Transportation Research Part D 100 (2021) 103023

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Evaluating smart charging strategies using real-world data from optimized plugin electric vehicles

Sierra I. Spencer, Zhe Fu, Elpiniki Apostolaki-Iosifidou, Timothy E. Lipman *

Transportation Sustainability Research Center, Inst. of Transportation Studies, Univ. of California – Berkeley, 2150 Allston Way, #280, Berkeley, CA 94704, United States

ARTICLE INFO

Keywords:
Smart charging
Electric vehicle
Renewable energy

ABSTRACT

Management of electric vehicle (EV) charging is likely to be critical in avoiding large increases in peak electricity demand and subsequent build outs of generation and distribution infrastructure. Additionally, management of EV charging can help to more effectively utilize renewable energy resources. This study analyzed charging data from a real-world pilot program, the largest household-based study to date to analyze the effectiveness of different smart charging use cases at reducing charging costs and increasing utilization of renewable energy. The study included six different use cases that featured varying optimization signals and driver incentives. Study results suggest that the optimizations are effective at shifting load from times of high grid costs and congestion, most notably during early evening hours, to times of lower grid costs in the early morning and midday. The study finds that 15–20% of charge was shifted out of any given hour and 20–30% of charge was shifted into a given hour in the most effective use cases. In addition to shifting charging across time periods, charging events were also effectively shifted to different locations during some use cases, such as from overnight at households to during the day at workplaces.

1. Introduction

In response to the mounting climate crisis, many governing bodies, electricity providers, and private companies have made increasingly aggressive goals and commitments to reduce their greenhouse gas (GHG) emissions over the next few decades. Transportation is a major component of anthropogenic GHG emissions; for example, in California, the transportation sector accounts for about 41% of all GHG emissions (CARB, 2020). Therefore, decarbonizing the transportation sector is critical to achieving the GHG emissions reductions necessary to mitigate the impacts of climate change.

As the electricity sector increasingly utilizes renewable energy sources, electrifying transportation becomes a viable method of reducing transportation emissions and meeting GHG reduction targets. The electric vehicle (EV) market is growing steadily in the U.S., led by the California market, where there are currently about 800,000 EVs of various types in California and about 1.8 million in the U.S. (CEC, 2021; Veloz, 2021). This is still only about 3% of California vehicle stock and less than 1% across the U.S., but the EV market is gaining momentum for light-duty vehicles as well as for heavier vehicles such as buses and trucks.

Aggressive transportation electrification implementation plans in the U.S. and other regions, including potential bans on sale of new combustion engine vehicles around 2035 in some regions, will lead to increased EV use and charging. This will occur at

* Corresponding author.
E-mail address: telipman@berkeley.edu (T.E. Lipman).

https://doi.org/10.1016/j.trd.2021.103023

Available online 9 September 2021

residential, workplace, and public charging locations and at a wide range of power levels from 1 to potentially over 250 kW per vehicle being charged. This will pose new challenges for local electricity distribution grids, especially with expected clustering effects around vehicle charging stations and depots. Along with transitions towards intermittent renewable energy sources for electricity generation, EV loads can represent both challenges and opportunities. There are challenges for when generation and load are not well coupled, creating power system imbalances, but then opportunities for better integration when they can be influenced to become more coincident.

At present, EV charging often takes place during existing electricity system peak times (from 4 to 9 PM) when the majority of drivers arrive home from work. The simultaneous charging of many EVs at these times increases the peak demand on the grid, potentially causing overloading of different grid components and congestion, and may thus require additional infrastructure investment at the distribution level (Shepero et al., 2018; Xiao et al., 2014; Spitzer et al., 2019; Brouwer et al., 2013; Rahman and Shrestha, 1993; CPUC, 2020). The increase in electricity demand may also result in additional generation capacity needs, which would require additional investments to ensure adequate electricity supplies.

These challenges of integrating EVs into electric grids can be addressed through managed EV charging, also known as smart charging. Smart charging allows EVs to be more smoothly integrated to the grid with reductions in load timing problems. Smart charging implementations include:

1. Unidirectional power flow management during EV charging, known as V1G, that enables EVs to shift the time of day of charging to better fit with grid conditions; and
2. Bidirectional power flow, known as vehicle-to-grid or V2G, that enables EVs to charge from the grid or discharge energy stored in their batteries to the grid, to go beyond simply just being able to modify the times that EVs charge but to effectively use EVs as stationary electricity storage devices.

Both V1G and V2G can be powerful strategies for grid operations management, with V2G offering opportunities for significantly more value (Szinai et al., 2020; Van Triel and Lipman, 2020). However, V2G offers a significantly higher degree of difficulty in implementation relative to V1G, with grid interconnection and vehicle battery warranty issues among other considerations (Gschwendtner, Sinsel, and Stephan, 2021).

Most of the research studies that have quantified the value of EV charge management have used modeled and simulated EV driver behavior (Coignard et al., 2018; Wolinetz et al., 2018; Donadee et al., 2019; Wen et al. 2020; Van Triel and Lipman, 2020). Donadee et al. (2019) simulate EV driving and charging behavior to assess the potential value of V1G and V2G. The study by Donadee et al. (2019) conducted two different methodologies for managing charging: one in which charge is managed against the rates that customers would face when charging their EVs and one in which charge is managed against the cost to the utility to provide the electricity. Coignard et al. (2018) quantifies the effects of EV adoption on California's net load or "duck" curve, where an abundance of solar production creates a deep midday valley in daily net load followed by a large ramp in the evening hours. The study finds that managed EV charging can provide essentially the same benefits as dedicated battery storage for the grid, but at a fraction of the implementation cost.

Szinai et al. (2020) quantify the value of EV charge management and the contribution of EVs to reducing solar curtailment in 2025. The study improves upon previous studies valuing EV charge management by representing more robust and granular simulated driving data. The study pairs the Behavior, Energy, Autonomy, Mobility (BEAM) model, which depicts driver activity and EV charging behavior, with PLEXOS, a market simulation software used to simulate grid operations, to simulate charging behavior under different EV adoption scenarios. The study finds that managed charging of 5 million EVs in California in 2025 can reduce renewable curtailment by up to 40% compared to unmanaged charging of the same number of EVs and can avoid up to 10% of annual grid operating costs.

Few studies have tested driver response to optimization signals and even fewer have been conducted at the scale of this study. The ChargeTO pilot conducted in Toronto was one of the first studies to quantify grid benefits from shifting residential EV charging from peak periods and driver responsiveness to allow for this type of charge shifting under different incentive structures, but with about 30 vehicles or about one-tenth the scale of the ChargeForward 2.0 study and with fewer and simpler use cases examined. The study was implemented using a FleetCarma smart charging system and found that incentives were generally effective at increasing driver willingness to have their charge shifted (Bauman et al., 2016).

One of the leading transmission system operators in Europe conducted a study that measured the benefit of optimized charging via simulations for Belgium and Germany. According to the report published in 2020, EV driver annual electricity costs will be reduced by 15 to 30% by 2030 with the deployment of smart charging compared to unmanaged charging. Also, with smart charging, the overall CO2 emissions of the power system are estimated to be decreased by 600,000 tonnes a year by 2030 (ELIA, 2020).

While these studies offer useful insight into potential future value of EV charge management, they do not reflect the value or optimization potential of managing household EV fleets in the near term. By utilizing real-world driver data, this study investigates actual driver behavior (i.e., revealed, not stated preference), willingness to respond to optimization signals, the effectiveness of various signals in yielding desired charging schedules, and the ability of each optimized use case to produce certain outcomes.

This study focuses on unidirectional flow and smart charging (i.e., V1G) and explores different use cases applied to participants of BMW's pilot EV charge management program, known as ChargeForward. This program started with an initial project in the San Francisco Bay Area, aimed to evaluate and test optimizations of EV charging with about 90 real-world, EV-owning households. A second program ChargeForward 2.0 that started in 2017 and concluded in 2020 included a total of about 400 households over the course of the study. This is believed to be the largest program to date worldwide to implement smart charging optimizations with real EV drivers in household settings.

Through analysis of the various examined use cases, this study explores and analyzes the effectiveness of electricity pricing signals, renewable energy production signals, and driver incentives on altering driver behavior and optimizing the timing and location of EV charging. This study also investigates how certain parameters, such as plugin frequency and battery size, affect the ability and effectiveness of charge optimization.

This paper is organized as follows. Section 2 describes the data and the use cases that are examined in the study. Section 3 presents the study analysis methodology and relevant limitations and caveats. The study results are presented in Section 4, and the study conclusions are discussed in Section 5.

2. Study data and use cases

Participants for the study were recruited by BMW and consisted of both battery EV (BEV) and plug-in hybrid EV (PHEV) drivers. After meeting basic screening criteria including willingness to be "opted in" to the program by default (with ability to override charge management events by smart phone), drivers had the option to participate in the pilot project. Participation in the program allowed BMW to receive information on the location and starting and ending time of driver parking, plugging, and charging events. To protect driver privacy, the exact geolocation data used in this analysis were "fuzzed out" to a 1-mile (1.6 km) radius prior to being made available to the university research team. Each event also included information such as the amount of vehicle charge and flags for whether the vehicle was determined to be in its designated "home" location and whether the vehicle had been "optimized" by BMW.

In order for their vehicle charging to be optimized, a participant needed to use a smartphone application to set their departure time and desired charge at that departure time. Given these parameters, during some charging events, BMW was able to optimize the charging by designating the necessary charge to occur during the most optimal time within the timeframe before the vehicle's departure time.

