Energy 341 (2025) 139302

Contents lists available at ScienceDirect

Energy

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

Assessment of vehicle-grid integration profitability subject to real-world driver behavior and electricity tariff

Hanif Tayarani [a,*], Aaron Rabinowitz [a], Alan Jenn [b], Gil Tal [a]

[a] University of California, Davis, Institute of Transportation Studies, 1590 Tilia St, Davis, CA, 95616 , United States
[b] University of California, Davis, Department of Civil and Environmental Engineering, 3120 Ghausi Hall, Davis, CA, 95616, United States

ARTICLE INFO

Keywords:
Battery electric vehicles
Bidirectional charging
Optimal charging strategies
Smart charging
Vehicle grid integration

ABSTRACT

The growing adoption of battery electric vehicles creates a need for optimized charging strategies that manage energy demand and charging costs. This study uses a dataset of 49,693 parking events and 11,271 charging sessions, which are collected from 50 vehicles, to investigate the impact of potential charging sessions on optimal VGI charging strategies within different utility territories in the United States, each with distinct pricing mechanisms. Our cost-benefit analysis shows that drivers can save between $3000 and $5000 annually in high-electricity price territories, while in low-price territories, savings can reach up to $400. However, if drivers keep their current charging behavior, they can save between $1500 and $3000 annually in high-price territories and around $200 in low-price territories. Beyond financial benefits, optimal strategies reduce emissions by shifting charging sessions to hours with more renewable generation, which reduces CO_{2eq} by up to 2 tonnes per vehicle each year on average. These results demonstrate the importance of potential charging behavior and pricing structures to maximize economic benefits. Our findings suggest that policy measures are necessary to support such programs. This study helps guide charging infrastructure planning and supports updating battery warranties to account for battery degradation caused by VGI participation.

1. Introduction

The growth of battery electric vehicles (BEVs) and renewable energy creates both opportunities and challenges for power systems [1]. BEVs reduce emissions from the transportation sector [2] and have the potential to support power systems with their battery storage capabilities [3]. One possible approach is Vehicle Grid Integration (VGI), which includes controlled unidirectional charging (V1G) and bidirectional charging through Vehicle-to-Grid (V2G). V1G manages charging times to help with load shifting. V2G allows energy to flow between BEVs and the grid, which can improve grid stability, support renewables, and reduce costs for drivers [3]. The success of VGI depends on several factors, which include charger cost and availability [4] and the potential impacts on battery life.

This study estimates the maximum economic benefits for drivers who join VGI programs under different electricity pricing structures. Since BEVs are parked for most of their lifetime [5], they can support the power grid without impacting driver convenience, and coordinating charging and discharging with renewable generation further improves grid stability without affecting driver convenience [6]. We examine how driving and charging behavior, charger speed, battery degradation, and rate plans affect the value of VGI. The analysis focuses on real-world behavior to identify barriers to participation and ensure benefits exceed costs. These results help show how optimal charging can deliver meaningful savings and encourage more drivers to adopt VGI.

Driver travel and charging behavior affect how often BEVs can support V1G and V2G. These behaviors impact the availability of vehicles for V1G and V2G services. Collecting empirical data on these behaviors is challenging, which leads many researchers to generate synthetic charging profiles for their studies [4,7–9]. These studies show strong potential for V2G but often miss key details such as trip timing and routine driving behavior. As a result, they may lead to less accurate results. Thus, differences in daily driving and parking patterns can change how much flexibility drivers can provide and how often they can participate in VGI programs [10].

Charging speed also affects the value of VGI. The main economic principle is time-arbitrage. BEV charging falls into two categories AC, and DC fast charging. AC charging includes two levels under SAE J1772 [11]. Level-1 uses 110 V and needs no special equipment. Level-2 uses 220 V and requires a dedicated installation. Studies show that Level-1

* Corresponding author.
E-mail addresses: htayarani@ucdavis.edu (H. Tayarani), arabinowitz@ucdavis.edu (A. Rabinowitz), ajenn@ucdavis.edu (A. Jenn), gtal@ucdavis.edu (G. Tal).

https://doi.org/10.1016/j.energy.2025.139302
Received 3 September 2025; Received in revised form 12 November 2025; Accepted 12 November 2025
Available online 15 November 2025
0360-5442/

limits V2G due to low power [4,7,12–14] while Level 2 provides enough speed to meet most needs [4,8,9,13,15–23]. Level-2 ranges from 1.44 to 19 kW and is common at homes and workplaces. DC-fast charging (50–350-kW) is limited to public stations due to high cost. VGI is best suited for long-duration, low-rate, and low-loss AC events as compared to time-constrained DC-fast events. This study focuses on Level-2 chargers between 6.6 and 19 kW, which offer the best mix of flexibility and practicality for home and workplace V2G.

This study also examines three charging speeds (6.6 kW, 12 kW, and 19 kW) to evaluate their impact on VGI services and economic viability. Studies on Level 2 chargers typically focus on three power ranges: low (1.5–6-kW) [3,9,19], medium (6–12 kW) [4,8,13,15–18,20–23], and high (above 12 kW) [14]. Most studies on medium and high-power chargers focus on workplace locations due to the assumed limitation on household power availability. This assumption does not apply in areas with newer housing. Thus, we need to test how well high-rate bidirectional charging performs both at home and at work if households install high-power AC chargers.

Battery degradation in BEVs is a concern for V2G programs [1]. Researchers use both theoretical and empirical methods to model it, but each has its limits. Theoretical models [9,12–14,16,18] simulate battery aging based on factors like charge-discharge cycles, depth of discharge, and temperature. These models help explain degradation but rely on assumptions that may not reflect real driving. Empirical models [15,17,21] use real-world BEV data to estimate battery degradation over time. We follow this second approach and use observed data to build our degradation mode. The dataset used in this study is large enough to make the results useful for general analysis (30).

Electricity prices and rate structures also shape the economic feasibility of VGI. Many customers pay under Time-of-Use (TOU) tariffs, which encourage off-peak consumption by setting lower prices during low-demand hours. VGI participants may also arbitrage against the tariffs by charging at off-peak times and selling back to the grid at on-peak times. Both the average price and the size of the peak-off-peak gap influence how much value drivers gain from VGI.

Many studies use TOU rates to analyze the economic value of VGI [16,21,23,24]. These studies show that VGI value increases with larger TOU price gaps, which range from under $0.10 to approximately $0.60/kWh. Many utilities offer an EV-Specific TOU Rate (EV-Rate) plan in addition to a TOU plan. The EV-Rate plan is a response to the increasing electricity demand caused by EVs and, often, features a lower average price but a more extreme difference between on and off-peak prices. For example, in California's PGE territory, the EV Rate gap reaches 32 cents in winter and 19 cents in summer, while the regular TOU Rate gap is only 21 and 3 cents, respectively.

Households and businesses pay fixed electricity rates, while utilities purchase electricity from regulated markets at dynamic prices. So If an operator aggregates enough vehicles, it may join these markets and respond to Real-Time (RT) prices, which reflect current grid conditions and needs. Several studies use day-ahead market prices to model the wholesale signals [8,9,12–14,18,20,22]. However, day-ahead prices matter more for generators that plan large energy deliveries through limited transmission lines. A VGI aggregator needs real-time prices on the consumer side to make fast and flexible decisions.

This study contributes to the field of VGI research in several ways. First, it utilizes empirical data to constrain VGI to observed behaviors, which utilizes a year-long dataset of actual BEV charging and driving behavior. This real-world data improves the accuracy of assessing when and where vehicles are available for VGI.

Second, it estimates how electricity tariffs shape the economic benefits of VGI and offers insights for tariff design. Third, it evaluates how different charging speeds influence VGI benefits, including the effect of required infrastructure upgrades.

2. Materials and methods

I. Charging Behavior and Potential Charging Sessions

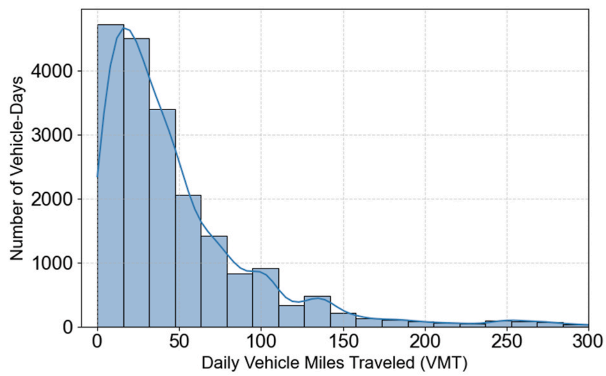
This research uses a subset of data from the eVMT project, a multi-year study conducted across California between 2015 and 2020 [25]. The eVMT project collected detailed real-world driving and charging data from BEV owners who volunteered to participate in a long-term monitoring program led by the UC Davis Electric Vehicle Research Center. From this dataset, we selected 50 vehicles (14 Chevrolet Bolts and 36 T Model S) with approximately one year of uninterrupted data each. We collected data from 2015 to 2020, depending on when each driver joined the study. The sample includes vehicles with diverse travel patterns across various California regions, but it is not random or fully representative of the state's entire EV population. Each vehicle contributed a second-by-second trip trajectory and charging sessions. In total, the dataset includes 49,693 parking sessions, of which 11,271 included actual charging events. We clustered Parking sessions by location into home, work, or other destinations using the DB-Scan method [26]. This dataset should be interpreted as an empirical case study rather than a statistically representative sample of the broader EV population.

Fig. 1 summarizes details of vehicle use and charging behavior in this sample. Fig. 1-a shows most vehicle days are under 50 miles for daily travel. Fig. 1-b reveals that most charging happens at home using Level 2 chargers, which account for about 62 % of total energy charged. Level 2 makes up 74 % of all charging, followed by DC Fast at 16 %, and Level 1 at 10 %. DC Fast charging takes place entirely at other (non-home, non-work) locations. Level 1 charging happens mostly at home, but its share is small. Workplace charging remains limited, contributing only about 5 % of the total, almost all through Level 2. And finally Fig. 1-c displays the types of chargers used by different vehicle models. Most charging sessions fall within the Level 1 (0–2 kW) and Level 2 (4–12 kW) range. About 20 % of sessions occur at 0–2 kW, mostly from Chevrolet Bolts. Teslas dominate the 6–12 kW range, which accounts for over 40 % of all sessions. High-power charging above 12 kW makes up about 14 % of sessions, almost entirely from Tesla vehicles. This highlights that Teslas tend to use higher-powered chargers more often than Bolts.

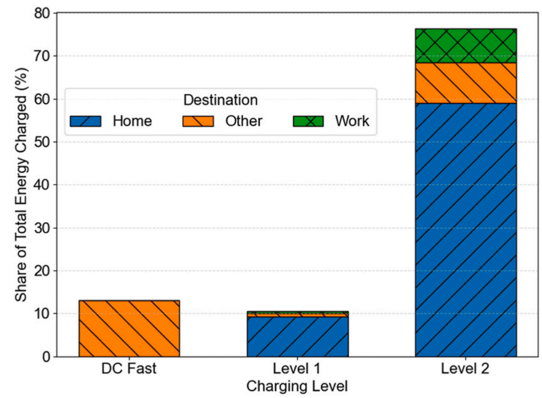
As shown in Fig. 2-a, vehicles spend on average more than 600 min at home and the workplace, whereas the average time spent at other locations is less than 210 min. The graph further reveals that the average parking time is closely related to the type of parking location, with home and workplace locations having the highest average durations. Fig. 2-b shows charging events at home and workplace locations last an average of approximately 300 and 270 min, respectively, compared to less than 180 min for other locations.

Additionally, data from the eVMT dataset indicates that most vehicles require less than 60 miles of range per day, considerably lower than most electric vehicles' full charge range. This finding suggests that a substantial portion of battery capacity remains unused daily, presenting an opportunity for V2G services without impacting the vehicle's daily operational requirements. Given these insights, workplaces and homes emerge as optimal locations for implementing V1G and V2G charging strategies due to the extended duration of vehicles' parking sessions, allowing for efficient energy exchange with minimal disruption to driving needs.

