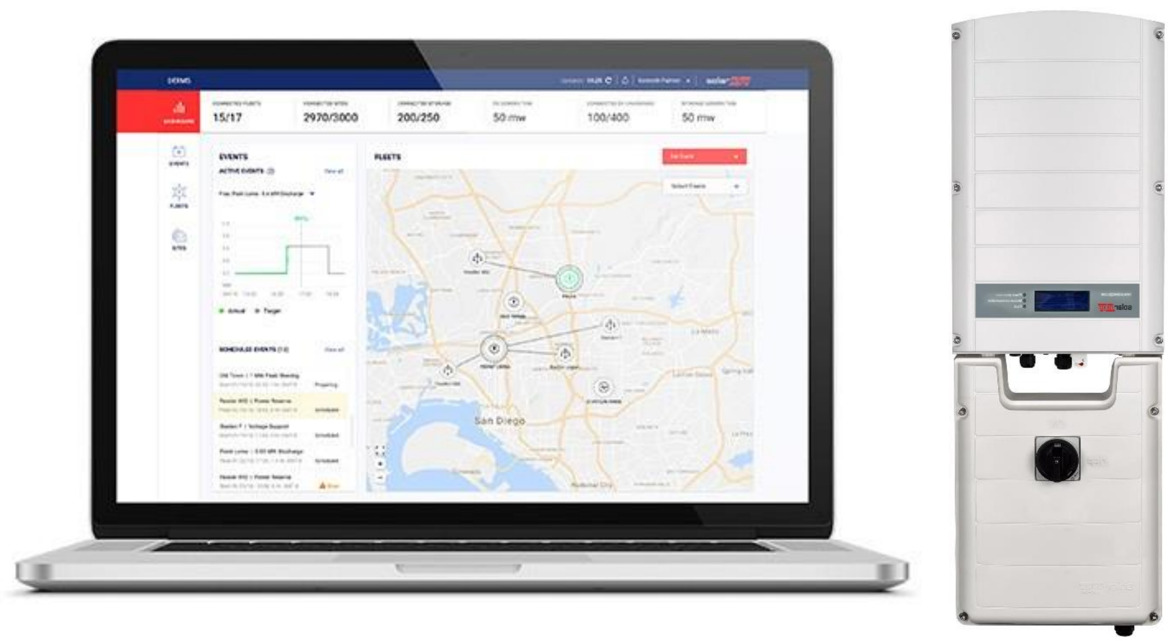
DR Emerging technology (DRET) BTM Residential Battery for Load Management Study

ET Project Number: ET22PGE7310



SolarEdge DERMs software and SolarEdge StorEdge Inverter

Project Manager: **Albert Chiu**
Pacific Gas and Electric Company

Prepared By: **Demand Side Analytics**
691 John Wesley Dobbs Ave NE, Suite V3
Atlanta, GA 30312

Issued: **August 2nd, 2023**

ACKNOWLEDGEMENTS

Pacific Gas and Electric Company's Emerging Technologies Program is responsible for this project. It was developed as part of Pacific Gas and Electric Company's Emerging Technology program under internal project number ET22PGE7310. Demand Side Analytics conducted this technology evaluation for Pacific Gas and Electric Company with overall guidance and management from the Demand Response Emerging Technology Team. For more information on this project, contact Albert Chiu at *AKC6@pge.com*.

LEGAL NOTICE

This report was prepared for Pacific Gas and Electric Company for use by its employees and agents. Neither Pacific Gas and Electric Company nor any of its employees and agents:

(1) makes any written or oral warranty, expressed or implied, including, but not limited to those concerning merchantability or fitness for a particular purpose;

(2) assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, process, method, or policy contained herein; or

(3) represents that its use would not infringe any privately owned rights, including, but not limited to, patents, trademarks, or copyrights.

ABBREVIATIONS AND ACRONYMS

DER	Distributed Energy Resource
DRET	Demand Response Emerging Technology
DR	Demand Response
HE	Hour Ending
P4P	Pay for Performance
RCT	Randomized Control Trial

FIGURES

Figure 1. Number of CAISO Alerts, Warnings, and Emergencies by Year 6
Figure 2: Residential Battery Storage Installed Nameplate Capacity in PG&E Territory 7
Figure 3: SolarEdge StorEdge Connectivity Diagram 9
Figure 4: Distribution of SolarEdge Inverter Age 10
Figure 5: SolarEdge DERMS Software 11
Figure 6: Dispatch of Sites is Alternated to Achieve a Flat Dispatch Shape at a Portfolio Level 12
Figure 7: SolarEdge Price Arbitrage Software 13
Figure 8: Customer Recruitment Timeline 14
Figure 9: Wave 1 Incentive Test Design 17
Figure 10: Wave 2 P4P and Push Notification Test Design 18
Figure 11: Application rate by Incentive Offerings 19
Figure 12: Application rate by Phone Call Outreach 20
Figure 13: Application rate by Push Notification Outreach 21
Figure 14: Application rate by Incentive Structure 22
Figure 15: Evaluation Data Sources 25
Figure 16: Comparison of PG&E and SolarEdge Net Load Data 26
Figure 17: Distribution of Battery Capacity Commitment to Program 27
Figure 18: State of Battery Charge 27
Figure 19: Average Customer Battery Charge/Discharge Shape – Average Summer Day 28
Figure 20: Avg. 4-9 PM Dispatch by Participant 29
Figure 21: Avg. Customer Load Shapes – Other Data Sources on Avg. Summer Day 30
Figure 22: Average Customer Battery Charge/Discharge Shape – 2022 Peak Weekday 31
Figure 23: Avg. Customer Load Shapes – Other Data Sources on 2022 Peak Weekday 32
Figure 24: Battery Fleet State of Charge During 2022 Peak Weekday 33
Figure 25: Event Dispatch Study Design 36
Figure 26: 2022 Events 37
Figure 27: Event Dispatch Success Rate 38

Figure 28: Discharge Event – Customer Battery Charge/Discharge Data 39
Figure 29: Discharge Event – Customer Net Load Shape 40
Figure 30: Charge Event – PG&E AMI Data 41
Figure 31: Shaped Discharge Event – Battery Charge/Discharge Data 42
Figure 32: Battery Charge + Discharge Event – Customer Net Load Shape 43
Figure 33: Average Event Impacts – By Data Source 44
Figure 34: Average Customer Event Impacts by Event Duration 45
Figure 35: Average Customer Event Impacts – By Advance Notice ... 46
Figure 36: Average Hourly Event Impacts – by Event Temperature Conditions (F) 46
Figure 37: Average Customer Impacts by Event Hour 47
Figure 38: Price Arbitrage Study Design 50
Figure 39: RTP Rate Hourly Shape 51
Figure 40: TOU Rate Hourly Shape 52
Figure 41: Shift in Price Arbitrage Shapes Compared to Control Shape 53
Figure 42: Price Arbitrage Following TOU Rate Price Shape 54
Figure 43: Price Arbitrage Following RTP Price Shape 55
Figure 44: Wave 1 and Wave 2 Enrollment Process 60
Figure 45: Wave 1 Enrollment Criteria 61
Figure 46: Wave 2 Enrollment Criteria 62
Figure 47: Probit Regression Outputs – Impact of Incentive on Enrollment 64
Figure 48: Probit Regression Outputs – Impact of Logged Incentive on Enrollment 64
Figure 49: T-Test Outputs – Impact of Phone Call On Enrollment 65
Figure 50: T-Test Outputs – Impact of Push Notification on Enrollment 65

TABLES

Table 1: Summary of Key Research Questions and Findings 2
Table 2: Sample Sign-up Incentive Options for a Customer with a $100/kWh Incentive and a 10 kWh Battery Capacity....... 16

Table 3: Enrollment Key Takeaways 22
Table 4: Typical Customer Battery Use Key Takeaways 33
Table 5: Load Shifting: Event Dispatch Key Takeaways 47
Table 6: Load Shifting: Price Arbitrage Key Takeaways 55
Table 7: Summary of Key Research Questions and Findings 56
Table 8: Detailed Load Impact Results for Battery Storage Events 66

EQUATIONS

Equation 1: Sign-Up Incentive Calculation 15

CONTENTS

EXECUTIVE SUMMARY 1

INTRODUCTION 6

ASSESSMENT OBJECTIVES 8

EMERGING TECHNOLOGY/PRODUCT 9

CUSTOMER RECRUITMENT TESTS 14

Recruitment Methods 14

Recruitment Methods 15
Incentive Structure 15

Study Design 16

Results 18

Key Takeaways 22

TYPICAL CUSTOMER BATTERY USE 24

Data Sources 24

Customer Back-Up Reserve Patterns 26

Typical Customer Battery Use 28

Customer Battery Use on Peak Days 30

Key Takeaways 33

SHIFTING BATTERY LOAD – EVENT DISPATCH 35

Study Design & Evaluation Methodology 35

Dispatch Success Rate 37

Event Day Load Impacts 38

Data Source Comparison 43

Key Drivers of Impact Magnitude 44

Key Takeaways 47

SHIFTING BATTERY LOAD – PRICE ARBITRAGE 49

Study Design & Evaluation Methodology 49

Price Signals 50

Results 52

Key Takeaways 55

CONCLUSIONS & RECOMMENDATIONS 56

APPENDICES 60

APPENDIX A: ENROLLMENT PROCESS & ELIGIBILITY CRITERIA 60

APPENDIX B: SAMPLE RECRUITMENT MATERIALS 62
APPENDIX C: ENROLLMENT ANALYSIS DETAIL 63
APPENDIX D: DETAILED LOAD IMPACT RESULTS 66

EXECUTIVE SUMMARY

PROJECT DESCRIPTION

PG&E's Demand Response Emerging Technology (DRET) Program initiated a residential Battery Study to investigate the potential to utilize residential photovoltaic solar systems paired with a home battery system to support state electric grid reliability. By default, residential batteries can be used help offset household energy use and can also be programmed to discharge when rates are high. However, the flexible resource is largely untapped when the grid is strained or electric prices are high. Many battery storage systems are used for back-up purposes only, and even if they are used to offset household energy use they may not export to the grid.

PG&E designed the study to learn more about how batteries are currently being used, to investigate the ability to recruit residential battery storage for grid operations, and to assess how batteries can be dispatched to better meet grid needs. In specific, 181 PG&E customers with SolarEdge inverters (which control the battery storage units), opted into the study and 120 sites passed technical screens. In exchange for incentives, participants allowed PG&E to manage the battery operations in response to hourly day-ahead market prices, TOU rates, and grid events. Customers elected the share of the battery storage made available for utility operations and the share of the battery reserved for backup storage. The study also implemented randomized control trials to assess how incentives and various recruitment techniques influenced participation rates.

There were four main research questions that the study sought to answer:

1. **What are the enrollment rates for battery storage demand response programs?**
    a. How do incentive amounts and outreach methods affect participation rates for existing battery owners?
2. **How are battery storage customers using battery storage on their own?**
    a. What are the settings selected by the customer? Back-up only, self-powered, or time-based response?
    b. How much of their battery do customers reserve for back-up?
    c. What are the typical charge and discharge patterns for a battery?
    d. How well does a customer's "natural occurring" battery use align with grid needs? What is the untapped value?
3. **How can we shift battery load to better meet grid needs?**
    a. How do batteries respond to event dispatch?
        i. What are the load impacts of dispatching battery storage?
        ii. What does a typical dispatch look like?
        iii. How successful was the battery response when dispatched for an event?
        iv. What are the key drivers of load impacts?

v. How did the impacts vary with the data source used for the evaluation?

b. How do batteries respond to price arbitrage?

i. Are batteries able to respond to price arbitrage regardless of a customer's rate?

ii. How do batteries currently respond to a time-of-use rate structure (TOU-C)?

iii. How do batteries currently respond to Day-Ahead market prices (RTP)?

4. Is the technology ready for a program?

a. How effective are existing algorithms?

b. What improvements need to be made to existing algorithms?

PROJECT FINDINGS/RESULTS

Table 1 summarizes the key research questions and findings from the study.

TABLE 1: SUMMARY OF KEY RESEARCH QUESTIONS AND FINDINGS

Research Question	Findings
What are the enrollment rates for existing battery storage customers?	181 customers and 6.5% accepted the offer to enroll in a battery storage study, and 120 customers met technical screening requirements for an overall enrollment rate of 4.5%.
What is the relationship between upfront incentive levels and enrollment rates?	Doubling the upfront incentive amount increases study participation by 1.64x.
What recruitment methods increase enrollment rates? By how much?	Phone calls improved enrollment rates by 3x, but there may be interviewer-specific effects. Push notifications increased enrollment rates by 10x.
What are the enrollment rates for a pay-for-performance incentive structure?	3.8% of customers pay-for-performance incentives (with no upfront incentive) accepted the offer. The overall enrollment rate, after technical screens was 2.4%.
Does the data from PG&E align with the SolarEdge data?	On average, the PG&E data is 10% smaller in magnitude compared to the SolarEdge data when comparing household net loads. The degree to which the two data sources aligned varied by participant, with approximately 40% of participants having almost identical PG&E and SolarEdge data.

How much power do people reserve for backup?	Customers typically committed either 50% or 80% (the maximum) of their battery capacity to the program, on average committing 64%. However, the fleet does not typically discharge below 60% of the overall battery capacity.
What are the typical charge and discharge patterns absent intervention?	On average, batteries start charging from solar when the sun rises and stop when they are fully charged. Charging typically starts at 8 AM and on average charge 4.7 kWh between 8 AM and 2 PM. Batteries typically start discharging at 4 PM, as the sun sets, and on average discharge 2.9 kWh between 4 PM and 9 PM.
How well does a customer's "naturally occurring" battery use align with grid needs? What is the untapped value?	On peak days, there is higher battery discharge for the average customer but there is a larger ramp in customer net load between 4 PM and 9 PM due to higher household load. There is also still a large amount of untapped capacity on peak days – 50% of the battery fleet was not discharged. Without intervention, the batteries tend to discharge earlier than on the net peak load hours or highest price hours.
What are the load impacts of dispatching battery storage?	During a 4-hour discharge event the average impact was 0.7 kW assuming 100% successful dispatch rate. During the first half of the summer there were no impacts from calling charge events. Once charge events were modified customer net usage increased 1.6 kW for a single hour during the charge window.
What did a typical dispatch look like?	SolarEdge discharge events typically had a flat load shed with consistent impacts across the entire event window. Charge events typically concentrated battery charging into a single hour leading to a spike in the customer's net load.
How successful was the battery response when dispatched for an event?	On average 67% of batteries successfully responded when dispatched for an event, but the overall fleet response rate varied over the course of the study. The relatively low response rate can be attributed to two factors. The first is that over the course of the summer some batteries went offline and were no longer able to receive signals. The second reason is that batteries received signals either from Ethernet or from WiFi, and the batteries on the WiFi signal went offline whenever there were WiFi issues.

What are the key drivers of load impacts?	Event duration was the largest driver of impact magnitude due to the SolarEdge event dispatch algorithm, which aim to provide a consistent demand reduction across the event window. Impacts were larger with more advance notice but there wasn't a strong relationship between the two. Weather conditions and event timing had a minimal influence on event impact magnitude.
How did the impacts vary based on the data source used for the evaluation?	When comparing SolarEdge net load impacts to SolarEdge end use impacts, there was on average a very small difference of 0.03 kW.
Are batteries able to respond to price arbitrage regardless of the customer's current rate?	Batteries were able to respond to both TOU rate structures and market day-ahead prices without exposing the customers to any actual changes in their rate. For example, customers on a tiered rate were able to respond to the time of use rate structure without shifting the customer to a TOU rate. Similarly, all participants were able to respond to market conditions without being exposed to day-ahead market prices.
How are the batteries able to respond to a time of use rate structure (TOU-C)?	The batteries responded to a time of use rate structure in one of two ways. The first response was a base setting that could be selected by the customer when they installed the battery. For the customer-selected TOU setting the battery discharged at the beginning of the peak price window. The second type of response was through price arbitrage. When implementing price arbitrage, the battery discharged when the rolling average price was at its peak. As a result, the battery discharged in the middle of the peak price window rather than at the start of the peak price window.
How are batteries able to respond to day-ahead market prices (RTP)?	The battery responded to day-ahead market conditions and discharged during the highest price period of the day, which typically occurred from 6-7 PM during the study period[1].

[1] Note that batteries responded to market prices in the fall, which had a daily price peak that was slightly earlier on average compared to summer months. In the summer the typical peak occurs between 7 PM and 9 PM.

PROJECT RECOMMENDATIONS

While this technology has a lot of potential, several aspects of the technology warrant further study. We recommend researching the following key questions when looking into the potential of this technology to reduce peak demand:

- How quickly do the batteries respond (latency) to external instructions?
- Can we improve battery manufacturers' algorithms to feed specific discharge (e.g., T&D load relief) and or charge shapes (e.g., load building) to the batteries?
- Are the batteries able to respond to over/under frequency and voltage?
- What load management use cases can be stacked realistically?
- What is the optimal design and cost-effectiveness of a battery storage program?
- What are costs of sustaining participation over multiple years of customers who allow their battery to be used for grid operations?
- Can successful communication rates to the battery be improved?
- Can pre-screening of sites be improved to minimize recruitment of sites that do not meet technical testing?

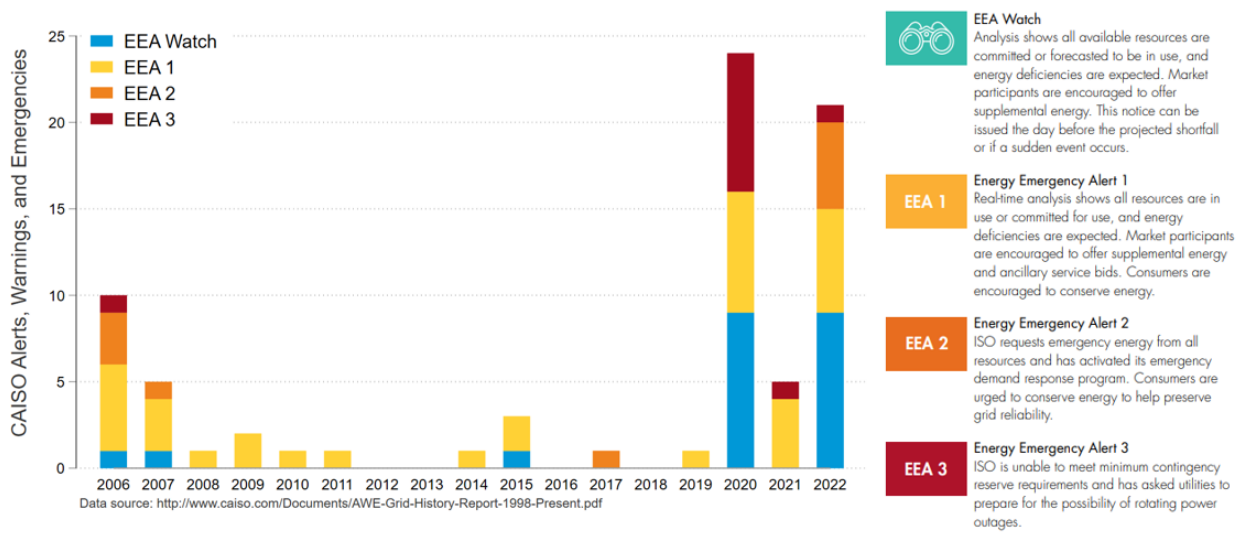
We also make the following observations for future battery storage study and programs:

- Future battery storage recruitment should leverage push notifications and battery storage apps, as this is a cost-effective method for improving enrollment rates.
- There is value to recruiting customers to a battery storage program. Customers are currently under-utilizing their batteries, and there is a lot of untapped potential on peak days.
- Event dispatch is currently a better method for achieving battery dispatch for long durations compared to price arbitrage.
- Price arbitrage allows customer load to follow specified price shapes without forcing a customer to change their rate. However, the current SolarEdge price arbitrage algorithms typically start discharge during the highest price hour and discharged the battery at its maximum authorized capacity for as long as the battery was able to discharge at that capacity. The strategy typically leads to a large kW impact during the first hour, but the impact drops off dramatically in the following hours. While discharging the maximum authorized capacity during the highest price hour helps to maximize customer savings, there is opportunity to refine the algorithm to get more consistent impacts for multiple high price hours.

INTRODUCTION

In recent years there has been an increase in the number of system emergencies due to extreme summer heat waves. During recent heat waves when the grid was under stress, CAISO dispatched DR to provide load reduction. Figure 1 shows the huge increase in alerts, warnings, and emergencies issued by CAISO in 2020 and 2022. Grid emergencies are expected to continue going forward. While maintaining the current capacity of DR programs is crucial for situations like these, developing new programs will be just as important to provide greater flexibility when responding to system emergencies. As system loads grow over time, through population growth and climate change, more resources will be needed to manage system peaks.

FIGURE 1. NUMBER OF CAISO ALERTS, WARNINGS, AND EMERGENCIES BY YEAR[2]

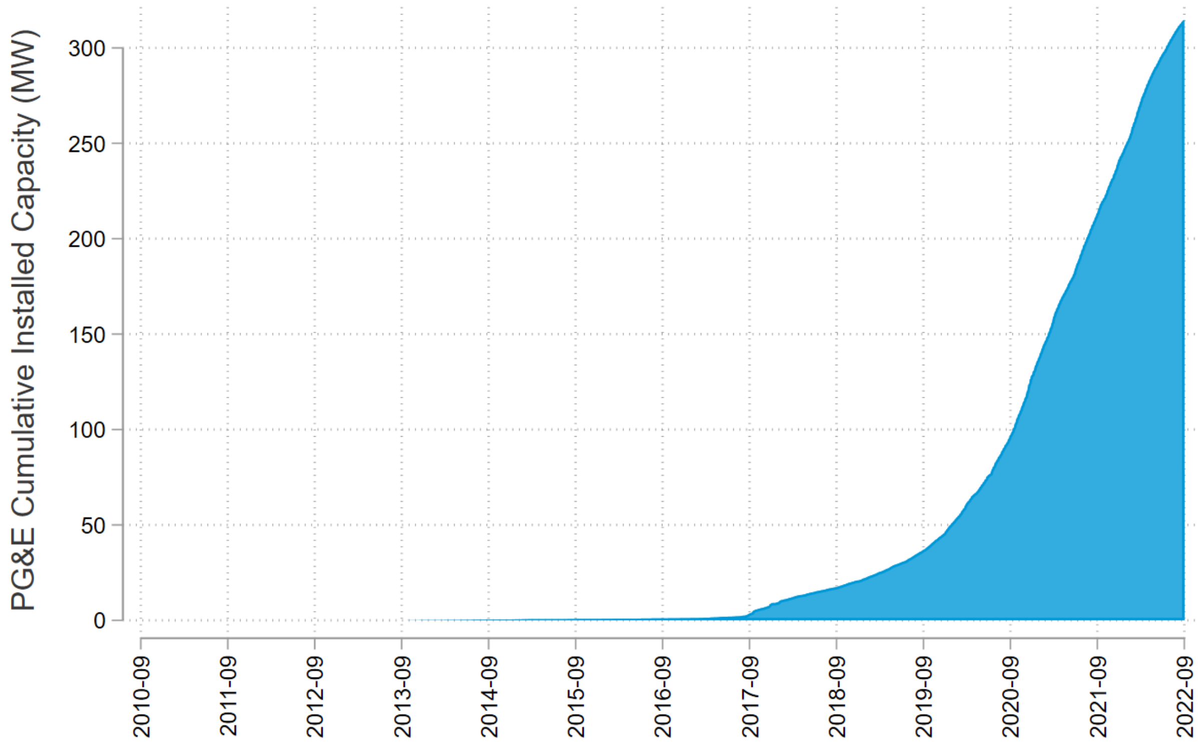


PG&E received direct feedback from DR aggregators and Distributed Energy Resource (DER) technology vendors that there is strong interest in participating in DR programs using residential battery storage, but they face barriers. Given their unique load patterns and energy usage, existing DR programs are not optimal for many residential and non-residential customers with battery storage technologies. In addition, customers may already be using these battery technologies to manage their household usage, leaving limited potential resources for grid needs. A key objective for PG&E was to enhance existing DR programs and remove barriers to allow customers with battery storage and solar to participate in DR. Residential battery storage was of particular interest because it is a flexible and growing resource, as shown in Figure 2. As of September 30, 2022, PG&E had

[2] http://www.caiso.com/Documents/Grid-Emergencies-History-Report-1998-Present.pdf

over 44,000 homes with battery storage systems, with a combined installed nameplate capacity of over 300 MW.[3]

FIGURE 2: RESIDENTIAL BATTERY STORAGE INSTALLED NAMEPLATE CAPACITY IN PG&E TERRITORY[4]



PG&E's Demand Response Emerging Technology (DRET) group initiated a Battery Study to investigate the potential for residential photovoltaic solar systems paired with a home battery system to support state electric grid reliability. By default, residential batteries can be used help offset household energy use and can also be programmed to discharge when rates are high. However, these batteries are often underused with regards to their ability to contribute to grid services. Many battery storage systems are used for back-up purposes only, and even if they are used to offset household energy use they may not export to the grid. PG&E designed the study to learn more about how batteries are currently being used, and to investigate the potential to recruit battery storage customers.