2.1. Study use cases

Six different use cases were operationalized over the initial course of the study, these having varying parameters such as the signal used to direct the optimizations, the permitted locations for optimizations, and the permitted times of day for optimizations. The use cases were established based on detailed discussions among the project team and sponsor agency. The multi-disciplinary project team consisted of researchers from a major automaker, a major electric utility, two electricity grid services companies, and the university. Key considerations in developing the initial set of use cases included targeting both driver plugin behavior as well as managing charging within their mobility patterns, as well as focusing on specific settings and optimization signals to try to understand differences in their implementation and ultimate results.

The use cases included different incentives for participants to perform certain behaviors, such as increasing the number of times a driver plugged in their EV or shifting the time of day that drivers charged. The incentive paid to drivers varied by use case, given the variability in nature and duration of the use cases. For example, in the Home 24-hour use case drivers were compensated $1 for each plugin at the appropriate time and an additional $1 if their vehicle charging was optimized in that charge event, meaning they could gain up to $2 per day in that use case. This relatively modest level of incentive was designed to elicit some degree of driver response, where the actual monetizable values of VGI are still being studied under a broad array and combinations of potential use cases in the future. The optimization objectives, parameters, permitted locations and times, and driver incentives of each of the six use cases in this study are summarized in Table 1.

For each use case, the study analyzed the number of plugins and optimizations, the amount and times of charge shifted during optimizations, and the grid operational cost savings to compare the effectiveness of each use case in achieving its objectives. The study also compared results across use cases to assess how different parameters impact driver behavior and charge optimizations.

3. Analysis methodology

The study analysis consisted of collecting data on EV driver charging behavior during the six BMW use cases listed in Table 1. These data were combined with additional data sets of electricity grid costs and generation characteristics to analyze the effectiveness of the use cases at minimizing the grid cost of supplying the electricity to charge the EVs and utilizing renewable energy. Steps in the analysis also included data validation, data cleaning, and compiling and visualizing the analysis results.

3.1. Vehicle charging optimizations

BMW used onboard vehicle telematics systems to collect driver data for the program. These data were sent to Olivine, Inc., a grid integration service provider, who utilized one of the following hourly data sets to drive the optimizations, depending on the use case:

- Day-ahead locational marginal price (LMP) provided by the California Independent System Operator via Kevala Analytics[1]
- Day-ahead renewable energy estimate provided by Pacific Gas & Electric (PG&E)

[1] LMP prices represent the real grid cost of providing electricity to a specific area, defined by the electricity transmission system.

Table 1
Use cases analyzed in the study.

Use Case	Dates	Opt. Signal	Opt. Locations	Opt. Times	Driver Incentives
Earth Week Renewable Energy	April 22–28, 2018	Day-ahead renewable energy availability	Home only	Daytime hours from 10 AM to 2 PM	Drivers were encouraged to plugin during mid-day hours with incentives offered for charging between 10 AM and 2 PM
Home Overnight	April 29 - July 10, 2018	Day-ahead LMP	Home only	4 PM–4 AM only	Drivers are incentivized to charge overnight in order to avoid evening peak time charging
Home 24 Hour	July 11 - Oct. 14, 2018	Day-ahead LMP	Home only	All hours	Driver response is tested over a 24-hour optimization mechanism
Driver Cohort Plugin Goal	Sept. 26 - Oct. 10, 2018	Day-ahead LMP	Home only	All hours	Drivers were incentivized to plugin more; drivers could unlock increasingly valuable sweepstakes opportunities as group performance improved; drivers were also incentivized to plugin during event hours
Overgeneration	Oct. 15 - Nov. 9, 2018	Day-ahead LMP	All locations	All hours	Drivers were incentivized to plug in during daytime hours in order to reduce overgeneration from solar energy
Transactive Energy Signal	Dec. 3–10, 2018	EPRI Transactive Energy Signal	Home only	All hours	Driver response is tested against EPRI transactive energy signal*

* Note: Transactive energy signals are used to manage power flows or exchanges of energy within electric power systems, using market-based signals to improve the efficiency and reliability of power grids.

- Transactive Energy (TE) prices provided by Electric Power Research Institute (EPRI)[2]

Olivine determined each vehicle's optimal charging schedule based on the objective to minimize price (LMP or TE) or maximize renewable energy usage, depending on the use case. Olivine passed the optimized charging schedule along to BMW, who adjusted vehicle charging through each vehicle's telematics system. Any BMW adjustments to vehicle charging resulted in the vehicle's charging session receiving an "optimized" flag in the dataset.

3.2. Plugin behavior analysis

The study developed a model to process and analyze the large amounts of driver data collected. Information from drivers and BMW was used to attach flags to each data point to specify if charging sessions were done at home and if they were optimized by BMW. After being cleaned and pre-processed, driver data with accompanying flags was processed to determine the unique number of plugins during each use case. Plugins were also filtered and separated into different groupings, such as home vs. not-home ("away"), optimized vs. not optimized, day of the week, and time of day, to help detect any differing patterns in plugins based on these factors. When organized by day type, plugin data were normalized based on the number of each day type in the use case timeframe and the number of participating vehicles to give per vehicle and per day results. Plugin behavior before and during use cases was compared to assess the effectiveness of use cases in increasing and/or shifting the timing and/or location of vehicle plugins compared to the control baseline.

3.3. Energy shifted analysis methodology

For this analysis, the reference charging scenario, or baseline, is defined as a charging event in which the vehicle begins charging immediately after being plugged in to its charger (i.e., the plugin start time is the same as the charging start time). This baseline charging scenario is uncontrolled with no charge management. The optimizations conducted cause most vehicle charging periods to shift from the baseline charging period. In other words, in most cases the optimized charging period differs from the baseline charging scenario in which the vehicle would have charged to its final state of charge immediately after being plugged in.

There are two different types of charge shifting that can occur, total and partial charge shifting. Total charge shifting occurs when the entire optimized charging time block is outside of the baseline charging block, resulting in all charge being shifted outside the baseline charging time. A schematic of total charge shifting is shown in Fig. 1 below.

Partial charge shifting has only a portion of the charging shifted outside the original charge time window. A schematic of partial charge shifting is shown below in Fig. 2.

For both types of charge shifting, the cleaned and pre-processed data is used to calculate the total amount of charging in kWh that occurs during a charging session. The difference between a vehicle's initial and final state of charge (SOC) during a given charging session can be multiplied by the vehicle's battery capacity to derive the energy (kWh) charged during that charging session. The kWh charged in charging sessions can be aggregated to give the total energy charged within the use case timeframe, for all the included

[2] The transactive energy signal utilizes economic signals that are more closely tied to balancing supply and demand across the entire grid (see: GridWise Architecture Council, https://www.gridwiseac.org/about/transactive_energy.aspx).

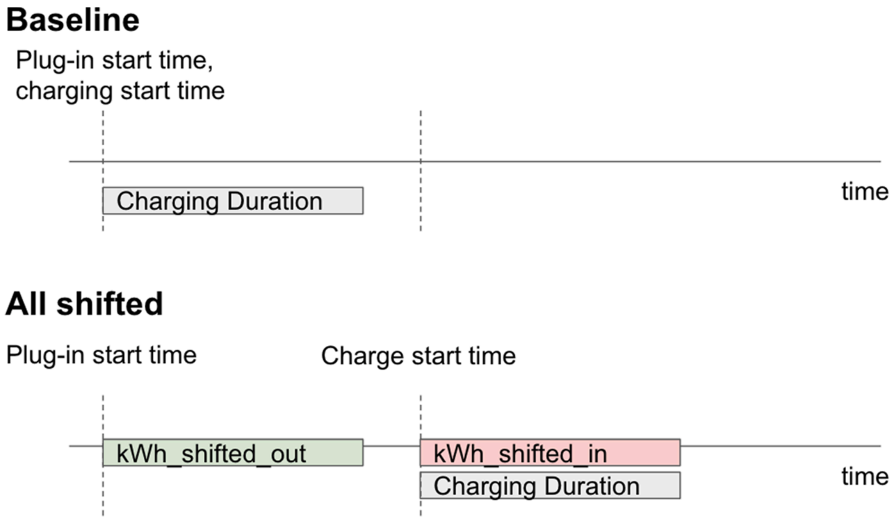

Fig. 1. Schematic showing charge that is all shifted.

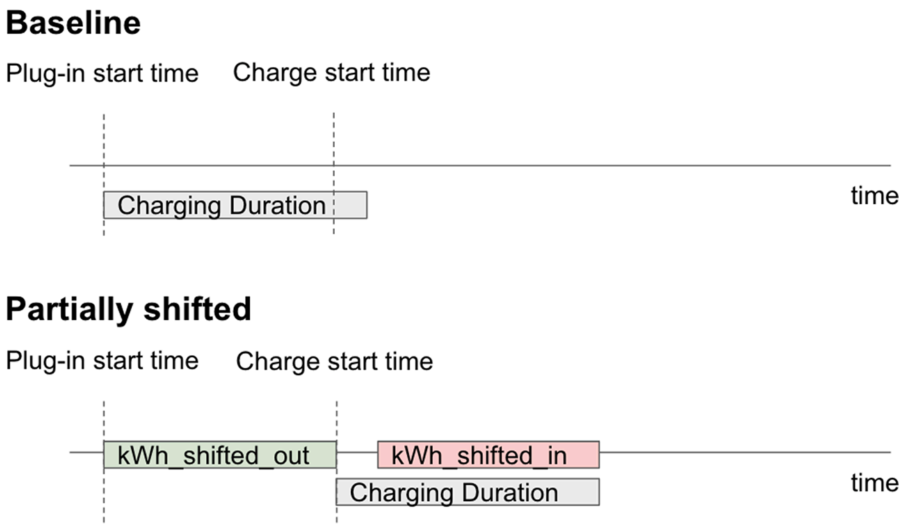

Fig. 2. Schematic showing charge that is partially shifted.

vehicles.

