Multi-Stage Charging and Discharging of Electric Vehicle Fleets

Matthew D. Dean[a], Felipe de Souza[b], Krishna Murthy Gurumurthy[b], Kara M. Kockelman[a*]

[a] The University of Texas at Austin, Department of Civil, Architectural and Environmental Engineering, 301 E. Dean Keeton St, Stop C1761, Austin, TX, 78712-1076, USA

[b] Argonne National Laboratory, Transportation and Power Systems Division, 9700 S Cass Ave, Lemont, IL, 60439, USA

*Corresponding Author (kkockelm@mail.utexas.edu)

Abstract

Fleets of electric vehicles will likely shift electricity demand, and the effect of upstream charging emissions will come from generation sources that are dispatched in response. This study proposes a multi-stage charging and discharging problem to translate low-cost energy transactions into vehicle dispatch decisions. A day-ahead charging optimization problem minimizes electricity prices and marginal emissions damages, with energy transactions becoming targets in an optimization-based dispatch strategy for an on-demand shared autonomous electric vehicle (SAEV) fleet. The framework was tested for Austin, Texas, using an agent-based simulator. Fleets can schedule charging to lower daily power costs (averaging 15.5% per SAEV, or $0.79) while reducing health damages from generation-related pollution (2.8% per SAEV, or $0.43). Fleet managers can increase profits ($8 per SAEV per day) by adopting a multi-stage charging and discharging strategy that can serve more passengers per day than price-agnostic dispatch strategies.

Keywords: Fleet Charging; Fleet Management, Emissions, Simulation Optimization, Bidirectional Charging, Shared Autonomous Electric Vehicles

1. Introduction

To meet Paris Agreement climate goals, year-2050 transport-related CO_2 emissions must be 70% to 80% below 2015 levels (Jaramillo et al., 2021). Disruptive technologies that usher in low-carbon, high-accessibility transportation, like shared autonomous electric vehicles (SAEVs), could decrease such emissions. Electrified mobility will play a key role in the decarbonization of transportation and power sectors, which account for 52% of US greenhouse gas (GHG) emissions (US EPA, 2020). Emissions reduction will depend on feedstock sources dispatched to meet charging demand (Holland et al., 2022). Electric vehicle (EV) adoption also enables co-benefits to the power system in the form of deferred utility-scale energy storage, less renewable energy curtailment, and possibly mobile power sourcing. Under extreme events, local and regional power grids may rely on EVs to discharge electricity via vehicle-to-grid (V2G) equipment or simply delay charging. At scale, EVs could lower power sector emissions by displacing coal and natural gas power plants while providing grid resilience and reliability benefits.

Local utilities may implement managed charging strategies to incentivize or directly control EV charging (Dean and Kockelman, 2022b). The objective is to avoid increasing the peak load, which determines generation and transmission capacity investments. By shifting demand away from the peak or injecting power back into the grid during this time, total power-system costs can fall for all customers (Anwar et al., 2022). Managed charging may come via predetermined time-of-use (TOU) price signals (TOU tariffs) or (often highly variable) wholesale electricity prices. Fleet managers may have one or many power providers (depending on market rules and geofence coverage), each with different retail prices.

If permitted, fleets may decide to buy electricity from a renewable developer at a negotiated rate (via a power purchase agreement) and receive verifiable renewable energy credits (RECs) for each megawatt-hour (MWh) of energy generated. Cruise is the first SAEV company known to the authors to purchase enough RECs to offset the energy demand from its fleet vehicles (Grant, 2021). In other words, one megawatt hour (MWh) of emissions-producing electricity flowing to vehicles is replaced with one MWh of zero-emissions electricity. Instead of procuring zero-carbon power and RECs as the power is generated (i.e., bundled RECs), fleets could purchase a set of unbundled RECs to claim zero-carbon charging operations at any time.

California's Low Carbon Fuel Standard (LCFS) is another policy lever that may reduce the cost of fleet charging, based on station capacity and charger utilization (CARB, 2021). If the credit calculation used real-time carbon intensity of charging sessions instead of an average annual grid estimate, fleet managers may have further incentive to align charging with intermittent renewable generation. On the other hand, fleets could face carbon taxes on their charging emissions. The social cost of carbon (SCC) will continue to increase over time because the incremental damage of more GHGs in the atmosphere rises with more emissions already present. Higher SCC values will motivate aligning charging with renewables. As a result of varying retail prices, carbon cost estimates, and EV policy incentives, the effect of charging costs on fleet operations warrants further investigation.

Of the SAEV agent-based simulation studies, fleet size varies with land use, trip density, and demand for this mode. One study simulating a fleet of 15,000 vehicles in the Austin metro (5,300 square miles with a population of 1.8 million) observed a median daily vehicle-miles traveled (VMT) of 215 mi per vehicle (Dean et al., 2022). The electricity demand from regional passenger service serving 6.3% of daily person-trips could reach 806 MWh, about the same daily electricity consumption from 27,400 US homes. Fleet vehicles will likely charge using direct current fast charging (DCFC) equipment to minimize downtime, which may amplify the region's peak demand. Unmanaged high-power fleet charging may require expensive upgrades to distribution system infrastructure up to revised resource adequacy planning at the generation and transmission system level (Anwar et al., 2022).

As the transportation and power sectors converge with vehicle electrification and the use of vehicles as mobile energy sources, there will be a greater emphasis on minimizing charging impacts. Electric utilities may use TOU prices or wholesale-indexed electricity prices to align the cost of producing power with energy consumption. Mobility companies may also wish to reduce their emissions impact because of regulatory requirements (e.g., Clean Miles Standard) or shareholder pressure (CARB, 2019). In this study, a fleet of on-demand SAEVs uses a multi-stage charging and discharging framework to minimize electricity purchasing costs and the emissions damages from electricity production. The framework includes a day-ahead charging and discharging optimization problem for a virtual fleet battery to determine the amount of electricity to buy or sell per hour. The energy transactions become targets in a within-day idle vehicle dispatch problem alongside cleaning and maintenance requirements. The optimization problems are tested within an agent-based travel demand simulator, POLARIS, with a synthetic trip dataset from the Austin, TX, region. Before the decision epoch for within-day idle vehicle dispatch, the fleet solves the day-ahead charging and discharging problem to update the virtual fleet battery's state of charge (SOC). As a rolling horizon problem, the next 24 hours of energy transactions are updated throughout the day to improve low-cost decision-making and ensure sufficiently high SOC for multi-day service.

The rest of the study is organized as follows. Section 2 summarizes the literature that contributes to the development of this multi-stage charging and discharging framework and the specific contributions of this study. Section 3 introduces the multi-stage charging and discharging strategy central to fleet management. Section 4 presents relevant details on the simulation environment for readers unfamiliar with POLARIS. Section 5 reviews case study details on travel demand, electricity prices, emission damages, and other simulation assumptions. Section 6 presents the results, while Section 7 discusses this study's results and limitations and provides a direction for future work. Section 8 concludes the study with an overview of the methods and applications for future fleet operators and policymakers.

2. Background

Many studies examine the likelihood of motorists using SAEVs for urban travel and the expected environmental benefits of electrifying ride-hail fleets. Previous fleet operations research includes economic evaluations, charging station provisioning for different battery ranges and fleet sizes, various dispatch strategies, and their impacts from a transportation perspective (e.g., average wait times, mode share, unoccupied travel). Meanwhile, the body of research examining EV-grid interactions is extensive. Work focusing on SAEVs and the electric grid include joint charging station and power distribution system planning (Estandia et al., 2021), managing energy system operations at charging stations (with or without batteries or on-site solar arrays) (Melendez et al., 2020) and studying the effect of electricity prices on charging decisions (Zhang and Chen, 2020).

Vehicle charging decisions and charging station selection vary widely (see Gurumurthy et al. (2022) for a synthesis) and are a microcosm of differences within transportation simulation. Differences in modeling assumptions and approaches can yield different outcomes and policy recommendations. Advanced vehicle-dispatch problems for rider assignment, rebalancing, and charging SAEVs that use optimization-based methods or reinforcement learning can improve fleet performance over prior heuristics (Al-Kanj et al., 2020; Dandl et al., 2020; Dean et al., 2022; Kim et al., 2022; Kullman et al., 2021; Yi and Smart, 2021). For example, Al-Kanj et al. (2020)

increased fleet revenues by 17% and the percentage of trips met from 74 to 95% with their lookahead reinforcement learning policy, relative to a myopic strategy. Kim et al. (2022) found that incorporating demand prediction into idle vehicle relocation reduced fleet investment and operating costs by 38%. Kullman et al. (2021) used a deep reinforcement learning method to increase fleet profit by 18% (versus Alonso-Mora et al.'s (2017) earlier strategy), and Dean et al. (2022) lowered average wait times by 39% and increased average daily trips per vehicle by 28%. Yi and Smart (2021) increased trips met by 11% and reduced unoccupied travel by 43%. Fleet managers are unlikely to ignore the benefits of optimization-based dispatch methods relative to early heuristic-based studies (like those used in Chen et al., 2016; Farhan and Chen, 2018; Loeb et al., 2018; Loeb and Kockelman, 2019; and Vosooghi et al., 2020). As battery costs decline, operating costs will rise as a fraction of fleet ownership costs and motivate further analysis of cost-saving control strategies.

Luke et al. (2021) developed a novel joint fleet size, charging station, and operating cost (electricity and generalized maintenance) minimization problem. To prevent a quadratic rise in the number of decision variables coming from disaggregate travel demand, they grouped the 46.8 mi^2 City of San Francisco into 25 cells. Although the study used arc flows to model time-varying travel times between origin-destination pairs, the congestion from 154,770 SAEVs was not captured. Compared to scaling up the number of chargers at existing charging stations, the proposed framework reduced peak charging costs by 10% by spreading charging demand among more charging stations. In addition to lowering station-level demand charge costs (in terms of peak power rate fees, priced at $/kW), there was 10% less empty VMT due to charging.

Iacobucci et al. (2021) expanded a prior model-predictive control strategy that considered repositioning and charging with dynamic electricity prices (Iacobucci et al., 2019) by adding bidirectional charging. Due to computational limits, the authors separated charging, repositioning, and vehicle assignment into different decision epochs and aggregated variables like SOC to reduce the problem size. They studied this control strategy for a fleet of up to 10,000 vehicles with demand from a Manhattan taxi trip dataset. Their control strategy cut charging costs in half and reduced emissions by 16-21%. Trip ends were aggregated to 200 nodes over a 22.8 mi^2 service area and travel time estimates for a five-day trip simulation came from a two-hour weekday morning peak. Similar to other studies, they assumed the additional generation needed for a peak load of 200 MW would come from the same generation sources, which may not be the case. Depending on the time of day, the additional power comes from available, unused capacity or peaker power plants that are generally less efficient.

Zhang and Chen (2020) used the agent-based simulation tool from Chen et al. (2016) to simulate 10% of the Seattle region's weekday travel demand with SAEVs. Their study focused on electricity rates (TOU and wholesale) to find the ideal number of vehicles to charge at each time step. Although electricity costs per vehicle-mile fell by 10-34%, the average percent of unoccupied travel increased by 1.4-1.9%. They found that fleet electricity cost savings were higher under volatile wholesale electricity prices, which supports the findings from Iacobucci et al. (2021). The simulation used hourly travel time estimates to reflect network congestion with a gridded Cartesian coordinate (2-D) system. Additionally, the authors used a low battery heuristic as the reference charging case, which can amplify the perceived benefits.

Li et al. (2022) evaluated the emission benefits of San Francisco Bay Area SAEVs compared to internal combustion engine vehicles (ICEVs) under various charging strategies through an economic dispatch grid and capacity expansion model. Data on daily travel demand came from ride-hailing datasets, scaled up for higher SAEV adoption (long-term). In 2030, 46%

of California’s electricity may come from solar generation (Li et al., 2022), which would incentivize daytime charging. If SAEV fleet owners face wholesale power prices and can shift charging, emissions reduction is likely to follow, thanks to intermittent zero-marginal cost generation. In general, fleet managers pursuing low-carbon charging strategies also save on purchasing costs, which are higher if carbon taxes apply.

Liao et al. (2021) performed an economic and environmental analysis over 30 years to compare the total costs of providing SAEV service in Ann Arbor, Michigan, with 100-mile and 250-mile range SAEVs. In their study, the cumulative cost of electric powertrains was 3.4% (250-mile range SAEVs) to 8.4% (100-mile range SAEVs) higher than gas-powered SAVs, even with lower fuel and maintenance costs. Long-range vehicles with heavier batteries increased SAEV energy consumption (5.2%) and GHGs (5.1%) but reduced fleet size and deadheading costs. And, if 250-mile SAEVs could sell electricity via V2G, their overall costs could be 20% lower than SAVs. Liao et al. (2021) estimated that V2G could save 60 tonnes of GHG emissions annually per vehicle but did not consider time-varying electricity prices or marginal (power plant) emissions.

Melendez et al. (2020) evaluated the optimal operations of a forward-looking charging hub for SAEV service where fleet managers had access to on-site solar generation, battery storage, bidirectional charging capability, and sold unoccupied charging windows to private EVs. Their study combined a power system optimal power flow model and a reformulated idle vehicle problem from Iacobucci et al. (2021). Melendez et al. (2020) found SAEV fleet owners have limited potential in earning non-transportation revenues with V2G, provided sufficient transportation demand and fluctuations in wholesale power (but numbers were not provided).

In summary, a few studies have evaluated charging and SAEV dispatch strategies to lower electricity costs (Iacobucci et al., 2021; Luke et al., 2021; Melendez et al., 2020; Zhang and Chen,

2020) relative to a price-agnostic (vehicle-dispatch) strategy. Their price-agnostic benchmarks are often charging heuristics (e.g., charge when the SOC falls below 60% or 20%) or based on real-world EV charging sessions or idle time (Li et al., 2022; Liao et al., 2021). As a result, their relative cost savings are probably biased high.

Of the three studies in Table 1 that include an emissions analysis, only Iacobucci et al. (2021) captured the cost of carbon within the cost-minimizing charging strategy. However, focusing only on carbon dioxide (CO_2) ignores the health and climate damages from other emissions, such as nitrogen oxides (NO_x), sulfur dioxide (SO_2), and particulate matter ($PM_{2.5}$) (Bridges et al., 2015). All Table 1 studies aggregated trip ends to select nodes or zones for their simulations or relied on real-world ride-hail trip data (Li et al., 2022) or synthetic SAEV trip data (Liao et al., 2022) in their optimization frameworks. The advantage of simulations with more realistic trip ends and networks is a more accurate portrayal of empty travel distances and traveler wait times. Moreover, this study's endogenous and dynamic traffic assignment (DTA) methods lead to vehicle-level energy consumption values that vary by route and congestion (Dean et al., 2022). Table 1's two node-to-node simulation studies also supplied charging stations at each node (Iacobucci et al., 2021; Melendez et al., 2020), resulting in no empty mileage due to charging, which is too optimistic.

