DYNAMIC SMART CHARGING THROUGH INTEGRATED AGENT-BASED AND OPTIMIZATION MODELING: IMPACTS ON FLEET OPERATIONS AND POWER GRIDS

Lin Su
Maseeh Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
301 E. Dean Keeton St, Stop C1761, Austin, TX, 78712
sulin@utexas.edu
ORCID: https://orcid.org/0000-0001-5507-0389

Krishna Murthy Gurumurthy, Ph.D.
Argonne National Laboratory, Transportation and Power Systems Division
9700 S. Cass Avenue
Argonne, IL 60439
kgurumurthy@anl.gov

Kara M. Kockelman, Ph.D., P.E.
(Corresponding Author)
Dewitt Greer Professor in Engineering
Maseeh Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
301 E. Dean Keeton St, Stop C1761, Austin, TX, 78712
kkockelm@mail.utexas.edu
Tel: 512-471-0210

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ABSTRACT

Coordinated vehicle-to-grid (V2G) strategies are increasingly important as electric vehicle (EV) adoption accelerates alongside emerging autonomous and shared mobility systems, placing growing pressure on power grids and charging infrastructure. This study develops an integrated simulation-optimization framework that embeds a rolling V2G optimization model within an agent-based model (ABM), enabling dynamic feedback between optimized (dis)charging decisions for mixed EV groups (fleet + household EVs) and evolving transportation system states. Using the Austin 6-county region as a case study, the framework evaluates the operation of a 15,000-vehicle shared autonomous electric vehicle (SAEV) fleet under time-varying electricity pricing and grid conditions to quantify impacts on charging demand, grid support, and emissions. Results show that unidirectional smart charging (V1G) reshapes temporal charging demand by concentrating roughly 36% of daily fleet charging during late-night hours (12 to 2 AM) and up to 28% during mid-day hours (11 AM to 1 PM). In contrast, charging between 6 and 8 AM is almost eliminated, while evening demand between 6 and 9 PM accounts for up to 20% of daily fleet charging. Fleet-only V2G preserves these coordinated charging patterns while enabling targeted fleet discharging during grid-stress periods, primarily under electricity prices with large intra-day variations (e.g., during extreme weather events). Allowing personal EV participation through combined fleet-plus-household V2G (Combined-V2G) further expands discharge capacity and temporal coverage, particularly during evening peak periods, when fleet availability for discharging becomes more constrained by passenger-service obligations. Environmental benefits are also pronounced. Across various pricing structures, V1G reduces daily net CO_2 emissions to roughly 52 to 55 kg/SAEV/day, while Fleet-V2G further lowers emissions to below 50kg/SAEV/day. Combined-V2G generates additional CO_2 savings. On average, Fleet-V2G achieves the lowest monetized CO_2 damage costs ($6.90/SAEV/day), compared with $7.50 under V1G and $7.24 under Combined-V2G. Similar patterns are observed for broader pollutant-related damage costs associated with NO_x and SO_2. Results suggest that coordinated charging strategies improve the temporal alignment of EV energy demand with power supply systems and pollutant-related damage costs, although realized benefits depend greatly on pricing structures, vehicle availability, and deployment of V2G infrastructure.

Key words: Electric vehicle, shared autonomous electric fleets, smart charging, agent-based model, simulation and optimization

1. BACKGROUND

Vehicle electrification has emerged as a worldwide trend, driven by advances in battery technology, declining vehicle costs, and supportive policies, including U.S. state-level programs such as New York's Drive Clean Rebate, Connecticut's CHEAPER program, and Massachusetts's MOR-EV program (Kennedy et al., 2025). Global electric vehicle (EV) sales reached a record high of over 20 million vehicles in 2025, accounting for 25% of all new car sales worldwide (IEA, 2026). In addition, a 300-km-range BEV is estimated to produce approximately 54% lower lifetime CO_2-eq emissions than a comparable internal combustion engine (ICE) vehicle and 32% lower emissions than an equivalent PHEV (IEA, 2024). Electrification is also occurring across commercial vehicles. For example, Lyft aims for 100% EVs on its platform by 2030, while Uber targets 100% zero-emission rides globally by 2040, with a 2030 goal for U.S., Canadian, and European cities (Lyft, 2020; Uber, 2020). Meanwhile, emerging technologies, including vehicle automation, shared mobility platforms, and electric powertrain development, are reinforcing this trend. Waymo has deployed around 2,500 fully autonomous EVs across San Francisco, Los Angeles, Phoenix, and Austin as of late 2025, and is expected to reach 3,500 vehicles by 2026 (Campbell, 2025a; Waymo, 2025).

The rapid growth of personal and fleet electrification places rising pressure on charging infrastructure and grid systems, requiring expansion of EV charging infrastructure and strategic deployment approaches, such as public-private collaboration (Su et al., 2024). In 2023, researchers at the National Laboratory of the Rockies estimated that about 1 million public Level 2 charging ports and 182,000 public DC fast charging (DCFC) ports would be needed in the U.S. by 2030 to support accelerated EV adoption (Wood et al., 2023). Without coordinated management, uneven spatial and temporal charging demand can exacerbate regional grid stress and local congestion at charging hubs. Bernard et al. (2025) found that public charging demand is highly responsive to price signals, enabling charging to shift away from peak periods towards lower-costs hours (e.g., midday, thanks to solar panels). As utilities and planners seek scalable solutions to maintain system reliability while supporting increasing charging demand, coordinated smart charging emerges as a promising strategy for mitigating peak loads, improving charge scheduling, and supporting grid operations.

Smart-charge management (SCM) is the coordinated and dynamic control of EV charging in response to grid load conditions, fleet operation needs, and real-time electricity prices, thereby mitigating costly distribution upgrades and delays in EVCS deployment caused by limited grid capacity (U.S. DOE, 2025a). In contrast to uncontrolled charging, also referred to as last-minute charging (LMC), where EVs are charged whenever they are plugged in, smart charging strategies include managed unidirectional charging (V1G) and bidirectional vehicle-to-grid (V2G) service. While V1G primarily smooths grid loads, V2G offers greater flexibility by enabling EVs to supply stored energy back to the grid during system stress or high-price hours. NovaCharge (2024) similarly notes that fast charging imposes concentrated loads on the grid, whereas scheduling optimization can reduce both operating costs and alleviate grid stress. Large-scale participation in smart charging, especially V2G, spans household (HH) EVs and commercial fleets such as shared automated EVs (SAEVs).

Fleet EVs are well-suited for V2G participation due to their predictable schedules, centralized management, and controllable operations. Driivz (2025) mentions that coordinated V2G scheduling allows fleet operators to generate new revenue streams, helping offset electrification costs. Kumar (2024) further highlights that commercial fleets such as delivery vans and transit/school buses characterized by predictable schedules and long idle windows, making them promising providers of grid services. SAEV fleets represent a growing component of urban mobility and offers additional opportunities for energy flexibility. Campbell (2025) reported that Waymo's automated EV fleets reached a deadheading of 44.3% in September 2025. Similarly, Raifman (2025) estimated that Waymo vehicles accumulated more than 304,000 unassigned passenger-service hours in March 2025. Although these idle periods reflect operational inefficiencies, they create substantial windows for coordinated smart charging, supported by centralized dispatching and real-time fleet management.

While personal EVs offer even greater long-term flexibility, their vehicle-grid integration (VGI) faces challenges due to unpredictable household travel, concerns related to battery degradation, and upfront cost of bidirectional chargers. Despite these barriers, their scales and long parking durations offer significant distributed energy storage potential, supported by National Household Travel Survey (NHTS) data, which indicate that household vehicles remain parked over 95% of the daytime on average (U.S. DOT, 2024; Kane, 2024; Raifman, 2025). Empirical evidence further supports the feasibility and economic benefits of managed HH EVs charging. Metcalfe et al. (2025) show managed charging can reduce peak household electricity demand by 42% while shifting nearly all charging to off-peak periods without increasing total electricity consumed, generating a consumer surplus, including annual bill savings ranging from £343 to £650 relative to a standard flat tariff. From the personal EV owner's perspective, lower charging costs, economic compensation, eco-friendliness, and improved charging safety are primary incentives for V2G participation (Driivz, 2023; Zhang et al., 2024). At scale, these distributed resources can deliver substantial system-level value. The Electric Power Research Institute (EPRI) estimates that V2G could generate up to one billion dollars in annual grid benefits in California by 2030 under high EV adoption scenarios of roughly 5 million vehicles, and with half of those personal EVs being V2G-enabled (EPRI Journal, 2020). These findings highlight the need for modeling frameworks that can jointly represent household-level V2G availability and interactions with fleet-based V2G participants to evaluate system-wide impacts.