A comparison strategy was thus created in the Python coding language to compare the baseline time of charging to the actual time of charging for "optimized" charging sessions. Vehicle plugin times were utilized to construct baseline charging scenarios for charging events that were optimized through a cost-minimization algorithm developed by the project partners. The timing and duration of these constructed baseline charging scenarios were then compared with the charging data collected from optimized vehicles. Outputs of the comparison included hourly amounts of charging energy in kWh that was removed, added, or kept the same for optimized charging compared to the baseline charging. Hourly outputs were averaged across all hours of similar day types in each use case to give average hourly charge shifts over the use case.

3.4. *Economic analysis methodology*

The economic analysis is conducted with a focus on the potential grid-side benefits of shifting load from higher to lower pricing periods, on both a participant fleet and per-vehicle basis. This differs from a customer bill or retail rate set of impacts that are somewhat disconnected under current rate structures but can be further informed by the grid-level cost analysis. This analysis can be considered as an economic evaluation of BMW's current charge optimization strategy and implementation.

Locational Marginal Price (LMP), the marginal cost of delivering the energy at that node and at that time, is the metric used to measure the potential grid-side benefits. LMP values vary each hour, and by accumulating LMPs throughout the charging duration, the price of a specific case can be calculated:

Reference Price = Reference charging kWh * LMP_reference time
Actual Price = Actual charging kWh * LMP_actual time

With the price of each case, the saving, or potential grid-side benefits, can be easily obtained:

Saving = Reference Price − Actual Price

With the Python-based script to reconstruct the baseline charging scenarios described above and incorporating LMP data, the economic saving for each charging event can be calculated. This provides the possibility to conduct the economic analysis on each use case. Although the LMP data were used as the signal in some use cases but not others, the LMP information was consistently used as the metric for measuring economic benefits across all use cases.

4. Study results

This section first presents results from the individual VGI use cases examined in the study and then describes findings from a comparison across all use cases. There were some changes during the study that impact that comparison somewhat, where the efficacy of the optimization routines improved somewhat from the early part of the study due to learning about their implementation. This and other study caveats are discussed below.

4.1. Earth Week use case

The "Earth Week" use case, which ran during the week of Earth Day from April 22–28, 2018, aimed to increase charging's utilization of renewables. During this use case, participants were encouraged to plugin more during the middle of the day, from 10 AM to 2 PM, when excess solar generation is highest. Charging was optimized based on a day-ahead renewable energy availability signal from PG&E. While participants were encouraged to plugin during mid-day hours at any location, BMW optimizations only occurred at drivers' designated home locations during this use case. Additional opportunities for increasing utilization of renewable energy thus exist for encouraging drivers to plug in and be available to charge at away from home charging locations as well.

During the Earth Week use case, vehicles that were optimized demonstrated a shift to have more charging occurring during mid-day hours compared to the charging in the week prior to the Earth Week use case. These results are shown in Fig. 3.

During the Earth Week use case, BMW's methodology for optimizations was still being improved and BMW could not yet access some of the key charging data. This use case demonstrates that even without BMW direct management of charging, drivers are capable of increasing the amount of mid-day charging by plugging in more and are willing to do so if incentivized.

Incentivizing more midday charging could be critical in absorbing the high amounts of solar on the grid during the day in California. The Earth Week use case did see more charging during evening hours and less during early morning hours; therefore, efforts to increase midday charging likely need to be paired with efforts to shift charging from evening peaks to optimize full-day charging schedules.

4.2. Home overnight use case

The next use case evaluated in this study is the "Home Overnight" use case, which ran from April 29-July 10, 2018. In this use case, BMW only optimized home charging that was during "overnight" hours, defined as between 4 PM and 4 AM. This use case aimed to shift residential charging during peak early evening times, often from 4 to 9 PM to overnight and early morning hours (12–6 AM).

BMW's methodology for optimizations was still being improved during this use case, as can be seen in Fig. 4. There were a low number of optimizations that occurred relative to the number of plugins, largely as a result of the optimization methodology and data access challenges. The amount of plugins per day was highest on weekdays, with about 110 per day, dropping to about 80 events per

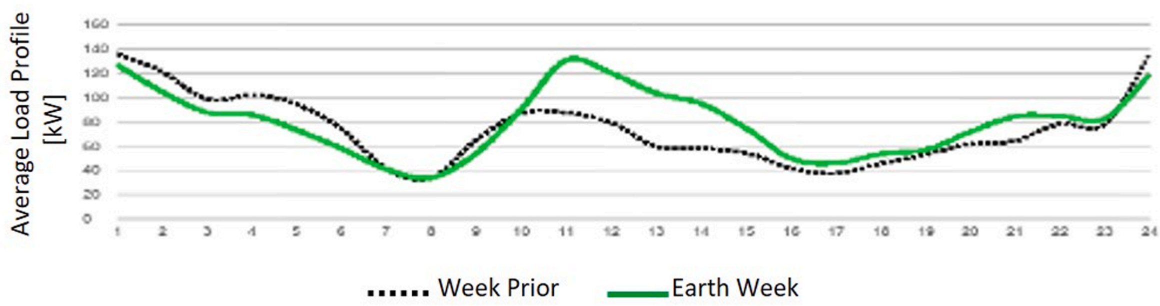

Fig. 3. Vehicle charging energy shifted by hour per day in earth week use case (kWh).

day on weekends. Optimizations were similarly somewhat higher on weekdays, with 9–12 optimization events, compared with 6–8 on the weekend days.

Fig. 5 below shows that any charge shifted during the optimizations that did occur during the Home Overnight use case was shifted in the ways expected: charge was shifted out of peak evening times into overnight and early morning hours. The hourly results in Fig. 5 represent an average of a given hour across the use case time frame.

Hours that show charge both shifted in and shifted out indicate that on some days, charge was shifted into that hour because that hour had a lower grid cost signal than other hours, and on some other days charge was shifted out of that hour because it had a higher grid cost than other hours.

In most cases, charge was removed from early evening hours, with the most charge removed from 7 to 8 PM. On some occasions, charge is shifted into the evening hours due to driver mobility constraints that require charging then to compensate from other changes in their charging patterns. Charge was most often moved to early morning hours, with charge additions reaching a peak from 3 to 4 AM. Optimizations during this use case only occurred overnight, so the small amount of charge shown shifted during the middle of the day is an artifact of random variations in charging behavior.

Another key takeaway from this use case is that even with optimizations limited to residential locations and overnight hours, there is still a significant potential for charge to be shifted to reduce charging costs and EV contribution to peak demand in the evening hours.

4.3. Home 24-Hour use case

From July 11-October 14, 2018, BMW repeated a similar use case as the Home Overnight use case but instead of restricting home optimizations to overnight hours, home optimizations were allowed at all hours of the day.

The BMW optimization methodology was significantly improved in August 2018. To overcome gaps in driver data, BMW began estimating remaining charge time for vehicles and therefore was able to optimize more vehicles and charging sessions during most of this use case and in future use cases. Optimizations reached an average of 34 optimizations per day on the peak day type (Thursday) of 60 total plugin events; this marked a significant increase from the Home Overnight use case, which had 8–12 optimizations per day on the peak day (Friday) out of 70 total plugin events.

As shown in Fig. 6, as expected, given the access to midday charging not included in the Home Overnight use case, the Home 24-Hour use case had more charging that was shifted in or out of midday hours. However, the amount of charging shifted in or out of these mid-day hours remained relatively small compared to the amount of charging that was shifted to and from early evening and early morning hours.

As discussed in more detail below, the grid operational cost savings from optimizing residential charging at all hours of the day was significantly greater than the savings from optimizing strictly overnight residential charging. Optimizations in the Home Overnight use case had an average grid operational cost saving of $0.211 per optimization whereas optimizations in the Home 24-Hour use case had an average grid operational cost saving of $0.336 per optimization.

It is worth noting that in the Home 24-Hour use case, some outliers with a high level of cost savings occur. Grid cost savings reached a maximum of $18.08 during one optimization event, which is significantly higher than the maximum savings achieved in a single optimization in other use cases. There are several possible explanations for the outliers in this use case: 1) the charge event has a particularly long plug-in period that allows the algorithm to optimize over longer pricing periods; 2) during the plug-in period, there is a large range in LMP price and the difference between the prices allows for greater savings; and 3) the total charged kWh is large (i.e., a large delta in the battery state of charge). These factors combined are believed to result in the unusually high grid cost optimization values in some cases in the Home 24-Hour use case.