Table 1 Summary of Selected SAEV Literature with Focus on Feature Differences.

Author(s), year	**Model Type**	**Electricity Prices**	**Sensitivity Analysis** [a]	**Charging Strategies** [b]	**Emissions Analysis** [c]	**Traffic Flow Model & Region Scale**
Luke et al., (2021)	• Analytical	• Retail (TOU) • Peak power rate fee	• Battery Capacity	• Strategy-specific	• N/A	• Zone-to-zone (arc routing) with hourly travel time matrices • San Francisco, CA (28 zones)
Iacobucci et al., (2021)	• Analytical & Traffic Simulation	• Wholesale (regional & seasonal)	• Fleet Size	• Strategy-specific • Nighttime • On-demand	• CO_2 (internalized)	• Node-to-node network loading with constant travel time matrix • Manhattan, NY (200 nodes)
Zhang and Chen (2020)	• Analytical & Traffic Simulation	• Wholesale • Retail (TOU) • Peak power rate fee	• Battery Capacity • Charging Speed	• Strategy-specific • Low-battery check • Fill-the-charger	• N/A	• 2-D Cartesian coordinate grid loading with hourly travel time matrices • Seattle, WA metro (193,600 zones)
Li et al., (2022)	• Analytical & Power System Simulation	• N/A	• Carbon tax • Occupancy Rate • Fleet Size	• Nighttime • Daytime Workplace • Daytime Public • Inverse to Netload • Inverse to Ride Requests • Uniform	• CO_2 (post)	• Lyft & Uber passenger-trip data (unspecified region)
Liao et al., (2022)	• Analytical	• N/A	• ±10% of Modeling Inputs (e.g., Electricity Price & Battery Capacity)	• V2G 50%	• CO_2 (post)	• Travel demand from prior SAV simulation with node-to-node routing with constant travel time matrices • Ann Arbor, MI (43.8 sq-mi area, unspecified # of nodes)
Melendez et al., (2020)	• Analytical	• Wholesale (day-ahead & real-time)	• Fleet Size • Charger Cords	• Strategy-specific	• N/A	• Node-to-node with hourly travel time matrices (to the nearest 15 min) • Tampa Bay, FL (12 nodes)
Present Study	• Analytical & Agent-Based Traffic Simulation	• Wholesale • Retail (TOU) • Peak power rate fees	• Battery Capacity • Charging Speed	• Strategy-specific • Price-agnostic	• CO_2, SO_2, NO_x, & $PM_{2.5}$ (internalized)	• Endogenous traffic & DTA model for door-to-door service routing • Austin, TX metro (39,573 locations)

[a] 30-year Costs include cost of owning, maintaining, and replacing fleets.
[b] Nighttime strategy means that SAEVs charge between 12 AM and 5 AM and, when the SOC is below 60%, during the daytime. On-demand strategy charges after each trip (if the vehicle remains idle/unneeded). Low-battery check requires charging when SOC falls below 20%. Fill-the-charger strategy keeps cords occupied throughout the day to reduce capital costs of charging infrastructure. V2G 50% means that bidirectional charging is available 50% of time the SAEV is parked (idle). Please refer to Li et al. (2022) for study-specific charging strategies.

[c] N/A: Not applicable, internalized means the strategy captured costs of carbon within the policy, post means an emissions analysis was done after the analytical model.

2.1 Contributions

Yi and Smart (2021) and Dean et al. (2022) proposed two optimization frameworks for charging and repositioning idle vehicles and compared numerical results to heuristic methods and disjoint vehicle decision-making processes. Both studies found benefits of adopting an optimization-based strategy that capture trade-offs between charging and repositioning vehicles at the same decision epoch. Moreover, both suggested that their approaches could distribute charging over many periods, specifically off-peak periods, but that future research on off-peak charging was warranted. Iacobucci et al. (2021) proposed a framework to minimize energy transactions and convey temporally aggregated optimal solutions to a short-time scale idle vehicle dispatch strategy. Zhang and Chen (2020) recognized that not all SAEV fleets pay wholesale prices, depending on their operating markets, so their case study included a retail TOU price profile. However, neither study used a joint charging and repositioning optimization-based problem to lower wait times, increase trips served, and reduce empty travel (Yi and Smart, 2021; Dean et al., 2022).

Simulation advances now allow for further disaggregation of traveler positions and network details to provide more realistic travel routing and congestion feedback, as pursued in this study. Iacobucci et al. (2021) included only CO_2 costs in energy purchase decisions, while Li et al. (2022) used a fixed carbon cost for an eight-year analysis period. There is a need to (1) recognize the costs of other power plant emissions and (2) anticipate how higher carbon costs may impact optimal SAEV fleet operations. This study reformulates Iacobucci et al.'s (2021) day-ahead energy transaction problem, Dean et al.'s (2022) optimization-based repositioning and charging, and Gurumurthy et al.'s (2022) SAEV-maintenance and cleaning requirements. This new multi-stage charging and discharging framework strengthens the argument for smart charging strategies while improving on the literature's cost savings estimates.

This study is the first to capture the health and climate damages of distinct fleet charging and discharging strategies. The pursuit of low charging costs depends on the electricity (retail) prices available to future fleet operators or exhibited in a day's wholesale market. Including a peak power rate (or demand charge in power systems) and different levels of carbon costs can indicate how rate design and regulations influence charging behavior and emissions. Model recognition of vehicle maintenance and cleaning requirements (which increase empty travel and the number of unmet trip requests) adds further realism to the results. As prior studies have shown, with transportation modeling limitations, SAEV fleets could reduce charging costs by at least 10% and emissions by at least 16% (Gurumurthy et al., 2022). This case study evaluates a multi-stage charging and discharging framework with 60 electricity price and carbon costs scenarios for a fleet of 90-kWh vehicles in the 6-county Austin, Texas region. A sensitivity analysis highlights how battery capacity and charging speed affect operational costs, queue times at charging stations, and the number of charging trips in a day. Results also reveal the benefits of reducing power emissions through operational changes, which can reduce the fleet's reliance on unbundled RECs to claim zero-carbon charging emissions. Although this study focuses on SAEVs, the methods and magnitude of findings may be transferable to other fleet vehicles, like autonomous delivery vans (for parcels, groceries, and take-out food).

Fleets can schedule charging to minimize charging emissions and avoid adding to the peak demand for electricity (often met with fossil-fuel peaker power plants). This study focuses on a day-ahead fleet charging and discharging problem that minimizes purchasing and societal electricity costs. Hourly electricity transactions (e.g., kWh of electricity bought or sold) become targets for an optimization-based idle-vehicle dispatch strategy. Trade-offs between charging and other decisions (e.g., vehicle assignment, repositioning, maintenance, and cleaning) depend on the expected cost savings, which are a function of exogenous factors (like electricity pricing and carbon taxes). However, powering large SAEV fleets (at scale) can change wholesale electricity production costs by turning on additional power plants or causing transmission congestion, resulting in a need for grid-level models where electricity pricing is endogenous. Instead of adding SAEV charging profiles to grid dispatch models (Li et al., 2022), this study uses marginal emissions (Holland et al., 2022). The framework tests different retail and wholesale electricity price profiles and SCC values to reveal insights for fleet managers in different regulatory environments.

3. Modeling Framework

A multi-stage charging and discharging strategy should reduce direct and indirect costs while meeting passenger demand. The first step is to define a day-ahead charging optimization problem to minimize these operational costs. The first problem solves the optimal bulk energy transactions for each hour of the upcoming 24-hour period. Since charging restricts vehicle supply, the manager may wish to reposition vehicles, given foresight into demand patterns. The manager can solve a within-day dispatch strategy in a shorter time step interval that balances competing vehicle and fleet priorities (e.g., (dis)charging, maintenance/cleaning, passenger service, and repositioning). Fig. 1 presents an overview of the inputs and outputs of this multi-stage process.

Different electricity price structures (e.g., flat, TOU, and wholesale) and emission rates can influence the day-ahead (dis)charging plan. The day-ahead charging and discharging problem solves the amount of electricity to buy or sell per hour for the next 24 hours. This problem is solved immediately before the within-day dispatch problem at each decision epoch (e.g., every 15 minutes) to address the mismatch between predicted and realized energy consumption that can arise from different distances traveled and inaccurate energy consumption prediction. The resulting buy-sell decision vector is then used in the within-day dispatch problem. The feedback between energy transactions and within-day idle vehicle dispatch is not limited to projecting energy demand for the remaining hours in the 24-hour simulation day but a rolling 24-hour period. As the day progresses, finding optimal solutions to the next 24-hour period can help to ensure that multi-day service is attainable by considering the fleet's SOC for day two while completing day one's operations. The remaining subsections explain the day-ahead charging and discharging problem, the feedback loop through a rolling horizon approach, and the within-day optimization-based idle vehicle dispatch problem.

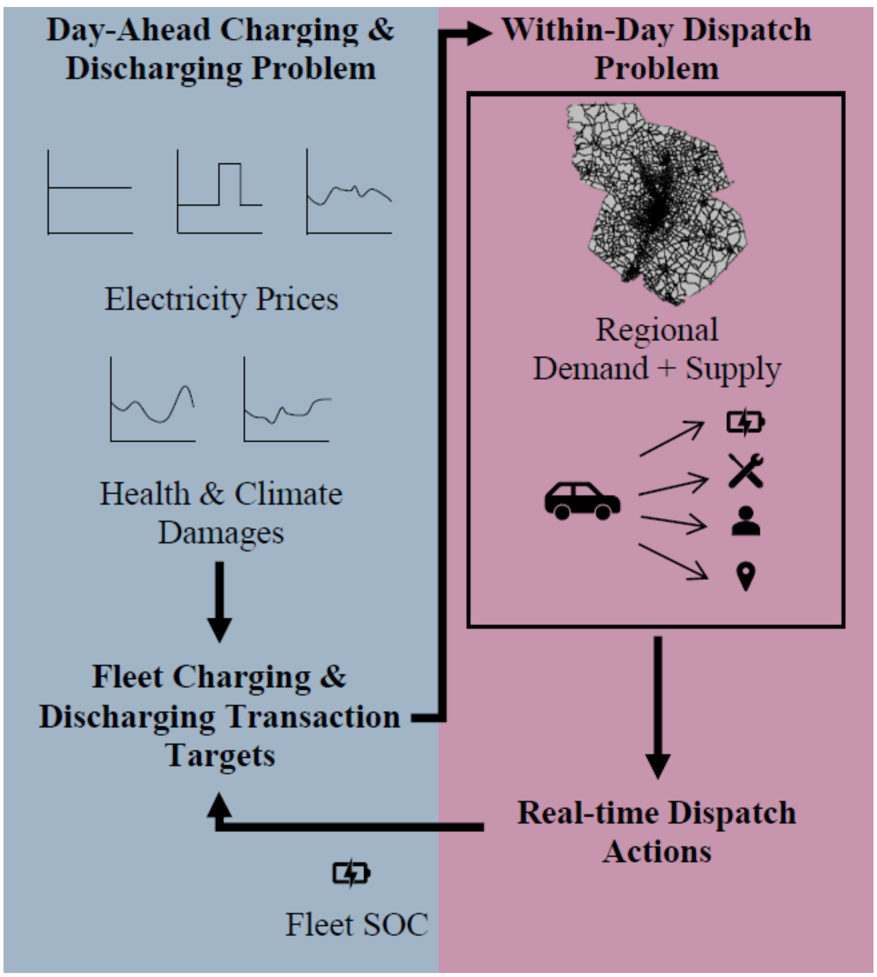

Fig. 1. Multi-stage charging and discharging framework.

3.1 Day-Ahead Charging and Discharging Problem

This study adapts the charging optimization problem from Iacobucci et al. (2021), which uses a virtual fleet battery to decide when and how much energy to charge (or discharge through V2G) at each decision time step. The nomenclature for this first problem is defined in Table 2 and explained below.

Table 2 Variables Needed for Day-Ahead Fleet-Battery Charging Optimization.

Type	Name	Description
Set	t	Charging time step ($t \in [1, T]$)
Decision Variables	$E_b(t)$	Aggregate energy to buy (charge) at time step t (kWh)
	$E_s(t)$	Aggregate energy to sell (discharge) at time step t (kWh)
Endogenous Variables	$Q(t)$	Aggregate energy stored in fleet at time step t (kWh)
	$E_b^{max}(t)$	Maximum allowable energy to buy at time step t (kWh)
	$E_s^{max}(t)$	Maximum allowable energy to sell at time step t(kWh)
	P_b^{max}	Peak power demand from buying energy (kW)
	$\widehat{q^*}$	Minimum forward average SOC target
Parameters	$d_i(t)$	Aggregate trip distance during time step t of trip type $i \in [p, d, r, c, m]$ (mi)
	$p_b(t)$	Cost to buy energy at time step t ($/kWh)
	$p_s(t)$	Cost to sell energy at time step t ($/kWh); assumed to be 25% less than $p_b(t)$
	p_d	Peak power rate fee ($/kW)
	$p_{dam}(t)$	Emission damages at time step t ($/kWh), considering NO_x, SO_2, $PM_{2.5}$, and CO_2
	γ_{cycle}	Price of discharging energy ($/kWh)
	ω	Energy efficiency of vehicles (kWh/mi)
	η	Roundtrip efficiency of a cycle
	V	Number of vehicles
	B	Battery capacity of each homogenous vehicle (kWh)
	$\tilde{Q}$	End of day SOC target (fleet average)
	$\tilde{q}$	Ideal forward average minimum SOC target
	H	Number of hours for forward average SOC estimation (scaled down at the end of day)
	M	Sufficiently large number to increase SOC at day's end
	q^{min}	Minimum average SOC of vehicles
	q^{max}	Maximum average SOC of vehicles

The objective function (Eq. 1) minimizes charging costs (internal and external) while ensuring the fleet average SOC at the end of the day is not severely low, such that it may harm multi-day fleet operations. The decision variables $E_b(t)$ and $E_s(t)$ are the amount of energy (in kWh) to buy or sell, respectively, at time step t. The electricity price $p_b(t)$ is set by the utility or the wholesale market. Due to minimum capacity requirements, a third-party aggregator will likely work with the fleet manager to sell stored electricity at a price $p_s(t)$. Since V2G can impact battery longevity (Wang et al., 2016), a degradation cost γ_{cycle} (in $/kWh) is added to any revenue gained from selling electricity. The total health and environmental effects of charging emissions, $p_{dam}(t)$, includes damages from CO_2, NO_x, $PM_{2.5}$, and SO_2. The damages from the criteria air pollutants are calculated using a statistical life value and the climate change effects of CO_2 are assessed using an SCC value (Azevedo et al., 2020). Additional details on health and climate damages can be found in Section 5.3. A peak power rate fee p_d is applied to the peak demand P_b^{max}, which is not location-specific in this study. Finally, the last term penalizes fleets with a low fleet average SOC at the end of the day. The absolute value difference in SOC between $\tilde{Q}$, which is the target for day's end fleet SOC, and the forecast of the virtual fleet battery SOC, $\frac{Q(T+1)}{VB}$, is multiplied by a large constant M to penalize a deviation from the target.