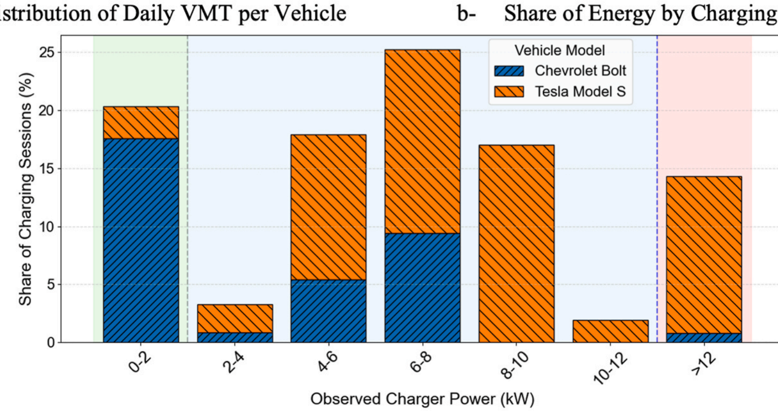
Considering home and workplace locations for implementing V1G and V2G charging strategies reveals a gap between average parking time and charging time. This indicates that vehicles are often parked but not plugged in at these charging locations. These unutilized parking sessions represent potential opportunities for additional charging events, providing operators with greater flexibility to manage V1G and V2G charging. By taking advantage of these sessions, operators can optimize energy transfer between the grid and vehicles when needed, enhancing grid stability and maximizing the benefits of V1G and V2G sessions. Therefore, it is crucial to evaluate the impact of these parking sessions



a- Distribution of Daily VMT per Vehicle

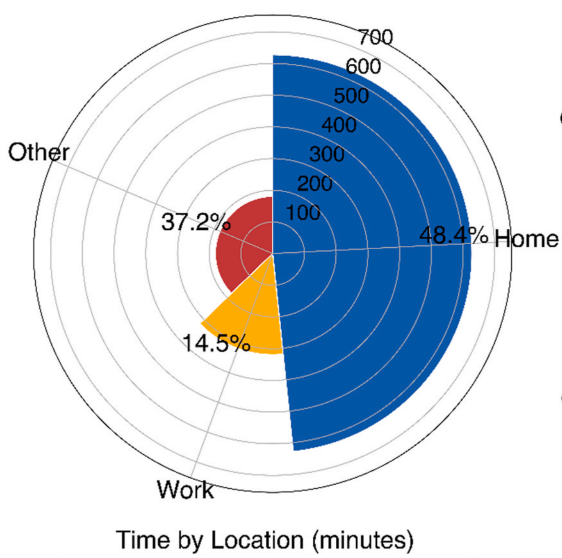


b- Share of Energy by Charging Level and Destination

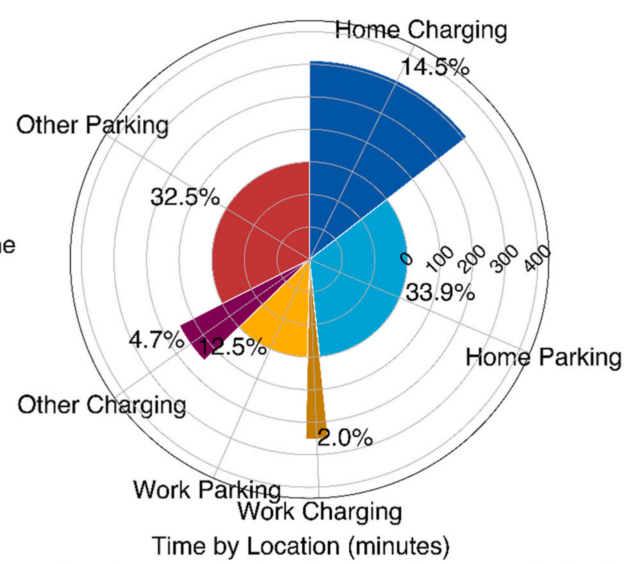


c- Share of charging sessions by charger power and vehicle model

Fig. 1. Charging behavior and travel patterns of BEVs. (a) Distribution of daily VMT shows that most vehicle-days fall below 50 miles, with a long tail extending past 200 miles. (b) Share of total energy charged, disaggregated by charging level (DC Fast, Level 1, Level 2) and location (Home, Work, Other). We observe that most energy is charged at home using Level 2 chargers. (c) Distribution of observed charger power by vehicle model. Each bar shows the share of charging sessions in a given power bin for Chevrolet Bolt and Tesla Model S. Level 1 (0–2 kW) and Level 2 (2–10 kW) ranges dominate, while Tesla vehicles also use higher-power charging.



a- Average parking time and frequency of parking sessions



b- Average charging time and frequency of charging sessions

Fig. 2. Parking and Charging Behavior of BEV Drivers at Various Destinations. (a) Figure-a shows the average daily time vehicles spend parked at home, work, or other locations. The angular width of each wedge reflects the frequency of trip destinations, while the radial length represents an average time parked at that location (in minutes). (b) Figure b splits this parking time into charging vs. non-charging sessions. Each wedge represents one of six categories: home charging, home parking (no charging), work charging, work parking, other charging, and other parking. The radial length indicates average time spent in each mode, and the angular width shows the frequency of sessions. Percentages indicate the share of total time across categories.

on optimal charging strategies to fully leverage their potential.

II. Battery Degradation

We use publicly available user-reported data from over 1800 T vehicles, spanning 2014 to 2024, which track battery range degradation over accumulated mileage and energy throughput. These data are separate from our eVMT dataset and serve as a proxy for real-world degradation trends. We fit a linear model to this dataset to provide a conservative estimate of battery value loss per kWh cycled. While degradation is not strictly linear, this approach avoids overfitting and gives us a practical estimate of the economic trade-off in our analysis.

Fig. 3 presents a detailed examination of the depreciation amounts in relation to cumulative kWh charged, explicitly focusing on Tesla vehicles over a ten-year period from 2014 to 2024. The linear trend, with a slope of approximately $0.0215 per kWh, indicates a modest increase in depreciation cost as cumulative kWh charged increases. This suggests a direct but relatively small relationship between energy charged and battery wear. However, the variability in data points around this trend line highlights those factors beyond the kWh charged, such as driving habits, environmental conditions, and battery management systems, which influence battery depreciation rates.

This graph shows the linear trend showing how battery depreciation increases as cumulative kWh charged grows. For every kWh charged, BEV owners lose approximately 2 cents of battery value, calculated based on 2023 prices. The red line represents the best-fit, highlighting the direct relationship between energy charged and depreciation amount. This model serves as a baseline for assessing the economic impact of participating in V2G programs, factoring in the gradual loss of battery value over time.

For V2G applications, understanding this depreciation relationship is necessary as it allows for optimizing V2G operations without excessively accelerating battery degradation. Knowing the depreciation cost can help develop strategies that maximize economic benefits while preserving battery health. For instance, an 80-kWh battery is shown to depreciate by less than $1700 after 1000 full charge cycles, suggesting that significant depreciation costs are unlikely in the short term.

Battery degradation in this study is estimated based on the cumulative energy charged during charging sessions. This approach serves as a proxy for estimating the effect of V2G operations, using the energy charged and discharged during bidirectional activities. While degradation is influenced by factors such as temperature, depth of discharge (DoD), and charge or discharge rate (C-rate), the linear relationship used here provides a simple and transparent estimate. The C-rate during normal driving ranges from about 0.5 C to 2 C, while Level 2 charging or discharging at 6.6–19 kW corresponds to about 0.08–0.25 C for an 80 kWh battery. Because the degradation data used in this model come from driving conditions, they reflect higher C-rate stress than expected during V2G operation. As a result, the estimated degradation is likely overestimated and represents a conservative upper bound of battery degradation, which ensures that the economic benefits of VGI are not overstated.

The optimal charging program was formulated and solved using a linear programming approach. The objective of the optimization program is to minimize the total cost, which includes the electricity cost and battery degradation cost, to meet the charging demand of the vehicles.

This study estimates total depreciation using the 2021 price of a 1-kWh battery pack, which is 139 [27]. Battery degradation is a key factor influencing the economics and practicality of V2G programs, as it constrains overcharging and over-discharging. A linear model is developed based on the observed relationship between battery capacity and mileage. The collected data on driving efficiency [28] was used to convert mileage into energy charged and link battery degradation directly to reductions in health and capacity.

This model uses data from various Tesla models, comprising 1800 data points [29]. Fig. 4-a visualizes this data, showing the remaining vehicle range after a full charge over various mileage levels from 2014 to 2023. This highlights a clear downward trend in battery health as the vehicle accumulates miles. Fig. 4-a shows that as vehicles accumulate mileage, their remaining battery capacity gradually decreases, but this decline is not uniform. For example, vehicles with over 150,000 miles generally report battery capacities of around 80–90 % of their original capacity. This trend provides insight into the real-world performance of BEV batteries over time, emphasizing that while some battery degradation is inevitable, significant losses in capacity occur primarily after extensive use.

Fig. 4-b establishes a linear regression model that links the kWh charged to the remaining battery capacity to further analyze the impact of charging on battery degradation. This real-world data helps quantify the degradation cost per kWh of energy, which is critical for estimating the long-term economic impact of frequent charging.

The slope of the regression line indicates a modest rate of decline in

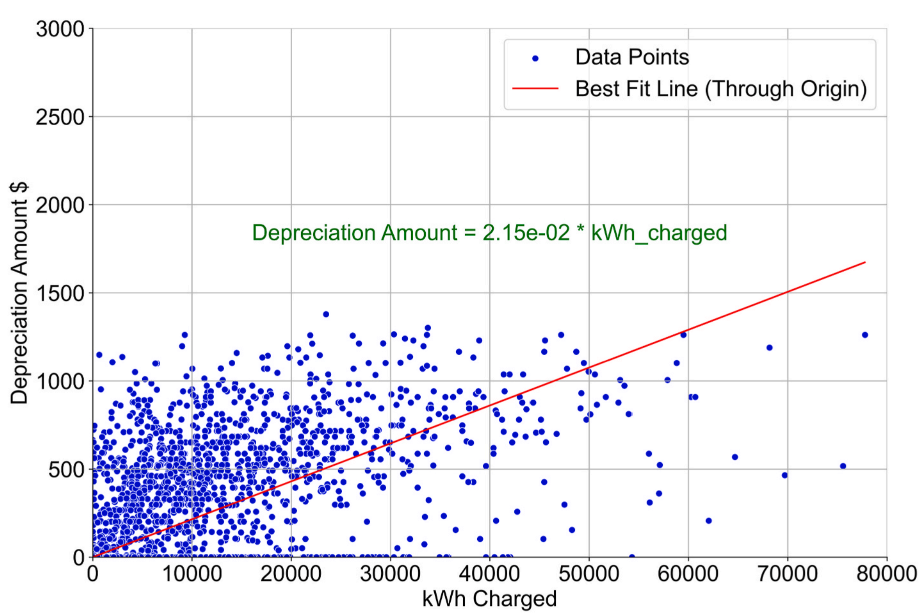
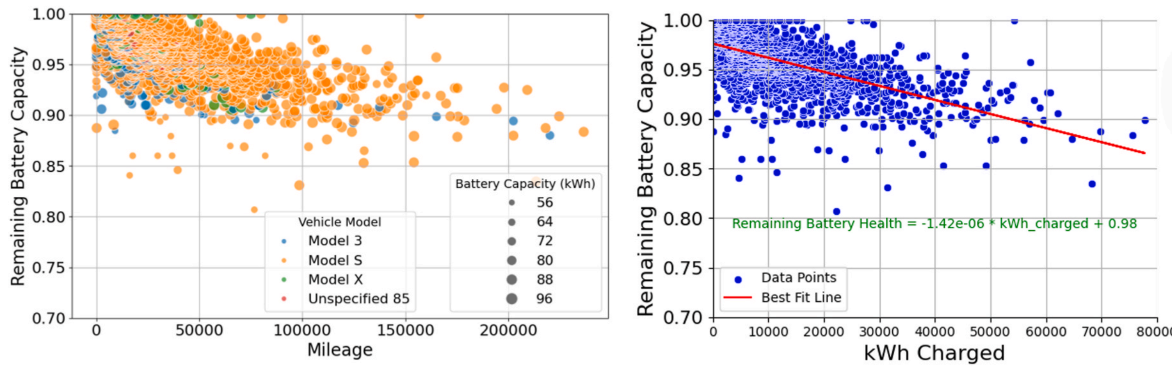


Fig. 3. Relationship Between Battery Depreciation and Cumulative kWh Charged in BEVs.



a- Reported remaining battery capacity over the mile traveled

b- Estimated battery capacity over the kWh charged

Fig. 4. Reported and Estimated Battery Capacity Degradation for Tesla Models Based on Mileage and kWh charged.
(a) The graph shows the reported remaining battery capacity versus miles traveled for various Tesla models. The data points represent battery health, with colors denoting the vehicle model and circle sizes indicating battery capacity (kWh). It shows that drivers can expect approximately 85 % of their battery capacity to remain after driving 200,000 miles. (b) The estimated battery capacity is shown as a function of kWh charged. The blue points represent data from Tesla vehicles, while the red line shows the best-fit linear regression. The result indicates the linear relationship between remaining battery capacity and cumulative kWh charged, showing a gradual decline. On average, drivers lose about 1.42e-6 of battery capacity for every kWh charged.

battery health as more energy is cycled through the battery. For example, after charging approximately 80,000 kWh, the battery retains about 80–85 % of its original capacity. The relationship here provides a crucial proxy for estimating how V2G operations involving frequent charging and discharging could impact battery lifespan. Importantly, this model assumes that the degradation rate is consistent with driving and V2G discharging, giving researchers a tangible metric to quantify the trade-offs between potential revenue from V2G participation and the increased degradation of the battery.