1.1 Research Gaps and Challenges

Despite these promising findings across diverse EV groups, most existing studies focus on a single participating EV group, typically modeling either personal/household EVs (Ding et al., 2022; Zhang et al., 2024; Huang and Sandström, 2025; Nadimi and Goto, 2026) or commercial EV fleets (Liao et al., 2021; Dean et al., 2023; Aktar et al., 2023; Yu et al., 2024) in isolation. Few studies consider combined fleet-plus-household V2G (Combined-V2G) participation by both fleet and personal EVs, even though interactions between these groups can significantly influence grid performance, fleet operation, and energy markets. As a result, the system-wide costs, benefits, and operational tradeoffs associated with coordinated participation across heterogeneous EV users remain underexplored.

Moreover, existing research often simplifies how EVs interact with both grid conditions and mobility needs. Many studies assume static traffic conditions or average travel patterns for EVs (Liao et al., 2021; Sun et al., 2021; Kobayashi et al., 2025), limiting their ability to capture operational constraints that shape real-world EV flexibility for V2G. Evaluations further indicate that behavioral non-adherence, time-varying traffic congestion, and grid uncertainty can reduce the realized value of optimized smart charging plans (U.S. DOE, 2025b; Brinkel et al., 2024; Jaworski et al., 2023). These limitations challenge examining smart charging strategies under dynamically evolving transportation environments, revealing a gap in existing VGI modeling approaches.

Addressing this gap requires a modeling framework that integrates vehicle behavior with system-level optimization. A two-way simulation–optimization approach can support this need by allowing optimized (dis)charging schedules to inform vehicle behavior, while simulated travel patterns, network congestion, and evolving state-of-charge (SoC) distributions feed back into the (dis)charging optimization module. Agent-based models (ABMs) capture individual mobility decisions, interactions with the grid, and vehicle status, while optimization models identify the most cost-effective energy transactions under time-varying electricity prices and grid conditions. Their interaction captures deviations between planned and actual energy use, enables timely adjustments, and supports a more comprehensive evaluation of Combined-V2G strategies.

1.2 Contribution

This study bridges the gap in V2G literature by evaluating coordinated smart charging for both personal EVs and commercial EV fleet within a dynamic modeling environment. An integrated simulation–optimization framework is developed to jointly manage (dis)charging decisions for diverse EV groups. The framework advances V2G approach by embedding a rolling 24-hour V2G optimization module within a large-scale agent-based simulation, enabling optimized energy decisions to adapt continuously to evolving travel demand and grid conditions.

The designed framework captures bidirectional feedback between optimized energy transactions and evolving travel behavior. Personal EVs participate in V2G service based on planned daily activities and SoC availability, while fleet EV following operational decisions, such as routing, service assignment, and vehicle reposition. By modeling travel behavior, charging infrastructure networks, electricity market conditions, and grid constraints, the framework enables a comprehensive assessment of economic outcomes, fleet performance, grid support potential, and pollutant-related impacts across multiple charging strategies.

Applied to a rapidly electrifying metropolitan region, the simulation-optimization model provides insight into how coordinated V2G participation influences fleet operations, grid-support behaviors, and economic outcomes under various smart charging strategies. The results offer valuable insights for fleet operators and planners seeking to design incentive programs, grid-management policies, and charging infrastructure deployment strategies.

The remainder of the paper is organized as follows. The next section presents the simulation–optimization methodology, including the agent-based travel simulation environment, the personal EV discharge potential estimation, and the coordinated day-ahead smart charging workflow. The subsequent section describes the case study area and corresponding model configuration. The Results and Discussion section then compares outcomes under uncontrolled charging and smart charging strategies, including V1G, Fleet-V2G, and Combined-V2G. The paper concludes with key findings, policy-relevant insights, study limitations, and directions for future research.

2. METHODOLOGY

This study develops an integrated simulation-optimization framework that embeds a day-ahead smart charging optimization module within a large-scale agent-based model (ABM) to evaluate coordinated smart charging between fleet and personal EVs. The simulation is implemented in POALRIS, a high-performance ABM that simulates and continuously updates agent and vehicle activities, travel patterns, and fleet operations across a 24-hour simulation day. The optimization module, formulated and solved in IBM CPLEX, uses these most recently updated system states to re-optimize charging and discharging schedules on a rolling 24-hour horizon for both fleet and personal EVs. The interaction between simulation and optimization allows optimized (dis)charging decisions to shape fleet operation, while POLARIS captures the resulting travel responses, congestion dynamics, and deviations between predicted and actual energy use.

Within this structure, personal EVs have flexible V2G availability that aligns with the corresponding agent's daily schedules. Their feasible discharge potential is quantified at each decision epoch (e.g., 15 minutes) based on current planned activities and grid conditions. By adjusting the model's charging and discharging controls for fleet and personal EVs, the framework can simulate various smart charging strategies, including V1G, fleet-only V2G, and combined fleet-plus-household V2G, enabling comparison with the LMC scenario. This design provides a more comprehensive and realistic representation of smart charging strategy, supported by multi-day operational continuity for fleet vehicles and accommodation of EV owners' activity patterns.

The following subsections describe the agent-based simulation model, the estimation of feasible discharge potential for personal EVs, and the coordinated day-ahead smart charging framework that integrates the CPLEX optimization module within the ABM.

2.1 Agent-based Travel Simulation

The simulation environment for this work is POLARIS, an activity-based and agent-based modeling platform developed in C++ and designed for computationally intense, large-scale transportation analysis (Auld et al., 2016). POLARIS has been widely applied in transportation simulation studies, including first-and-last-mile service analysis (Huang and Verbas, 2021), multi-stage fleet charging (Dean et al., 2023) and charging infrastructure planning (Dean et al., 2022; Su et al., 2025), and shared autonomous (electric) vehicle operations (Gurumurthy et al., 2021), highlighting its wide use across diverse transportation research.

POLARIS generates a synthetic population using demographic data from regional metropolitan planning organizations and the U.S. Census Bureau, using the ADAPTS framework to generate representative person-level characteristics, such as gender, age, and race, alongside household-level attributes including size, income, and number of employees (Auld and Mohammadian, 2009; Auld and Mohammadian, 2012). Each agent's daily activities are planned through activity generation models that consider activity types and demographic factors, then organized using activity planning order model to achieve temporal flexibility and planning horizons for different activities (Auld et al., 2011; Auld and Mohammadian, 2012). Trips and vehicles are loaded onto the POLARIS road network, using a time-dependent traffic assignment model (Verbas et al., 2018). The model outputs detailed link-level trajectories for all trips within the study region and records traveler-and-vehicle-level travel information, such as charging activities, trip distance, ride request of fleet, etc. (Moawad et al., 2021).

Within this framework, both fleet and personal EVs are modeled as mobility agents whose actions are driven by agents' needs. Fleet EVs follow operator-level strategies for trip assignment, repositioning, and maintenance. Ride requests are matched to available vehicles using a zone-based heuristic that checks detour distance, range feasibility, and service-quality constraints, such as maximum pickup delays (Gurumurthy et al., 2020). The model continuously updates each fleet EV's state of charge (SoC) and evaluates whether upcoming requests are feasible. A vehicle is assigned to new trips only when it SoC exceeds a minimum threshold and sufficient for the predicted energy demand of the next ride (Gurumurthy et al., 2021). Personal EVs follow similar vehicle-level charging logics but are aligned with daily activity schedules and home-work patterns of their corresponding agents.

POLARIS enables a more realistic representation of agents' activities, mobility needs, and fleet operations. Key operational metric, including vehicle-miles traveled (VMT) and charging patterns, and regional configuration are exported to the day-ahead optimization model in CPLEX. The simulation-optimization integration ensures that V2G participation remains operationally feasible, maintaining fleet service quality and respecting personal activity schedules while evaluating alternative smart charging strategies.

2.2 Discharge Potential from Personal EVs

Before incorporating personal/HH EVs into the day-ahead optimization framework, their maximum feasible discharge potential at each hourly time step is quantified. Following the eligibility criteria of Metcalfe et al (2025), only HH EVs that are either already parked at home or have a scheduled activity destination of home, with access to home chargers and equipped with V2G-compatible hardware, are eligible to participate in V2G operations. In addition, an EV's SoC must exceed a predefined threshold to ensure basic mobility needs are preserved. Variables used to identify eligible HH EVs for V2G participation and to quantify their discharging potentials are summarized in Table 1, along with example assumptions.