The virtual battery $Q(t)$ is the aggregate energy stored in vehicle battery packs at time step t. The charging and discharging decisions at time step t impact the energy stored in the virtual battery at the next time step $t+1$, as well as the estimated energy consumption from vehicle actions (Eq. 2). Electricity consumption is estimated as the linear combination of distances from passenger pickup, drop-off, repositioning, charging, and maintenance trips ($p, d, r, c,$ and m, respectively) times a uniform energy efficiency measure (in kWh/mi). Prior simulation run data is used to adjust hourly mileage estimates and the battery efficiency parameter.

$$\min \sum_{t=1}^{T} \left(E_b(t)(p_b(t) + p_{dam}(t)) - E_s(t)(p_s(t) - \gamma_{cycle}) \right) + P_b^{max} p_d + |\tilde{Q} - \frac{Q(T+1)}{VB}| M \qquad (1)$$

$$\text{s.t.} Q(t+1) = Q(t) + E_b(t) - \frac{E_s(t)}{\eta} - \omega \left(d_p(t) + d_d(t) + d_r(t) + d_c(t) + d_m(t) \right), \forall t \in T \quad (2)$$

$$q^{min} \le \frac{Q(t)}{VB} \le q^{max}, \forall t \in T \qquad (3)$$

$$\widetilde{q^*} \leq \frac{\sum_{h=1}^{H} \frac{Q(t)}{VB}}{H}, \forall t \in T \tag{4}$$

$$0 \leq E_b(t) \leq E_b^{max}(t), \forall t \in T \tag{5}$$

$$0 \leq E_s(t) \leq E_s^{max}(t), \forall t \in T \tag{6}$$

$$\frac{E_b(t)}{\Delta t} \leq P_b^{max}, \forall t \in T \tag{7}$$

$$Q(\cdot), E_b(\cdot), E_s(\cdot) \in \mathbb{R}^+ \tag{8}$$

Eq. 3 imposes constraints on the SOC level for physical and logistical reasons. The fleet average SOC is the ratio of aggregate energy stored $Q(t)$ to the total battery capacity. If the fleet is composed of vehicles with the same designed battery capacity, then the denominator is simply fleet size V times the rated battery capacity B.

Equation 4 adds a forward average minimum SOC level constraint, which is computed before calling the solver. This constraint requires the fleet average SOC over H hours be sufficiently high to prevent severe fleet average depth of discharge, which can negatively affect supply and may lead to unreliable passenger service during special event days. The forward average SOC target, $\widetilde{q^*}$, is the minimum between the smallest allowable fleet average SOC value, $\tilde{q}$, and the predicted recovery in SOC from max charging: $\frac{\left(\sum_{h=1}^{H} Q(t)+E_b^{max}(t)-\omega\left(d_p(t)+d_d(t)+d_r(t)+d_c(t)+d_m(t)\right)\right)}{HVB}$. Charging and discharging actions are limited to the number of available chargers and their maximum power draw (Eq. 5 and Eq. 6). Thus, fleet charging station design configuration (in kW) limits the maximum energy bought or sold. This problem setup assumes that the fleet utilizes all chargers, does not share infrastructure with personal EVs, and the local power company does not impose time or station-varying power limits because of distribution grid capacity constraints. Equation 7 finds the peak power draw from the fleet to calculate the peak power rate fee, if one exists. Lastly, there are non-negativity constraints for the virtual battery and these charging decisions (Eq. 8).

Once the day-ahead charging optimization problem is solved, the charging and discharging decisions are recorded and used as targets for a discrete time step optimization-based dispatch problem.

3.2 Rolling Horizon Day-Ahead Charging and Discharging

The electricity consumption forecast in the day-ahead problem is imperfect and should adapt to real-time performance. The day-ahead problem is solved before the idle vehicle dispatch problem to account for changes in the current fleet average SOC. This rolling horizon approach connects the two optimization problems and ensures that the fleet prepares for the next day's service. In practice, a fleet manager starts with day-ahead wholesale prices. As the day progresses, the fleet manager could update this price vector with new within-day prices, which may improve cost savings.

3.3 Cost-Sensitive Optimization-based Idle Vehicle Dispatch

An extension to the existing joint optimization-based problem that only considered repositioning and charging (Dean et al., 2022) is proposed here. First, day-ahead (dis)charging decisions that minimize total electricity costs replace price-agnostic charging decisions. Second, the dispatch problem now includes routine maintenance trips. This new control strategy may improve SAEV forecasts, especially when the fleet is responsive to electricity and carbon prices.

This problem finds optimal charging, repositioning, and maintenance decisions from the same set of idle SAEVs at each decision epoch. Although a sequential or decomposed sub-problem approach could solve for within-day actions, this study uses a joint problem to weigh fleet benefits from different combinations of dispatch decisions (with (dis)charging targets from the rolling horizon day-ahead problem). The control strategy minimizes zonal supply deficits based on current and projected supply and demand. Table 3 defines the variables needed for this problem.

The supply of available vehicles s_j in zone j only counts idle vehicles or vehicles en route with a final destination in zone j. To avoid counting vehicles with a low SOC, all vehicles must have an SOC greater than SOC^{min}. In this study, historical demand f_j of the previous hour is used as the expected demand since the contribution is not in SAV demand prediction. As a result, this study does not imply perfect knowledge of future demand. Like in Dean et al. (2022), δ_j represents the supply deficit. The objective function (Eq. 9) minimizes the expected cost of dispatching vehicles, the penalty from supply deficits, a penalty for not adhering to the day-ahead (dis)charging decisions, and a penalty for performing a maintenance trip when the cost is higher than the reward.

Table 3 Variables Needed for Within-Day Joint Optimization-Based Vehicle-Dispatch Strategy.

Type	Name	Description
Sets	I	Set of vehicles $i \in I$
	I_j	Set of vehicles at zone *j*, $I_j \subseteq I$
	J	Set of zones $j \in J$
Decision Variables	r_{ij}	Vehicle *i* repositions to zone *j* (binary)
	m_{ij}	Vehicle *i* goes to a service depot in zone *j* (binary)
	d_{ij}	Vehicle *i* goes to discharge at a charging station in zone *j* (binary)
	c_{ij}	Vehicle *i* goes to charge at a charging station in zone *j* (binary)
Endogenous Variables	s_j	Supply of vehicles in zone *j*
	δ_j	Slack variable for zone *j* to guarantee a non-negative supply deficit
	q_i	Current SOC of vehicle *i*
	R_b	Largest possible remainder of energy bought (equal to “budget”)
	R_s	Largest possible remainder of energy sold (equal to “budget”)
	v_i	Vehicle *i* has enough SOC to leave zone *j* (binary)
	e_i^b	Energy to charge vehicle *i*
	e_i^s	Energy to discharge from vehicle *i*
Exogenous Variables	f_j	Expected demand in zone *j*
	x_{ij}	Travel distance estimate between zones for vehicle *i*
	$E_b^*(t)$	Maximum allowable energy to buy at time step t (kWh)
	$E_s^*(t)$	Maximum allowable energy to sell at time step t (kWh)
Parameters	$\overline{p_b}$	Average price of electricity ($/kWh)

ω	Energy efficiency of vehicles (kWh/mi)
α	Reward for maintenance trip ($, valued to a max travel distance cost: $\omega p_b x_{ij}$)
p_j	Penalty for supply deficit in zone *j*, assumed to be constant ($)
D_j	Number of maintenance depots in zone *j*
M	Penalty for deviating from day-ahead energy transactions ($/kWh)
B	Battery capacity of each homogenous vehicle (kWh)
q^{min}	Minimum average state of charge of vehicles
q^{max}	Maximum average state of charge of vehicles
n	Number of optimization time steps in the day-ahead time step t (e.g., n = 4 if the control strategy time step is every 15 minutes)
P_c	(Dis)charge rate of each vehicle (kW)
T	Control strategy time step duration (hr)
q_{V2G}^{min}	Minimum SOC required for a vehicle to discharge energy
SOC^{min}	Minimum SOC

The first term prioritizes dispatching vehicles to nearby zones to reduce energy consumption. The decision variables r_{ij}, m_{ij}, d_{ij}, and c_{ij} are the number of vehicles that should be dispatched from vehicle i's current zone to destination zone j for the specific trip type. The first letter denotes the trip type (*r* = repositioning, *m* = maintenance, *d* = discharging, and *c* = charging). The second term rewards vehicle dispatch actions to minimize zonal supply deficits up to the opportunity cost for that origin zone p_j. Although written as a zone-specific parameter, a constant value is used. The third term rewards adherence to (dis)charging values found from the rolling horizon day-ahead solution. If fleet managers have contracts to provide electricity to the grid and cannot meet their obligation, the penalty may offset the manager's costs of purchasing electricity at market price. The fourth term incentivizes low-cost maintenance trips, provided that the traveling cost is less than α. Regarding the reward for low-cost maintenance trips (i.e., fourth term in Equation 9), a maintenance trip for vehicle i to zone j would have a non-positive cost so long as $\alpha > 0$ and $x_{ij}\omega\overline{p_b} \le \alpha$. This comparison can be made since vehicles make at most one operation and can select only one destination zone.

$$min \sum_{i\in I, j\in J} x_{ij}\omega\overline{p_b}(r_{ij} + m_{ij} + d_{ij} + c_{ij}) + p_j \sum_{j\in J} \delta_j + M(R_b + R_s) - \alpha m_{ij} \quad (9)$$

s.t. $0 \leq \sum_{j \in J}\left(r_{ij} + m_{ij} + d_{ij} + c_{ij}\right) \leq 1,\; i \in I$ (10)

$$0 \leq \frac{E_b^*(t)}{n} - \sum_{i \in I} e_i^b c_{ij} \leq R_b, \tag{11}$$

$$0 \leq \frac{E_s^*(t)}{n} - \sum_{i \in I} e_i^s d_{ij} \leq R_s, \tag{12}$$

$$\sum_{i \in I}\left(r_{ij} v_i + m_{ij} + d_{ij} + c_{ij}\right) - \sum_{i \in I_j}(r_{ji} + m_{ji} + d_{ji} + c_{ji}) v_i + \delta_j \geq f_j - s_j,\; j \in J \tag{13}$$

$$\sum_{i \in I} m_{ij} \leq D_j,\;\; j \in J \tag{14}$$

$$r_{ij}, m_{ij}, d_{ij}, c_{ij} \in \{0,1\},\; i \in I, j \in J \tag{15}$$

$$0 \leq \delta_j \quad j \in J \tag{16}$$

Equation 10 is an exclusivity rule that allows up to one dispatch action for vehicle i, since the decision variables are binary. Equations 11 and 12 calculate the remaining energy from within-day actions and the scheduled day-ahead blocks of energy. The constraints assume that the day-ahead energy transaction targets (i.e., buying and selling) are used uniformly across the number of within-day decision epochs: $\frac{E_b^*(t)}{n}, \frac{E_s^*(t)}{n}$. The minimum amount of electricity that a vehicle assigned to charging will need at the decision epoch, $e_i^b c_{ij}$, is calculated from a maximum function: $e_i^b c_{ij} = max(0, min(B(q^{max} - q_i), P_c T))$. The non-negative amount of electricity is either the amount from charging at maximum power draw ($P_c T$) or the maximum SOC recoup ($B(q^{max} - q_i)$). Since this constraint uses the current SOC of the vehicle q_i and not the predicted SOC once at the charger, this problem underestimates the electricity required. Similarly, Equation 12 sums up across all vehicles the amount of discharged energy and the estimation for each vehicle, $e_i^s d_{ij}$, is calculated from a separate maximum function: $e_i^s d_{ij} = \begin{cases} 0, & q_i < q_{V2G}^{min} \\ max\left(0, min\left(B\left(q_i - q^{min}\right), P_c T\right)\right), & q_i \geq q_{V2G}^{min} \end{cases}$.

A vehicle can only discharge power if the SOC is greater than or equal to a minimum threshold, $q_i \geq q_{V2G}^{min}$. Before solving the problem, all vehicles with an SOC below q_{V2G}^{min} are eliminated from the choice set of discharging. The minimum amount of discharged energy is non-negative and is either the amount from discharging at maximum speed during the decision epoch duration ($P_c T$) or the maximum SOC discharge potential ($B\left(q_i - q^{min}\right)$).

Equation 13 is a zonal supply and demand relationship. The lefthand side of the inequality constraint adjusts supply from the decision variables directly: the supply of dispatched vehicles to or from zone j and the slack variable δ_j. The binary constant v_i adjusts zonal supply to prevent vehicles with a low SOC from counting towards supply. Thus, r_{ij} is eliminated for vehicles with $v_i = 0$. The righthand side of the inequality constraint, $f_j - s_j$, is expected future demand minus the existing supply of available vehicles (i.e., a supply deficit minimization expression). Equation 14 ensures that the number of vehicles sent to a depot for maintenance does not exceed the current availability at that zone: $\sum_{i \in I} m_{ij} \leq D_j,\ \ j \in J$. Equation 15 ensures that all vehicle dispatch decision variables are binary, and Equation 16 is a non-negativity condition for the slack variable.

The modifications made in this study to the idle vehicle dispatch problem from Dean et al. (2022) include adding two new decision variables (discharging and maintenance), setting an upper bound on maintenance trips based on depot bays (Eq. 14), and introducing limits on charging and discharging based on exogenous targets (Eq. 11 and Eq. 12). If the (dis)charging limits were based on charging infrastructure, the problem would closely resemble the prior study. Since Equations 11 and 12 may not guarantee integer solutions if the problem was formulated as a Linear Programming problem, the problem as written requires the binary decision variables be integer (Eq. 21). However, in several cases, the Integer Linear Programming problem had similar objective values across decision epochs as a Linear Programming problem, where Eq. 15 sets each decision variable between 0 and 1. The case study reports findings using the Linear Programming model, where non-exact solutions are found.

Unlike in Iacobucci et al. (2021), where charging, trip assignment, and repositioning occur at different decision epochs, the joint problem resolves dispatch decisions at the same decision epoch. This study assumes a temporal resolution of 15 minutes for the joint problem, while the day-ahead charge scheduling problem provides hourly values. As in Dean et al. (2022), variable elimination can reduce the computational burden of the problem. All vehicles that have traveled to a depot location for maintenance are eliminated as choices in the maintenance vehicle choice set. Maintenance of vehicles is also limited to those with a battery capacity less than $B - P_c T_m$, where T_m is the duration of a maintenance session. Since SAEVs can safely charge during maintenance sessions, it is reasonable that a fleet would want to maximize downtime productivity and not send vehicles with sufficiently high battery levels. Additionally, to prevent a large mismatch between buying electricity at low-cost periods and charging during maintenance, the fleet cannot dispatch vehicles to depots when the day-ahead solution decides not to purchase electricity.

