Silicon Valley Clean Energy

Innovation Onramp: ev.energy GridShift Evaluation

SUBMITTED TO: Silicon Valley Clean Energy

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Abstract

Silicon Valley Clean Energy (SVCE) conducted the GridShift pilot program to assess the impact of a telematics-based managed electric vehicle (EV) charging services App on customers with EV's in Santa Clara County. The study period for this report was from February 2021 through October 2021. A comparison group of non-participants and participants was created by matching on weekly loads prior to the start of the pilot. The study examined the impact of the GridShift App throughout the year (steady state) and on days when low-carbon events were called. Data from this pilot program was provided to ADM Associates, Inc. (ADM) who assessed impacts on energy usage (kWh), demand (kW), greenhouse gas emissions ($C0_2$), changes in customer bills, cost-effectiveness, and customer satisfaction. In aggregate, the GridShift EV Charging App consistently reduced energy use, shifted use off-peak, reduced customer bills, and lowered the carbon footprint of customer EV charging. In addition, App users reduced energy consumption with statistically significant kWh savings, indicating a hypothesized behavioral impact due to App feedback on charging energy use and costs. Low-carbon emissions events pushed customers to charge more during low carbon emissions event hours and resulted in 3.78 lbs. CO_2 savings per event, per customer, and a reduction of 0.78 kW during Resource Adequacy windows. App users displayed mixed levels of satisfaction with the pilot, with some users confused about whether charging during low-carbon events would occur during part-peak hours and increase their costs. Lastly, telematics-based charging approaches had 37% lower life cycle costs than installation of smart charging hardware. These findings indicate positive net benefits from the pilot, and future iterations of this program, with larger numbers of participants, will provide even more precise estimates and conclusions.

Study Overview

Program Summary

Silicon Valley Clean Energy (SVCE) is a public, not-for-profit, community-owned agency that provides clean energy in Santa Clara County. As a part of their commitment to community engagement, SVCE initiated the Innovation Onramp program which provides grant funding to support innovation aimed at achieving deep decarbonization in Santa Clara and beyond.

Through this program, SVCE has funded a pilot with ev.energy, Inc. (ev.energy) for a telematics-based managed electric vehicle (EV) charging services pilot (GridShift Pilot).

The GridShift EV Charging App allows customers to align their EV charging with based on electricity rate and carbon intensity of on the California grid. This is supplemented with low-carbon events that are designed to further encourage customers to charge when the grid is clean by notifying users when there are substantial amounts of clean energy available on the grid and rewarding participants with rewards points that can be redeemed for electricity bill credits.

Evaluation Summary

This evaluation included:

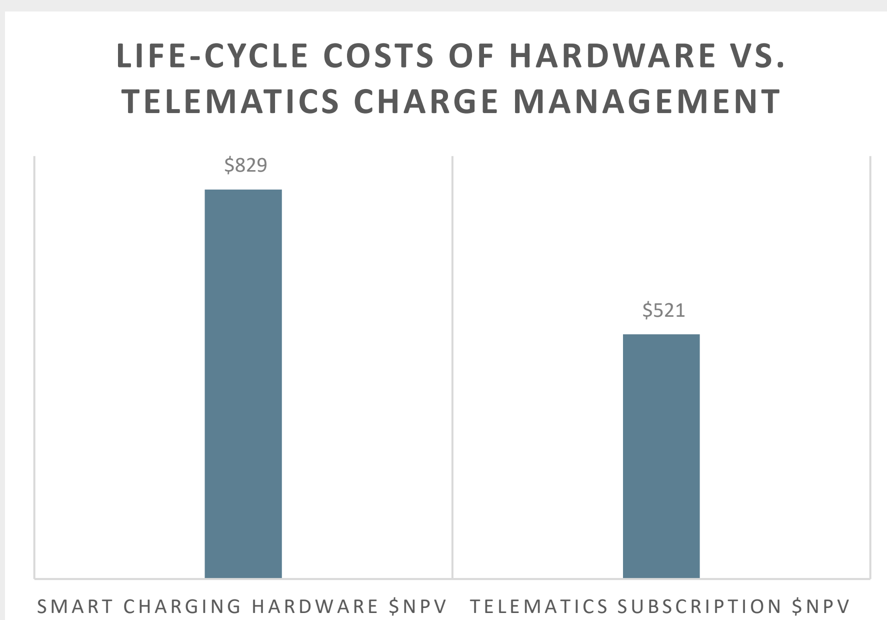
- Analysis of EV load data from 50 single-family Pilot participants out of 52 total participants (96%) for the period of February 2021 to October 2021
- Matched billing data from 50 non-participant households (drawn from 1,495 eligible households)
- Surveys with 38 out of 69 (55%) Pilot participants
- Estimation of impacts of the GridShift EV Charging App treatments:
  - Treatment 1: long-term charging management
  - Treatment 2: Low Carbon Events, pushing EV charging to periods where the grid is supplied with cleaner energy
- Analysis of the cost-effectiveness of telematics-based approaches for charging management

Value from Telematics-based Charge Management

The GridShift app uses a telematics-based approach to provide managed charging. This requires an open API from the original equipment manufacturer (OEM). Managed charging introduces benefits for multiple parties:

- **Vehicle owners:** convenience from greater of their charging.
- **Grid operators:** the opportunity to manage EV charging loads.

Telematics-based approaches have a 37% lower life cycle cost than the installation of smart charging hardware.



Steady-State Impacts

In aggregate, the GridShift EV Charging App consistently reduced energy use, shifted use off-peak, reduced customer bills, and lowered the carbon footprint of customer EV charging.

Some users reported increased energy costs – impacts from GridShift depend on the baseline charging load profile.

Energy

- 255 annual kWh savings per-participant
- 17,595 total kWh savings
- 3.45 total coincident peak kW reduction

Greenhouse Gas

- 248 lbs. of CO_2 reduced per partiicpant
- 17,112 total lbs. CO_2 reduced - equaling four gasoline-fueled cars taken off the road

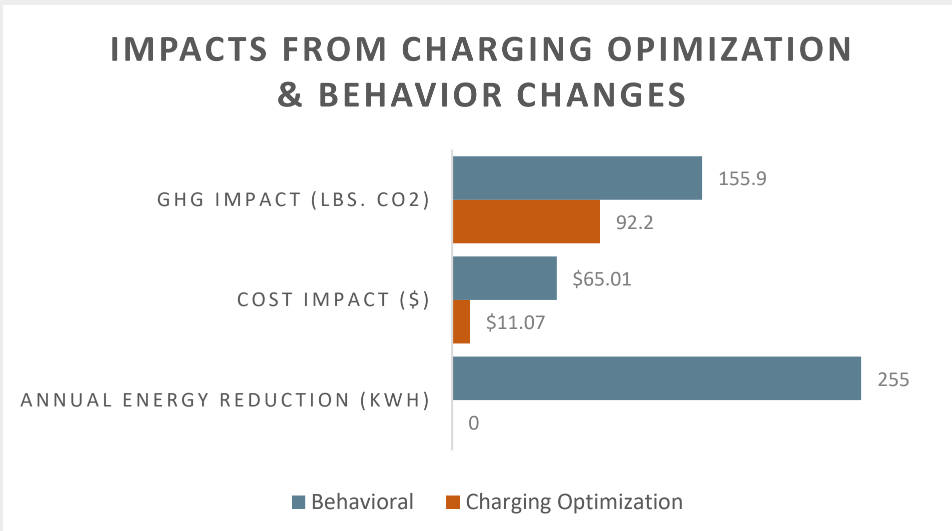
Financial Impacts

- $76 in annual bill savings per-participant
- $5,244 in total annual bill savings

Behavioral vs. Optimization Impacts

App users reduced energy consumption; the GridShift app only redirects EV charging, but users displayed statistically significant kWh savings.

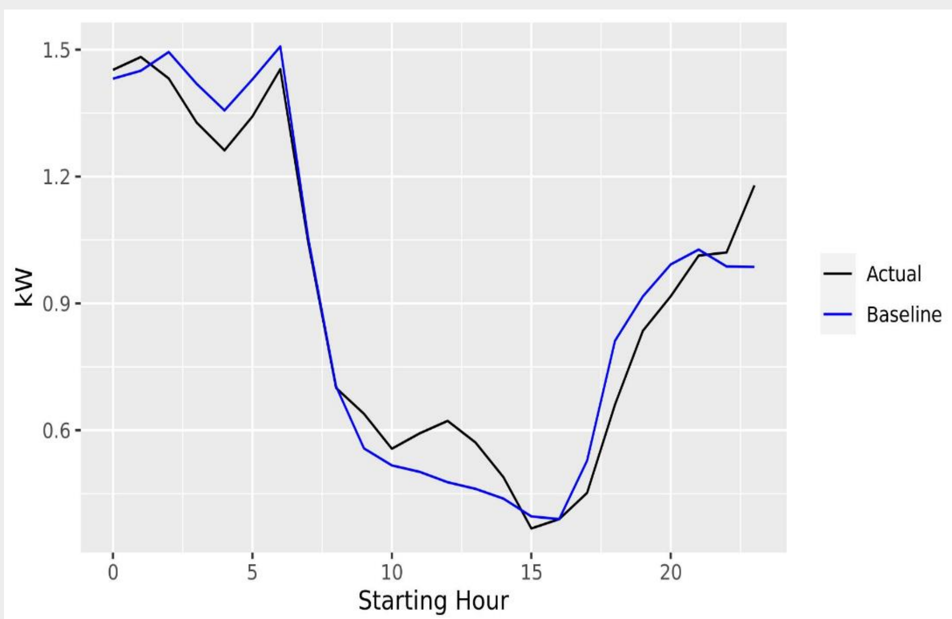
The GridShift app provides feedback on charging energy use and costs, so a behavioral impact is hypothesized.



Emissions Events

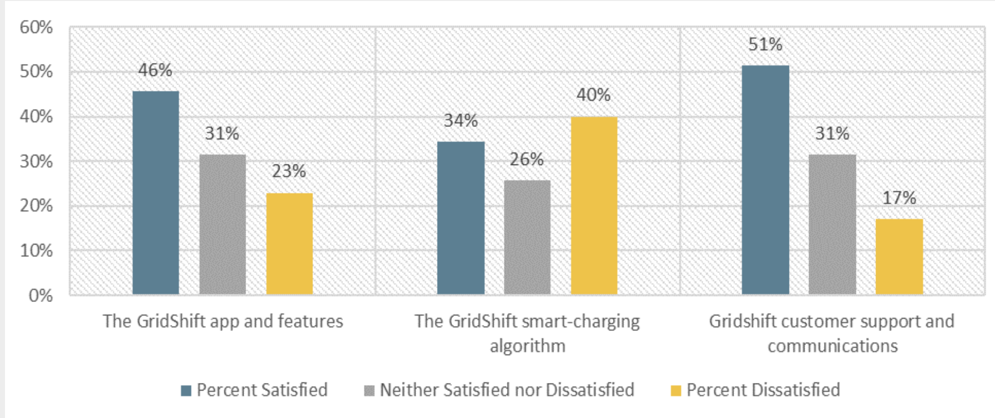
Emissions events guide charging toward periods with cleaner energy supply. Averaged across 17 emissions events, GridShift impacts per-customer were:

- 1.19 kWh shifted
- .078 kW reduced during Resource Adequacy windows
- 3.78 lbs. CO_2 saved from the shift to cleaner energy periods



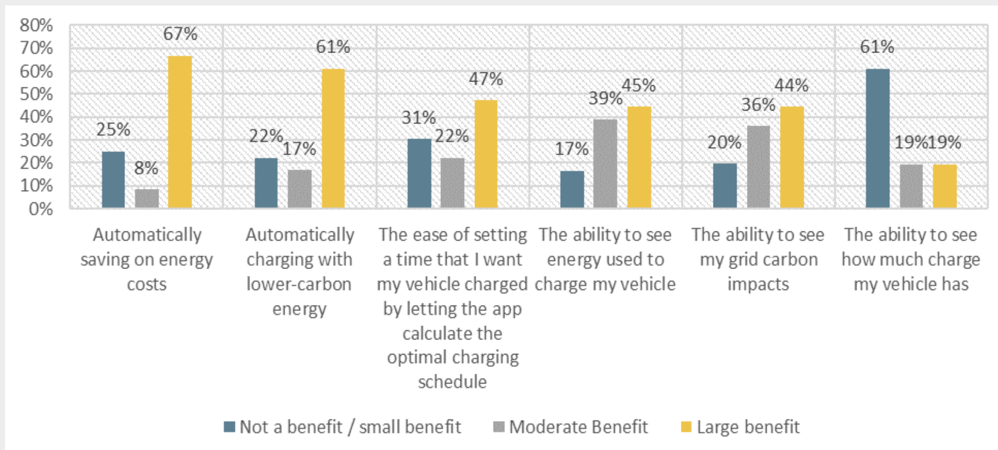
Mixed levels of satisfaction with the pilot.

- 46% satisfied with GridShift app & features
- 34% satisfied with GridShift smart-charging algorithm
- 51% with GridShift customer support / communications



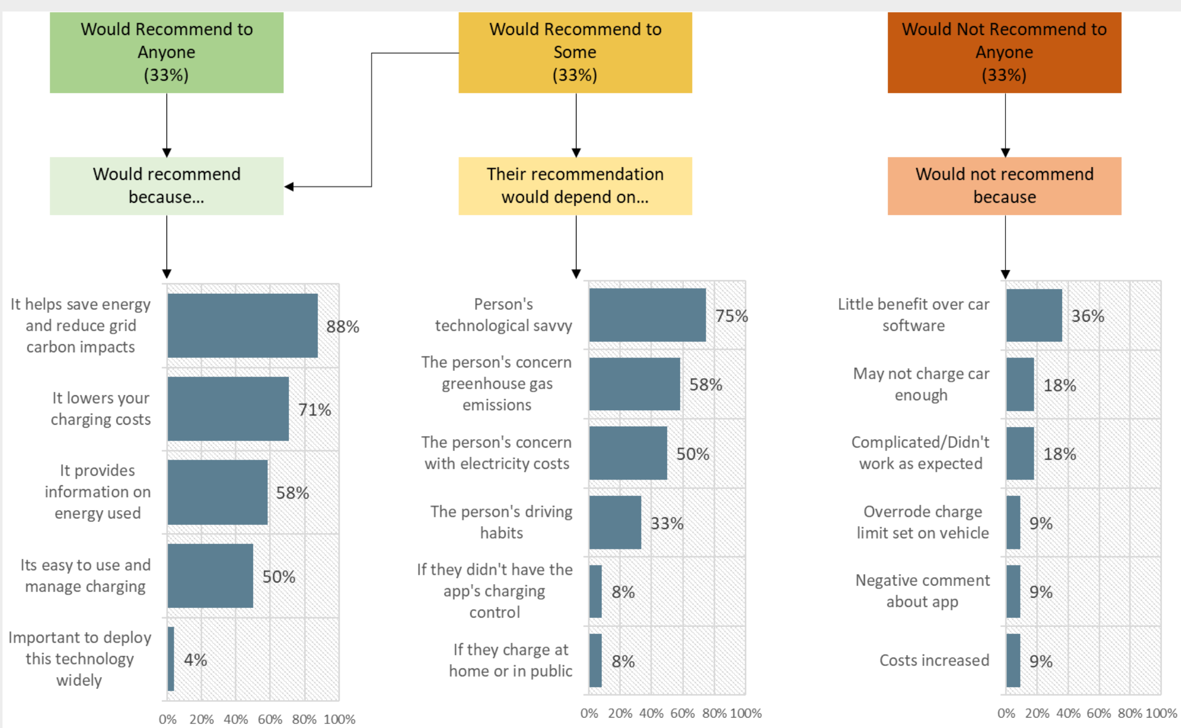
Users cite automated savings as a "large benefit" of the Pilot

- 67% cited automated cost savings, 61% cited automated carbon reduction.
- Other benefits cited include energy & carbon visibility



User Promotion

Promotion versus detraction from GridShift Pilot customers was driven by perception of whether it added benefit above and beyond what is already available in their car's software. Conditional promoters suggest that recommending GridShift to other users depends largely on the would-be user's technological savviness.



