sizes to create analysis dataset
▪ Estimate DR impacts by demand response program and industry, for all of California
	▪ Apply the estimated average impacts by industry to customer loads under simulated events:
	  ▪ 10 events/ summer for CBP
	  ▪ 1 event/ summer for BIP
	▪ Estimate only for customers who are not existing participants
		▪ Estimate solar loads based on system size recommendations under each solar strategy
		▪ Estimate battery loads impacts based on system size recommendations under each operations strategy
			▪ Combine solar loads, battery impacts, and DR impacts to construct new load profiles for each customer under each scenario

Prepare Analysis Dataset

The load impact analysis required a variety of data sources. While most were provided by SDG&E, some were estimated by DSA. DER system size recommendations were calculated for each customer in the previous step of the analysis as described above. DSA also estimated demand response impacts by DR program and industry. The SDG&E data on CBP was highly clustered and only had information for a handful of retail chain customers. In order to accurately represent all the industries that can participate in the CBP and BIP program, DSA used statewide available data on demand response reductions for the BIP and CBP programs across California. These estimates are used in the analysis as a proxy for a given customer's load reduction under each program type, based on their industry classification. The characteristics, interconnections, size recommendations, and DR impacts for each customer were then combined with hourly interval data to form the complete analysis dataset for all non-residential customers.

Estimate Customer Demand Response Impacts

The estimated demand response impacts for each customer was calculated based on the average impacts by industry from the statewide BIP and CBP programs (both day-ahead (CBP-DA) and day-of (CBP-DO) options). For customers not already enrolled in CBP or BIP, DSA applied load reductions on simulated event days assuming that they behaved as an average current participant. The DSA team modeled a standard number of demand response events based on historic trends: 1 event per summer for BIP and 10 events per summer for both CBP-DA and CBP-DO. To the extent possible, actual demand response days were used to construct the load impacts. Because the customers of interest in this analysis are not existing DR customers, their consumption history is not perturbed on these days, allowing the evaluation team to more accurately model the customer's response during periods of grid stress. The load impacts for each customer were applied to their existing loads on event days and then the team proceeded with the analysis.

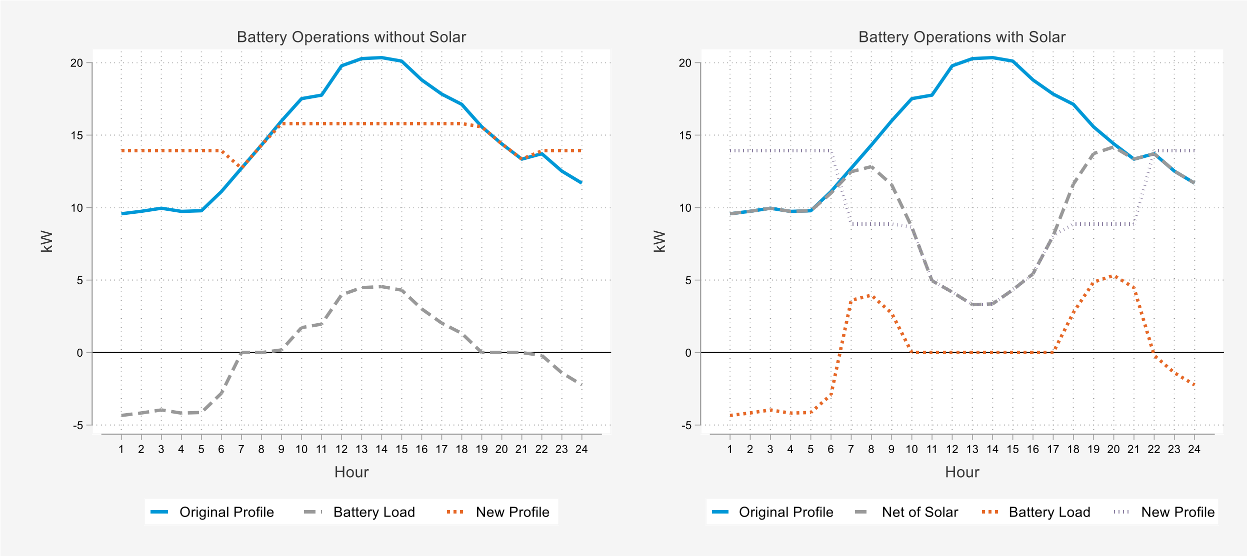
Estimated DER Impacts

Battery load impacts were estimated for four battery operations strategies:

1. **No battery**: no battery loads were modeled
2. **Demand response only:** batteries are only dispatched during event hours with the goal of minimizing demand during the event
3. **Peak shaving**: batteries are dispatched on each customer's top 5 demand days per month, with the goal of minimizing demand charges. On DR event days, the DR strategy applies (minimize use during DR hours)
4. **Load shifting**: batteries are dispatched every day with the goal of minimizing demand charges. On DR event days, the DR strategy applies (minimize use during DR hours)

For each customer, battery load impacts were estimated based on estimated storage system size. The peak shaving and load shifting strategies using a combined peak-shaving/trough-filling algorithm. This approach essentially looks to reduce peak demand by discharging the battery as completely as possible such that the new net customer load is flat. Similarly, the battery is charged by filling in troughs, or areas of low demand such that new demand charges are minimized. Figure 14 shows an example of what the optimization does with an average customer load and a 7kW battery. Note that in the original profile, the peak demand for the customer was 20kW while in the new profile, the peak demand is 15.5kW. Similarly, the battery charge fills in low-demand periods while avoiding charging so much during a given period that any off-peak hour is now subject to a demand charge.

FIGURE 14: BATTERY CHARGE OPTIMIZATION EXAMPLE



Solar loads were estimated across three solar scenarios:

1. **No solar**: no solar loads were estimated
2. **Solar + battery without charging**: solar loads were estimated and applied to a customer's gross loads prior to running the battery algorithm. Excess solar was exported to the grid.
3. **Solar charging battery**: solar loads were estimated and used to charge the battery on non-peak days and hours. Any excess solar above what the battery could use to charge was applied to the customers' gross loads, and any excess above that was exported to the grid.

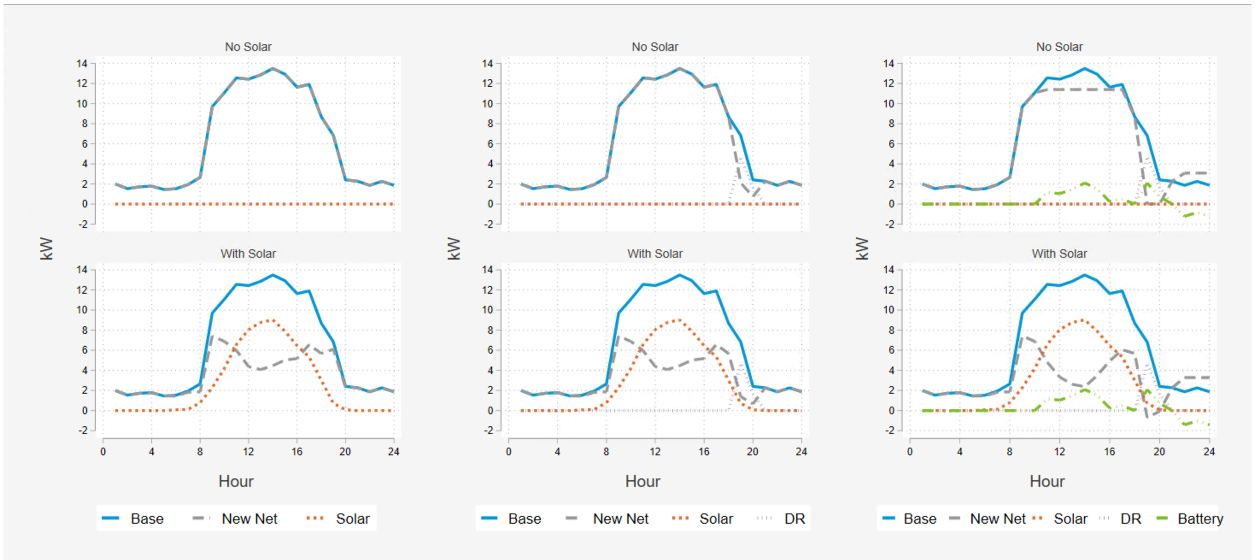
For customers with an existing solar system, their actual solar loads were added back to the customer's net loads to provide a gross baseline load for all customers. Solar production was then estimated for each customer based on recommended solar system size and 8,760 coincidence factors for inland or coastal San Diego.

CONSTRUCT NEW LOAD PROFILES

The final step in the process was to run the simulation analysis for each customer in the sample. There were 27 simulations for each customer. The variables in each simulation were demand response program, demand response days, solar strategy, battery strategy, and peak days (if applicable). The solar load profiles, demand response impacts, and battery impacts were combined as needed under each simulation to construct a new, net load profile under each simulation.

Figure 15 provides an example of the impact of demand response, battery storage, and solar on a customer's load. The first panel shows the effect of including solar on a customer's net load, while the middle panel shows DR impacts and the third panel shows the inclusion of a battery using a peak-shaving algorithm. In all panels, the grey dashed line shows the net load after all the DR and DERs have been applied.

FIGURE 15: SIMULATED LOAD PROFILE EXAMPLE



ESTIMATE BILL IMPACTS

The final step in the analysis was to estimate the bill impacts of each simulated scenario. This process involved three steps: (1) calculating base bill, (2) calculating the bill under each scenario, and (3) assessing the bill impacts of each scenario.

DATA SOURCES AND METHODOLOGY

The bill analysis was built off of the load simulations for each customer. DSA obtained the relevant tariffs from SDG&E's website for the three commercial rates – AL-TOU, DG-R, and TOU-A and the commercial demand response program incentives and penalties.

The first step of the analysis was to estimate the current monthly bills for each customer. The second step was to calculate the bill for each combination of demand response programs, rates (if valid), and DERs. The third step was to estimate the bill impacts of each scenario for all customers. Figure 16 provides additional detail on these three steps.

FIGURE 16: BILL IMPACTS ANALYSIS – METHODOLOGY OVERVIEW

STEP 1: CALCULATE CURRENT BILLS FOR EACH CUSTOMER

- Calculate baseline bills for a 12-month period using each customer's existing load and current rate to estimate energy expenditure with no incremental DR, storage, or solar

STEP 2: ESTIMATE MONTHLY BILLS UNDER EACH SCENARIO

- Calculate DR incentive payments for eligible customers
- Estimate monthly bills based on the load profile, rate, and demand response program combination of each scenario

STEP 3: ASSESS THE BILL IMPACTS OF EACH SCENARIO

- Compare current bills to the estimated bills for each scenario to assess the bill impacts of each combination of DR participation and DERs

CALCULATE CURRENT BILLS

DSA used the actual energy consumption data and rates of each customer to estimate monthly energy expenditures under their existing combination of demand response participation and solar/storage installations. These current bills provided the baseline for estimating the bill impacts of each simulated scenario.