Table 1. Variables for V2G Eligibility and Discharging Potential of HH EVs

Symbol	Description
t	Simulation time step, $t \in [0, T]$
$I(t)$	Set of personal EVs eligible for V2G at time step *t*; $i \in I$
$E_{is}^{max}(t)$	Individual maximum discharge capacity of HH EV *i* during time step *t*
$SoC_i(t)$	SoC of HH EV *i* at the beginning of time step *t* (e.g., 40%)
SoC^{min}	Minimum allowable SoC for V2G discharge (e.g., 30%)
P_i	Discharge power of HH EV i's home charger (e.g., 7 kW)
Δt	Expected duration of the next discharge interval (e.g., 0.25 hour)
B_i	Battery capacity of HH EV i (e.g., 74 kWh)
$E_{Is}^{max}(t)$	Aggregate HHEV discharge capacity (kWh) at time step *t*

The set of eligible EVs at each time step is denoted as $I(t)$. For each eligible personal EV $i \in I(t)$ at time step *t*, the maximum feasible energy (kWh) available for discharging over Δt time interval, $E_{is}^{max}(t)$, is calculated as Eq. (1). It takes the minimum of two values: the energy deliverable at the home charger's discharge power rate P_i over Δt period, and the usable battery energy, given by the product of EV's battery capacity (in kWh) B_i and the difference between EV's current $SoC_i(t)$ and a predefined minimum SoC allowed for discharging, denoted as SoC^{min}. This ensures the discharge is limited by both charger power constraints and available battery energy above the minimum SoC threshold.

$$E_{is}^{max}(t) = \min\{P_i\, \Delta t, \left(SoC_i(t) - SoC^{min}\right)B_i\} \tag{1}$$

The aggregate discharging potential across all participating HH EVs at time step *t*, denoted $E_{Is}^{max}(t)$, is then obtained by summing the individual discharge capacities, as shown in Eq. (2), yielding the aggregate maximum feasible energy to sell from personal EVs.

$$E_{Is}^{max}(t) = \sum_{i \in I} E_{is}^{max}(t) = \sum_{i \in I} \min\{P_i \, \Delta t, \left(SoC_i(t) - SoC^{min}\right) B_i\} \tag{2}$$

This aggregate value represents the total feasible discharging energy from participating HH EVs and serves as an upper bound in the following smart charging optimization model.

2.3 Coordinated Day-ahead Smart Charging Model

This work integrates the day-ahead optimization framework developed in Su et al. (2026) with the POLARIS agent-based simulation platform to model coordinated smart charging between the commercial EV fleet and other EVs, including firm-owned and personal ones. In this work, HH EVs are used as representative personal EVs within POLARIS, although the framework can be extended and applied to various privately owned EV types.

The integrated model operates on a rolling 24-hour planning horizon. At each simulation hour, time-varying inputs (such as electricity prices, pollutant intensity, grid load, and grid committed capacity) are updated so that the current hour becomes the start of the next 24-hour window. The optimization module then re-solves energy transaction schedules in this horizon at each 15-minute timestep, using the most recent simulated fleet and HH EV states. The objective is to minimize the total energy-related costs over the entire simulation day while maintaining fleet service reliability. Cost components include fleet electricity cost, health-damage cost, V2G revenues earned by both fleet and HH EVs, battery degradation costs, and large penalties for deviations from the target end-of-day fleet SoC to support multi-day operational continuity. For example, when the simulation reaches 6 AM on the simulation day, the model optimizes hourly energy decisions for the subsequent 24-hour period, from 6 AM that day to 6 AM the following day, ensuring that (dis)charging decisions align with upcoming operational needs.

This design enables flexible evaluation of several charging strategies, including LMC, V1G, fleet-only V2G (Fleet-V2G), and Combined-V2G involving both fleet and HH EVs. This framework creates a two-way feedback loop where optimization informs EV behavior and activity plans, while the simulation captures operational dynamics such as travel demand, network congestion, and spatial and temporal vehicle availability, and feeds the resulting system state back to the optimization step. Compared to methods that assume perfect adherence to optimized schedules and do not consider traffic or activity patterns, the proposed model captures dynamic feedback between optimization decisions and simulated system conditions, reflecting more realistic adjustments driven by real-time simulated fleet conditions. Figure 1 shows the overall workflow.

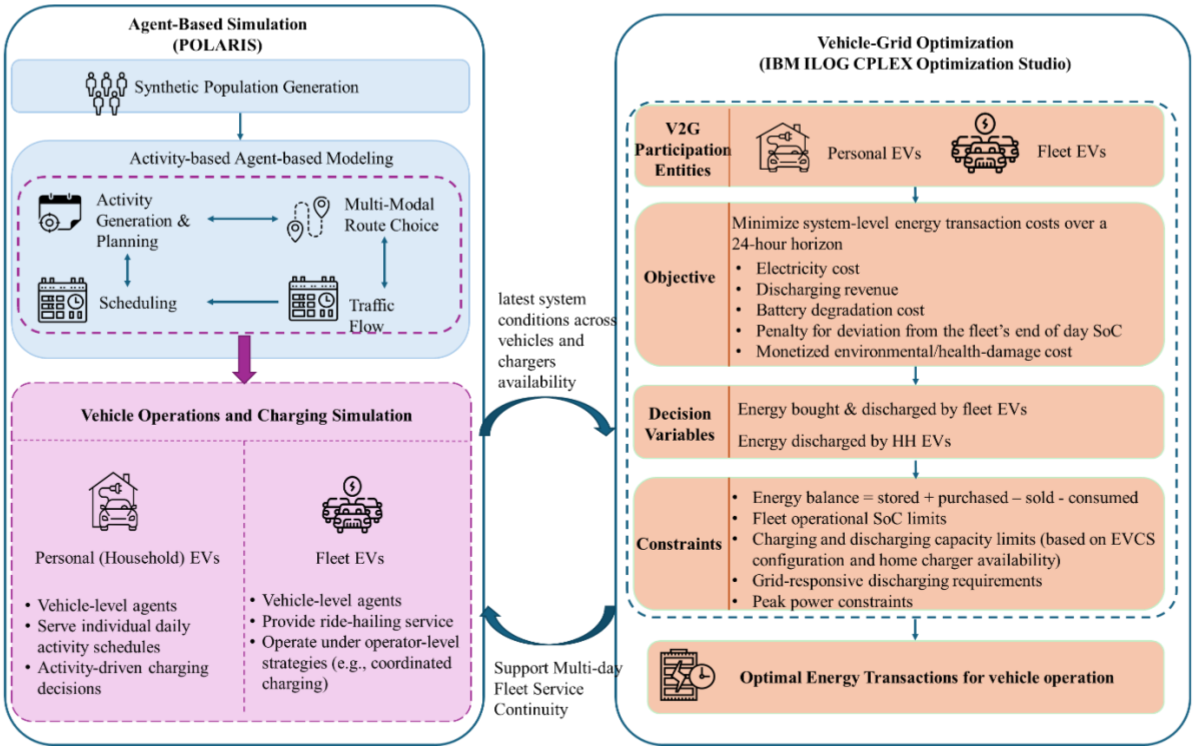

Figure 1. Simulation-Optimization Framework for the Coordinated Charging Model

The optimization determines three hourly decision variables: fleet charging and discharging energy, and aggregated HH EV discharging energy. Notably, HH EV charging is not modeled as a decision variable, reflecting the reality that utility operators typically lack the authority to control residential charging behavior driven by individual commuting needs and home charging preferences. To implement the optimized energy transactions, a within-day dispatch optimization model from Dean et al. (2023) is adopted to plan and assign tasks to fleet vehicles, including (dis)charging, maintenance, passenger service, and repositioning.

3. CASE STUDY

Austin, Texas, is selected as the case study area, considering its rapid EV adoption, active development of automated EV fleets, and supportive charging infrastructure network. Austin is leading the statewide transition to electric mobility, accounting for roughly 19.13% of all EVs registered in Texas and holding the highest EV share among major Texas metropolitan areas, with 5.13% of all registered vehicles being electric as of December 2025 (Dallas-Fort Worth Clean Cities, 2025). The region continues to advance its electrification goal through the Austin Climate Equity Plan, which targets 40% of all VMT to be electric by 2030 (City of Austin, 2020). Support for this transition is reflected in the city's expanding public and private charging-network development and local utility incentive program. According to ChargePoint's national scoring of EV-supportive regions, which considers population, EV adoption, and supplied EVCS, ranks Austin 4th nationwide, following the San Francisco Bay Area, Seattle, and San Diego (ChargePoint, 2025). Austin Energy, the region's primary utility, offers rebates for charger purchase or installation, and runs the Power Partner EV program, which enables the utility to remotely adjust enrolled Level 2 chargers or qualified vehicles during periods of high system demand to help manage grid loads (Austin Energy, 2025).