1 Impact Methodology

ADM employed the following approaches to estimate impacts for the GridShift Pilot program:

- *Propensity Score Matched Comparison Group with AMI meter data* involves estimating demand impacts by comparing usage for participants with a matched control group. This modeling effort included consumption data from participant and control customers.
- *Prior Day Matching Customer Baseline (CBL) with AMI meter data* involves estimating demand impacts for participants by comparing their usage during low carbon events with prior day usage. This modeling effort included consumption data from participant customers.

The following sections describe in further detail ADM' activities towards meeting these Pilot Goals, followed by the resulting verified impact estimates.

1.1 Data Utilized

ADM utilized the following data provided by SVCE:

- Hourly AMI data for participants and non-participants with electric vehicles.
- 30-minute charging and cost data providing the kW and $/kWh for each participant on the GridShift app.
- 30-minute emissions data providing lbs. of CO_2 per kWh from 2020 to 2021.

1.2 Treatment Group Cohort Creation

ADM utilized the GridShift app charging session data to determine whether participants were being treated. ADM identified treated customers as those with at least one unique charging session ID in four of the five treatment months. ADM defined a period of five treatment months from which to estimate impacts. These months were chosen because they had the largest number of participants using the GridShift app (as determined by the charging data) and these months coincided with Treatment 1 (Steady State) and Treatment 2 (Low Carbon Emissions Events).

The following dates define the treatment periods ADM utilized to estimate impacts:

Treatment 1 Period: January, February, and May 2021

Treatment 2 Period: Low Carbon Events in March and April 2021.

1.3 Treatment 1 (Steady State) Impact Methodology

ADM estimated program impacts for Treatment 1 using a matched control group. Treatment 1 was applied to all customers who signed up for the GridShift app. For Treatment 1, participants' charging is primarily optimized to reduce retail costs to the customer (selecting customers on EV-2A, EV-A, EV-B, TOU rates, and standard rates and moving charging to off-peak times), with a secondary optimization applied to minimize emissions.

1.3.1 Matched Control Group

A matched comparison group was created using a Propensity Score Matching (PSM) approach. With the PSM approach, a propensity score is estimated for treatment customers (i.e., those who received Treatment 1 and Treatment 2) and a group of customers who did not receive the treatment using a logit model. Customers in the treatment and control groups were matched based on average weekly pre-period usage and exactly matched based on their quartile of average hourly load during hour 1:00 (charging peak) and hour 16:00 (mid-day peak). ADM found that this combination of matching variables produced the closest match for average pre-period annual, monthly, weekly, and hourly usage.

SVCE provided hourly AMI data for non-participant customers with electric vehicles from which ADM selected control customers.

1.3.2 Methodology for Annualizing Treatment 1 Impacts

Using the matched control group, ADM estimated annualized Treatment 1 impacts with a difference-in-difference regression model. The model estimates usage as a function of the weather, cohort (treatment vs. control), pre- vs. post-period, and hour. The regression model is specified in Equation 1-1 below:

Equation 1-1: Regression Model

$$Usage_{it} = \beta_0 + \sum_{h=1}^{24} \beta_h * Hour_h + (\beta_1 * HDD_{it)} + (\beta_2 * CDD_{it}) + (\beta_3 * Post_{it}) + (\beta_4 * Treatment_{it}) + (\beta_5 * Post_{it} * Treatment_{it}) + (\beta_6 * HDD_{it} * Post_{it} * Treatment_{it}) + (\beta_7 * CDD_{it} * Post_{it} * Treatment_{it}) + \varepsilon_{imy}$$

Where:

$Usage_{it}$	=	Customer i's average daily energy usage at time t
β_0	=	Intercept of the regression equation
$Hour_h$	=	An indicator variable equal to one for each hour of the day h
β_h	=	The coefficients on the hour of the day h
β_1, β_2	=	The coefficients on Heating Degree Days and Cooling Degree Days
HDD_{it}	=	Heating Degree Days for customer i at time t
CDD_{it}	=	Cooling Degree Days for customer i at time t
$Post_{it}$	=	An indicator variable equal to one for each hour in the post-period, and zero otherwise
β_3	=	The coefficient on the Post variable
$Treatment_{it}$	=	An indicator variable equal to one for each participant, and zero otherwise

β_4 = The coefficient on the Treatment variable

β_5 = The coefficient on the Post and Treatment interacted indicator variables. This measures the treatment effect independent of the weather.

β_6, β_7 = The coefficients on Heating Degree Days and Cooling Degree Days interacted with the Post and Treatment indicator variables. This measures the treatment effect as a function of HDD and CDD (i.e., the change in usage per day due to treatment per HDD/CDD)

ε_{imy} = The error term.

ADM also interacted the Post and Treatment indicator variables with the hourly dummy variables to estimate the treatment effect for each hour of the day. Extrapolation was then made to Typical Meteorological Year (TMY)[1] data.

Using the historical weather data from San Jose Mineta Airport, ADM calculated Heating Degree Days (HDD) and Cooling Degree Days (CDD) for use in the regression analysis. HDDs are calculated as temperature values under the heating setpoint (65°F), while CDDs are calculated as temperature values over the cooling setpoint (65°F). The setpoint values for HDDs and CDDs were determined by running regressions with multiple setpoints from 65°F through 75°F. ADM chose the setpoint combination with the highest adjusted R-squared value, demonstrating the best fit for the data.

1.4 Treatment 2 (Low Carbon Emissions Events) Impact Methodology

ADM estimated program impacts for Treatment 2 using prior day matching and a matched control group. Treatment 2 consisted of low carbon emissions events where customer vehicles would be charged during the event if their vehicle was connected to the charging unit.

For Treatment 2, customers were notified via the app a day in advance of an event time where the grid is especially clean, and that if their vehicle is plugged in during the event time, the platform would automatically charge their vehicle during the event period.

1.4.1 Prior Day Matching

ADM tested a variety of day matching models to address demand reductions associated with the GridShift program. Three different Customer Baseline models (CBLs) were built, including a 5-of-5 unadjusted baseline, a 10-of-10 unadjusted baseline, and a mixed model that assigns the best fitting CBL model on a customer-specific basis.

ADM determined that using prior-hour (or other day of event) adjustment factors would be inappropriate as the load shifting from Treatment 2 events impact all hours surrounding the event. In addition, using a X-of-Y prior day averaging method (e.g., 3-of-10) was also found to be inappropriate since the low carbon emissions events were not called on the highest usage days but were called on days and times with the lowest carbon emissions.

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[1] https://nsrdb.nrel.gov/data-sets/archives.html

For a 5-of-5 baseline, ADM examined the load data from the most recent five non-event, non-holiday days with the same weekday type relative to the event day and calculated the mean demand usage values.

For a 10-of-10 baseline, ADM examined the load data from the most recent ten non-event, non-holiday days with the same weekday type relative to the event day and calculated the mean demand usage values.

For the mixed model, customers are assigned the model that minimized bias on proxy days. Proxy days were defined as non-event, non-holiday days with the highest loads during the months when low carbon emissions events were run (March-April 2021). In addition, proxy days must have had similar temperature ranges as those observed during low emissions event days. For instance, to be considered a proxy day, the average and maximum temperature had to fall between the average and maximum temperature range observed on low emissions event days to ensure proxy days had similar weather as event days.

ADM used proxy days to determine the ability of the CBL models to predict actual usage for each customer by calculating average bias and error across hours for the average proxy day.

1.4.2 Matched Control Group

The methodology for the matching control group baseline estimate for Treatment 2 is provided in Section 1.3.1.

1.4.3 Event Window

ADM examined the full event day to determine the hours for which the charging algorithm is shifting charging. ADM defined the event window for each low carbon emissions event as the 12 hours before and after the midpoint of the event time. For example, if the event was called from 12-2 PM on March 6, 2021, then the event window would be from 1 AM on March 6th to 1 AM on March 7th.

2 Impact Results

The following section summarizes findings for the GridShift Pilot program. ADM used AMI meter data, charging data, and emissions data provided by SVCE to evaluate Treatment 1 (Steady State/GridShift app) and Treatment 2 (Low Carbon Event) impacts.

ADM summarized charging characteristics for participants using the GridShift app charging data. Participants were included in the sample if they had at least one charging session ID per month from February 2021 to October 2021. This date range was selected to ensure coverage across every season and enough participants for the sample (n=25).

The average charging duration for a participant was 3.50 hours for a single charging session. As shown in Table 2-1, weekend charging was slightly higher than weekday charging on average.

Table 2-1 Average Participant kW Load During Charging

Day Type	Average kW During Charging	Average Max kW During Charging
Weekday	1.080	2.410
Weekend	1.231	2.719

Figure 2-1 shows the charging load shape by day type. The least amount of charging is done during SVCE's peak hours from 4:00 PM to 9:00 PST. Only 4.9% of participant charging took place during peak hours. This suggests that the GridShift app is working by helping customers charge mostly during off peak hours. In addition, most charging occurs between 12:00 AM and 6:00 AM.

Figure 2-1 Charging Load Shape by Day Type

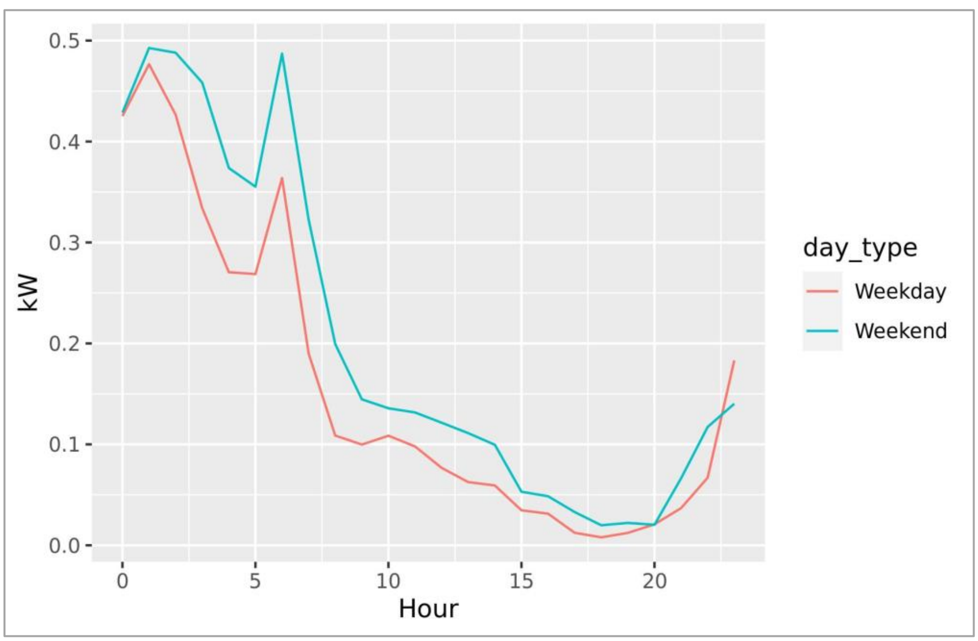


Figure 2-2 provides the charging load shape by day and season. Charging is slightly higher in fall and winter, but the overall load shapes are similar between seasons.

Figure 2-2 Charging Load Shape by Day Type and Season

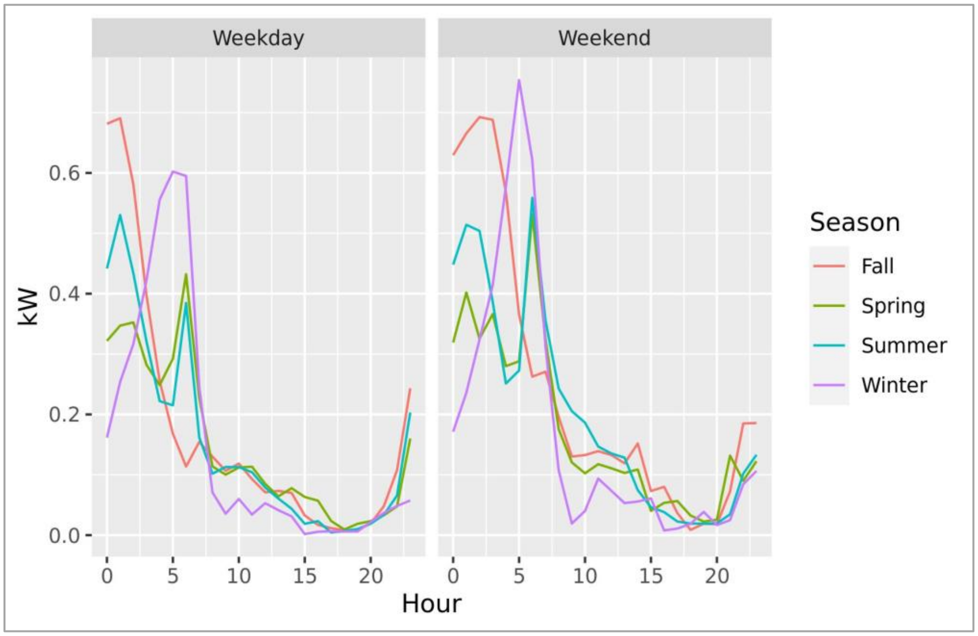
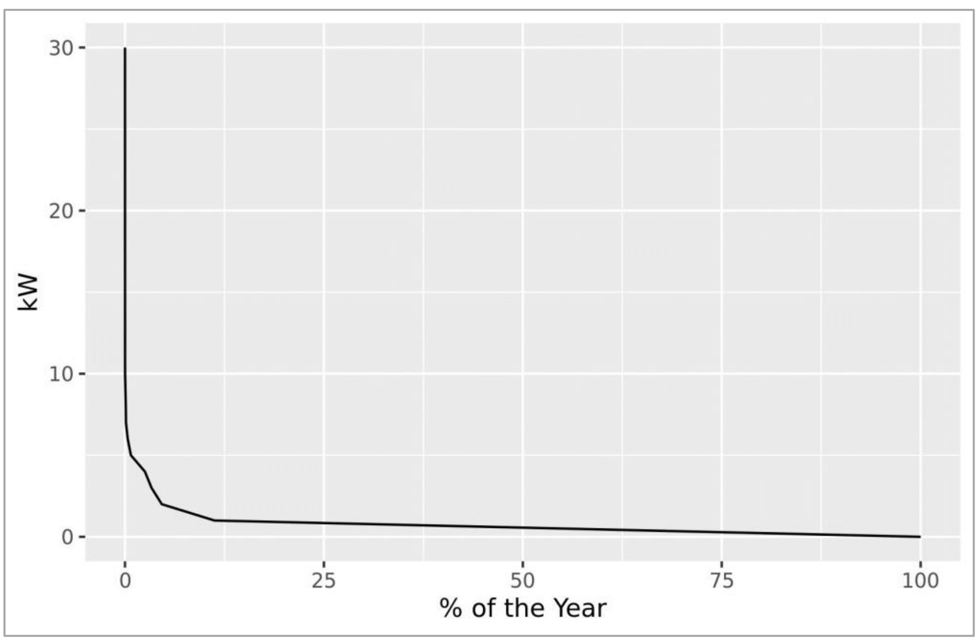


Figure 2-3 provides a load duration curve, which displays the percent of the year the average participant had a given kW load. As depicted, charging load was 0 kW 89% of the time, between 1-2 kW 8% of the time, and greater than 2 kW 3% of the time[2].