ESTIMATE MONTHLY BILLS FOR EACH SCENARIO

The next step was to calculate bills for each scenario, using the simulated load profile for each customer, appropriate rate, and DR incentives/penalties (if applicable). Bills were calculated as realistically as possible for each customer. DSA verified if a customer was eligible for the combination of rates and demand response under each scenario. DSA also considered each customer's Critical Peak Pricing (CPP) participation and any existing capacity reservation charges for large customers. If a customer was enrolled on a CPP rate, the CPP impact was still applied to non-DR scenarios, but removed for DR scenarios. For example, for a customer who is currently on a CPP rate and not already participating in demand response, the monthly bill for a scenario with BIP participation would include the impact of moving from the CPP rate to a demand response rate along with the impact of demand response participation (included in the scenario's load profile).

ASSESS THE BILL IMPACTS OF EACH SCENARIO

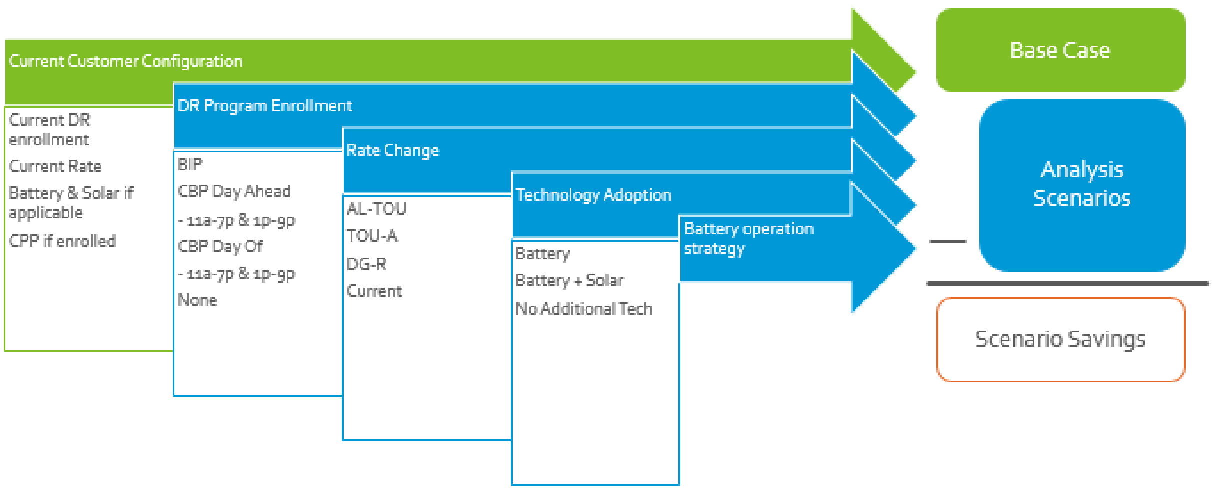
Once all customers had estimated bills for every valid scenario, bill impacts were calculated by comparing the monthly bills of each scenario to the monthly current bills. The monthly impacts were then summed to estimate the impact of each scenario on annual energy expenditures.

Results

Overview of Results

The analysis explored 27 scenarios for each non-residential customer, across different combinations of demand response program enrollment, rates, technology adoption, and battery operations strategy (if applicable). Figure 17 illustrates the options available under each scenario.

Figure 17: Scenario Combinations



Energy and bill savings are calculated for each scenario, which are then used to select the optimal combination for each non-residential customer. The results also allow SDG&E to identify high-value customers and customer characteristics to inform targeted marketing strategies. In the following sections, results are organized by the type of technology adoption. The first section presents the results for demand response only, with no solar or battery adoption. The second explores the results for the combination of demand response and battery storage. Section 5.4 explains the result for the combination of demand response with both solar and battery adoption.

Targeting for Demand Response

Propensity

For the purposes of the analysis, Demand Response was broadly defined as participation in at least one of SDG&E's commercial demand response programs. DSA received data from SDG&E on customer participation in five programs; the Base Interruptible Program (BIP), the Capacity Bidding Program (CBP), the AC Summer Saver Program (new and old versions), and the Smart Thermostat Program (new and old versions). Details on

SDG&E's current demand response offerings are provided in the Current Demand Response Programs section. Table 5 summarizes the results of the final demand response propensity model.

TABLE 5: DR PROPENSITY FINAL MODEL - VARIABLES AND COEFFICIENTS

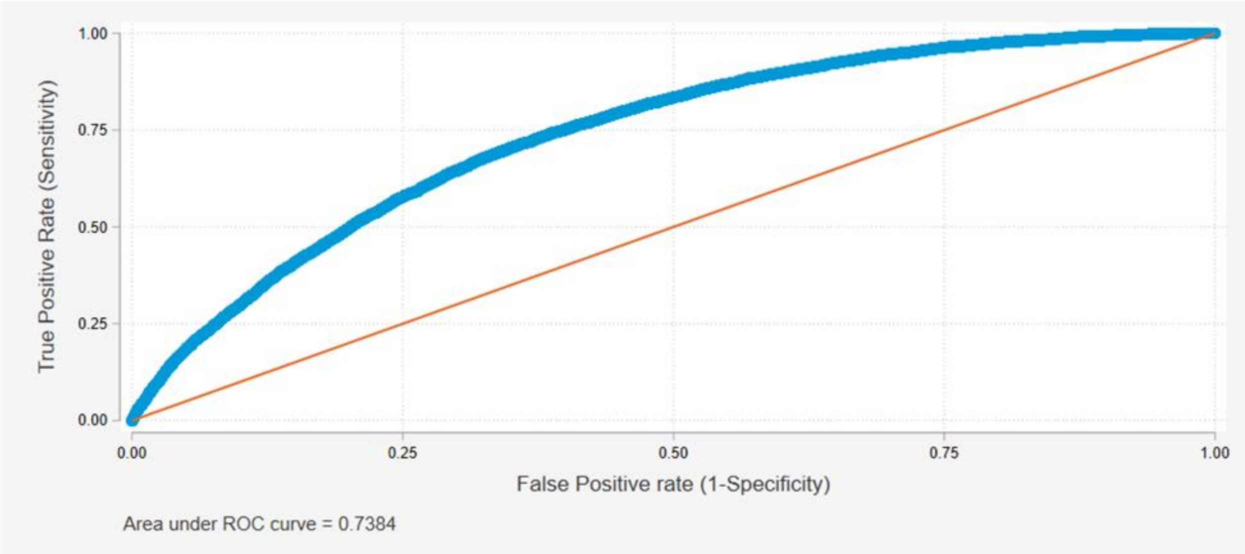
PREDICTIVE VARIABLE	COEFFICIENT
Annual Max kWh (Natural Log)	0.224
Correlation	0.393
Standard Deviation of Annual kWh	-0.001
Class Size*	-0.054
Number of Accounts Bins**	Varies
Zip Code**	Varies
NAICS Code**	Varies

* The coefficient on class size is for "Small" rate customers.

** Number of Accounts Bins, Zip Code, and NAICS code are categorical variables with more than two categories, so the coefficients vary.

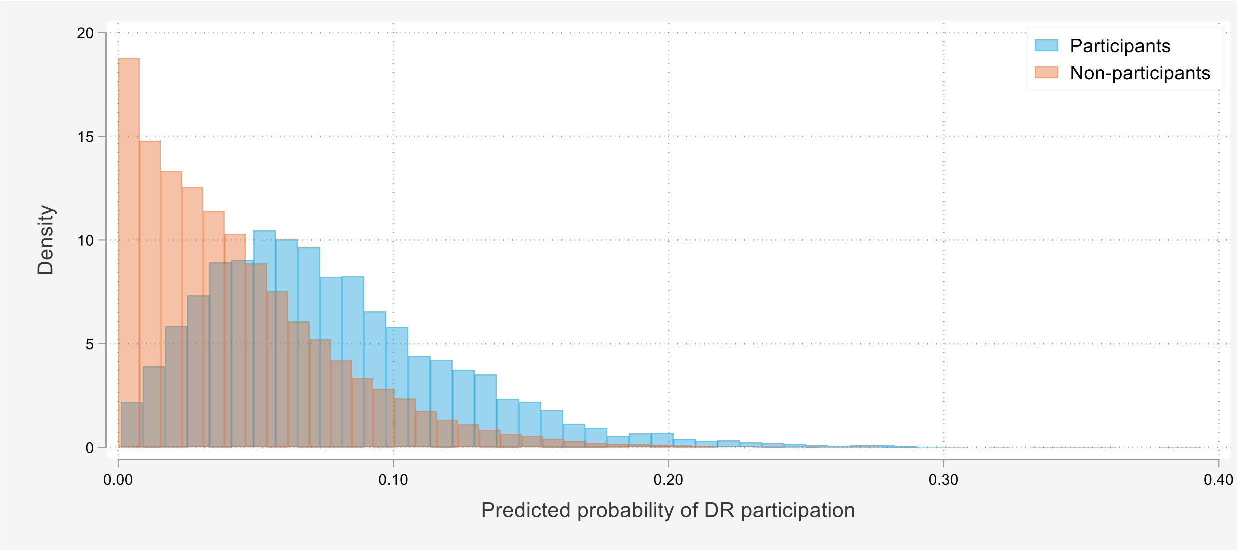
Figure 18 shows the area under the ROC curve for the final DR propensity model. The AROC value for this model was 0.7384. The curve summarizes how well the model correctly detects DR participants and avoids misclassifying non-participants. The closer the area under the curve is to 1.0 (the closer to blue line is to the upper left corner), the better it performs.

FIGURE 18: DR PROPENSITY FINAL MODEL – AREA UNDER ROC CURVE



The model was able to detect demand response participation, demonstrated by the distinct propensity distributions for DR and non-DR customers in Figure 19.

FIGURE 19: DR PROPENSITY FINAL MODEL – DISTRIBUTION OF PREDICTION PROPENSITIES



However, these probabilities are only based on historical records of demand response participation from 2016 to 2020, and do not reflect different levels of marketing intensity or incentives. It is possible that the model is predicting higher participation likelihood in the types of customers that have received more intense marketing for demand response programs in the past. Similarly, there may be subsets of customers that have never been marketed to who are showing lower propensities for enrollment. Although the model does generally align with expectations for customer characteristics that would be more likely to participate in demand response, it is important to be aware that the model may be detecting some historical marketing disparity.

Model Insights

Figure 20 visualizes the results of the demand response propensity model, indicating which factors increase or decrease the likelihood of DR program participation.

FIGURE 20: FACTORS IN DEMAND RESPONSE PROPENSITY

Many of the load variables displayed strong relationships with demand response. DSA tested models with multiple load variables to select the one that was most predictive, which was annual max kWh. Customers with higher maximum yearly load (and in general, higher load) are more likely to participate in demand response. The "correlation" variable is the correlation between outdoor temperature and energy usage and provides a measure of a given customer's weather sensitivity. Customers that are more weather sensitive are more likely to participate in demand response. The effect of standard deviation was very small, but significant. It could suggest that customers with more consistent loads are more likely to participate in DR. Class size is a categorical variable indicating the size category of each customer's rate. The coefficient on class size shows that customers on "small" rates are less likely to participate in demand response than those on "large" rates.