4. Simulation Environment

The proposed framework is analyzed in POLARIS, which is an activity-based, agent-based modeling framework capable of simulating large-scale transportation simulations on high-performance supercomputers and is written in C++ (Auld et al., 2016). The simulation creates a synthetic population through an iterative proportional fitting process to control for person-level (e.g., gender, age, race) and household-level attributes (size, income, number of workers). Calibrated activity duration and start time, mode, and destination choice models forecast an agent's activities. A time-dependent dynamic traffic assignment model routes vehicles on a road network with background freight and interstate personal vehicle traffic (Verbas et al., 2018).

The simulation records link-level trajectories for all vehicle trips in the region at discrete simulation time steps (6 seconds in this study). SAEVs inherit features of vehicles, like battery capacity, SOC, occupancy, origin and destination locations, and ownership information. While SAEVs perform vehicle-level actions, like dropping off a passenger or entering and existing a maintenance depot, the fleet operator deals with strategy-level actions. Assigning passenger requests to vehicles and other dispatch decisions (e.g., repositioning, charging, discharging, maintenance, and cleaning trips) are all strategy-level actions.

All new requests for an SAEV come with the requested passenger's pickup and drop-off location. The assignment of vehicles to passengers uses a zone-based heuristic (Gurumurthy et al., 2020) to check vehicle availability starting within the pickup zone and searching outwards by the fastest travel time between zones (if needed). The checks ensure the closest SAEV has sufficient range to serve the additional trip and the pickup time does not exceed the service maximum wait time of 15 minutes. If the closest SAEV is occupied, checks ensure that the new passenger does not delay the total travel time of the riders already in the vehicle beyond the service's advertised maximum delays (e.g., 10 minutes and 15%). If multiple SAEVs are available within the pickup zone, the SAEV idle the longest is dispatched to the new passenger. If there are no vehicles within a 15-minute zonal travel time window, the next simulation time step attempts to solve this unmet trip request. If the request was not matched within the maximum wait window, the total number of vehicles considered for the trip gets recorded alongside the unmet trip's request (e.g., location, request time, person ID).

5. Case Study

This study simulates SAEV service within the 6-county Austin region (5,300 square miles) to compare the advantages of multi-stage charge scheduling under different electricity price schemes and carbon prices. Travel demand, electricity price, emission estimates, and the benchmark dispatch strategy are described in this section.

5.1 Travel Demand Data

The mode choice model was calibrated to the 2017-2018 household travel survey (provided by the region's metropolitan planning organization) and adjusted to reflect future travelers' expected utilization of on-demand SAEVs. Fare components include a $0.50/mile fee and a $0.25/minute fee. The value of travel time savings parameter of 20% reduces the in-vehicle travel time disutility of traveling in a shared vehicle since passengers can now make better use of their time. The alternative specific constants for this mode were scaled up by 50%, and a vehicle ownership reduction model from Menon et al. (2019) is adapted to approximate future vehicle ownership levels. Similar demand estimations were performed by Dean et al. (2022). SAEV trip demand for a typical weekday's travel demand was generated according to these adjustments to increase adoption levels to 7.1% of the region's person-trips. All subsequent scenarios used the same SAEV demand dataset. Fixed demand creates a fairer comparison between dispatch strategies when considering electricity price inputs and SCC values. While all scenarios use the same demand table, the fleet operator is not aware of future demand patterns and is reacting to the prior hour's demand, which can increase costs (Kim et al., 2022).

5.2 Electricity Data

The electricity bill for an Austin-based fleet may include a monthly peak power rate fee ($12.25/kW), connection fee ($500/month), and volumetric-based fees (Austin Energy, 2022). For simplicity, the study assumes Austin Energy either uses a flat rate of $0.07/kWh or a new TOU rate with two tiers: peak 2:00 PM to 7:00 PM at $0.23/kWh and off-peak at $0.035/kWh. Historical wholesale prices in the Austin load zone of the Texas electricity grid (i.e., ERCOT) were obtained for every Wednesday in 2019. Like Zhang and Chen (2020), four wholesale price profiles were selected: *no peak* (hourly price variance is less than 25), *spike* (maximum price exceeds \$100/MWh), *peak* (daily maximum deviates more from the daily average than the daily minimum), and *off-peak* (opposite of peak). This classification scheme resulted in a share of 21%, 44%, 31%, and 4%, respectively. A random day's price profile was selected for *spike* and *peak* pricing, while the average price was used for the others. Fig. 2 plots the historical price curves in grey with green color used to show the randomly sampled or average price profile used in the case study. The lavender line and shading represent the mean price and 95% confidence interval. The monthly peak power rate fee was rescaled to a 24-hour period to equal \$0.0395/kW (Luke et al., 2021).

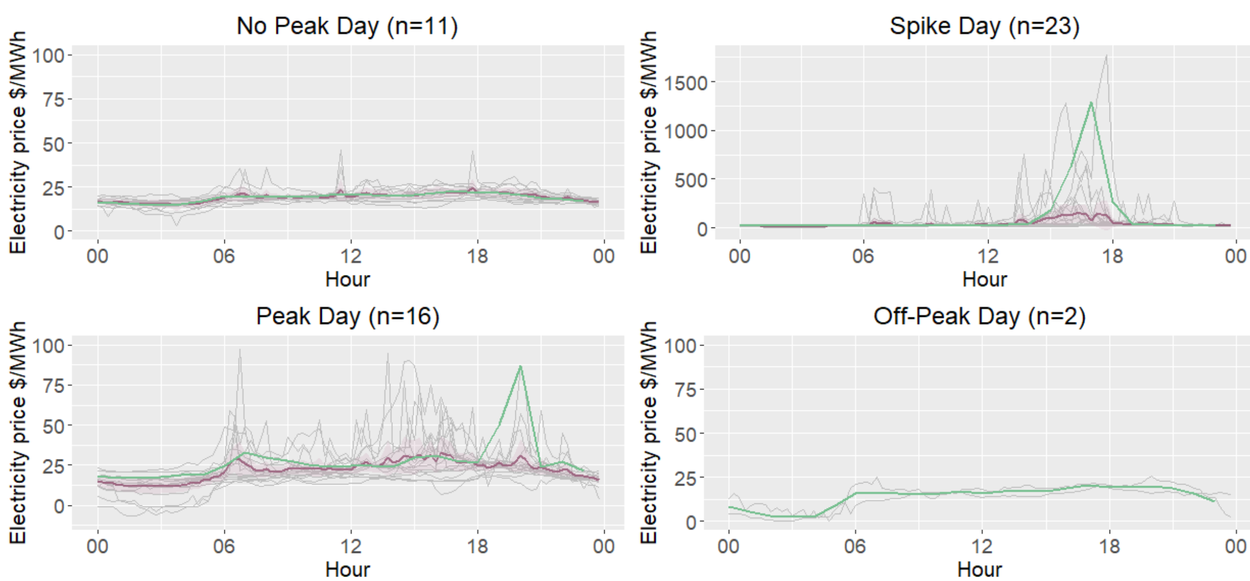

Fig. 2. Sampled wholesale electricity prices in the Austin load zone of the Texas electricity grid in 2019 on Wednesdays by price profile.

Note: The green line is the randomly sampled (or average, in the case of the no peak day and off-peak day) curve used in the case study. The lavender line is the mean with a 95% confidence interval shading. The title for each of the price profiles includes the number (n) of Wednesdays in 2019 that mimic the 4 price profiles.

5.3 Emissions Cost Data

Hourly marginal health and environmental damages from 2018 were obtained from Azevedo et al. (2020). A caveat in applying marginal emissions is that the original data used to compile estimates includes power generation sources with at least 25 MW of generating capacity and does not consider nuclear or intermittent renewables, biasing the estimate up. It also implies that future marginal generators are the same as 2018 sources. The hourly health damages include an SCC value of \$40/metric ton of CO_2 (in 2010 USD) and a value of statistical life of \$8.8 million (in 2010 USD) for health damages from SO_2, NO_x, and $PM_{2.5}$. To estimate monetary damages from marginal pollution, Azevedo et al. (2020) used reduced-form air quality models to estimate the additional premature mortality cases and multiplied them by a statistical value of life. Fig. 3 plots the values used in this study in 2021 USD, assuming \$40/metric ton of CO_2 (in 2010 USD). Interestingly, marginal costs in Texas are lower between the peak hours of 4 PM and 8PM than off-peak hours of 1 AM and 4 AM, which may not be reflected in other regions (Graff Zivin et al., 2014; Holland et al., 2022). The 24-hour average marginal emissions (priced in \$/MWh) are highest for CO_2 (\$27.30/MWh), followed by SO2 (\$19.44/MWh), direct PM2.5 (\$5.84/MWh) and NOx (\$3.47/MWh). Marginal emission damages for each criteria air pollutant estimate premature death costs, while the SCC monetizes the climate effects of CO_2. Since SAEVs and at-scale EV adoption may alter the demand for electricity, it is important to understand the impact of turning on or ramping up power output. Marginal emission factors model this effect. This effect is modeled via marginal emission factors. Readers interested in a comparative analysis of models and methods to calculate power grid emission factors can refer to Ryan et al. (2016).

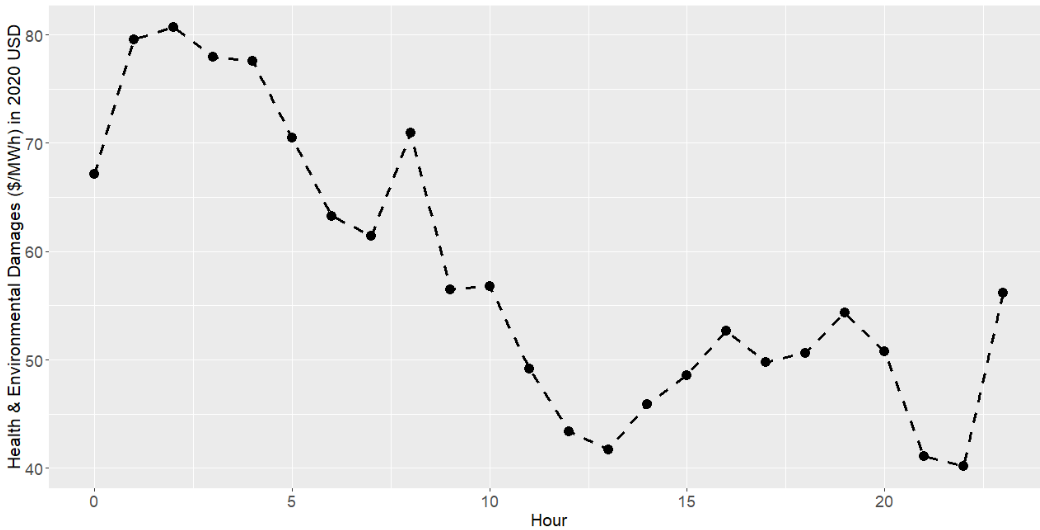

Fig. 3. Hourly health and environmental damages ($/MWh) of the Texas power grid.

5.4 Fleet and Charging Station Assumptions

Fleet vehicles have a battery capacity of 90 kWh to reduce the frequency of charging trips and are assumed to access fleet-owned bidirectional 120 kW charging stations to reduce downtime. As with other battery-electric vehicles, the fleet imposes SOC lower (15%) and upper bounds (95%) to avoid enhanced degradation. Thus, the effective battery capacity is 72 kWh (or roughly 240 miles). Although 120 kW is faster than most fast-charging equipment (e.g., 50 kW), it follows automaker trends of increasing vehicle and power draw capabilities. The power draw follows a uniform rate at maximum power, biasing charging times down from more realistic models where kW varies with SOC. Discharging is assumed to follow a uniform power injection rate of 10 kW. Daily energy consumption values from SAEVs are predicted using macroscopic routing outputs from a microscopic (i.e., link-level) machine-learning model (Moawad et al., 2021). On average, every 14.7 square miles in this 6-county region has a fleet-owned charging station, with a ratio of 5.7 cords to every station (Dean et al., 2022). Fig. 4 maps the EV charging stations (EVCS) in white and the maintenance depots in green.

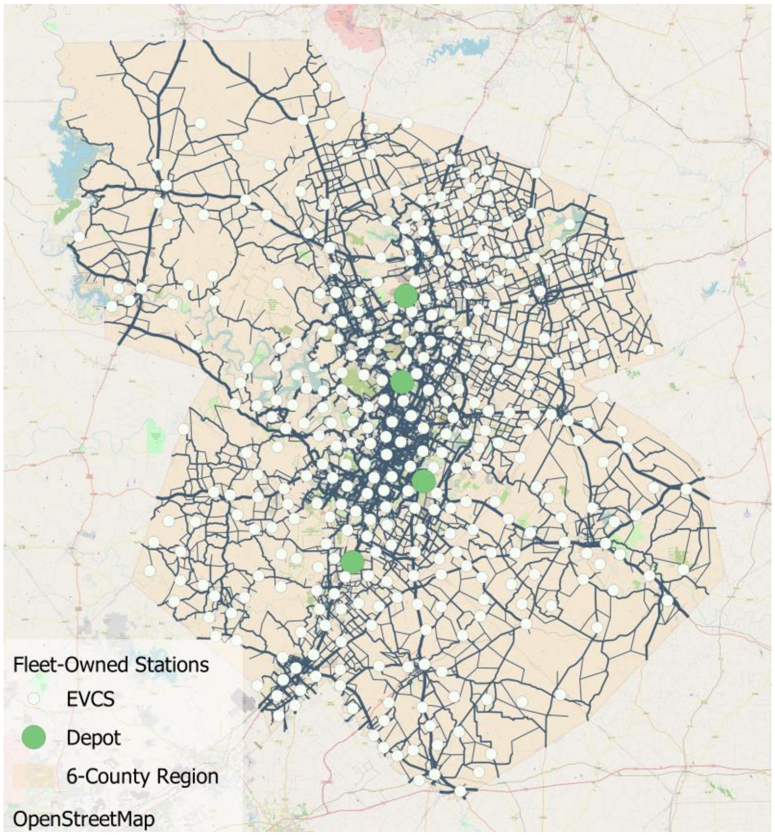

Fig. 4. Fleet-owned charging stations and maintenance depot locations in the 6-County Austin, TX service area.