Figure 2-3 Load Duration Curve



[2] A few participants may have had multiple vehicles such that their max load at any given time could have been greater than the max charging load for a single vehicle.

Lastly, ADM calculated a standard deviation of 80.08 and a mean of 89.48 for the total number of charging events during peak and part-peak hours between February and October 2021 (CV of 0.89).

2.1 Treatment 1 (Steady State) Impacts

This section summarizes the results of Treatment 1, capturing Steady State impacts of the GridShift app.

2.1.1 PSM Control Group Creation

ADM matched treatment and control customers with a 1-to-1 ratio using nearest neighbor matching without replacement to create a matched control group. ADM matched on 11 pre-period months beginning on January 1, 2020, through November 30, 2020. ADM did not use December 2020 for matching because it was apparent in the AMI data that participants had begun Treatment 1 and were using the GridShift app in that month.

Table 2-2 Summary of Matching Customer Counts

Description	Control	Treated
All	1,568	52
Customers w/ Complete Pre-period Data	1,495	50
Matched	50	50

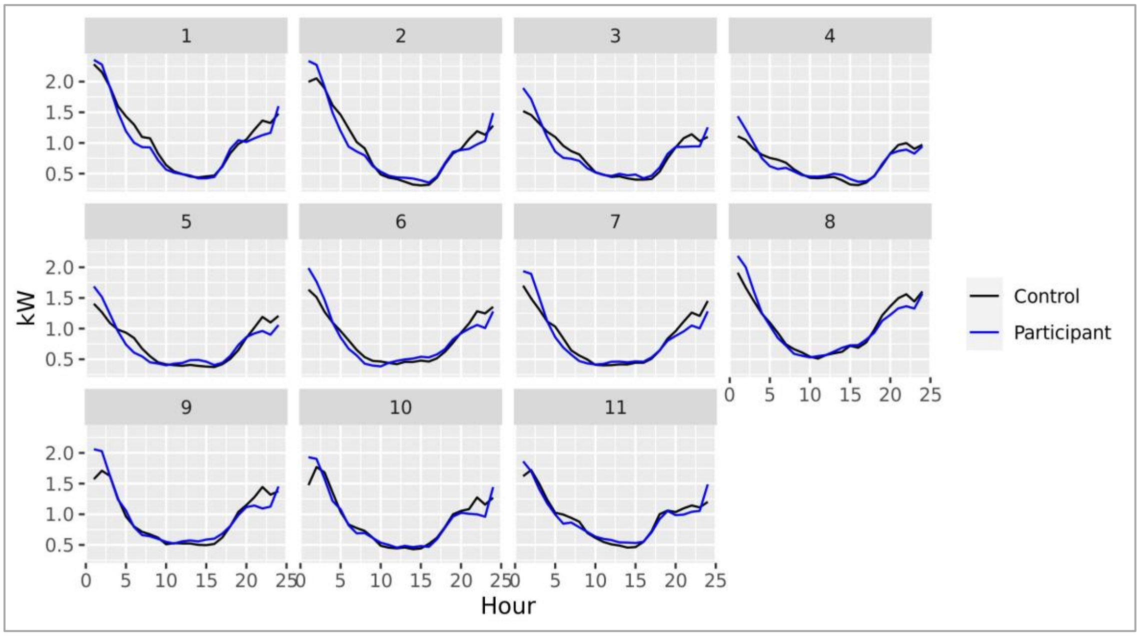
Table 2-3 provides the results of a t-test for each month in the pre-period after matching for the participant customers and matched control customers. No pre-period months show statistically significant differences in average daily usage between participant and matched control customers. In addition, ADM tested for differences in average daily usage spanning the entire pre-period and found no statistically significant difference between participants and matched control customers (p-value = 0.49). Therefore, a valid control group was created from which to estimate baseline usage for the participants.

Table 2-3 Monthly Pre-period Usage T-test Post Matching

Pre-Period Month	Participant Average Daily Usage (kWh/day)	Control Average Daily Usage (kWh/day)	Average Daily Usage Difference (kWh/day)	P-value	Statistically Significant Difference
Jan	24.71	26.04	-1.33	0.081	No
Feb	22.73	22.96	-0.23	0.757	No
Mar	19.89	19.90	0.00	0.995	No
Apr	16.17	15.97	0.20	0.680	No
May	17.71	17.92	-0.20	0.725	No
Jun	19.96	19.94	0.02	0.982	No
Jul	19.77	20.11	-0.33	0.601	No
Aug	24.94	25.01	-0.07	0.926	No
Sep	23.07	22.57	0.50	0.486	No
Oct	21.69	21.76	-0.07	0.915	No
Nov	22.58	22.62	-0.04	0.948	No

Figure 2-4 provides average hourly pre-period kW after matching. Overall, the hourly load shapes indicate a good match for the participant and control groups.

Figure 2-4 Average Hourly Pre-period kW After Matching



2.1.2 Matched Control Group Results

Table 2-4 provides the annualized impacts for Treatment 1 (Steady State) for the average participant using the matched control group. Net reductions in kW, peak kW[3], kWh, cost, and GHG emissions occur for the average participant.

Table 2-4 Annualized Impacts Treatment 1 (Steady State)

Average Actual kW per Participant	Average Baseline kW per Participant	Average kW Impact per Participant	Average Peak kW Impact per Participant	Total kWh Impact per Participant	Total Cost Impact ($) per Participant	Total GHG Impact (lbs. CO2) per Participant
0.759	0.788	-0.029	-0.050	-255.062	-$76.078	-248.139

In addition,

Table 2-5 provides hourly annualized impacts for Treatment 1 using the matched control group. Reductions in kW, kWh, cost, and GHG emissions occur between the hours of 5 PM and 3 AM, while increases in the above impacts occur between 4 AM and 4 PM. This is the expected result of the GridShift app, which was expected to shift demand away from peak-period charging and towards off-peak period and/or during hours with low carbon emissions.

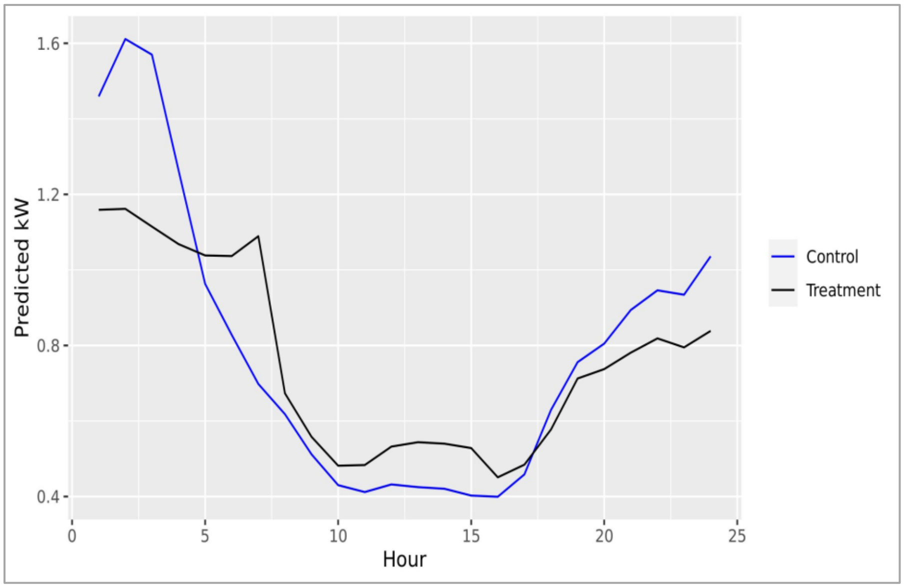
[3] Peak kW impacts were calculated for SVCE's RA window which is 4pm to 9pm.

Table 2-5 Hourly Annualized Impacts Treatment 1 (Steady State)

Hour	Average Actual kW per Participant	Average Baseline kW per Participant	Average kW Impact per Participant	Total kWh Impact per Participant	Total Cost Impact ($) per Participant	Total GHG Impact (lbs. CO2) per Participant
0	1.159	1.459	-0.300	-109.883	-$22.011	-74.607
1	1.162	1.611	-0.450	-163.643	-$33.324	-111.615
2	1.115	1.570	-0.455	-166.148	-$33.378	-113.861
3	1.068	1.264	-0.196	-71.426	-$14.438	-49.084
4	1.038	0.963	0.075	27.446	$5.621	19.046
5	1.037	0.828	0.209	76.179	$15.793	52.659
6	1.089	0.698	0.391	142.751	$29.297	95.306
7	0.673	0.618	0.055	20.124	$4.346	11.626
8	0.558	0.512	0.046	16.909	$3.573	7.921
9	0.482	0.430	0.052	18.815	$3.937	7.859
10	0.483	0.412	0.072	26.109	$5.526	10.212
11	0.532	0.432	0.100	36.564	$7.618	13.938
12	0.544	0.425	0.119	43.414	$9.098	16.251
13	0.540	0.421	0.119	43.575	$9.551	16.453
14	0.528	0.403	0.126	45.896	$10.532	18.183
15	0.451	0.399	0.051	18.794	$6.993	8.042
16	0.484	0.459	0.026	9.407	$4.255	4.274
17	0.578	0.629	-0.052	-18.878	-$6.903	-11.506
18	0.713	0.756	-0.043	-15.797	-$6.022	-10.301
19	0.737	0.805	-0.067	-24.635	-$9.286	-16.634
20	0.781	0.894	-0.113	-41.227	-$15.463	-27.866
21	0.819	0.946	-0.127	-46.453	-$14.634	-31.377
22	0.795	0.934	-0.139	-50.892	-$15.991	-34.378
23	0.839	1.036	-0.197	-72.062	-$20.768	-48.681
All Hours	0.759	0.788	-0.029	-255.062	-$76.078	-248.139

Figure 2-5 provides a visualization of the annualized impacts for each hour of the day for the participants (Treatment) versus the matched control group.

Figure 2-5 Annualized Load Shape for Treatment 1 (Steady State)



2.1.3 Parsing Technological Versus Behavioral Impacts

The primary function of the GridShift app is to redirect charging needs to periods that are price- and carbon-optimized. The annual kWh savings found in the model would indicate that beyond this, there is an impact from the app that is resulting in lower charging need. This could only happen through reduced vehicle miles traveled, as the app does not have a means to produce energy use reductions. It is possible that engagement with the app increased awareness of energy use and costs, which could for some users result in fewer miles traveled (perhaps through reduced discretionary trips, increased carpooling, etc.).

To separate behavioral impacts, ADM recalculated energy use for the treatment cohort by scaling their load shape to align with the energy use of the control cohort:

$$kWh_{Trt_{Adj},t} = \frac{kWh_{Ctrl_{Annual}}}{kWh_{Trt_{Annual}}} \times kWh_{Trt_t}$$

Where,

$kWh_{Trt_{Adj},t} = Treatment\ group\ kWh\ in\ hour\ t, adjusted\ to\ align\ with\ control\ group$

$kWh_{Trt_{Annual}} = Treatment\ annual\ kWh$

$kWh_{Ctrl_{Annual}} = Control\ group\ annual\ kWh$

In the analysis, ADM then parsed the cost and carbon impacts between the two load shapes.

Table 2-6 Annualized Impacts Treatment 1 (Steady State)

	Total kWh Impact per Participant	Total Cost Impact ($) per Participant	Total GHG Impact (lbs. CO2) per Participant
Optimization	0	-$11.07	-92.24
Behavioral	-255.062	-$65.01	-155.90

Total	-255.062	-$76.08	-248.139

2.2 Treatment 2 (Low Carbon Emissions Events) Impacts

This section summarizes the results of Treatment 2 (low carbon emissions events). SVCE called 17 events in March and April 2021, as shown below. Events were called between 8:30 AM PST and 3:00 PM PST.

Figure 2-6 Low-Carbon Event Dates & Times

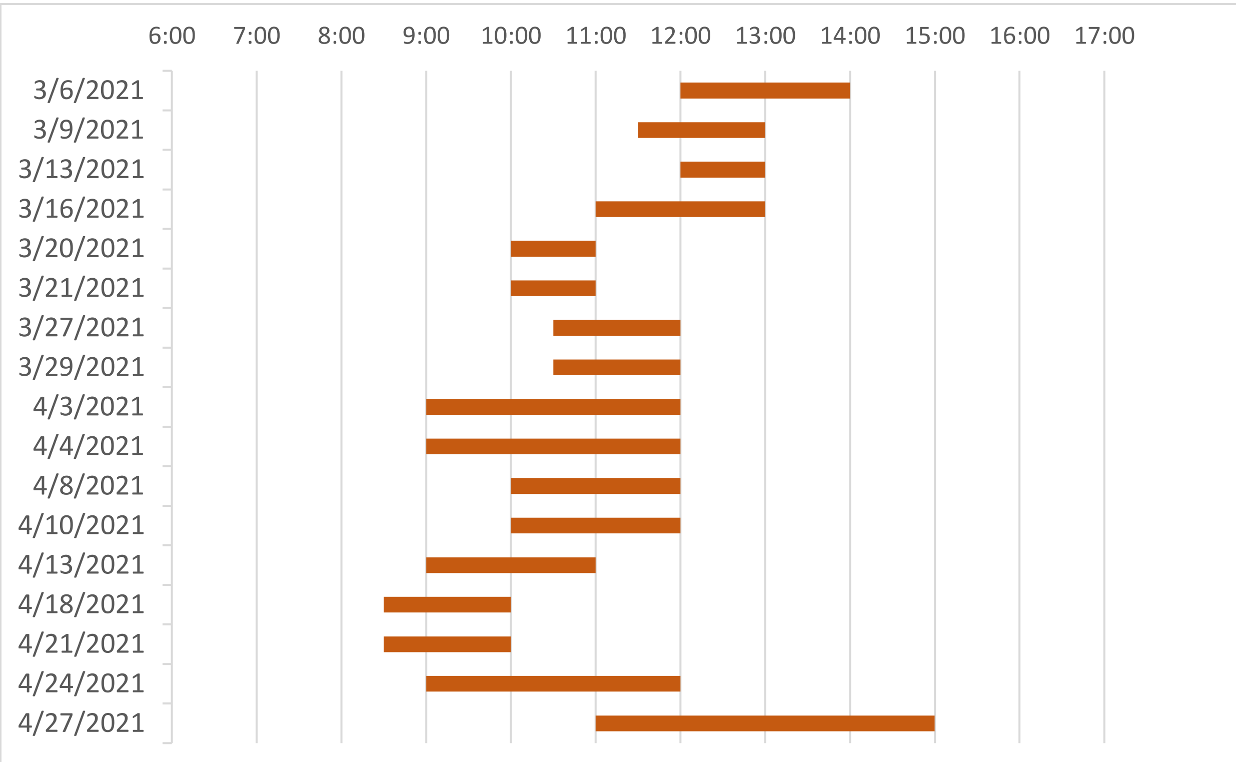


Table 2-7 summarizes average impacts during the low carbon emissions events for the two baselines: prior day matching (CBL) and PSM. For CBL baseline, the impacts are net impacts for Treatment 2 (Low Carbon Events) because the baseline is the participant's own usage on non-event days and all participants in the treatment cohort were using the GridShift app during months when low carbon emissions events were called. For the PSM baseline, control customers were not using the GridShift app and therefore impacts include both Treatment 1 and Treatment 2. Average impacts are higher with the matched control baseline compared to the CBL baseline which includes only the impact for Treatment 2.