III. Electricity Grid Dataset

The electricity pricing scenarios used in this study include two rate structures offered by Pacific Gas & Electric (PGE) in California, Duquesne Light Company (DLC) in Pennsylvania, Con Edison (ConEd) in New York, and Austin Energy (AE) which are TOU-Rates, commonly used by most households, and the EV-Rate plan designed for BEV owners. Additionally, a RT-Rate was introduced in this study to simulate wholesale market pricing.

The TOU-Rate is widely used by utilities customers and adjusts electricity prices based on peak and off-peak hours, which encourage consumers to shift usage to lower-cost periods. The EV-Rate plan, introduced by utility operators for BEV owners, offers more advantageous pricing structures for charging vehicles, making it more attractive for households with electric vehicles. The final rate structure considered is RT-Rate, which fluctuates based on current grid demand and supply conditions, offering the most dynamic pricing model. However, since vehicles are typically located on the consumer side of the grid, direct access to wholesale market prices (RT-Rate) is not available. To incorporate this, we estimate RT-Rate at the consumer level to simulate the potential financial benefits of aligning charging behavior with fluctuating grid prices. This approach ensures we account for the variability in electricity costs while considering practical consumer-side constraints.

The TOU and EV-Rate plans offered by PGE, ConEd, show a large gap

Table 1
Detailed electricity pricing structures for TOU, EV-Rate, and commercial rate across four California utility territories[30–33].

Utility	Pricing Scheme	Season	Weekday Prices (Peak/Mid-Peak/Off-Peak, $/kWh)	Weekend Prices (Peak/Mid-Peak/Off-Peak, $/kWh)	Month Range	Peak Times	Mid-Peak Times
PGE	TOU-Rate	Summer	0.610/N/A/0.500	0.610/N/A/0.500	6–9	16–21	N/A
		Winter	0.490/N/A/0.460	0.490/N/A/0.460	10–5	16–21	N/A
	EV-Rate	Summer	0.640/0.530/0.320	0.640/0.530/0.320	6–9	16–21	15–16, 21–24
		Winter	0.510/N/A/0.320	0.510/0.490/0.320	10–5	16–21	N/A, 21–24
	Commercial	Summer	0.298/0.078/0.102	0.298/0.078/0.102	6–9	16–21	9–14
		Winter	0.298/0.078/0.102	0.298/0.078/0.102	10–5	16–21	9–14
DLC	TOU-Rate	Summer	0.091/N/A/0.091	0.091/N/A/0.091	6–11	0–24	N/A
		Winter	0.088/N/A/0.088	0.088/N/A/0.088	12–5	0–24	N/A
	EV-Rate	Summer	0.125/0.079/0.057	0.125/0.079/0.057	6–11	13–21	6-13, 22-23
		Winter	0.125/0.079/0.057	0.125/0.079/0.057	12–5	13–21	6–13
	Commercial	Summer	0.153/0.096/0.068	0.153/0.096/0.068	6–9	13–21	6-13, 22-23
		Winter	0.194/0.129/0.104	0.194/0.129/0.104	10–5	13–21	6–13
ConEd	TOU-Rate	Summer	0.352/N/A/0.024	0.352/N/A/0.024	6–9	8–24	N/A
		Winter	0.130/N/A/0.024	0.130/N/A/0.024	10–5	8–24	N/A
	EV-Rate	Summer	0.330/N/A/0.023	0.330/N/A/0.023	6–9	8–24	N/A
		Winter	0.122/N/A/0.023	0.122/N/A/0.023	10–5	8–24	N/A
	Commercial	Summer	0.524/N/A/0.019	0.524/N/A/0.019	6–9	8–22	N/A
		Winter	0.258/N/A/0.019	0.258/N/A/0.019	10–5	8–22	N/A
AE	TOU-Rate	Summer	0.108/N/A/0.108	0.108/N/A/0.108	6–9	0–24	N/A
		Winter	0.108/N/A/0.108	0.108/N/A/0.108	10–5	0–24	N/A
	EV-Rate	Summer	0.108/N/A/0.108	0.108/N/A/0.108	6–9	0–24	N/A
		Winter	0.108/N/A/0.108	0.108/N/A/0.108	10–5	0–24	N/A
	Commercial	Summer	0.158/N/A/0.158	0.158/N/A/0.158	6–9	0–24	N/A
		Winter	0.158/N/A/0.158	0.158/N/A/0.158	10–5	0–24	N/A

between peak and off-peak electricity price hours (Table 1). In many cases, peak rates can exceed \$0.60 per kWh with a range of about \$0.61/kWh to \$0.64/kWh, while off-peak EV-Rates may drop below \$0.30/kWh in PGE. These large price gaps encourage BEV owners to charge during off-peak hours, which can help lower grid stress, make less dependent on fossil fuel generation, and increase the share of renewable resources in the generation mix. Given the state's focus on renewable energy and grid optimization, these rates offer a distinct advantage for BEV owners [30]. However, AE has lower overall rates and a flat pricing structure in comparison with utilities. This flat structure means AE customers have less financial motivation to shift all their charging to off-peak times.

PGE's electricity rate is higher than the rates in states like Texas and Pennsylvania. The average electricity rate in Pennsylvania is about 8.9¢/kWh, while Texas rates are flat and are 10.8¢/kWh. The large gap between peak and off-peak prices in California's TOU and EV-Rate plans suggests a strong economic incentive to shift energy consumption away from peak hours. However, the elevated rates may discourage consumers from adopting BEVs without clear savings through optimal charging strategies.

We need RT-Rates on the consumer side so vehicles can respond effectively to grid conditions, which include for congestion pricing and power losses and utility company profit. Fig. 5 displays RT-Rate signals for 2023 at the PGE, DLC, ConEd, and AE nodes. Because these rates are only provided at the generation level, an adjustment is required to reflect distribution-side factors, where vehicle charging and discharging occur. This adjustment considers transmission limits, congestion, and profit for utility operators. We assume a third-party aggregator coordinates vehicle charging based on the RT electricity signal. Fig. 5 shows the adjusted consumer RT-Rate, which considered these constraints. Equation (1) shows how the adjustment factor is estimated and applied to the generation-side local marginal price (LMP) to estimate a real-time price on the consumer side. Equation (1) applies a scalar multiplier to wholesale LMPs to reflect real-world adjustments utilities make when setting consumer-facing rates, including allowances for distribution system losses, non-energy costs, and regulated profit margins. This approach allows the aggregator to optimize vehicle charging schedules according to real-time grid conditions while also taking utility company costs and profits into account in the final price.

$$\sum_{t=1}^{24} C_t^{load}.C_t^{TOU\ rate} = \omega \sum_{t=1}^{24} \sum_{j=1}^{n} C_{t,j}^{load}.C_{t,j}^{LMP} \tag{1}$$

$n \in \{PG\&E\ nodes\}$

In this Equation, C_t^{load} represents the demand load at time t on the consumer side, and $C_t^{TOU\ rate}$ is the TOU-Rate applied at that time. On the generation side, $C_{t,j}^{load}$ and $C_{t,j}^{LMP}$ correspond to the load demand and LMP at time t at node j, respectively, with n representing the utility nodes.

Solving this equation returns ω, which is the scaling factor that converts RT-Rates from the generation side to prices on the consumer side. This formulation ensures the alignment of real-time pricing signals with demand and supply conditions. The implications of these pricing mechanisms can encourage drivers to participate in vehicle-to-grid

Fig. 5. Comparison of Wholesale and Consumer Real-Time Electricity Prices for Four Utilities. Each row represents one utility company (PGE, DLC, ConEd, AE). The left column shows real-time wholesale prices (locational marginal prices, LMPs), and the right column shows estimated consumer prices after adjusting for distribution losses, administrative fees, and utility margins. These prices represent the rates that flexible EV charging would face under real-time pricing. Price spikes vary across territories. PGE shows fewer but intense peaks, with consumer prices reaching over \$7500/MWh. DLC and ConEd experience more frequent but moderate spikes, often between \$500 and \$1500/MWh. AE has the fewest price spikes, but some peaks exceed \$2500/MWh.

programs. Higher electricity prices in PGE, ConEd, and AE burden BEV owners more, but they also create more incentives for optimal charging behavior, particularly with V2G programs. The broader rate gap offers incentives to shift charging to off-peak periods. Thus, with this shift, V2G participation will become more financially attractive. However, utility territories with lower rates and less fluctuation rates, like DLC, may not provide the same financial incentive for V2G programs.

IV. Problem Statement

The optimal charging framework considers various decision-making factors, such as vehicle plugin sessions, charging types (V1G and V2G), charging locations, charging speeds, and pricing mechanisms (TOU, EV-Rate, and RT-Rate). Additionally, the optimization process considers the drivers' travel behavior needs in real-time to determine the most efficient charging rate by considering factors such as the vehicle's state of charge (SOC), battery capacity, and energy demand for each time interval (Fig. 6).

The flowchart illustrates the decision-making process for optimizing BEV charging and discharging behavior based on multiple electricity rates (TOU, EV-Rate, RT-Rate) and the vehicle's charging behavior characteristics. Starting with the electricity rate plan and the vehicle's status (driving or parked), the model calculates energy consumption or gathers input data when parked, such as departure time, location, and required state of charge (SOC) for the subsequent charging. The system assigns the optimal charging or discharging rate, considering energy prices, charging efficiency, and battery degradation costs. Battery degradation is monitored throughout, and costs are incorporated into the charging strategy. The process ensures that the battery reaches the desired SOC while minimizing costs and battery degradation, creating an optimal charging schedule for the given electricity rate and vehicle conditions. The decision flow accounts for real-time updates in the BEV's status and grid signals, leading to efficient charging and discharging strategies.

The mathematical formulation of the optimal charging model aims to minimize the total cost of vehicle charging while considering drivers' travel needs and economic factors. The objective function considers two primary components: charging cost and battery degradation costs.

Equation (2) shows the cost function in this study, which is structured as follows:

$$Min\ imize \sum_{v\in V}\sum_{t\in T}\left(EC_t.\ Xch_{v,t} + BattC_{v,t_{ch}}\right) \tag{2}$$

Where EC_t is electricity price at time t, $Xch_{v,t}$ is the amount of electricity charged by vehicle v at time t. Also $BattC_{v,t_{ch}}$ is battery degradation cost of charging vehicle v at time t.