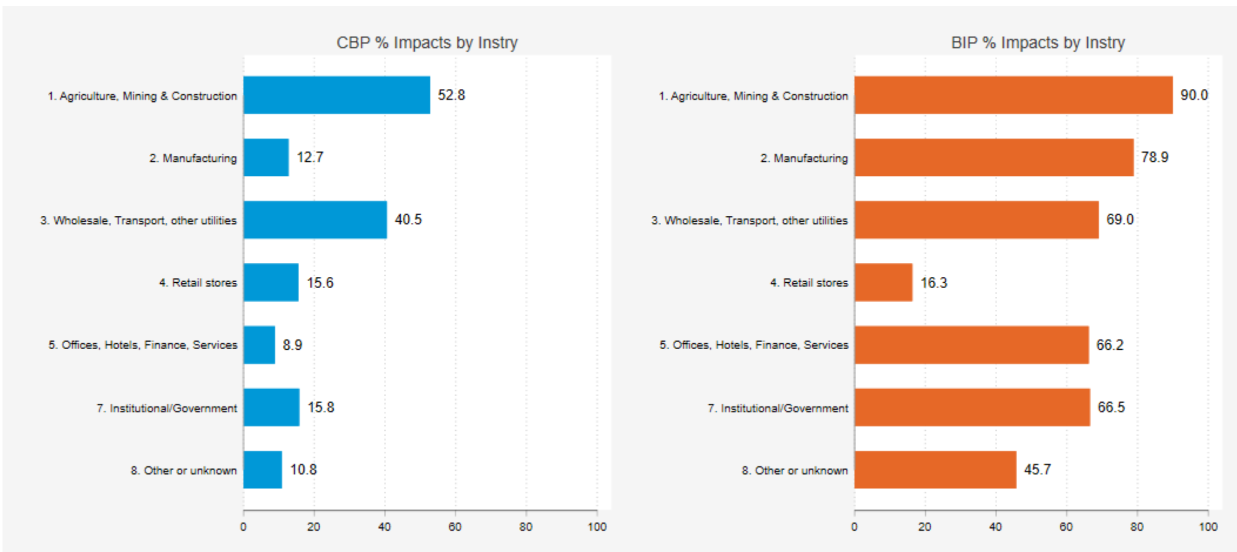
The remaining variables were categorical with multiple groups, so the coefficients varied by grouping. "Number of accounts" is a highly skewed, continuous variable that provides the number of accounts associated with a single customer name. While nearly 50% of customers had 3 accounts of less, a small number of customers had many accounts, in particular, six customers had more than 1,000 accounts associated with their customer name. To account for these outliers and get a better idea of the relationship between demand response and number of accounts, the number of accounts bins variable was created by grouping number of accounts into evenly distributed quintiles, which was included in the final model. Customers with more than 50 accounts were nearly 50% less likely to participate in demand response than customers with only one accounts. The zip code variable used in the model used the service address zip wherever there were at least 100 demand response customers. Zip codes with less than 100 demand response customers were aggregated up to the zip 3 level to ensure there was enough demand response variation within each zip code. Some of the zip codes with the highest likelihood for demand response were 92019, 91977, and 92110. Zip codes with the lowest likelihood were 92101, 92123 and those with zip 3 level 926. The same process was used for NAICS codes, using the first two digits of the NAICS code wherever possible, and aggregating to only the first digit of the NAICS code when the groups of customers were too small for meaningful model interpretation. Industries with the highest propensities to participate in demand response programs were retail trade (44, 45), education (61), and accommodation and food (72), while the industries with low propensities to participate were agriculture, forestry, fishing and hunting (1), and mining and utilities (2).

The results of the demand response propensity modeling exercise provide two useful outputs. First, identifying general customer segments that are more likely to participate in demand response, such as industry and customer size, is useful to inform marketing and incentive strategy for SDG&E's commercial demand response programs. Second, the individual propensity scores for non-residential customers were included as predictors in the targeting model to identify the non-residential customers who benefit most from a combination of battery storage and demand response programs.

Expected Reductions

DSA estimated average demand response reductions by program and industry, using data for all of California. Figure 21 displays the impact estimates for each demand response program by industry. Across the state of California, the Baseline Interruptible Program tends to provide larger percent impacts than the Capacity Bidding Program for all industries, reflective of larger capacity payments and the historical targeting of large customers. Across programs, the Agriculture, Mining, and Construction industries achieve the largest percent reductions, followed by Wholesale, Transport, and Other Utilities. Although the Manufacturing industry had the second largest percent impacts under BIP, the impacts for Manufacturing under CBP were relatively small. In both programs, the Retail industry achieved low impacts compared to other industries. Because retail is primarily customer-facing, retail businesses tend to have less flexibility to reduce load significantly without compromising the comfort of their customers.

FIGURE 21: DEMAND RESPONSE REDUCTION ESTIMATES BY INDUSTRY

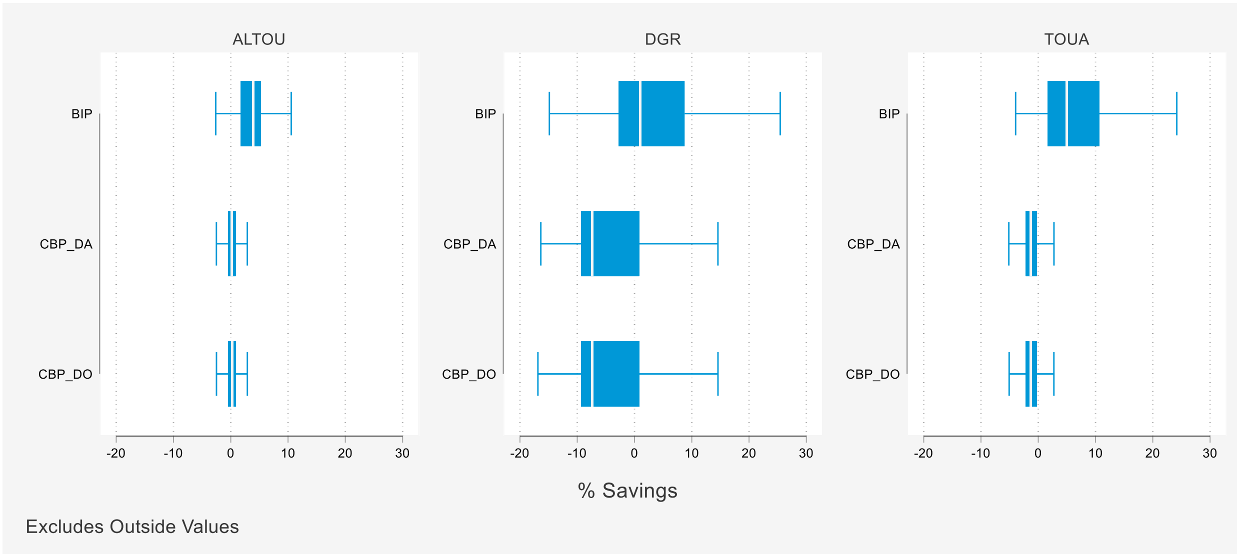


Three demand response scenarios were used in the load simulations analysis, BIP, CBP Day-Ahead (CBP-DA), and CBP Day-Of (CBP-DO). Due to the similarity of payments and events in the 11am-7pm and 1pm-9pm versions of each CBP-DA and CBP-DO, they were combined in to one program for the analysis. Impacts were applied based on the base program (CBP-DA, CBP-DO, or BIP), and customer's industry.

BILL IMPACTS

Figure 22 shows the average percent bill savings across the three demand response programs and rates for demand response only. The BIP program provides higher incentives overall and resulted in higher percent savings across all three rates. Percent savings varied for the CBP Day-Of and Day-Ahead programs. Under the AL-TOU rate, CBP programs achieved positive savings on average, resulting from customers coming off of the CPP rate and avoiding paying the Capacity Reservation Charge. For TOU-A, customers actually pay more on average, since they do not have to pay the CRC and lose the benefit of the peak period discount associated with the CPP rate.

FIGURE 22: PERCENT SAVINGS ACROSS DR ONLY SCENARIOS



TARGETING FOR DR + BATTERY

PROPENSITY

There are 142 SDG&E non-residential customers that currently have storage installations and had pre-installation load data. This represents only 0.04% of all customers in the dataset. The goal of this step in the analysis was to capture the likelihood that each customer without a battery system would install battery systems. Pre-installation usage characteristics are especially important as storage systems can make drastic modifications to customer consumption patterns. To accurately identify customers who do not currently have storage but would be good candidates for a system, pre-installation characteristics of current storage customers provides useful data to train the propensity model.

DSA conducted exploratory analysis on the relationship between battery installations and various customer and load characteristics. After identifying characteristics that appeared to be most predictive of storage systems, DSA used a probit model to assess the probability of each customer to install a storage system. DSA performed out-of-sample testing to evaluate the ability of each model to predict which customers actually have batteries installed. DSA tested a total of 43 distinct models. Table 6 summarizes the results of the final battery propensity model.

TABLE 6: BATTERY PROPENSITY FINAL MODEL - VARIABLES AND COEFFICIENTS

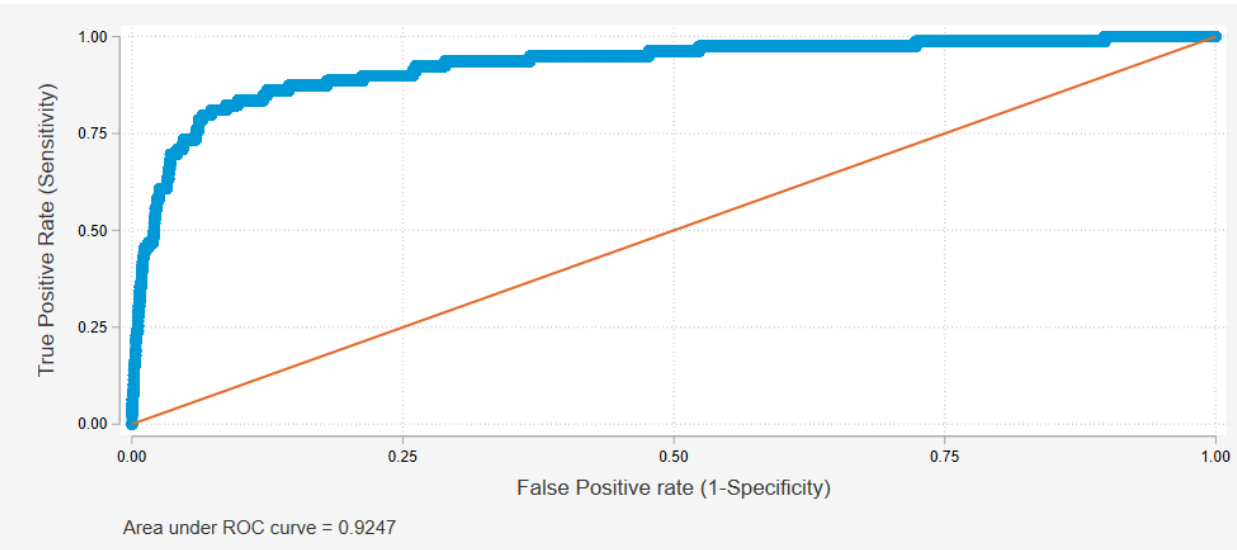
PREDICTIVE VARIABLE	COEFFICIENT
Average Peak kW (Natural Log)	0.273
Correlation	-0.185

Rate*	Varies
NAICS Code*	Varies

* Rate and NAICS code are categorical variables with more than two categories, so the coefficients vary.