[3] https://www.californiadgstats.ca.gov/download/interconnection_rule21_projects/. Downloaded October 31, 2022. Last updated September 30,2022. Note that this value includes all storage projects, not just storage projects tied to PV.

[4] https://www.californiadgstats.ca.gov/download/interconnection_rule21_projects/. Downloaded October 31, 2022. Last updated September 30,2022. Note that this value includes all storage projects, not just storage projects tied to PV.

ASSESSMENT OBJECTIVES

The study's key objective was to assess how batteries can be dispatched to better meet grid needs. Additionally, the study wanted to determine how to best recruit battery storage customers for future storage programs. There were four main research questions that the study sought to answer:

1. **What are the enrollment rates for battery storage demand response programs?**
    a. How do incentive amounts and outreach methods affect participation rates for existing battery owners?
2. **How are battery storage customers using battery storage on their own?**
    a. What are the settings selected by the customer? Back-up only, self-powered, or time-based response?
    b. How much of their battery do customers reserve for back-up?
    c. What are the typical charge and discharge patterns for a battery?
    d. How well does a customer's "naturally occurring" battery use align with grid needs? What is the untapped value?
3. **How can we shift battery load to better meet grid needs?**
    a. How do batteries respond to event dispatch?
        i. What are the load impacts of dispatching battery storage?
        ii. What does a typical dispatch look like?
        iii. How successful was the battery response when dispatched for an event?
        iv. What are the key drivers of load impacts?
        v. How did the impacts vary with the data source used for the evaluation?
    b. How do batteries respond to price arbitrage?
        i. Are batteries able to respond to price arbitrage regardless of a customer's rate?
        ii. How are batteries able to respond to a time-of-use rate structure (TOU-C)?
        iii. How are batteries able to respond to Day-Ahead market prices (RTP)?
4. **Is the technology ready for a program?**
    a. How effective are existing algorithms?
    b. What improvements need to be made to existing algorithms?

EMERGING TECHNOLOGY/PRODUCT

Almost all batteries used for this study were LG chem batteries with usable capacity of 9.8 kWh per battery. Almost 90% of participants had only one battery and the remaining participants had two or more batteries. The age of customer batteries varied, with interconnection dates ranging from March 2018 to May 2022. All sites had SolarEdge inverters, which recorded data and were used to remotely control participant batteries. Over 90% of the recruited inverters were the SolarEdge StorEdge model, which was available from 2018 to 2022. The StorEdge model was superseded by the SolarEdge Home Inverter in mid-2022. Figure 3 depicts the StorEdge connectivity set-up in the home.

FIGURE 3: SOLAREDGE STOREDGE CONNECTIVITY DIAGRAM

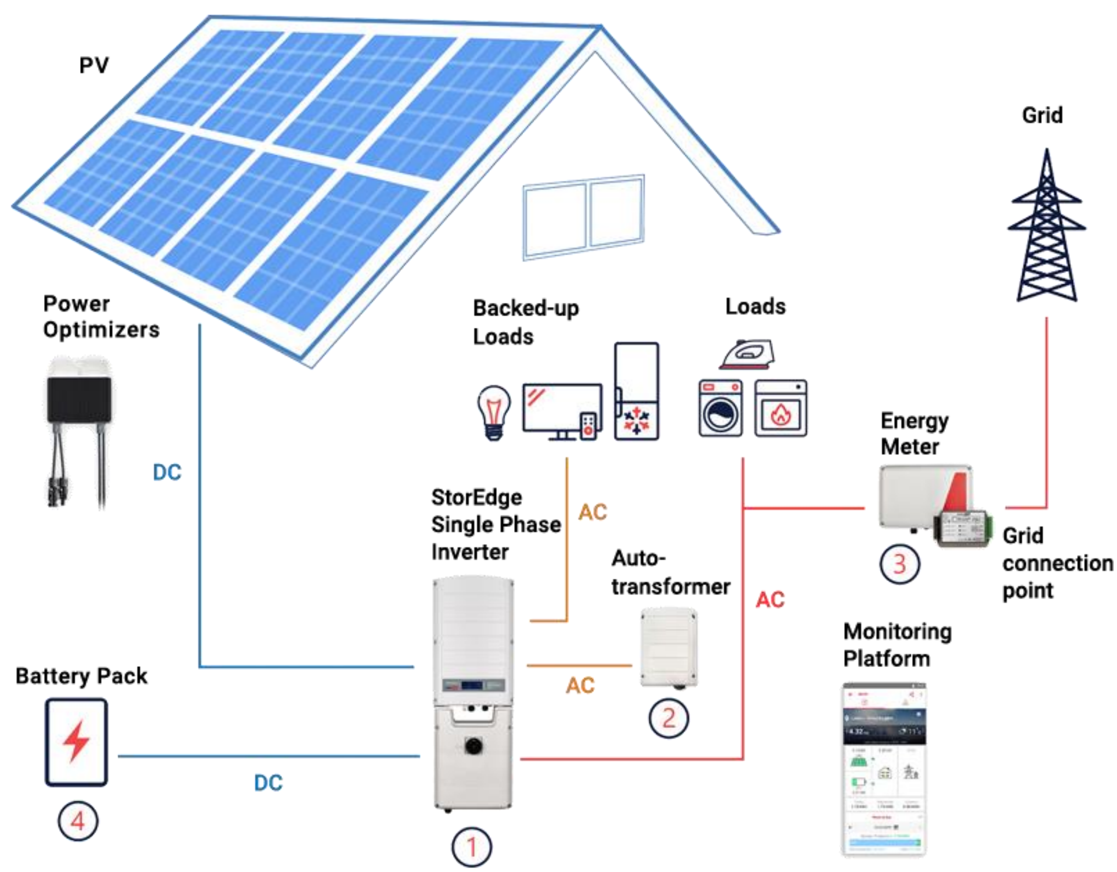
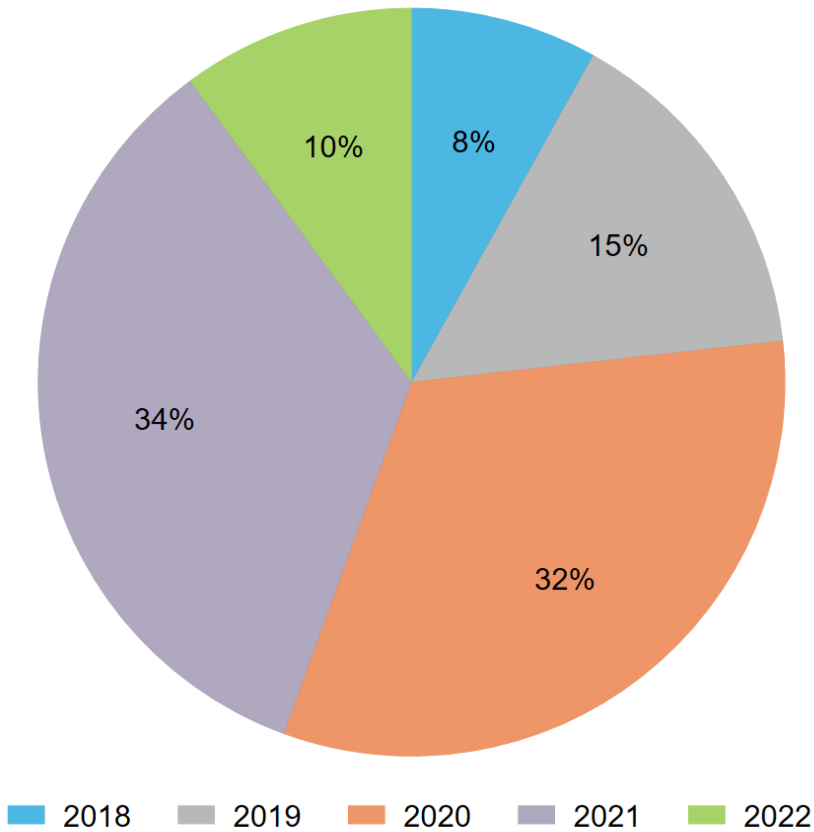


Figure 4 depicts the distribution of batteries by installation year. Almost half of the batteries were installed in 2021 or 2022, approximately one-third were installed in 2020, and the remaining batteries were more than two years old.

FIGURE 4: DISTRIBUTION OF SOLAREDGE INVERTER AGE



SolarEdge inverters recorded data and remotely controlled all participant batteries. The SolarEdge inverters communicate with homeowner devices using either Ethernet or wireless connectivity, and can record data for household load, solar generation, and battery charge/discharge data[5]. The inverter also has several operation modes available for the battery as a default. When setting up the battery during installation, the installer will set the battery settings for the homeowner. The homeowner can select from the following settings:

- Back-up;
- Maximize self-consumption; and
- Time of use cost saving.

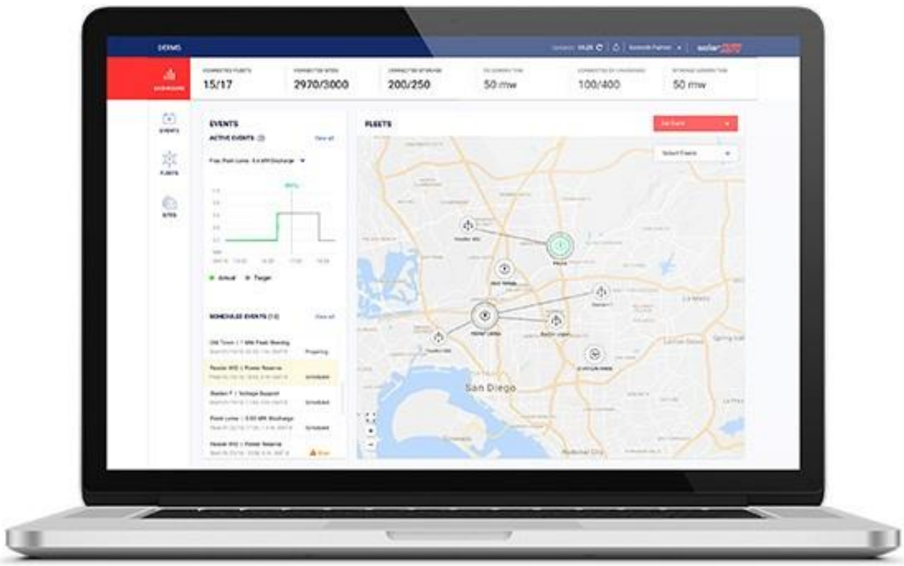
The inverter also allows the homeowner to select a portion of their battery to be reserved in case of an outage.

The inverter allows SolarEdge to remotely control the batteries using two different methods. The first method is through event dispatch. The SolarEdge DERMs software, depicted in Figure 5, can call both charge and discharge events. Charge events are designed to ensure that the battery fleet is fully charged prior to a discharge event. For charge events the batteries charge until full using solar generation. Initial charge events did not demonstrate a charging profile that was different from the control group charge shape. Later in the season, SolarEdge designed a charge event that would delay when a battery begins to charge (i.e.

[5] Specific inverter capabilities varied with the age and type of inverter.

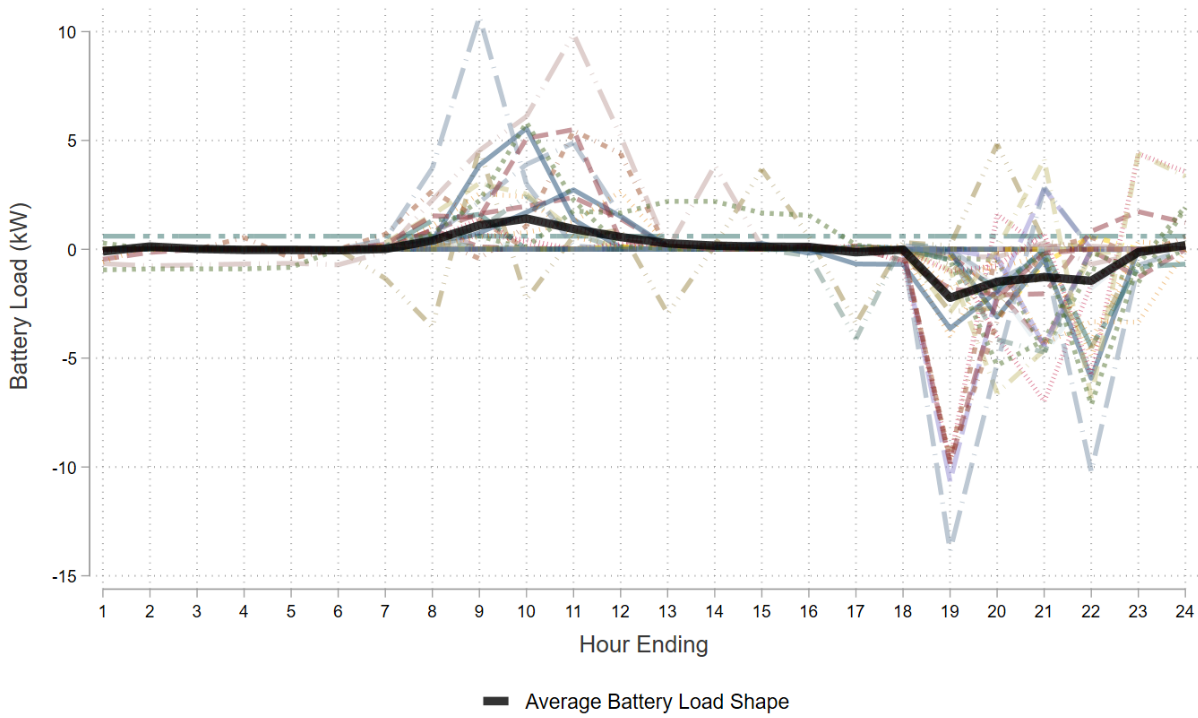
not starting charging when solar comes online but instead delaying charging until 11 AM when there is greater over-generation from solar). The battery fleet would still charge from solar and still charge until the battery was full.

FIGURE 5: SOLAREDGE DERMS SOFTWARE



Discharge events discharge a pre-specified kWh value over a selected event window. The event dispatch algorithm is designed to generate a flat dispatch shape across the event window for the entire fleet. The algorithm generates the flat shape by dispatching different residential batteries at different times. Figure 6 depicts how the algorithm is implemented for a four-hour event dispatched from 6-10 PM.

FIGURE 6: DISPATCH OF SITES IS ALTERNATED TO ACHIEVE A FLAT DISPATCH SHAPE AT A PORTFOLIO LEVEL



Note: 50 sample battery load profiles for 6/7/2022.

The second method for shifting battery load is what we refer to in this report as "price arbitrage". The SolarEdge price arbitrage software is depicted in Figure 7. With the price arbitrage method, the battery follows a price signal to maximize customer savings based on the hourly price shape. The algorithm discharges the battery when the rolling average price is highest. The price shape can change from day-to-day. Importantly, the batteries can be dispatched based on day-ahead hourly prices even when the customer bills are not exposed to them. For the study, PG&E shifted customer load using event dispatch from May through the beginning of September and shifted customer load using price arbitrage from mid-September through the beginning of November.

FIGURE 7: SOLAREDGE PRICE ARBITRAGE SOFTWARE

At the start of the study the evaluation team had also planned to investigate a secondary technology by working with LG to recruit customers that did not currently own battery storage systems. LG had planned to install LG- RESU 16H Prime BESS battery storage systems along with Lumin smart panels or Eaton smart breakers. The goal of this aspect of the study was to test how smart panels and smart breakers could be used in conjunction with residential battery storage to better meet grid needs. However, the study was unable to recruit enough customers in time to gather data and implement the study. As a result, we were unable to gather data on these technologies and did not include them in this report.

Customer Recruitment Tests

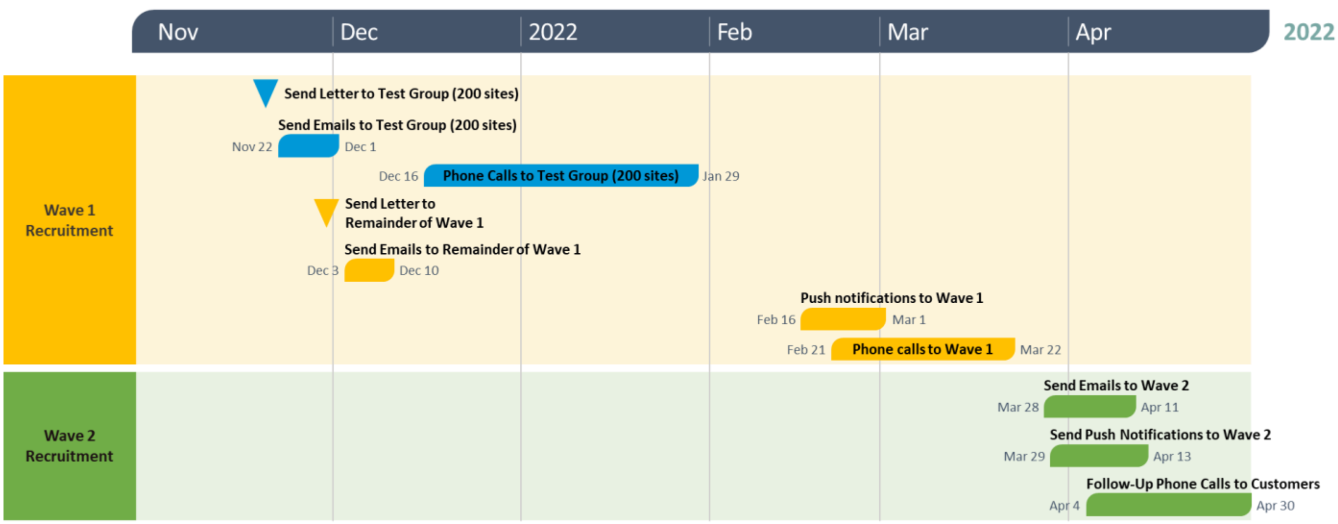
For the study, the evaluation team reached out to a total of 2,826 customers with SolarEdge inverters with the goal of recruiting at least 100 customers to participate in the study. We also implemented randomized control trials to quantify the relationship between incentive levels and customer enrollment, and the effectiveness of various recruitment techniques. Figure 8 depicts the recruitment timeline for the study. We recruited customers in two separate waves. The first wave of recruitment took place from November 2021 through March 2022. The second wave of recruitment lasted from March 2022 through April 2022.

We evaluated the following key questions around battery storage recruitment:

1. What are the enrollment rates for existing battery storage customers?
2. What is the relationship between incentive levels and enrollment rates?
3. What recruitment methods increase enrollment rates? By how much?
4. What are the enrollment rates for a pay-for-performance incentive structure?

The remainder of this section details the methodology, results, and key findings for customer recruitment.

FIGURE 8: CUSTOMER RECRUITMENT TIMELINE



Recruitment Methods

To recruit the battery storage customers for the study we implemented a multi-modal recruitment strategy, including customer letters, emails, push notifications and phone calls. We also explicitly varied these recruitment modes via randomized control trials to assess how customer enrollment rates varied with incentive levels and the recruitment modes used.

RECRUITMENT METHODS

Wave 1 and Wave 2 each had two separate recruitment strategies. For Wave 1, each customer initially received the following:

- 1 Letter
- 3 emails.

After initial recruitment efforts, there were still many customers in the recruitment pool that had not enrolled. For the remaining customers, the team employed the following recruitment strategies to improve enrollment rates:

- Phone calls for 50% of the remaining customers (randomly assigned); and
- Push notifications to 75% of the remaining customers (randomly assigned).

It should be noted that the pool of remaining customers consisted of sites that had not yet enrolled. As a result, the enrollment rates for these tests were lower than sites that enrolled in response to the initial offer. However, the tests were useful for assessing the effectiveness of different strategies to drive incremental enrollments.

For Wave 2, we recruited customers using the following methods:

- Email (all customers);
- Push notifications (80% of customers, randomly assigned); and
- Phone calls (all customers who started but had not yet submitted an application).

For greater detail on the recruitment process and examples of the recruitment materials sent to customers please see Appendices A and B.

INCENTIVE STRUCTURE

Approximately 85% of customers were offered a one-time sign up incentive, which paid customers based on the battery kWh that they were willing to commit to the program. For the one-time sign up incentive structure, the customers were allowed to select the percent of their battery capacity that they wished to commit to the program. The equation below depicts how each customer's total incentive was calculated:

EQUATION 1: SIGN-UP INCENTIVE CALCULATION

$$Total\ Incentive = Customer\ battery\ capacity\ (kWh) * \%\ Commitment * Incentive\ (\$/kWh)$$

The customer was allowed to select between 50% and 80% of their battery to commit to the program. The more of the battery that they were willing to commit the greater the incentive to the customer. Table 2 depicts the incentive options for a sample customer with a 10 kWh battery and an incentive of $100/kWh.

TABLE 2: SAMPLE SIGN-UP INCENTIVE OPTIONS FOR A CUSTOMER WITH A $100/KWH INCENTIVE AND A 10 KWH BATTERY CAPACITY

	50 % Commitment	60% Commitment	70% Commitment	80% Commitment
Customer Total Incentive	$500	$600	$700	$800

Because the incentive was based on the kWh commitment to the program, customers with a larger battery or multiple batteries were eligible for larger incentives than a customers with fewer or smaller batteries, even though the incentives per battery kWh ($/kWh) were the same.

Each customer received a portion of their incentive up-front for signing up for the program and the remainder of their incentive at the end of the study if they remained enrolled in the program through the end of September 2022. If, for example, the sample customer in Table 2 receives 70% of their incentive up front and commits 80% of their battery to the program, then they receive $560 for signing up for the program and $240 for staying enrolled in the program through the end of September 2022.

Approximately 15% of customers were randomly assigned to receive performance based incentives without a sign-up incentive. These customers were offered $2 per kWh discharged during study events. The pay-for-performance customers were similarly allowed to select the portion of their battery that they wished to commit to the program and were shown their expected incentive range based on their percent commitment and the number of events that the study expected to dispatch over the course of the summer.

To determine how the total incentive and the different incentive structures appealed to customers, we intentionally varied the incentive in a randomized control trial (RCT) design, which is described in more detail in the next section.