1. SOC Balance Constraint

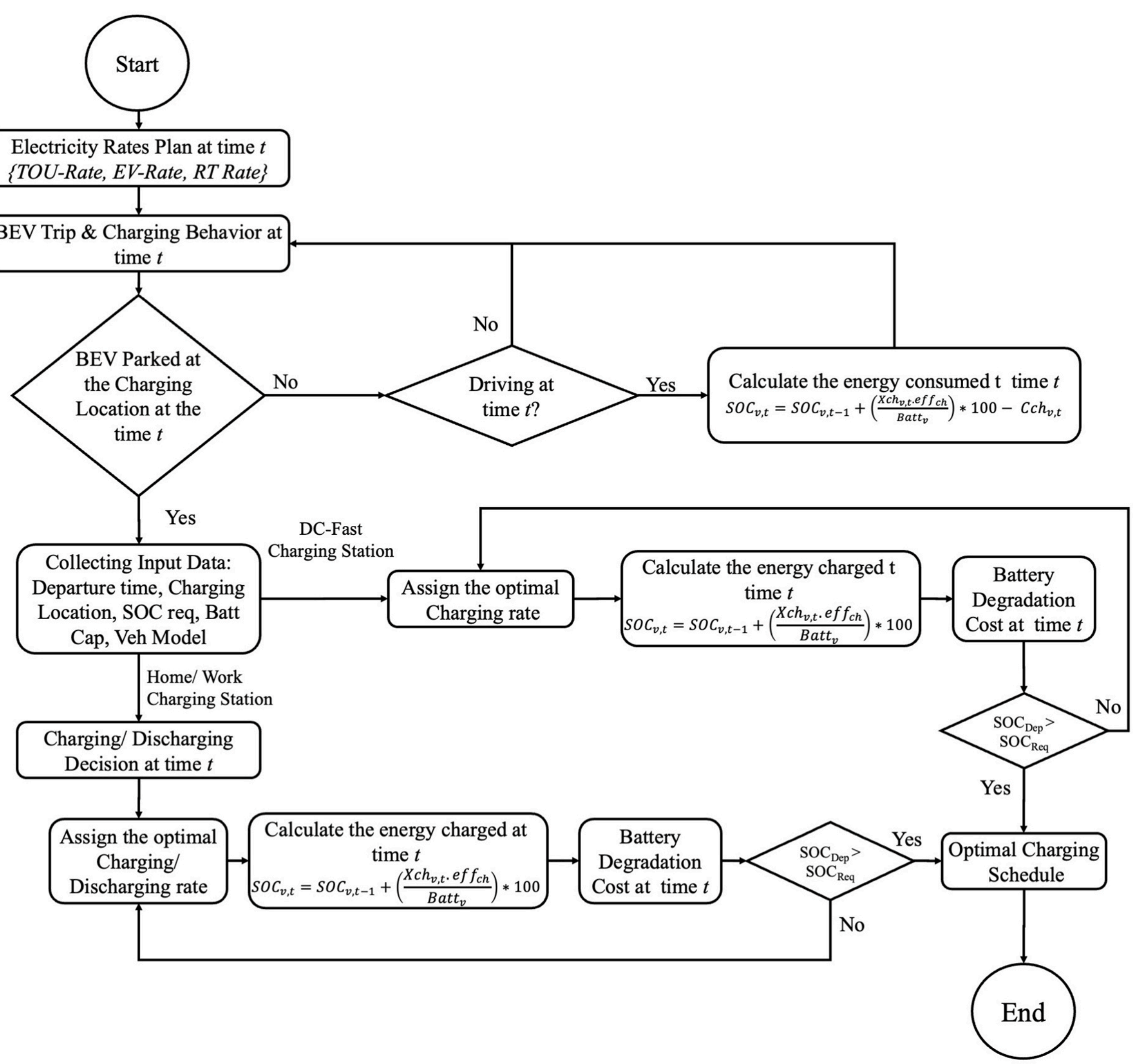


Fig. 6. Decision-making flowchart for optimizing BEV charging and discharging strategies.

The SOC for vehicle v at time t is calculated based on the SOC of the vehicle at time *t-1*, considering any charging occurring during this hour and any travel that occurred during this hour. Both charging and driving activities can take place within 1-h intervals, as this study uses a 1-h time interval.

$$SOC_{v,t} = SOC_{v,t-1} + \left(\frac{Xch_{v,t} \cdot eff_{ch}}{Batt_v}\right)*100 - Cch_{v,t} \tag{3}$$

Where $SOC_{v,t}$ is SOC of vehicle v at time t, eff_{ch} is charging efficiency of BEVs, which is considered %95 in this study, $Batt_v$ is battery capacity of vehicle v, $Cch_{v,t}$ is total kWh consumed by vehicle v at time t.

2. Minimum Charging Rate Constraint

In this study, the discharging rate is constrained to various level-2 charging rates ranging from 6.6 kW to 19 kW. This constraint ensures that the discharging rate does not exceed the assigned value, thereby maintaining the practicality of V2G operations. At each location (Home, Work), the discharging rate is set based on the charger's capacity, allowing the operator to effectively manage and optimize the discharging program.

$$Xch_{v,t} \geq \begin{cases} -Max_{t,l} \in \{6.6, 12, 19\}\ kW, V2G, \\ 0 \in \{6.6, 12, 19\}\ kW, V1G \end{cases} \tag{4}$$

$$Xch_{v,t} \leq \begin{cases} Max_{t,l} \in \{6.6, 12, 19\}\ kW, V2G, \\ Max_{t,l} \in \{6.6, 12, 19\}\ kW, V1G \end{cases} \tag{5}$$

3. Maximum DC-fast Charging Rate Constraint

One of the most critical constraints in BEV charging is the limitation during DC-fast charging. This study considers different DC-fast charging rates for different model based on the actual data. For instance, the Tesla Model S can handle up to 150-kW, while the Chevrolet Bolt can handle up to 50-kW. This unique constraint helps to achieve realistic charging behavior. This is a key insight often overlooked in other research where a single charging rate is assumed for all vehicles in case studies.

$$Xch_{v,t_{ch_{DC}}} \leq \begin{cases} 150\ kW, Tesla, \\ 50\ kW, Bolt \end{cases} \tag{6}$$

4. Minimum SOC at Departure Constraint

Having a full year of real BEV data allows us to understand actual BEV charging behavior. This comprehensive data helps estimate dynamic energy requirements at the end of charging sessions, ensuring sufficient energy to reach the next session. To avoid fully depleting the battery and maintain its health, a 15 % SOC buffer is considered, preventing the battery from dropping below 15 % and ensuring drivers have enough charge for their needs.

$$SOC_{v,t_{dep}} = SOC\_REQ_{v,t_{dep}} + \%15 \tag{7}$$

Where $SOC_{v,t_{dep}}$ is the SOC of the vehicle v at the departure time and $SOC\_REQ_{v,t_{dep}}$ is the SOC that vehicle v needs at the departure time to reach to the next charging sessions without any trips' disruption.

5. SOC Buffer Constraint

Another buffer constraint is applied hourly during discharging sessions to prevent over-discharging, which can harm battery health. To protect the battery, the SOC must remain above 15 %, ensuring the V2G process does not cause deep discharges and safeguards battery longevity.

$$SOC_{v,t_{ch_{v2g}}} = \%15 \tag{8}$$

Where $SOC_{v,t_{ch_{v2g}}}$ is SOC of vehicle v at discharging during V2G optimal charging program.

6. Battery Degradation Constraint

The battery degradation model uses historical data to analyze battery health relative to the distance traveled. It estimates the required charge and calculates the cumulative charge for each vehicle. Equations (8) and (9) determine the charge amount and estimate total degradation. The degradation cost, based on the degradation level, is then included in the objective function.

$$BattD_{v,t_{ch}} = D\_slope_v . \sum_{t=1} Xch_{v,t_{ch_{v2g}}} \tag{9}$$

$$BattC_{v,t_{ch}} = BattD_{v,t_{ch}} - BattD_{v,t_{ch-1}} \tag{10}$$

Where $BattD_{v,t_{ch}}$ represents the cumulative depreciation of battery of vehicle v at time t_{ch} which indicates the charging sessions. D_slope_v is the slope of the linear regression that correlates cumulative charges of the vehicle with the depreciation amount of the battery. $BattC_{v,t_{ch}}$ denotes degradation cost at the time interval t.

V. Post-Processing Analysis for Identifying Optimal Charging Scenarios

The post-processing framework estimates the long-term economic viability of V1G and V2G participation by calculating discounted cost savings and accounting for battery replacement costs. The approach uses an adjustment factor to model real-world pricing and incorporates battery degradation costs, infrastructure costs, and discounting over the study duration. The total cost savings are calculated using Equations 10–13, which applies discounting and accounts for battery replacement costs and charging infrastructure expenses. This process ensures that the estimated net savings reflect real-world conditions, including battery replacement cost due to the degradation if the battery health drops under %80 from increased cycling due to V2G.

1. Annual Savings with Discounting

The first component of the post-processing is the calculation of annual savings. This is determined by comparing the electricity cost under baseline pricing mechanisms (TOU or EV-Rate) with the optimal charging cost for each vehicle. The annual savings are then discounted over the expected lifetime of the vehicle using a 5 % interest rate to represent the time value of money:

$$Discounted\ Annual\ Saving = \sum_{v=1}^{n_v} \sum_{t=1}^{T_v} \frac{C_B - C_{opt}}{(1+i)^t} \tag{10}$$

Where n_v is the total number of the vehicles, T_v is the total lifetime of the battery under the regular V1G charging, and i is the discount factor, which in this study is considered 5 %.

2. Battery Replacement Costs

The second component considers battery replacement cost, which is modeled based on each vehicle's charging behavior and driving patterns. The function estimates the number of battery replacement cycles required over the study period based on the total battery lifetime under regular V1G charging before a replacement is needed. The cost of each battery replacement is discounted to its present value using the same interest rate:

$$Discounted\ Battery\ Cost = \sum_{v=1}^{n_v} \sum_{c=1}^{\lambda_c} \frac{\rho_c \times B_v}{(1+i)^{Replacement\ Year_c}} \tag{11}$$

Where λ_c total number of replacement cycles if the vehicle participates in the V2G program, ρ_c is the battery pack price/kWh derived from Ref. [27] for the year of the replacement and B_v is the battery capacity of the vehicle v.

3. Charging Infrastructure Costs

The framework also includes the upfront cost of charging infrastructure. For V2G scenarios, a one-time cost of bidirectional chargers is derived from Ref. [34]. For V1G scenarios, the cost depends on the charging speed, with higher costs assigned to 19 kW chargers compared to 6.6 kW and 12 kW chargers [35]:

$$IC_v = \begin{cases} BC & if\ V2G \\ UC_1 & if\ V1G\ 12\ kW \\ UC_2 & if\ V2G\ 19\ kW \end{cases} \tag{12}$$

The optimal charging scenario for each vehicle is identified as the one that provides the highest value, returned by Equation (13).

$$\sum_{v=1}^{n_v} \left(\sum_{t=1}^{T_v} \frac{C_{B,v} - C_{opt,v}}{(1+i)^t} - \sum_{c=1}^{\lambda_c} \frac{\rho_c \times B_v}{(1+i)^{Replacement\ Year_c}} - IC_v \right) \tag{13}$$

VI. Sensitivity Analysis

This study tests how sensitive the results are to key technical and policy parameters that shape the value of V2G. The analysis includes battery pack replacement cost, bidirectional charger upgrade cost, charger efficiency, and the social cost of carbon (SCC).

Battery replacement cost varies across three cases, baseline, 10 % lower, and 20 % lower, which represent future cost reductions from mass production and technology improvement. Bidirectional charger upgrade cost also varies across baseline, 10 % lower, and 20 % lower because of the same effects of mass production and technology improvement. Charger efficiency ranges from 0.90 to 0.96, covering the typical performance of most hardware and inverters. The SCC takes three levels, which are 0 \$/tonne CO_2 representing current conditions where consumers do not pay for carbon emissions, 191 \$/tonne CO_2 based on the EPA 2023 central estimate, and 280 \$/tonne CO_2 as a high-policy case. Each parameter changes independently while other assumptions remain fixed.