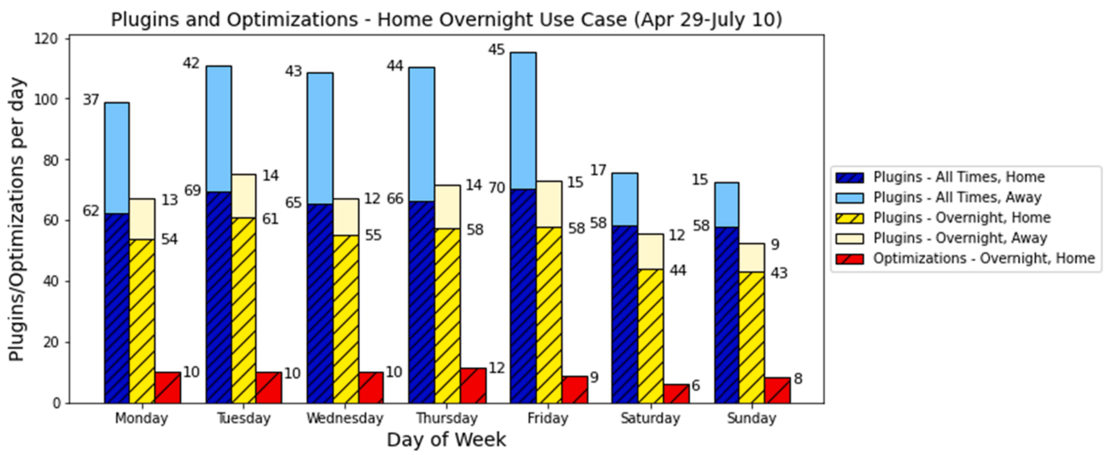

Fig. 4. Vehicle plugins and optimizations by day of the week for home overnight use case.

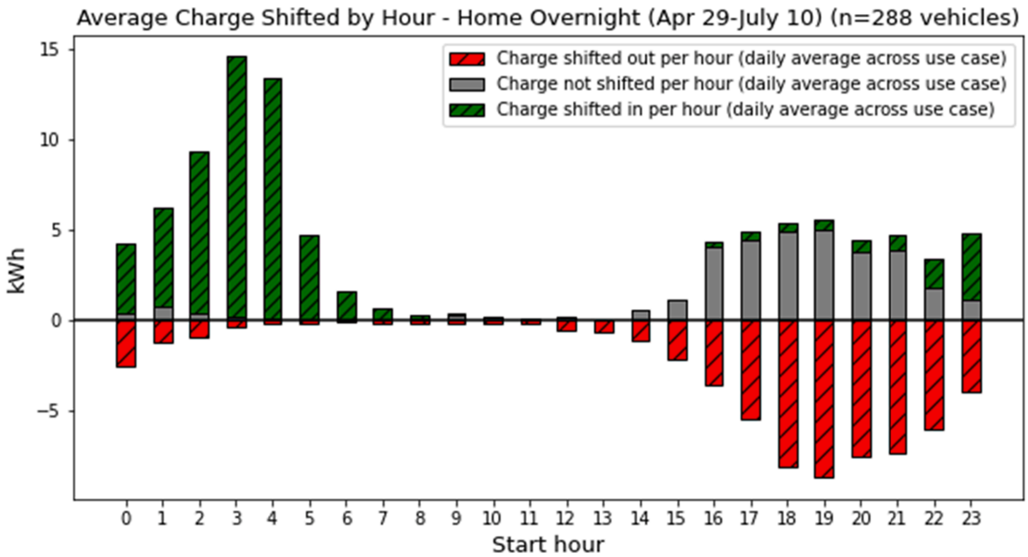

Fig. 5. Vehicle charging energy shifted by hour per day in home overnight use case (kWh).

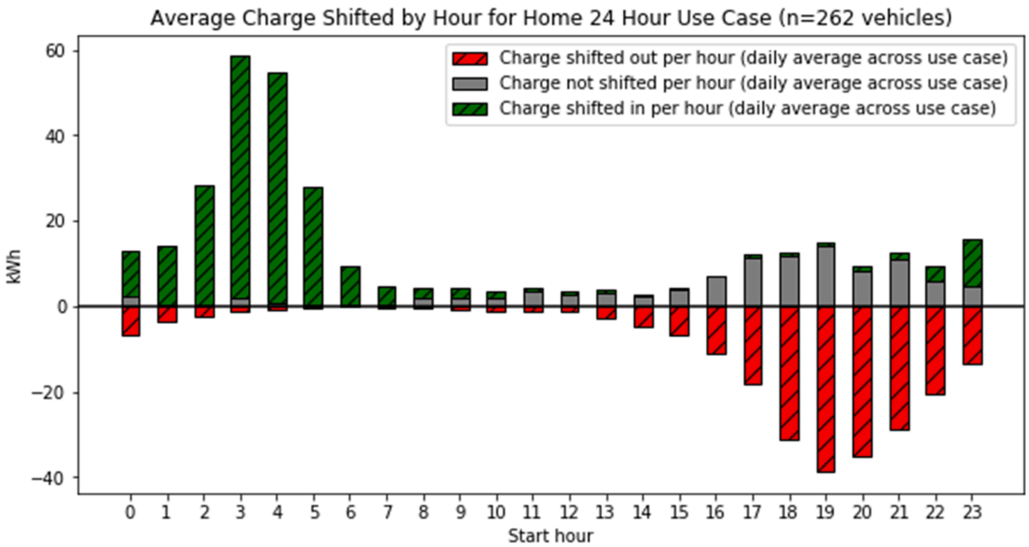

Fig. 6. Vehicle charging energy shifted by hour per day in home 24-hour use case (kWh).

4.4. Driver Cohort Plugin Goal use case

The “Driver Cohort Plugin Goal” use case, conducted from September 26-October 10, 2018, focused on increasing the number of vehicle plugins as a way of increasing charging flexibility. The Home 24-Hour use case continued running in the background for the duration of this use case, but during this time period, participants were asked to individually plugin more. Participants were incentivized to increase their number of plugins through a sweepstakes with prizes that got better with increasing group participation. This use case tested the ability for non-monetary incentives that are based on larger group performance to achieve fleet-wide goals.

As shown in Table 2, there was a distinct increase in the number of plugins during this use case compared to the two weeks leading

Table 2
Increase in plugin and optimization behavior relative to baseline from driver cohort plugin goal use case.

Day Type	Plugins - All Locations	Plugins - Home	Optimizations - Home
Weekday	+46.1 percent	+38.3 percent	+34.8 percent
Weekend	+8.3 percent	+17.2 percent	+28.4 percent

up to the use case, with the number of plugins increasing by as much as 46% for weekday plugins across all locations. In the two weeks leading up to the use case, drivers plugged in on average 0.556 times per day, whereas during the use case those same drivers plugged in on average 0.678 times per day. This is found to be statistically significant at the 99 percent level (p-value of 0.003) with a paired T-test. The number of optimizations also increased, with average optimizations per day rising from 0.367 times in the two weeks prior to the use case to 0.422 times per day during the use case. However, this difference was not calculated to be statistically significant (p-value of 0.181) (see Table 3).

Despite an increase in the number of optimizations, the percent of charging that was optimized from the total kWh charged at home was found to slightly decrease (−2.1%) during the Driver Cohort Plugin Goal use case. However, optimized charging that was shifted increased by an average of 16.3% compared to the two weeks prior to the use case.

These results suggest that drivers are able to plugin more than they typically do, and that a greater number of plugins can lead to a greater number of optimizations. Although a similar amount of charging in kWh was optimized during times with the higher number of plugins, the results suggest that optimizations that occur with more plugins may be able to shift more charging, therefore making the optimizations that occur more effective.

4.5. Renewables Overgeneration use case

The Overgeneration use case, conducted from October 15-November 9, 2018, focused on absorbing excess renewables produced during mid-day hours. Optimizations during this use case were conducted based on an overgeneration signal and occurred both at home and away charging locations. Although drivers were encouraged to plug in as much as possible during midday hours, the use case also featured “event hours” during which excess renewable generation was highest and participants were sent notifications to plug in. If participants plugged in during these event hours, they received financial incentives.

The Overgeneration use case was the first use case to include away-from-home optimizations. As can be seen in Fig. 7, the majority of optimizations still occurred at home. A large portion of the optimizations, especially on weekend days, occurred during the targeted mid-day hours.

As shown in Fig. 8, the Overgeneration use case realized much more charging during midday hours compared to the previous use cases. This use case was the first one in which notable amounts of charge were shifted into daytime hours, especially during the 10 AM–2 PM targeted hours. Additionally, there were significant amounts of charging that took place during daytime hours that did not have to be shifted because the charging was already occurring at optimal times. And as in the previous use cases, large amounts of charge were shifted out of early evening hours and into early morning hours.

Fig. 9 below shows the plugins and optimizations during the seven event hours that were called during the Overgeneration use case compared to similar hours during non-event days. The number of plugins between event and non-event hours are relatively similar for all events. Events on weekdays had a significantly larger number of optimizations occur during the event hours compared to non-event hours. Events on Saturdays had a relatively similar number of optimizations as non-event hours.

Fig. 10 below presents a comparison of the total and optimized amount of charging in kWh between the seven event hours and non-event hours. There was no consistent pattern to the total amount of charge that occurred during event and non-event hours, with some events having more charging during event hours and some events having less charging than non-event hours. There was, however, consistently more optimized charging that occurred during event hours compared to non-event hours.

These results would suggest that efforts to boost the number of plugins during a given hour did not yield significant changes in plugin behavior. The increased number of optimizations was likely a result of the optimization signal being applied to vehicles that were plugged in rather than a change in participant behavior.

4.6. Transactive Energy Signal use case

The final use case, run from December 3–10, 2018, optimized charging against a transactive energy signal (TES) developed by the Electric Power Research Institute (EPRI). The EPRI TES incorporates economic signals but ones that are more closely tied to balancing supply and demand across regions of the grid rather than the more localized LMP price signals used in other use cases. This concept is being promoted more broadly by the GridWise Architecture Council, formed by the U.S. Department of Energy.