STUDY DESIGN

We tested the effectiveness of customer recruitment strategies over two separate waves, each drawing from a different enrollment pool[6]. To test the effectiveness of each enrollment strategy we employed randomized control trials (RCTs), where each member of the recruitment pool was randomly assigned their recruitment strategy and incentive. Wave 1 tested:

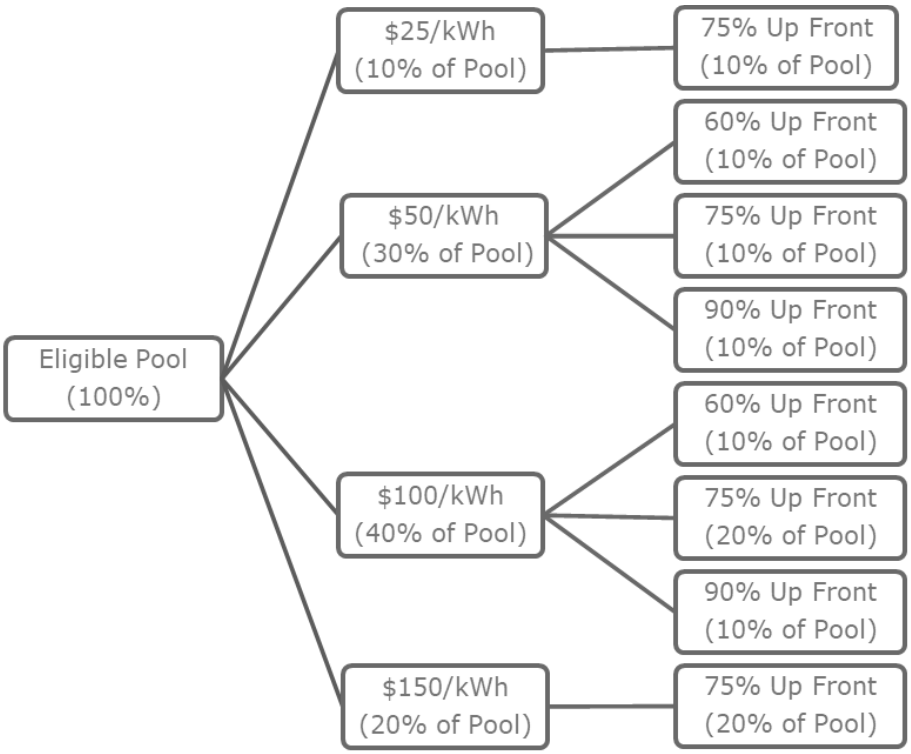
1. The relationship between the magnitude of sign-up incentives and enrollment rates;
2. The effect of incremental follow up phone calls on enrollment rates; and
3. The impact of share of incentives paid up-front incentive on enrollment rates.

Each customer was randomly assigned an incentive rate, the percent of the incentive that was paid up-front, and whether they would receive a phone calls. Figure 9 depicts the incentive assignment and up-front payment assignments. Customers

[6] See Appendix A for more information on how each enrollment pool was developed.

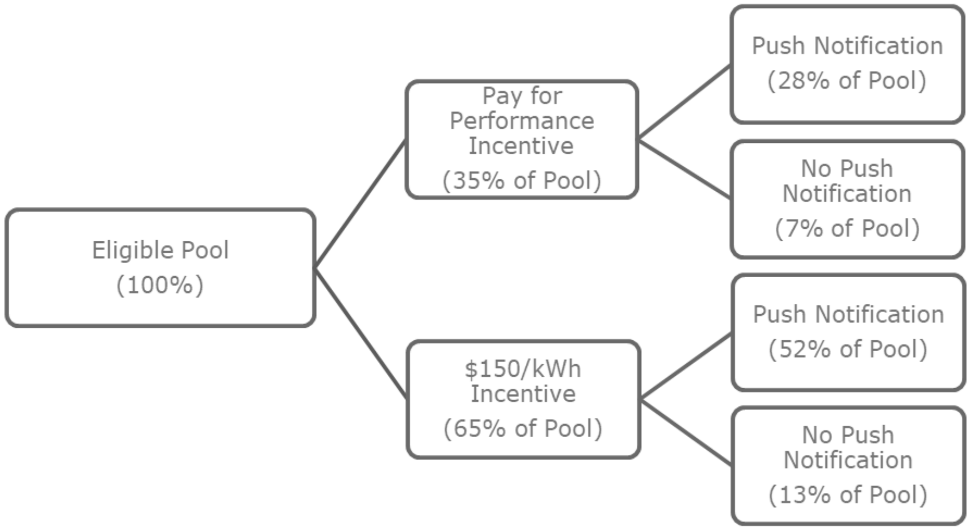
were randomly assigned to an incentive based on the battery kWh made available in the amount of $25/kWh, $50/kWh, $100/kWh, or $150/kWh. They also randomly assigned to receive 60%, 75%, or 90% of their incentive up-front. In addition, a subset of the customers in the Wave 1 recruitment pool were randomly assigned to receive a follow up phone call. We called 50% of the remaining recruitment pool after initial recruitment efforts, calling approximately 350 customers.

FIGURE 9: WAVE 1 INCENTIVE TEST DESIGN



The wave 2 recruitment tested the efficacy of push notifications and customer willingness to enroll in a program with a P4P incentive structure. Like Wave 1, we randomly assigned push notifications and a P4P incentive structure to a subset of the recruitment pool to determine the variation in enrollment as a result of these recruitment strategies. Figure 10 depicts the random assignment for Wave 2.

FIGURE 10: WAVE 2 P4P AND PUSH NOTIFICATION TEST DESIGN



RESULTS

We measured enrollment as a function of two separate metrics. The first metric was the application rate, which indicates that the customer elected to enroll in the program and submitted an application. The second metric was the customer enrollment rate, which includes all customers who submitted an application and passed all the post-application technical screens. Overall, 181 customers (6.5%) of the enrollment pool applied to participate, and 120 customers met the post-application technical screening requirements, for an enrollment rate of 4.5%.

Because of the RCT design, we were able to measure enrollment rates as a function of each of the recruitment efforts that we employed. Because customers had no control over the technical requirements, we compare application rates for the remainder of the section.

Figure 11 depicts the application rate for the four different incentive levels offered in Wave 1. While the application rate increases as the incentive rate increases, the largest increase in application rates occurs between the $100/kWh and $150/kWh incentives. While the relationship between application rates and incentives is nonlinear, we find that doubling the incentive increases application rates by 1.64X (the marginal effect).

FIGURE 11: APPLICATION RATE BY INCENTIVE OFFERINGS

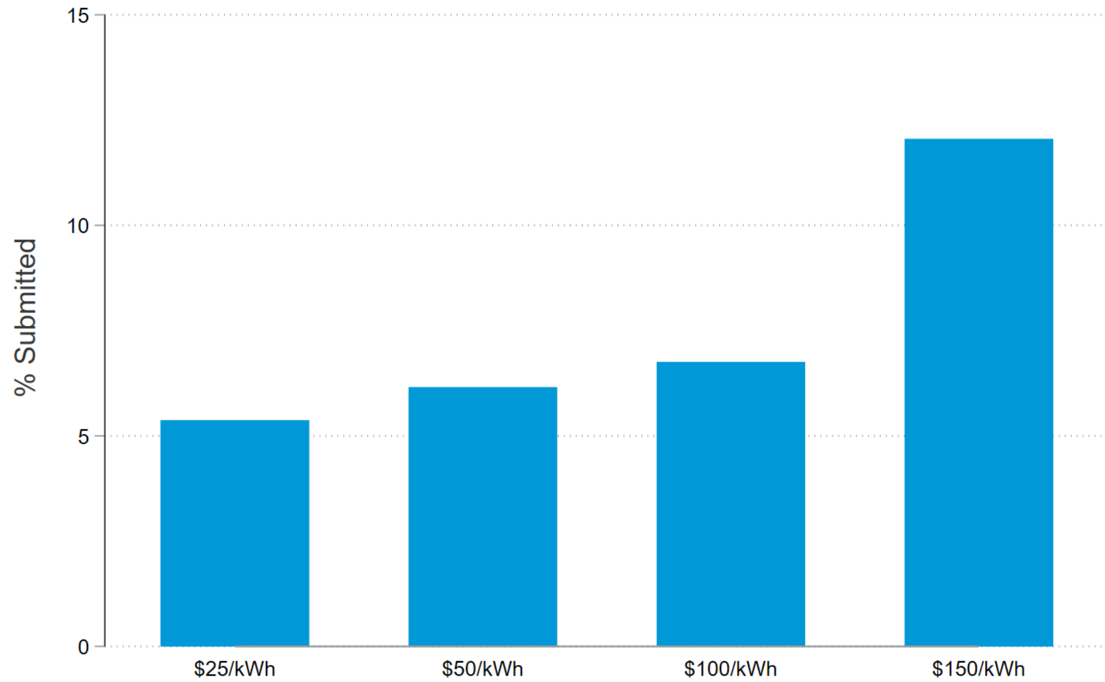


Figure 12 compares the application rates for customers who did and did not receive follow up recruitment phone calls for Wave 1. Among the remaining recruitment pool, customers who received a phone call had a application rate more than triple that of customers who did not receive a phone call during Wave 1.

FIGURE 12: APPLICATION RATE BY PHONE CALL OUTREACH

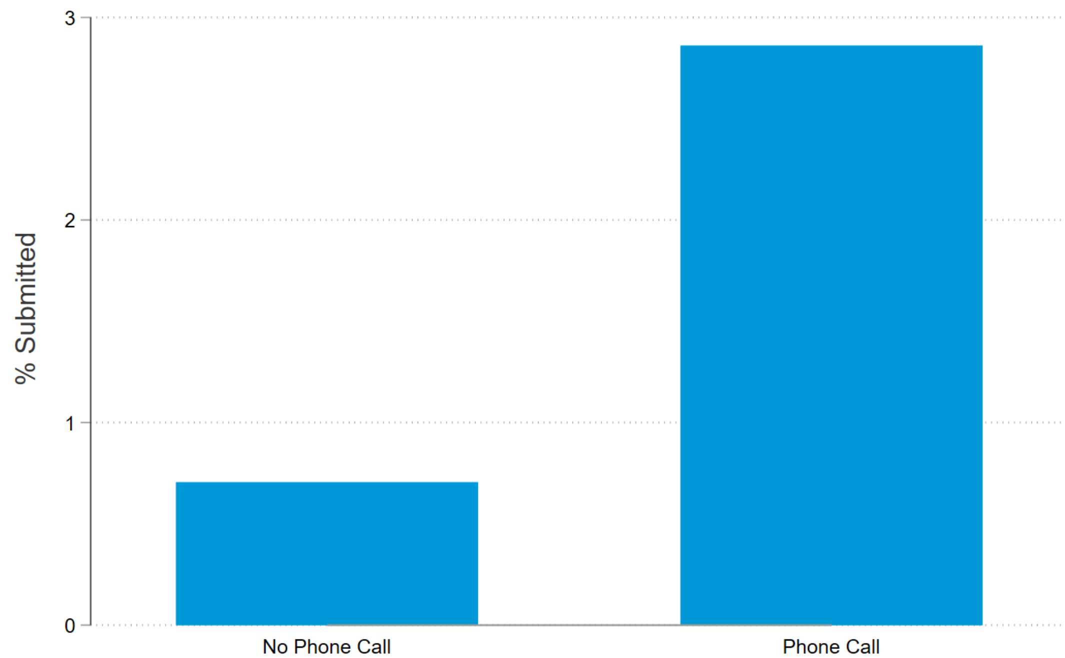


Figure 13 compares the application rates for customers who received or did not receive a push notification for Wave 2. Similar to the phone call recruitment method, customers who received a push notification had more than triple the enrollment rate compared to customers who did not receive a push notification.

FIGURE 13: APPLICATION RATE BY PUSH NOTIFICATION OUTREACH

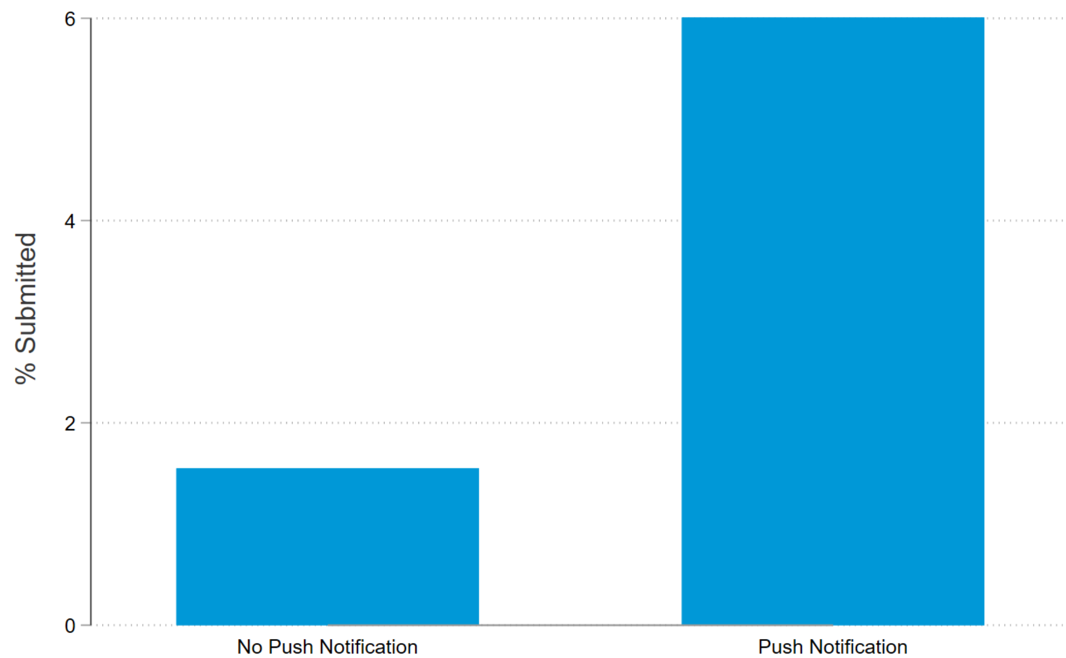
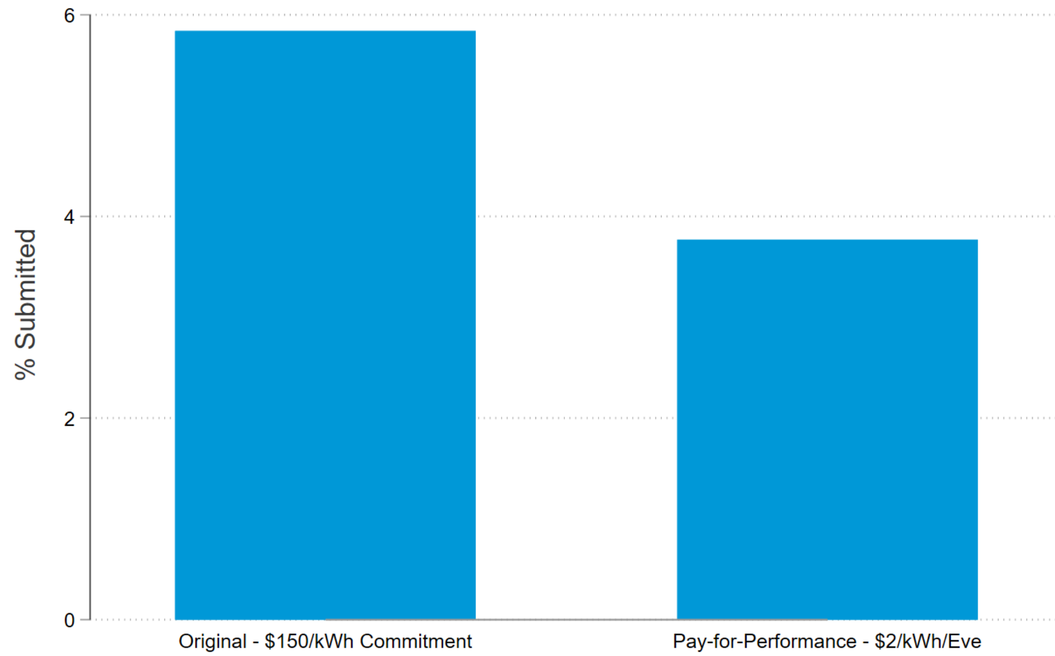


Figure 14 compares the application rate for the two different incentive structures that were offered to customers during Wave 2 enrollment. Even though the $150/kWh one-time sign-up incentive was much higher incentive than the P4P incentive structure[7], 3.8% of customers submitted an application for the P4P structure compared to an application rate of 5.8% for the original incentive structure.

[7] The average incentive for a P4P participant for one year of participation was $212, compared to an average incentive of $1,108 for the average one-time sign-up incentive. However, the total incentive would potentially change with multiple years of participation.

FIGURE 14: APPLICATION RATE BY INCENTIVE STRUCTURE



KEY TAKEAWAYS

Based on the enrollment findings, we can draw several conclusions around participation rates for existing battery storage customers. Table 3 summarizes the key questions and findings for customer battery storage enrollment.

TABLE 3: ENROLLMENT KEY TAKEAWAYS

Research Question	Findings
What are the enrollment rates for existing battery storage customers?	181 customers and 6.5% accepted the offer to enroll in a battery storage study, and 120 customers met technical screening requirements for overall enrollment rate of 4.5%.
What is the relationship between upfront incentive levels and enrollment rates?	Doubling the upfront incentive amount increases study participation by 1.64x.
What recruitment methods increase enrollment rates? By how much?	Phone calls improved enrollment rates by 3x, but there may be interviewer-specific effects. Push notifications increased enrollment rates by 10x.

What are the enrollment rates for a pay-for-performance incentive structure?	3.8% of customers pay-for-performance incentives (with no upfront incentive) accepted the offer. The overall enrollment rate, after technical screens was 2.4%.

TYPICAL CUSTOMER BATTERY USE

Once customers enrolled in the battery storage program, we were able to gather their data and assess the behavior of battery storage customers absent intervention. We gathered data from January 2022 through October 2022 on all days when customers did not respond to event or price arbitrage signals. In order to determine typical customer behavior, we looked at several different end uses, including customer net metered consumption and at customer behind-the-meter usage for battery storage, solar, and household consumption.

We examined the following key research questions when looking at typical customer battery use:

- How much power do people reserve for backup?
- What are typical charge and discharge patterns?
- How well does their "natural battery use" with grid needs? What is the untapped value?

The remainder of this section details the data sources, customer usage patterns, and key takeaways for typical customer battery use.

DATA SOURCES

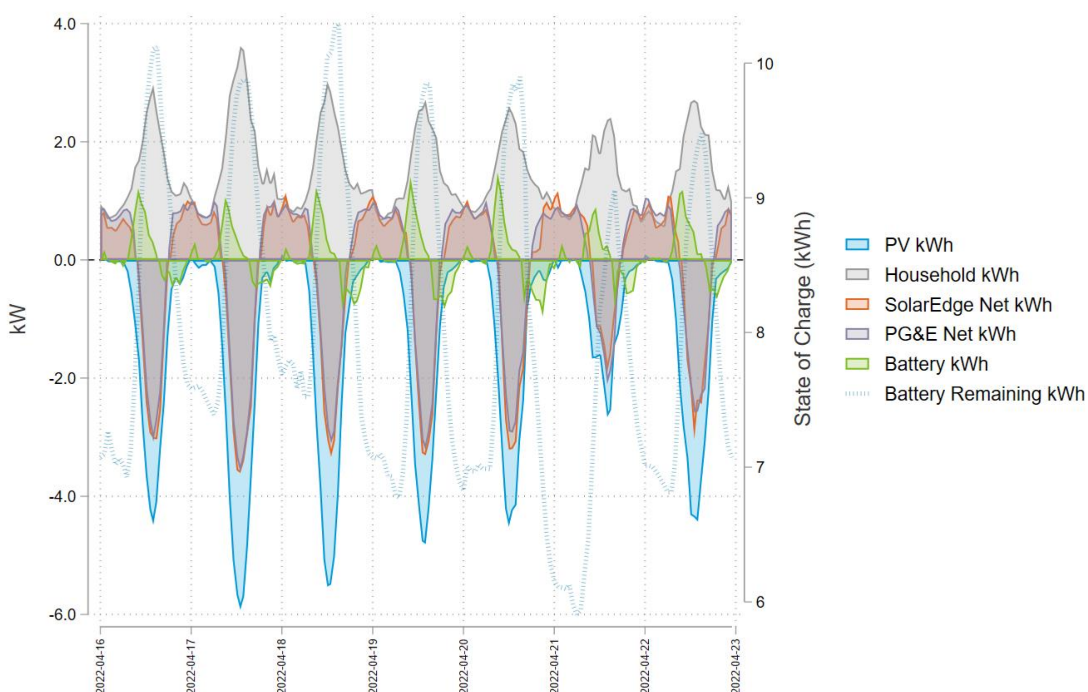
To determine customer battery use patterns the research team used both end-use metered (sub-meter) data and net household data to determine the battery charge/discharge patterns and the change to the customer net load. SolarEdge and PG&E provided the evaluation team with several different metered data sources at both the end-use and net household level. As a part of the analysis, the evaluation team assessed the quality of the end use data and household level data provided by SolarEdge. The evaluation team also gathered demographic information from customers when they enrolled in the program. The data sources for the evaluation included:

- **PG&E Participant characteristics**, which provided additional demographic information about program participants, including their rate, climate zone, EV status, and installation date of their battery storage system.
- **Participant-submitted demographic data**, including the customer's EV ownership status and the square footage of their household.
- **SolarEdge-metered historic participant battery charge/discharge data** in 5-minute increments from the start of when the customer successfully enrolled in the study, for up to 11 months total. A sample load shape of the data over time can be seen in Figure 15, where positive load indicates the battery is charging and negative load indicates the battery is discharging.
- **SolarEdge-metered historic participant solar discharge data** in 5-minute increments from the start of when the customer successfully enrolled in the study, for up to 11 months total. A sample load shape of the data over time can be seen in Figure 15, where negative load indicates solar generation.
- **SolarEdge-metered historic participant household data** in 5-minute increments from the start of when the customer successfully enrolled in the study, for up to 11 months total. A sample load shape of the data over time

can be seen in Figure 15, where positive load indicates the household consumption – excluding any battery storage or solar generation.

- **SolarEdge-metered historic participant net load data** in 5-minute increments from the start of when the customer successfully enrolled in the study, for up to 11 months total. A sample load shape of the data over time can be seen in Figure 15, where negative load indicates net discharge to the grid and positive load indicates net consumption from the grid.
- **SolarEdge-metered battery remaining kWh** in 5-minute increments from the start of when the customer successfully enrolled in the study, for up to 11 months total. A sample load shape of the data over time can be seen in Figure 15 on the second axis, where the kWh indicates the remaining battery capacity.
- **PG&E-metered participant household level data** in 15-minute increments for a total of 11 months for all participants. As with the SolarEdge participant net load data, positive load indicates net consumption from the grid and negative load indicates net discharge to the grid.
- **Weather data from the California Weather Advisory Council,** including temperature and solar radiation, for the relevant climate zones and zip codes of program participants.