Figure 23 shows the area under the ROC curve for the final DR propensity model. The area under the ROC curve (AUC) value for this model was 0.9247. The curve summarizes how well the model correctly detects battery storage participants and avoids misclassifications. The closer the area under the curve is to 1.0 (the closer to blue line is to the upper left corner), the better it performs.

FIGURE 23: BATTERY PROPENSITY FINAL MODEL – AREA UNDER ROC CURVE



Model Insights

Figure 24 visualizes the results of the propensity model, indicating which factors increase or decrease the likelihood of battery installation.

FIGURE 24: FACTORS IN BATTERY ADOPTION PROPENSITY

One of the strongest predictors of battery installations was customer size. This was reflected both through the customer's business size classification (Large or Small) and through load variables. Both large peak loads (natural log of average peak demand) and average consumption (annual kWh bins) indicated a higher likelihood to install a storage system. Industry was also a strong predictor, with Manufacturing customers being by far the most likely to adopt battery systems compared to all other industries.

Recommended Battery Size

In order to evaluate the impact of adopting a DER, each customer must have an estimate of the size of the system they would choose to install. To construct this estimate, DSA relied on information about existing battery adopters to construct a model that would recommend a battery size based on unique customer characteristics. For battery system size recommendations, DSA used storage system capacity data (kW) from the subset of customers with battery installations and pre-treatment data. The battery system size variable was skewed by very large customers, so the dependent variable, battery system size in kW, was normalized through the natural log transformation.

DSA conducted exploratory analysis to identify potential predictors of battery system size. DSA then developed and tested six model specifications using a linear regression model. Table 7 presents the results of the final model. The final model was then used were to predict a battery system size for every customer that does not currently have a storage system in place.

Table 7: Battery Size Final Model - Variables and Coefficients

Predictive Variable	Coefficient
Annual Max kWh (Natural Log)	0.72
Annual Percentile Load	0.01
Annual Load Factor	-2.10

Model Insights

Each of the three variables included in the final battery size model is related to load size. Annual max consumption provides perspective on the highest consumption levels each customer reaches throughout the year. Percentile load provides the percentile rank of annual load for each customer in the dataset. The strongest indicator of all three was annual load factor, which provides insight on each customer's daily load patterns. Larger load factors indicate "peaky" loads, meaning that the customer's load varies greatly throughout the day, while low load factors suggest that a customer's consumption levels are fairly constant throughout the day. Customers with large load factors might have larger system sizes because they need the battery to take on a large portion of their load when demands spike during the day in order to balance out their net demand.

Savings per kW and Return on Investment

Figure 25 presents the average percent bill savings across the two battery operations strategies and three time-of-use rates. Bill savings were negligible for both peak shavings and load shifting on the TOU-A rate. Since TOU-A has no demand charges, peak shaving does not result in bill savings. On the other two rates, ALTOU and DGR, load shifting resulted in higher bill savings on average than peak shaving. Although peak shaving does result in some savings, load shifting was more effective because it is applied every day, rather than just on peak days.

Figure 25: Percent Savings Across DR + Battery Scenarios

Targeting for DR + Battery + Solar

Propensity

There are 1,589 commercial customers with solar installations and sufficient pre-installation data in SDG&E's territory. The goal of the propensity analysis was to capture the likelihood that each customer without solar would install an on-site solar system.

DSA conducted visual and bivariate analysis to explore the relationship between solar installations and customer and load characteristics. Once DSA identified the variables that had the strongest relationships with solar, DSA employed a probit model to evaluate the likelihood of each customer installing a storage system. DSA performed out-of-sample testing to evaluate the ability of each model to identify the customers that actually have solar installations. DSA tested a total of 45 distinct models. Table 8 presents the variables and coefficients from of the final solar propensity model.

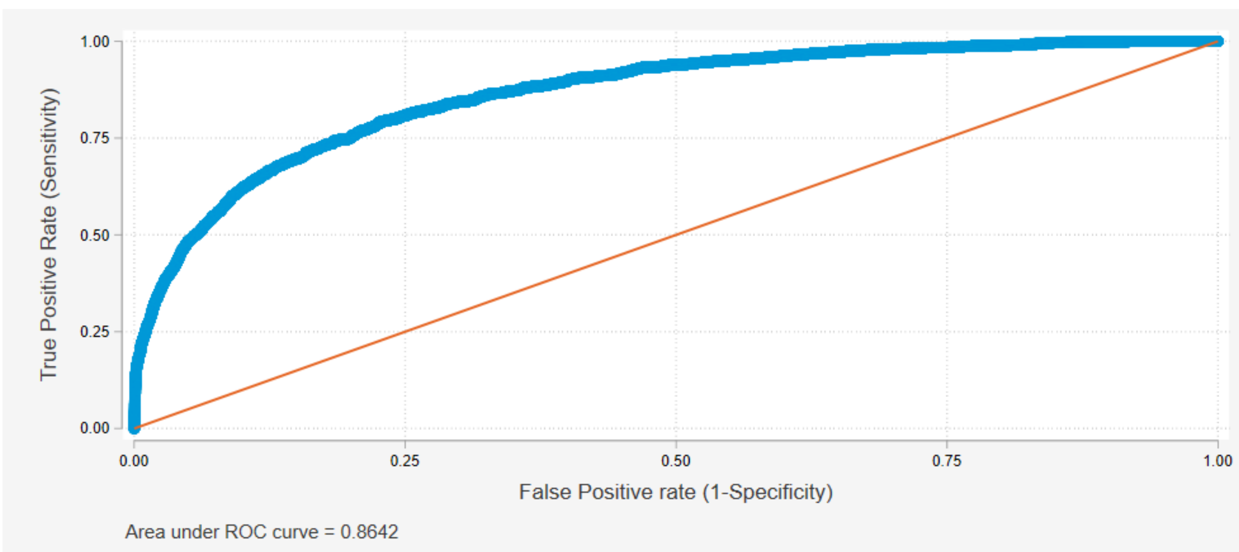
TABLE 8: SOLAR PROPENSITY FINAL MODEL - VARIABLES AND COEFFICIENTS

Predictive Variable	Coefficient
Annual Average kWh (Natural Log)	0.365
Peak Load Factor	-2.110
Rate*	Varies
NAICS Code (1 Digit Level)*	Varies

* Rate and NAICS code are categorical variables with more than two categories, so the coefficients vary.

Figure 26 shows the area under the ROC curve for the final DR propensity model. The AROC value for this model was 0.8642. The curve summarizes how well the model correctly detects solar adopters and avoids misclassifying non-participants. The closer the area under the curve is to 1.0 (the closer to blue line is to the upper left corner), the better it performs.

FIGURE 26: SOLAR PROPENSITY FINAL MODEL – AREA UNDER ROC CURVE



Model Insights

Figure 27 visualizes the results of the solar propensity model, indicating which factors increase or decrease the likelihood of solar installation.

FIGURE 27: FACTORS IN SOLAR ADOPTION PROPENSITY

Once again, large average loads and large class size were indicators of a higher likelihood for adoption. Weather sensitivity also reappears as a predictor, however unlike the demand propensity model, more weather sensitive loads actually decrease the likelihood for a customer to install solar systems. Different industries also exhibited varying tendencies to adopt solar. The industry variable used in this model was the two digit NAICS code, which includes more granular classifications than the single digit NAICS. Warehousing, storage, and postal service businesses were much more likely to adopt solar than any other industries, followed by schools and construction businesses. The industries with the lowest propensity to adopt solar were professional services, such as IT and finance, and retail businesses. These distributions make sense in terms of the amount of space required to install solar. Warehouses and storage facilities sell space and are likely have space where solar can be installed, while professional service and retail businesses are much more likely to lease their premises or be located in urban areas where there is no room for a solar system.

RECOMMENDED SOLAR SIZE

To predict solar system sizes for each customer, DSA used solar system capacity data (kW) from each of the customers with solar installations and pre-treatment data. Since solar size is highly skewed by large customers, the natural log of solar system size in kW was the dependent variable.

DSA performed exploratory analysis on potential predictive variables before testing 14 model specifications using a linear regression model. Table 9 presents the variables and coefficients from the final model. Once the model was finalized, solar system sizes were predicted for each customer as their recommended system size.

TABLE 9: SOLAR SIZE FINAL MODEL - VARIABLES AND COEFFICIENTS

Predictive Variable	Coefficient
Annual 95th percentile of demand kW (Natural Log)	0.848
Rate Size*	-0.535

Industry**	Varies
Industry interacted with rate size**	Varies

* Coefficient on Rate Size is for the "Small" rate class. ** Rate and industry code are categorical variables with more than two categories, so the coefficients vary.

Model Insights

All of the predictive variables in the final model are related to load size. Max Peak kW bins quantify the size of each customer through their peak demand, while the annual percentile load compares their annual consumption levels to all other customers. The rate size indicator distinguishes between customers on small commercial or large commercial rates. In all three cases, customer size is associated with larger solar system sizes.

Savings per kW and Return on Investment

Figure 28 shows the average percent bill savings for each rate and battery operations strategy when solar is incorporated to charge the battery. In general, adding solar increases savings by reducing energy charges. Again, load shifting resulted in higher average percent savings than peak shavings, however, shaving every day means that the battery must be charged rapidly overnight, leading to increase non-coincident peak demand charges.