Austin has also emerged as an early deployment city for automated electric ride-hailing services. By the end of 2025, Waymo operated over 100 SAEVs across a roughly 90-square-mile service area, while Tesla launched a pilot robotaxi fleet of about 30 vehicles with plans to expand to other metropolitan markets (Campbell, 2025b; Lambert, 2025). The factors mentioned above highlight Austin's suitability for examining integrated EV charging and grid-interactive operations.

Within this context, this study models regional travel activity across the 6-county Austin metropolitan region, covering approximately 5,300 square miles with 2,160 zones. This large-scale configuration provides a representative setting for evaluating coordinated (dis)charging and grid-interactive behaviors of personal EVs and EV fleets under time-varying electricity market and grid conditions.

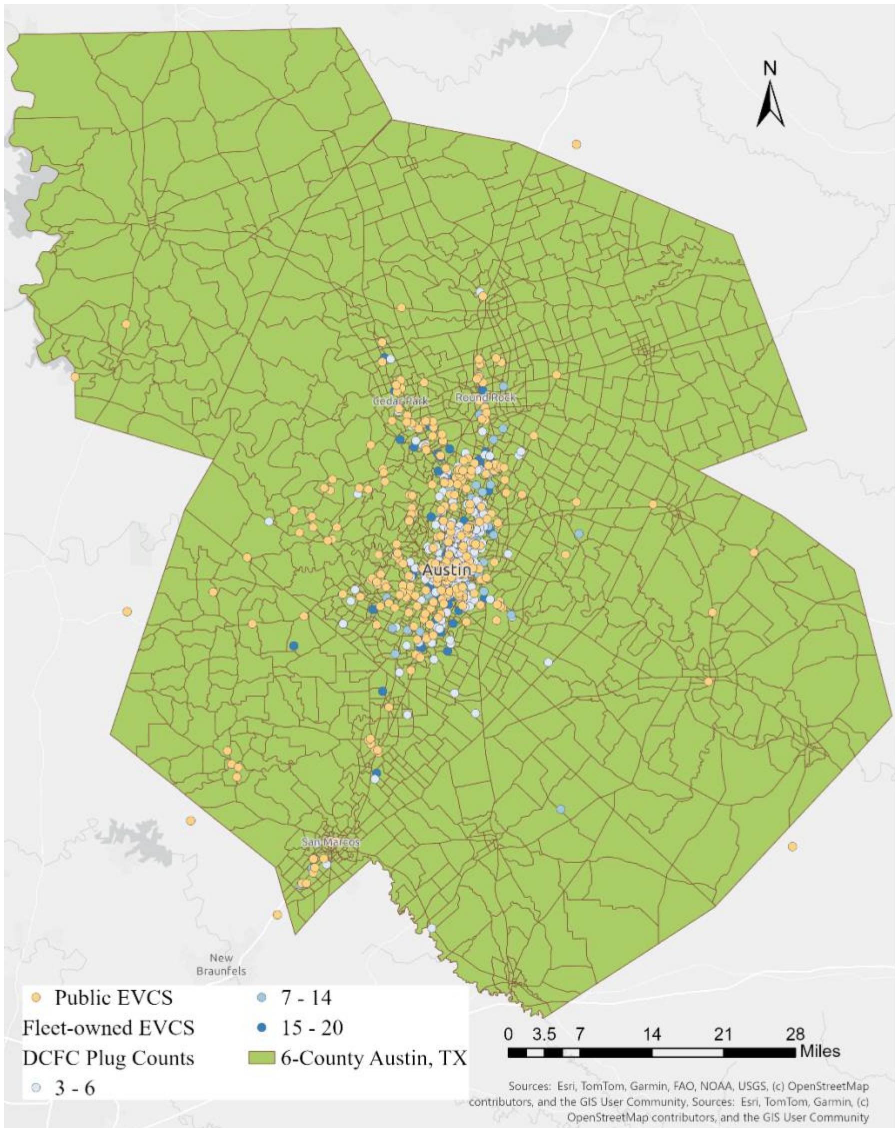

Figure 2. Austin 6-county Region, TX, along with EVCS distribution

A ride-hailing fleet of 15,000 homogenous SAEVs is simulated within the Austin 6-county region to serve traveler demand and ride-hailing requests. Each SAEV is equipped with a 90-kWh battery that provides about a 300-mile range under full capacity. To reflect V2G-related energy demands, battery-health considerations, and degradation associated with frequent charging cycles, the operational SoC is restricted between 10% and 100%. This yields an effective usable range of around 270 miles once fully recharged. The ride-hailing fare structure includes a \$2 base pickup fee, \$0.90/mile, and \$0.25/minute. To encourage ride sharing, travelers who opt for shared rides receive a 40% fare discount on the $0.54 per-mile and $0.15 per-minute charges.

The SAEV fleet and personal EVs are supported by a strategically deployed charging-station network that integrates both public and fleet-owned/private charging infrastructure. Prior studies have highlighted the benefits of a public-private (PP) EVCS strategy (Su et al., 2024; Su et al., 2025), which opens fleet-owned charger access for broader EV users. This approach enables charger-sharing during use and makes the fleet eligible for public incentives, thus improving charger use, lowering required investment, and reducing charging delays. Figure 2 shows the spatial distribution of all public EVCS based on Alternative Fueling Station Locators (Department of Energy, 2025c), along with the sited PP EVCS that serve personal EVs and the SAEV fleet within the study region. On average, the Austin 6-county region contains approximately one PP EVCS per 10 square miles, with each station housing about 7.8 DCFC plugs rated at 120 kW. The SAEV fleet is assumed to rely exclusively on DCFC chargers for both charging and discharging to support high-use and reduce charging downtime. This assumption aligns with the current industry of minimizing downtime to remain competitive in the ride-hailing market (NovaCharge, 2024). Personal EVs, in contrast, can use either DCFC or Level 2 chargers at the charging stations or Level 2 home chargers; however, their discharging activities are limited to home chargers. Only HH EVs with access to home charging are considered eligible for participation in fleet-plus-household V2G operations.

Given that V2G adoption typically requires costly charging infrastructure upgrades and advanced bidirectional chargers, which can limit large-scale household participation, this study assumes a 40% participation rate based on Li et al. (2024). Together, these HH EVs and EV fleets form the set of grid-interactive entities evaluated in the smart charging and related operational behaviors within the study area.

3.1 Electricity Market and Grid Conditions

The Electric Reliability Council of Texas (ERCOT) manages the only fully independent electricity grid in the United States and coordinates energy supply for most of Texas. It covers roughly 90% of the state's electric demand and includes major metropolitan areas such as Austin, San Antonio, Houston, and Dallas-Fort Worth (ERCOT, 2025a). For wholesale market settlement, ERCOT is divided into multiple load zones, including Austin Energy's service area.

Within this system, the analysis incorporates time-varying electricity prices to capture the economic conditions relevant to EV charging and V2G operations. The time-of-use (TOU) fare structure is referred to the Austin Energy Electric Tariff (City of Austin, 2025), which uses a lower rate of $26.77/MWh during late-night and early-morning hours (10 PM to 7 AM), and a mid-peak rate of $41.18/MWh during morning and afternoon (7 AM to 5 PM), and an evening peak rate of $140/MWh between 5 PM and 10 PM.

To characterize real-time pricing, hourly locational marginal prices (LMPs) for the Austin Energy load zone were obtained from ERCOT from November 2024 through October 2025 to enable a year-round analysis (GridStatus, 2025a). Following classification methods used in prior studies (Zhang and Chen, 2020; Dean et al., 2023; Su et al., 2025), hourly LMP observations were sorted into four categories based on price variability and deviation patterns: Peak, No-Peak, Off-Peak, and Spike, with corresponding shares of 61.3%, 6.2%, 6.2%, and 26.3%, respectively. This grouping highlights the diversity of real-time electricity prices in ERCOT and enables the model to reflect both normal and extreme system conditions. Figure 3 shows each LMP category, with navy blue curves indicating daily LMP by hour under that category and a red curve representing the category-level average.