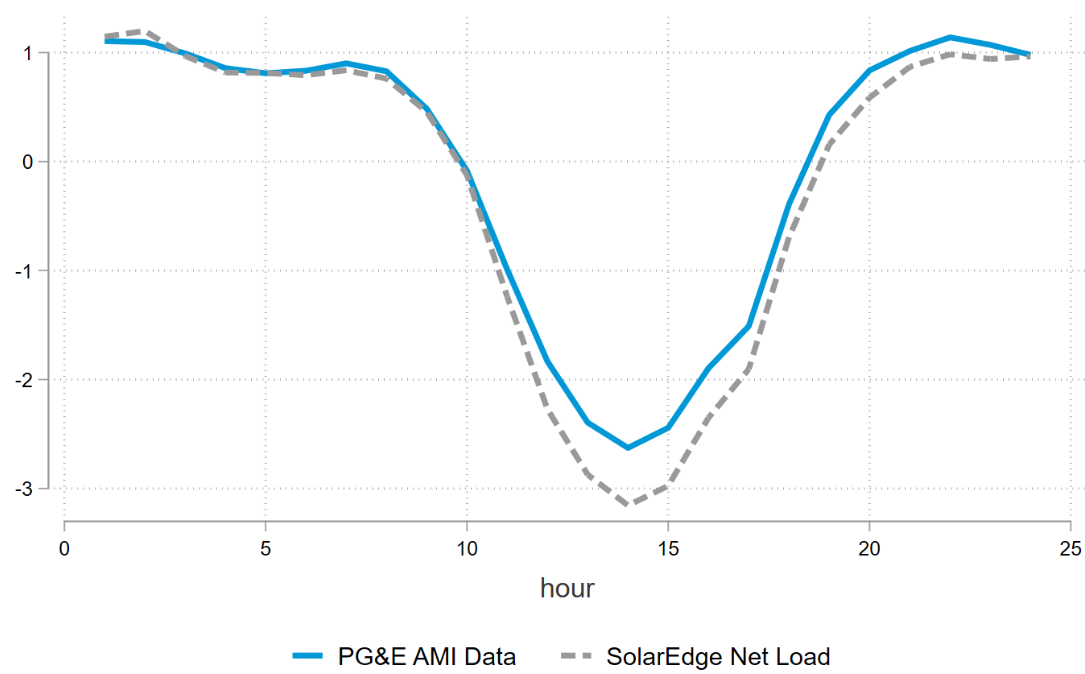
FIGURE 15: EVALUATION DATA SOURCES



Both PG&E and SolarEdge provided net load data for each customer during the study period. We compared the two data sources as a proxy for the quality of SolarEdge metering. Figure 16 compares the two data sources for the average participant on an average day. On average the overall magnitude of the PG&E AMI data (distance from 0) is 10% lower than that of the SolarEdge data. This difference varies by participant, with approximately 40% of participants having almost identical net loads when comparing PG&E and SolarEdge data and the remaining participants showing SolarEdge net loads that were either consistently higher or consistently lower compared to the PG&E AMI data net loads. The SolarEdge StorEdge had Current Transformers (CT's) sensors to measure net load fitted at the site during time of installation. The SolarEdge Home Inverter launched in 2022 has factory fitted and calibrated CT's

While PG&E data and SolarEdge data were similar when both data sources were available, the SolarEdge data had less overall coverage compared to PG&E data. On average, the team only successfully retrieved 85% of the available data for the fleet for each day over the study period and on some days data was not available. Because of these differences, we assessed load impacts for both data sources separately and do not directly compare them in this report.

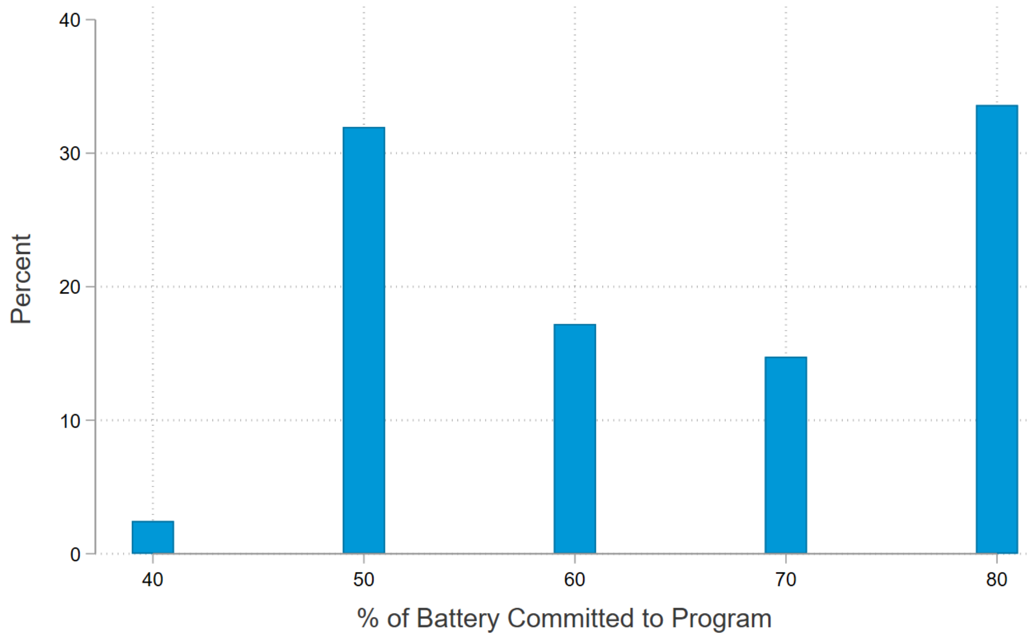
FIGURE 16: COMPARISON OF PG&E AND SOLAREDGE NET LOAD DATA



CUSTOMER BACK-UP RESERVE PATTERNS

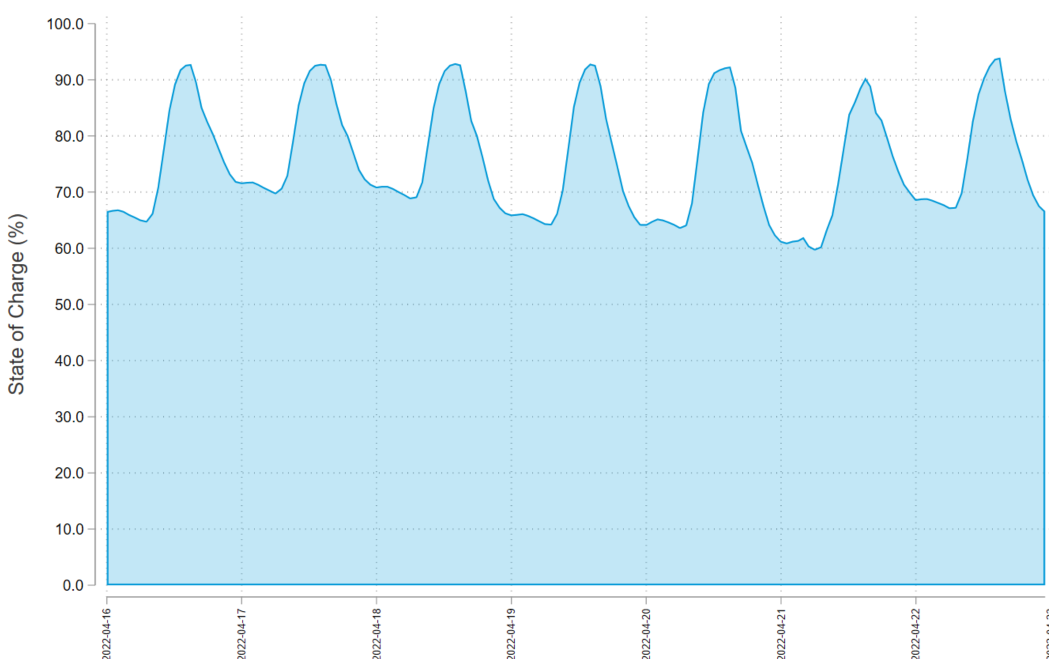
When operating their batteries customers are allowed to select a specific portion of their battery to be reserved as backup in case of an outage. When enrolling in the program, almost all customers were allowed to commit between 50-80% of their battery to the program, while reserving the remainder for back-up power. P4P customers were allowed to commit as little as 40% to the program. Figure 17 depicts the distribution of the percent commitment to the program selected by participants. When selecting the percent of their battery to commit to the program, customers typically selected one of the two extremes (50% or 80%) to commit to the program.

FIGURE 17: DISTRIBUTION OF BATTERY CAPACITY COMMITMENT TO PROGRAM



Absent intervention, customers were allowed to dispatch their batteries as they had prior to enrolling in the program. Figure 18 depicts the state of charge for the fleet during a typical week. We can see that at the fleet level, the overall state of charge does not dip below 60%, indicating that there is a significant amount of capacity available for dispatch during times of grid need.

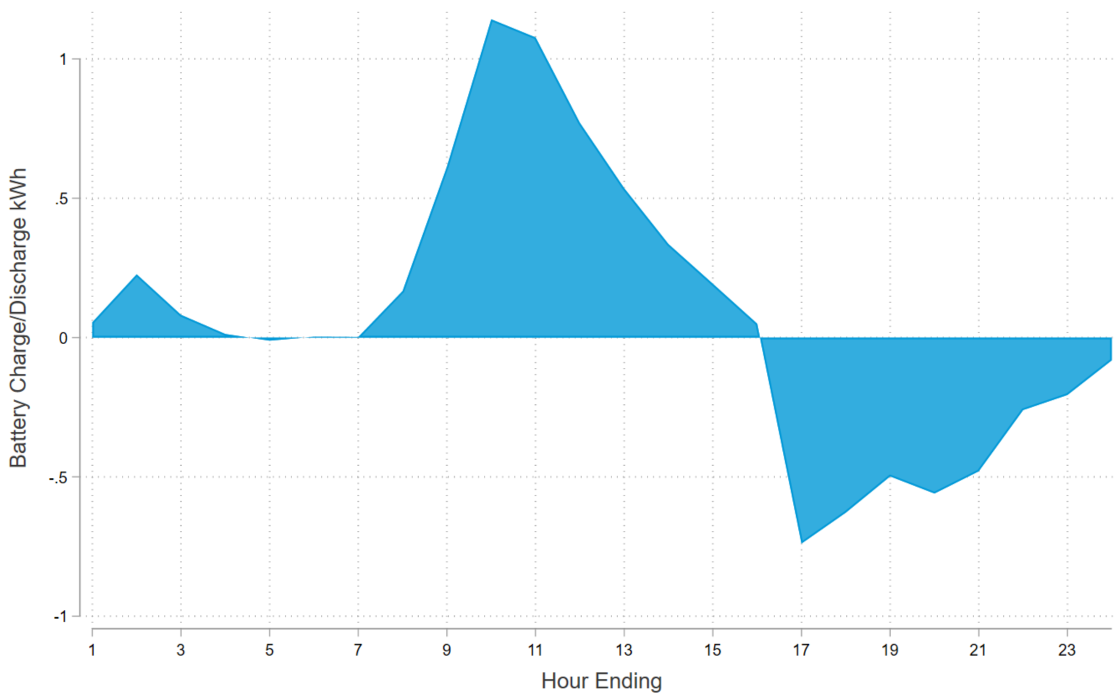
FIGURE 18: STATE OF BATTERY CHARGE



Typical Customer Battery Use

Figure 19 depicts the charge and discharge patterns of an average participant's battery on an average summer day absent any intervention. We can see that the battery typically charges in the morning when solar generation begins and stops charging at the start of the time-of-use peak price window (4 PM). At 4 PM the battery starts discharging, with some amount of discharge continuing through the remainder of the evening. Between 4 PM and 9 PM, when customers on TOU rates experience higher prices, the batteries discharge 0.5 kW to the grid on average and discharge a total of 2.9 kWh, which is significantly lower than the battery's full capability. There is also a slight increase in the battery discharge at 7 PM. This is from customers in the maximize self-consumption mode, which has batteries begin to discharge once solar goes offline. In the summer, this typically took place between 7 PM and 9 PM.

Figure 19: Average Customer Battery Charge/Discharge Shape – Average Summer Day



The relatively low average discharge rate during the peak window is largely due to differences in battery discharge patterns across customers. Figure 20 depicts the average 4-9 PM charge and discharge pattern for customer batteries across all study participants. While some batteries are discharging 4 kW on average between 4 and 9 PM, many customers are not discharging their batteries at all. The customers who do not discharge their battery are the largest contributors to the available capacity for the fleet overall. This is due to the variation in the customer-selected settings. Batteries set to the time of use cost savings setting will discharge their battery starting at the beginning of the TOU peak window. Similarly, batteries in the maximize self-consumption mode will begin to discharge when solar goes offline, which also occurs between 4 PM and 9 PM. The batteries that do not discharge in the evenings are those that are in back-up mode.

FIGURE 20: AVG. 4-9 PM DISPATCH BY PARTICIPANT

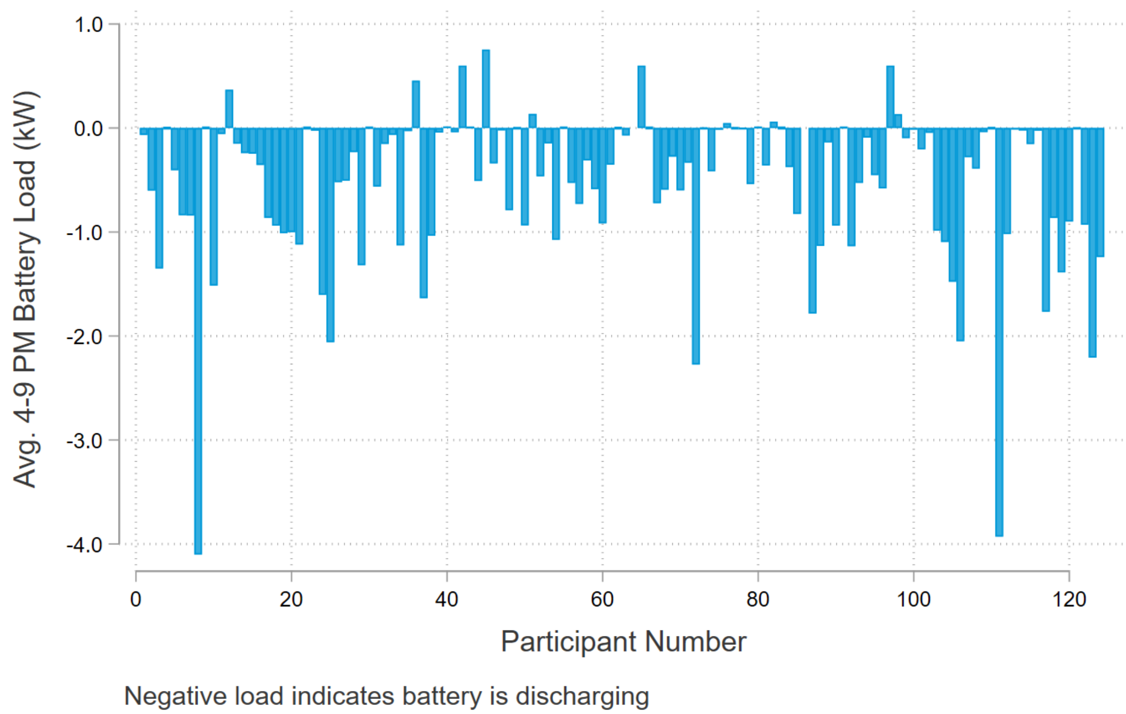
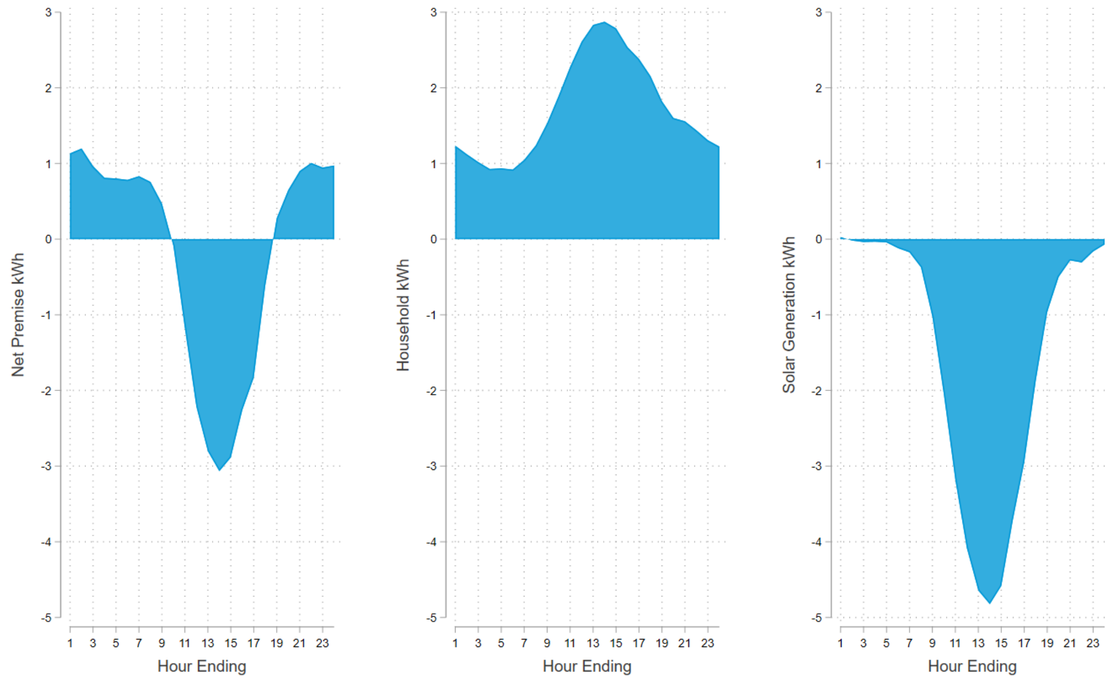


Figure 21 depicts the average customer loads on summer days from other end uses absent intervention. The first panel in the figure depicts customer net load. We can see that the net load for the average customer is largely negative during daylight hours when solar production is high, with net positive consumption peaking at around 1 kW from 6 PM through 9 AM the following day. The increase in net load tends to occur in the evening from 4 PM to 9 PM as solar goes offline, and there is a slight notch in the increased net load from battery discharge during the evening hours.

The second panel depicts the average household consumption absent any additional DER load. We can see that the household summer load is tied to cooling load and peaks in the late afternoon, earlier than the peak of the customer's net load. The third panel depicts the solar generation for the average customer. The solar load is tied to daylight hours and the peak generation occurs in the early afternoon.

FIGURE 21: AVG. CUSTOMER LOAD SHAPES – OTHER DATA SOURCES ON AVG. SUMMER DAY



CUSTOMER BATTERY USE ON PEAK DAYS

While average summer consumption patterns can be useful, they do not depict how customers behave during times of grid stress when there are extreme temperature conditions. We therefore separately examined customer battery use during the 2022 peak weekday, which occurred on September 6, 2022. Figure 22 depicts battery charge and discharge patterns during the peak weekday. Customers discharged more during the peak period, with an average discharge of 0.9 kW during peak hours (4-9 PM). However, there is still additional capacity available to be discharged during these periods.

FIGURE 22: AVERAGE CUSTOMER BATTERY CHARGE/DISCHARGE SHAPE – 2022 PEAK WEEKDAY

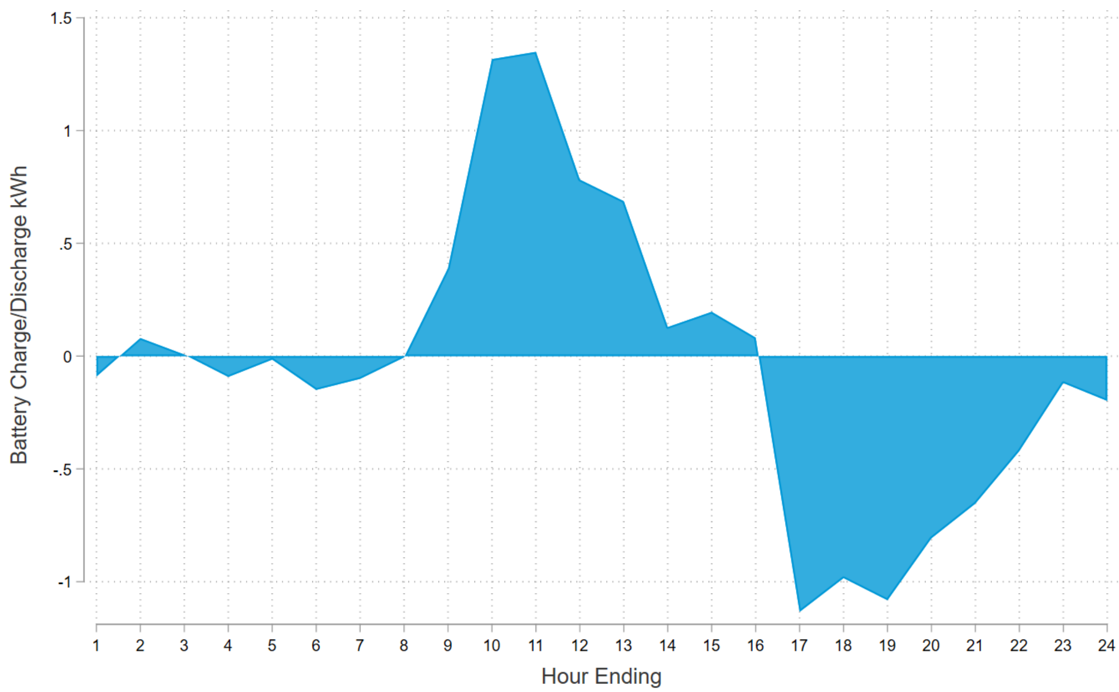
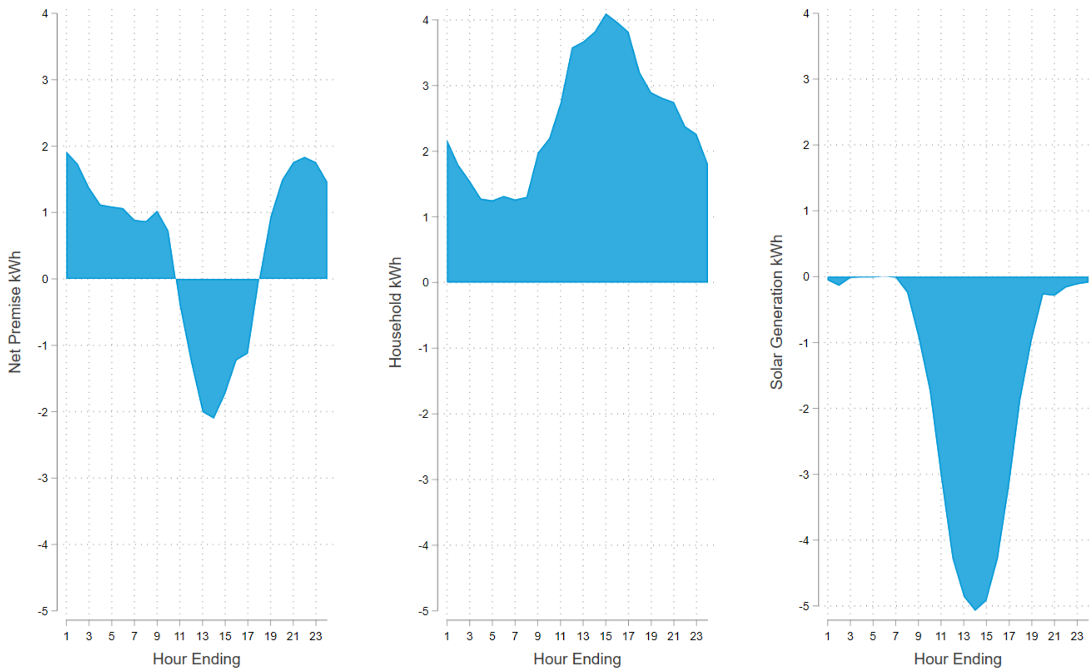


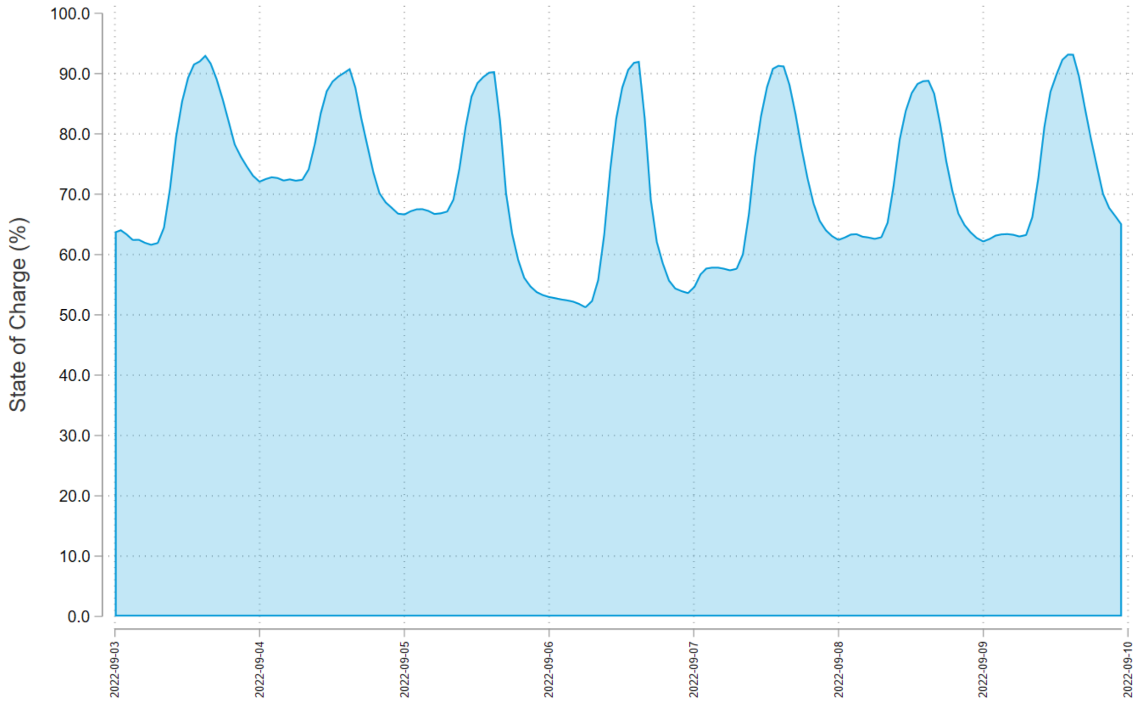
Figure 23 depicts the consumption from other end uses during the peak period. On peak days we see much higher household consumption with similar PV generation, which leads to a much steeper ramp in net load during the evening hours. Similar to the average weekday, we do see a notch from battery discharge beginning at 4 PM but there is still a steep ramp later in the evening.