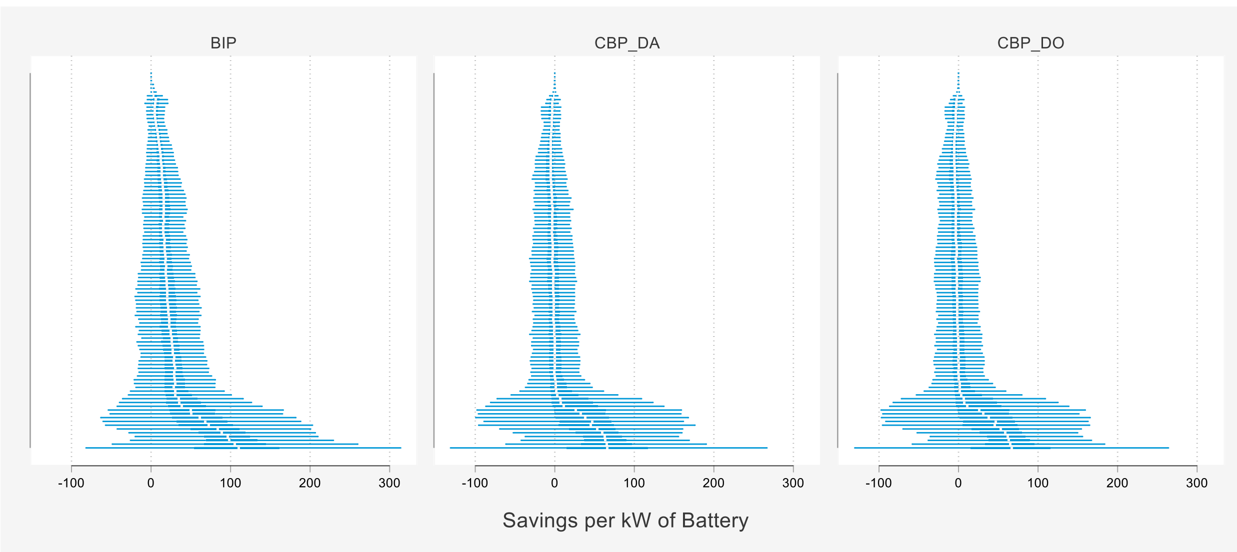
Figure 28: Percent Savings Under DR + Solar + Battery Scenarios

Characteristics of High Value Customers

As discussed in Optimization Framework, there are multiple dimensions across which customers are considered to be good targets for demand response program enrollment: factors: the likelihood of demand response enrollment or DER adoption, the expected peak load reduction, and the bill savings associated with the DR and DER adoption. While precise targeting cut-offs are hard to determine without a full accounting of the customer recruitment costs and DER costs, some general observations can be made. Based on the analysis completed, there are clearly opportunities to enroll additional customers in SDG&E's demand response programs based on their likelihood to enroll and the savings they can expect from participation.

Figure 29 shows the distributions of battery adoption likelihood and expected savings per kW of installed storage for all non-residential customers under a peak-shaving operations strategy with no added solar. Customers near the 100th percentile of battery adoption (at the top of the vertical axis) have characteristics that make them more likely to install a storage system than other customers. In general, these customers also have a smaller, yet still positive average savings per kW of battery installed. It's likely that these customers are larger, as discussed in the battery propensity results, and so savings per kW installed is likely to be diluted by a larger denominator. Conversely, customers who may not have the characteristics of existing battery customers, and who have lower installation propensities do see higher bill savings per kW of installed battery. This might be a further incentive for these customers to install a battery system. These trends hold across demand response programs, with little variation between BIP, CBP-DA and CBP-DO.

FIGURE 29: BATTERY TARGETING ANALYSIS

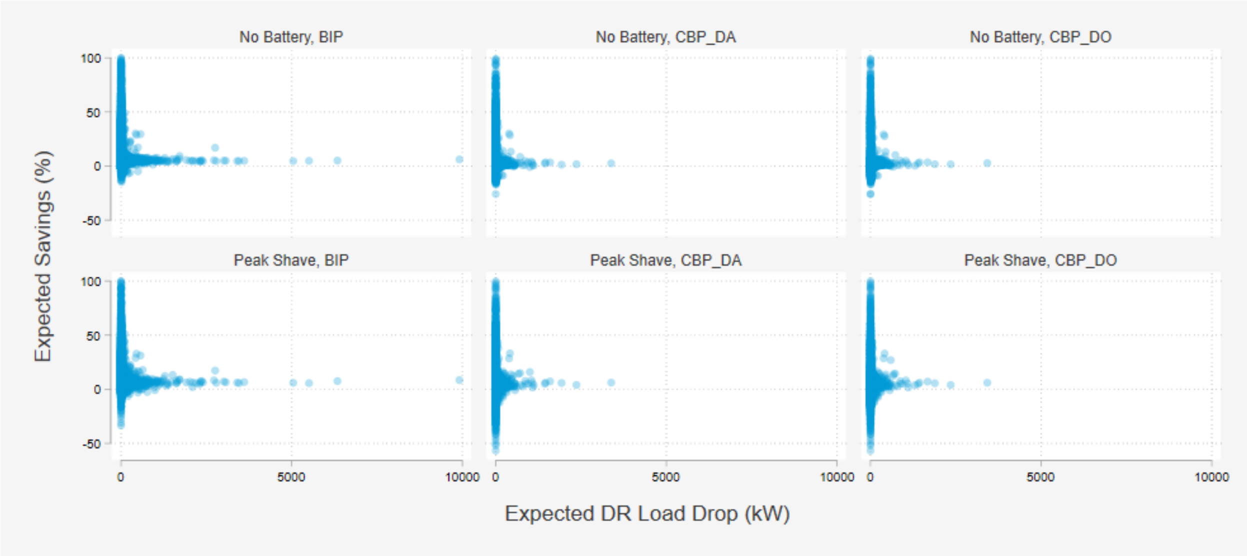


In general, the BIP program offers customers the opportunity to save more money per kW of committed reduction compared to the CBP Day Ahead or Day Of programs, as shown in Figure 29. In this graph, the vertical axis represents individual demand response enrollment likelihood percentiles, where a higher number indicates a higher likelihood of enrollment. The higher savings values for BIP are a result of higher capacity payments available for BIP customers, especially compared to the Day Ahead option for CBP as BIP is intended to be an emergency program to reduce load during periods of grid stress. While in all cases, there are customers for whom enrollment in demand response would result in bill savings, BIP offers more customers the opportunity to save money regardless of how likely they are to participate. For the CBP options, higher likelihood to participate is associated with a higher chance of negative bill savings. Nevertheless, customers with a positive savings rate and a high likelihood of enrollment do exist and should be prioritized for targeting.

FIGURE 30: DEMAND RESPONSE TARGETING ANALYSIS

Finally, the customers targeted for demand response participation should expect to see overall bill savings associated with enrollment as well as providing substantial load reductions during DR events. Figure 31 shows the distribution of percent bill savings compared to expected DR load drop. While high bill savings and large load reductions are the goal of this targeting exercise, it is clear that many customers who stand to save may not offer substantial load reductions on their own. This may be an opportunity for demand response aggregators to identify and recruit smaller customers into a larger offering in SDG&E's territory. The current SDG&E CBP program yields approximately 20kW of demand response per customer. An aggregator that could enroll 100 customers could provide 2MW of load relief during an event

FIGURE 31: SAVINGS TARGETING ANALYSIS



ONLINE TOOL

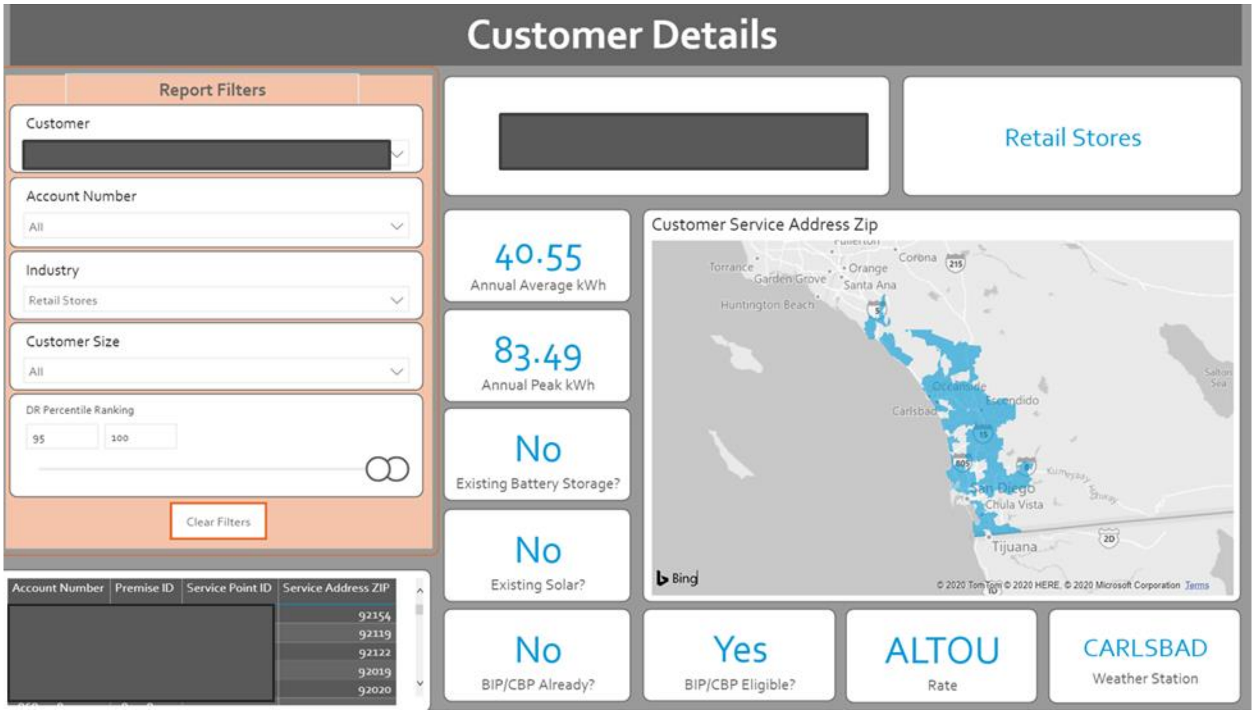
To provide a comprehensive and accessible tool to SDG&E, DSA used the result datasets to create a Microsoft Power BI dashboard for easy querying. This dashboard can be used by demand response program managers to identify customers who may benefit from enrolling in demand response programs, or by SDG&E account executives in conversations with customers about DER and DR adoption scenarios. This tool shows the customer adoption likelihood and estimated bill savings for a subset of the modeled scenarios. The final version of the dashboard includes four views with distinct functions: Customer Details, DR & DER Rankings, Customer Savings Portal, and Reporting.

- **Customer Details**: allows the user to search within specific customer segments, such as industry, size, and savings ability to locate specific customers.
- **DR & DER Rankings**: for a selected customer, view their DR and DER adoption likelihood for a variety of scenarios.
- **Customer Savings Portal**: for a selected customer, view their estimated bill savings for a variety of DR programs, DER adoption and operations strategies.
- **Reporting**: export scenario analyses for all or a subset of customers, industries, or DR programs.

These functions give the users flexibility to explore the data in various ways. For example, SDG&E staff can use the rankings to tailor marketing strategies to the top ranked customers or facilitate a discussion with customers regarding their potential bill savings and optimized recommendations.