Optimizations in this TES use case only took place at home locations. The optimizations against the TES yielded a similar hourly profile to other use cases that used an LMP price signal for optimizations. One notable difference, shown in Fig. 11 below, is that in the TES use case, a larger amount of early evening charging was kept in the early evening hours rather than being shifted out. Also, the

Table 3
Driver cohort plugin goal use case charging behavior.

Charging Behavior Category	Change (percent)
kWh charged per vehicle per day that plugged in during time frame	+20.1%
kWh charged per vehicle that plugged in at home during time frame	+2.7%
Optimizations per vehicle per day	+10.2%
kWh charged per optimization (average relative to baseline)	−11.8%
kWh shifted per optimization (average relative to baseline)	+2.6%
Percent of charging that was optimized from total kWh charged at home (average relative to baseline)	−2.1%
Percent of optimized charging that was shifted (average relative to baseline)	+16.3%

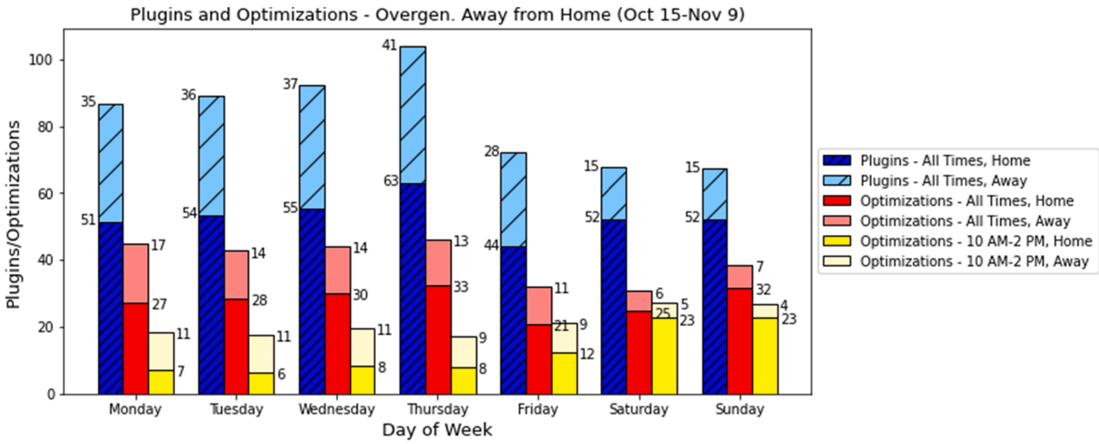

Fig. 7. Vehicle plugins and optimizations by day of the week for overgeneration use case.

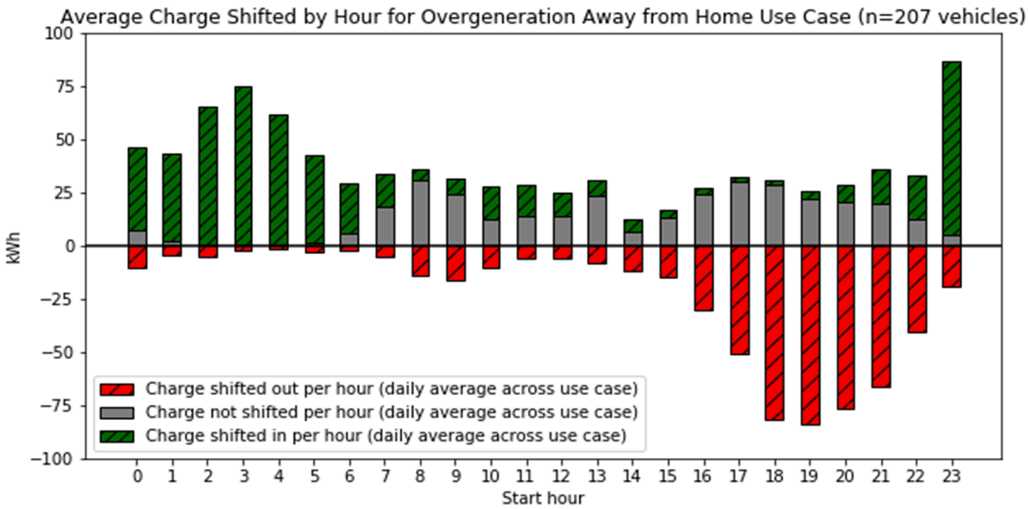

Fig. 8. Vehicle charging energy shifted by hour per day in overgeneration use case (kWh).

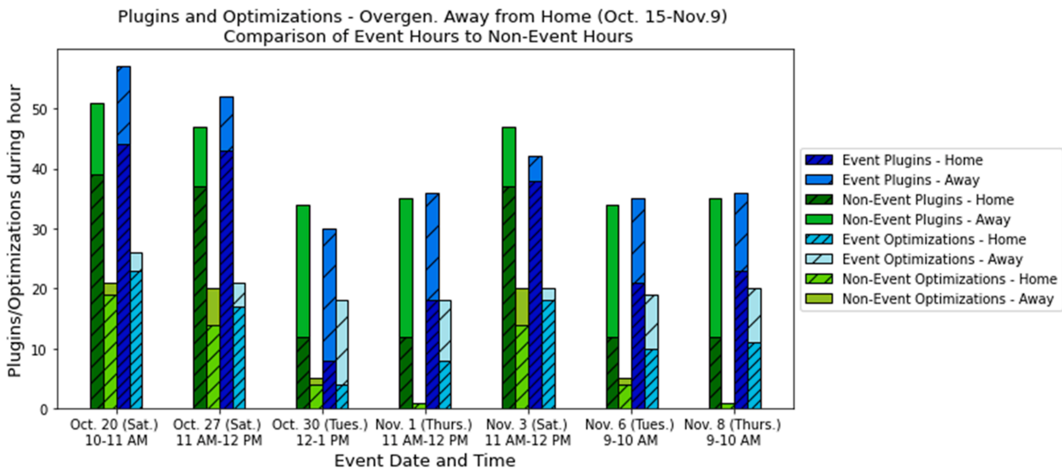

Fig. 9. Plugins and optimizations for overgeneration away from home use case.

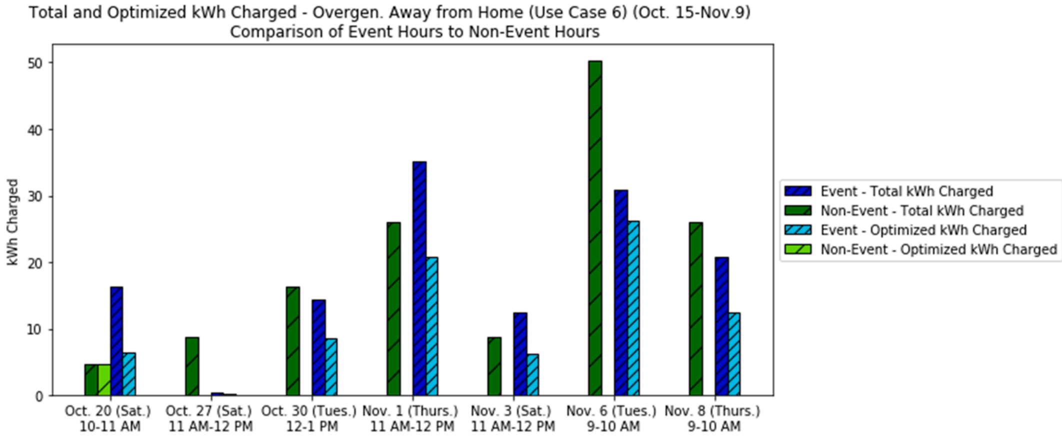

Fig. 10. Comparison of response for event hours for overgeneration away from home use case.

average grid operational cost savings for this use case were higher than other use cases, averaging around $0.77 per optimization.

4.7. Comparative analysis of all use cases

Comparing results across all use cases allows for analysis of how different optimization signals, charging and optimization parameters, and how participant behavior impacts the amount of charging that can occur at times of different grid conditions. This includes when stress on the grid results in higher costs, and other times when the cost of serving load is low.

In comparing the average number of plugins per vehicle per day across all use cases, shown in Fig. 12, plugins were highest during the Driver Cohort Plugin Goal; this is consistent with that use case's goal of increasing the number of plugins. Other use cases saw drivers plugging in between once every two to three days. This suggests that encouragement to increase the frequency of plugins, at least over a short time period, can yield noticeable increases in the number of plugins. However, even the highest frequency of plugins is still relatively low, with plugins consistently less than once per day.

Fig. 13 shows the average number of optimizations per vehicle per day. The average optimizations per day were highest during the Driver Cohort Plugin Goal and TES use cases. The number of optimizations generally increased throughout the study, largely due to the improvements in the optimization methodology that were made as the study went on.

Fig. 14 shows the percentage of home charging that was optimized out of total home charging in each use case and also how optimizations increased during the Home 24-Hour use case due to the improved optimization methodology. A maximum of around 70% of home charging being optimized out of all home charging was achieved during the Driver Cohort Plugin Goal use case.