System-level grid conditions were evaluated using ERCOT's real-time grid load and committed generation capacity records for the same period, ensuring consistency with the LMP datasets (GridStatus, 2025b & 2025c). Since ERCOT's system-level data are significantly larger in scale than the city-level setting of this study, grid capacity and load were rescaled to reflect the grid conditions at the City of Austin. This scaling is based on the ratio between Austin Energy's peak demand record of 3.07 GW in August 2023 and ERCOT's statewide peak of 85.508 GW during the same period (Arnim et al., 2024; ERCOT, 2025b). Planning reserve margins are commonly used to ensure planned generation and capacity are sufficient to meet electricity demand, and recommendations from the North American Electric Reliability Corporation (NERC) generally set this buffer between 10% and 20% (Lawson, 2022). However, ERCOT's own reserve forecasts indicate its reserve needs are often above the typical planning range, such as a forecasted margin of 22.2% for summer 2023, 29.4% for summer 2024, and rose to 46.7% for summer 2025 due to delayed resource support (ERCOT, 2022; ERCOT, 2023). To reflect these planning considerations and to account for the increasing electricity demand introduced by scalable EV fleet operations, this study uses a 21% reserve-margin threshold to identify grid-stress conditions. This ensures that V2G activation aligns with the grid-stress period, supporting the grid while respecting vehicles' availability and flexibility to meet personal planned daily travel schedules.

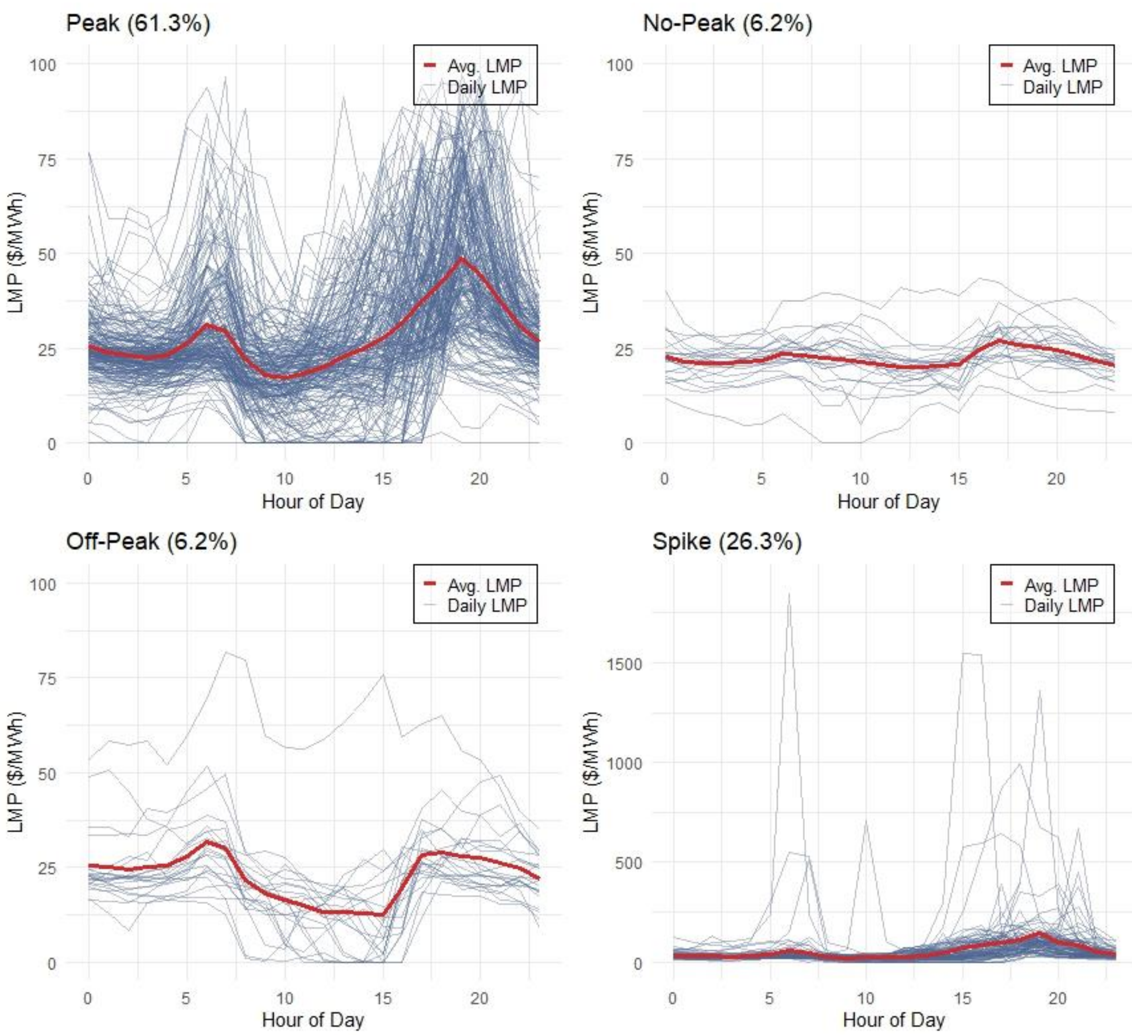

Figure 3. Categorized Hourly LMP Tariffs for the ERCOT Austin Energy Load Zone

3.2 Pollutant Data

Power-sector pollutant outputs are evaluated using publicly available, high-resolution datasets. Hourly average emission factors (in lb/MWh) for CO_2, NO_x, and SO_2 in the ERCOT region are obtained from a dataset, developed by the National Renewable Energy Laboratory (2023) (recently renamed the National Laboratory of the Rockies) and compiled from federal sources, including the Environmental Protection Agency. These data provide regionally resolved, hourly profiles of generation-related pollutant intensities.

To monetize pollutant-related externalities within the optimization framework, this study adopts representative marginal damage valuations reported by Dean et al. (2023). Pollutant-specific damage costs per metric ton are set at \$140/ton for CO_2, \$4,750/ton for NO_x, and \$16,600/ton for SO_2, based on recent estimates from the U.S. Department of Transportation (2025) and Rhodes (2023). These values are used to translate pollutant intensity factors into corresponding economic cost signals, enabling the evaluation of system-level economic outcomes and associated health impacts.

4. RESULTS AND DISCUSSIONS

4.1 SAEV Fleet Performance under Alternative Charging Strategies

The impacts of alternative charging strategies on SAEV fleet service outcomes are summarized in Table 2. Under the LMC, each SAEV averagely serves around 30 passenger-trips per day with a median passenger wait time of nearly 5 minutes. After introducing unidirectional coordinated charging (V1G), each SAEV serves roughly 31 ride requests per day, while median wait times remain at a similar level (4.8 minutes). Average daily vehicle-mile traveled (VMT) per SAEV rises from 255 miles under uncontrolled charging to roughly 285 miles under smart charging strategies, accompanied by a higher empty VMT share at about 34%. These changes reflect additional repositioning and charging-related movements associated with aligning vehicle availability with charging opportunities.

Enabling bidirectional charging for fleet EVs (Fleet-V2G) and further incorporating HH EV participation (Combined-V2G), introduces minor variations relative to V1G across key fleet-service indicators. Across most pricing structures, median passenger wait times remain below 5 minutes, while average daily passenger-trips served stay near 31 trips per SAEV. Differences in wait times, passenger-trip served, and VMT remain limited, suggesting that strategically scheduled discharging does not significantly affect ride-hailing service performance. These findings reflect the designed simulation-optimization framework, where charging and discharging decisions remain constrained by operational requirements, ensuring that energy transactions do not disrupt mobility services.

Table 2. Fleet Service Performance under Alternative Pricing and Charging Strategies

Electricity Price	Strategy	Median Passenger Wait Time (minutes)	Avg. Daily Person-trips Served per SAEV	Avg. Daily VMT per SAEV (miles)	Avg. Fleet Empty VMT share (%eVMT)	Median Travel Distance per SAEV Trip (miles)	Avg. Fare per Ride Request (\$)	Avg. Daily Passenger-service Revenue per SAEV (\$)
Last-minute Charging (LMC)		4.90	30.29	254.77	29.44	11.31	13.64	413.24
Spike	V1G	4.72	30.82	285.73	34.16	11.27	13.84	426.56
	Fleet-V2G	4.80	30.70	283.58	33.78	11.36	13.90	426.74
	Combined-V2G	4.82	30.67	283.23	33.92	11.39	13.91	426.74

TOU	V1G	4.87	30.72	284.53	33.79	11.49	13.97	429.20
	Fleet-V2G	4.55	30.97	284.04	34.15	11.15	13.74	425.50
	Combined-V2G	4.63	31.05	286.76	34.41	11.31	13.81	428.75
Peak	V1G	4.77	30.73	284.55	33.91	11.29	13.88	426.43
	Fleet-V2G	4.80	30.70	283.58	33.78	11.36	13.90	426.74
	Combined-V2G	4.78	30.89	286.13	34.16	11.33	13.86	428.20
No-Peak	V1G	4.77	30.68	284.86	33.74	11.35	13.95	427.90
	Fleet-V2G	4.77	30.63	284.02	33.91	11.36	13.92	426.31
	Combined-V2G	4.72	30.94	288.17	34.60	11.36	13.88	429.47
Off-Peak	V1G	4.80	30.84	284.18	33.62	11.39	13.91	428.93
	Fleet-V2G	4.80	30.70	283.58	33.78	11.36	13.90	426.74
	Combined-V2G	4.82	30.67	283.23	33.92	11.39	13.91	426.74

Passenger-service revenue also remains relatively stable across smart charging strategies, generally ranging from approximately \$425 to \$429/SAEV/day. The highest passenger-service revenue is observed under the No-Peak Combined-V2G scenario (\$429/SAEV/day), followed closely by the TOU-based V1G and Combined-V2G cases. These results indicate that the proposed energy-cost-aware V2G framework can strategically coordinate charging and discharging decisions while maintaining broadly consistent ride-hailing service performance.