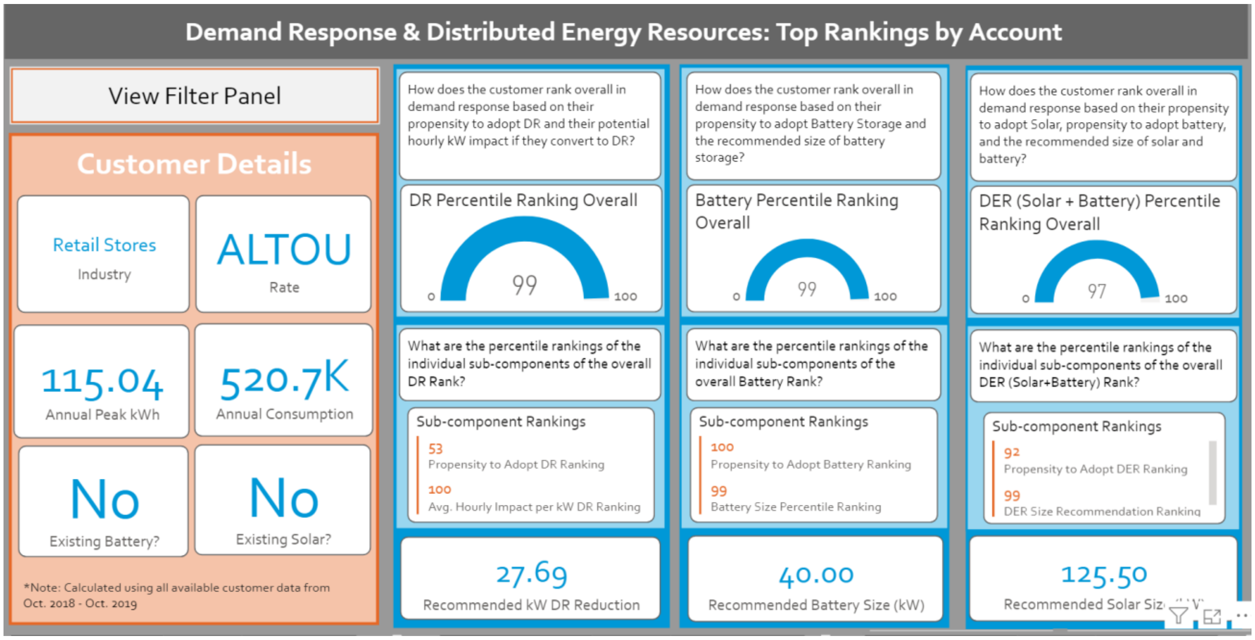
The first page of the dashboard is the Customer Details page, which allows the user to filter the results by category (industry or customer size) or result ranges (demand response ranking or percent savings). The user also has the option to filter to a specific customer, by customer name or account number. These filters provide the user with the flexibility to focus on specific customers or customer segments as needed, and the DR and DER Rankings and Customer Savings Portal update according to the group selected Once the user has filtered to the desired customer or customer group, the interface displays a variety of information on that group, including a list of accounts, a map of the service territory, and other customer characteristics. Figure 32 provides an example of the Customer Details page filtered by industry and DR percentile ranking.

FIGURE 32: CUSTOMER DETAILS EXAMPLE



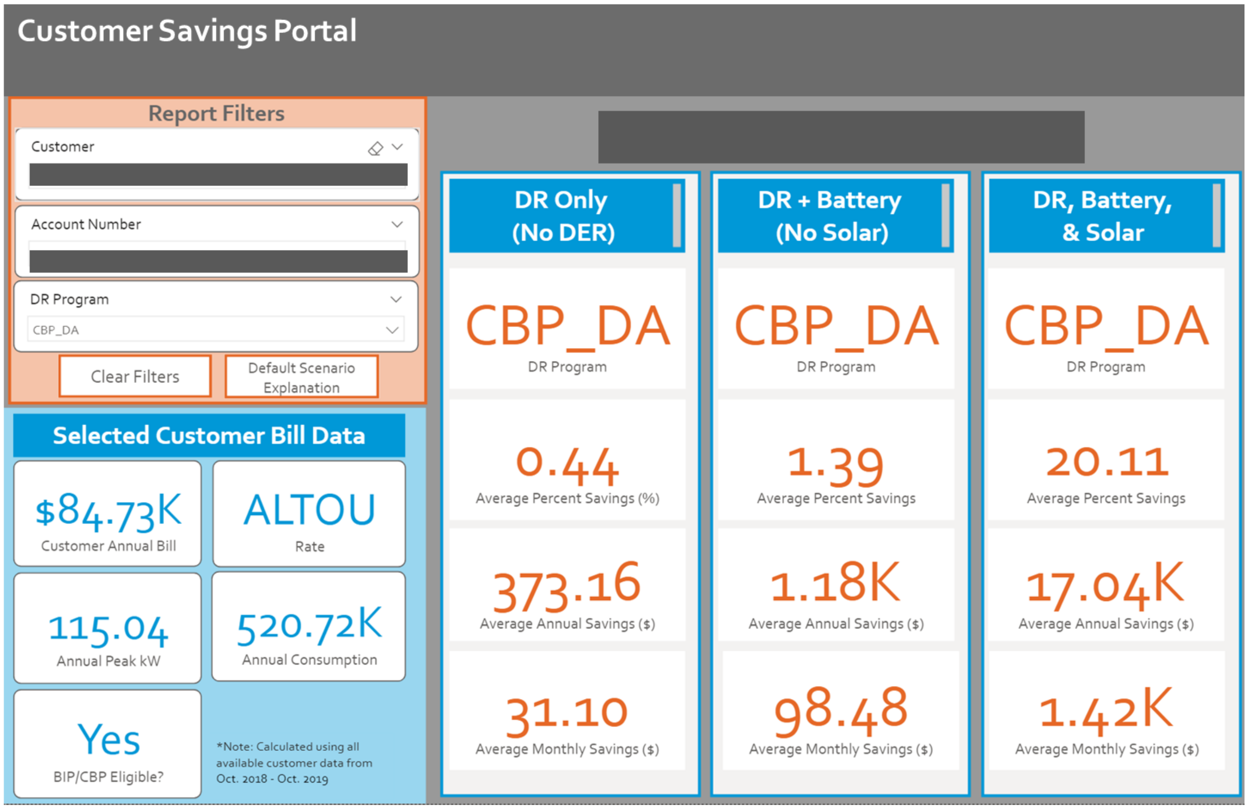
The DR and DER Rankings page provides details on the selected customer group's rankings and size recommendations. The left side of the page display key metrics, including annual energy consumption and peak demand and customer characteristics. The right side of the page breaks down the rankings into three sub-groups, demand response only, demand response with a battery installation, and demand response with solar and battery. Each sub-group includes the customer's propensity to adopt and size recommendation, as well as an overall ranking that combines propensity and size. Figure 33 shows the DR and DER Rankings page.

FIGURE 33: DR AND DR RANKINGS EXAMPLE



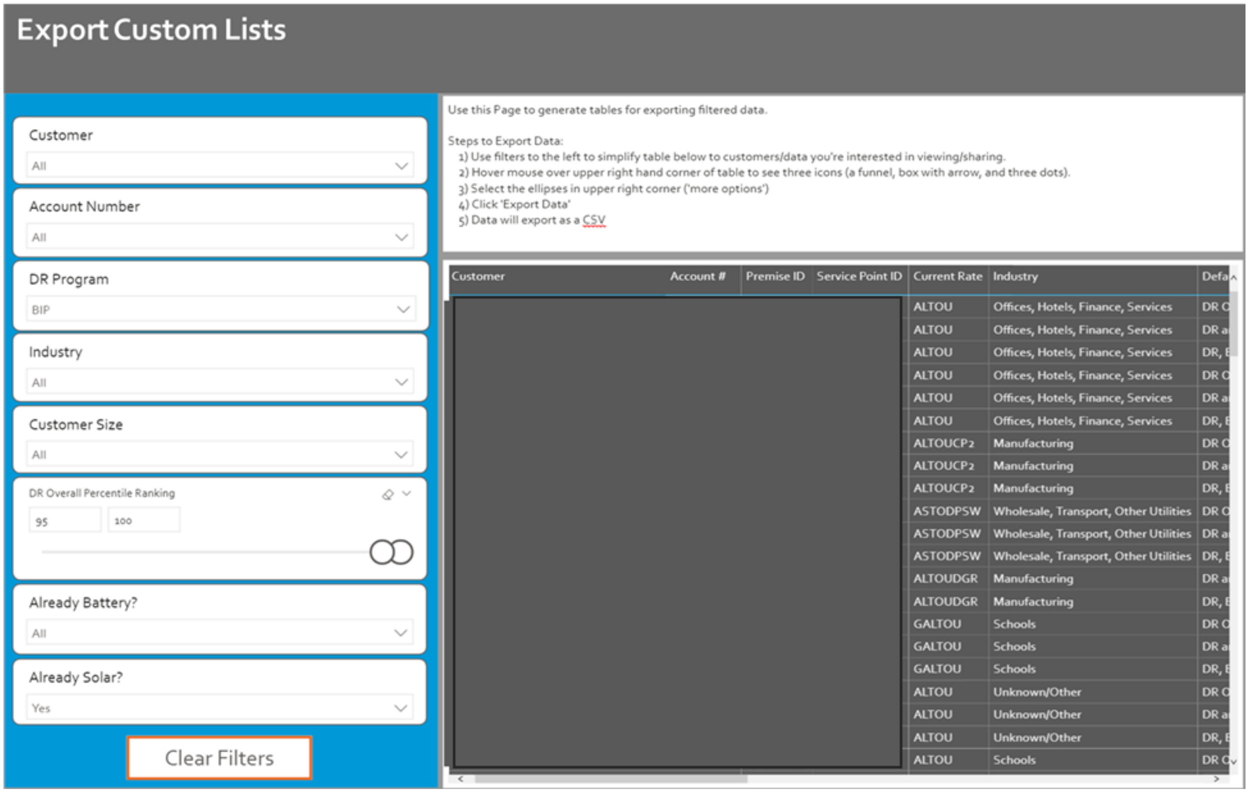
The Customer Savings Portal summarizes the results of the bill analysis for the three simulations, demand response only, demand response and battery, and demand response and DER (combined battery and solar). The user also has the option to select the specific demand response program they are interested in. The left side of the panel includes information on the customer's annual bill and energy usage and indicates if they are eligible for demand response. The right side provides detail on the customer's average percent savings, annual savings, and monthly savings for each of the three sub-groups under the selected demand response program. Figure 34 presents an example of the Customer Savings Portal.

FIGURE 34: CUSTOMER SAVINGS PORTAL EXAMPLE



Finally, the Reporting tab provides the user with the opportunity to generate custom reports for the customer or segment they are investigating. The page allows the user to select to the desired customer group in a similar manner to the Customer Details page, plus additional filters for the demand response program and if customers already have a battery or solar installation. The user can view the instructions and a preview of the report on the right side of the page, before exporting the data to a CSV file. Figure 35 shows an example of the Reporting interface.