FIGURE 23: AVG. CUSTOMER LOAD SHAPES – OTHER DATA SOURCES ON 2022 PEAK WEEKDAY



Finally, Figure 24 depicts the available capacity during the week where the peak weekday occurred. We can see that although batteries discharged during times when the grid was under stress (September 6 and September 7), more than 50% of battery fleet capacity was still available for dispatch, indicating untapped potential that could be accessed by PG&E.

FIGURE 24: BATTERY FLEET STATE OF CHARGE DURING 2022 PEAK WEEKDAY



KEY TAKEAWAYS

Table 4 summarizes the key questions and findings for typical customer battery use.

TABLE 4: TYPICAL CUSTOMER BATTERY USE KEY TAKEAWAYS

Research Question	Findings
Does the data from PG&E align with the SolarEdge data?	On average, the PG&E data is 10% smaller in magnitude compared to the SolarEdge data when comparing household net loads. The degree to which the two data sources aligned varied by participant, with approximately 40% of participants having almost identical PG&E and SolarEdge data.
How much power do people reserve for backup?	Customers typically committed either 50% or 80% (the maximum) of their battery capacity to the program, on average committing 64%. However, the fleet does not typically discharge below 60% of the overall battery capacity.

What are the typical charge and discharge patterns absent intervention?	On average, batteries start charging from solar when the sun rises and stop when they are fully charged. Charging typically starts at 8 AM and on average charge 4.7 kWh between 8 AM and 2 PM. Batteries typically start discharging at 4 PM, as the sun sets, and on average discharge 2.9 kWh between 4 PM and 9 PM.
How well does a customer's "naturally occurring" battery use align with grid needs? What is the untapped value?	On peak days, there is higher battery discharge for the average customer but there is a larger ramp in customer net load between 4 PM and 9 PM due to higher household load. There is also still a large amount of untapped capacity on peak days – 50% of the battery fleet was not discharged. Without intervention, the batteries tend to discharge earlier than on the net peak load hours or highest price hours.

SHIFTING BATTERY LOAD – EVENT DISPATCH

We leveraged two methods for accessing the untapped battery storage potential among participants. The first method, which we discuss here, was event dispatch. The SolarEdge DERMs software can call both charge and discharge events. Charge events are designed to ensure that the battery fleet is fully charged prior to a discharge event. Discharge events discharge a pre-specified kWh value over a selected event window.

To determine how batteries responded to event dispatch, we designed an operations plan that tested how batteries performed under varied event conditions and for different event types. We aimed to answer the following key questions:

- What are the load impacts of dispatching battery storage?
- What did a typical dispatch look like?
- How successful was the battery response when dispatched for an event?
- What are the key drivers of load impacts? How do the load impacts vary by:
  - Event timing
  - Event duration
  - Advance Notice; and
  - Weather conditions.
- How did the impacts vary based on the data source used for the evaluation?

The remainder of this section describes the methodology, results, and key takeaways for shifting participant battery load through event dispatch.

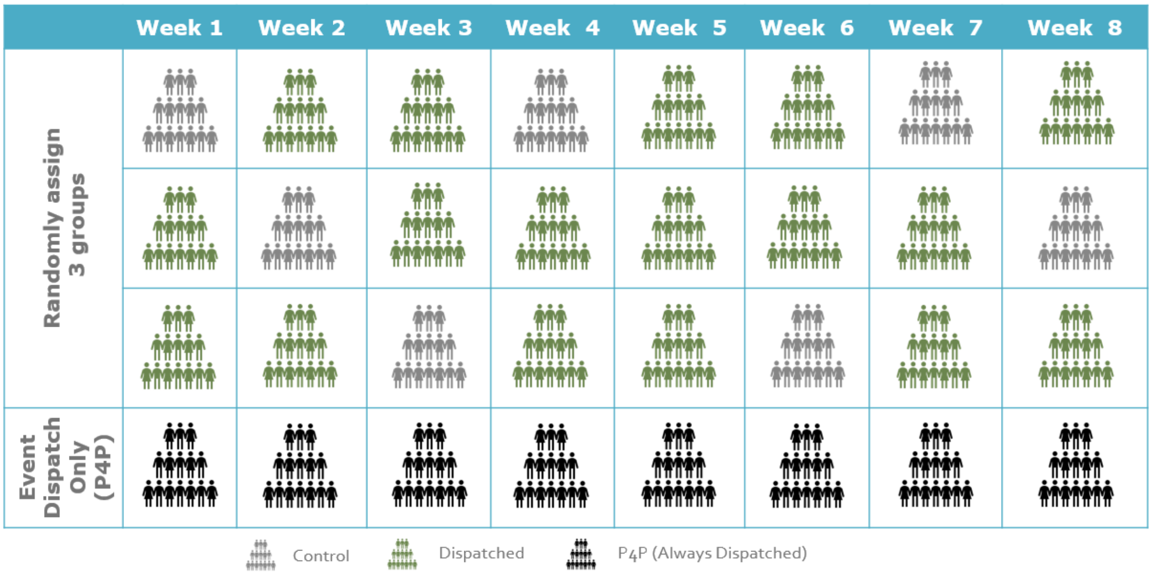
STUDY DESIGN & EVALUATION METHODOLOGY

Customers that were recruited using the sign-up incentive method were randomly assigned to one of three groups. These groups were alternately available for event dispatch each week and their availability for dispatch rotated through each week. The design allowed us to implement a randomized control trial for the purpose of evaluation. Additionally, the design allowed our team to call more events without increasing the number of events that participants experienced. P4P customers participated in all events because they were paid based on the kWh dispatched.

The primary evaluation method was a randomized control trial analyzed using a difference-in-differences panel regression. Figure 25 below summarizes the core concept of the randomized control. For each event day, participants with connected devices are randomly assigned to be dispatched or serve as a control. Because the sites are randomly assigned, they are equivalent in all aspects, but some differences can occur due to sampling. On the event day, all sites except those assigned to serve as a control group are dispatched. The control group is used to establish the baseline of what loads would have been if sites hadn't been dispatched. The control sites are in the same geographic locations, experience the same weather, and have same characteristics – the only difference is that one group was dispatched while another group was not. With large enough sample sizes, the approach produces very precise load impacts estimates.

During some weeks, as indicated by week 5 in the figure below, all three groups were dispatched without a control group to determine the total MW available for the program. For these events, we ran a within-subjects panel regression to estimate impacts for the event.

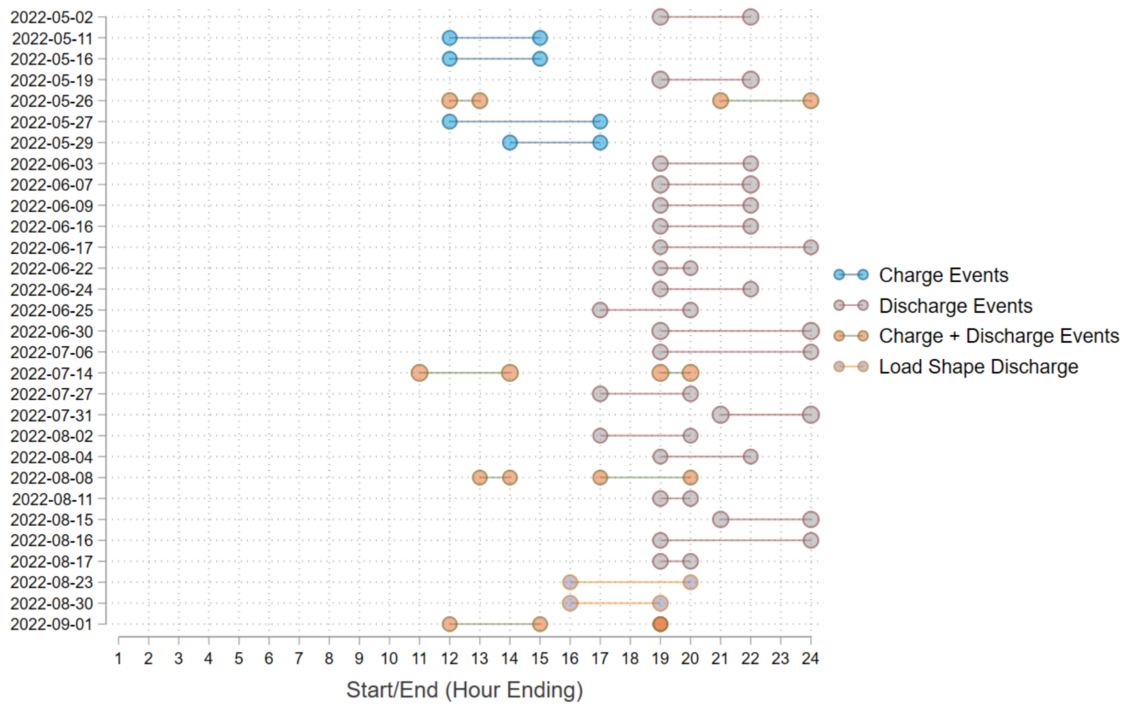
FIGURE 25: EVENT DISPATCH STUDY DESIGN



We called a total of 34 events over the course of 2022. The operations plan varied the type of dispatch, event start time, event duration, and advance notice (not pictured in the figure below). Events were dispatched over weather conditions ranging from a maximum daily temperature of 61ºF to a maximum daily temperature of 88ºF to determine if there was a relationship between impacts and temperature. The base event duration was 4 hours, but we also called events with a duration of 1 hour, 2, hours, and 6 hours. The base advance notification was 24 hours, but we also gave advance notice of 6 hours, 3 hours, and 1 hours. Finally, the base start time for discharge events was 6 PM, but we also began discharge events at 4 PM and 8 PM.

We called four different types of events over the course of the summer. The first two event types called charge events and discharge events separately, the third event type combined charge events and discharge events together into a single day, and the fourth event type called consecutive one hour events with pre-specified kWh values for each event to determine if the battery fleet could dispatch a shape that was not flat. Figure 26 depicts the characteristics of all the events that were called over the course of the summer, including event type, start time, and event duration. Advance notice is not included in the graphic below. See Appendix C for detailed event impacts for each event, including the advance notice and event temperature.

FIGURE 26: 2022 EVENTS

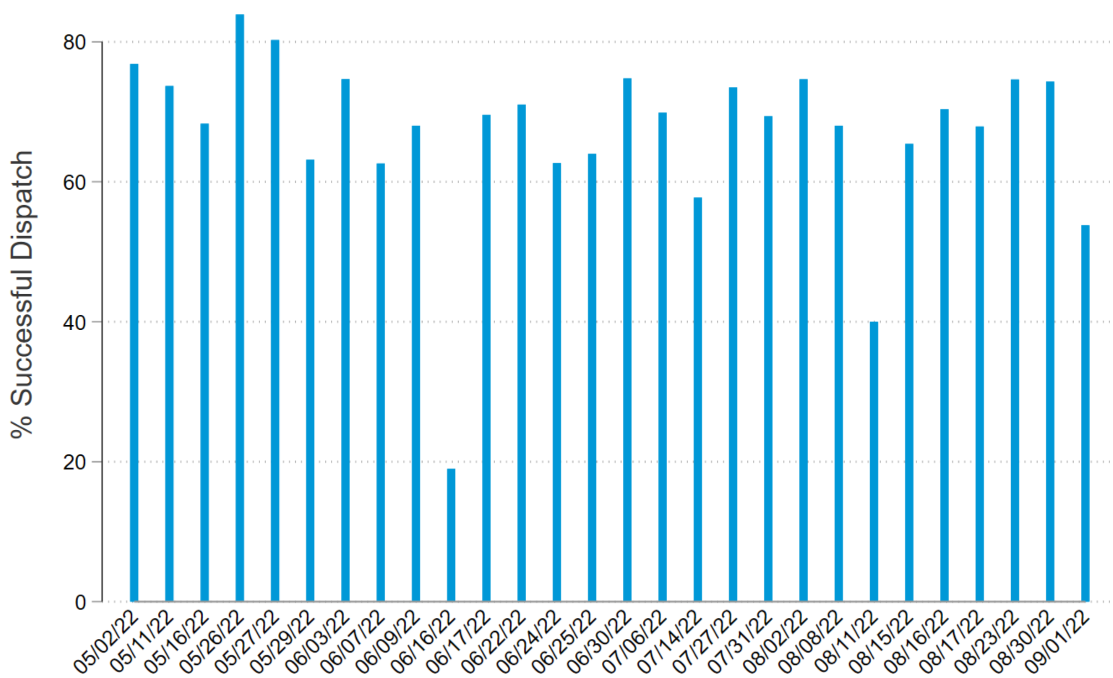


DISPATCH SUCCESS RATE

When batteries are dispatched, a signal is sent to the battery using either Ethernet of Wireless connectivity. However, not all batteries respond to the signal when it is sent out. We refer to the number of batteries that successfully respond to the signal here as "dispatch success rate". The fleet's dispatch success rate varied over the course of the summer. On average dispatch success rate was 67% but rose as high as 80% and dipped as low as 20%. Figure 27 depicts the dispatch success rate for each event. There are several factors that affected dispatch success rate. The first is the fact that over the course of the summer some batteries went offline and were no longer able to receive signals. The second reason is that batteries received signals either from Ethernet or from WiFi, and the batteries on the WiFi signal went offline whenever there were WiFi issues.

The impacts reported in the remainder of this section depict impacts that are scaled to a dispatch success rate of 100% so that we can make comparisons across different event conditions and data sources. Unscaled impacts for each event along with the dispatch success rate can be found in Appendix C.

FIGURE 27: EVENT DISPATCH SUCCESS RATE



EVENT DAY LOAD IMPACTS

While there was variation in event impacts, each event type tended to follow a distinct charge and discharge pattern. The following figures depict representative load reductions for each dispatch type from both the battery charge-discharge data and from the PG&E AMI data. For detailed event impacts for each individual event day please see Appendix C. The load shapes in this section are all hour-ending (HE).

Figure 28 depicts the load impacts for a discharge event on June 3, 2022 looking only at the battery charge/discharge load. During the event window of 6-10 PM (HE19 – HE22), the largest impact is in the first hour, and the lowest impact is in the third hour. The impacts are relatively consistent over the dispatch period.

FIGURE 28: DISCHARGE EVENT – CUSTOMER BATTERY CHARGE/DISCHARGE DATA

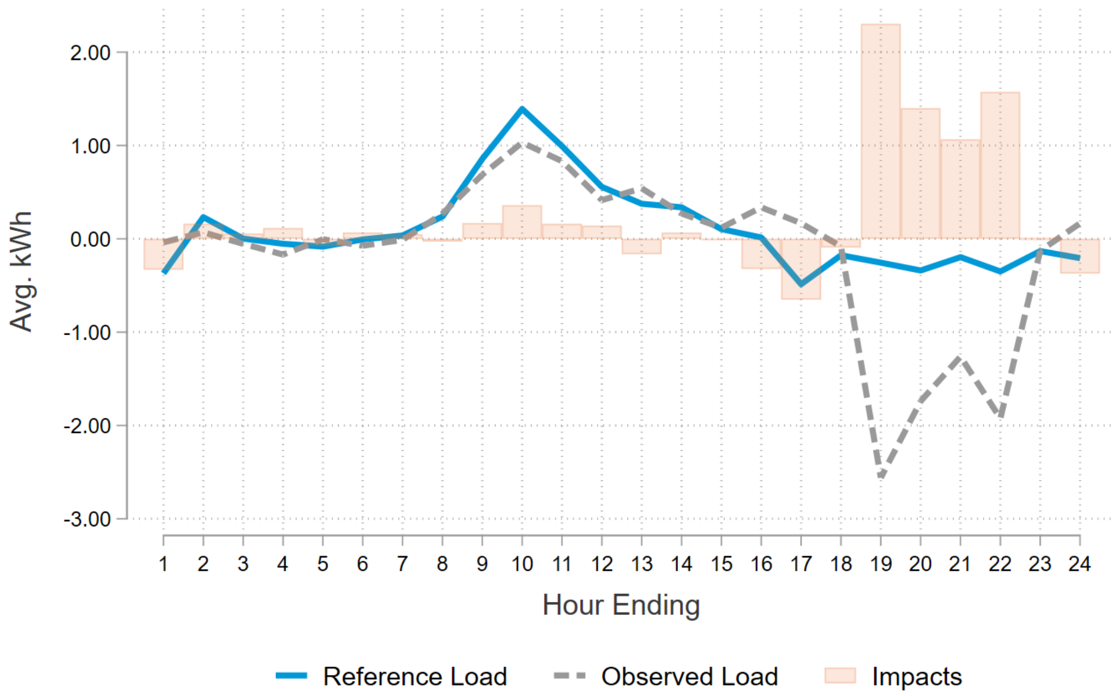


Figure 29 depicts the load impacts for June 3, 2022 at the household net load level, using data collected via PG&E's smart meters. There is a clear consistent reduction in household net load during the event window of 6-10 PM (HE19 – HE22). The highest impact is in the first hour of the event, but the impacts are all relatively similar across the event window. If we compare the household net load and battery charge/discharge load shapes, the impact shapes are similar but the battery charge/discharge impacts are higher compared to the household net load impacts, where the impact is more difficult to distinguish since the data include other end uses besides the battery.

FIGURE 29: DISCHARGE EVENT – CUSTOMER NET LOAD SHAPE

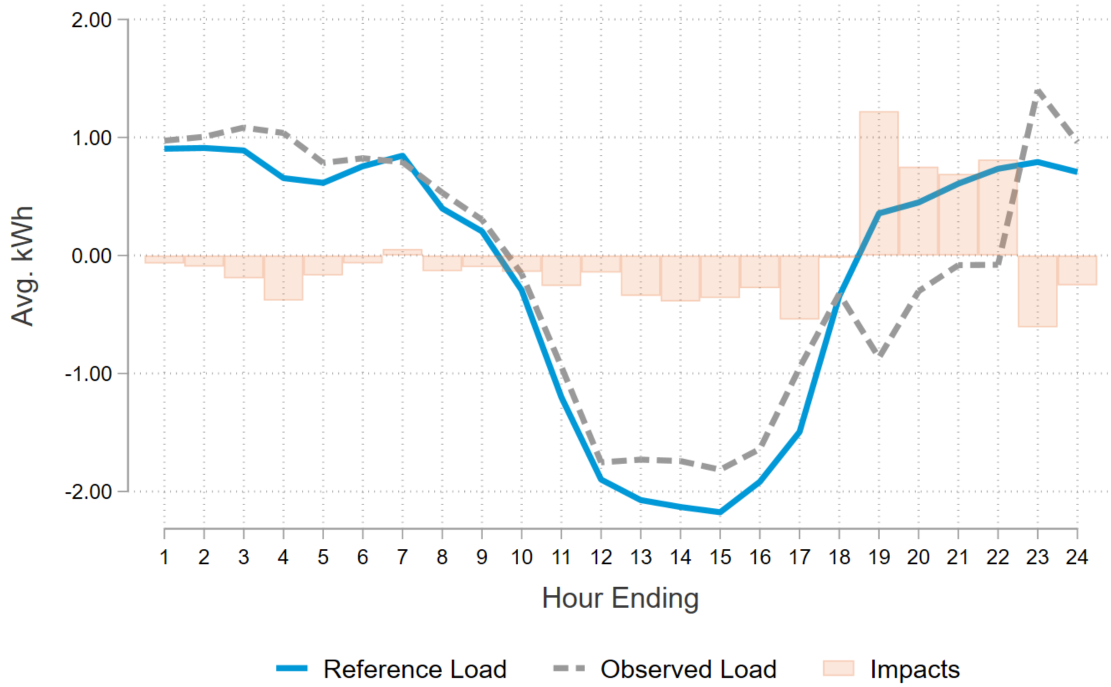


Figure 30 depicts the customer load shape for a charge event called on May 29, 2022 from 2 PM to 6 PM (HE 15 – HE 18). Prior to September, charge events functioned to ensure that batteries were full prior to discharge events. As such, they did not delay charging at all prior to a charge event. The result, as we can see in the figure below, is that the batteries have already stopped charging by 2 PM when the charge event below was called. As a result, there is no visible change in battery charge/discharge patterns during the event. SolarEdge later changed the algorithm for the charge event so that charging was delayed until a charge event was called. This algorithm was implemented for the charge and discharge event on September 1, 2022. The results of the event can be seen in Figure 32.

