Evaluating utility electric vehicle managed charging programs

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ABSTRACT

As the pace of electric vehicle (EV) adoption has quickened in recent years, more utilities have begun piloting EV managed charging pilot programs designed to shift EV charging to off-peak hours, minimize the addition of on-peak load, and measure EV drivers' responsiveness to various price and behavioral signals. The authors evaluated one of these programs – National Grid's SmartCharge Rhode Island program – to assess the effects of the piloted intervention on off-peak charging behavior and to develop insights that will be used to inform future managed charging programs.[1]

The pilot was designed to capture aspects of both managed and unmanaged charging behavior, measure the dominant effects driving any observed off-peak shift, and facilitate a rigorous evaluation. Charging data was collected from approximately 385 participants using devices connected to participants' vehicles. EV drivers were incentivized to charge off-peak with per-kWh off-peak charging rebates.

Analysis indicates that the off-peak charging rebates resulted in a measurable shift off-peak, with participants who received off-peak charging rebates beginning 7% more of their charging sessions off-peak across all vehicle types. The effect was even more pronounced for battery-electric vehicles (BEVs), with Tesla and non-Tesla BEVs initiating 11.5% and 12.7% more of their charging sessions off-peak than plug-in hybrid EVs (PHEVs) with access to the rebates.

Introduction

The International Energy Agency's (IEA) Global EV Outlook 2021 projects that the number of electric vehicles (EVs) circulating globally will reach 140 million by 2030, compared with roughly 10 million today (IEA 2021). Recent EV adoption data also points to a rapid shift in customer awareness of and interest in EVs, with the US reaching a critical tipping point – "the start of mass EV adoption" – in the first half of 2022, in which 5% of new car sales were EVs (Randall 2022). This growth will have substantial impacts on the electric grid (Van Triel and Lipman 2020), particularly as advancements in battery technology lead to increased range (Coltura 2021) and energy density (Markus 2021), requiring not only more energy to fully charge one's battery but also faster charging rates to do so conveniently. To better understand the local grid impacts from EV charging and to inform the design of time of use (TOU) electric rates, utilities across the country are piloting managed charging programs designed to shift EV charging load off-peak. These programs typically leverage incentives of varying structure and magnitude, including per-kWh rebates that simulate TOU rates and peak avoidance reward structures, which reward EV drivers for conducting a percentage of their charging off-peak or never charging on-peak. Proven managed charging strategies will be critical to supporting the market growth of EVs, the electrification of public transit, and the seamless absorption of millions of EVs onto the grid, and the authors believe that all utilities will require tools for effectively managing EV charging load.

Managed charging strategies can be classified as either *active* or *passive* managed charging. In *active managed charging*, a utility or market aggregator can control when an EV charges and how much

[1] Note that as of May 2022, National Grid Rhode Island is now Rhode Island Energy (a PPL company).

power it draws (or potentially sends back to the grid) using signals sent remotely to a vehicle or charger, after taking into account grid and driver-provided constraints. Active managed charging strategies can be used for demand response, peak load management, to absorb excess renewable generation, or to supply ancillary services to the grid.

Passive managed charging, on the other hand, leverages a number of mechanisms, including monetary incentives and behavioral messaging, to influence EV drivers to delay their charging until off-peak hours. Drivers may use tools, such as smart chargers with scheduling capabilities, in-vehicle systems, or other devices to achieve the desired off-peak charging shift, but they are ultimately responsible for internalizing the signals they receive and determining whether and how to act on them by altering their charging behavior. The program discussed in this paper is an example of a passive managed charging program.

The utilities and program administrators that develop and launch managed charging programs conduct evaluations to increase their understanding of both "managed" (i.e., exposed to price or behavioral signals) and "unmanaged" (i.e., not exposed to price or behavioral signals) EV charging behavior, assess the effectiveness of the piloted interventions in shifting charging off-peak, identify other factors that impact charging behavior, and develop learnings to inform the design of future programs. The data collected through these programs and evaluations can also be incorporated into utilities' rate design, system planning, and forecasting efforts.

The following sections describe the managed charging program design, data analysis approach, and statistical analysis. We close with a summary of findings and conclusions.