Table 2-7 Average Per-Participant Impacts During Low Carbon Emissions Event Windows

Baseline Method	Treatment Type	Average kW Impact	Average Peak kW Impact	Total kWh Impact	Cost Impact ($)	GHG Impact (lbs. CO2)
Prior Day Matching	Low Carbon Events	-0.003	-0.077	-1.189	-$0.683	-3.781
PSM Matched	Steady State + Low Carbon Events	-0.003	-0.062	-1.029	-$1.124	-10.719

2.2.1 Prior Day Matching Model Selection and Performance

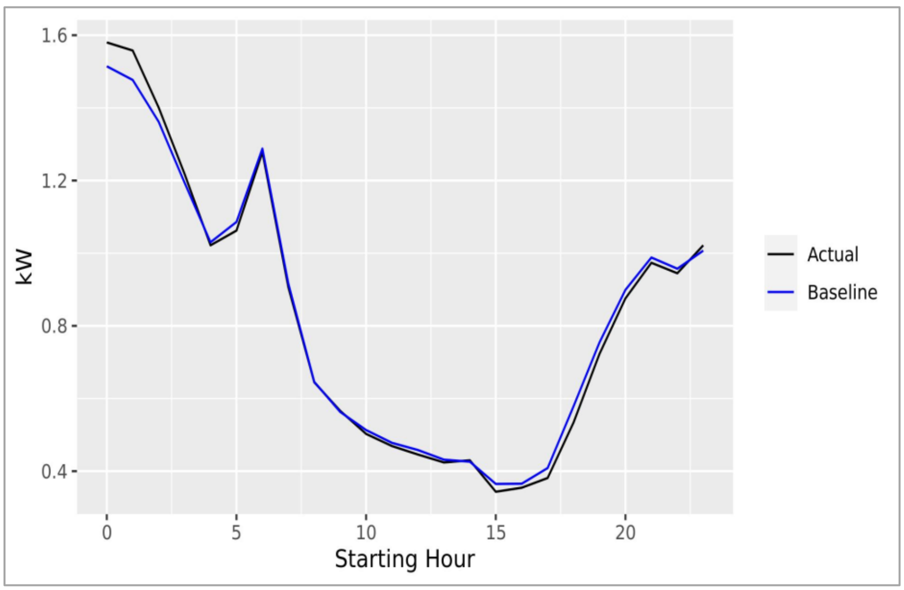
Table 2-8 provides model fit statistics for each prior day matching (CBL) model. The mixed model has the lowest average bias on proxy days and was selected for the baseline.

Table 2-8 Prior Day Matching Model Fit Statistics

Model	RRMSE	RMSE	Bias	Weighted Bias
Mixed Model (customer-specific)	0.035	0.029	1.3%	0.2%
Unadjusted 5-of-5 CBL	0.034	0.028	1.4%	0.3%
Unadjusted 10-of-10 CBL	0.054	0.044	4.0%	2.5%

Figure 2-7 shows the load shape during proxy days for the best fitting prior day matching mixed model. There is little difference between baseline usage and actual usage during most hours. The baseline has a downward bias during between 12 AM-2 AM and an upward bias between 3 PM-10 PM. The selected baseline is performing well on average with only a slight upward average hourly bias of 1.3%.

Figure 2-7 Load Shape During Proxy Event Days with Prior Day Matching Model



2.2.2 Prior Day Matching Results

This section summarizes impacts for Treatment 2 (Low Carbon Emissions Events) using the prior day matching methodology. The values are marginal impacts for Treatment 2 (Low Carbon Events) because the baseline is the participant's own usage on prior days and all participants in the treatment cohort were using the GridShift app during the months when low carbon emissions events were called.

Table 2-9 provides average kW, peak kW[4], kWh, cost, and GHG emissions impacts by event day. Reductions occur during the event window for the average event. Some events do not show net

[4] Peak kW impacts were calculated for SVCE's RA window which is 4pm to 9pm.

reductions, indicating that charging reductions may occur outside the 24-hour event window[5], or that the baseline performs well for an average event but may not perform well for individual events.

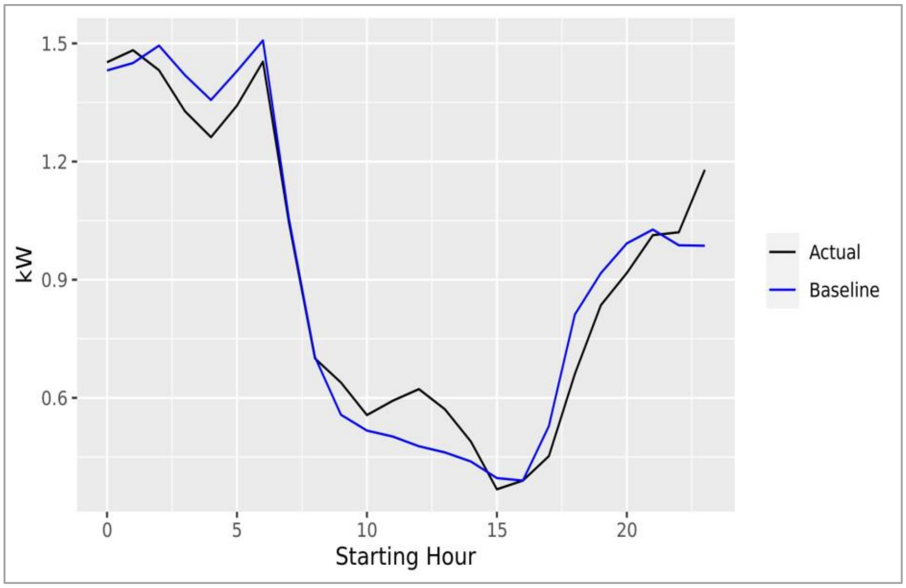
Table 2-9 Treatment 2 Per-Participant Results by Low Carbon Emission Event

Low Carbon Event Day & Time	Average Actual kW	Average Baseline kW	Average kW Impact	Average Peak kW Impact	Total kWh Impact	Total Cost Impact ($)	GHG Impact (lbs. CO2)
3/6/2021 12PM-2PM	0.926	0.998	-0.071	-0.132	-1.713	-$0.458	-0.996
3/9/2021 11:30AM-1:30PM	0.937	0.884	0.053	0.116	1.260	$0.427	0.274
3/13/2021 12PM-1PM	0.968	0.985	-0.017	-0.070	-0.409	-$0.089	-0.688
3/16/2021 11AM-2PM	0.995	0.990	0.005	-0.052	0.114	-$0.073	-0.052
3/20/2021 10AM-1PM	0.998	0.980	0.018	-0.175	0.437	-$0.036	0.383
3/21/2021 10AM-1PM	0.953	0.980	-0.028	-0.139	-0.662	-$0.183	-0.308
3/27/2021 10:30AM-1:30PM	1.041	0.978	0.064	-0.205	1.535	$0.159	0.667
3/29/2021 10:30AM-1:30PM	0.806	0.897	-0.091	0.032	-2.179	-$0.427	-2.316
4/3/2021 9:00AM-3PM	1.006	0.954	0.052	-0.213	1.237	$0.173	0.318
4/4/2021 9:00AM-3PM	0.863	0.954	-0.091	-0.157	-2.184	-$0.542	-1.494
4/8/2021 10:00AM-2PM	0.885	0.793	0.092	0.013	2.215	$0.456	1.569
4/10/2021 9:00AM-2PM	0.916	0.954	-0.038	-0.247	-0.922	-$0.276	-0.910
4/13/2021 9:00AM-2PM	0.734	0.757	-0.024	0.005	-0.570	-$0.034	0.017
4/18/2021 8:30AM-1:30PM	0.907	0.919	-0.012	-0.071	-0.291	-$0.108	-0.475
4/21/2021 8:30AM-1:30PM	0.829	0.781	0.048	0.046	1.148	$0.334	0.643
4/24/2021 9:00AM-3:00PM	0.777	0.919	-0.142	-0.126	-3.397	-$0.819	-2.364
4/27/2021 11:00AM-4:00PM	0.904	0.771	0.133	0.065	3.190	$0.813	1.949
All Events	0.908	0.911	-0.003	-0.077	-1.189	-$0.683	-3.781

Figure 2-8 provides the average participant load shape across all low carbon emissions event, using the prior day averaging baseline.

Figure 2-8 Average Load Shape During Low Carbon Emissions Event Window

[5] The methodology examines load shift during a 24-hour window surrounding the event, however a customer may charge less due to the event outside the 24-hour event window (e.g., the event may have delayed or reduced charging more than 12 hours after the event was over, and it is not captured in the 24-hour event window.



The largest reductions occurred between 1 AM and 6 AM, with additional reductions between 4 PM and 9 PM. The load increases between 8 AM and 2 PM (typical event hours).

Table 2-10 provides impacts for the average participant across all low carbon emissions events by hour.

Table 2-10 Low Carbon Emissions Events Per-Participant Results by Hour

Hour	Average Actual kW	Average Baseline kW	Average kW Impact	Total kWh Impact	Total Cost Impact ($)	Total GHG Impact (lbs. CO2)
0	1.452	1.435	0.017	0.295	$0.058	0.198
1	1.483	1.453	0.030	0.508	$0.104	0.344
2	1.432	1.502	-0.070	-1.190	-$0.238	-0.803
3	1.328	1.424	-0.097	-1.644	-$0.336	-1.130
4	1.262	1.358	-0.097	-1.641	-$0.336	-1.137
5	1.342	1.439	-0.097	-1.651	-$0.345	-1.150
6	1.454	1.510	-0.057	-0.962	-$0.196	-0.663
7	1.044	1.054	-0.010	-0.169	-$0.034	-0.104
8	0.700	0.703	-0.003	-0.050	-$0.010	-0.021
9	0.639	0.558	0.080	1.368	$0.290	0.400
10	0.556	0.517	0.039	0.664	$0.145	0.161
11	0.593	0.501	0.092	1.559	$0.345	0.332
12	0.622	0.476	0.146	2.481	$0.550	0.508
13	0.571	0.460	0.111	1.882	$0.425	0.387
14	0.489	0.437	0.052	0.879	$0.195	0.173
15	0.368	0.396	-0.028	-0.483	-$0.154	-0.105
16	0.390	0.391	-0.001	-0.009	-$0.003	-0.002
17	0.452	0.529	-0.077	-1.312	-$0.442	-0.435

18	0.661	0.812	-0.151	-2.566	-$0.871	-1.318
19	0.835	0.917	-0.082	-1.389	-$0.460	-0.916
20	0.917	0.992	-0.075	-1.272	-$0.409	-0.854
21	1.013	1.028	-0.015	-0.258	-$0.077	-0.172
22	1.020	0.988	0.032	0.551	$0.163	0.364
23	1.179	0.990	0.189	3.219	$0.953	2.162
All Hours	0.908	0.911	-0.003	-1.189	-$0.683	-3.781

2.2.3 Matched Control Group Results

This section summarizes impacts for Treatment 1 (Steady State/GridShift app) and Treatment 2 (Low Carbon Emissions Events) using the PSM control group methodology. The impacts here include Treatment 1 impacts because the control group customers did not utilize the GridShift app.

Table 2-11 provides impacts for kW, peak kW[6], kWh, cost, and GHG emissions for the average participant for each event day. Net reductions for each of the calculated impacts occur during the event window for the average event. However, some events do not show net reductions which indicates that charging reductions may occur outside the 24-hour event window, or that the baseline performs well for an average event but may not perform well for individual events (perhaps due to the small sample size (n=50 control; n= 50 treatment)).

Table 2-11 Treatment 1 and Treatment 2 Results by Low Carbon Emission Event

[6] Peak kW impacts were calculated for SVCE's RA window which is 4pm to 9pm.

Low Carbon Event Day & Time	Average Actual kW per Participant	Average Baseline kW per Participant	Average kW Impact per Participant	Average Peak kW Impact per Participant	Total kWh Impact per Participant	Total Cost Impact ($) per Participant	Total GHG Impact (lbs. CO2) per Participant
3/6/2021 12PM-2PM	0.896	0.926	-0.030	-0.259	-0.726	-$0.394	-1.120
3/9/2021 11:30AM-1:30PM	0.888	0.983	-0.095	-0.175	-2.286	-$0.638	-1.845
3/13/2021 12PM-1PM	0.946	0.860	0.086	-0.027	2.070	$0.400	0.368
3/16/2021 11AM-2PM	0.943	0.903	0.041	0.030	0.976	$0.147	0.215
3/20/2021 10AM-1PM	0.949	0.999	-0.050	-0.122	-1.193	-$0.417	-0.975
3/21/2021 10AM-1PM	0.913	0.859	0.053	-0.132	1.282	$0.237	0.616
3/27/2021 10:30AM-1:30PM	1.016	0.897	0.119	-0.049	2.851	$0.508	1.264
3/29/2021 10:30AM-1:30PM	0.794	0.980	-0.186	0.041	-4.475	-$0.900	-4.521
4/3/2021 9:00AM-3PM	0.977	1.018	-0.041	-0.388	-0.993	-$0.461	-1.097
4/4/2021 9:00AM-3PM	0.828	0.852	-0.024	-0.051	-0.578	-$0.160	-0.730
4/8/2021 10:00AM-2PM	0.870	0.694	0.176	0.058	4.217	$0.907	2.074
4/10/2021 9:00AM-2PM	0.884	0.921	-0.037	-0.088	-0.886	-$0.177	-1.202
4/13/2021 9:00AM-2PM	0.717	0.834	-0.116	-0.044	-2.796	-$0.582	-1.626
4/18/2021 8:30AM-1:30PM	0.897	0.768	0.129	0.058	3.108	$0.604	0.524
4/21/2021 8:30AM-1:30PM	0.817	0.797	0.021	-0.003	0.501	$0.130	-0.122
4/24/2021 9:00AM-3:00PM	0.763	0.902	-0.138	0.017	-3.323	-$0.740	-2.568
4/27/2021 11:00AM-4:00PM	0.882	0.831	0.051	0.072	1.222	$0.412	0.026
All Events	0.881	0.884	-0.003	-0.062	-1.029	-$1.124	-10.719

Figure 2-9 provides the average participant load shape across all low carbon emissions event windows using the PSM matched baseline. For the average event, the largest reductions occurred in the early morning hours between 8 PM and 5 AM. As expected, the load increased between the hours of 8 AM and 2 PM which corresponds to when most events were called. In addition, there is a load increase between 5 AM and 8 AM, which corresponds to the influence of Treatment 1 (Steady State).