FIGURE 30: CHARGE EVENT – PG&E AMI DATA

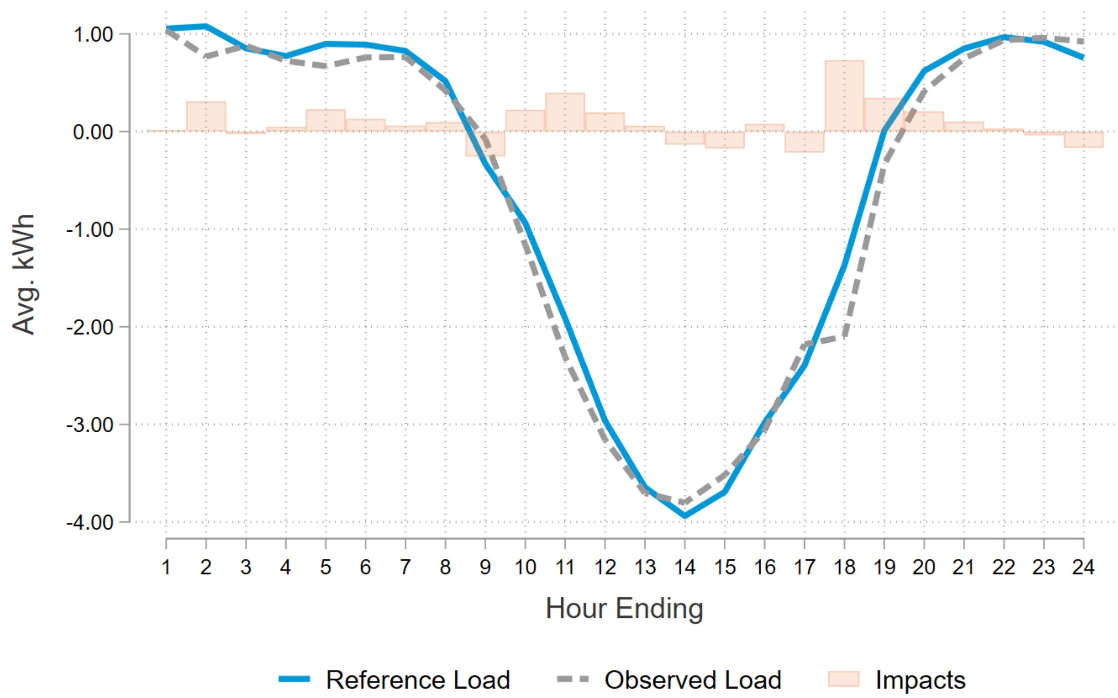


Figure 31 depicts the impacts for a shaped discharge event called on August 23, 2022. The blue bars depict the shape that was sent to the batteries and the orange bars depict the shape of the battery impacts after the battery was dispatched. While similar, the impact shape does not perfectly align with the shape sent to the batteries. It is likely that a larger number of batteries would need to be included in the dispatch or a larger distinction would need to be made from hour to hour to get a precisely shaped dispatch during an event that is not flat.

FIGURE 31: SHAPED DISCHARGE EVENT – BATTERY CHARGE/DISCHARGE DATA

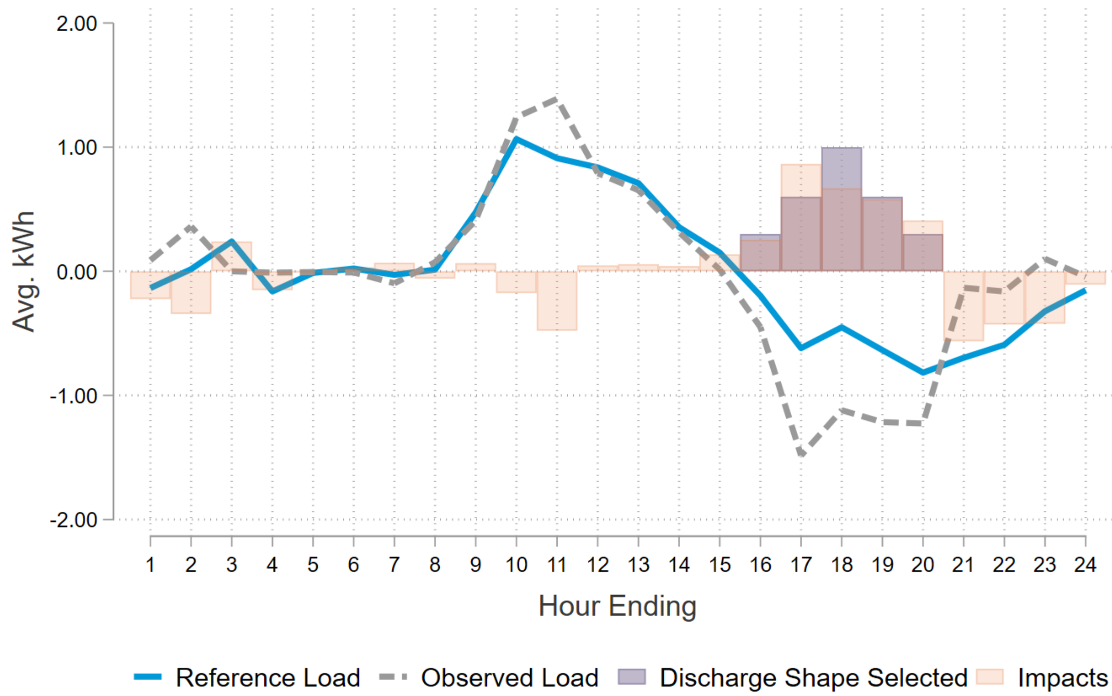
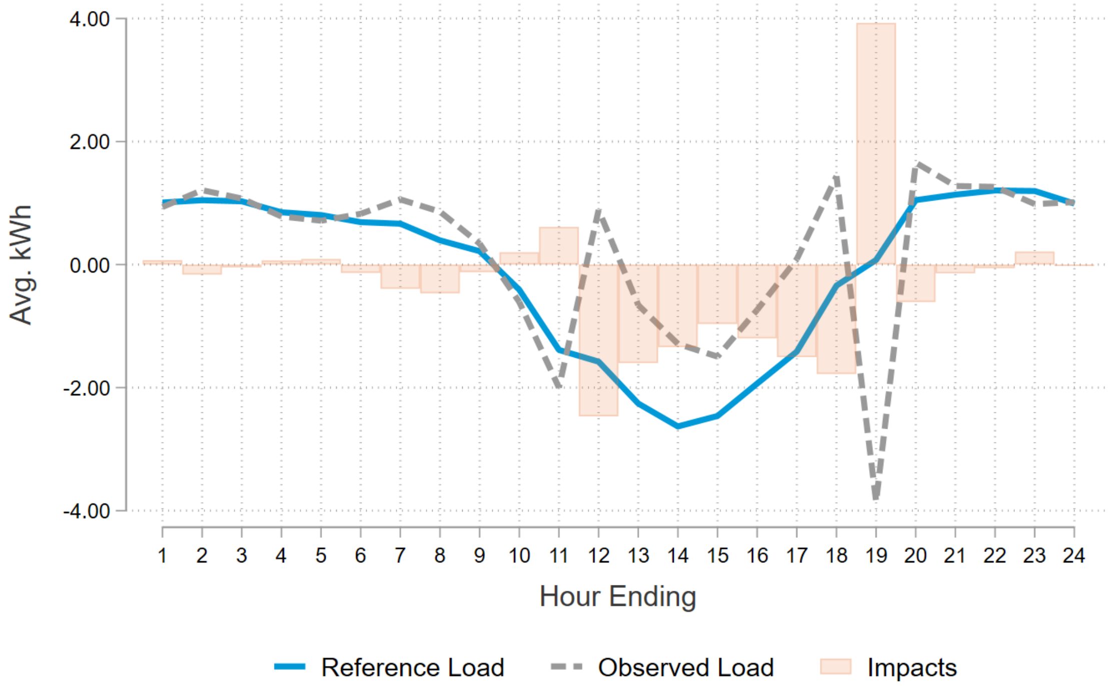


Figure 32 depicts the load impacts for September 1, 2022 at the household net load level. On this day, a charge event was called at 11 AM lasting four hours and a discharge event was called at 6 PM lasting a single hour. During the charge event the net load increases for a single hour as the batteries charge until they are full and the remainder of the event there is reduced discharge to the grid. The single hour dispatch occurs at 6 PM and there is a much larger drop in customer net load compared to the 4-hour event with the average customer impact of almost 4 kW compared to the 0.7 kW demand reduction for the 4-hour event.

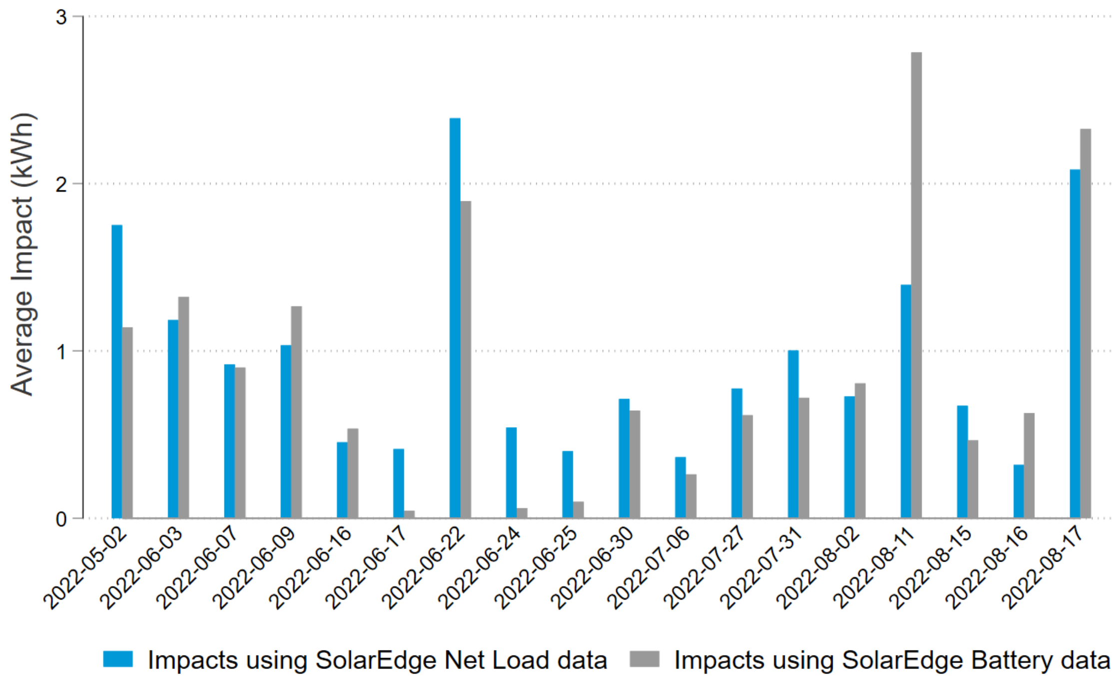
FIGURE 32: BATTERY CHARGE + DISCHARGE EVENT – CUSTOMER NET LOAD SHAPE



DATA SOURCE COMPARISON

As seen in Figure 28 and Figure 29, impacts do vary depending on which data source is being used for individual events. However, on average the impacts are relatively similar. Load impacts measured using SolarEdge net load data were 4% (0.03 kW) lower than impacts measured using SolarEdge battery charge/discharge data. Figure 33 compares the impacts for discharge-only events that were called over the course of the summer. We can see that although there was some variation on individual event days, overall, the impacts are very similar.

FIGURE 33: AVERAGE EVENT IMPACTS – BY DATA SOURCE



KEY DRIVERS OF IMPACT MAGNITUDE

The study operations intentionally varied event duration, advance notice, temperature, and dispatch hour in order to allow us to quantify how each of these factors affected performance and load impacts. The following figures illustrate how each event characteristic influenced the impact magnitude for discharge events.

Figure 34 depicts the average discharge event demand reductions by event duration. The shortest events have by far the largest impacts, with impacts decreasing as the event duration increases. Event duration was by far the largest driver of impact magnitude, as the SolarEdge algorithm was designed to create consistent impacts over the entire event window. The total available kWh of the fleet is spread over the event window and the average hourly impact decreases as the event window grows larger. Because of this strong relationship, our other examinations of the drivers of event impacts only include 4-hour durations to avoid confounding duration with other potential drivers of impact magnitude.

FIGURE 34: AVERAGE CUSTOMER EVENT IMPACTS BY EVENT DURATION

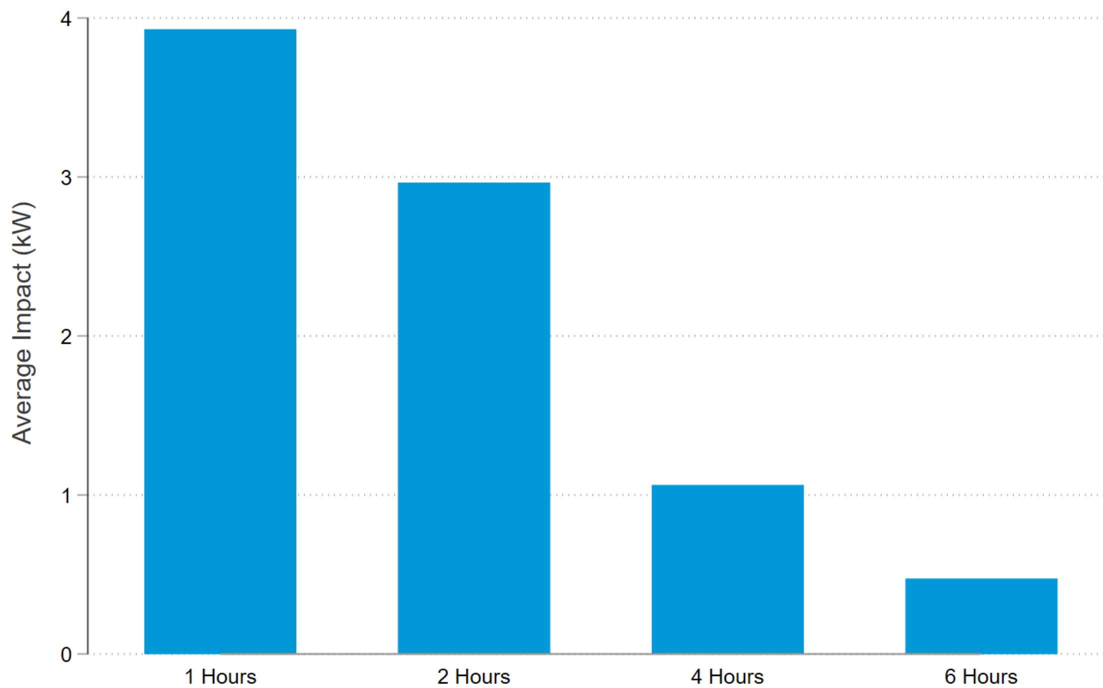


Figure 35 compares the event impacts across the advance notice the batteries received before they are dispatched for an event. Overall, events with a full day's notice (24 hours) had the highest impacts. More notice is generally better as the battery has more time to fully charge and hold back its charge prior to being dispatched. However, there is not a large difference between advance notice of 6 hours and advance notice of 1 hour and the overall difference in impacts is relatively small.

FIGURE 35: AVERAGE CUSTOMER EVENT IMPACTS – BY ADVANCE NOTICE

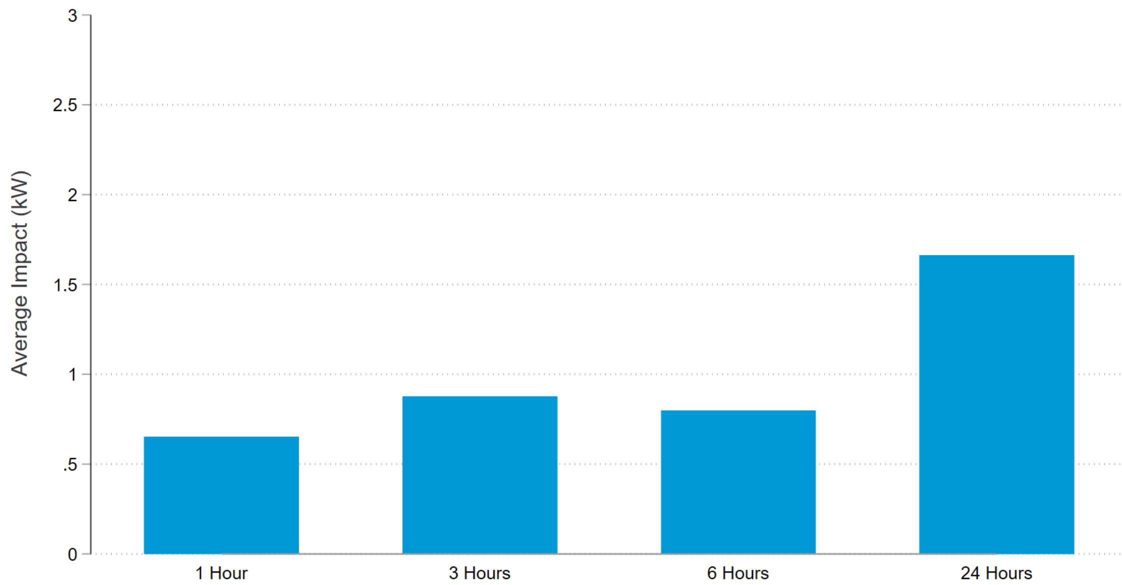


Figure 36 compares the hourly impacts for different weather conditions. Only 4-hour events are included in the figure below. We can see that while the event temperature ranges from 55ºF to almost of 85ºF there is little change in impacts as the weather gets warmer with a trend line that is almost completely flat.

FIGURE 36: AVERAGE HOURLY EVENT IMPACTS – BY EVENT TEMPERATURE CONDITIONS (F)

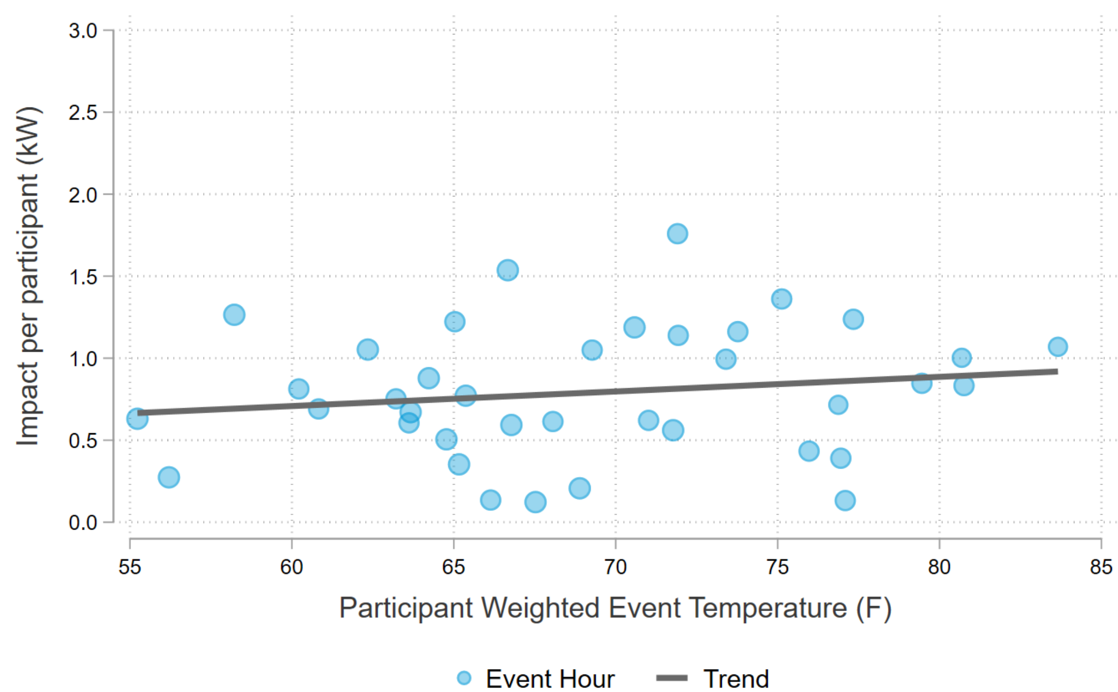
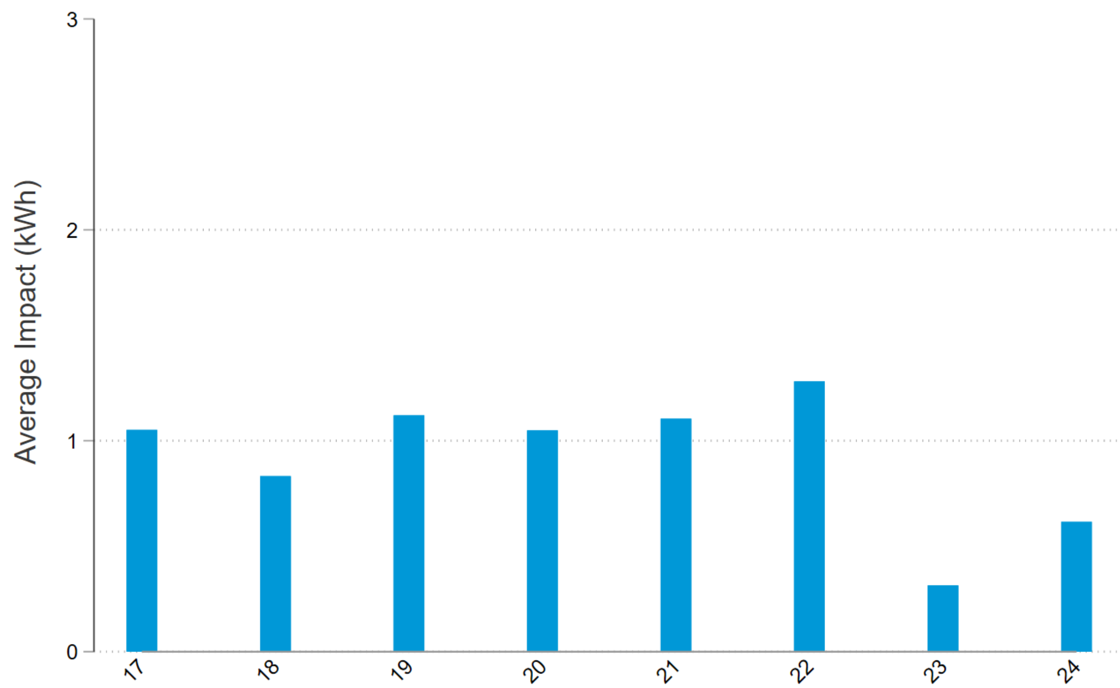


Figure 37 compares the average event demand reductions by event hour. Overall, impacts remain relatively similar regardless of when the event takes place. This is consistent with the flat discharge shape we see during events. Note that this graph includes 4 hour events only.

FIGURE 37: AVERAGE CUSTOMER IMPACTS BY EVENT HOUR



KEY TAKEAWAYS

Table 5 depicts the key takeaways for shifting customer load using battery event dispatch.

TABLE 5: LOAD SHIFTING: EVENT DISPATCH KEY TAKEAWAYS

Research Question	Findings
What are the load impacts of dispatching battery storage?	During a 4-hour discharge event the average impact was 0.7 kW assuming 100% successful dispatch rate. During the first half of the summer there were no impacts from calling charge events. Once charge events were modified customer net usage increased 1.6 kW for a single hour during the charge window.
What did a typical dispatch look like?	SolarEdge discharge events typically had a flat load shed with consistent impacts across the entire event window. Charge events typically concentrated battery charging into a single

Research Question	Findings
	hour leading to a spike in the customer's net load.
How successful was the battery response when dispatched for an event?	On average 67% of batteries successfully responded when dispatched for an event, but the overall fleet response rate varied over the course of the study. The relatively low response rate can be attributed to two factors. The first is that over the course of the summer some batteries went offline and were no longer able to receive signals. The second reason is that batteries received signals either from Ethernet or from WiFi, and the batteries on the WiFi signal went offline whenever there were WiFi issues.
What are the key drivers of load impacts?	Event duration was the largest driver of impact magnitude due to the SolarEdge event dispatch algorithm, which aim to provide a consistent demand reduction across the event window. Impacts were larger with more advance notice but there wasn't a strong relationship between the two. Weather conditions and event timing had a minimal influence on event impact magnitude.
How did the impacts vary based on the data source used for the evaluation?	When comparing SolarEdge net load impacts to SolarEdge end use impacts, there was on average a very small difference of 0.03 kW.