Pilot Design Overview

Launched in 2019, National Grid's SmartCharge Rhode Island (SCRI) Program aims to understand EV charging patterns and the effect of rebates in shifting EV charging from on-peak to off-peak hours. The program peak period is defined as the hours of 1 p.m. to 9 p.m. on all days, including holidays and weekends. Participants' charging activity was measured by an in-vehicle monitoring device provided by Geotab ("C2 device") that plugs into a vehicle's onboard diagnostics (OBD) port and records data while the vehicle is plugged in and charging (but not when the vehicle is plugged in and not charging); data from the C2 device was uploaded wirelessly, requiring no intervention from the participant to share their charging data. The authors conducted a randomized controlled trial (RCT) to evaluate the program and determine the effects of rebates and other variables on participant charging behavior, with participants randomly assigned to either the control or treatment group.[2] Though the program is ongoing at the time of this writing (September 2022), this paper covers only the evaluation of the program's first full year, which spanned September 1, 2019, through August 31, 2020.

Program recruitment began in June 2019 and was targeted toward known or likely EV drivers – including battery-electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) – within National Grid's Rhode Island territory. The initial marketing materials advertised the opportunity for participants to receive \$50 for enrolling, agreeing to share their charging data, installing their C2 device, and completing their first charge; participants could also earn an additional \$50 for each year they kept the device plugged in during the multi-year program. None of the participants were aware of the off-peak charging rebates during the recruitment phase. Approximately 385 participants enrolled in the program and were randomly assigned to either the control or treatment group on a rolling basis during the recruitment period. Upon program launch in September 2019, the control group received access to an

[2] An RCT is a highly structured and rigorous experimental approach used to test the effect of a treatment on a group of participants, minimizing bias by randomly allocating participants across treatment and control groups.

online dashboard showing their charging behavior, while the treatment group received access to the same dashboard as well as rebates for off-peak charging. Rebates are 6 cents per kWh charged off-peak in the summer months (June through September) and 4 cents per kWh charged off-peak during the non-summer months. All charging was eligible for off-peak charging rebates, including charging that occurred outside of National Grid Rhode Island territory and both home and away-from-home charging.

Randomized Group Assignment

As discussed above, participants were randomly assigned to either the control or treatment group prior to the program launch in September 2019. Group assignments took place on a rolling basis as participants completed the necessary steps to enroll in the program. The program leveraged a stratified approach, described below.

The primary group assignment characteristic was the vehicle type, determined based on the vehicle model. Vehicles were classified as being either PHEVs, non-Tesla BEVs, or Tesla BEVs. These vehicle strata were selected primarily to control for relevant technology differences between each vehicle type. Tesla BEVs were defined as any Tesla vehicle – Model S, Model 3, or Model X[3] – while non-Tesla BEVs were defined as any non-Tesla all-electric vehicle. This distinction was made to capture the fact that, at the time of program launch, Tesla had the highest market share among EV manufacturers and its vehicles had access to its proprietary Supercharger network of DC fast chargers, sometimes at subsidized or zero cost. PHEVs have both an electric battery and an internal combustion engine; they have limited electric range, typically between 10 and 50 miles. In the future, the authors may consider stratifying based on manufacturer-agnostic factors such as battery size (kWh) or electric range (miles); however, the fact that the battery size and electric range were not readily available in the tracking data and could not always be accurately determined due to different vehicle trim options guided the decision to use a manufacturer-based approach for SCRI.

The random group assignment process also controlled for two additional variables: the length of time the participant had been driving an EV and whether the participant lived in a multi-EV household. The authors hypothesized that participants who had had an EV for longer were more likely to have settled into charging habits that could be more difficult to shift. They also hypothesized that the charging behavior of participants in multi-EV households could be affected by the other EVs charging at that location. Whenever multiple EVs from the same household enrolled in the program, they were placed in the same group to avoid introducing bias.

Data Cleaning and Analysis

This section contains an overview of the data used in the evaluation.

Charging Data Overview

This section outlines the structure of the data and the available data fields, as measured using the C2 device and provided to National Grid by Geotab. Each record in the data represents a charging interval, defined as an up-to-15-minute-long period, ending and/or starting on the quarter hour, with associated charging data recorded during the interval. A charging session is comprised of one or more charging intervals and represents a discrete charging "event," defined as the moment power began to flow to the vehicle to the moment it stopped flowing. Charging intervals and charging sessions have unique

[3] The Model Y was not compatible with the C2 device at the time of this study.

alphanumeric identifiers to facilitate aggregation and segmentation; individual vehicles also have unique numeric IDs.