5.5 Benchmark Comparison of an Optimization-based Idle Vehicle Dispatch

Multi-stage charging and discharging results are compared to an optimization-based repositioning and charging strategy from Dean et al. (2022). This strategy from the literature (called price-agnostic here) uses a linear program (LP) with a three-pronged objective function to minimize travel time from dispatch decisions, increase the SOC of idle vehicles, and avoid zonal supply deficits. Previously ignored and no longer a side issue due to heightened attention on public transit cleaning procedures, cleaning and maintenance heuristics are added to the benchmark for a suitable comparison. Gurumurthy et al. (2022) found that the share of unoccupied miles due to these additional trips could be as high as 9-13%. In addition to an increase in empty travel, served demand decreased by 2.5% in their Chicago case study. The benchmark optimization-based model is modified below in Equations 17 – 22 to match similar notation (Table 3) used in the proposed model.

$$min \sum_{i\in I, j\in Z} t_{ij}\left(r_{ij} + c_{ij}\right) - \alpha \sum_{i\in I, j\in Z} c_{ij}(SOC^{max} - SOC_i) + \beta \sum_{j\in Z} \delta_j \tag{17}$$

$$\text{s.t. } 0 \le \sum_{j\in J}\left(r_{ij} + c_{ij}\right) \le 1, i \in I \tag{18}$$

$$\sum_{i\in I} c_{ij} \le C_j, j \in J \tag{19}$$

$$\sum_{i\in I}\left(r_{ij}v_i + c_{ij}\right) - \sum_{i\in I_j}(c_{ji} + r_{ji})v_i + \delta_j \ge f_j - s_j, j \in J \tag{20}$$

$$r_{ij}, c_{ij} \in \{0,1\}, i \in I, j \in J \tag{21}$$

$$0 \le \delta_j,\ j \in J \tag{22}$$

The strategy here will opportunistically charge vehicles when zonal supply deficits, δ_j, are minimized and the travel time, t_{ij}, for a charging trip, c_{ij}, is less than or equal to $\alpha(SOC^{max} - SOC_i)$. This study scaled up the weights from the demand priority scenario in Dean et al. (2022) to create a representative comparison for a fleet that serves more trips and has additional downtime requirements (e.g., maintenance and cleaning): α = 370 and β = 2700.

The heuristic cleaning policy from Gurumurthy et al. (2022) sends a vehicle that has completed 15 consecutive passenger trips to the nearest maintenance depot for a 10-minute thorough sanitization procedure. This heuristic applies to both the benchmark and proposed framework. The maintenance policy includes a pre-assigned maintenance hour (uniformly distributed) and a heuristic to override the assignment hour when the destination is close to a depot. If an SAEV becomes idle after completing a movement action (i.e., finished repositioning/ charging/discharging/cleaning/dropping off a passenger), the vehicle will check whether the current simulation time step is within the assigned maintenance hour. If true, the SAEV finds the nearest maintenance station. When a new rider gets added to a vehicle, the operator calculates the distance from the drop-off location to the nearest depot. If the final destination is within x miles (such as 2 miles), (1) the assigned maintenance hour gets revised to the simulation's current hour, and (2) the SAEV becomes unavailable for future passenger assignments. As a result, the vehicle goes in for maintenance.

5.6 Scenarios

We studied 60 scenarios for day-ahead charging and discharging that are distinguished by their electricity price ($/kWh), peak power rate fee (binary, $/kW), and SCC value ($40/tonne of CO_2 to $200/tonne of CO_2 by steps of 40, all in 2010 USD). To ensure fair comparisons in electricity purchasing and health damage costs, fleet average SOC starts at 90%, and buying decisions at the end of the day are stopped when the fleet average SOC returns to 90%. Table 4 lists the assumed input values used in the multi-stage charging and discharging strategy. Additionally, vehicles may charge from a low SOC or absolute range check, whichever is first (15%, 30 mi). The parameter used to reward low-cost maintenance trips, α, is set to 2 mi. The penalty for failing to adhere to rolling horizon energy values is the average electricity price over the day (for charging) and a 25% reduction on this value for discharging.

Table 4 Parameter Assumptions in the Multi-Stage Charging and Discharging Strategy.

Variable	Description	Input Value	Source or Justification
p_d	Daily peak power rate fee (if present)	$0.0395/kW	Based on Luke et al. (2021)
γ_{cycle}	Cycling cost of discharging energy	$0.025/kWh	Iacobucci et al. (2021)
ω	Energy efficiency of vehicles	0.279 kWh/mi	Simulation data using Moawad et al. (2021) energy consumption model
η	Roundtrip efficiency of a cycle	0.95	Müller et al. (2022)
V	Number of vehicles	15,000	Dean et al. (2022) using a ratio of 1 SAEV per 125 residents
B	Battery capacity of each vehicle	90 kWh	Dean et al. (2022)
$\tilde{Q}$	End of day SOC target	90%	Set to starting target
$\tilde{q}$	Ideal forward average minimum SOC target	60%	Engineering judgment
H	Number of hours for forward average SOC estimation (scaled down at the end of day)	5	Engineering judgment

M	Sufficiently large number to increase SOC at the end of the day	2,500,000	Engineering judgment
q^{min}	Minimum average SOC of vehicles	20%	Gurumurthy et al. (2022)
q^{max}	Maximum average SOC of vehicles	100%	Technical requirement
p_j	Penalty for supply deficit	\$2,200	Dean et al. (2022)
n	Number of decision epochs per hour (within-day)	4 (every 15 min)	Dean et al. (2022)
q_{V2G}^{min}	Minimum SOC for a vehicle to discharge energy	40%	Engineering judgment

6. Results

The results are organized into the following sections: mobility performance, energy consumption profiles, and electricity and emission costs.

6.1 Mobility Impacts of Multi-Stage Charging and Discharging

The rolling horizon day-ahead charging and discharging strategy determines the amount of electricity to buy or sell per hour. The new within-day problem then finds the lowest operating costs for vehicle assignment by considering optimal (dis)charging energy targets and maintenance requirements. The pursuit of lower electricity costs, however, should not come at the expense of lost passenger revenue, particularly since failing to provide a vehicle to a passenger within their acceptable wait time (e.g., 15 min) may lead the passenger to stop using the service.

The price-agnostic approach brings in a daily revenue of nearly \$684 per vehicle compared to \$705 with the multi-stage strategy (Table 5). Trip revenue was estimated using the same SAEV fare structure when creating the fixed demand data (see Section 5.1). Fleet managers can increase passenger revenue by an average of 3.1% across electricity price types, assuming typical weekday travel demand. Charging vehicles in advance of demand allows the fleet to meet more trips and increase vehicle-miles traveled (Table 6). Instead of opportunistically charging low SOC vehicles when supply deficits are low, as in the price-agnostic strategy, the multi-stage strategy prepares for drops in fleet average SOC due to historical travel demand. Using Becker et al.'s (2020) Austin vehicle production costs, the average daily profit per vehicle (excluding amortized charging supply equipment costs) with multi-stage charging was \$464–\$475 versus \$456–\$467 with price-agnostic, depending on the SCC. Even with higher passenger revenue, higher SAEV utilization increases other costs, namely cleaning, tolls, depreciation, vehicle wear, and battery degradation. Fig. 5 displays the relative change in revenues and costs across the twelve electricity and power pricing scenarios using an SCC value of \$40/tonne CO_2. The black dots show the relative increase in daily per-SAEV profit by pricing scenario.

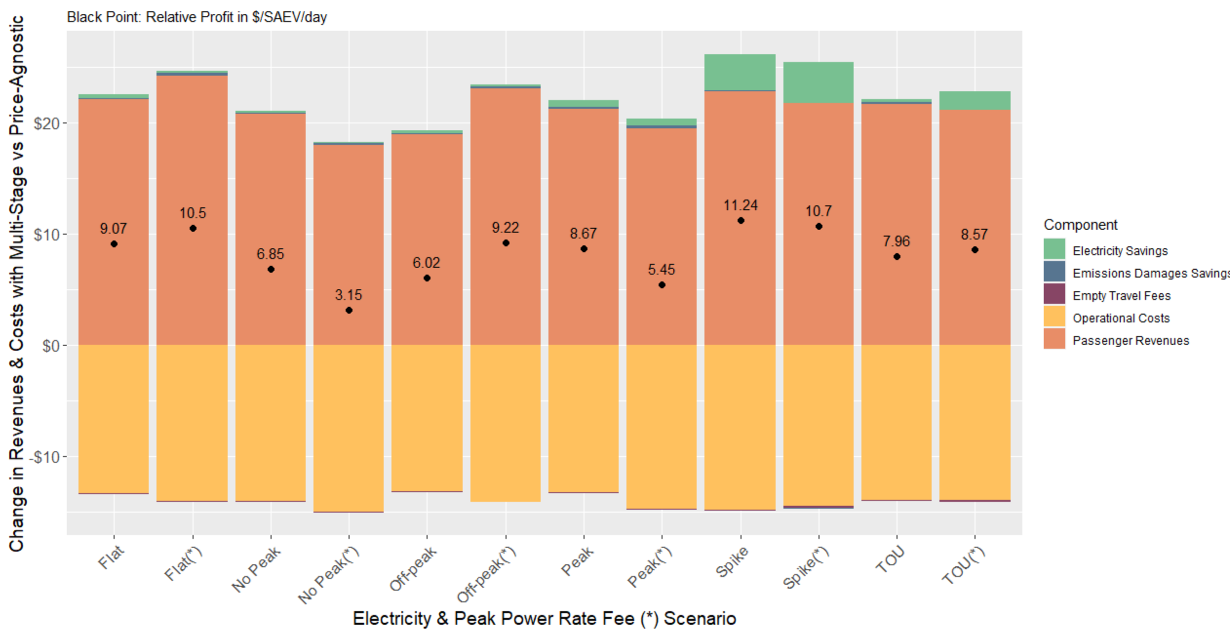

Fig. 5. Change in revenue and costs with Multi-Stage versus Price-Agnostic by electricity and peak power rate fee scenario.

The median number of daily person-trips per SAEV increased to 29 from 28 with the multi-stage strategy, which explains why a higher percentage of vehicles meet the 15 consecutive trip threshold for cleaning (85% versus 79%) (Table 6). The average SAEV travels an additional 19 miles/day due to more passenger and cleaning trips. While both dispatch strategies find the least-cost vehicle-to-zone choices for charging trips, the price-agnostic strategy does not have a penalty term to improve adherence with price-sensitive (dis)charging decisions. Thus, the portion of unoccupied VMT due to charging with day-ahead is higher (Fig. 6).

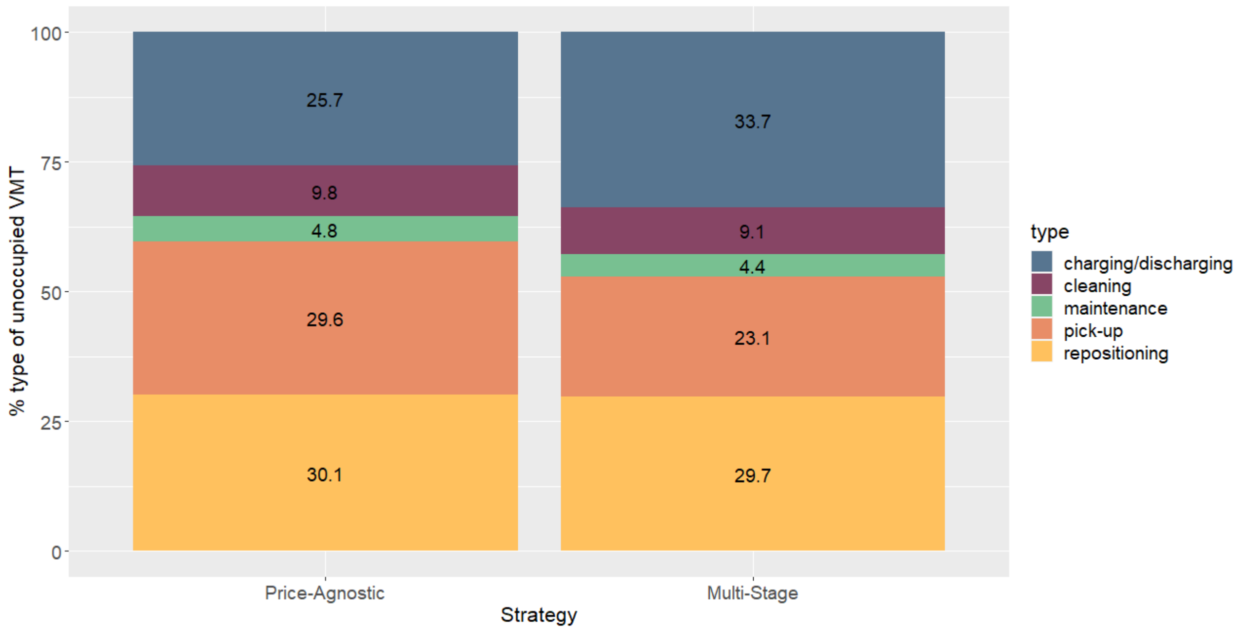

Fig. 6. Share of unoccupied VMT by type for Price-Agnostic and Multi-Stage frameworks.

TABLE 5 Daily Per-SAEV Passenger Revenue and Electricity Purchasing Cost Comparison by Control Strategy and Electricity Price.

Electricity Price (Peak Power Rate Fee)	Avg Daily Passenger Revenue (per SAEV) across all non-zero SCC prices				Avg Daily Electricity Purchase Costs (per SAEV) across all non-zero SCC prices			
	Price-Agnostic ($)	**Multi-Stage ($)**	**% Increase**	**$ Revenue Increase**	**Price-Agnostic ($)**	**Multi-Stage ($)**	**% Decrease**	**$ Electricity Savings**
Flat	$683.8/veh/d	$705.5/veh/d	3.1%	$21.76/veh/d	$6.46/veh/d	$6.13/veh/d	5.0%	$0.32/veh/d
Flat (*)	$683.8	$705.4	3.1%	$21.58	$6.76	$6.53	3.5%	$0.24
TOU	$683.8	$704.3	2.9%	$20.54	$6.13	$5.88	4.0%	$0.24
TOU (*)	$683.8	$704.9	3.0%	$21.13	$6.43	$5.45	15.3%	$0.99
No Peak	$683.8	$705.6	3.1%	$21.84	$1.77	$1.61	9.2%	$0.16
No Peak (*)	$683.8	$702.7	2.7%	$18.95	$2.08	$1.99	4.1%	$0.08
Peak	$683.8	$704.8	3.0%	$21.06	$2.87	$2.24	22.1%	$0.64
Peak (*)	$683.8	$705.2	3.0%	$21.37	$3.18	$2.55	19.6%	$0.62
Spike	$683.8	$706.8	3.3%	$22.99	$7.79	$5.31	31.9%	$2.49
Spike (*)	$683.8	$705.8	3.1%	$22.01	$8.10	$4.48	44.7%	$3.62
Off-peak	$683.8	$705.4	3.1%	$21.56	$1.37	$1.10	19.6%	$0.27
Off-peak (*)	$683.8	$705.2	3.0%	$21.39	$1.67	$1.50	10.3%	$0.17

Note: (*) = A peak power rate fee ($/kW) is added. “SCC” = social cost of carbon. Results are in 2021 USD.