4.2 EV Charging and Discharging Profiles and Grid-support Response

Hourly EV energy transaction patterns change as the level of charging coordination and grid interaction increases. Figure 4 presents the temporal distribution of fleet charging (grey bars) and discharging (yellow bars), and HH EV discharging (red bars), along with grid profiles. Under LMC, charging remains broadly distributed throughout the daytime. Since charging decisions are primarily driven by vehicle operational needs rather than electricity prices or grid conditions, charging demand remains substantial during periods that may coincide with elevated grid stress.

Introducing coordinated charging through V1G strategically reshapes the temporal distribution of fleet charging demand. Across pricing structures, roughly 36% of total daily fleet charging under V1G occurs during late-night hours (12 to 2 AM), while another 21% to 28% concentrates during mid-day hours (11 AM to 1 PM). In contrast, charging between 6 and 8 AM is almost eliminated. Evening charging between 6 and 9 PM also falls by approximately 26% to 34% relative to LMC, accounting for up to 20% of daily charging demand. These patterns indicate substantial temporal redistribution of charging demand toward lower-cost and lower-stress periods when electricity prices and grid conditions are generally more favorable.

Transitioning from V1G to Fleet-V2G preserves the observed charging pattern while introducing targeted, grid-responsive discharging. Fleet discharge remains temporally concentrated and occurs only when both grid-support needs and economic conditions justify participation. As shown in Figure 4, fleet discharging under Spike and TOU pricing becomes most pronounced during evening peak periods (roughly 7 to 11 PM), closely aligning with higher electricity prices and grid demand period. In contrast, fleet discharging under No-Peak and Off-Peak pricing remains relatively limited, reflecting weaker arbitrage incentives after accounting for battery degradation and operational constraints. These results suggest that electricity pricing plays a key role in shaping the timing and intensity of V2G participation, driving energy-cost-aware coordinated behavior. Pricing structures with stronger intra-day variation amplify load shifting and more strongly discourage charging, or justify discharging, during high-price evening periods.

Allowing HH EV participation through Combined-V2G further expands both the capacity and temporal coverage of grid support. Relative to Fleet-V2G, fleet charging and discharging patterns remain largely unchanged, while HH EVs provide additional distributed discharge across broader time windows, particularly during evening periods when fleet availability becomes more constrained by ride-hailing service obligations. Under Spike pricing, HH EV discharge extends from the afternoon through late evening, while TOU and Peak pricing also show concentrated HH EV support during evening peak periods. This distributed support complements fleet-side V2G participation and broadens system-level grid responsiveness. Although HH EV discharge remains relatively small in magnitude, these findings demonstrate the potential for scalable distributed grid support as EV adoption and V2G-capable infrastructure continue to expand.

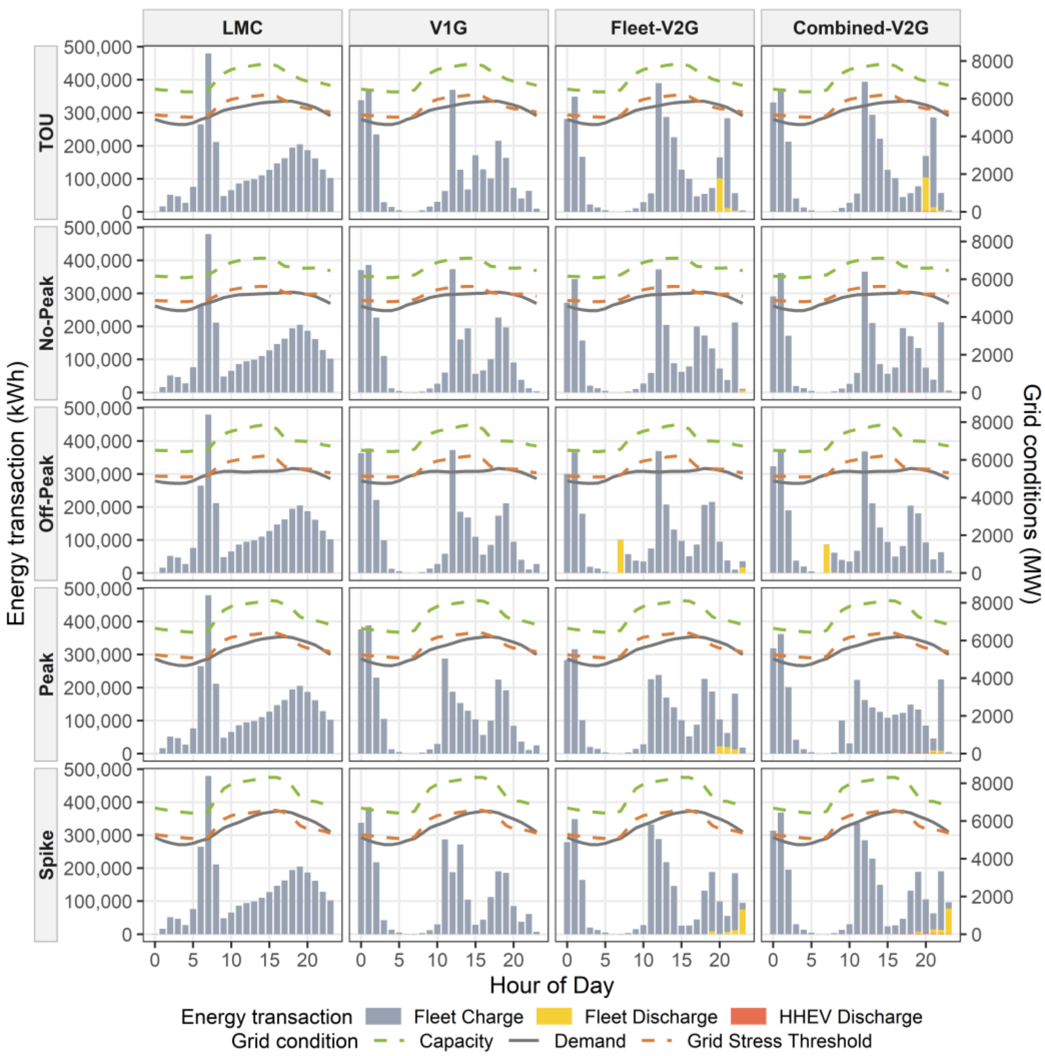

Figure 4. Hourly EV Energy Transactions and Grid Conditions by Charging Strategies and Pricing

Figure 4 reveals a clear progression in charging and discharging behaviors as the level of coordination increases. LMC follows operational charging needs and remains insensitive to electricity prices and grid

Figure 4 reveals a clear progression in charging and discharging behaviors as the level of coordination increases. V1G introduces substantial load shifting by reallocating charging away from grid-stress and high-cost periods. Fleet-V2G preserves these coordinated charging patterns while adding targeted fleet-based discharge support during grid-stress periods. Combined-V2G further enhances grid responsiveness by incorporating distributed HH EVs into the response pool, expanding both the capacity and temporal flexibility of discharge support, particularly under electricity prices with strong intra-day variation.

4.3 Pollutant Outputs and Health-damage Implications

Pollutant outputs and monetized damage costs under alternative charging strategies and five electricity pricing structures are summarized in Table 4. Since differences in fleet activity (e.g., daily VMT per SAEV) are observed across scenarios, environmental impacts are evaluated using both per-SAEV and VMT-normalized intensity metrics. HH EVs contributions are evaluated at the aggregate levels, since per-vehicle impacts remain relatively small while system-level impacts remain meaningful. In addition to CO2 outputs, monetized CO2 and pollutant-related damage costs (including those associated with NOx and SO2) are also evaluated to capture broader societal implications associated with smart charging strategies.