Figure 2-9 Average Load Shape During Low Carbon Emissions Event Window

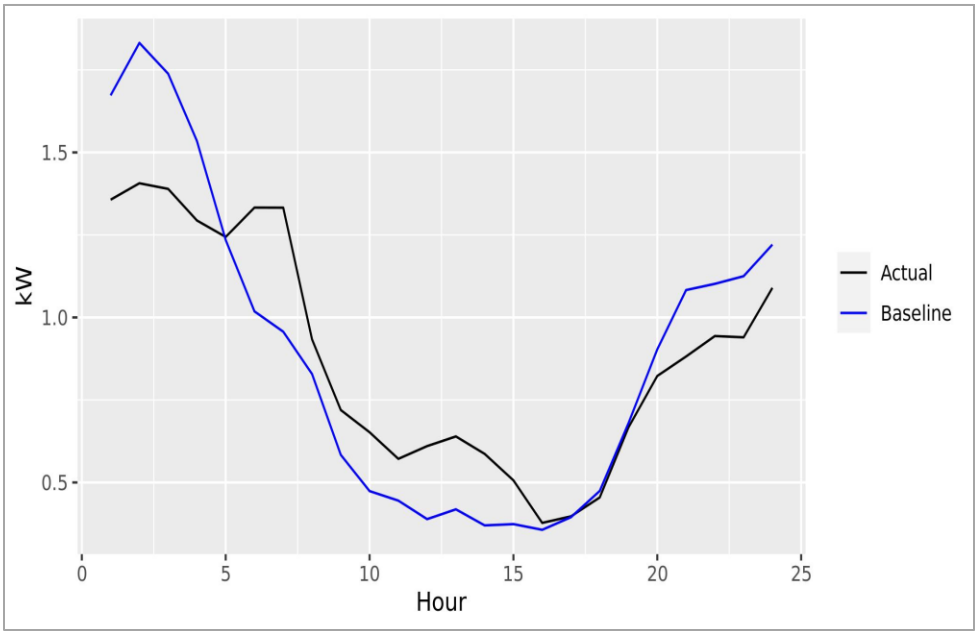


Table 2-12 provides impacts for Treatment 1 and Treatment 2 for the average participant across all low carbon emissions events by hour.

Table 2-12 Treatment 1 and Treatment 2 Impacts During Low Carbon Events by Hour

Hour	Average Actual kW	Average Baseline kW	Average kW Impact	Total kWh Impact	Total Cost Impact ($)	Total GHG Impact (lbs. CO2)
0	1.357	1.673	-0.316	-5.374	-$1.052	-3.699
1	1.407	1.832	-0.425	-7.229	-$1.479	-5.022
2	1.389	1.738	-0.349	-5.932	-$1.192	-4.215
3	1.294	1.535	-0.241	-4.094	-$0.818	-2.828
4	1.244	1.235	0.009	0.157	$0.022	0.393
5	1.333	1.018	0.314	5.345	$1.114	4.054
6	1.333	0.957	0.376	6.388	$1.317	4.457
7	0.934	0.829	0.105	1.783	$0.357	0.967
8	0.719	0.584	0.136	2.310	$0.478	0.801
9	0.652	0.474	0.178	3.030	$0.631	0.809
10	0.572	0.445	0.127	2.152	$0.459	0.459
11	0.610	0.389	0.221	3.762	$0.813	0.802
12	0.639	0.419	0.221	3.754	$0.824	0.842
13	0.587	0.370	0.217	3.683	$0.827	0.793
14	0.506	0.374	0.133	2.253	$0.476	0.454
15	0.378	0.357	0.021	0.356	$0.113	0.074
16	0.397	0.395	0.003	0.043	$0.014	-0.015
17	0.455	0.474	-0.020	-0.336	-$0.116	-0.264
18	0.667	0.680	-0.013	-0.220	-$0.074	-0.265
19	0.823	0.903	-0.081	-1.370	-$0.428	-0.997
20	0.882	1.083	-0.201	-3.422	-$1.066	-2.428
21	0.944	1.102	-0.158	-2.690	-$0.782	-1.920
22	0.940	1.125	-0.185	-3.150	-$0.885	-2.245
23	1.090	1.221	-0.131	-2.229	-$0.677	-1.725
All Hours	0.881	0.884	-0.003	-1.029	-$1.124	-10.719

2.2.4 Comparison of Baseline Methods

A direct comparison between the baseline methods cannot be made because using a PSM control group means the impacts with the matched control group baseline include both Treatment 1 (Steady State/GridShift app) and Treatment 2 (Low Carbon Events), while the CBL method includes only the impact from Treatment 2.

However, in assessing the performance of the mixed CBL model, which is comprised of the 5-of-5 and 10-of-10 unadjusted CBL models, we found the mixed CBL performed the best of any CBL model and had average bias and error in the range normally seen for this type of baseline in other DR programs.

ADM determined that using prior-hour (or other day-of-event) adjustment factors would be inappropriate as the load shifting from low carbon events impacts all hours surrounding the event. In addition, using a X-of-Y prior day averaging method (e.g., 3-of-10) was also found to be inappropriate since the low carbon emissions events were not called on the highest usage days but were called on days and times with the lowest carbon emissions. ADM tested two X-of-Y unadjusted baseline models (a 3-of-10 CBL and 5-of-10 CBL) and found bias on proxy days of over 12%, indicating very poor model fit.

If low carbon events continue to be called with the same criteria as in 2021, the unadjusted CBL model should continue to perform well. On the other hand, if low carbon events become subject to a weather-based calling criteria (i.e., called only on the hottest days in summer), the unadjusted CBL model will very likely have much higher bias and model error than what was found for these low carbon events. In this case, switching to a X-of-Y CBL model and/or an event-day adjusted CBL model could be warranted.

3 Survey Findings

The following section presents the detailed findings of the survey.

3.1 Respondent Background

As shown in the table below, 76% of respondents used the app to managing charging for their primary charger. Another 22% said that they do not drive a vehicle managed by GridShift.

Table 3-1 Vehicle Managed by GridShift App

Vehicle Charged by GridShift	Percent of Respondents (n = 37)
GridShift manages charging for primary vehicle	76%
GridShift manages charging for another vehicle	3%
Does not drive a vehicle managed by GridShift	22%

Eighty-eight percent of the respondents who said they do not drive a vehicle managed by the GridShift app also said they do not have the app installed on their phone.

Table 3-2 Has App Installed on Phone

	GridShift Manages a Vehicle they Drive	
	Yes (n = 29)	No (n = 8)
Has app installed on their phone	93%	13%
Does not have app installed on their phone	7%	88%

Respondents are generally “early adopters” with 60% of the sample stating they like to have the newest technology and another 32% that say they like to adopt a new technology but once it has been available for some time (see Table 3-3). These findings are not surprising given that this pilot project tested new software for use with electric vehicles.

Table 3-3 Respondent Attitudes Toward New Technology

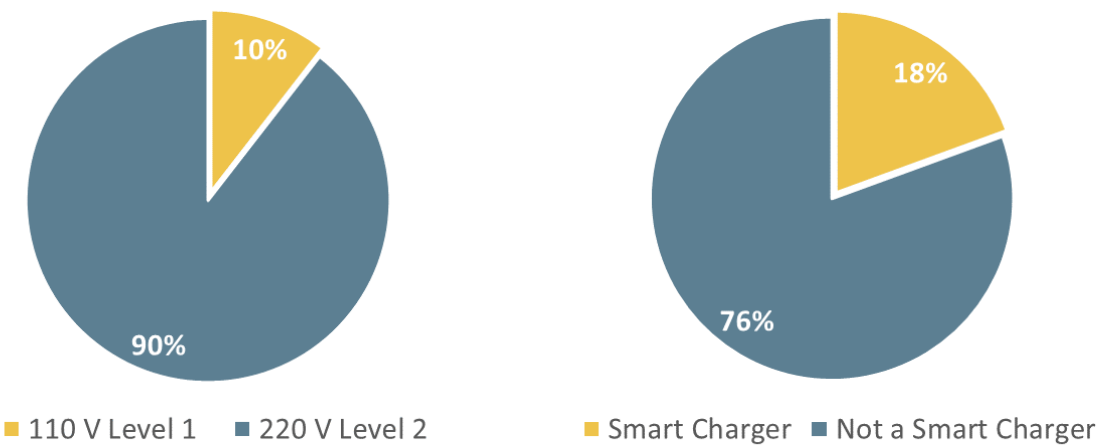
Attitude Toward New Technology	Percent of Respondents (n = 37)
I like to have the newest technology and tell others about my experience with it.	60%
I like to adopt new technology once it has been available for some time and the benefits are established.	32%
I only adopt new technology when the benefits are obvious, and the price is low.	8%
I am not interested in adopting new technology at this time.	0%

3.2 Charging Equipment and Previous Charging Practices

3.2.1 Charging Equipment

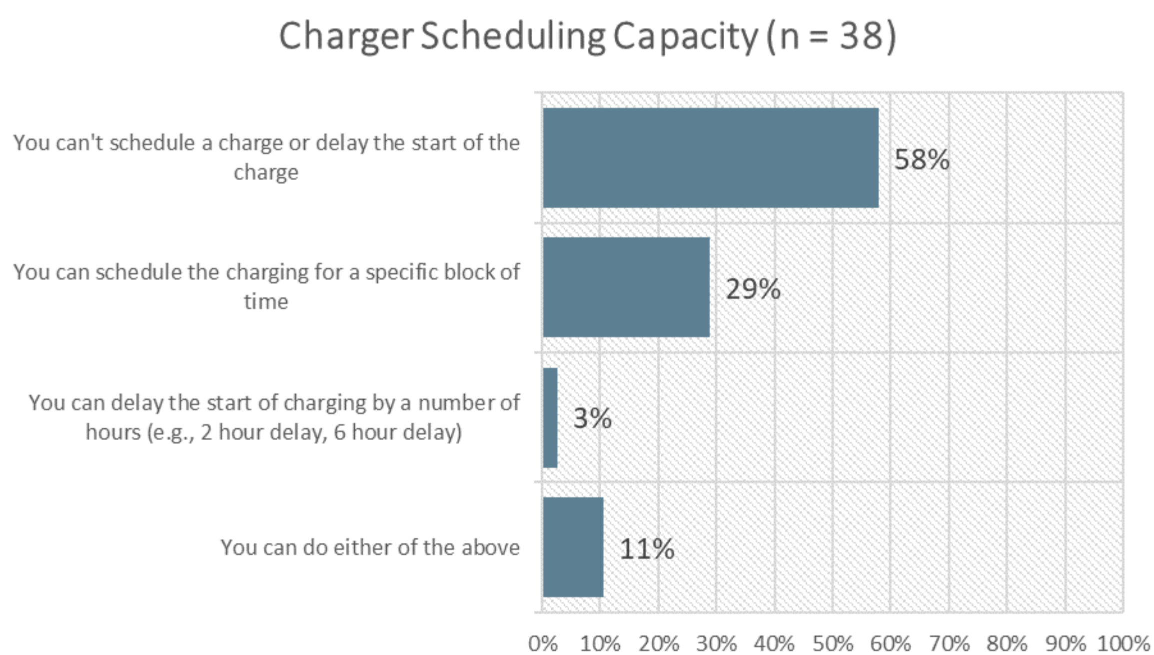
Ninety percent of participants had a Level 2 charger and 18% have a smart charger.

Figure 3-1 Charger Type (n = 38)



All respondents have the capacity to schedule charging using their vehicles app or software and 43% have a charger that allows delayed or scheduled charging. The figure below provides additional detail on the scheduling capacity of the charger.

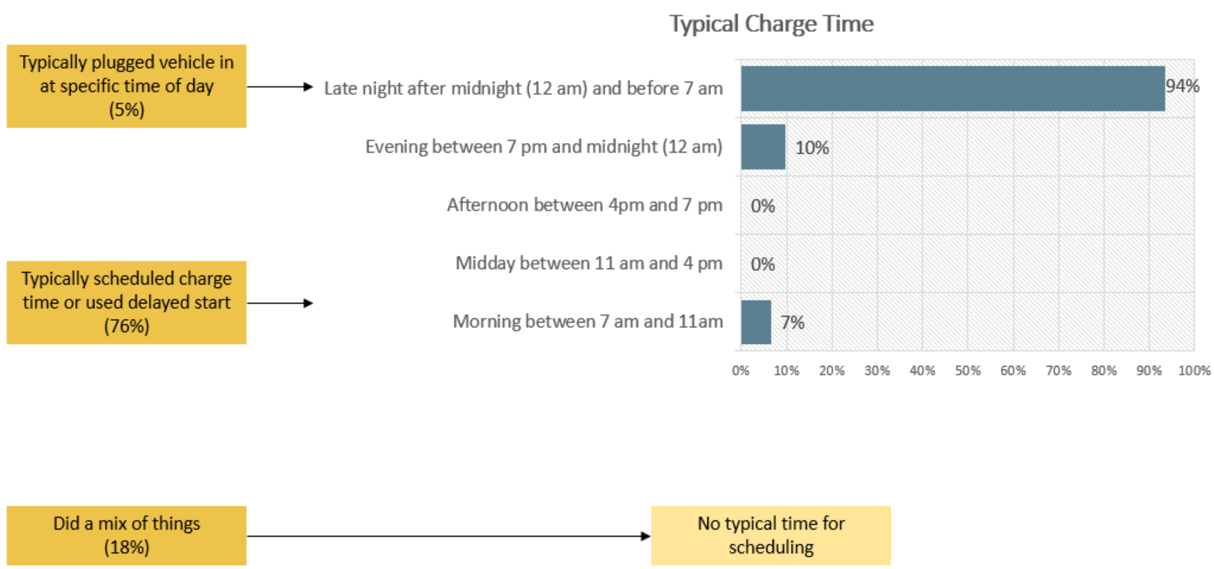
Figure 3-2 Charger Scheduling Capacity



3.2.2 Charging Practices

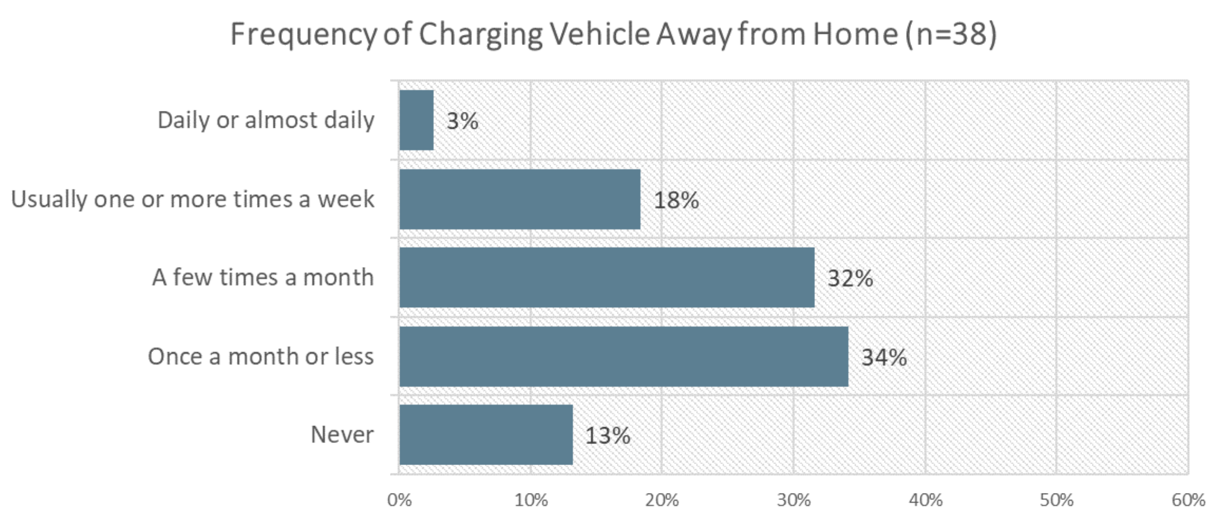
Seventy-six percent of participants stated that they typically charged their vehicle between midnight and 7am. Figure 3-3 summarizes customer charging practices before participating in the pilot. Eighty-one percent of respondents said that they typically charge their vehicle at a specific time either by plugging it in at a specific time or by scheduling the charge or using delayed start. Ninety-four percent of participants reported that they charge between midnight and 7 am. Note that the totals exceed 100% because respondents could select multiple charge periods.