SHIFTING BATTERY LOAD – PRICE ARBITRAGE

The second method for shifting battery load is through price arbitrage. The price arbitrage method has the battery follow a price signal to maximize customer savings based on the price shape, discharging the battery when the rolling average price is highest. The price shape can change from day-to-day and does not need to be based on the customer's actual rate. We designed two price shapes for customers to follow using the price arbitrage algorithm, and aimed to answer the following key questions around shifting battery load through price arbitrage:

- Are batteries able to respond to price structures without changing the customer's current rate?
- How do the battery algorithms respond to a time-of-use structure (TOU-C)?
- How do the battery algorithms respond to day-ahead hourly prices (also called real time prices, or RTP)?

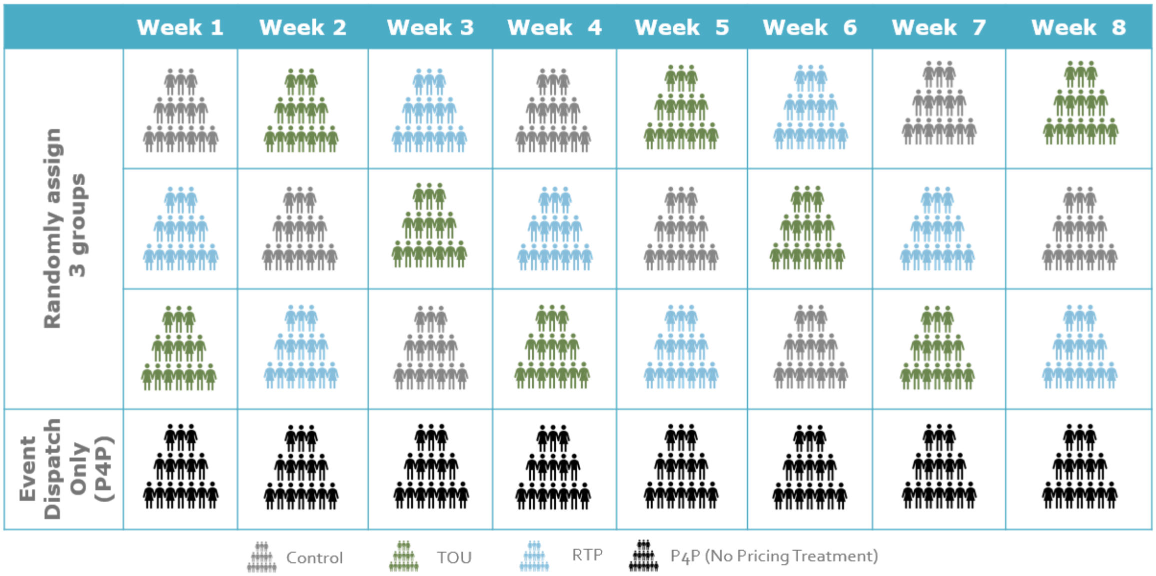
The remainder of this section details the methodology, results, and key takeaways for how the battery algorithms shifted customer load using price arbitrage.

STUDY DESIGN & EVALUATION METHODOLOGY

Customers that were recruited using the sign-up incentive method were randomly assigned to one of the same three groups that were used for assigning event dispatch. These groups were alternately assigned to one of three price arbitrage signals each week and rotated through each week. Pay-for-performance participants did not receive any price arbitrage signals, and so they are not included in this section of the report. The price signals were sent to customer from September 15 through November 1, and so they do not overlap with any of the event impacts discussed in the previous section. It should be noted that customer batteries could be programmed to follow any price signal regardless of the customer's current rate. The batteries could follow different rate structures or respond to market conditions without exposing the customer to different price signals.

The design allowed us to implement a randomized control trial for the purpose of evaluation. The primary evaluation method was a randomized control trial analyzed using a difference-in-differences panel regression. Figure 38 below depicts the study design used to test the impacts of pricing and summarizes the core concept of the randomized control. For each event day, participants with connected devices are randomly assigned to be dispatched or serve as a control. Because the sites are randomly assigned, they are equivalent in all aspects, but some differences can occur due to sampling. Each day, two groups respond to a price signal while the third group is held back as a control. The control group is used to establish the baseline of what loads would have been if sites hadn't responded to the price arbitrage signal. The control sites are in the same geographic locations, experience the same weather, and have same characteristics – the only difference is that one group was dispatched while another group was not. With large enough sample sizes, the approach produces very precise load impacts estimates.

FIGURE 38: PRICE ARBITRAGE STUDY DESIGN

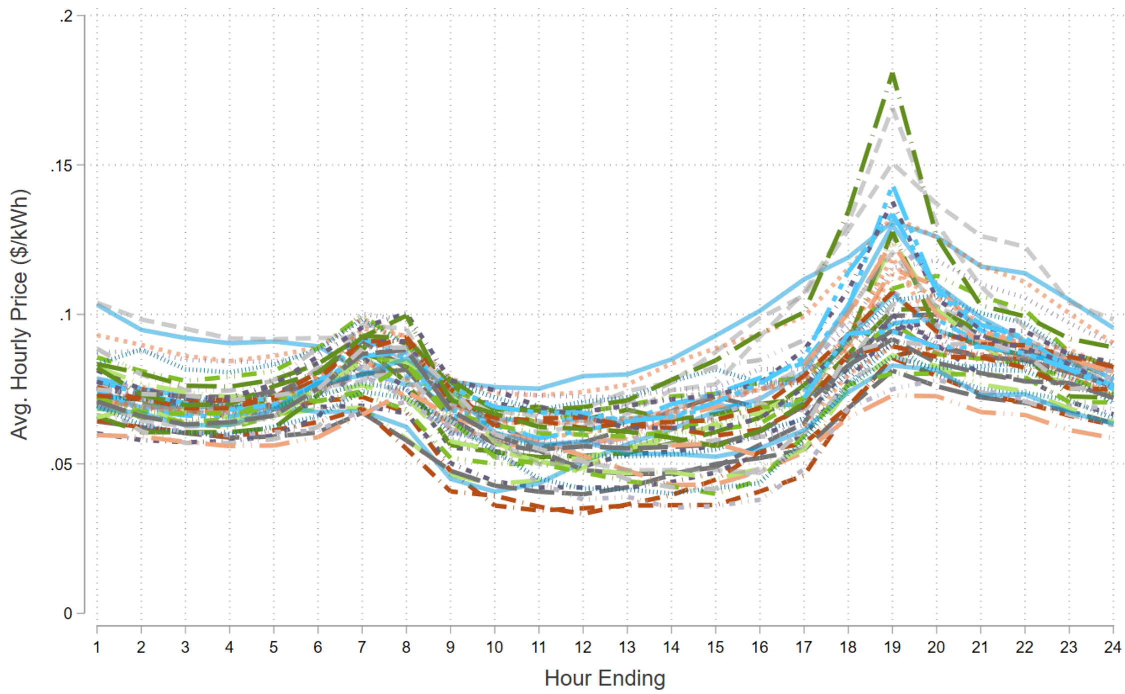


PRICE SIGNALS

The batteries followed one of two possible price signals, or "rates". The first price signal, or the "RTP rate", was pulled directly from the Day-Ahead Market for the PG&E territory (known and the PG&E DLAP[8]). The RTP rate was a 24-hour load shape with prices that varied each hour and changed each day. Figure 39 depicts the daily shape of the RTP prices over a 24-hour period across the analysis window. We can see that the rate varies each day and could change both in terms of shape and in terms of price magnitude. The rate was the same for all customers and was not scaled in any way as the goal was to determine whether the battery could follow the shape of the prices. Typically the rate had two peaks each day, with a smaller peak in the morning, lower rates in the mid-afternoon, and the highest peak from 6-7 PM.

[8] CAISO Day-Ahead Market prices can be downloaded from OASIS: http://oasis.caiso.com/mrioasis/logon.do

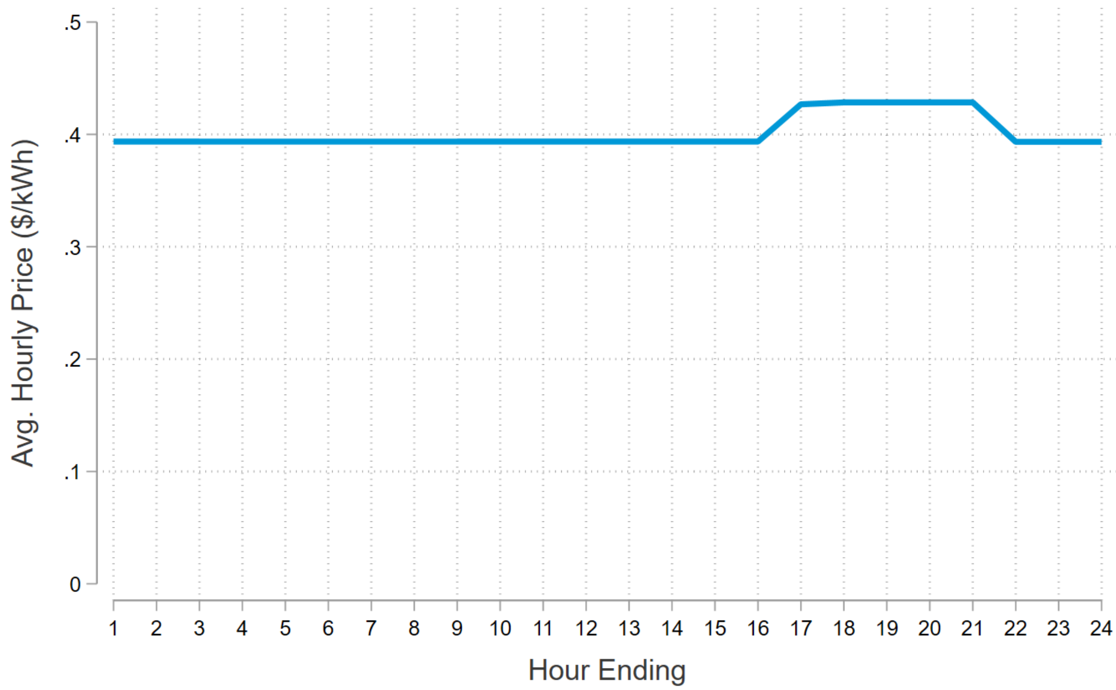
FIGURE 39: RTP RATE HOURLY SHAPE



The second price shape was the "TOU-C rate", which was based on current PG&E TOU-C rate. The price was a fixed time-of-use structure and did not vary from day-to-day, with a lower price in the off-peak period and a higher price during the peak period[9]. Just as with the RTP rate, the TOU-C rate shape was the same for all customers and did not vary based on tiers as the goal was to see whether battery could follow the price shape. Figure 40 depicts the average hourly price shape for TOU-C.

[9] PG&E TOU-C rate details can be found here: https://www.pge.com/pge_global/common/pdfs/rate-plans/how-rates-work/Residential-Rates-Plan-Pricing.pdf

FIGURE 40: TOU RATE HOURLY SHAPE



RESULTS

Figure 41 compares the average weekday load shapes for each pricing group. The solid blue line depicts the control line, the dotted orange line depicts the shape of the TOU group, and the dashed gray line depicts the shape of the RTP group. The blue line includes customers that are discharging because of their base mode, which includes TOU cost saving, maximize self-consumption, or back-up mode. The control battery discharges at the start of the 4-9 PM window when on the time of use cost-saving mode or at 6 PM when solar goes offline if in maximize self-consumption mode. Both groups participating in price arbitrage concentrate their discharge in a single hour that corresponds to the highest price for their respective rate structures (6-7 PM). Compared to the control group, which typically has its peak dispatch from 4-5 PM, the price arbitrage battery groups discharge later in the evening. Interestingly, both price arbitrage shapes dispatch at the same time, which is explored in more detail in Figure 41 and Figure 42.

FIGURE 41: SHIFT IN PRICE ARBITRAGE SHAPES COMPARED TO CONTROL SHAPE

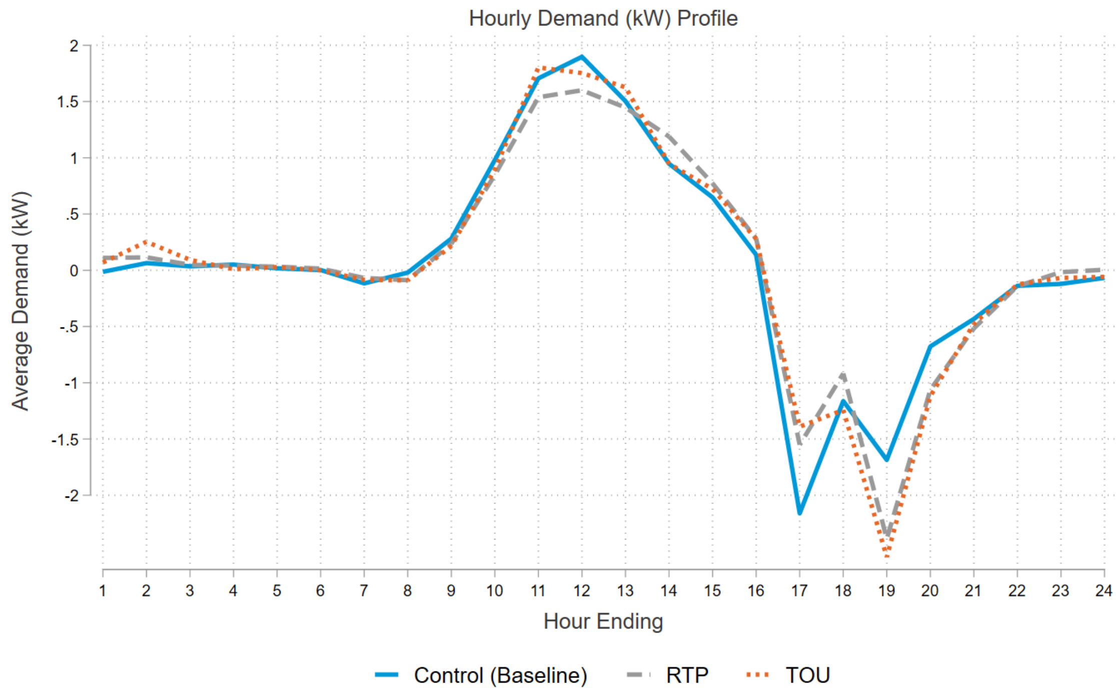


Figure 42 compares the TOU price arbitrage dispatch shape to the TOU price shape. The price arbitrage algorithm is designed to dispatch the battery when the rolling average price is the highest. As the TOU price is flat, the rolling average price is the highest in the middle of the peak window, from 6-7 PM. As a result, the battery discharges from 6-7 PM. The control battery discharges at the beginning of the TOU peak period starting at 4 PM, reflecting the time of use cost-saving customer mode. Relative to the control shape, the TOU-C price arbitrage battery reduces its discharge amount by 0.8 kW from 4-5 PM and increases its discharge by 0.9 kW from 6-7 PM when the rolling average price is at its peak.

FIGURE 42: PRICE ARBITRAGE FOLLOWING TOU RATE PRICE SHAPE

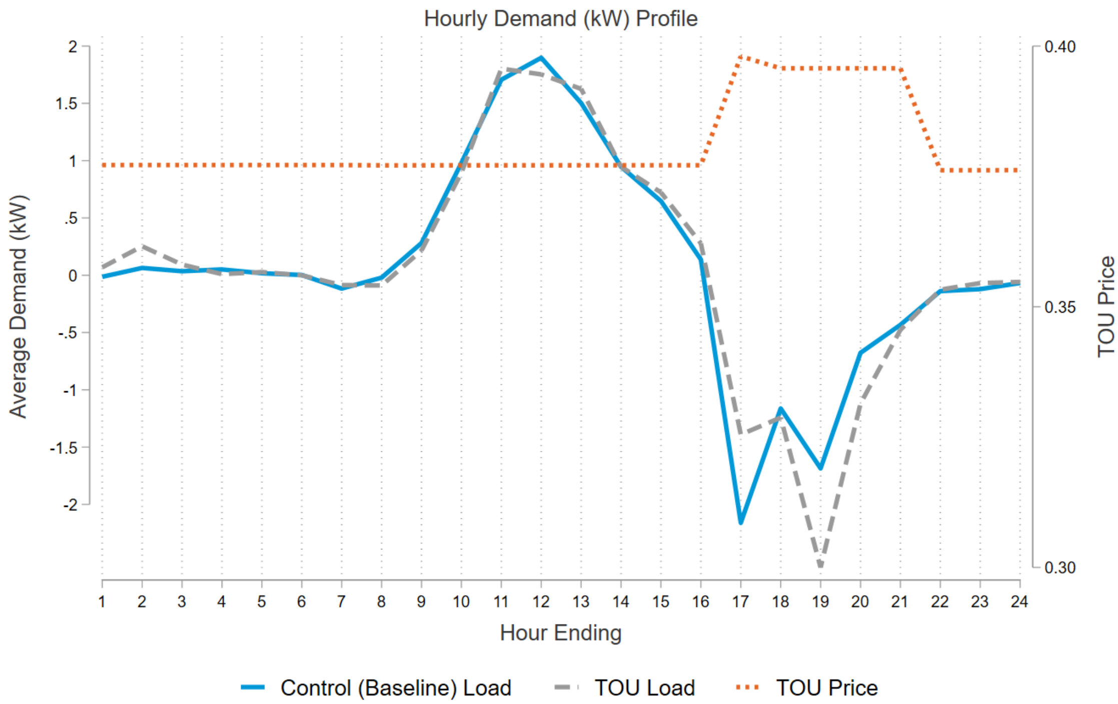
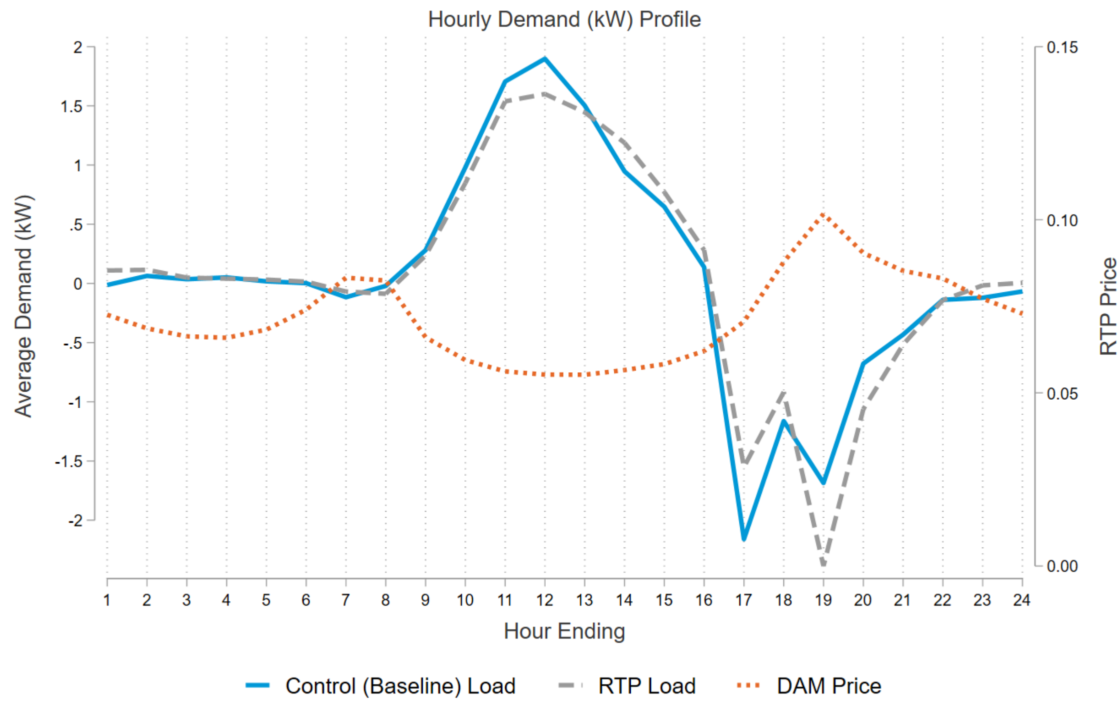


Figure 43 compares the RTP dispatch shape to the RTP price shape. As with the TOU price, the price arbitrage algorithm is designed to dispatch the battery when the rolling average price is the highest. The rolling average price is the highest when RTP price peaks, from 6-7 PM. As a result, the battery discharges from 6-7 PM. The control battery discharges at the beginning of the TOU peak period starting at 4 PM, reflecting the time of use cost-saving customer mode. Relative to the control shape, the TOU-C price arbitrage battery reduces its discharge amount by 0.6 kW from 4-5 PM and increases its discharge by 0.7 kW from 6-7 PM when the rolling average price is at its peak.

FIGURE 43: PRICE ARBITRAGE FOLLOWING RTP PRICE SHAPE



KEY TAKEAWAYS

Table 6 summarizes the key takeaways for shifting battery storage load using price arbitrage.

TABLE 6: LOAD SHIFTING: PRICE ARBITRAGE KEY TAKEAWAYS

Research Question	Findings
Are batteries able to respond to price arbitrage regardless of the customer's current rate?	Batteries were able to respond to both TOU rate structures and market day-ahead prices without exposing the customers to any actual changes in their rate. For example, customers on a tiered rate were able to respond to the time of use rate structure without shifting the customer to a TOU rate. Similarly, all participants were able to respond to market conditions without being exposed to day-ahead market prices.
How are the batteries able to respond to a time of use rate structure (TOU-C)?	The batteries responded to a time of use rate structure in one of two ways. The first response was a base setting that could be selected by the customer when they installed the battery. For the customer-

	selected TOU setting the battery discharged at the beginning of the peak price window. The second type of response was through price arbitrage. When implementing price arbitrage, the battery discharged when the rolling average price was at its peak. As a result, the battery discharged in the middle of the peak price window rather than at the start of the peak price window.
How are batteries able to respond to day-ahead market prices (RTP)?	The battery responded to day-ahead market conditions and discharged during the highest price period of the day, which typically occurred from 6-7 PM.

CONCLUSIONS & RECOMMENDATIONS

There is strong evidence that residential battery storage has a large amount of untapped potential and when controlled remotely can contribute to grid services. Table 7 summarizes the key research questions for the study as well as our findings.