Smart charging strategies notably reduce both emissions and associated monetized damages relative to the LMC (about 65 kg CO2/SAEV/day and 0.25 kg CO2/VMT). Across the five pricing structures, V1G lowers net daily CO2 outputs to approximately 52 to 55 kg/SAEV/day. The CO2 intensity also falls by 24% to 28% (reaching about 0.18 to 0.19 kg/VMT) relative to LMC. These reductions indicate that coordinated charging potentially improves the temporal alignment between charging demand and lower-emission grid periods. As shown in Section 4.2, V1G strategically shifts charging away from late-afternoon hours when electricity prices and health damage rates are typically higher, toward mid-day windows that often coincide with lower grid stress and greater renewable energy availability. The strongest V1G performance is observed under Spike and TOU pricing, where net daily CO2 outputs decline to roughly 52 kg/SAEV/day and total monetized damage costs fall to an average of $11.82/SAEV/day.

Fleet-only V2G provides additional environmental benefits through strategically timed bidirectional discharge. Across all pricing schemes, Fleet-V2G achieves the lowest per-SAEV and VMT-based emission metrics, along with the lowest monetized damage costs among the evaluated strategies. Relative to V1G, Fleet-V2G further reduces net daily CO2 outputs by roughly 1 to 5 kg/SAEV/day, lowering net emissions to below 50 kg/SAEV/day across most pricing structures. Similarly, net CO2 intensity falls further to below 0.18 kg/VMT. Fleet-V2G also achieves the lowest total monetized damage costs, averaging below $11/SAEV/day across pricing structures (including approximately $7/SAEV/day from CO2 and $4/SAEV/day from pollutant-related damages). The strongest Fleet-V2G performance occurs under TOU and Spike pricing, where stronger intra-day price variation creates greater opportunities for strategically timed discharging during high-value and high-stress periods. Under TOU pricing, Fleet-V2G achieves the lowest net daily CO2 output (48.50 kg/SAEV/day), while under Spike pricing it achieves the lowest VMT-normalized CO2 intensity (0.17kg/VMT).

Allowing HH EV participation through Combined-V2G expands the available discharge resource and temporal flexibility, enabling larger system-level environmental benefits under favorable pricing structures. Relative to Fleet-V2G, Combined-V2G generally produces slightly higher per-SAEV and VMT-normalized emissions, although these metrics remain consistently below those observed under V1G. One possible explanation is that part of the environmental benefits become redistributed across EV groups after HH EV participation is introduced, with distributed HH EV discharge partially replacing fleet-based discharge activities under Fleet-V2G. Monetized health-damage costs follow patterns similar to those of the emission metrics, reaching an average of $11.41/SAEV/day.

Despite the slightly higher fleet-level emission metrics relative to Fleet-V2G, Combined-V2G generates substantial aggregate CO2 and pollutant savings through distributed HH EV participation, particularly under electricity prices with strong intra-day variation. The largest HH EV-related CO2 savings occur under Spike pricing, where HH EV participation contributes roughly 4,170 kg/day of aggregate CO2 savings, followed by Peak (2,524 kg/day) and TOU pricing (2,274 kg/day). In contrast, HH EV-related savings remain much smaller under flatter pricing structures, falling to approximately 1,396 kg/day under No-Peak pricing and only 474 kg/day under Off-Peak pricing. These results suggest that distributed HH EV participation becomes more effective when price signals create strong incentives for discharging. Under flatter and lower-value price signals, weaker arbitrage opportunities are insufficient to offset V2G-related costs, thereby limiting HH EV participation and resulting in smaller or negligible air-quality benefits.

The above results highlight that realized gains depend on the alignment between discharge opportunities and high-pollutant or high-value grid periods. Coordinated charging improves societal outcomes primarily through temporal shifting of energy use. V1G represents a first step by incorporating health-damage considerations into charging decisions. Fleet-V2G further enhances these benefits through strategically timed bidirectional discharge, while Combined-V2G expands system-level gains by incorporating distributed HH EVs into the response pool.

Table 4. Carbon Impacts Across Charging Strategy and Electricity Price

Electricity Pricing	Strategy	Daily CO_2 per SAEV (kg)	Daily CO_2 Reduction per SAEV (kg)	Net Daily CO_2 per SAEV (kg)	Net CO_2 Intensity per SAEV (kg/VMT)	Daily CO_2 Savings by HHEV (kg)	Daily Net CO_2 Damage Cost per SAEV ($)	Daily Net Pollutant Damage Cost per SAEV ($)
Baseline	LMC	64.56	0.00	64.56	0.25	0.00	9.04	4.75
Spike	V1G	52.49	0.00	52.49	0.18	0.00	7.35	4.23
	Fleet-V2G	51.24	2.24	48.99	0.17	0.00	6.86	3.94
	Combined-V2G	53.62	2.31	51.31	0.18	4170.48	7.18	4.15
TOU	V1G	52.45	0.00	52.45	0.18	0.00	7.34	4.20
	Fleet-V2G	51.32	2.83	48.50	0.17	0.00	6.79	3.96
	Combined-V2G	54.42	2.81	51.60	0.18	2273.72	7.22	4.24
Peak	V1G	54.67	0.00	54.67	0.19	0.00	7.65	4.43
	Fleet-V2G	50.25	1.29	48.96	0.17	0.00	6.85	3.86
	Combined-V2G	53.47	0.35	53.12	0.19	2524.39	7.44	4.27
No-Peak	V1G	54.40	0.00	54.40	0.19	0.00	7.62	4.38
	Fleet-V2G	50.79	0.13	50.65	0.18	0.00	7.09	4.00
	Combined-V2G	51.48	0.00	51.48	0.18	1396.30	7.21	4.08
Off-Peak	V1G	53.89	0.00	53.89	0.19	0.00	7.54	4.35
	Fleet-V2G	51.75	2.58	49.17	0.17	0.00	6.88	3.92
	Combined-V2G	52.99	1.92	51.06	0.18	473.87	7.15	4.10

4.4 Fleet-level Economic Implications

Daily per-SAEV economic outcomes under alternative charging strategies are summarized in Figure 5. The economic metrics include daily electricity cost, passenger-service operating cost and profit, and overall fleet-operator profit. Passenger-service profit is calculated as passenger-service revenue minus operating cost, while fleet-operator profit additionally accounts for electricity costs, discharging revenues, and battery degradation costs associated with V2G participation. Averaged across the five tariff pricings, daily fleet-operator profit increases from $298.22/SAEV/day under LMC to $305.93 under V1G, $306.20 under fleet-V2G, and $306.10 under Combined-V2G, corresponding to average gains of 2.6%, 2.7%, and 2.6%, respectively. These results suggest that coordinated charging consistently improves fleet-level economic outcomes, while the incremental value of bidirectional V2G remains more sensitive to electricity price structures and discharge opportunities.

Under V1G, passenger-service profit remains consistently high, generally ranging from approximately $311 to $314/SAEV/day, representing gains of roughly $4 to $7/SAEV/day relative to LMC. Fleet-operator profit under V1G ranges from approximately $302 to $310/SAEV/day, with the strongest performance observed under Off-Peak (about $310/SAEV/day) and No-Peak pricing ($308/SAEV/day). These gains are accompanied by notable reductions in electricity costs, particularly under Spike and TOU pricing (by about $4/SAEV/day), where coordinated charging lowers average daily electricity costs. As discussed in Section 4.2, these economic improvements primarily reflect the temporal redistribution of charging demand away from high-price periods toward late-night and midday windows with more favorable electricity prices and grid conditions.

Fleet-V2G further improves profitability relative to V1G under Spike, TOU, and Peak pricing, although the incremental gains remain relatively modest. The strongest Fleet-V2G performance occurs under Peak pricing, where fleet-operator profit increases by $2.29/SAEV/day to $308.21/SAEV/day, supported by relatively low electricity costs ($4.84/SAEV/day) and high passenger-service profit ($313.02/SAEV/day). Fleet-V2G also performs strongly under Spike pricing, supported by lower electricity costs and additional discharge value during high-price periods. In contrast, under No-Peak and Off-Peak pricing, Fleet-V2G reduces operator profit relative to V1G by $1.09 and $1.83/SAEV/day, respectively. These results suggest that when price variation is weak, or when low-price charging periods are already broadly available, bidirectional discharge does not necessarily generate additional fleet-level economic benefits after accounting for operational and battery-related costs.