FIGURE 35: REPORTING EXAMPLE



Conclusions

The purpose of the project was to conduct an analysis and develop tools for incorporating battery storage into Demand Response (DR) programs. The two main objectives were to:

Analyze the full population of SDG&E non-residential customers to identify the benefits and optimal combinations of demand response, distributed energy resources (with a focus on batteries), and rates for each individual customer,

To use this analysis to develop a tool that provides unique savings estimates and recommendations for each customer based on their characteristics. This tool can be used to identify the product mix that maximizes benefits for both SDG&E and the customer.

Adoption and Enrollment Propensity

DSA conducted an enrollment propensity analysis to determine the characteristics of customers that were more likely to enroll in demand response or to install solar PV or storage systems. The results of that analysis are summarized in Table 10.

Table 10: Characteristics that Influence Adoption of DR and DERs

Resource	Characteristic Associated with Low Likelihood	Characteristics Associated with High Likelihood
Demand Response	• Small rate • Higher variability in loads • Agricultural, Mining, & Forestry customers • More premises associated with an account	• Larger loads • More weather sensitive loads • Retail, Education, & Lodging customers • Certain zip codes
Battery Storage	• Small rate • Public Administration, Professional Services, Mining, Utility, and Construction customers	• Larger peak loads • Higher overall consumption • Manufacturing customers
Solar PV	• Small rate • More weather sensitive loads • Retail, Professional Services customers	• Higher overall consumption • Warehouse, Storage, Postal, and Education customers

Customer Savings Opportunities

Customers have a variety of ways to save money by enrolling in DR, with or without additional DER installations. In general, customers can reduce their total consumption which influences volumetric charges they are exposed to. They can also shift consumption away from peak periods to manage coincident and non-coincident demand charges. Finally, they can claim a participation incentive after enrolling in demand response. These incentives can be comprised of a fixed monthly capacity credit and/or a performance credit for each event, measured by a settlement baseline. As summarized in Table 11, the interaction of DR, Battery, and Solar installation and operations strategies can have varying effects on a customer's bill. Of course, these results depend heavily on DR program elected, battery and solar sizes, and the customer's operational characteristics.

Table 11: DR and DER Strategy Impacts on Customer Bills

	Volumetric Charges (kWh)	Demand Charges (kW)	DR Incentives
DR Only	↔ no significant change	↔ no significant change	↑ participation incentive
DR + Battery Peak	↓ slight decrease due to battery charge/discharge roundtrip efficiency	↑↑ shift away from peak periods, reduce peak demand charges	↑ participation incentive
DR + Battery Shift	↓ slight decrease due to battery charge/discharge roundtrip efficiency	↑ reduce peak demand charges, but may increase non-coincident demand due to overnight charging	↔ participation incentive offset by permanent shifting away from peak in baseline period
DR + Battery Peak + Solar	↑↑ solar reduces energy consumption from grid	↑↑ shift away from peak periods, reduce peak demand charges	↓↓ participation incentive offset by lower net demand able to be shed
DR + Battery Shift + Solar	↑↑ solar reduces energy consumption from grid	↑ reduce peak demand charges, but may increase non-coincident demand due to overnight charging	↓↓ participation incentive offset by permanent shifting away from peak in baseline period and lower net demand able to be shed

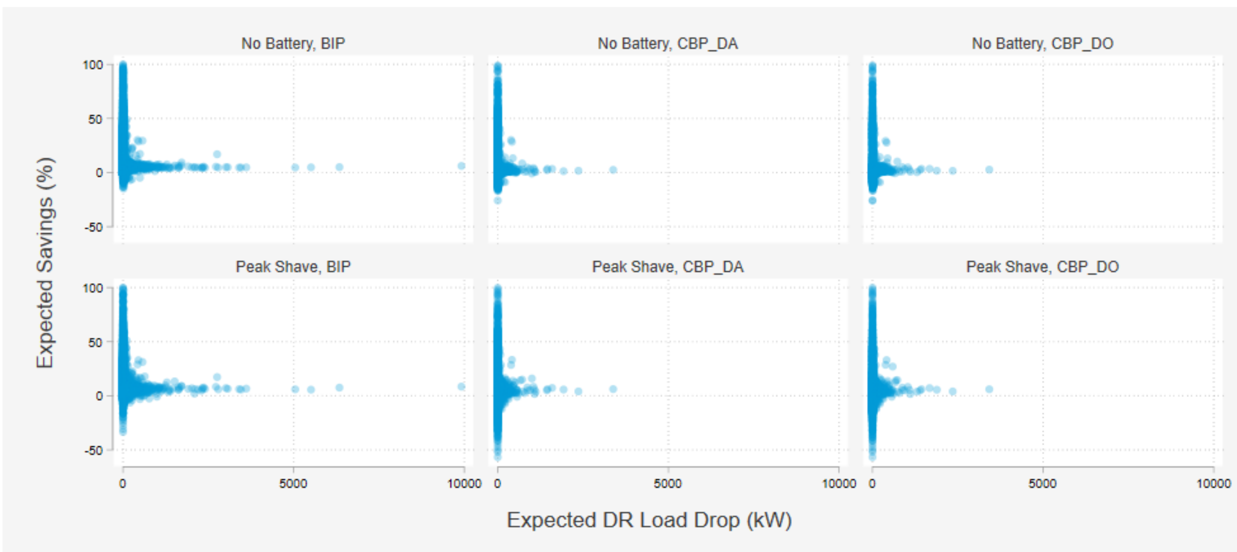
Identifying High-Value Customers

The framework used to identify high-value customers in this analysis was threefold:

1. Customers who were likely to enroll in demand response (or install battery or solar technology)
2. Customers who could reduce their use during peak periods where demand response was required
3. Customers who stood to save on their annual bills by participating and/or installing the technology

In general, DSA found that many customers stand to benefit from participating in demand response, either directly through SDG&E or through an aggregator. Even without adding a battery or solar technology, customers can save significant amounts on their annual bill by enrolling. The BIP program tended to provide higher incentives for participation compared to CBP.

FIGURE 36: SAVINGS TARGETING ANALYSIS



RECOMMENDATIONS

The analysis provided several insights into which customers are more likely to enroll on DR programs, customer bill savings, and the interaction of DR with battery storage and solar. However, the most tangible outcome of the study was making the information available, useful, and actionable for program managers, account representatives, and, by connection, customers.

Recommendation	Explanation
Update the analysis and tool annually	Due to customer turnover, the results and tool need to be updated periodically. In addition, right now, there is still limited experience with battery storage and the adoption propensity score should be updated as the penetration of battery storage increases.
Consider dedicated load shifting programs for battery storage to ensure capacity grid benefits	Behind-the-meter battery storage does not fit neatly into demand response programs or as a load modifying resources. Battery storage is an incremental resource on the system, but are not always used in a manner to maximize overall benefits. Programs are needed to either ensure they are dispatched at the right time, or engage in daily shifting of demand away from peak hours. Traditional demand response baselines are not adequate for resources that shift and provide incremental capacity on a daily basis.
Track use of the tool and outreach efforts to customers	The tool provides the ability of account representatives to target the customers most likely to enroll, deliver reductions, and experience bills savings. It is, however, critical to understand who is using it, how often, and if outcomes improve when high value sites are targeted versus not.

APPENDICES

PROPENSITY ANALYSIS MODEL DETAIL

BATTERY

TABLE 12: BATTERY PROPENSITY FINAL REGRESSION RESULTS

battery	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ln_max_peak	.2732106	.031831	8.58	0.000	.210823	.3355982
corr	-.1851317	.1287115	-1.44	0.150	-.4374016	.0671383
naics1						
1	0	(empty)				
2	-.4899964	.2265705	-2.16	0.031	-.9340663	-.0459264
3	-.2621793	.1661943	-1.58	0.115	-.5879142	.0635556
4	-.4913657	.1590744	-3.09	0.002	-.8031458	-.1795857
5	-.7212762	.1650286	-4.37	0.000	-1.044726	-.397826
6	-.4747948	.1625507	-2.92	0.003	-.7933884	-.1562013
7	-.6998726	.183357	-3.82	0.000	-1.059246	-.3404996
8	-.7363447	.2152591	-3.42	0.001	-1.158245	-.3144445
9	-.7987366	.2810825	-2.84	0.004	-1.349648	-.2478251
approxrate						
DGR	.4977751	.1569295	3.17	0.002	.1901989	.8053513
TOUA	-.3057061	.1209563	-2.53	0.011	-.5427762	-.0686361
_cons	-3.298547	.1906978	-17.30	0.000	-3.672308	-2.924786

SOLAR

TABLE 13: SOLAR PROPENSITY FINAL REGRESSION RESULTS

solar	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ln_annual_mean_kwh	.2702017	.02115	12.78	0.000	.2287484	.3116549
corr	-.0182982	.0403341	-0.45	0.650	-.0973516	.0607551
ann_sizebins_equal						
2	-.2219716	.1327066	-1.67	0.094	-.4820717	.0381286
3	-.0723298	.1312801	-0.55	0.582	-.3296341	.1849745
4	-.0110983	.1345913	-0.08	0.934	-.2748923	.2526957
5	.0140467	.1377774	0.10	0.919	-.2559921	.2840855
6	.2145908	.1403373	1.53	0.126	-.0604652	.4896468
7	.2616295	.1456721	1.80	0.072	-.0238826	.5471416
8	.3135469	.1522387	2.06	0.039	.0151644	.6119293
9	.5543912	.1597982	3.47	0.001	.2411925	.86759
10	.842263	.1824021	4.62	0.000	.4847614	1.199765
naics1						
1	-.4326757	.1214141	-3.56	0.000	-.6706431	-.1947084
2	-.3444868	.0510367	-6.75	0.000	-.4445169	-.2444567

3	-.8764102	.0622883	-14.07	0.000	-.998493	-.7543273
4	-.8621524	.0495884	-17.39	0.000	-.9593438	-.764961
5	-.6724252	.0404447	-16.63	0.000	-.7516953	-.593155
6	-.6138401	.0452964	-13.55	0.000	-.7026194	-.5250608
7	-.9638623	.0582969	-16.53	0.000	-1.078122	-.8496026
8	-.4601063	.0427283	-10.77	0.000	-.5438522	-.3763604
9	-.5157049	.0678623	-7.60	0.000	-.6487126	-.3826972
approxrate						
DGR	1.493449	.0673097	22.19	0.000	1.361525	1.625373
TOUA	.2782017	.0441753	6.30	0.000	.1916197	.3647838
ann_loadfactor	-3.391631	.1254025	-27.05	0.000	-3.637415	-3.145847
_cons	-1.720401	.1363159	-12.62	0.000	-1.987576	-1.453227