Figure 3-3 Charging Practices before Participation in GridShift (n = 38)



Twenty-one percent of respondents reported that they charge away from home one or more times a week or daily or almost daily.

Figure 3-4 Away from Home Charging Practices



3.3 Motivations for Participating in Pilot and Concerns

Financial, environmental, and the chance to try new software and technology were primary motivations for participating in the GridShift pilot. Sixty-eight percent of respondents said they were motivated to save on energy costs and 66% were motivated to reduce their carbon emissions. Fifty-five percent of respondents wanted to try new technology (see Figure 3-5). When asked what the priority was in terms of saving on costs vs. reducing greenhouse gas impacts, respondents were equally split in terms of their interest in each type of benefits and a similar share said both were equally important (see Figure 3-6).

Figure 3-5 Reasons for Participating in GridShift Pilot

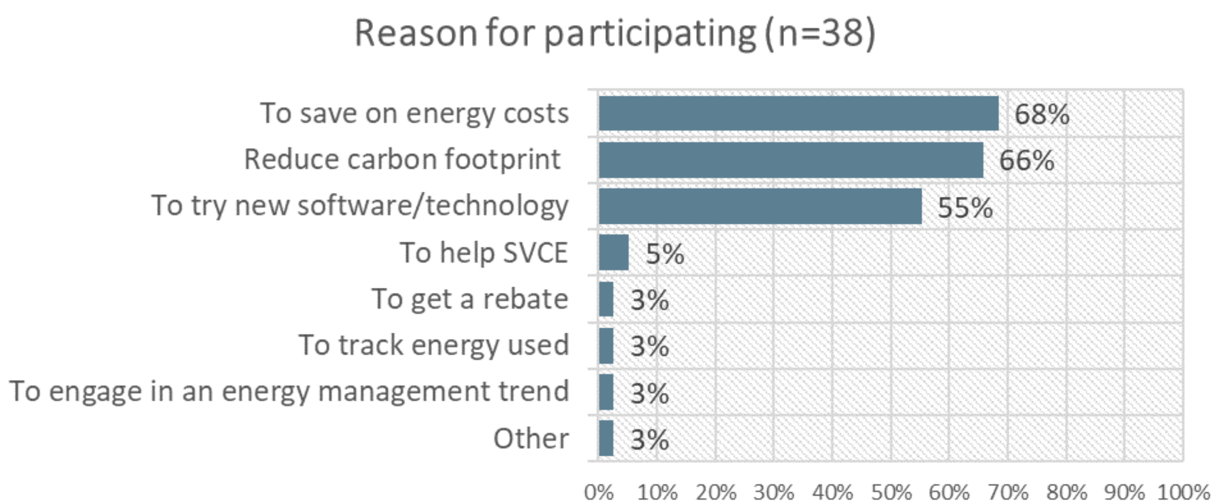
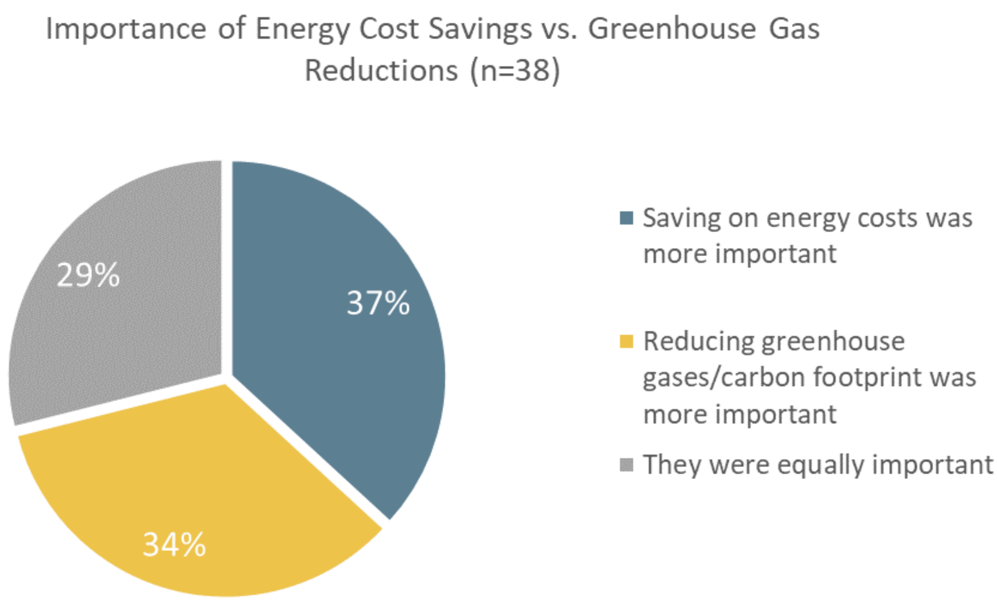
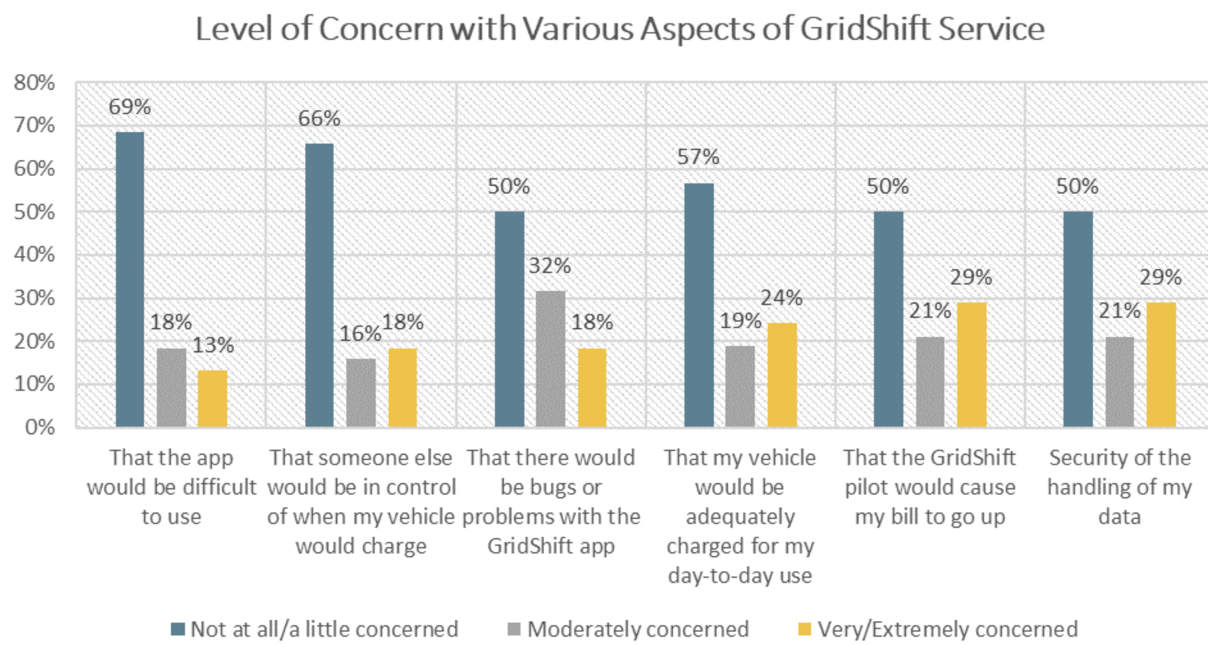


Figure 3-6 Importance in Cost Savings vs. Greenhouse Gas Reductions as Motivation for Participating



Concerns about data security and effects on electricity costs were most common among participants. Overall most participants reported small to moderate concerns with the rated aspects of the GridShift service. Data security and the impacts on costs were a significant concern for 29% of the participants. Relatively few were concerned that the app would be difficult to use (13%), that someone else would be in control of their vehicle charging (18%), or that there would be bugs or problems with the apps (18%).

Figure 3-7 Initial Concerns with GridShift Service

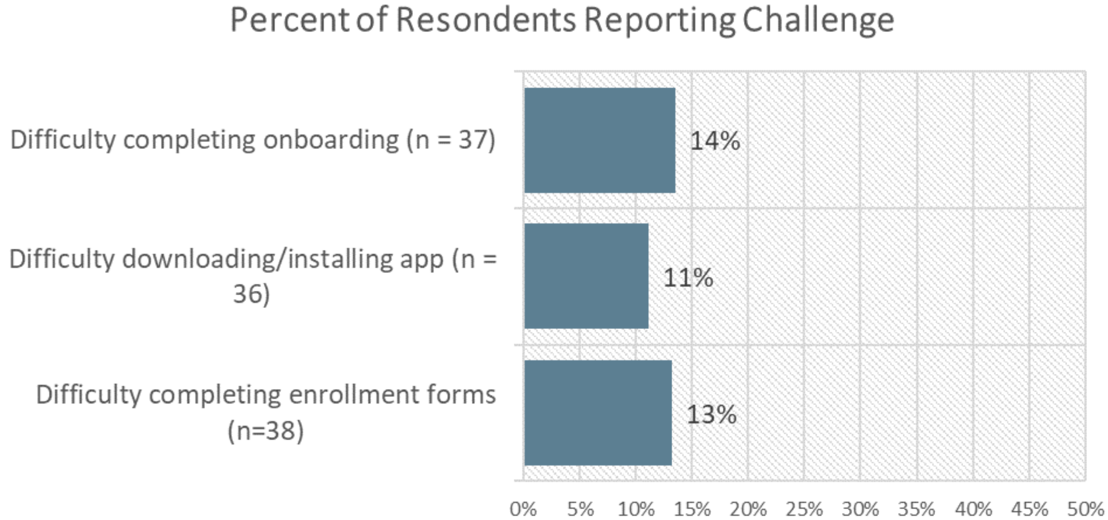


3.4 Enrollment Process Feedback

Few participants reported challenges with the enrollment process. Less than 15% of respondents reported challenges with completing the onboarding, downloading and installing the app, or completing the enrollment forms (see Figure 3-8). A few respondents provided additional information on the difficulties they had with the application. The issues noted were:

- The app download was not sent after registering.
- Difficulty signing in.
- Unable to register.
- The person’s phone was too old to support the app.
- It was not clear how to use it with multiple vehicles.
- It took longer than expected to complete the onboarding.

Figure 3-8 Enrollment Challenges Faced by Participants



3.5 Feedback on the App and Overall Experience with the Pilot

3.5.1 How Participants Engaged with the Pilot

Some participants disabled the app because of charging issues or because they believed the app was redundant with their vehicle software. As shown in Table 3-4, 21% of participants disabled the app. Five respondents mentioned this was due to charging. Additionally, two respondents reported that they used their Tesla software or app instead. One respondent disabled it by accident.

Table 3-4 Participant Disabling App (n = 38)

Has not disabled app	Disabled app but still uses it	Disabled app and is not using it
79%	5%	16%

Reasons given for disabling the app

"I can't charge when it needs me too."

"It wasn't charging when I needed it to."

"Car would not be fully charged before leaving for work in the mornings."

"It charged beyond the 80% max limit that I set in the vehicle software."

"I encountered several instances of the car charging in the middle of the highest time of use rate. Support confirmed that this might be an issue with us having two cars on our account."

Participants primarily used the app to view information on energy consumption and costs. As shown in Figure 3-9, 63% of participants used the app to view historical charging consumption/costs, 61% used it to view electricity used, and 53% used it to view energy costs or cost savings. Thirty-seven percent used the app to view carbon intensity of their charge. Additionally, as shown in Table 3-5, most participants are not using the boost button to quickly charge their car or use it infrequently.