TABLE 6 Daily Mobility Performance Comparison by Control Strategy and Electricity Price.

Electricity Price (Peak Power Rate Fee)	Avg Daily Trips per SAEV	% Trips Met by Fleet	Avg Daily VMT per SAEV	Fleet Average % eVMT	Median Wait Time (min)	Avg Daily Charging Trips per SAEV	Avg Daily Cleaning Trips per SAEV
Price-Agnostic	27.17	97.00%	277.7	34.1%	4.7	3.22	0.79
Flat	27.92	99.68%	295.6	36.3%	4.8	2.04	0.84
Flat (*)	27.85	99.43%	296.6	36.7%	4.9	2.19	0.84
TOU	27.91	99.64%	296.5	36.5%	4.9	2.02	0.85
TOU (*)	27.65	98.72%	296.5	37.3%	5.0	2.15	0.84
No Peak	27.93	99.72%	296.6	36.5%	4.8	2.04	0.84
No Peak (*)	27.93	99.70%	297.8	36.8%	4.8	2.22	0.85
Peak	27.85	99.44%	295.5	36.4%	5.0	2.08	0.83
Peak (*)	27.98	99.90%	297.6	36.7%	4.7	2.32	0.86
Spike	27.97	99.87%	297.6	36.8%	4.8	2.11	0.84
Spike (*)	28.01	99.98%	297.2	36.8%	4.6	2.47	0.86
Off-peak	27.91	99.63%	295.4	36.3%	4.8	2.04	0.84
Off-peak (*)	27.98	99.89%	296.7	36.6%	4.8	2.28	0.86

Note: (*) = A peak power rate fee ($/kW) is added. "eVMT" = Empty VMT.

TABLE 7 Daily Per-SAEV Health and Climate Damages from Electricity Generation by SCC and Electricity Price.

Electricity Price (Peak Power Rate Fee)	Avg Daily Health and Climate Damages (per SAEV) \$40/tonne CO_2 (2010 USD)				Avg Daily Health and Climate Damages (per SAEV) \$200/tonne CO_2 (2010 USD)			
	Price-Agnostic (\$)	**Multi-Stage (\$)**	**% Decrease**	**\$ Damages Avoided**	**Price-Agnostic (\$)**	**Multi-Stage (\$)**	**% Decrease**	**\$ Damages Avoided**
Flat	\$5.16/veh/d	\$5.07/veh/d	1.7%	\$0.09/veh/d	\$15.62/veh/d	\$15.15/veh/d	3.0%	\$0.48/veh/d
Flat (*)	\$5.16	\$4.94	4.2%	\$0.22	\$15.62	\$15.00	4.0%	\$0.63
TOU	\$5.16	\$5.06	1.9%	\$0.10	\$15.62	\$15.11	3.3%	\$0.51
TOU (*)	\$5.16	\$5.23	(1.4%)	(\$0.08)	\$15.62	\$15.31	2.0%	\$0.32
No Peak	\$5.16	\$5.06	1.8%	\$0.10	\$15.62	\$15.13	3.2%	\$0.49
No Peak (*)	\$5.16	\$4.95	4.1%	\$0.21	\$15.62	\$15.18	2.8%	\$0.44
Peak	\$5.16	\$4.99	3.2%	\$0.17	\$15.62	\$15.22	2.6%	\$0.41
Peak (*)	\$5.16	\$4.97	3.7%	\$0.19	\$15.62	\$15.10	3.4%	\$0.52
Spike	\$5.16	\$5.11	0.9%	\$0.05	\$15.62	\$15.25	2.4%	\$0.37
Spike (*)	\$5.16	\$5.29	(2.5%)	(\$0.13)	\$15.62	\$15.61	0.1%	\$0.02
Off-peak	\$5.16	\$5.08	1.5%	\$0.08	\$15.62	\$15.18	2.8%	\$0.44
Off-peak (*)	\$5.16	\$4.95	4.1%	\$0.21	\$15.62	\$15.10	3.3%	\$0.52

Note: (*) = A peak power rate fee (\$/kW) is added. "SCC" = social cost of carbon. Results are in 2021 USD.

6.2 Fleet Charging and Discharging Profiles

The day-ahead strategy determines the amount of electricity to buy or sell for the next 24 hours to minimize total electricity costs. Fig. 7 shows the (dis)charging energy profiles by electricity price type ($/kWh) and peak power rate fee ($/kW) relative to the price-agnostic strategy (SCC = $40/tonne CO_2). When fleets face a daily fee on their peak power draw, the strategy can spread charging into other low-cost periods while ensuring adequate fleet average SOC. The plot shows lower electricity consumption bars under TOU and spike wholesale prices with peak power rate fees (light yellow) than without these $/kW fees (dark grey).

Interestingly, TOU with $/kW fees led to the most amount of discharged electricity (totaling 85.1 MWh). In this scenario, the average SAEV providing V2G services supplied 42.5 kWh of electricity. Although TOU electricity price variation is not as volatile as the wholesale energy market, the fleet can reduce its electricity costs through energy arbitrage when it knows prices in advance and the price difference is sufficiently high (6.57x in this study). Although the peak period was 2-7 PM, discharging ramped up until 8 PM before gradually declining. This finding suggests that day-ahead buying and selling should consider not only charging station availability but the effect of slower discharging rates on future charging station availability. This study used a first-in, first-out queueing policy at charging stations, which may explain temporal shifts between decisions and outcomes.

6.3 SAEV Electricity Costs

The multi-stage strategy reduces daily electricity costs, regardless of the electricity pricing type (e.g., fixed or wholesale). Table 5 shows the average difference (% and $) in passenger revenue and electricity purchase costs between the two strategies. These values are averaged across all five SCC scenarios for a typical day’s trips. Table 7 shows the average difference in health and environmental damages under low and high SCC prices ($40 and $200/tonne CO_2). Fleet managers will likely adopt the multi-stage (dis)charging strategy because it can increase profit, mostly due to increases in passenger revenue. At the same time, fleet managers may pay 15.5% less on electricity purchasing costs (or $0.79 per SAEV per day). Prior research has shown lower per-mile costs with SAEVs compared to internal combustion engine vehicles (Bauer et al., 2018), partially due to lower "fuel" costs (e.g., up to 6% of operating costs per vehicle-mile in Austin (Becker et al., 2020)). Depending on the electricity prices set by the utility or the wholesale market, fleet managers can decrease daily per-vehicle costs by $0.08 to $3.62. Flat electricity prices, which do not incentivize shifting charging demand, offer the least savings (average 5% without $/kW fees versus 3.5% with). The highest cost saving was found in the wholesale spike with $/kW fees scenario (44.7%), similar to findings in Iacobucci et al. (2021).

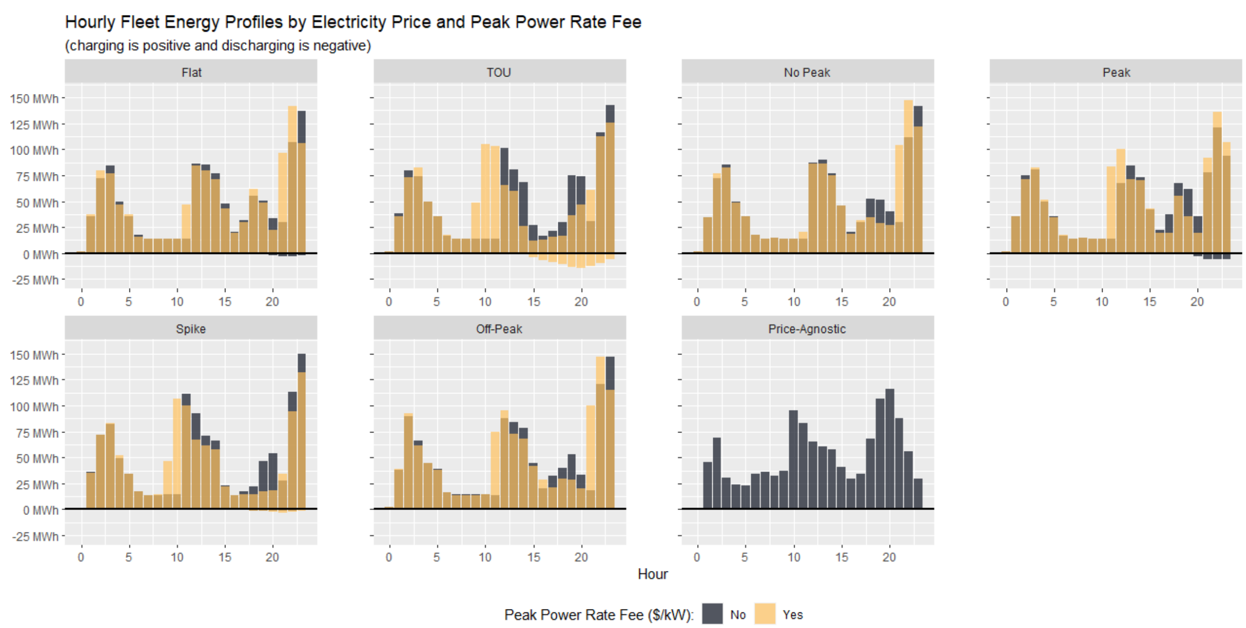

Fig. 7. Hourly SAEV fleet energy profiles by electricity type and peak power rate fee.
(Note: Assumes a $40 SCC in 2010 USD in the climate damages calculation)

The price-agnostic strategy's objective function includes an opportunistic charging term, which may explain why the baseline has higher electricity demand. The objective function trades off between charging low-SOC vehicles with minimizing zonal supply deficits. So long as the zonal supply deficit is kept to a minimum, the strategy will charge vehicles. As a result, the average SAEV will visit a charging station 3.2 times per day versus an average of 2.2 with day-ahead charging (Table 6).

In general, pursuing a joint minimization of direct and indirect electricity costs can reduce health and climate damages from power plant emissions. Absent a carbon tax, the health damages from electricity generation rise in all but one pricing scenario (TOU) relative to price-agnostic control (Table 8). If the fleet ignores carbon costs, the average amount of CO_2 per SAEV can fall in a third of pricing scenarios (e.g., flat, TOU, TOU with $/kW fees, and spike). Policy interventions like carbon taxes can reduce charging emissions and health damages from power generation (Table 7). At $200/tonne CO_2, the day-ahead solution will always reduce upstream emissions. In contrast, the lowest SCC value leads to higher damages when the electricity price includes a $/kW fee and uses retail TOU or wholesale pricing with a spike (Table 7). Increasing SCC can ensure a more consistent reduction in health damages of around 2.8% per vehicle per day. The average per-vehicle emission damages savings is between $0.10 and $0.43 (for SCCs of 40 and 200, respectively). A 15,000-vehicle fleet in Austin could avoid $3,280–$9,375 in health and environmental damages per day by switching to this multi-stage strategy.

TABLE 8 Daily Per-SAEV Health Damages and Carbon Dioxide Release from Electricity Generation by Control Strategy Without Internalizing Social Costs.

Electricity Price (Peak Power Rate Fee)	**Avg Daily Health Damages (per SAEV)**				**Avg Daily kg CO_2 Charging Emissions (per SAEV)**			
	Price-Agnostic ($)	**Multi-Stage ($)**	**% Increase**	**$ Damages Added**	**Price-Agnostic (kg CO_2)**	**Multi-Stage (kg CO_2)**	**% Increase**	**kg CO_2 Added**
Flat	$2.05/veh/d	$2.20/veh/d	7.1%	$0.16/veh/d	52.6 kg CO_2/veh/d	51.0 kg CO_2/veh/d	(3.1%)	(1.6) kg CO_2/veh/d
Flat (*)	$2.05	$2.21	7.6%	$0.17	52.6	54.1	2.73%	1.5
TOU	$2.05	$2.04	(0.3%)	($0.01)	52.6	48.7	(7.5%)	(3.9)
TOU (*)	$2.05	$2.18	6.3%	$0.14	52.6	51.6	(2.0%)	(1.0)
No Peak	$2.05	$2.37	13.6%	$0.32	52.6	53.7	1.9%	1.1
No Peak (*)	$2.05	$2.22	7.7%	$0.17	52.6	54.1	2.7%	1.5
Peak	$2.05	$2.30	11.1%	$0.26	52.6	53.0	0.7%	0.4
Peak (*)	$2.05	$2.34	12.4%	$0.29	52.6	53.8	2.1%	1.2
Spike	$2.05	$2.19	6.8%	$0.15	52.6	52.3	(0.6%)	(0.3)
Spike (*)	$2.05	$2.27	9.8%	$0.22	52.6	53.1	1.0%	0.5
Off-peak	$2.05	$2.38	14.2%	$0.34	52.6	54.4	3.2%	1.8
Off-peak (*)	$2.05	$2.25	8.9%	$0.20	52.6	54.3	3.2%	1.7

Note: (*) = A peak power rate fee ($/kW) is added. "SCC" = social cost of carbon. Results are in 2021 USD

6.4 Sensitivity Analysis with Battery Capacity and Charging Speed

The prior sections summarized results from a comprehensive set of simulations of an on-demand SAEV fleet operating in the 6-County Austin, TX metro by varying electricity prices, peak power rate fees, and the cost of carbon within a joint health and climate emissions damages estimate. The sensitivity of the comparison between the proposed multi-stage charging and discharging strategy and the price-agnostic benchmark is evaluated here with respect to battery capacity and charging speed. All twelve electricity and power scenarios are studied using an SCC value of $40/tonne of CO_2 in 2010 USD. Charging speed is set at 120 kW when shifting battery capacity, and vehicle battery capacity remains 90 kWh when shifting charging speed.

Fig. 8 presents two bar plots to show how increasing vehicle battery capacity can reduce the frequency of charging trips in a day and increase queue time at charging stations (when there is a queue). Also, the median wait time that customers experience decreases as battery capacity increases since fewer vehicles need to charge at once, but only for the proposed framework. The results indicate that multi-stage charging and discharging can improve the quality of the service, albeit with long wait times at charging stations. The increase in profits per 75-kWh vehicle per day (using the same analysis shown visually in Fig. 5) is between -$0.01 and $6.76, depending on the day's electric bill ($/kWh and $/kW). The loss is an outlier since the next lowest change in operating profits between strategies is $2.09. For 60-kWh vehicles, the increase in daily per-vehicle profit is between $1.48 and $12.70. These ranges are comparable to Fig. 5's 90-kWh fleet, which shows an additional daily per-vehicle profit of $3.15 to $11.24.