Demand Response

Table 14: Demand Response Propensity Final Regression Results

dr	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ln_annual_max_kwh	.2236439	.0100722	22.20	0.000	.2039028	.2433851
corr	.3925626	.0244159	16.08	0.000	.3447083	.4404169
zip_model						
321	0	(empty)				
919	-.2065506	.057393	-3.60	0.000	-.3190389	-.0940624
920	-.3769046	.0627279	-6.01	0.000	-.499849	-.2539602
921	-.241411	.0531106	-4.55	0.000	-.3455059	-.1373161
925	0	(empty)				
926	-.6998585	.0796553	-8.79	0.000	-.8559801	-.5437369
91910	.0999486	.0616277	1.62	0.105	-.0208395	.2207367
91942	-.3472493	.0766932	-4.53	0.000	-.4975653	-.1969333
91950	.08906	.0589311	1.51	0.131	-.0264427	.2045627
91977	-.0452865	.0824523	-0.55	0.583	-.2068899	.116317
92019	.1096782	.0850546	1.29	0.197	-.0570257	.2763821
92020	-.2976584	.0717656	-4.15	0.000	-.4383163	-.1570005
92021	.05676	.0818435	0.69	0.488	-.1036503	.2171704
92024	-.2627357	.0814655	-3.23	0.001	-.4224051	-.1030662
92025	-.0011111	.0683686	-0.02	0.987	-.1351111	.1328888
92028	-.0645017	.077457	-0.83	0.405	-.2163147	.0873112
92064	.1112592	.0692788	1.61	0.108	-.0245248	.2470431
92069	.0727189	.079695	0.91	0.362	-.0834804	.2289183
92071	-.1435799	.074325	-1.93	0.053	-.2892541	.0020944
92078	-.2024761	.082447	-2.46	0.014	-.3640693	-.0408829
92101	-.3015428	.0621136	-4.85	0.000	-.4232831	-.1798024
92103	.1644826	.0627048	2.62	0.009	.0415835	.2873816
92109	.0856644	.063307	1.35	0.176	-.0384151	.2097439
92110	.279103	.0564867	4.94	0.000	.1683912	.3898148
92111	-.073605	.0675738	-1.09	0.276	-.2060472	.0588372
92121	-.106201	.0650757	-1.63	0.103	-.233747	.0213451
92123	-.2876445	.0735028	-3.91	0.000	-.4317073	-.1435818
92126	-.0566473	.0697251	-0.81	0.417	-.1933059	.0800113
92128	.0489179	.0746035	0.66	0.512	-.0973022	.195138
92154	0	(omitted)				
naics_model						
1	-.2780008	.1081023	-2.57	0.010	-.4898775	-.0661241
2	-.5855604	.1157786	-5.06	0.000	-.8124823	-.3586386

3	.119933	.0493094	2.43	0.015	.0232884	.2165775
4	-.0873224	.0622163	-1.40	0.160	-.2092641	.0346192
5	-.4437172	.0493528	-8.99	0.000	-.5404469	-.3469874
9	-.434067	.0663409	-6.54	0.000	-.5640928	-.3040411
23	.0757309	.040947	1.85	0.064	-.0045238	.1559855
33	.0344523	.045911	0.75	0.453	-.0555316	.1244362
42	.1347732	.0450695	2.99	0.003	.0464385	.2231079
44	.227899	.033424	6.82	0.000	.1623891	.2934088
45	.3972846	.0403651	9.84	0.000	.3181706	.4763987
52	.1438782	.0400959	3.59	0.000	.0652917	.2224646
53	-.0227712	.0332257	-0.69	0.493	-.0878923	.0423499
54	.1214693	.0365726	3.32	0.001	.0497884	.1931502
56	.2215209	.0513523	4.31	0.000	.1208723	.3221695
61	.3903649	.0396032	9.86	0.000	.3127441	.4679857
62	.1228236	.0345094	3.56	0.000	.0551863	.1904608
71	.166229	.0482758	3.44	0.001	.0716101	.2608479
72	.3210525	.0330613	9.71	0.000	.2562536	.3858514
81	.2790212	.0305821	9.12	0.000	.2190813	.3389611
sd_kwh	-.0018597	.0004058	-4.58	0.000	-.0026551	-.0010644
ann_sizebins_equal						
2	-.2397566	.0419011	-5.72	0.000	-.3218812	-.157632
3	-.2757279	.0418561	-6.59	0.000	-.3577644	-.1936914
4	-.2363284	.0420058	-5.63	0.000	-.3186582	-.1539986
5	-.2676768	.0425182	-6.30	0.000	-.3510109	-.1843427
6	-.28363	.043354	-6.54	0.000	-.3686022	-.1986578
7	-.3728243	.0449131	-8.30	0.000	-.4608523	-.2847963
8	-.376866	.0464823	-8.11	0.000	-.4679696	-.2857623
9	-.4872648	.0494777	-9.85	0.000	-.5842392	-.3902903
10	-.7094966	.0587832	-12.07	0.000	-.8247095	-.5942837
rate_size						
Small	-.0541068	.0267603	-2.02	0.043	-.1065561	-.0016575
weather_stn						
CAMPO	-.3929982	.1110176	-3.54	0.000	-.6105887	-.1754078
CARLSBAD	-.1771309	.0573485	-3.09	0.002	-.2895319	-.0647298
GILLESPIE FIELD	.0565143	.0490126	1.15	0.249	-.0395487	.1525772
LINDBERGH FIELD	-.3345254	.0467957	-7.15	0.000	-.4262433	-.2428074
MIRAMAR	-.1135131	.0504506	-2.25	0.024	-.2123944	-.0146318
MONTGOMERY FIELD	-.1916046	.048706	-3.93	0.000	-.2870666	-.0961427
OCEANSIDE	-.1246593	.0595963	-2.09	0.036	-.2414659	-.0078527
RAMONA	-.0780892	.0607623	-1.29	0.199	-.1971811	.0410027
SANTA ANA	.0231323	.0771479	0.30	0.764	-.1280747	.1743394
_cons	-1.664004	.079373	-20.96	0.000	-1.819572	-1.508435

System Size Recommendations

Solar

Table 15: Solar Size Recommended Model

ln_solar_size	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ln_ann_p95kwh	.8480991	.0151795	55.87	0.000	.818323	.8778751

rate_size						
Small	-.5354377	.1332541	-4.02	0.000	-.7968283	-.2740472
industry						
Institutional/Gove~t	-.0602866	.1234327	-0.49	0.625	-.3024118	.1818385
Manufacturing	-.1611658	.1410583	-1.14	0.253	-.4378651	.1155336
Offices, Hotels, F..	-.0907221	.1205316	-0.75	0.452	-.3271564	.1457122
Retail Stores	.044817	.1422145	0.32	0.753	-.2341504	.3237843
Schools	-.1479425	.1203045	-1.23	0.219	-.3839314	.0880463
Wholesale, Transpo..	-.2725145	.1515885	-1.80	0.072	-.5698698	.0248408
Unknown/Other	-.3449848	.1757572	-1.96	0.050	-.6897494	-.0002203
Religious Orgs	-.060014	.1268364	-0.47	0.636	-.3088158	.1887878
rate_size#industry						
Large# Agriculture, Minin..	0	(omitted)				
Large# Institutional/Gove~t	0	(omitted)				
Large#Manufacturing	0	(omitted)				
Large# Offices, Hotels, F..	0	(omitted)				
Large#Retail Stores	0	(omitted)				
Large#Schools	0	(omitted)				
Large# Wholesale, Transpo..	0	(omitted)				
Large#Unknown/Other	0	(omitted)				
Large#Religious Orgs	0	(omitted)				
Small# Agriculture, Minin..	0	(omitted)				
Small# Institutional/Gove~t	.3019852	.1499598	2.01	0.044	.0078247	.5961456
Small#Manufacturing	.4403624	.1860495	2.37	0.018	.0754084	.8053164
Small# Offices, Hotels, F..	.5142423	.1391166	3.70	0.000	.2413518	.7871328
Small#Retail Stores	.1896282	.1852743	1.02	0.306	-.1738051	.5530615
Small#Schools	.4216004	.2081624	2.03	0.043	.0132699	.8299309
Small# Wholesale, Transpo..	.6676976	.1850208	3.61	0.000	.3047617	1.030634
Small#Unknown/Other	.4227714	.189967	2.23	0.026	.050133	.7954099
Small#Religious Orgs	.516197	.1546609	3.34	0.001	.2128148	.8195791
_cons	1.122244	.1293347	8.68	0.000	.8685415	1.375947

Battery

Table 16: Battery Size Recommended Model

ln_battery_size	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ln_annual_max_kwh	.7152402	.0781183	9.16	0.000	.5595862	.8708942
ann_percentileload	.0112363	.0060611	1.85	0.068	-.0008406	.0233132
ann_loadfactor	-2.100016	.4890798	-4.29	0.000	-3.074529	-1.125503
_cons	.9763344	.2788874	3.50	0.001	.4206392	1.53203

BULK ANALYSIS MODEL DETAIL

The bulk analysis model involved several computational steps that will be outlined below. No regression modeling was performed and therefore there are no direct regression outputs to display. The steps to produce the bulk analysis are as follows:

1. Clean and construct analysis dataset
    a. Aggregate and clean datasets
        i. Identify active customers
        ii. Identify a full year of data for each active customer
        iii. Add current DR enrollments and current DER sizes, if available
        iv. Simulate DR events for each CPP, BIP, CBP-DA and CBP-DO
    b. Make analysis dataset
        i. Combine all data together
        ii. Flag customers who are currently enrolled in DR
        iii. Flag customers who have current DERs enrolled
        iv. Compute a gross load estimate for customers with solar already using the coincidence factors provided by SDG&E
2. Simulate effects of DER loads
    a. Compute and apply demand response impacts
        i. Estimate impacts by industry type and program and apply the percent impacts to each customer on the simulated event days
        ii. Compute enrolled customer characteristics (FSL, nominated kW etc) based on average impacts and historic program achievement rates
    b. Compute and apply solar loads
        i. Use the recommended system size for each customer and the coincidence factors provided by SDG&E
    c. Compute optimal battery charging and discharging strategy
        i. Use the recommended battery size for each customer and compute optimal loads for each customer using a combined peak-shaving/trough-filling algorithm. Apply battery load reductions first to event hours if an event day
        ii. For peak day shaving, operate the battery on the top 5 days of each month. For the daily load shifting, operate the battery every day
    d. Stack load modifying profiles and re-compute net load
3. Compute bill impacts
    a. Compute base bill
        i. Using the customer's current rate and CPP enrollment

ii. Compute exiting DR incentives if applicable (model 9 CPP events for CPP customers)

b. Compute simulated bill

i. For each simulation, use the estimate of new delivered load to construct the bill for each valid rate

1. A customer's overall size dictates whether they are eligible to be billed under AL-TOU, TOU-A or DG-R rates

2. Apply the CPP (default) version of the rate for scenarios with no other DR enrollments or if the customer is not eligible for other DR

c. Compute DR incentives

i. Use the BIP and CBP tariffs to compute the incentive payments dependent on FSL, nominated kW and/or program performance for each customer and each event.

d. Compare existing bill and incentives with new simulated bills and incentives