Figure 3-9 GridShift App Features Used by Participants

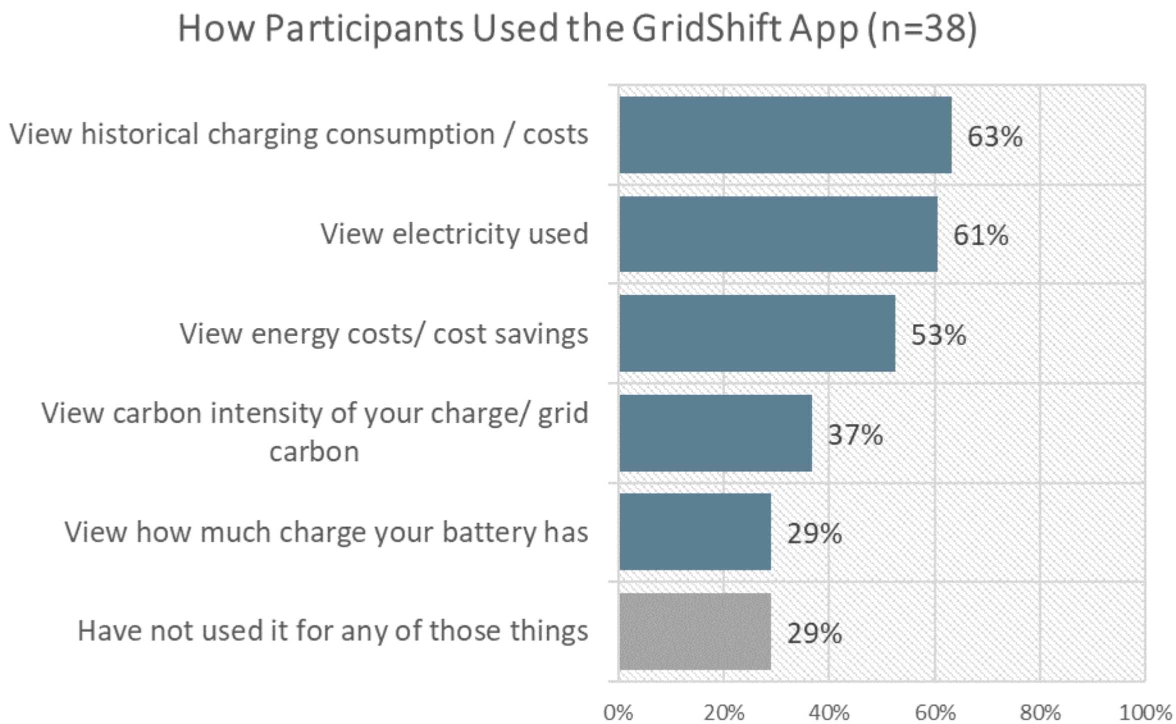
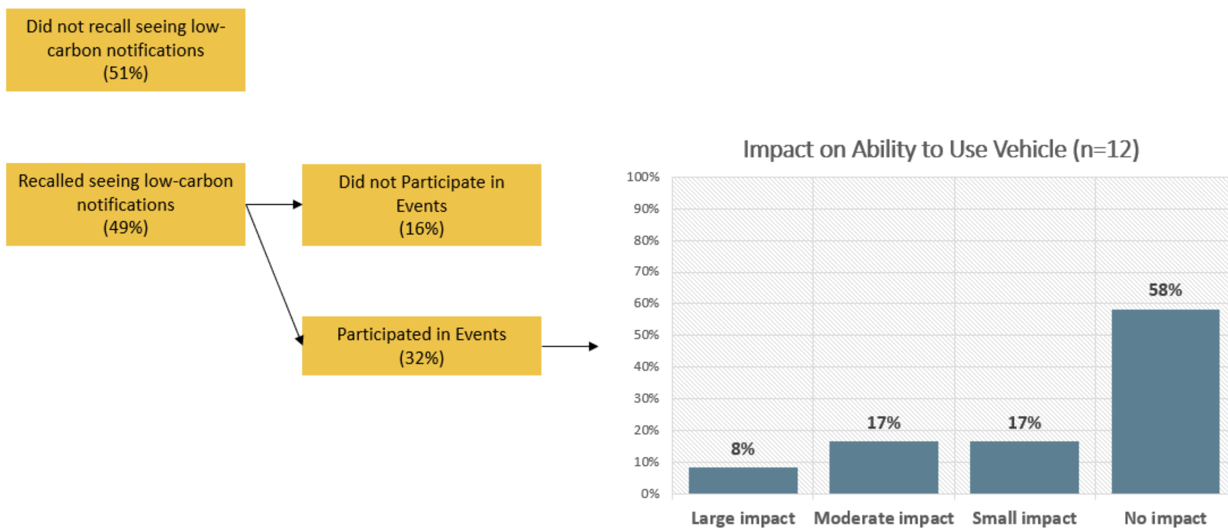


Table 3-5 Use of Boost Button

Frequency of Using Boost Button	Percent of Respondents (n=38)
Daily	0%
A few times a week	3%
Once or twice a week	3%
Less than once a week	16%
I have never used the boost button	79%

Thirty-two percent of pilot participants participated in a carbon event and 75% of these customers reported either no impact or a small impact on their ability to use their vehicle. Thirty-two percent of participants reported that they participated in an event. Among the event participants, 25% reported a moderate to large impact of the event on their ability to drive their vehicle, but the remainder reported either no impact or a small impact. Additionally, 51% did not recall seeing a low carbon notification.

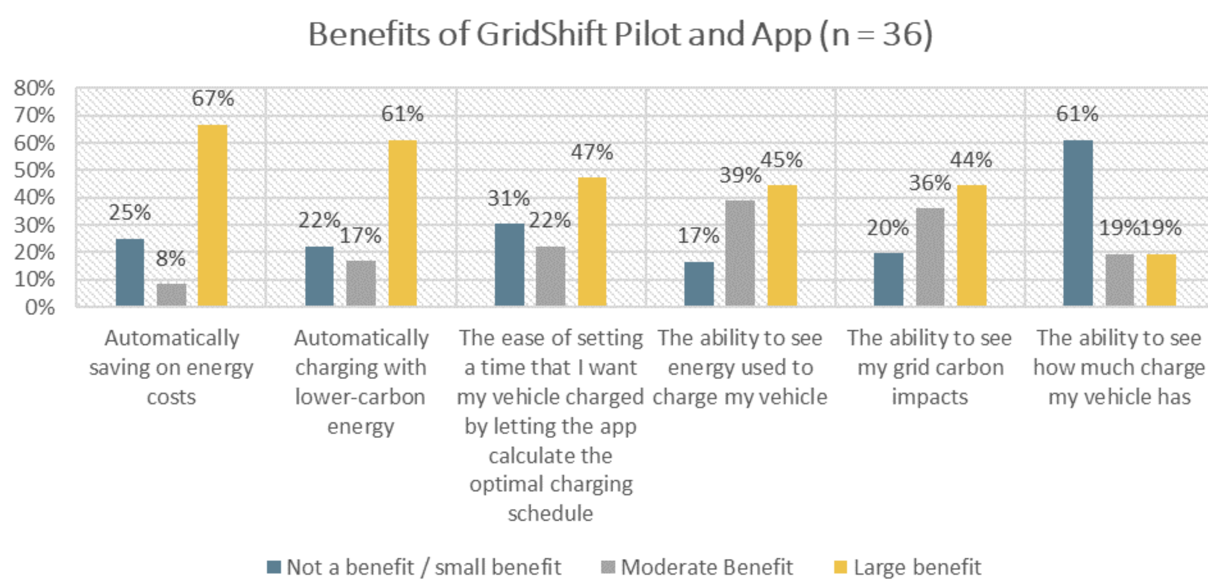
Figure 3-10 Participation in Low-Carbon Events



3.5.2 Benefits of GridShift Pilot and App

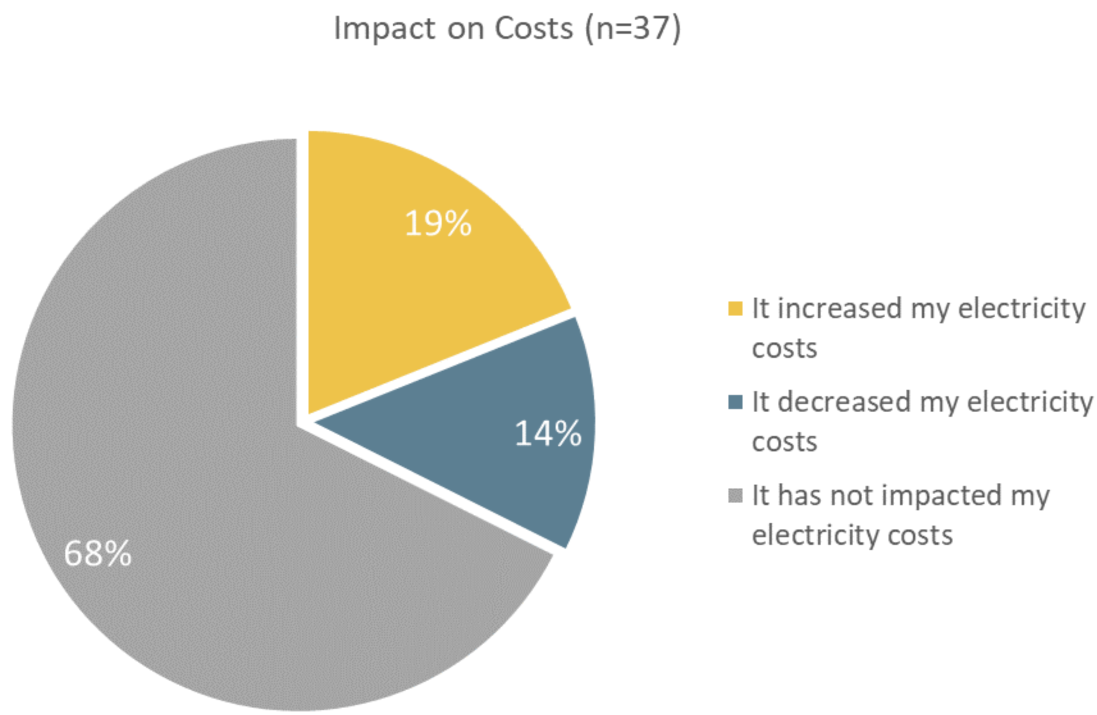
Automatically saving on energy costs and charging with low carbon energy were the aspects of the pilot that respondents most commonly reported as a large benefit. Those benefits were cited as a large benefit by 67% and 61% of respondents, respectively. Less beneficial aspects were the ease of setting the time when the vehicle charged (47%), the ability to see energy used by the vehicle (45%), and the ability to see grid carbon impacts (44%, see Figure 3-11). The least beneficial feature was the ability to see how much charge is remaining.

Figure 3-11 Perceived Benefits of GridShift Pilot and App



Participants provided a mixed assessment of the GridShift app on their charging costs. As shown in Figure 3-12, 68% of participants reported that the app had no impact on their electricity costs, while 19% thought that it increased their costs and 14% thought it decreased their costs.

Figure 3-12 GridShift Impact on Costs



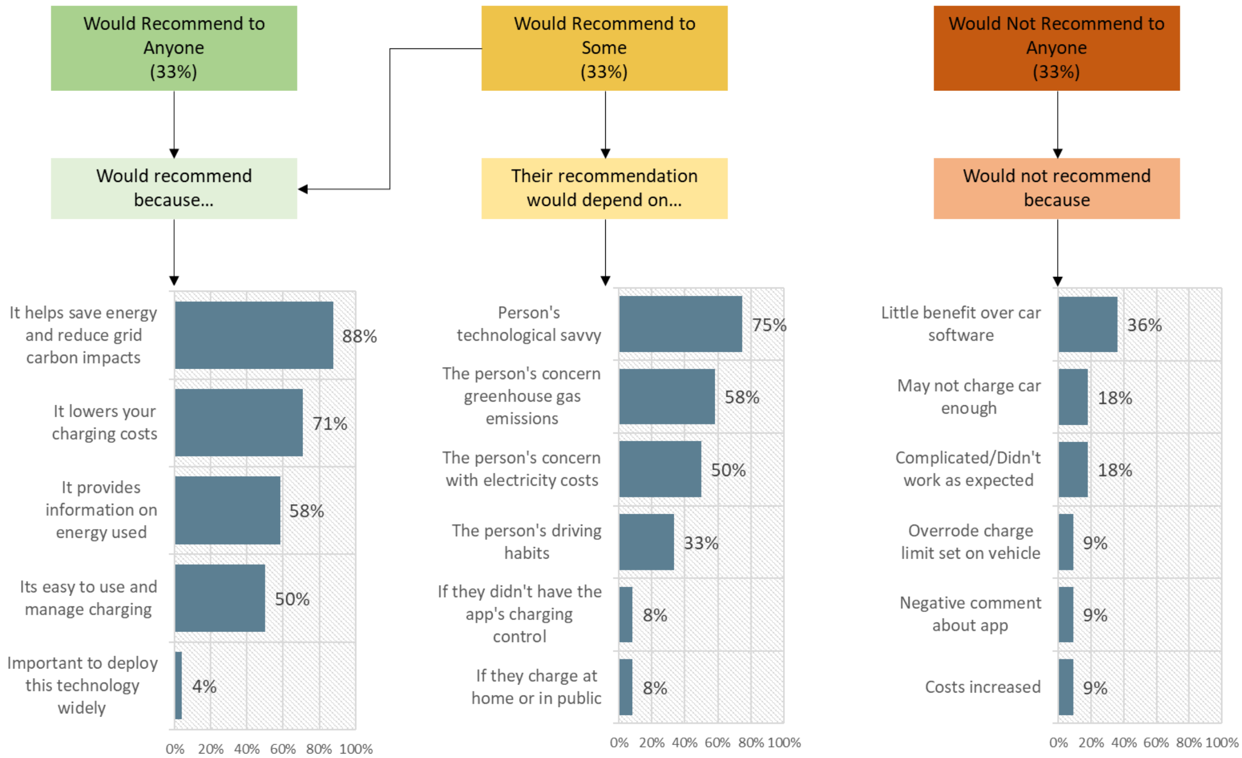
3.5.3 Participant Recommendations for Other Customers

Participants were evenly split between whether they would recommend GridShift to anyone, to certain people, or not recommend it to anyone – 33% gave each of those responses. Figure 3-13 summarizes participants views on if they would recommend the app and the reasons for recommending it, factors that would affect whether they recommended it, and reasons for not recommending it.

- *Why someone would recommend GridShift:* Key benefits cited were reduction of carbon impacts (cited by 88%) and lowering of charging costs (cited by 71%). Secondary benefits included information on energy used (cited by 58%) and ease of managing charging (cited by 50%).
- *Factors that would prevent someone from recommending the app:* The most often cited factor was the person's technological savviness, mentioned by 75% of respondents who would recommend GridShift to some people. This suggests that for some participants, the application may not be ready for mass-market adoption but better targeted towards a savvier customer group. Other considerations were the likely benefits a customer would receive such as their concern with greenhouse gas emissions (mentioned by 58%) and electricity costs (mentioned by 50%). Additionally, the participants driving habits were a consideration for 33% of respondents.
- *Why someone would not recommend GridShift:* A top reasons for not recommending the app was because it didn't provide any benefit over the vehicle charging software (33% mentioned

this). Other concerns raised were that their vehicle may not be charged enough (18%) or that the app was complicated or didn't work as expected (18%).