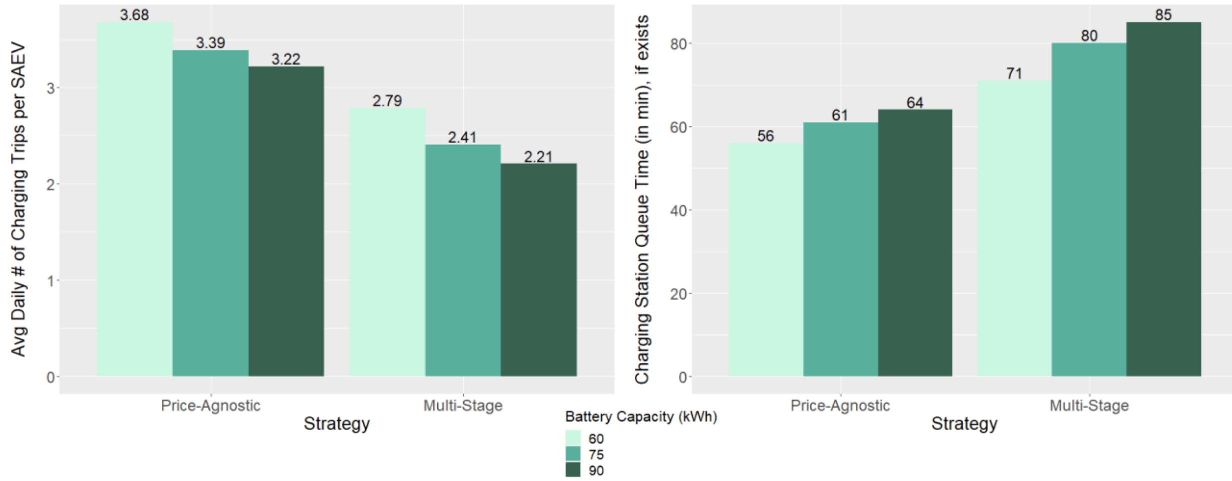

Fig. 8. Change in SAEV fleet service by changing battery capacity.
(Note: SCC = $40/tonne CO_2 in 2010 USD and Charging Speed is 120 kW)

Similarly, Fig. 9 shows the sensitivity of two metrics for charging speed at the fleet-owned chargers. Increasing charging speed in three levels (60 kW, 90 kW, and 120 kW) can increase the frequency of charging trips in a day and decrease queue time at charging stations (when there is a queue). The proposed multi-stage charging and discharging strategy has an upper bound on buying energy based on charging speed and number of chargers. Higher charging speeds mean more of the fleet's recoup of SOC can be done within a low-cost hour, which may lead the fleet to chase lower electricity costs and dispatch more vehicles, albeit at slightly higher percent empty travel. Faster charging also can reduce downtime and improve response times for passenger service. The increase in profits using 60 kW chargers with a 90-kWh vehicle per day (using the same analysis shown visually in Fig. 5) is between $6.04 and $15.36, depending on the day's electric bill ($/kWh and $/kW). For 90 kW chargers, the increase in daily per-vehicle profit is between $2.78 and $8.89. These ranges are comparable to Fig. 5's 120 kW charging speed, which shows an additional daily per-vehicle profit of $3.15 to $11.24.

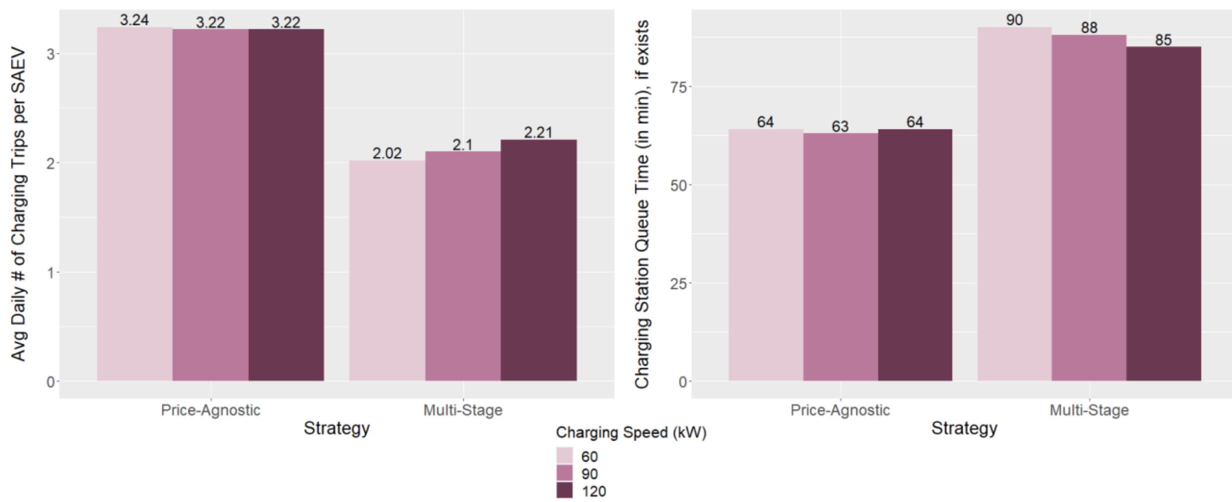

Fig. 9. Change in SAEV fleet service by changing charging speed.
(Note: SCC = $40/tonne CO_2 in 2010 USD and Battery Capacity is 90 kWh)

7. Discussion

7.1 Power System Impacts

A 15,000-vehicle fleet in Austin (serving about 7.1% of the region's daily person-trips) with a baseline control strategy (Dean et al., 2022), called price-agnostic in this study, consumed 1,364 MWh of electricity per day. Austin's peak demand in 2019 was 2,810 MW (4–5 PM), and the price-agnostic charging and repositioning strategy for SAEVs could add an additional 29.6 MW (or 1.05% of the existing peak electricity demand for this region). In contrast, the multi-stage charging and discharging framework, which includes marginal emissions damages (often higher at the peak), reduced the average peak demand to 18.3 MW (shaving the peak by 38%). Since power distribution systems are designed around the peak demand, shifting flexible loads from SAEV fleets could allow the utility to avoid costly infrastructure upgrades that would be passed to all customers. Estimates on the marginal distribution system costs vary by utility and scope (i.e., based on load, number of customers, and load diversification) and range from $148/kW to $1,520/kW (Cutter et al., 2021). The multi-stage charging and discharging strategy can provide peak shaving benefits of $0.01 to $0.13 per SAEV per day, assuming a 25-year design life for substations. Higher benefits are received when SAEVs pay for the real cost of producing electricity (i.e., time-varying or wholesale prices).

7.2 Empty Travel Impacts

Increases in empty VMT affect all travelers and may be penalized in the future (Dean and Kockelman, 2022a). The revenue-miles average vehicle occupancy (AVO) across all strategies, including the price-agnostic base, was at least 1.95. The percentage of unoccupied VMT in the 5,300 square mile service area is higher than in Dean et al. (2022) (34%–37% versus 24%), likely due to maintenance and cleaning trips (Gurumurthy et al., 2022), which are performed in only four locations in this region. Supply shortages from maintenance and cleaning may also explain why AVO increased from 1.64 to 1.95. Assuming a 35% empty VMT allowance for a sprawling service area and a 5-cent road usage fee on any additional empty travel, the fleet would face an average daily penalty of $0.09 per vehicle. Although small relative to passenger revenue, the region's transportation authorities could collect anywhere from $310,000 to $430,000 in additional revenue annually (depending on daily and seasonal changes in passenger demand). The price-agnostic strategy had 34.1% empty VMT and would avoid penalties under the assumed 35% cap (Table 6). A limitation of this study is that demand generation did not include surge pricing or recover costs from picking up passengers in exurban neighborhoods, which would likely reduce deadheading miles. A high empty VMT cap may also limit service to areas with a higher density of trip ends (i.e., geofences), which may have equity impacts because housing costs usually decline with distance from the downtown (Gurumurthy and Kockelman, 2022).

7.3 Fleet Charging Infrastructure

Managed charging can be implemented with existing EVs and charging infrastructure, provided communication capabilities exist between the fleet manager and either the vehicle or charger. V2G requires having an EV and charging station with bidirectional charging capabilities. Future proofing fleet-owned charging station investments may allow SAEVs to take advantage of non-transportation revenues (e.g., grid services) or, at the very least, lower costs through energy arbitrage. If fleets use only bidirectional charging equipment, vehicles that are contractually obligated to discharge may face queueing delays unless fleet managers prioritize discharging commitments by disconnecting charging vehicles (see results from the TOU with $/kW fees scenario). Alternatively, fleet managers can work with utilities to determine the value of V2G services to the local power distribution network and build out bidirectional chargers in select locations. Collaborations between EV fleets and utilities could allow for better EV-grid outcomes.

7.4 Retail Electricity Prices and Peak Power Rate Fees

Although fixed retail electricity prices, either flat or TOU, provide certainty to fleets in multi-year cost projections, they have some of the highest electricity costs (Table 5). If Texas allowed fleet customers within municipally-owned electric utility regions, like Austin, to opt into wholesale electricity prices, the fleet manager could significantly reduce their electric bills from current levels. However, Texas residential or small commercial customers cannot have wholesale-indexed retail prices (Public Utility Commission of Texas, 2022). Even in a volatile wholesale power price scenario (e.g., spike), the average daily electricity cost per vehicle was $5.31, which was less than all fixed retail prices ($5.45 to $6.53). Thus, considering electricity prices in dispatch decisions can protect the fleet from volatile and unusual price spikes (e.g., $1287/MWh versus a daily average of $20.53/MWh). However, wholesale electricity prices are usually lower than retail prices offered by utilities (Fig. 2). If fleets use price-agnostic dispatch strategies and the wholesale price spikes, per-vehicle electricity costs could be $1 to $2 more than under fixed retail rates (Table 5).

Thus, fleets that elect to pay wholesale prices should adopt a charging strategy that insulates them from volatile prices.

All electricity price scenarios where health damages increased also had peak power rate fees. Although these add-on fees have the effect of shaving peak charging, this study finds that shifting the charging load could increase marginal emissions. The increase in health damages is relatively small (1.4%–2.5%, or 8–13 cents per vehicle per day) (Table 7). Utilities should carefully review how adding peak power rate fees may increase upstream pollution, depending on the hourly marginal emission rates of their region.

This study has lower electricity cost savings than Iacobucci et al. (2021) – 15.5% per SAEV per day versus their 52% average. However, 52% may be too high because there is no comparison to retail prices and a simple charging alternative called "on-demand." This present study finds the average cost savings (across all non-zero carbon cost scenarios) for days with a spike in wholesale prices was 31.9% to 44.7% (with or without a peak power rate fee). In contrast, a multi-stage charging and discharging framework may only save between 3.5% and 15.3% in purchasing costs with retail prices relative to a price-agnostic optimization-based charging strategy. If one averages the cost savings from Iacobucci et al. (2021) without on-demand charging, the average savings is 32% (and the median is 25.8%). Zhang and Chen (2020) used a low-battery charging heuristic as a comparison and started vehicles at the beginning of the day with a full charge. As a result, most SAEVs trigger a charging decision in the afternoon when electricity prices are higher.

7.5 Renewable Energy Credits

Multi-stage charging and discharging can avoid the daily release of up to 904 tonnes of CO_2, with an average of 654 tonnes of CO_2 avoided in the studied area. The average SAEV could reduce 43.6

kg of CO_2 per day with this multi-stage (dis)charging strategy. For comparison, the average US passenger vehicle emits 4.6 tonnes of CO_2 each year (U.S. Environmental Protection Agency, 2022). It would take 106 days for an SAEV to remove one gas-powered passenger vehicle from the road solely by implementing a different control strategy. In contrast to 60 tonnes of CO_2 savings per California vehicle per year in Liao et al. (2021), this study finds an Austin SAEV would save at most 15.9 tonnes of CO_2 per year with a charging and discharging strategy.

If an Austin fleet were to purchase unbundled RECs to reduce upstream charging emissions and claim charging comes from 100% renewable energy, there would be an additional average daily cost of $9,134, assuming a cost of $6.60/MWh (Heeter et al., 2021). Fleets could instead align their charging with low-carbon generation through this strategy to reduce their carbon footprint at no extra cost while reducing their REC bill by 3.6%. This study shows that the increase in passenger revenue per SAEV per day can more than offset the cost of internalizing health and climate damages from electricity emissions (scope 2 activity) using a carbon cost of $200/tonne of CO_2 in 2010 dollars. A fleet not required to pay carbon pricing could internally use a high SCC to increase profits (from serving more trips per vehicle per day and reducing direct electricity purchasing costs, Tables 5 and 6).

A fleet operator could maximize the uptime of vehicles to increase passenger revenue and purchase unbundled RECs to reduce the impact of charging emissions that comes from ignoring real-time health and climate damages from their operations. However, purchasing inexpensive unbundled RECs does not encourage the expansion of zero-carbon renewable power. An alternative strategy is to sign a long-term power purchase agreement from a newly constructed zero-carbon power plant, which supports new capacity additions. Power purchase agreement prices for utility-scale solar are valued around $30/MWh to $40/MWh in the continental US ($20/MWh in California) (Bolinger et al., 2022), while onshore wind averages $30/MWh ($20/MWh in the central US) (Wiser et al., 2022).

7.6 Framework Assumptions and Limitations

The multi-stage charging and discharging framework has several modeling assumptions, which can impact results. The day-ahead problem uses a virtual fleet battery, which aggregates individual vehicle information, to reduce problem size. The fleet must rely on a reliable energy consumption prediction to estimate how much energy to buy or sell to lower purchasing costs while reaching the end-of-day SOC target. Although the simulation environment uses an energy consumption model that can track vehicle-level energy usage (in kWh), the day-ahead problem reads in hourly mileage estimates and a single energy efficiency parameter (in kWh/mi). Since energy efficiency depends on weather, traffic, and built environment effects (e.g., temperature, vehicle speeds, and gradients), modelers could use previous hourly energy consumption outputs instead of a mile-equivalent factor to improve solutions.

A downside of using an average fleet battery to make charging and discharging decisions and relying on historical energy consumption estimates is that the optimal decision set may result in individual battery levels that are insufficient to meet travel demand. On the other hand, an advantage of aggregating battery levels is reducing problem size to keep the computational time low. Additionally, predicting energy consumption demand for individual vehicles depends on passenger-vehicle assignments. For example, an SAEV assigned to a reverse-commute trip may not find another passenger as quickly as a vehicle operating predominately within the central business district. As a result, the estimate for future energy is location and time specific and requires knowledge about expected routes for some *n* trips in the future.

The last term of the day-ahead charging and discharging problem (Eq. 1) imposes a steep penalty if the fleet's average SOC at the end of the day deviates from the target. An alternative approach is to formulate the day's end SOC target as a constraint instead of an objective term. However, this could lead to infeasible problems under certain circumstances. By using a sufficiently large number to penalize deviation from a target SOC, the fleet can almost always solve the problem of charging and discharging. During days when the 24-hour ahead day's end SOC target is not attainable, the rolling horizon framework should allow the fleet to exploit low-demand and low-cost periods to raise the fleet average SOC.