3. Result

I. Cost-benefits

This section analyzes the annual value of VGI strategies. The main optimization includes battery degradation costs but excludes infrastructure upgrades, battery replacement, and discounting, since these costs remain constant and will be evaluated in post-processing. Two scenarios for bidirectional charger locations were evaluated: at home and work, and only at home. Although charging can happen at any location, discharging to the grid is limited to the selected locations. We consider four different utility territories across the US, including Pacific Gas & Electric (PGE) in California, Duquesne Light Company (DLC) in Pennsylvania, Con Edison (ConEd) in New York, and Austin Energy (AE) in Texas, each with a different pricing structure.

a. TOU-Rates Plan

The results for the TOU pricing scenario show variations in the benefits of optimal charging strategies among the four utility territories studied (Fig. 7). These benefits reflect potential savings or revenue by subtracting electricity and battery degradation costs from the baseline scenario. The highest savings happen in ConEd, where vehicles with 19 kW bidirectional chargers save over \$4000 on average. This outcome is mainly due to ConEd ‘s large gap between peak and off-peak and the timing of tiers in its TOU-Rates. These two factors can increase financial returns for drivers who participate in V2G. In PGE territory, 19 kW chargers also produce high savings, although less than in ConEd. Higher returns from faster chargers reflect the charger’s ability to transfer more energy during periods with larger price differences. DLC and AE show lower benefits compared to other territories, with maximum savings under \$700 for all charging speeds. This result is caused by DLC and AE’s flat TOU-Rate structure.

Across all regions, 12 kW chargers provide moderate savings, while 6.6 kW chargers offer the least. Slower charging limits energy arbitrage and reduces benefits. Electricity pricing also matters. Territories with larger price gaps, like ConEd and PGE, offer greater incentives, while flat rates in DLC and AE lower V2G value. These results show that both pricing and charging speed shape the economic potential of V2G.

b. EV-Rates Plan

The second set of graphs for all utility territories shows how EV-Rate pricing affects the value of VGI (Fig. 7). The lower off-peak price and wider gap between peak and off-peak rates in EV-Rate structures lead to larger economic benefits for VGI. ConEd and AE provide meager savings under the EV-Rate, with an additional benefit less than \$50 in compare with TOU-Rate, whereas PGE can offer additional benefit as much as \$2500 for the 19 kW charging speed. This gap of over \$2500 highlights how each utility’s rate structure shapes the financial attraction of V2G and other optimal charging strategies.

Higher speeds provide diminishing returns for EV-Rate tariffs. Although 19 kW chargers bring the highest savings, the extra amount earned over 12 kW chargers is often small. In DLC, ConEd and AE, for instance, the difference is below \$100. This means that while higher speeds can transfer more energy during valuable price windows, the added costs for faster charging equipment may not always be justified. There is also little difference in savings between installing a bidirectional charger only at home versus installing chargers at both home and work.

EV-Rate pricing can increase financial returns for BEV owners, especially when there are bigger peak-to-off-peak price gaps. However, the benefits of higher-speed chargers and dual installations appear limited. In many cases, a 12 kW bidirectional charger can achieve the majority of cost savings.

c. Real-Time Rates Plan

This section compares the economic benefits of optimal VGI under RT-Rate with those of uncontrolled charging at the same rate. In PGE, uncontrolled charging under RT-Rates costs more than under TOU and EV-Rates (Fig. 7). This higher cost explains why residential customers prefer a tiered price structure to reduce the risks from real-time price fluctuations. However, drivers who use optimal charging with RT-Rates may achieve much higher financial benefits than TOU or EV-Rates. For example, in PGE territory, optimal V2G with a 19 kW bidirectional charger under RT-Rates can save up to \$10,495, which is much higher than the \$3746 and \$6135 savings possible under TOU and EV-Rates, respectively.

Across all territories, the additional profit from having two chargers in no change in plugging behavior is usually under \$100 compared to a single home charger, which is insufficient to cover the infrastructure upgrade cost of the second charger. However, if drivers plug in more often during parking sessions, a single bidirectional home charger can increase benefits by over 25 % in most territories, except PGE and AE. This suggests that home-only V2G may be the most cost-effective option in many regions. Also, battery degradation costs are higher under RT-

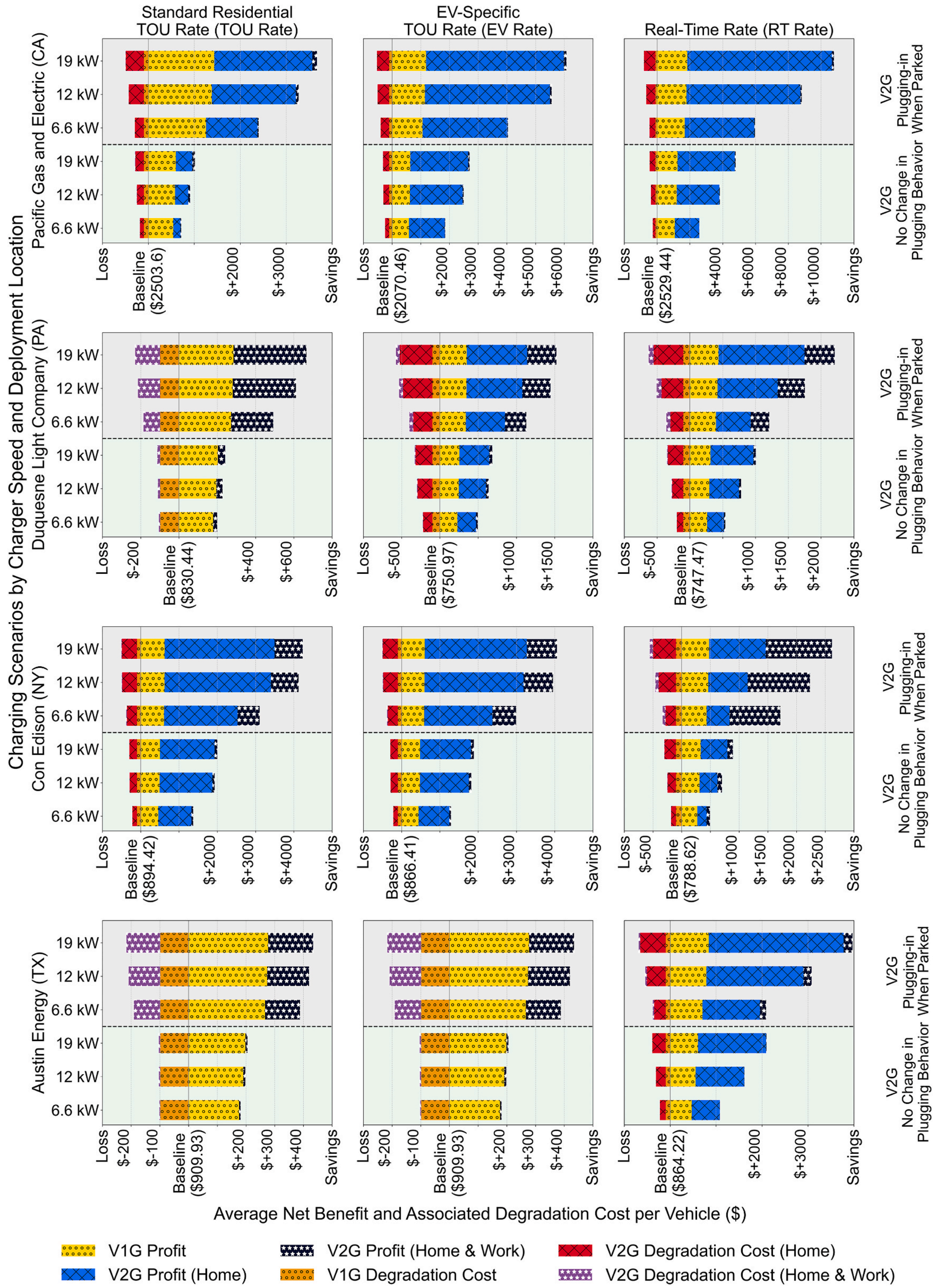


Fig. 7. Average Net Benefit and Battery Degradation Costs for V1G and V2G Under Different Pricing Schemes Across Four Utility Territories. Each row corresponds to one of the four utilities in the US (PGE, DLC, ConEd, and AE), and the columns compare: 1- TOU-Rate optimal charging vs. TOU baseline, 2- EV-Rate optimal charging vs. EV-Rate baseline, 3- RT-Rate optimal charging vs. RT baseline. The RT-Rate consistently provides the highest net benefits, especially at the 19 kW charging speed. The EV-Rate delivers the second-highest returns due to the higher gap between peak and off-peak prices. V1G provides smaller benefits compared to V2G in the "plugging in when parked" scenario. However, in the "no change in plugging" scenario, especially in regions with flatter electricity price structures, the net benefits of V1G and V2G are very close. Battery degradation costs are largely offset by the substantial V2G and V1G savings. The degradation costs for using one or two bidirectional chargers are nearly the same, so their values overlap in most cases. However, smart charging has much lower degradation costs than bidirectional charging, except in regions with flat electricity rates.

Rates due to longer V2G windows and more cycling. However, the economic gains often outweigh these costs. In PGE, for example, drivers can save over $10,000 using optimal high-speed V2G charging.

Territorial differences matter as well. DLC, which has relatively low electricity prices, sees only modest improvements in RT-Rate profits compared to TOU-Rates, especially when compared to PGE and AE. In contrast, territories like PGE and AE, where the price gap under RT-Rates is larger, allow drivers to earn more from optimal charging strategies.

Charging speed affects the financial benefits of VGI, but the gains from moving beyond 12 kW depend on charging behavior. If drivers change their charging behavior, the benefit from faster charging depends more on regional prices. In PGE, where real-time prices fluctuate sharply, the benefit from 19 kW charging can exceed $2000. In most territories, 12 kW chargers provide the best cost-performance balance. Real-time rates raise VGI profitability and may attract drivers who respond to price signals.

II. Virtual Miles as a Measure of V2G Battery Impact

V2G raises concerns about balancing the battery's intrinsic and extrinsic value. The intrinsic value relates to preserving the battery's capacity for reliable driving over its lifetime, while the extrinsic value reflects revenue from selling energy and supporting the grid. V2G increases battery use, which may lead to faster degradation and a shorter lifetime. The concept of "virtual miles" helps us see how V2G affects battery life by linking the discharged energy to actual miles driven. Fig. 8 shows how virtual miles vary by region. Although patterns are broadly similar, pricing structure and charging behavior cause noticeable differences.

High-power Level-2 chargers (19 kW) lead to the highest virtual miles. Under the RT-Rate, virtual miles range from 53,000 in ConEd to over 84,000 in PGE when drivers change their charging behavior. When drivers follow the EV-Rate, virtual miles drop in PGE and AE, while DLC and ConEd show only a small change. This suggests that in PGE and AE, the EV-Rate lowers the financial incentive to discharge energy back to the grid.

However, if drivers keep their current plug-in behavior, the virtual miles are much lower. Virtual miles in this scenario range between about 10,000 and 40,000 miles under the RT-Rate, depending on the region.