For each charging interval, the data included the following fields:

- Vehicle key
- Interval ID
- Session ID
- Start and end time
- Session location (provided as "In National Grid territory," "Out of territory," or "No GPS/Inaccurate GPS")
- Maximum charge rate (kW)
- Total charged energy (kWh)
- Starting and ending state of charge (SOC, %)
- Vehicle make, model, model year, and trim (decoded from the vehicle identification number [VIN])

As described above, the C2 device only captures data when the vehicle is actively charging; thus, if a vehicle is plugged in but programmed to delay charging until a certain time, the device does not begin recording data until the vehicle starts to receive power.

Data Cleaning

The authors implemented quality control (QC) checks to ensure that blank, invalid, and inaccurate data was flagged for removal from the analysis. Examples of data the team omitted from the analysis include negative kWh or kW data, charge rates that exceeded a given EV model's maximum charge acceptance rate (kW), and "false start" sessions that were either shorter than two minutes in duration or resulted in less than 0.15 kWh of charging across a charging session. Following the application of QC flags, the authors filtered the data to remove all charging intervals that failed QC. Approximately 90% of charging intervals passed QC.

Data Analysis

The authors conducted initial data analysis in Python, including the QC described above, to quantify high-level program statistics and develop charging load profiles with 15-minute resolution. This analysis focused on understanding charging behavior at an aggregate level, before focusing on on-peak vs. off-peak considerations, as well as the development of visualizations of aggregate charging behavior. Only data that passed QC was included in this analysis, which included the following steps:

1. Calculating vehicle-level and program-level statistics, including total kWh charged and number of charging sessions by month, group, and vehicle type.
2. Constructing per-vehicle average charging load profiles with 15-minute resolution and aggregating them by vehicle type and group (treatment vs. control); we further segmented load profiles by month and day type (weekday vs. weekend).

To assess the program's effectiveness, we also calculated two metrics related to participants' off-peak charging behavior:

1. The percentage of kWh charged off-peak by month for each vehicle (charging load approach)

2. The percentage of charging sessions initiated off-peak by month for each vehicle (session start time approach)

These metrics were calculated as percentages to automatically control for differences in driving behavior, travel and commuting patterns, and vehicle type across participants. Focusing on the proportion of charging occurring off-peak, rather than the total kWh charged off-peak, puts both long- and short-range EVs and participants with long and short commutes on the same basis.

There is a good reason for focusing on these two metrics. The charging load approach directly reflects the program design of rewarding drivers for shifting charging off-peak, where more off-peak charging equates to more rebates earned. However, the timing of when a vehicle consumes kWh is a function of several factors, including the plug-in time, the vehicle's state of charge at plug-in, the battery size, and the speed of the charger. For example, it would be possible for someone to repeatedly plug in at 8 p.m. (on-peak) and spend four hours charging at a fixed rate; while 75% of their kWh would be charged off-peak in this scenario, they still contributed to higher on-peak load from 8–9 p.m. and may not have internalized the goal of the program. The session start time approach, on the other hand, captures the extent to which a participant has internalized the intent of the managed charging program by either delaying their charging manually or by setting a charging schedule in-vehicle or through a smart charger. Note that the session start time approach is not as robust when it comes to charging sessions initiated prior to the peak period (off-peak) that then extend into the on-peak hours. However, since most charging sessions are initiated later in the day, this approach has worked well in our evaluations to date.

Statistical Regression Methodology

To assess the effectiveness of the off-peak charging rebates, the authors developed two linear regression model to test the effect of several independent variables on two separate dependent variables representing off-peak charging performance: 1) the per-vehicle monthly percentage of kWh charged off-peak (charging load approach), and 2) the per-vehicle monthly percentage of charging sessions initiated off-peak (session start time approach). Both metrics provide valuable insight into how EV drivers charge their vehicles, as described in the previous section.

The regression models took the form shown below:

$$y = \beta_0 + \beta_1 T + \beta_2 S + \beta_3 L + \beta_4 (S \times T) + \beta_5 (L \times T) + \beta_6 (Oct) + \beta_7 (Nov) + \beta_8 (Dec) + \beta_9 (Jan) + \beta_{10} (Feb) + \beta_{11} (Mar) + \beta_{12} (Apr) + \beta_{13} (May) + \beta_{14} (Jun) + \beta_{15} (Jul) + \beta_{16} (Aug) + \beta_{17} K$$

The coefficients above ($\beta's$) represent the incremental increase in off-peak charging that results from turning on the respective variables; β_0 represents the "base case" of control group PHEVs charging in September 2019. Variable definitions are provided in Table 1, below.