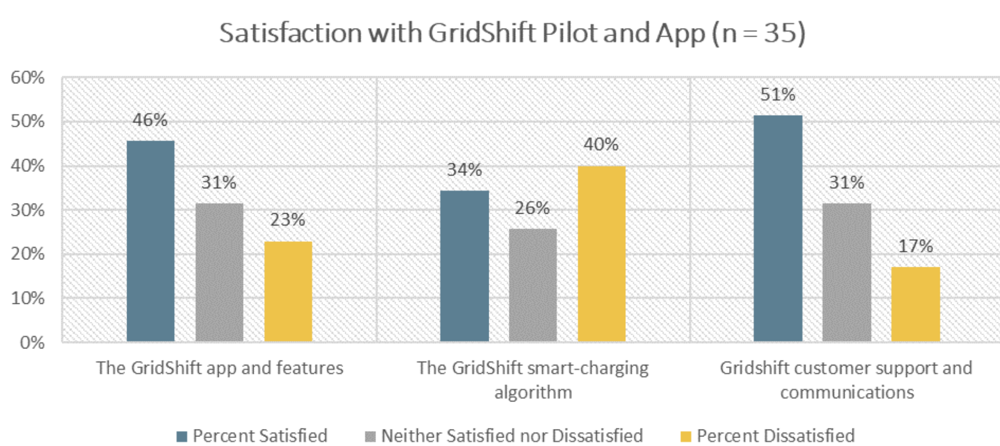
Figure 3-13 Participant Perspectives on Recommending GridShift to Others (n = 36)



3.5.4 Overall Satisfaction with the Pilot

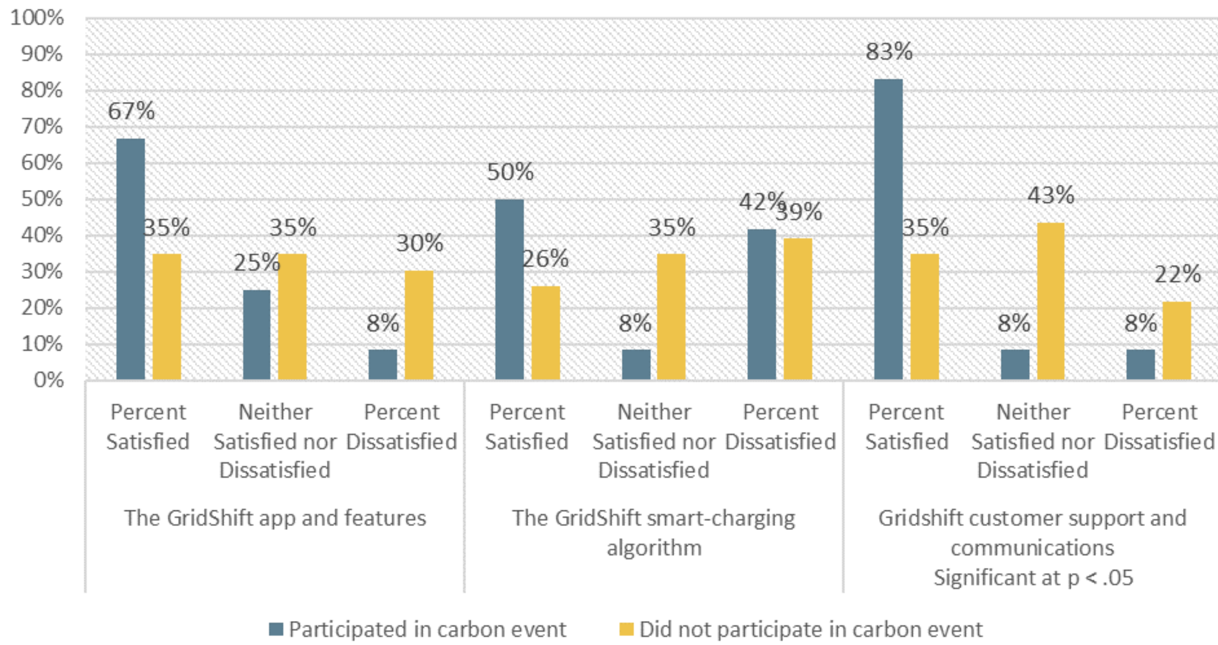
Participants reported mixed levels of satisfaction with the pilot. Figure 3-14 summarizes participant satisfaction with the GridShift Pilot and app. Forty-six percent of respondents were satisfied with the GridShift app and features and 51% were satisfied with GridShift customer support and communications. Participants were less satisfied with the GridShift charging algorithm (34% were satisfied with it) and 40% were dissatisfied with it.

Figure 3-14 Satisfaction with GridShift Pilot and App



Participants in carbon events tended to be more satisfied with the program. Figure 3-15 summarizes participant satisfaction by participation in a carbon event. In general, carbon event participants tended to be more satisfied with the rated aspects of the pilot – 67% of carbon event participants were satisfied with the GridShift app and features compared to 35% of non-participants, 50% of carbon event participants were satisfied with the GridShift smart-charging algorithm compared to 26% of non-participants, and 83% of carbon event participants were satisfied with GridShift customer support and communications vs. 35% of non-participants. However, the difference in satisfaction with GridShift customer support and communications was the only statistically significant difference.

Figure 3-15 Satisfaction by Participation in Carbon Events



Comments about Cost Savings

“Transmission costs which is the major factor in the utility bills. You do not save a lot by charging at home. Pennies saved with a lot of setting up slow charging process when super chargers are available does not make any sense to charge at home”

“I would like to see the app enabling more cost-saving and anytime charging.”

“I mentioned before -- low carbon events often seem to take place in the early afternoon, which is Peak for my time-of-use plan, so I don't see how I'm saving on my own energy costs compared to charging in the middle of the night like I usually do”

Twelve respondents also provided narrative feedback on the pilot. The most common comments were negative comments about carbon events and about cost savings.

Comments about Carbon Events

*“Most users won't care *when* the grid is low. They will care whether they saved money *and* their car is readily charged by when they need it. Working with their schedule (I need it tomorrow by 08:00) is a better approach than plugin between 09:00 - 14:00 so the grid is less used. The app should automatically figure when it's time to charge based on what the owner's needs are. I was definitely confused - once a grid shift event passed, what will happen "tomorrow"? Will it again try to charge during those scheduled times *only* (it seems it did) instead of auto-cancelling and allowing normal charge because I needed it by so-and-so time the next day.”*

“I am extremely disappointed that I took extra effort to charge during low carbon events and didn’t get any credits as promised.”

“I participle in the low carbon events but the app doesn't seem to acknowledge my participation in it until much later. I collected the points for a discount, the points were deducted, but no indication that it gave the credit.”

The topics of narrative feedback are summarized in Table 3-6.

Table 3-6 Summary of Additional Comments

Comment Category	Count	Percent of Respondents (n = 12)
Carbon event negative comment	3	25%
Cost savings - negative comment	3	25%
App does not provide new benefit	1	8%
Auto-enable and auto-cancel the charge schedule and make boost immediately available	1	8%
Carbon event occurs during peak TOU rate	1	8%
Carbon event rewards positive	1	8%
General negative comment	1	8%
General positive comment	1	8%
Seems like a hassle	1	8%
Better integration of Tesla Supercharge data	1	8%

3.6 COVID19 Driving Impacts

Respondents reported that they are driving about half of the miles they drove prior to COVID19. Respondents reported driving an average of 246 miles per week before COVID19 and an average of 124 miles per week in the last month.

Table 3-7 COVID19 Impacts on Average Miles Driven per Week

Pre-Covid Miles Driven per Week (n = 31)	Miles Driven per Week in Last Month (n = 32)
246	124

4 Benefits & Costs of Telematics-based Approach to Smart Charging

The telematics-based approach to smart charging used for ev.energy serves in-part as a substitute for hardware-based controllable/managed charging. Hardware-based charging entails the installation of a smart/internet-connected vehicle charger that allows for external signals to trigger managed charging.

Benefits and costs associated with the two approaches are as follows:

4.1 Charging Hardware Purchase Cost

ADM found nine models of consumer-ready smart chargers with the capability to allow modes of control similar to the ev.energy telematics-based approach. The average purchase price for these chargers was $984, with a median value of $899.

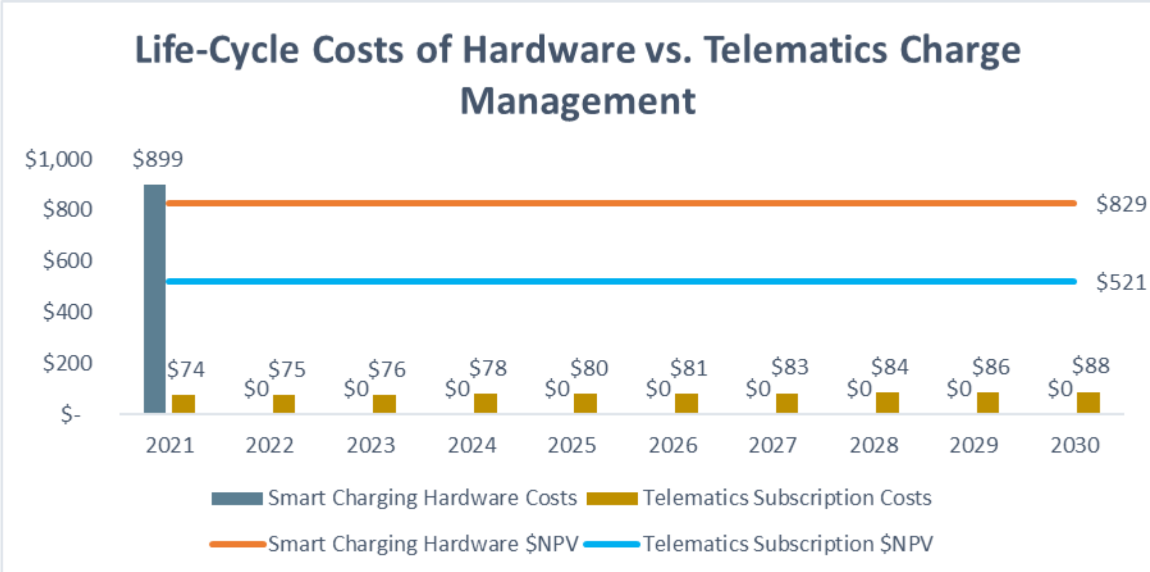
4.2 Telematics Cost

The cost of telematics is not easily quantifiable; if provided by an OEM to a customer, the added cost to the customer would be $0. However, there is a cost borne by the OEM that may be difficult to quantify. As a proxy, we are including the monthly subscription fee for High Mobility, who provides telematics access and analysis for BMW, Ford, Mercedes-Benz and MINI. Pricing for individual vehicle services ranges from €2.10 to €6.69 ($2.93 - $9.32 USD) per month for continuous access. At the midpoint value, this $73.50 per year.

4.2.1 Cost-benefit Comparison

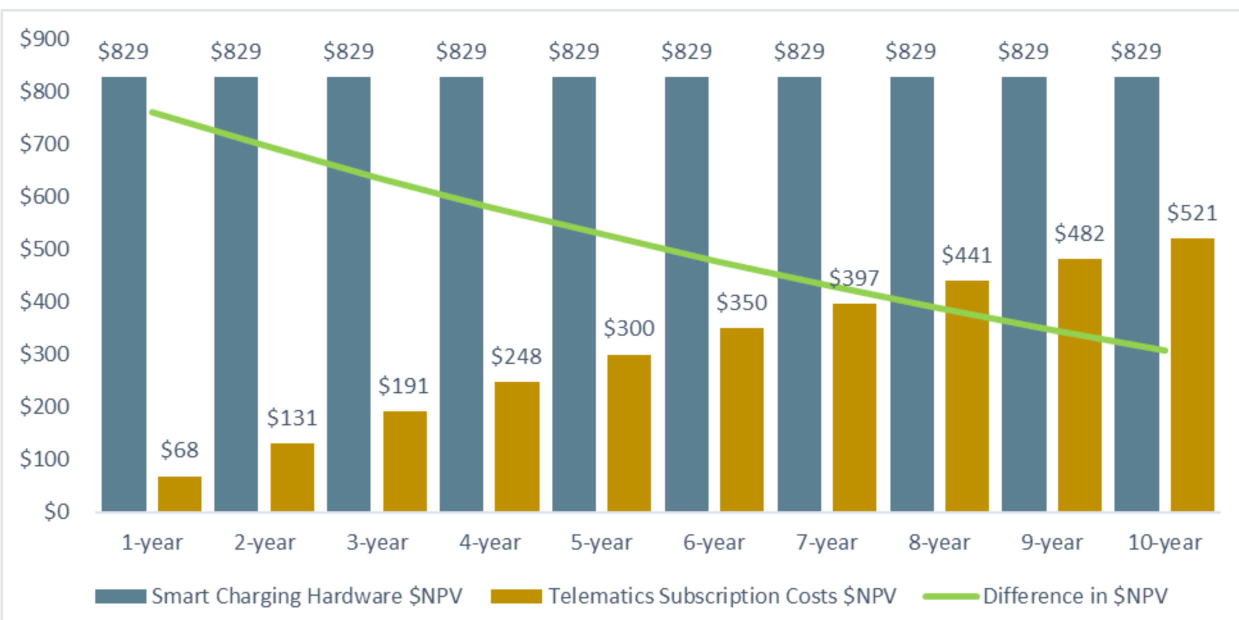
The analysis period for this cost-benefit comparison is 10 years (consensus estimates on rated useful life of charging hardware). Telematics costs are escalated by 2% annually (long term consumer price index). The net present value (NPV) from the customer perspective is evaluated over this timespan. As shown in Figure 4-1, the NPV of the telematics-based approach is $328 (37%) lower than the smart charging hardware approach.

Figure 4-1 Charging Hardware vs. Telematics Subscription Fee Approach



The full 10-year life of residential charging hardware reflets the point of closest convergence in NPV for the charging hardware versus telematics approaches under these cost assumptions. After year 10, the average residential customer will require new charging hardware. Prior to year 10, the costs for charging hardware remain unchanged while fewer costs are incurred under the telematics subscription. This is summarized in Figure 4-2.

Figure 4-2 Comparison of $NPV at Differing Analysis Period Lengths



4.3 Benefits of EVSE vs. 240V Plug

The benefits of charging hardware compared against a simple 240V plug from the customer perspective are largely tied to aesthetics and convenience:

- Finished appearance. An installed hardware charge station may be considered by some consumers to be better in appearance than a 240V plug.
- Permanent charging hookup. If a customer is using a 240V plug, they will need to connect and disconnect their charge cable from the vehicle and the outlet. With a charge station, they will be able to do so just via disconnecting the vehicle.
- Controllable shutoff/safety. Charge stations add an extra layer of protection against potential safety hazards as they contain an internal circuit breaker. This would be a back-up redundancy as most EVs have a similar capability on-board.

4.4 Benefits of Smart EVSE vs. Non-networked EVSE

The benefits of smart EVSE above and beyond those of non-networked EVSE are centered around added convenience from mobile device control, if the end-user is using an EV that does not have smart phone integration in place (such as TeslaFi).

5 Recommendations

5.1 High-Level Strategy Recommendations

- Encourage more OEMs to move to open APIs. The cost savings per-customer for telematics-based approaches are significant; the NPV is 37% lower, and the cost of the alternative (smart charging hardware) adds increased upfront costs for EV owners.

5.2 Program Planning Recommendations

- Use the charging optimization impacts when planning larger program rollouts. 63% of the GHG reductions found in the steady-state operation (Treatment 1) were the result of behavioral changes in response to energy use and cost visibility. It is not certain that this behavioral impact would occur at program-scale across a broader demographic range of customers.
- Plan for analysis of behavioral impacts. If rolled out to a larger population, SVCE should ensure that a control group can be maintained and that behavioral impacts can be examined further. This could be expanded upon with randomized testing of conservation messaging.
- Focus recruitment on customers without pre-existing smart charging hardware. The most common reason for stating that they would not recommend GridShift to other users is "little benefit over car software". The addition of managed charging adds greater marginal benefit to EV owners that either 1) have a non-networked third-party charging station or 2) are directly using a 110V or 220V outlet.

5.3 Emissions Event Analysis Recommendations

- Utilize a mixed model to estimate savings for the low carbon events. A single CBL model on its own may systematically overestimate baseline usage and demand reductions.
- Use 10-of-10 or 5-of-5 unadjusted CBL models for the mixed model to estimate the baseline for the low carbon events.
- Utilize proxy event days to estimate bias and error when determining which CBL model to select for estimating baseline usage.
- Obtain 30-minute AMI data. Most customers have hourly AMI data and calling events on the half-hour make it difficult to determine impacts during the event time itself.