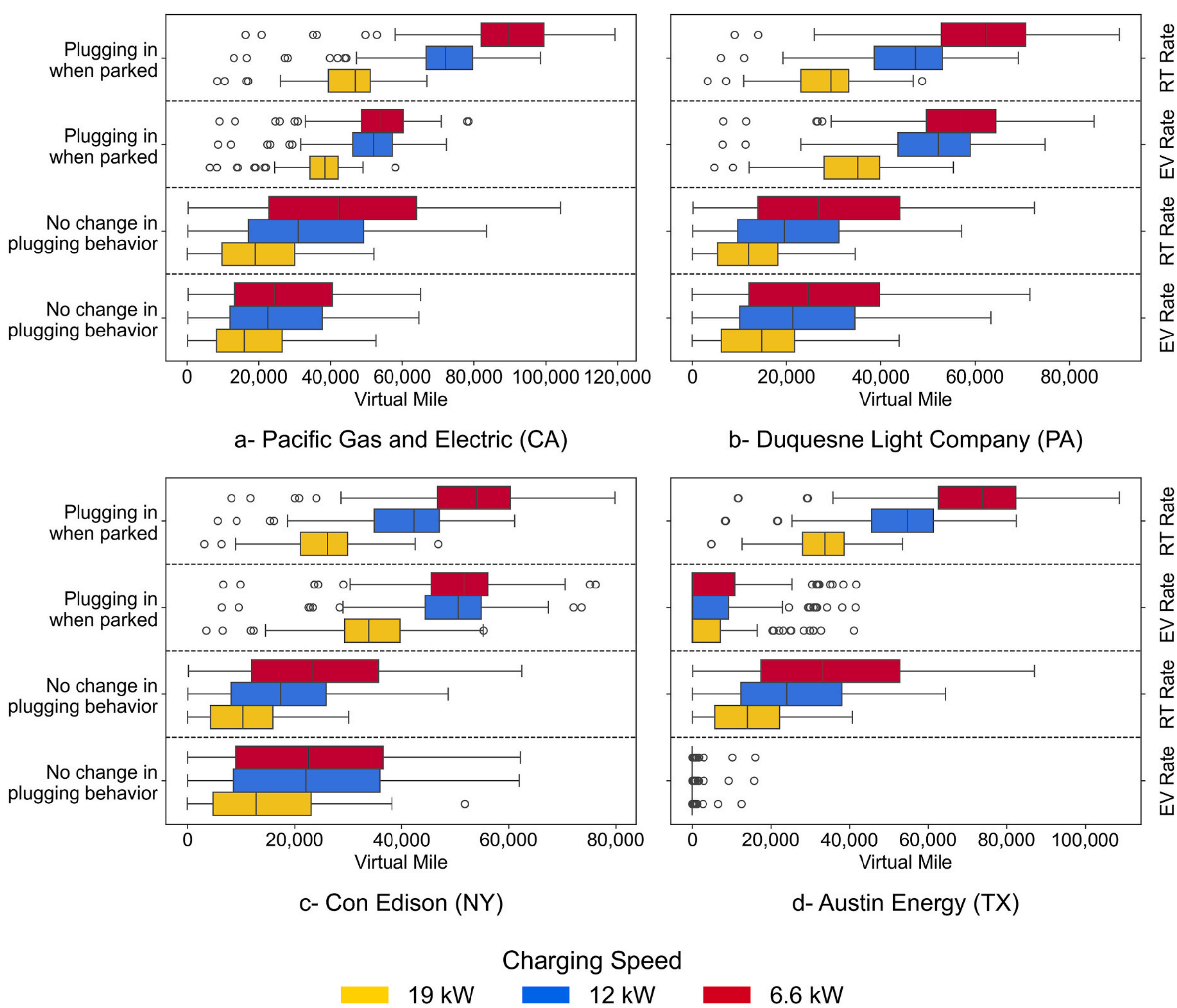


Fig. 8. Distribution of Virtual Miles Under Various Charging Speeds, Behaviors, and Pricing Schemes Across Four Utility Territories. These boxplots show the distribution of virtual miles accumulated annually under V2G scenarios in four utility service regions. Virtual miles measure how much battery degradation is imposed on the vehicles from V2G, which equals the energy needed to drive that many miles. Each panel compares two driver behaviors ("plugging in when parked" vs. "no change in plugging behavior"), three charging speeds (6.6 kW, 12 kW, and 19 kW), and two pricing mechanisms: EV-Rate and RT-Rate. We exclude the TOU-Rate here because Fig. 7 shows it performs worse than both the EV and RT-Rate structures in terms of cost savings. If drivers choose to participate in V2G, they are more likely to opt into the EV or RT rate plans. Each boxplot shows the interquartile range (IQR), median, and 1.5 × IQR whiskers. Circles represent outliers beyond the whiskers. Notably, in "plugging in when parked" scenarios, vehicles using 19 kW chargers may exceed 100,000 virtual miles/year, aligning with warranty thresholds used by automakers.

PGE and AE show a sharp drop in virtual miles under the EV-Rate. In AE, most vehicles stay below 1000 virtual miles under EV-Rate. In contrast, DLC and ConEd show only a slight difference between the EV and RT-Rates. Virtual miles in these regions stay mostly stable. These results show that charging behavior and local rates shape how much battery degradation drivers face from V2G.

III. Emissions Impacts of Optimal Charging Strategies

Optimal charging strategies also reduce GHG emissions. Although the model focuses on cost, shifting charging times lowers reliance on peaker plants, which reduces total emissions. Drivers who follow these strategies help cut environmental impacts. Fig. 9 compares annual CO_{2eq} reductions under the RT-Rate across all utility territories.

Among all utilities, PGE shows the strongest emissions reductions. In this region, low-cost electricity often comes from renewables. As a result, both V1G and V2G reduce emissions more than in other territories. V1G reduces CO_{2eq} by about 250 kg per vehicle each year under both behaviors. V2G cuts emissions further, from 400 kg to nearly 2 tonnes annually. In contrast, DLC, ConEd, and AE show smaller gains. In most cases, reductions stay under 100 kg, and emissions sometimes increase when cheap electricity comes from coal or gas. These results show that emissions benefits depend on local grid mix and whether low-carbon hours match off-peak prices. Faster chargers like 19 kW enhance these benefits by responding quickly to price signals, which often align with cleaner energy.

These results show that emissions depend on charging behavior, speed, and local grid mix. We need to add a carbon cost to the optimization to avoid higher emissions in regions with a carbon intensive generation mix. Thus, we will be sure that the charging aligns with cleaner power and is financially optimal if we include a carbon or social cost based on fuel in our cost function.

IV. Sensitivity of V2G savings to efficiency, battery cost, charger cost, and carbon pricing

The sensitivity analysis evaluates the average annual savings over the vehicle's lifetime, which accounts for battery replacement when needed due to V2G operation, the cost of charger upgrades, and the applied discount rate. Based on earlier findings, the RT-Rate in PGE provides the highest monetary benefit among all utilities. Therefore, the sensitivity analysis focuses on this region under the RT-Rate pricing structure. The 19 kW charger provides the highest benefit among all charging speeds. Lower bidirectional charger efficiency or higher battery costs reduce total savings, while higher carbon prices slightly lower the benefit of smart charging but improve V2G profitability, especially when drivers change their charging behavior. Median annual benefits remain positive under all tested conditions.

Fig. 10 shows the sensitivity analysis for PGE under the RT Rate pricing structure. This case is selected because the large gap between peak and off-peak prices creates strong energy arbitrage opportunities and higher savings for drivers. The first column presents the effect of

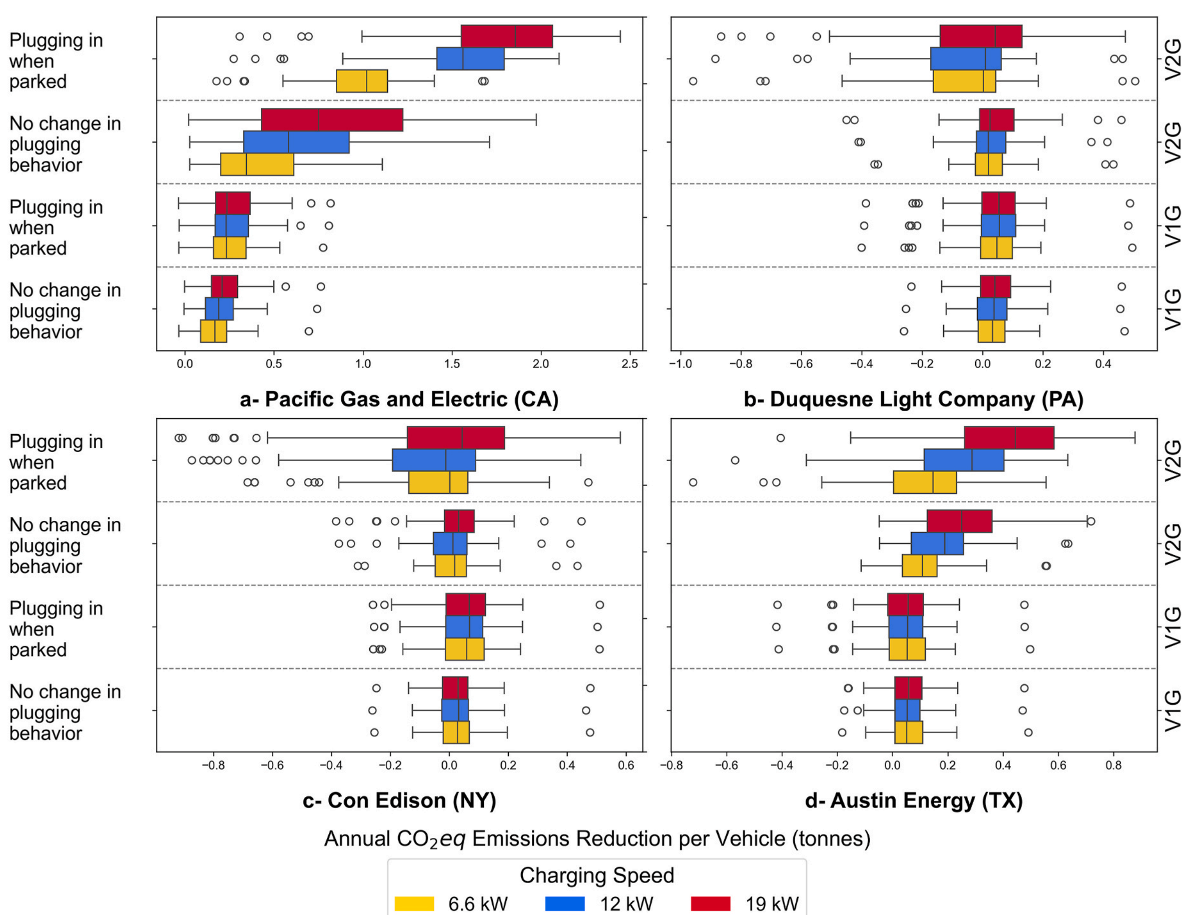


Fig. 9. Annual CO_{2eq} Emission Reductions from V1G and V2G Participation Across Different Charging Speeds and Behaviors. These boxplots show how much CO_{2eq} each vehicle can save annually by using either V1G or V2G optimal charging under two scenarios of "plugging in when parked" and "no change in plugging behavior". Three charging speeds (6.6 kW, 12 kW, 19 kW) are considered in the study of the impact of the charging speed on CO_{2eq} reduction. The four utilities shown, PGE, DLC, ConEd, and AE operate in different electricity markets (CAISO, PJM, NYISO, and ERCOT, respectively), which leads to different environmental outcomes.