Table 1. Summary of independent variables used in regression

Independent Variable	Symbol(s)	Variable Type	Potential Values	Variable Properties
Off-peak charging price signal	T	Dummy, main effect	Control: T = 0 Treatment: T = 1	Tests the effect of the off-peak price signal on off-peak charging performance
Vehicle type	S, L	Dummy, main effect	PHEV: S = 0, L = 0 Non-Tesla BEV: S = 1, L = 0 Tesla BEV: S = 0, L = 1	Tests the effect of vehicle type on off-peak charging performance

Price signal: vehicle type interaction	S x T, L x T	Dummy, interactive effect	Multiplication of (S x T) and (L x T)	Measures the incremental off-peak performance of a *treatment group* non-PHEV vs. a control group vehicle
Program activity	K	Continuous, main effect	Represents hundreds of kWh charged per month or tens of charging sessions per month (model-dependent)	Tests the effect of a participant's level of charging activity on off-peak charging performance, with the intent of measuring whether more charging activity (sessions or kWh per month) translates into greater program engagement or an improved understanding of the off-peak price signal
Month	Oct, Nov, Dec, Jan, Feb, Mar, Apr, May, Jun, Jul, Aug	Dummy, main effect	For each month variable, the variable is equal to 1 if the data was recorded in that month and 0 if not; September 2019 is the base case and is not assigned a variable	Tests for non-linear effects of time on the observed behavior – specifically, is there a statistically significant behavior change in response to a higher rebate (summer months) or the COVID-19 pandemic?

Results and Findings

This section presents a selection of results and findings stemming from the authors' evaluation.

Aggregate Charging Behavior Analysis

Table 2, below, summarizes the overall program charging activity recorded between September 1, 2019, and August 31, 2020. For this analysis we focused solely on aggregate charging behavior – not yet focusing on on-peak vs. off-peak considerations – to assess the similarity of the two groups' behavior and to allay concerns that the groups were fundamentally unbalanced, which could hinder drawing conclusions about the effectiveness of the off-peak rebates later in the analysis. The two groups were expected to behave similarly on a per-vehicle aggregate charging behavior basis, given the random group allocation process.

Table 2. SCRI Program Summary Statistics

Group	Vehicle Stratum	Vehicle Count*		kWh Charged**		Charge Sessions‡	
		Total	Percent of Group	Overall	Per Vehicle	Overall	Per Vehicle
Control	PHEV	79	44%	107,842	1,365	27,498	348
	Non-Tesla BEV	56	31%	113,592	2,028	11,490	205
	Tesla BEV	43	24%	163,426	3,801	19,567	455
Total Control	All	178	100%	384,860	2,162	58,555	329
Treatment	PHEV	67	38%	84,148	1,256	21,043	314
	Non-Tesla BEV	62	35%	116,338	1,876	14,088	227
	Tesla BEV	47	27%	187,681	3,993	15,256	325
Total Treatment	All	176	100%	388,168	2,205	50,387	286
Overall Total		354		773,027	2,184	108,942	308

* The authors ran a Chi Square Test to test the equivalency of the control and treatment groups. With a p-value of 0.670, the test indicates there is no statistically significant difference in the groups' composition.

** The authors ran an independent samples t-test to assess the statistical significance of differences in the amount of kWh charged per vehicle. Across all vehicle types, the differences observed between the control and treatment group were not found to be statistically significant (90% confidence level), which indicates that the drivers in each group behave similarly in terms of the overall volume of charging they do (though the timing of that charging differs significantly between the two groups).

‡ The authors ran an independent samples t-test to assess the statistical significance of differences in the number of charge sessions per vehicle per month. Across all vehicle types, the differences observed between the control and treatment group were not found to be statistically significant (90% confidence level), which indicates that the drivers in each group behave similarly in terms of how often they plug in (though the timing of those charging sessions differs significantly between the two groups).

Several observations can be drawn by examining the high-level program charging data.