Fig. 15 shows the average amount of charging shifted in and out of each hour for each use case. Values below zero represent charge shifted out of a given hour and values above zero represent charge shifted into a given hour, with zero representing that either no

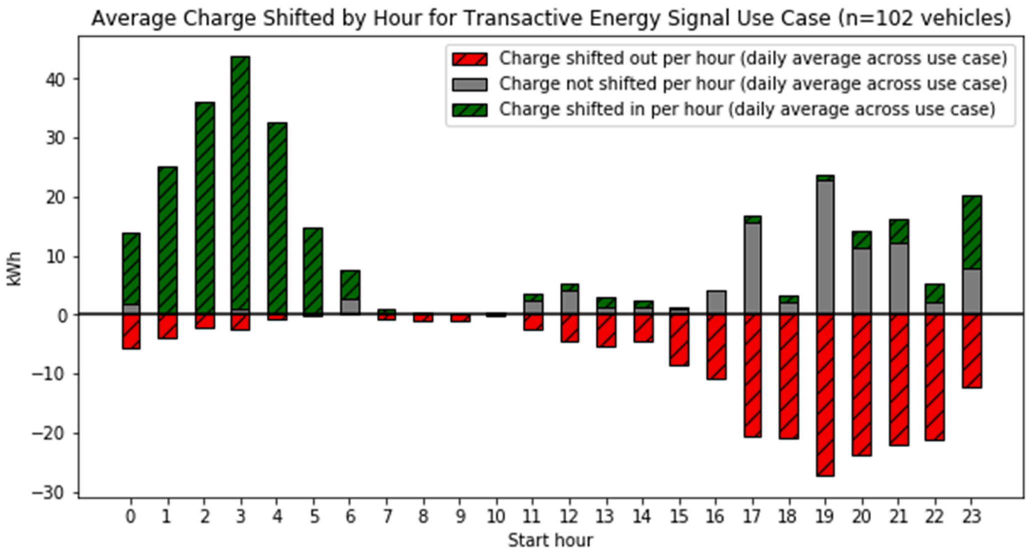

Fig. 11. Vehicle Charging Energy Shifted by Hour per Day in Transactive Signal Use Case (kWh).

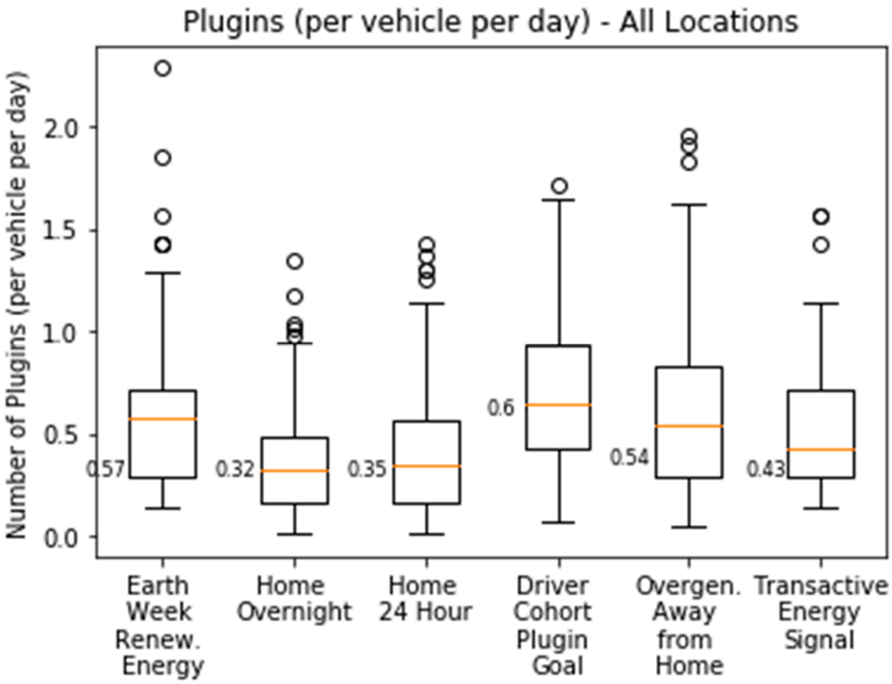

Fig. 12. Counts and statistical spread of plugins per day by use case.

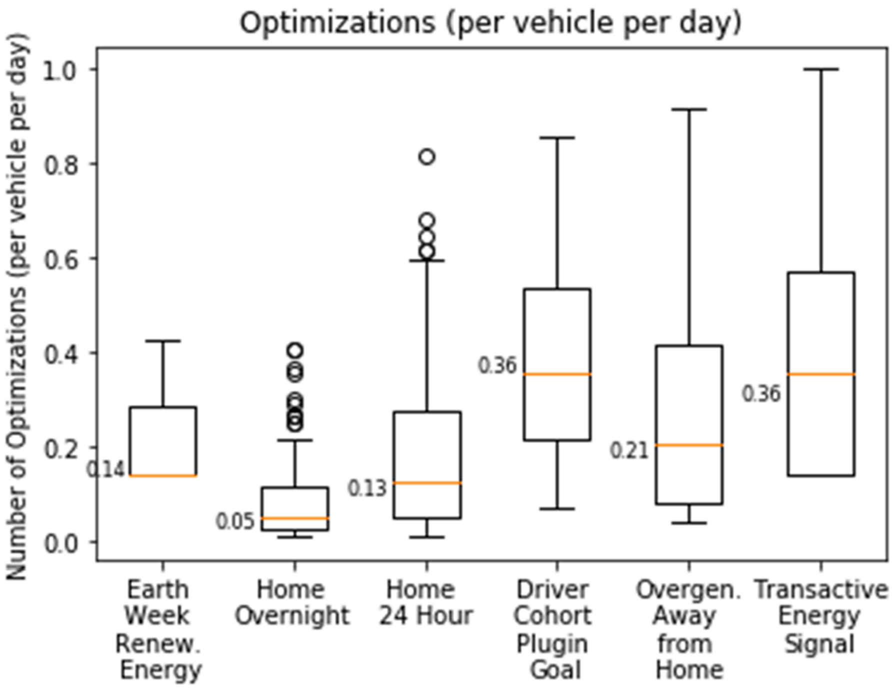

Fig. 13. Counts of optimizations per day by use case.

charge occurred or that no charge was shifted.

As can be seen in Fig. 15, most use cases shifted an average of 15–20% of charging out of peak early evening hours and shifted 20–30% of charge into off-peak early morning hours. Relative to the amount of charge shifted into overnight hours, there was much less charge shifted into mid-day hours in all use cases. The use case that shifted the most charge into midday hours was the Overgeneration use case. This is likely due to a combination of the Overgeneration use case emphasis on increasing the number of plugins

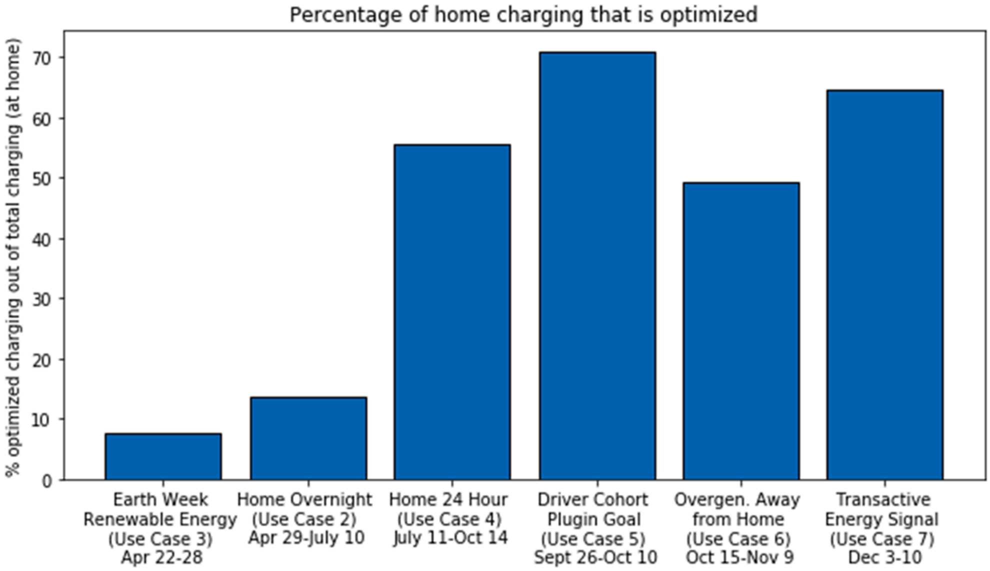

Fig. 14. Percentage of home charging that is optimized by use case.

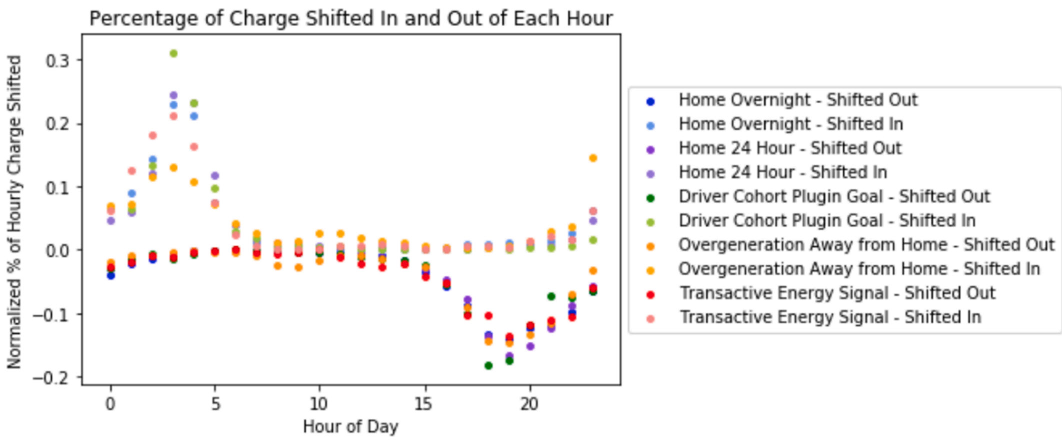

Fig. 15. Normalized hourly charge shifted by use case and hour of day.

and amount of charging during midday hours and the use case inclusion of away from home charging. Since many vehicles are parked away from home during midday hours when drivers are at work, there was less opportunity to optimize and shift charging in the middle of the day when the optimization location was limited to home.