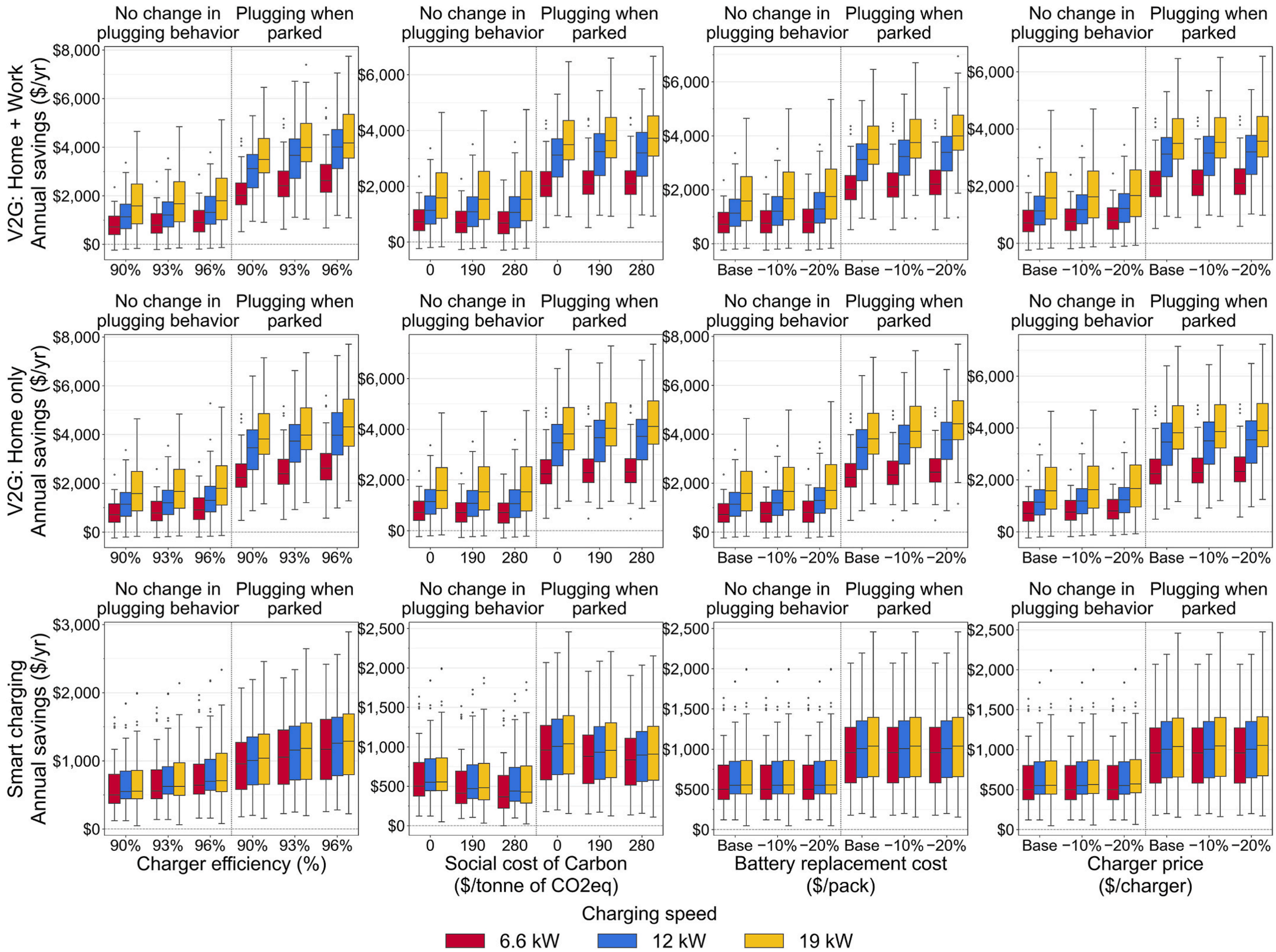


Fig. 10. Sensitivity of annual V2G and V1G savings to charger efficiency, carbon pricing, battery replacement cost, and charger price. Boxplots show the distribution of annual driver savings under different assumptions for (left to right) charger efficiency, social cost of carbon, battery replacement cost, and bidirectional charger price. Each column pair represents "no change in plugging behavior" (left) and "plugging when parked" (right). Rows correspond to deploying bidirectional chargers at home and work, only at home, and unidirectional smart charging. Colors indicate charging speed, which are 6.6 kW (red), 12 kW (blue), and 19 kW (yellow). Boxes represent the interquartile range, with whiskers extending to 5th to 95th percentiles.

charger efficiency. For the 6.6 kW charger, improving efficiency from 90 to 96 % increases annual savings from about $890 to $1125 for smart charging, representing a 26 % increase. For the plugging when parked scenario for the same charger rate, the same efficiency gain raises annual savings from about $2266 to $2,693, equal to a 19 % increase. The improvement is stronger under 12 kW and 19 kW chargers, where vehicles stay connected longer and can make better use of low-cost charging hours.

This figure also shows how considering the SCC impacts annual savings. As the SCC increases from $0 to $280/tCO$_2$, annual savings from smart charging decline across all charging speeds, which reflects the higher cost of electricity related emissions. For example, under 19 kW smart charging, savings shows a 12 % reduction. In contrast, V2G scenarios show the opposite trend. Annual savings rise slightly with higher SCC. Vehicles that discharge energy to the grid help reduce emissions during carbon-intensive hours. As the SCC increases, this reduction becomes more valuable, which leads to higher savings for V2G scenarios. Under 19 kW charging, V2G savings rise by about 7 %, while smart charging savings drop by about 12 % as the SCC increases from 0 to 280 $/t CO$_2$. Higher carbon prices therefore make bidirectional charging more beneficial, while smart charging becomes slightly less attractive when emissions are priced.

Capital costs for battery replacement and chargers remain fixed under smart charging, since vehicles in this mode neither require bidirectional hardware nor experience additional battery cycling. Therefore, only V2G cases are sensitive to changes in these parameters. When the charger price decreases by 20 %, annual savings for V2G increase by about 4–11 %, depending on the charging speed and charging behavior. The effect is stronger for vehicles connected at both home and work, where higher utilization spreads fixed infrastructure costs more effectively. Similarly, when the battery price decreases by 20 %, annual savings rise by about 8–15 %, with larger gains under 19 kW that cycle the battery more frequently. Thus, V2G performance is more sensitive to battery cost than to charger cost, which highlights the importance of declining battery prices for improving the profitability of bidirectional charging.

4. Discussion and conclusion

This study looks at the optimal charging strategy from an individual driver's perspective, which balances electricity costs and potential V2G revenue. This section adds infrastructure upgrade costs, discounting, and battery replacement over the vehicle's lifetime, which ends when the battery requires replacement under normal charging. This allows us

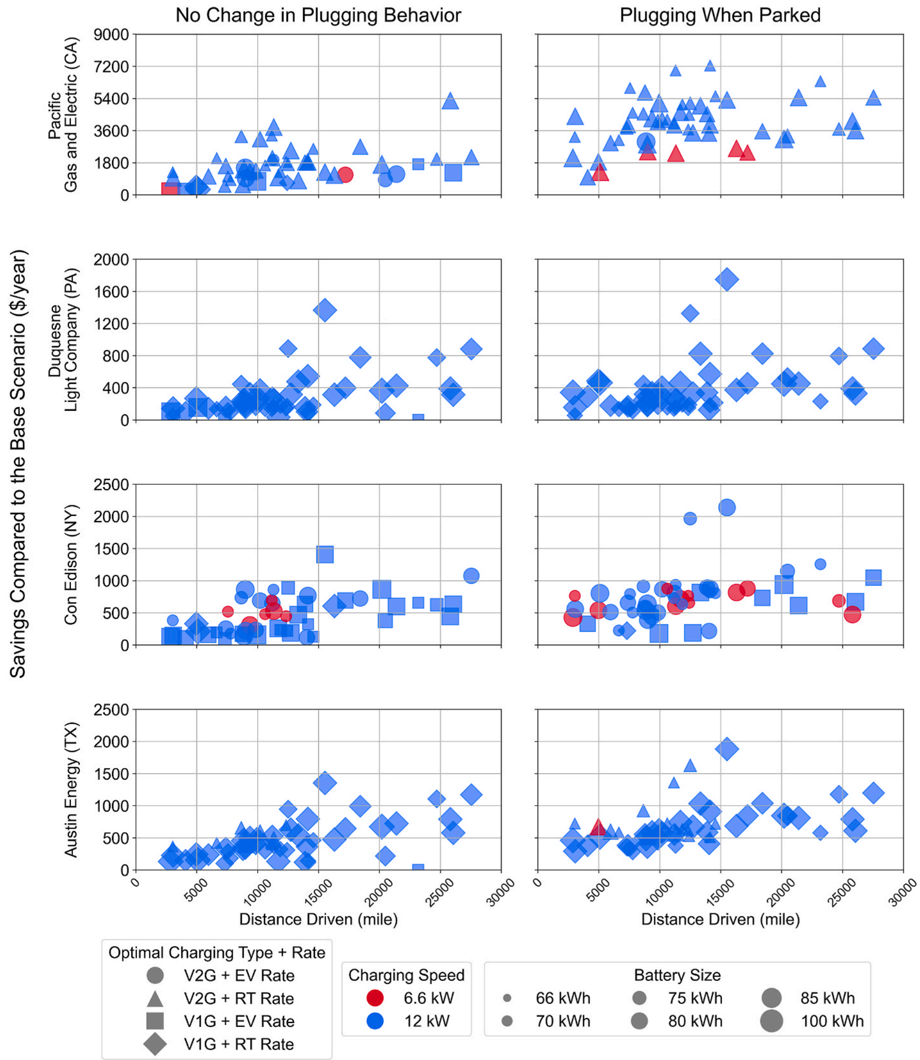


Fig. 11. Optimal individual charging strategies across four U.S. utility territories. Each scatter plot shows the relationship between annual driving distance (x-axis) and yearly savings compared to the baseline scenario (y-axis), under two charging behaviors of "no change in plugging" and "plugging when parked." The four rows represent utility regions: PGE, DLC, ConEd, and AE. Marker shape indicates the optimal charging type and rate plan (V1G or V2G under EV or RT-Rates). Marker color reflects charging speed (6.6 kW, 12 kW), and marker size corresponds to battery capacity.

to estimate the actual cost-benefit of V2G for drivers.

Our results show that using all available parking sessions to charge can greatly improve financial returns (Fig. 7). After including infrastructure upgrades, discounting, and battery replacement costs, PGE shows the highest financial gains from V2G under both charging behavior scenarios (Fig. 11). Drivers who change their behavior and plug in while parked save more each year. Under the "no change" scenario, most drivers save between $1500 and $3000 per year. With active plugging, many reach between $3000 and $7000. ConEd has the second most profitable electricity rate structure. Without changing behavior, most drivers save between $500 and $1500. With active plugging, many over $1000. DLC and AE show smaller gains. In DLC, active plugging increases savings by about $200 per vehicle. In AE, some drivers gain slightly more with active behavior, but most stay below $1000. On average, benefits rise by $200 to $400, with a few outliers exceeding $1500.

In PGE, DLC, and AE, RT-Rates give the highest financial returns for V1G and V2G. Real-time price fluctuations in these regions create strong arbitrage opportunities that cover battery and infrastructure costs. ConEd is the exception. Most vehicles select the EV-Rate, which offers a wide price gap up to 31 ¢/kWh between peak (33 ¢/kWh) and off-peak (2 ¢/kWh), and a long peak period from 8 a.m. to midnight. These features make the EV-Rate more valuable than the RT-Rate for vehicles with limited flexibility. Charging speed also affects profitability. The 12 kW charger gives the best tradeoff between cost, energy flexibility, and battery degradation. It delivers the highest net benefit across most regions. In flat-rate regions like DLC and AE, 6.6 kW chargers often appear optimal because their lower cost offsets limited arbitrage. These results show that faster charging is not always the best option. The 19 kW option is not included in this comparison because bidirectional chargers at this power level are not yet available in the mass market. Vehicles can charge at 19 kW but cannot discharge at the same rate. The analysis focuses on 6.6 kW and 12 kW chargers, which represent the practical range of bidirectional charging options available today.

PGE and ConEd show strong V2G adoption, with more than 80 % of vehicles selecting V2G strategies. In contrast, V1G is more common in DLC and AE (80 %), where price gaps are smaller and parking windows are shorter. These differences highlight how pricing structure and behavior shape the value of bidirectional charging. Across all regions, 12 kW chargers appear most frequently as optimal, offering the best balance of cost, battery health, and energy flexibility.

These findings show that maximizing potential charging sessions can improve both financial savings and emissions outcomes by increasing flexibility in when to charge or discharge. Medium-speed chargers, like

12 kW, offer strong lifetime savings when aligned with off-peak hours and low-carbon hours and partly offset battery degradation costs. The concept of virtual miles is important for warranty design, since V2G operations accelerate battery degradation without adding physical distance. Current regulations from agencies like the EPA and CARB base battery warranties on time and physical mileage but do not account for the extra cycles from V2G, which can add an additional annual mileage equivalent. Revising these regulations to include virtual miles would protect both manufacturers and consumers from unexpected battery replacement expenses.

The analysis also shows that rate structure plays a major role in shaping VGI value. Real-time pricing creates greater opportunities not only for total savings but also for operational flexibility. Even in regions with small TOU or EV-Rate gaps, RT-Rate pricing still provides strong incentives when combined with optimal managed-charging strategies. These rate effects are directly connected to emission outcomes, since aligning charging with low-carbon hours can reduce CO_2 compared to uncontrolled charging.

Although this paper focuses on driver benefits, coordinated participation also brings value to the power system. V2G participation can help utilities avoid costly grid upgrades by reducing peak demand that occurs only a few times each year. Coordinated charging and discharging improve grid stability by balancing short-term fluctuations in demand and supply. They help absorb excess renewable generation that would otherwise be curtailed when vehicles charge during low-demand or high-renewable hours. Policymakers can support this through targeted incentives for bidirectional chargers and by ensuring that drivers share in the value they create for the grid.