TABLE 7: SUMMARY OF KEY RESEARCH QUESTIONS AND FINDINGS

Research Question	Findings
What are the enrollment rates for existing battery storage customers?	181 customers and 6.5% accepted the offer to enroll in a battery storage study, and 120 customers met technical screening requirements for overall enrollment rate of 4.5%.
What is the relationship between upfront incentive levels and enrollment rates?	Doubling the upfront incentive amount increases study participation by 1.64x.
What recruitment methods increase enrollment rates? By how much?	Phone calls improved enrollment rates by 3x, but there may be interviewer-specific effects. Push notifications increased enrollment rates by 10x.
What are the enrollment rates for a pay-for-performance incentive structure?	3.8% of customers pay-for-performance incentives (with no upfront incentive) accepted the offer. The overall enrollment rate, after technical screens was 2.4%.
Does the data from PG&E align with the SolarEdge data?	On average, the PG&E data is 10% smaller in magnitude compared to the SolarEdge data when comparing household net loads. The degree to which the two data sources aligned

	varied by participant, with approximately 40% of participants having almost identical PG&E and SolarEdge data.
How much power do people reserve for backup?	Customers typically committed either 50% or 80% (the maximum) of their battery capacity to the program, on average committing 64%. However, the fleet does not typically discharge below 60% of the overall battery capacity.
What are the typical charge and discharge patterns absent intervention?	On average, batteries start charging from solar when the sun rises and stop when they are fully charged. Charging typically starts at 8 AM and on average charge 4.7 kWh between 8 AM and 2 PM. Batteries typically start discharging at 4 PM, as the sun sets, and on average discharge 2.9 kWh between 4 PM and 9 PM.
How well does a customer's "naturally occurring" battery use align with grid needs? What is the untapped value?	On peak days, there is higher battery discharge for the average customer but there is a larger ramp in customer net load between 4 PM and 9 PM due to higher household load. There is also still a large amount of untapped capacity on peak days – 50% of the battery fleet was not discharged. Without intervention, the batteries tend to discharge earlier than on the net peak load hours or highest price hours.
What are the load impacts of dispatching battery storage?	During a 4-hour discharge event the average impact was 0.7 kW assuming 100% successful dispatch rate. During the first half of the summer there were no impacts from calling charge events. Once charge events were modified customer net usage increased 1.6 kW for a single hour during the charge window.
What did a typical dispatch look like?	SolarEdge discharge events typically had a flat load shed with consistent impacts across the entire event window. Charge events typically concentrated battery charging into a single hour leading to a spike in the customer's net load.
How successful was the battery response when dispatched for an event?	On average 67% of batteries successfully responded when dispatched for an event, but the overall fleet response rate varied over the course of the study. The relatively low response rate can be attributed to two factors. The first is that over the course of the summer some batteries went offline and were no longer able to receive signals. The second reason is that batteries received signals either from Ethernet

	or from WiFi, and the batteries on the WiFi signal went offline whenever there were WiFi issues.
What are the key drivers of load impacts?	Event duration was the largest driver of impact magnitude due to the SolarEdge event dispatch algorithm, which aim to provide a consistent demand reduction across the event window. Impacts were larger with more advance notice but there wasn't a strong relationship between the two. Weather conditions and event timing had a minimal influence on event impact magnitude.
How did the impacts vary based on the data source used for the evaluation?	When comparing SolarEdge net load impacts to SolarEdge end use impacts, there was on average a very small difference of 0.03 kW.
Are batteries able to respond to price arbitrage regardless of the customer's current rate?	Batteries were able to respond to both TOU rate structures and market day-ahead prices without exposing the customers to any actual changes in their rate. For example, customers on a tiered rate were able to respond to the time of use rate structure without shifting the customer to a TOU rate. Similarly, all participants were able to respond to market conditions without being exposed to day-ahead market prices.
How are the batteries able to respond to a time of use rate structure (TOU-C)?	The batteries responded to a time of use rate structure in one of two ways. The first response was a base setting that could be selected by the customer when they installed the battery. For the customer-selected TOU setting the battery discharged at the beginning of the peak price window. The second type of response was through price arbitrage. When implementing price arbitrage, the battery discharged when the rolling average price was at its peak. As a result, the battery discharged in the middle of the peak price window rather than at the start of the peak price window.
How are batteries able to respond to day-ahead market prices (RTP)?	The battery responded to day-ahead market conditions and discharged during the highest price period of the day, which typically

	occurred from 6-7 PM during the study period[10]..

While this technology has a lot of potential, several aspects of the technology warrant further study. We recommend researching the following key questions when looking into the potential of this technology to reduce peak demand:

- How quickly do the batteries respond (latency) to external instructions?
- Can we improve algorithms to feed specific discharge (e.g., T&D load relief) and or charge shapes (e.g., load building) to the batteries?
- Are the batteries able to respond to over/under frequency and voltage?
- What use cases can be stacked realistically?
- What is the optimal design and cost-effectiveness of a battery storage program?
- What are costs of sustaining participation over multiple years of customers who allow their battery to be used for grid operations?
- Can successful communication rates to the battery be improved?
- Can pre-screening of sites be improved to minimize recruitment of sites that do not meet technical testing?

We also make the following observations for future battery storage study and programs:

- Future battery storage recruitment should leverage push notifications and battery storage apps, as this is a cost-effective method for improving enrollment rates.
- There is value to recruiting customers to a battery storage program. Customers are currently under-utilizing their batteries, and there is a lot of untapped potential on peak days.
- Event dispatch is currently a better method for achieving battery dispatch for long durations compared to price arbitrage.
- Price arbitrage allows customer load to follow specified price shapes without forcing a customer to change their rate. However, the current price arbitrage algorithms typically target a single hour for battery discharge in order to maximize customer savings.

[10] Note that batteries responded to market prices in the fall, which had a daily price peak that was slightly earlier on average compared to summer months. In the summer the typical peak occurs between 7 PM and 9 PM.

APPENDICES

APPENDIX A: ENROLLMENT PROCESS & ELIGIBILITY CRITERIA

Figure 44 summarizes the enrollment process for the study for Wave 1 and Wave 2. For Wave 1, customers were pre-screened based on their PG&E enrollment criteria and contacted if they were eligible for the study. For Wave 2, customers were contacted if they were PG&E customers and were screened for PG&E eligibility requirements after they submitted an application. All customers received an additional technical screen from SolarEdge after they submitted an application. All customers received a unique enrollment ID that was tied to their incentive structure. To enroll, the customer went to the enrollment website and entered their enrollment ID. The customer then selected the percent of their battery that they wished to commit to the program, entered additional demographic information, signed a participation agreement, and finally submitted an application. Once the customer submitted an application PG&E and DSA confirmed met the study eligibility criteria and SolarEdge performed technical checks on the battery system to determine if the customer met the technical requirements for enrolling in the program. If a customer passed the eligibility screens then they were accepted into the program and received their sign-up incentive. Throughout the study customers were able to unenroll at any time. If they unenrolled before the end of September 30, 2022 then they were ineligible to receive their study incentive. Only three customers unenrolled prior to the end of September.

FIGURE 44: WAVE 1 AND WAVE 2 ENROLLMENT PROCESS

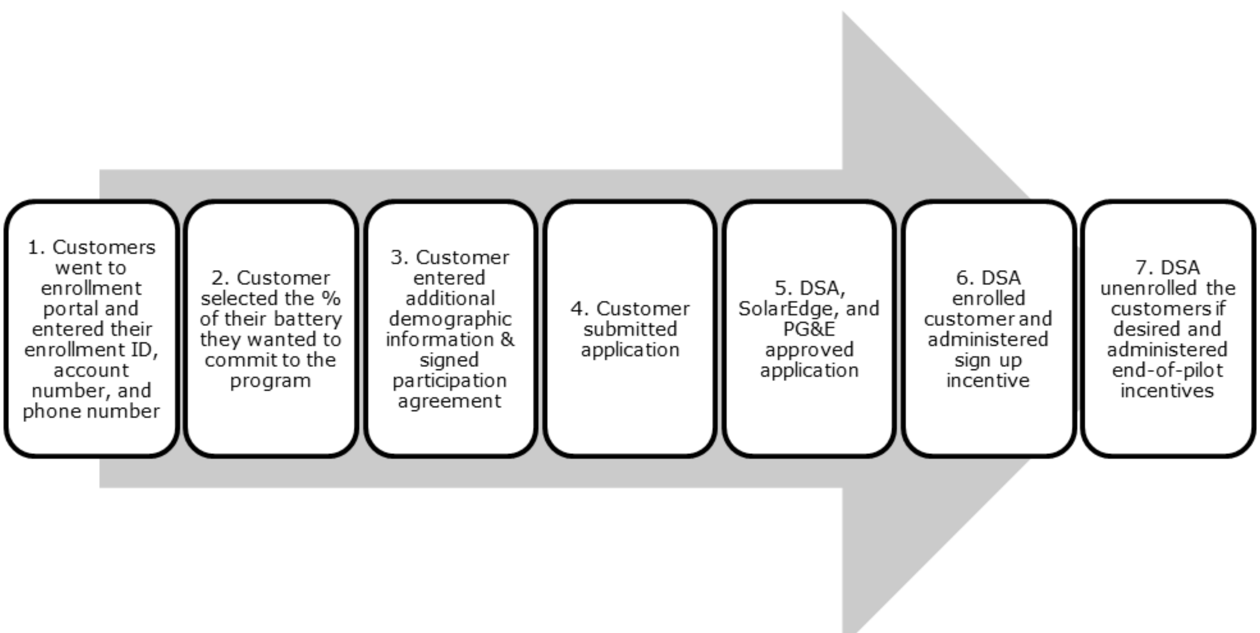


Figure 45 summarizes the enrollment criteria to be eligible for Wave 1 recruitment. At the time of recruitment there were approximately 25,000 residential storage customers in PG&E territory. DSA determined which customers had inverters by mapping SolarEdge and PG&E

addresses using a privacy-preserving cryptographic hashing technique. Approximately 1,800 customers had SolarEdge inverters, and 1,500 customers met the PG&E criteria to enroll in the program. Customers who were ineligible included customers who were on medical baseline and customers already enrolled in another demand response program.

FIGURE 45: WAVE 1 ENROLLMENT CRITERIA

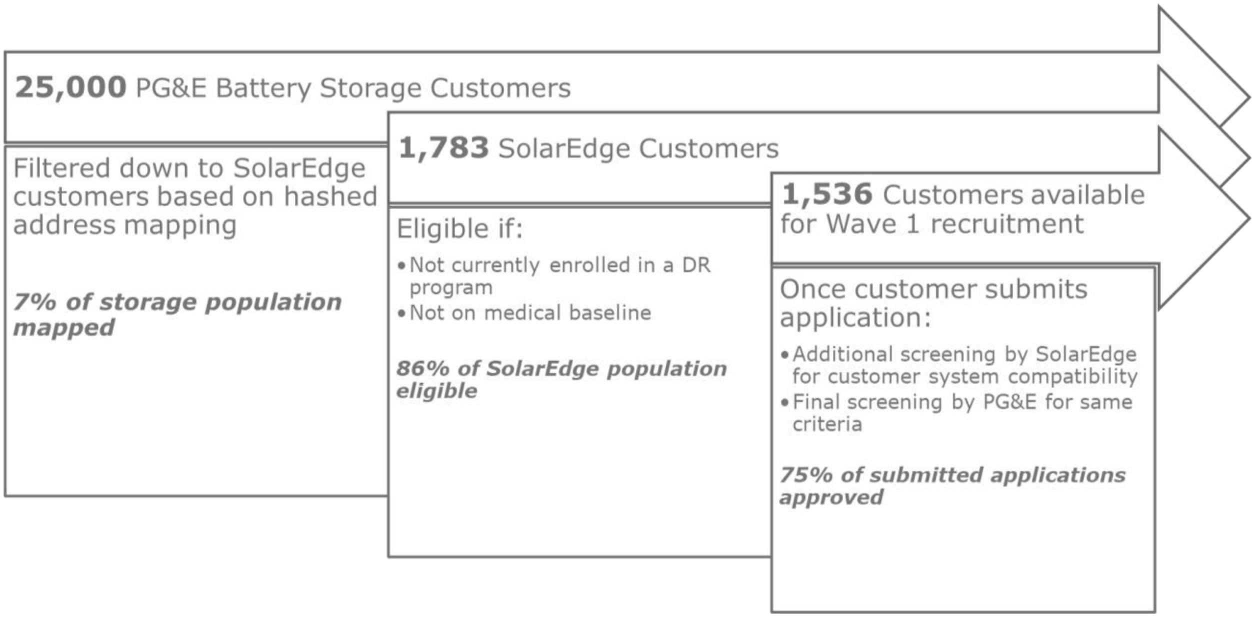
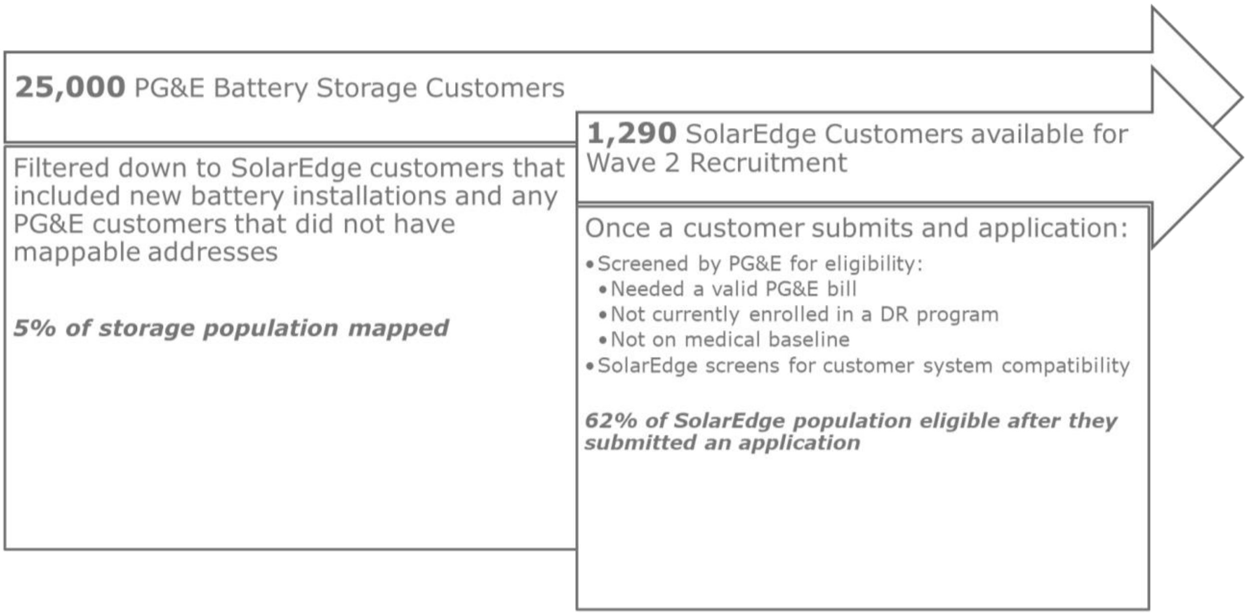


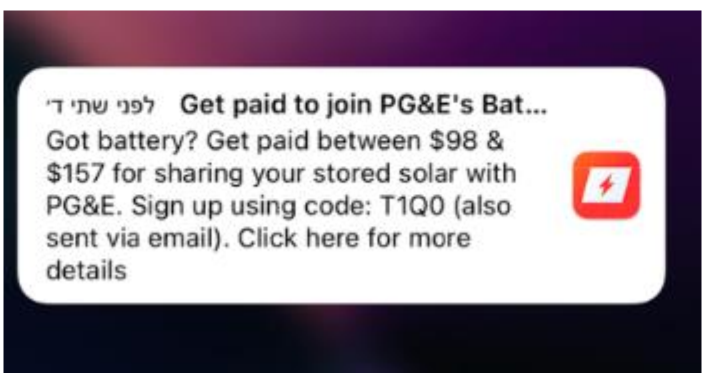
Figure 46 summarizes the enrollment criteria to be eligible for Wave 2 recruitment. The recruitment pool included all PG&E customers that had not been recruited in Wave 1, which included customers with no mapped address and customers with new battery installations. Approximately 1,300 customers were available for recruitment. Once recruited, customers received an eligibility screen after they submitted an application. Because customers were not pre-screened for eligibility there was a lower eligibility rate after customers submitted an application compared to Wave 1. Customers needed to meet the same eligibility criteria for Wave 2 as they did for Wave 1.

FIGURE 46: WAVE 2 ENROLLMENT CRITERIA



APPENDIX B: SAMPLE RECRUITMENT MATERIALS

Below are samples of the push notification message and the email/letter sent out to customers for recruitment. In both recruitment messages customers were shown an incentive range, which showed their minimum and maximum incentive depending on how much of their battery they elected to commit to the program. The letter sent out to customers for recruitment used the same format as the customer email.



Dear Sample Customer,

California needs energy now more than ever, and as a SolarEdge system owner with a battery, you can help.

By participating in PG&E's Battery Storage Pilot, you can receive between $98 and $157 and help keep the grid clean and reliable.

The best part? Participation will not affect solar energy production, Investment Tax Credit, or net metering incentives.

How the Program Works
If your application is approved by PG&E, SolarEdge will remotely discharge your battery according to PG&E instructions. The program is subject to the terms and conditions which may be found at pge-battery-pilot.com.

To enroll or for more information, visit pge-battery-pilot.com. Your unique 4-digit code is T1Q0.

If you have any questions or concerns about the pilot, please feel free to email your questions to admin@pge-battery-pilot.com.

Thanks for powering your home with us,

The SolarEdge team on behalf of Pacific Gas and Electric Company

Pacific Gas and Electric Company

SolarEdge, 700 Tasman Dr., Milpitas, CA 95035, USA

APPENDIX C: ENROLLMENT ANALYSIS DETAIL

For the enrollment analysis we estimated enrolment likelihood using both t-tests and probit models. The following figures are detailed model outputs from the analysis.

All analysis looked at the percentage of customers who submitted an application rather than the enrolment rate because customers had no control over the technical requirements. To estimate the effect of incentive on submission rates we performed a probit regression on both the incentive and the log of the incentive level. Figure 47 and Figure 48 depict the regression outputs.

FIGURE 47: PROBIT REGRESSION OUTPUTS – IMPACT OF INCENTIVE ON ENROLLMENT

```
Probit regression                               Number of obs     =      1,533
                                                LR chi2(1)        =       8.68
                                                Prob > chi2       =     0.0032
Log likelihood = -404.09169                     Pseudo R2         =     0.0106
```

submitted	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
incentive_kwh	.0034323	.0011708	2.93	0.003	.0011376	.005727
_cons	-1.755	.1203361	-14.58	0.000	-1.990854	-1.519145

FIGURE 48: PROBIT REGRESSION OUTPUTS – IMPACT OF LOGGED INCENTIVE ON ENROLLMENT

```
Probit regression                               Number of obs     =      1,533
                                                LR chi2(1)        =       6.72
                                                Prob > chi2       =     0.0096
Log likelihood =  -405.0724                     Pseudo R2         =     0.0082
```

submitted	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
incentive_kwh_log	.2335974	.091714	2.55	0.011	.0538413	.4133535
_cons	-2.465937	.4084606	-6.04	0.000	-3.266505	-1.665369

For the remaining recruitment methods we performed a 2-sample t-test. Figure 49 depicts the t-test outputs when comparing the application submission rates for customers who did and did not receive a phone call. Figure 50 depicts the t-test outputs when comparing the application submission rates for customers who did and did not receive a push notification.

FIGURE 49: T-TEST OUTPUTS – IMPACT OF PHONE CALL ON ENROLLMENT

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
No	709	.0070522	.0031449	.0837397	.0008777	.0132267
Yes	734	.0286104	.0061575	.1668224	.0165219	.0406988
combined	1,443	.018018	.0035029	.1330625	.0111468	.0248893
diff		-.0215582	.0069862		-.0352623	-.007854

```
    diff = mean(No) - mean(Yes)                                   t =  -3.0858
Ho: diff = 0                                     degrees of freedom =     1441

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0010         Pr(|T| > |t|) = 0.0021          Pr(T > t) = 0.9990
```

FIGURE 50: T-TEST OUTPUTS – IMPACT OF PUSH NOTIFICATION ON ENROLLMENT

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	258	.0155039	.0077066	.1237857	.0003278	.0306799
1	1,032	.0600775	.0074007	.2377456	.0455554	.0745997
combined	1,290	.0511628	.0061369	.2204151	.0391235	.0632021
diff		-.0445736	.0152978		-.0745849	-.0145623

```
    diff = mean(0) - mean(1)                                      t =  -2.9137
Ho: diff = 0                                     degrees of freedom =     1288

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0018         Pr(|T| > |t|) = 0.0036          Pr(T > t) = 0.9982
```

Appendix D: Detailed Load Impact Results

Table 8 depicts the load impact results for all events dispatched over the course of the summer using both PG&E AMI data and SolarEdge battery end use data. Note that for some days the SolarEdge data was not available and so only PG&E AMI data results are included. The event duration, event start time, max daily temperature, and dispatch success rate are also included for reference.

Table 8: Detailed Load Impact Results for Battery Storage Events

Date	Event Type	Event Start (Hour Start)		Event Duration		Advance Notice		Max Daily Temp.	Number of Batteries Dispatched	Dispatch Success Rate	PG&E AMI Data Avg. Load Impact (kWh)		Battery End Use Data Avg. Load Impact (kWh)	
		Charge Event	Discharge Event	Charge Event	Discharge Event	Charge Event	Discharge Event				Charge Event	Discharge Event	Charge Event	Discharge Event
5/2/22	Discharge		19		4 hours		24 hours	61.34	104	77%			0.30	1.75
5/11/22	Charge	12		4 hours		24 hours		65.29	82	74%	0.02	0.17		
5/16/22	Charge	12		4 hours		6 hours		68.82	90	68%	0.05	-0.06		
5/19/22	Discharge		19		4 hours		24 hours	71.34	128				0.93	-
5/26/22	Charge + Discharge	12	21	2 hours	4 hours	24 hours	24 hours	70.51	96	84%	-0.40	0.03	0.53	0.74
5/27/22	Charge	12		6 hours		24 hours		69.9	82	80%	0.23	0.13	0.09	0.12
5/29/22	Charge	14		4 hours		24 hours		72.46	82	63%	-0.09	-0.19	-0.04	-0.07
6/3/22	Discharge		19		4 hours		6 hours	65.03	83	75%			0.65	1.18
6/7/22	Discharge		19		4 hours		3 hours	70.58	117	63%			0.55	0.92
6/9/22	Discharge		19		4 hours		1 hour	80.75	83	68%			0.68	1.03
6/16/22	Discharge		19		4 hours		24 hours	63.84	88	19%			0.93	0.45
6/17/22	Discharge		19		6 hours		24 hours	63.31	75	70%			0.27	0.41
6/22/22	Discharge		19		2 hours		24 hours	77.22	75	71%			1.68	2.39
6/24/22	Discharge		19		4 hours		24 hours	75.97	83	63%			0.28	0.54

6/25/22	Discharge		17		4 hours		24 hours	79.46	83	64%			0.51	0.40
6/30/22	Discharge		19		6 hours		6 hours	66.04	120	75%			0.42	0.71
7/6/22	Discharge		19		6 hours		3 hours	69.05	91	70%			0.42	0.37
7/14/22	Charge + Discharge	11	19	4 hours	2 hours	24 hours	1 hour	80.85	76	58%	-0.01	0.18	1.59	1.35
7/27/22	Discharge		17		4 hours		3 hours	77.34	91	73%			0.80	0.78
7/31/22	Discharge		21		4 hours		6 hours	66.67	120	69%			0.64	1.00
8/2/22	Discharge		17		4 hours		6 hours	83.66	76	75%			0.52	0.73
8/4/22	Discharge		19		4 hours		6 hours	75.09	73				0.60	-
8/8/22	Charge + Discharge	13	17	2 hours	4 hours	24 hours	3 hours	78.32	83	68%	-0.23	-0.11	0.83	1.05
8/11/22	Discharge		19		2 hours		6 hours	72.83	83	40%			1.78	1.39
8/15/22	Discharge		21		4 hours		1 hour	71.77	116	65%			0.20	0.67
8/16/22	Discharge		19		6 hours		1 hour	83.48	89	70%			0.24	0.32
8/17/22	Discharge		19		2 hours		3 hours	76.32	89	68%			1.42	2.08
8/23/22	Load Shape Discharge		16		5 hours		24 hours	87.68	72	75%			0.21	0.41
8/30/22	Load Shape Discharge		16		4 hours		24 hours	80.09	82	74%			0.26	-0.05
9/1/22	Charge + Discharge	12	19	4 hours	1 hour	24 hours	3 hours	88.23	115	54%	-0.97	-	2.11	-