The results shown in Fig. 15 demonstrate that these optimizations can successfully shift charge from hours with high grid costs and congestion into hours with lower grid costs. With greater emphasis on away from home and midday charging, a larger amount of charge can be shifted into midday hours to absorb excess renewables and take advantage of the resulting low grid costs. As renewables increasingly penetrate the grid, daytime excess renewables will continue to increase and prices during midday hours will likely continue to decline, making this timing of charging an increasingly valuable opportunity for charge management.

Fig. 16 below depicts the grid operational cost savings across use cases. The average grid operational cost savings per optimization were relatively consistent across use cases, ranging from $0.20 to $0.35 per kWh, but were notably higher during the TES use case, reaching $0.77 per kWh. This suggests that the TES may be most aligned with the grid costs incurred during vehicle charging sessions. The outliers of high price savings observed during the Home 24-Hour use case are excluded from Fig. 16.

Fig. 17 offers a comparison between BEV and PHEV performance. Performance is depicted by the percentage of plugins and charging energy in kWh for each vehicle type, with red dots indicating the percentage of each vehicle type in the fleet. From Fig. 17, we can see that BEVs make up about 75% of the participating fleet and PHEVs make up about 25%, but the exact ratio varies from use case to use case due to small differences in the participating vehicles in each use case.

As can be seen in Fig. 17, BEVs and PHEVs plugins closely matched their relative makeup in the fleet. However, the portion of charging done by BEVs exceeded the portion of vehicles that were BEVs in each use case. This result shows that BEV and PHEV drivers

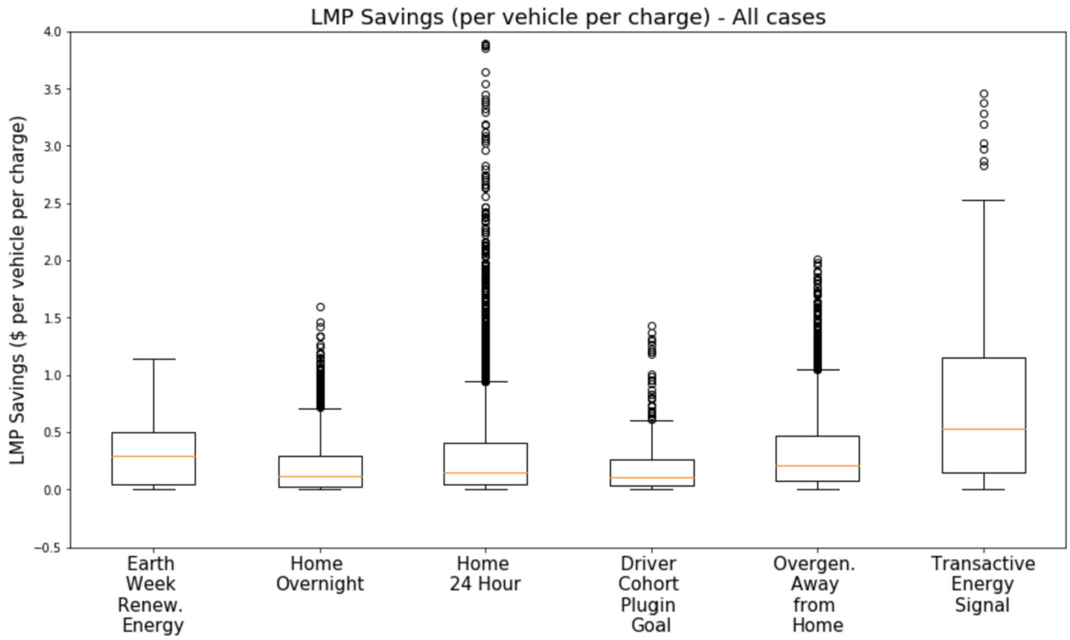

Fig. 16. LMP savings per vehicle and charge event by use case.

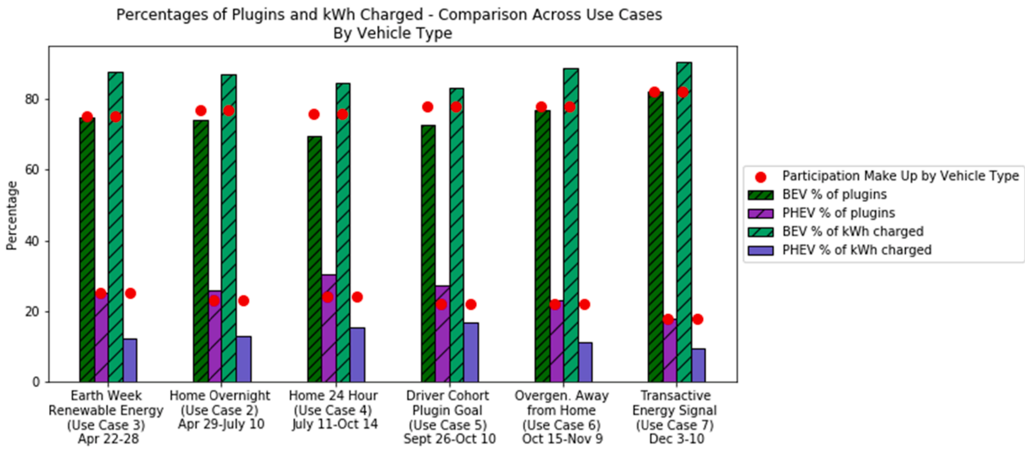

Fig. 17. Percentage of plugins and charging energy by vehicle type and use case.

are equally likely to plugin their vehicles, but BEVs are able to charge more, which is logical given their larger battery packs.

Fig. 18 compares the BEV and PHEV portion of optimized charging that was shifted for each use case by vehicle type. Prior to the study, there were unclear expectations for the relative abilities of BEVs and PHEVs to be optimized. Given the smaller battery size of PHEVs and the shorter time needed to charge, PHEVs may have been expected to offer greater charging flexibility and therefore allow for a greater portion of charging to be optimized. However, with Level 2 chargers and the larger battery pack to store charge, BEVs may also have sufficient charge unused from a day of driving and be able to charge fast enough to still achieve a high level of flexibility.

As can be seen in Fig. 18, BEVs were able to achieve a much higher percentage of charging that was shifted in each use compared to PHEVs. This offers confirmation of the idea that the larger battery packs and sufficient charging power and time can allow for BEVs to offer greater flexibility in charging.

In looking across all use cases, this study demonstrated with a high level of confidence that optimizations are effective at shifting load from periods of high grid costs and congestion in the early evening to hours with lower grid costs in the early morning. These findings support the claims that unmanaged charging could significantly contribute to the peak load and managed charging could effectively shift load to off-peak times while still satisfying driver charging needs.

The results, particularly from the Overgeneration = use case, also suggest that greater emphasis on midday charging and away-from-home optimizations could allow for more charge to be shifted into midday hours. This can be done to take advantage of the

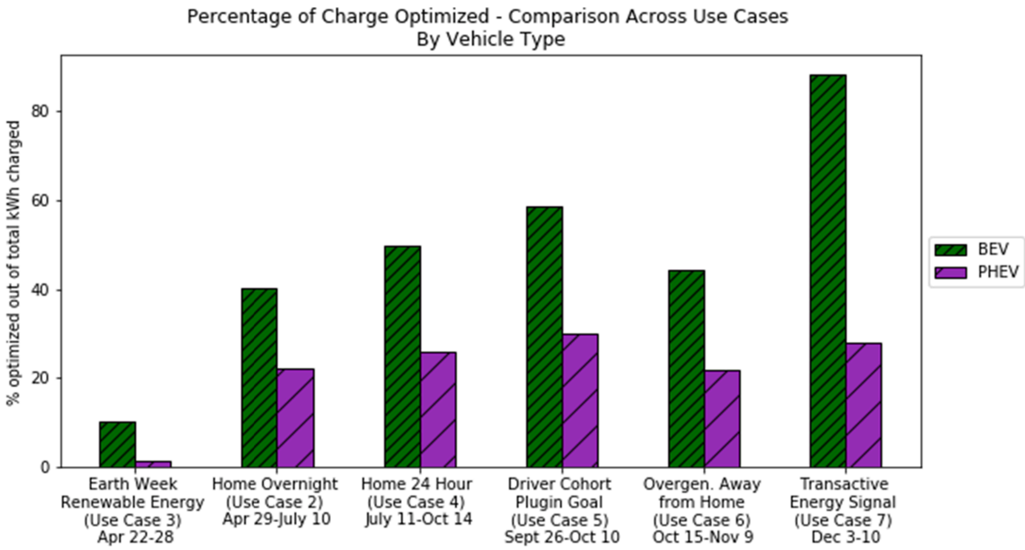

Fig. 18. Percentage of optimized charge shifted by vehicle type and use case.

excess renewables that are often generated in the middle of the day in areas with good solar power resources. Additional efforts are needed to more fully explore this potential and how it can be most effectively implemented. Factors that require additional consideration in optimizing away-from-home charging include the availability of charging infrastructure as well as behavioral factors such as driver schedule predictability and vehicle dwell times at certain types of locations.