Combined-V2G does not uniformly increase fleet profitability beyond fleet-only V2G. It performs best under Peak pricing, where Combined-V2G reaches the highest profit among all scenarios at $308.12/SAEV/day, representing a $1.27/SAEV/day increase over Fleet-V2G. Under TOU and Off-Peak pricing, Combined-V2G remains close to Fleet-V2G in terms of profitability. In contrast, Combined-V2G lowers fleet profit relative to Fleet-V2G under No-Peak pricing, where profit declines by $1.35/SAEV/day. These results suggest that expanding V2G participation beyond the fleet can maintain or provide additional value under high-variation pricing structure, but does not guarantee higher fleet profit when price signals are flatter or when household discharge potentially substitutes for fleet-side arbitrage opportunities.

Overall, the economic results indicate that fleet profitability is primarily shaped by passenger-service profit, while electricity costs, discharge revenues, and degradation costs remain small but still meaningful. V1G consistently lowers electricity costs and improves operator profit. However, the incremental value of V2G is more sensitive to the tariff structures. Fleet-only and Combined-V2G provide the obvious benefits when electricity prices show strong evening peaks or sharp intra-day variation, while their advantages diminish under flatter pricing.

Figure 5. Per-SAEV Daily Economic Components Across Electricity Prices and Charging Strategies

Note:
[1] Daily passenger-service profit per SAEV is calculated as: Daily passenger-service revenue per SAEV - Daily operating cost per SAEV
[2] Daily Profit per SAEV = Daily passenger-service profit per SAEV- Daily electricity cost per SAEV + Daily discharging revenue per SAEV – Daily battery discharging degradation cost per SAEV

4.5 Comparative Implications of Coordinated Charging Strategies

The four charging strategies represent increasing levels of energy coordination and grid interaction, each offering distinct advantages depending on technical readiness, tariff structures, and EV participation scale. Across the evaluated scenarios, coordinated charging consistently improves temporal alignment between EV energy transactions, electricity prices, grid-stress conditions, and pollutant-related damage costs, while maintaining broadly comparable ride-hailing service outcomes.

Uncontrolled charging represents typical charging behavior in which charging follows vehicle energy needs without responding to electricity prices, pollutant intensity, or grid-stress conditions. Coordinated charging through V1G strategically reshapes charging demand by shifting charging toward lower-cost and lower-stress periods. This temporal redistribution produces most of the realized economic and environmental gains observed across the coordinated strategies. Since V1G does not require bidirectional charging infrastructure, it represents a practical near-term strategy for large-scale smart charging deployment when V2G infrastructure is limited or costly.

In contrast, Fleet-V2G and Combined-V2G require additional bidirectional charging capability, resulting in higher upfront costs than conventional chargers. Although the incremental vehicle-side upgrade for V2G compatibility is relatively modest, typically estimated at $200 to $400 per vehicle for onboard power electronics and control modules (Steward, 2017), the primary economic barrier is associated with V2G-capable charging infrastructure. As of 2025, a bidirectional Level 2 charger typically costs about $1,200 to $2,500, while installation, permit, utility interconnection equipment, and electrical upgrades can increase total installed costs to roughly $1,700 to $4,000 per charger (Shop Energy Prices, 2025). Although these costs are expected to decline as EV adoption expands and charging technologies mature, early deployment may remain constrained in the near term.

For fleet operators, V2G deployment often involves higher-power DCFC infrastructure capable of supporting large-scale fleet (dis)charging operations. Conventional 50-kW DCFC systems commonly cost around $4,000 to $10,000 per charger, while V2G-capable DCFC chargers can increase costs to between $5,000 and $15,000 per charger depending on charging power, interconnection requirements, and communication modules (Shop Energy Prices, 2025). For comparison, standard residential Level 2 chargers typically cost about $400 to $800 per unit, whereas bidirectional V2G chargers generally cost $1,200 to $2,500, with total costs ranging from approximately $1,700 to $4,000 after accounting for permit, installation, and utility interconnection equipment (Shop Energy Prices, 2025). Fleet operators deploying large numbers of V2G chargers may benefit from economies of scale through bulk-purchase discounts (approximately 10% to 20%) and streamlined installation processes, reducing total installation costs to roughly $1,100 to $2,000 per charger for large fleet installations (Shop Energy Prices, 2025). Fleet-V2G becomes more practical once bidirectional equipment is available within fleet charging facilities, where centralized control enables coordination of vehicle availability with grid-response needs. This situation may resemble the early-stage charging infrastructure deployment, where higher upfront costs are initially absorbed by charging network providers or fleet operators before widespread household adoption. Fleet discharge during strategically selected hours provides grid-responsive flexibility and modest revenues beyond the economic gains achieved through V1G.

These cost considerations help explain the distinct practical roles of the evaluated charging strategies. V1G represents the most immediately deployable and scalable smart charging strategy because it requires minimal infrastructure upgrades while already capturing most of the realized economic and environmental benefits observed in this study. Fleet-V2G becomes increasingly attractive as bidirectional DCFC infrastructure matures within centralized fleet charging facilities, where coordinated vehicle scheduling and higher charger use can better justify additional investment costs. Combined-V2G offers the broadest long-term flexibility and distributed grid-support potential by incorporating HH EV participation, particularly strong intra-day price variation. As EV ownership expands and residential chargers become more advanced and widespread, broader participation from both fleet and HH EVs through Combined-V2G may unlock larger system-level benefits by combining centralized fleet coordination with distributed residential energy support. However, its large-scale deployment likely depends on continued reductions in bidirectional charger costs, wider availability of V2G-compatible vehicles, and stronger utility incentive programs that improve participation economics for HH EV owners. Overall, the results suggest a gradual pathway for increasingly coordinated charging development.

5. CONCLUSION

This study investigates how smart charging strategies can support electric mobility systems and power-grid operations under increasingly electrified and automated transportation systems. To address the gap between mobility dynamics and grid-responsive energy management, this research proposes an integrated simulation-optimization framework that embeds a rolling day-ahead V2G optimization model within the agent-based simulation environment. This design enables dynamic feedback between optimized (dis)charging decisions and evolving system states, capturing interactions across mixed EV groups. Using the Austin 6-county region as a case study, the analysis examined how alternative charging strategies influence fleet operations, charging demand, grid-support behavior, environmental impacts, and fleet-level economic outcomes under varying electricity pricing structures.

Results show that smart charging reshapes energy transactions temporal patterns without significantly disrupting SAEV fleet operations. V1G captures system-level benefits by strategically shifting charging away from high-cost and high-stress periods toward lower-cost and lower-stress periods (e.g., mid-day hours). Building on this, V2G strategies provide additional but modest benefits by enabling targeted discharging during grid-stress periods. These incremental gains arise from limited energy-arbitrage and grid-supports, and do not compromise fleet service performance. Combined participation of fleet and HH EVs expands discharge capacity and temporal flexibility, with HH EVs complementing fleet constraints and contributing to reductions in pollutant-related damages. However, the magnitude of these benefits depends on tariff structures, grid conditions, and vehicle availability.

Despite these contributions, several limitations remain. HH EV participation in V2G does not explicitly capture vehicle-level decision-making or behavioral heterogeneity. In the absence of a preference-based model, HH EV V2G participation is approximated using an exogenously specified rate. Thus, the modeled HH EV discharging reflects a capacity-driven estimate and should be interpreted as indicative of potential system-level contributions under favorable conditions, rather than precise predictions of realized household behavior. In addition, although the rolling optimization framework updates charging and discharging schedules using the most recent simulated system states, it does not explicitly forecast future-hour travel demand. Instead, recent travel demand is used as an approximation for near-term fleet service needs. Assumptions regarding V2G participation rates, charging infrastructure availability, and bidirectional charger deployment also do not fully reflect near-term market conditions, and the high upfront cost of V2G equipment may further limit widespread adoption. Importantly, Combined V2G implementation requires coordination among multiple agencies, including utilities, grid operators, fleet operators, charging service providers, thus introducing additional operational complexities.

Future research can address these limitations by incorporating stochastic optimization approaches to better capture uncertainty in both transportation and power systems. Integrating short-term travel demand forecasting into smart charging schedules would allow charging and discharging decisions to more directly account for anticipated fleet service needs. Vehicle-level behavioral models, particularly for HH EV participation and charging preferences, would further improve realism and policy relevance. Incorporating more detailed representations of infrastructure investment costs can also refine economic assessments. In addition, future work can explore scalable coordination mechanisms and incentive designs to support multi-agency participation, as well as extend the framework to other regions and market structures.

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7. AUTHORS STATEMENT

Lin Su: Writing – original draft, Resources, Investigation, Methodology, Data curation, Conceptualization. Krishna Murthy Gurumurthy: Writing – review & editing, Supervision, Methodology. Kara M. Kockelman: Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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