- Charging volume and frequency reflect differences in vehicle strata composition.
    - Across vehicle types, PHEVs recorded the most charging sessions and charged the least kWh across both groups, suggesting that these vehicles need to charge more frequently as a result of their small battery size (kWh).
    - Tesla BEV drivers charged the most kWh of any vehicle type across both groups, a result of their larger battery sizes, which can be used to drive longer distances and thus require more charging.
    - In both groups, non-Tesla BEVs fell between the other two types in terms of kWh charged, reflecting the broad range of vehicles, battery sizes, and technologies included in this group.
- The overall amount of charging (kWh) was statistically equivalent between the control and treatment groups when normalized by the count of vehicles in each group; the control group charged 2,162 kWh/vehicle and the treatment group charged 2,205 kWh/vehicle (a delta of less than 2%).
    - This observation is consistent with the program goal of shifting when charging occurs, rather than the amount of charging taking place.

Statistical Regression Analysis Results

Following this initial high-level analysis, the authors developed two linear regression models to test the effect of several independent variables on two separate dependent variables representing off-peak charging performance: 1) the per-vehicle monthly percentage of kWh charged off-peak (charging load approach), and 2) the per-vehicle monthly percentage of charging sessions initiated off-peak (session start time approach). As discussed earlier, both metrics provide valuable insight into how Rhode Island EV drivers charge their vehicles, with the charging load approach being grounded in the program's off-peak rebate structure and the session start time approach better capturing the extent to which participants internalized the intent of the price signal. We focus on the session start time model in this paper for brevity and because we consider it the better estimate of the program's impact. The regression model was structured using the following form:

$$y = \beta_0 + \beta_1 T + \beta_2 S + \beta_3 L + \beta_4 (S \times T) + \beta_5 (L \times T) + \beta_6 (Oct) + \beta_7 (Nov) + \beta_8 (Dec) + \beta_9 (Jan) + \beta_{10} (Feb) + \beta_{11} (Mar) + \beta_{12} (Apr) + \beta_{13} (May) + \beta_{14} (Jun) + \beta_{15} (Jul) + \beta_{16} (Aug) + \beta_{17} K$$

Table 3 summarizes the resulting parameter values. All of the unstandardized coefficients (except for the base case) represent the incremental per-vehicle percentage of off-peak charging introduced by turning on the respective variable – e.g., the model estimates that 41% (β_0 in Table 3) of control group PHEV charging sessions started off-peak and that control group Tesla BEVs start an additional 8.8% of charging sessions off-peak (β_3 in Table 3). The parameters are additive; as such, the model indicates that 68.3% of treatment group Tesla BEV charging sessions were initiated off-peak ($\beta_0 + \beta_1 + \beta_3 + \beta_5 = 41.0\% + 7.0\% + 8.8\% + 11.5\% = 68.3\%$).

Table 3. Overall Rebate Intervention Session Start Time Model

Coefficient symbol	Variable	Unstandardized coefficient	Standard error	P-value (statistical significance)
β_0	Base case: control group PHEVs	41.0%	1.9%	0.000
β_1	Treatment	7.0%	1.3%	0.000
β_2	Non-Tesla BEV	-3.4%	1.4%	0.019
β_3	Tesla BEV	8.8%	1.5%	0.000
β_4	Non-Tesla BEV-treatment	12.7%	2.0%	0.000
β_5	Tesla BEV-treatment	11.5%	2.1%	0.000
β_6	October 2019	1.7%	2.4%	0.459

β_7	November 2019	5.2%	2.3%	0.021
β_8	December 2019	6.8%	2.3%	0.003
β_9	January 2020	4.8%	2.2%	0.032
β_{10}	February 2020	5.4%	2.2%	0.015
β_{11}	March 2020	7.5%	2.2%	0.001
β_{12}	April 2020	8.5%	2.3%	0.000
β_{13}	May 2020	2.3%	2.3%	0.311
β_{14}	June 2020	0.5%	2.3%	0.813
β_{15}	July 2020	-0.4%	2.3%	0.852
β_{16}	August 2020	1.2%	2.3%	0.603
β_{17}	Tens of charging sessions per month	0.7%	0.1%	0.000

This model leads us to several findings regarding the off-peak session start time performance:

- Participants belonging to the treatment group initiated 7% more of their charging sessions off-peak, indicating that the off-peak price signal had the desired effect (statistically significant).
- The impact of the off-peak price signal was not uniform across all vehicles.
    - Non-Tesla BEV and Tesla BEV drivers in the treatment group charged 12.7% and 11.5% more off-peak than PHEV drivers in the treatment group, respectively (both statistically significant).
    - The authors believe that greater access to tools that support scheduled charging accounted for some of these vehicle type differences among treatment group members. This was supported by a participant survey that showed that 76% of Tesla and non-Tesla BEV drivers were aware of tools for controlling their EV charging vs. 56% of PHEV drivers.
- Vehicle type had a statistically significant effect on the observed off-peak charging behavior absent an off-peak price signal; however, the direction of the impact was not uniform.
    - Tesla BEV drivers started 8.8% **more** of their charging sessions off-peak than PHEVs even without an off-peak price signal, suggesting they may have a technology edge over PHEVs or potentially receive outside marketing regarding off-peak charging.
    - Control group non-Tesla BEV drivers initiated 3.4% **fewer** of their charging sessions off-peak than control group PHEVs.
    - Notably, non-Tesla BEV drivers charged significantly more kWh off-peak but initiated fewer charging sessions off-peak, supporting the dual focus on charging load and session start time to more fully assess the off-peak rebate's effectiveness.

- Time had a statistically significant impact on the off-peak session start performance for November and December (in 2019) and January, February, March, and April (in 2020). We believe there are several factors that drove this observed behavior, described below.
    - On average from November to February, 5.5% more charging sessions were initiated off-peak across all vehicles than in September 2019. We initially expected to observe the opposite, as we anticipated that greater in-car heater use in the winter months would increase charging overall and could push session start times earlier. The observed winter off-peak shift may be the result of changes to typical schedules, perhaps related to colder temperatures, shorter days, or the holidays.
    - In March and April, the two months in which Rhode Island was most deeply impacted by COVID-19, charging sessions were initiated off-peak 7.5% and 8.5% more frequently than in September 2019, respectively, across all vehicles. This shift was likely driven by a significant decrease in charging outside the home, such as at workplaces and retail locations, which is more likely to occur on-peak. The absence of this charging would skew the percentage of off-peak at-home charging proportionally higher. However, without more granular geographical data, it was not possible to verify this.
    - Notably, COVID-19 did not have a dampening effect on off-peak charging performance. As charging overall decreased significantly, it appears that on-peak charging dropped off more than off-peak.

It is worth noting that the charging load approach model revealed many of the same findings as described above. The off-peak shift observed under that model was also significant, reinforcing the fact that the rebates are effective, and also exhibited a strong dependence on vehicle type, further reinforcing the takeaway that participants' ability to effectively respond to an off-peak price signal depends in part on their awareness of and access to technology that facilitates scheduling charging.

Key Findings and Takeaways

The following key findings were developed through this evaluation:

- Off-peak rebates are effective in shifting EV charging.
- The effect of an off-peak price signal is not uniform for all vehicle types, with Tesla and non-Tesla BEVs exhibiting a greater off-peak shift than PHEVs across both regression models.
- Additional factors had an effect on when participants initiated their charging sessions, including seasonality effects, weather/temperature, and the COVID-19 pandemic. More research is required to develop a more nuanced understanding of the effect each of these factors had on off-peak charging in the SCRI Program.

It is encouraging to see the interventions piloted through this managed charging program having a measurable effect on real-world charging behavior. Looking forward, there is much more work to be done on both the program implementation and evaluation side, including designing and piloting new managed charging strategies to help utilities meet their changing needs, especially in a future with high EV adoption. Since the completion of this study, the authors have continued to work with National Grid Rhode Island to explore alternative incentive structures and the testing of behavioral "nudges" to shift load off-peak more effectively. As more utilities begin piloting managed charging programs in the near future, we expect to see a growing number of novel managed charging approaches designed to:

- Shift load to different times of the day (perhaps to soak up excess mid-day solar generation)

- Increase demand response event participation
- Intelligently schedule charging to smooth out spiky load profiles
- Export power back to the grid under certain conditions

As these programs evolve over time, it may be necessary to explore targeted updates to the evaluation framework described in this paper in order to accurately capture the impacts of those programs. On the evaluation side, there is more work to be done to develop robust statistical analysis approaches that effectively capture the variability of individual charging behavior and model the factors shaping charging behavior, including price and information signals, behavioral messaging, vehicle type, weather, and time.

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