Instead of a zone-specific opportunity cost parameter, this study used a constant value in the within-day idle vehicle dispatch problem. Although fleet operators would be wise to use historical trip revenue as a weight for the supply deficit variable, the authors felt that introducing more complexity would make it difficult to tease out differences in electricity prices, peak power rate fees, and carbon costs. This dispatch problem also assumes that the hourly day-ahead energy transaction targets (i.e., buying and selling) are divided uniformly across the number of within-day decision epochs. Since the within-day decision epochs occur at quarter-hour intervals, it becomes necessary to translate hourly targets into smaller time steps to dispatch vehicles to charging stations. However, the day-ahead problem could scale to quarter-hours if prices are available every fifteen minutes. More frequent decision epochs (like every 5 minutes) could reduce costs even further because each epoch would likely have fewer dispatch decisions and could better adapt to large changes in electricity prices.

The first term of the within-day idle vehicle dispatch problem penalizes dispatch costs by estimating how much it would cost to charge the vehicle from dispatch travel alone. There are other distance costs to consider that could be considered, namely depreciation, tolls, wear and tear, battery degradation, and insurance. Adding a constant parameter to travel distance could reduce the frequency of some long-distance idle vehicle dispatch decisions. The idle vehicle dispatch problem excludes passenger assignment as a decision variable. Testing well-known passenger assignment strategies, such as Alonso-Mora et al. (2017), in large-scale simulations, could improve heuristic assignment methods but may worsen computational performance because of the size of the problem.

The study used an idle vehicles dispatch strategy to consider vehicles for discharging. An alternative approach that can lead to a near-instantaneous discharging outcome is to stop currently charging vehicles and send power back to the power grid. An additional improvement that can avoid the temporal shift between optimal energy arbitrage hours and outcomes shown in Fig. 7 is to stop discharging once the amount of energy to sell is zero. The energy profile in Fig. 7 indicates that some hours show both charging and discharging outcomes. While it is plausible that the optimal hourly decision is to buy and sell electricity – to avoid a self-imposed day's end SOC deviation penalty and to obtain revenues from energy arbitrage – this study assumed low-battery SAEVs could independently go charge.

The study used marginal emissions damages because SAEVs represent a new demand for electricity that corresponds to an increase in electricity generation. However, the emissions estimates come from historical data, and future changes in the grid could significantly affect the reliability of these estimates. For example, the retirement of inefficient and carbon-intensive fossil fuel power plants, like baseload coal, the new construction of natural gas power plants, utility-scale wind and solar, transmission expansion, and expanded carbon trading schemes could significantly alter the generation and transmission operations of the grid (Ryan et al., 2016). Using power grid operation models with future generation and transmission inputs is one approach to incorporating a forward-looking analysis into this framework.

The idle-vehicle dispatch problem was solved as an Integer Linear Programming problem for the case where wholesale prices spike in the day with an added peak power rate fee. Then, it was solved by removing the integer constraint (i.e., as a Linear Programming problem), although the matrix is not guaranteed to be totally unimodular in every instance. The objective value and solution vector (for charging, discharging, repositioning, and maintenance trips) were similar, albeit with higher solve times when enforcing integer solutions. In this study, the results shown used the Linear Programming solver to ensure efficient solve times across different decision scenarios. Since a non-integer solution is not practically feasible for vehicle decisions, the fleet operator ignored all solutions less than 0.85. In practice, discarding non-integer solutions while not resolving the need (i.e., supply deficits or low fleet average SOC) creates an incentive to remedy the issue in future decision epochs.

7.7 Future Work

This study used marginal emission damages to estimate the effect additional SAEV electricity demand may have on human health and the climate. However, the study did not couple this transportation simulation with a unit commitment and economic dispatch model that would show whether SAEVs can influence wholesale power prices by shifting the equilibrium point on supply and demand curves. With increasing EV adoption levels, integrated transportation and power models may be better suited to analyze the least-cost idle vehicle dispatch strategies. Modelers studying large-scale regions, like the 6-County Austin metro, may consider how transmission constraints or locally varying demand for electricity may lead to a few hours of the day where wholesale electricity prices vary by charging station. If the marginal difference between charging stations is higher than the cost of dispatch, then a new charging station assignment problem may be warranted. Although this strategy reveals lower health damages from increasing electricity demand, the analysis does not link perturbations in emissions with those most exposed to additional pollutants. Further work may show the distributional effects of changes in local air pollution from increased reliance on SAEVs for urban travel.

The numerical experiments in this study used charging station inputs from Dean et al. (2022), which considered the effects of charging station locations and plugs, and manually sited maintenance and cleaning depots. A sensitivity analysis varied battery capacity and charging speed but did not examine charging station or cord density. Although station siting and sizing were not within the scope of this study, future work should use advanced charging station location problems (within a joint fleet size problem, like Luke et al. (2021)). The authors also assumed that fleet owners will staff maintenance depots around the clock, but future work could restrict maintenance and cleaning to typical working hours. Future research may also study the effects of zoning and remnant power grid limitations on EV fleet charging operations by restricting charging station locations and size.

The case study assumed the SAEV fleet only offered shared services (i.e., a private ride was not available for a higher fare) to encourage de-congestion benefits. Although everyone was forced into this shared service, not everyone was successfully matched with another passenger en route because of maximum detour delay and directionality constraints (see Dean et al. 2022 for more details). Future work should include a willingness to pool model to consider whether an agent would consider a discounted shared service given their demographics and trip information. Moreover, modelers should simulate trips with multiple riders in a single request (i.e., multi-party trips) to simulate realistic party size distributions found in present-day ride-hailing trip data sets (e.g., Chicago's Transportation Network Providers Trip Data Portal).

8. Conclusions

The future of shared passenger mobility is widely expected to be powered by all-electric powertrain technology. If autonomous vehicle technology advances and cities nudge residents into shared vehicular modes or active travel, daily travel may increasingly be taken using a system of on-demand SAEVs. The present study sought to investigate how a fleet could improve idle vehicle dispatch by lowering the cost of charging. A multi-stage charging and discharging framework translated optimal fleetwide energy transactions into vehicle-to-zone dispatch decisions at discrete decision-making epochs within the day. Since actions from one day affect the next, the hourly day-ahead energy transaction problem is solved for the next 24-hour period at each within-day epoch. This rolling horizon approach also prevents a large divergence between energy consumption forecasts and within-simulation battery levels.

This new multi-stage framework was compared to a price-agnostic optimization-based charging and repositioning joint strategy in the literature, which showed improved performance relative to disjoint strategies, including charging heuristics. New maintenance and cleaning requirements are also added to improve realism in vehicle downtime and empty travel. A numerical analysis of this method was simulated within POLARIS to take advantage of its endogenous traffic and dynamic traffic assignment algorithms and computationally efficient model of the 6-County Austin, TX region.

Fleets may operate in regions with retail prices set by utilities, which provide stability in prices, but are more expensive than the wholesale power market. As the power system transitions to zero-carbon energy sources, including intermittent wind and solar, and electricity demand rises with EVs, utilities may want to shift the cost of power onto consumers. This study investigated how retail prices (flat and TOU) and four wholesale price profiles (off-peak, peak, no peak, and spike), with or without a peak power rate fee, can influence charging and discharging decisions.

By intentionally aligning fleet charging with low-cost hours in the day-ahead price market, the fleet operator could withstand temporary spikes in wholesale prices and have a lower daily electricity bill than if they paid a flat retail energy price. Daily savings on direct electricity costs averaged 15.5% per SAEV (or $0.79), and climate and health damage avoidance averaged 2.8% per SAEV (or $0.43). The simulation results were for a fleet serving a median 29 daily trips per vehicle. Although the percentage of unoccupied VMT is higher for the 5,300 square mile service region than in prior studies, new maintenance and cleaning requirements at just four depots suggest deadheading travel will continue to be high. That said, the revenue-miles AVO was at least 1.95 across all scenarios, indicating that sharing rides among strangers can mitigate high empty travel.

Although peak power rate fees can help reduce the impact of many EVs charging at once, this price add-on could increase health and climate damages. This trade-off between deferred capacity investments and societal emission damages is a topic worthy of more discussion. Additionally, if the fleet only pursues lower electric bills and does not internalize the emissions damages from electricity generation, the fleet can increase societal costs for everyone. With this proposed strategy (and a non-zero carbon cost), an Austin fleet of 15,000 SAEVs can align charging with lower cost periods to avoid a daily release of an average of 656 metric tons of CO_2, equivalent to 142 US passenger vehicles' annual CO_2 emissions.

Although a fleet could purchase unbundled renewable energy credits for every kWh of energy consumed, this accounting does not spur additional zero-carbon generation capacity. By reducing a fleet's charging emissions damages in real-time, the fleet can purchase fewer credits and correct for the spatio-temporal mismatch between zero-carbon generation elsewhere and damages from electricity demand.

9. CRediT Authorship Contribution Statement

Matthew D. Dean: Conceptualization, Methodology, Software, Writing – original draft, Visualization. **Felipe de Souza:** Conceptualization, Methodology, Software. **Murthy Gurumurthy:** Conceptualization, Software. **Kara M. Kockelman:** Supervision. All authors reviewed, edited, and approved the final version of the manuscript.

10. 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 study.

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12. Appendix

The hourly electricity price profiles used in the simulations of this study are explained and the wholesale price curves are plotted in Section 5.2. The data for these plots is shown below in Table A.1.

Table A.1 Hourly Electricity Prices in Case Study

	Retail Prices ($/MWh)		**Wholesale Prices ($/MWh)**			
Hour	**Flat**	**Time-of-Use (TOU)**	**No Peak Day**	**Peak Day**	**Spike Day**	**Off-Peak Day**
12:00 AM	$70/MWh	$35/MWh	$16.42/MWh	$18.23/MWh	$19.23/MWh	$8.16/MWh
1:00 AM	70	35	16.06	17.04	18.52	5.59
2:00 AM	70	35	15.24	16.82	17.80	3.36
3:00 AM	70	35	14.94	17.66	16.76	2.69
4:00 AM	70	35	15.33	18.68	16.94	2.67
5:00 AM	70	35	17.24	19.08	16.79	8.66
6:00 AM	70	35	19.79	24.40	18.25	16.11
7:00 AM	70	35	19.57	32.63	18.02	16.06
8:00 AM	70	35	19.38	29.72	18.08	15.98
9:00 AM	70	35	19.12	27.91	18.29	15.51
10:00 AM	70	35	19.10	25.01	19.61	16.10
11:00 AM	70	35	20.43	23.86	23.26	16.76
12:00 PM	70	35	20.36	24.41	26.99	15.61
1:00 PM	70	230	20.47	24.64	32.00	16.74
2:00 PM	70	230	20.05	23.93	37.85	16.89
3:00 PM	70	230	20.50	30.00	175.82	17.17
4:00 PM	70	230	21.70	31.08	627.98	18.56
5:00 PM	70	230	22.52	27.66	1,287.35	20.24
6:00 PM	70	35	21.72	26.43	266.06	19.22
7:00 PM	70	35	21.50	50.41	27.39	19.38
8:00 PM	70	35	20.57	87.40	36.51	20.18
9:00 PM	70	35	18.67	23.89	23.61	18.47
10:00 PM	70	35	18.43	27.00	21.46	16.11
11:00 PM	70	35	16.78	21.39	18.74	11.48

All simulations were run using 2 compute nodes (30 tasks per node) with a clock rate of 2.45 GHz and 256 GB RAM. The computational solve time (in sec) for the simulation hours of 6-8 AM are shown below in Table A.2. The multi-stage problem solve time includes the rolling horizon day-ahead problem and the within-day vehicle dispatch problem under the \$40/tonne CO_2 scenario. All scenarios took under 1 hour and 45 minutes, including pre-simulation and post-simulation data processing.

Table A.2 Computational Solve Time by Strategy

Electricity Price (Peak Power Rate Fee)	6:00 AM	6:15 AM	6:30 AM	6:45 AM	7:00 AM	7:15 AM	7:30 AM	7:45 AM	8:00 AM
Price-agnostic	16 sec	16 sec	18 sec	15 sec	9 sec	6 sec	4 sec	2 sec	1 sec
Flat	3	3	2	2	3	0	1	1	0
Flat (*)	3	2	2	3	3	2	1	1	0
TOU	3	2	2	3	3	2	1	1	0
TOU (*)	3	2	3	2	3	2	1	1	0
No Peak	3	2	2	2	2	1	1	1	0
No Peak (*)	3	2	2	2	3	1	1	1	0
Peak	3	2	2	2	3	1	1	1	0
Peak (*)	3	2	2	2	3	2	1	1	0
Spike	3	2	2	2	2	2	2	1	0
Spike (*)	3	2	2	2	3	1	1	1	0
Off-peak	3	2	2	2	3	2	1	1	0
Off-peak (*)	3	2	2	2	2	2	1	1	0

Note: * = A peak power rate fee (\$/kW) is added.

The range of annual empty VMT revenue is not intended to be used for budgetary purposes and is only illustrative. The average daily empty VMT fee for the 15,000-vehicle fleet across all health damage scenarios was \$1,322.35. Since these results are based on a typical workday's travel demand patterns, the authors assumed a lower bound of 65% and an upper bound of 90% from a linear projection of daily demand for the year.

The price-agnostic strategy led to a daily electricity demand of 1,383.94 MWh. Assuming the fleet buys unbundled RECs at a price of \$6.60/MWh (Heeter et al., 2021), the base cost is \$9,134.01. With the multi-stage (dis)charging strategy, the fleet has a daily electricity demand of 1,333.63 MWh (on average across all health damage scenarios). Their new energy demand would reduce their REC bill to \$8,801.95 (or by 3.6%). Given that the average CO_2 emission factor for Texas in 2019 was 0.996 lbs/kWh (Holland et al., 2022) and the multi-stage charging strategy avoided the release of an average 654 tonnes of CO_2, the fleet could claim 1,447.61 MWh of carbon-free" power, although that ignores other generation-related pollutants. Table A.3 presents the average daily CO_2 savings for the Austin SAEV fleet relative to the price-agnostic charging strategy when there is a reduction in damages from the studied strategy. The results are averaged across all non-zero SCC scenarios.

Table A.3 Average Daily CO_2 Emission Savings from Charging an SAEV Fleet

Electricity Price	**Avoided Tonnes of CO_2 from 15,000-veh Fleet per Day**
Flat	800 tonnes CO_2/day
Flat (*)	760
TOU	870
TOU (*)	540
No Peak	779
No Peak (*)	608
Peak	823
Peak (*)	483
Spike	709
Spike (*)	45
Off-peak	782
Off-peak (*)	499

Note: * = A peak power rate fee ($/kW) is added.

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