4.8. Study caveats and limitations

This study represents part of an ongoing effort by the project researchers to analyze EV driver response to EV charge management strategies. Over the course of the study, the effectiveness of the applied algorithms and managements strategies evolved and improved, thus enabling the later study use cases to generally be more effective. Drivers also likely adapted to responding to the ability to opt out of optimization events as they learned the study parameters and depending on their overall project participation, in ways for which the study was not controlled. The incentives paid to participants (on the order of a few dollars per day) were also somewhat arbitrarily selected to elicit the targeted level of response for the study, where future research is needed to see what incentive levels can be supported through actual grid-support market mechanisms. Also, the study was conducted in the San Francisco Bay Area, a generally affluent area and with relatively high education and adoption of EV levels compared with other parts of California and the U.S.

4.9. Next steps for research

There are a number of planned next steps for this research to address the study caveats mentioned above, and the emerging developments for V1G and V2G in the EV marketplace. These include further expanding the study population of vehicles to 1,000 or more participating households in a subsequent phase to collect an even larger data set, and with a wider array of participating households and mixes of BEVs and PHEVs. Also planned for further examination are additional use cases, such as EV charging optimizations designed for more careful alignment of charging load shapes with power outputs from specific regional renewable energy production facilities. This could help to avoid potential curtailment of power from the facilities when at some time periods power demands fall short of generation output. Finally, we propose to further study the prospects for household and workplace based V2G as well as V1G, using the detailed vehicle parking and charging behavioral data that can be collected from vehicle telematics systems with manufacturer participation. Finally, additional research is needed to better understand driver motivations for participating in programs of this kind, including the level and type of monetary incentives, and/or desire to participate to help improve the use of renewable energy and reduce environmental pollution from power production.

5. Conclusions

EVs are poised to play a critical role in the decarbonization of the transportation sector. Management of the increased electric load from EVs is essential to minimizing the cost and infrastructure necessary to serve the additional load from EV charging. The BMW and PG&E ChargeForward program demonstrated the ability for smart charging to integrate the interests and skills of EV drivers, automakers, and utilities to economically satisfy drivers' charging needs while reducing the impact of EV charging load on grid infrastructure. The ChargeForward pilot implemented six different smart charging use cases in the San Francisco Bay Area in the 2017–2019 timeframe, involving approximately 400 total households.

This study is believed to be the largest implementation and analysis of smart charging optimizations with real EV drivers. The following findings are useful in assessing the potential for drivers to satisfy their charging needs and minimize charging costs while simultaneously reducing the impact of increased load from EVs on the grid.

With regard to driver engagement in the study, drivers were actively engaged and motivated by different incentives. For example, in the Driver Cohort Plugin Goal use case, drivers were incentivized to increase their number of vehicle plugins. The result suggests that encouragement to increase the frequency of plugins, at least over a short time-period, can yield noticeable increases in the number of plugins and therefore charging flexibility. This use case realized the highest percentage of home charging optimized, with 70% of home charging being optimized.

Next, the optimizations were effective at shifting charging out of peak evening times into overnight and early morning hours. For example, in the Overgeneration use case, on average, 63% of total daily charge was shifted outside peak times. This demonstrates that charge can be shifted out of peak demand times while still satisfying driver charging needs.

Also, in several of the use cases, BMW and PG&E also sought to encourage more midday charging to absorb excess solar generation at these times that is now occurring in California during many months of the year. The Overgeneration use case offered incentives for drivers to plug in during hours when solar overgeneration was most likely, resulting in an additional 6% of daily charging to take place between the hours of 10 AM and 2 PM. Efforts to boost mid-day charging should be paired with the emphasis on shifting charging from evening peaks to optimize full day charging schedules.

An examination of grid operational cost savings revealed that the average savings per optimization were relatively consistent across use cases, ranging from $0.20 to $0.35 per kWh of charge shifted, but with relatively large variability. Savings were notably higher during the TES use case, reaching $0.77 per kWh. These results demonstrate that with a well-designed optimization routine, smart charging can effectively reduce the grid costs of serving EV electricity load.

As EV penetration grows in cities and communities worldwide, charge management becomes critical to reducing the costs and grid impacts of increased electric load from EV charging. Without scalable charge management programs or incentives that align driver behavior with lower cost charging schedules, the grid is likely to require large amounts of distribution upgrades and more generation resources will be necessary. However, as demonstrated in this study, scalable optimization algorithms and incentive structures can yield driver participation that yields charging of EVs in a manner that smooths the electricity demand ramp of EVs, absorbs large amounts of solar energy generation, and contributes to operational electricity costs savings.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The Total Charge Management of Electric Vehicles project that underlies this research paper effort was led by BMW of North America, LLC and Pacific Gas and Electric Company. The project was assisted by the University of California - Berkeley, Olivine Inc., and Kevala Analytics, Inc. The project was funded by the California Energy Commission under EPIC Grant 15-084. The project team particularly thanks Adam Langton and Alissa Harrington from BMW of North America, LLC and Karim Farhat from Pacific Gas and Electric Company for their research contributions to the project, as well as Matthew Fung from the California Energy Commission for his management of the EPIC grant award.

References

Bauman, J., Stevens, M.B., Hacikyan, S., Tremblay, L., Mallia, E., Mendes, C.J., 2016. Residential smart-charging pilot program in toronto: results of a utility controlled charging pilot. World Electric Vehicle J. 8 (2), 531–542. https://doi.org/10.3390/wevj8020531.

Brouwer, A.S., Kuramochi, T., van den Broek, M., Faaij, A., 2013. Fulfilling the electricity demand of electric vehicles in the long-term future: An evaluation of centralized and decentralized power supply systems. Appl. Energy 107 (C), 33–51. https://doi.org/10.1016/j.apenergy.2013.02.005.

California Air Resources Board (CARB), 2020. "Current California GHG Emission Inventory Data," https://ww2.arb.ca.gov/ghg-inventory-data.

Coignard, J., Saxena, S., Greenblatt, J., Wang, D., 2018. Clean vehicles as an enabler for a clean electricity grid. Environ. Res. Lett. 13 (5), 16. https://doi.org/10.1088/1748-9326/aabe97.

California Energy Commission. "Zero Emission Vehicle and Infrastructure Statistics," Web resource: https://www.energy.ca.gov/data-reports/energy-insights/zero-emission-vehicle-and-charger-statistics (accessed March 18, 2021).

California Public Utilities Commission. Final Report of the Joint Agencies Vehicle-Grid Integration Working Group. DRIVE OIR Rulemaking 18-12-006, 30 June 2020. https://gridworks.org/wp-content/uploads/2020/07/VGI-Working-Group-Final-Report-6.30.20.pdf.

Donadee, J., Shaw, R., Garnett, O., Cutter, E., Min, L., 2019. Potential benefits of vehicle-to-grid technology in California: high value for capabilities beyond one-way managed charging. IEEE Electrif. Mag. 7 (2), 40–45. https://doi.org/10.1109/MELEC.650899610.1109/MELE.2019.2908793.

ELIA Group. Accelerating to net-zero: redefining energy and mobiliy, November 2020: Accessed at: https://www.elia.be/-/media/project/elia/shared/documents/elia-group/publications/studies-and-reports/20201120_accelerating-to-net-zero-redefining-energy-and-mobility.pdf.

Gschwendtner, C., Sinsel, S.R., Stephan, A., 2021. Vehicle-to-X (V2X) implementation: an overview of predominate trial configurations and technical, social, and regulatory challenges. Renew. Sustain. Energy Rev. 145, 2. https://doi.org/10.1016/j.rser.2021.110977.

Rahman, S., Shrestha, G.B., 1993. An investigation into the impact of electric vehicle load on the electric utility distribution system. IEEE Trans. Power Delivery 8 (2), 591–597. https://doi.org/10.1109/61.216865.

Shepero, M., Munkhammar, J., Widen, J., Bishop, J.D.K., Bostrom, T., 2018. Modeling of photovoltaic power generation and electric vehicles charging on city-scale: a review. Renew. Sustain. Energy Rev. 89, 61–71. https://doi.org/10.1016/j.rser.2018.02.034.

Spitzer, M., Schlund, J., Apostolaki-Iosifidou, E., Pruckner, M., 2019. Optimized integration of electric vehicles in low voltage distribution grids. Energies 12 (21), 4059. https://doi.org/10.3390/en12214059.

Szinai, J.K., Sheppard, C.J.R., Abhyankar, N., Gopal, A.R., 2020. Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management. Energy Policy 136. https://doi.org/10.1016/j.enpol.2019.111051.

Van Triel, F., Lipman, T.E., 2020. Modeling the future California electricity grid and renewable energy integration with electric vehicles. Energies 13, 5277. https://doi.org/10.3390/en13205277.

Veloz. Sales Dashboard. Web resource: https://www.veloz.org/sales-dashboard/ (accessed March 18, 2021).

Wen, W., Wang, L., Zhu, M., Peng, Z., Yao, F., 2020. Research on the impact of different charge and discharge modes of electric vehicles on power grid load. J. Phys. Conf. Ser. 1549, 042147. https://doi.org/10.1088/1742-6596/1549/4/042147.

Wolinetz, M., Axsen, J., Peters, J., et al., 2018. Simulating the value of electric-vehicle–grid integration using a behaviourally realistic model. Nat. Energy 3, 132–139. https://doi.org/10.1038/s41560-017-0077-9.

Xiao, H., Huimei, Y., Chen, W., Hongjun, L., 2014. A survey of influence of electric vehicle charging on power grid. In: 2014 9th IEEE Conference on Industrial Electronics and Applications, Hangzhou, pp. 121–126. https://doi.org/10.1109/ICIEA.2014.6931143.