These operational findings connect directly to policy and tariff design. Dynamic real time pricing should include clear limits that protect customers from high bills, with export compensation linked to local wholesale prices and peak periods aligned with renewable generation hours. Programs should include managed-charging defaults with easy opt-out options and simple automation through vehicle or charger apps. Utilities can support installation of bidirectional-ready Level-2 chargers that provide a strong cost performance balance and should simplify interconnection and metering so exported energy is credited fairly. Daytime charging and V2G pilots at workplaces can increase flexibility without requiring additional home chargers. Tariffs should avoid high fixed or demand charges that reduce the value of smart charging and instead use small performance-based fees that reward grid support.

The optimization model in this study assumes perfect foresight of electricity prices and vehicle travel schedules. This setup represents the upper limit of potential savings under ideal coordination. In practice, both drivers and aggregators face uncertainty in price signals and trip timing. This uncertainty reduces the ability to fully capture price differences and motivates the use of rolling-horizon or stochastic control instead of perfect-information scheduling. The results of this study should therefore be interpreted as an upper benchmark, while the consistent savings across different tariffs suggest that the main conclusions remain valid under realistic uncertainty.

Also, battery degradation is modeled linearly in this study to maintain transparency and computational simplicity. Future work should apply non-linear, C-rate-sensitive models to better capture temperature and cycling effects.

Another challenge is access to representative, high-resolution data on EV driver behavior. Although our sample does not represent the entire U.S. EV fleet, it captures a wide range of driving patterns in California. As EV adoption grows, this work helps clarify how V2G could perform in regions with different electricity rates and grid conditions. Future research should expand this analysis to include more utilities, emerging retail markets, and datasets reflecting post-2020 driving behavior. The dataset used in this study includes 50 volunteer BEVs monitored for about one year each between 2015 and 2020. This sample is not statistically representative by geography, climate, or household type. The results may differ in other regions such as ConEd, DLC, and AE due to differences in driving patterns and grid conditions. Broader datasets are needed to capture regional and behavioral diversity, and future studies should include climate-related battery effects to improve external validity.

Although optimized VGI provides clear financial and environmental benefits, several real-world barriers still limit large-scale adoption. Bidirectional chargers remain costly and not yet standardized across automakers, which creates warranty and compatibility issues. Driver participation depends on convenience, charger access, and trust in aggregators. Current utility regulations in many states restrict vehicle energy export or lack clear credit mechanisms for small distributed-energy resources. The Net Energy Metering (NEM) framework in California currently limits compensation for exported electricity by using an avoided-cost calculation rather than full retail credit. This structure reduces the value of exported energy from distributed resources such as EVs and may discourage participation in V2G programs until vehicle-specific export tariffs are introduced. Market signals such as real-time pricing and aggregator access to wholesale markets are also limited in many areas. Policymakers and utilities must coordinate standards and incentives to overcome these barriers and ensure that both drivers and grid operators benefit from VGI programs.

This study includes four utility territories such as PGE, ConEd, DLC, and AE, that represent diverse electricity rates, pricing structures, and grid conditions across the United States. This regional diversity allows us to test how V2G performance varies under different market settings. In high price, renewable-aligned areas such as PGE, V2G offers large financial and environmental gains. In contrast, regions with flatter rates or higher-emission generation, such as DLC, show smaller or more mixed outcomes. These comparisons indicate that VGI strategies should be adapted to local grid and pricing conditions.

We assume a full pass-through of cost savings from aggregator to EV owner. While this reflects a theoretical best-case for consumer benefit, in practice, third party aggregators may retain a share of the value depending on market structure, risk allocation, and contract design. The analysis also does not quantify the option value of faster home charging, for example, the ability to depart with a higher state of charge during unexpected trips, which may slightly bias results toward slower charging speeds.

CRediT authorship contribution statement

Hanif Tayarani: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Aaron Rabinowitz:** Methodology, Formal analysis, Conceptualization. **Alan Jenn:** Visualization, Supervision, Conceptualization. **Gil Tal:** Supervision, Conceptualization.

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.

Data availability

Data will be made available on request.

References

[1] Aguilar Lopez F, Lauinger D, Vuille F, Müller DB. On the potential of vehicle-to-grid and second-life batteries to provide energy and material security. Nat Commun 2024;15:4179. https://doi.org/10.1038/s41467-024-48554-0.
[2] Cantor C. No doubt about it: EVs really are cleaner than gas cars. BloombergNEF 2024. https://about.bnef.com/blog/no-doubt-about-it-evs-really-are-cleaner-than-gas-cars/. [Accessed 26 June 2024].
[3] Brinkel N, van Wijk T, Buijze A, Panda NK, Meersmans J, Markotić P, et al. Enhancing smart charging in electric vehicles by addressing paused and delayed

charging problems. Nat Commun 2024;15:5089. https://doi.org/10.1038/s41467-024-48477-w.
[4] Ginigeme K, Wang Z. Distributed optimal vehicle-to-grid approaches with consideration of battery degradation cost under real-time pricing. IEEE Access 2020;8:5225–35. https://doi.org/10.1109/ACCESS.2019.2963692.
[5] Esmaili A, Oshanreh MM, Naderian S, MacKenzie D, Chen C. Assessing the spatial distributions of public electric vehicle charging stations with emphasis on equity considerations in king county, Washington. Sustain Cities Soc 2024;107:105409. https://doi.org/10.1016/j.scs.2024.105409.
[6] Chen J, Zou Y, Zhang J, Zhang X. Optimal charging and discharging strategy for workplace electric vehicle charging stations with renewable energy and power network constraints. Energy 2025;336:138422. https://doi.org/10.1016/j.energy.2025.138422.
[7] Li S, Zhao P, Gu C, Huo D, Li J, Cheng S. Linearizing battery degradation for health-aware vehicle energy management. IEEE Trans Power Syst 2023;38:4890–9. https://doi.org/10.1109/TPWRS.2022.3217981.
[8] Al-obaidi AA, Farag HEZ. Optimal design of V2G incentives and V2G-Capable electric vehicles parking lots considering cost-benefit financial analysis and user participation. IEEE Trans Sustain Energy 2024;15:454–65. https://doi.org/10.1109/TSTE.2023.3307633.
[9] Rahman MM, Gemechu E, Oni AO, Kumar A. The development of a techno-economic model for assessment of cost of energy storage for vehicle-to-grid applications in a cold climate. Energy 2023;262:125398. https://doi.org/10.1016/j.energy.2022.125398.
[10] Yun S, Woo J, Kwak K. Unlocking peak shaving: how EV driver heterogeneity shapes V2G potential. Energy 2025;329:136773. https://doi.org/10.1016/j.energy.2025.136773.
[11] J1772_202401: SAE electric vehicle and Plug-in hybrid electric vehicle, conductive charge coupler - SAE international 2024. https://www.sae.org/standards/content/j1772_202401/. [Accessed 22 August 2025].
[12] Ebrahimi M, Rastegar M, Mohammadi M, Palomino A, Parvania M. Stochastic charging optimization of V2G-Capable PEVs: a comprehensive model for battery aging and customer service quality. IEEE Trans Transp Electrific 2020;6:1026–34. https://doi.org/10.1109/TTE.2020.3005875.
[13] Khezri R, Steen D, Wikner E, Tuan LA. Optimal V2G scheduling of an EV with calendar and cycle aging of battery: an MILP approach. IEEE Transactions on Transportation Electrification 2024:1. https://doi.org/10.1109/TTE.2024.3384293.
[14] Zheng Y, Shao Z, Lei X, Shi Y, Jian L. The economic analysis of electric vehicle aggregators participating in energy and regulation markets considering battery degradation. J Energy Storage 2022;45:103770. https://doi.org/10.1016/j.est.2021.103770.
[15] Chandra Mouli GR, Kefayati M, Baldick R, Bauer P. Integrated PV charging of EV fleet based on energy prices, V2G, and offer of reserves. IEEE Trans Smart Grid 2019;10:1313–25. https://doi.org/10.1109/TSG.2017.2763683.
[16] Shibl MM, Ismail LS, Massoud AM. Electric vehicles charging management using deep reinforcement learning considering vehicle-to-grid operation and battery degradation. Energy Rep 2023;10:494–509. https://doi.org/10.1016/j.egyr.2023.07.008.
[17] Gong J, Wasylowski D, Figgener J, Bihn S, Rücker F, Ringbeck F, et al. Quantifying the impact of V2X operation on electric vehicle battery degradation: an experimental evaluation. eTransportation 2024;20:100316. https://doi.org/10.1016/j.etran.2024.100316.
[18] Huang P, Tu R, Zhang X, Han M, Sun Y, Hussain SA, et al. Investigation of electric vehicle smart charging characteristics on the power regulation performance in solar powered building communities and battery degradation in Sweden. J Energy Storage 2022;56:105907. https://doi.org/10.1016/j.est.2022.105907.
[19] Bhoir S, Caliandro P, Brivio C. Impact of V2G service provision on battery life. J Energy Storage 2021;44:103178. https://doi.org/10.1016/j.est.2021.103178.
[20] Signer T, Baumgartner N, Ruppert M, Sandmeier T, Fichtner W. Modeling V2G spot market trading: the impact of charging tariffs on economic viability. Energy Policy 2024;189:114109. https://doi.org/10.1016/j.enpol.2024.114109.
[21] Tian X, Cheng B, Liu H. V2G optimized power control strategy based on time-of-use electricity price and comprehensive load cost. Energy Rep 2023;10:1467–73. https://doi.org/10.1016/j.egyr.2023.08.017.
[22] Tepe B, Figgener J, Englberger S, Sauer DU, Jossen A, Hesse H. Optimal pool composition of commercial electric vehicles in V2G fleet operation of various electricity markets. Appl Energy 2022;308:118351. https://doi.org/10.1016/j.apenergy.2021.118351.
[23] Wei H, Zhang Y, Wang Y, Hua W, Jing R, Zhou Y. Planning integrated energy systems coupling V2G as a flexible storage. Energy 2022;239:122215. https://doi.org/10.1016/j.energy.2021.122215.
[24] Li Y, Su H, Chen X, Liu J, Shi R. A V2G scheduling strategy based on electric vehicle users' willingness model. 2021 IEEE 5th conference on energy internet and energy system integration (EI2). Taiyuan, China: IEEE; 2021. p. 237–43. https://doi.org/10.1109/EI252483.2021.9712928.
[25] Tal G, Karanam VC, Favetti MP, Sutton KM, Ogunmayin JM, Raghavan SS, et al. Emerging technology zero emission vehicle household travel and refueling behavior. 2021.
[26] Tayarani H, Ramadoss TV, Karanam V, Tal G, Nitta C. Forecasting battery electric vehicle charging behavior: a deep learning approach equipped with micro-clustering and SMOTE techniques. https://doi.org/10.48550/arXiv.2307.10588; 2023.
[27] Slowik P, Isenstadt A, Pierce L, Searle S. Assessment of light-duty electric vehicle costs and consumer benefits in The United States in the 2022–2035 time frame n.d..
[28] Cars Electric. Solar & clean energy. Tesla 2024. https://www.tesla.com/. [Accessed 5 September 2024].
[29] Tesla battery survey. https://docs.google.com/forms/d/e/1FAIpQLSfrteuONm9qylEh0lgLTu6FzP2qR8-3mHTt6e53849ombZ03w/viewform?usp=embed_facebook. [Accessed 27 June 2024].
[30] Residential rate plan pricing. Pacific Gas and Electric Company 2024. https://www.pge.com/assets/pge/docs/account/rate-plans/residential-electric-rate-plan-pricing.pdf.
[31] Austin energy. https://austinenergy.com/rates/residential-rates. [Accessed 22 August 2025].
[32] Con Edison. https://www.coned.com/en/accounts-billing/your-bill/time-of-use. [Accessed 22 August 2025].
[33] Duquesne light company. https://www.duquesnelight.com/service-reliability/service-map/rates/tariff-resources. [Accessed 22 August 2025].
[34] 2024 promotions & deals | GM energy. https://gmenergy.gm.com/for-home/guidance/promotions. [Accessed 26 December 2024].
[35] Chevrolet GM. Genuine parts PowerUp+ level 2 charger | 85642869 | chevrolet parts 2024. https://parts.chevrolet.com/product/gm-genuine-parts-powerup-level-2-charger-85642869. [Accessed 26 December 2024].