SYNERGIES BETWEEN CHARGING AND REPOSITIONING STRATEGIES FOR SHARED AUTONOMOUS ELECTRIC VEHICLE FLEETS

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ABSTRACT

The emergence of on-demand shared autonomous electric vehicle (SAEV) service will provide local air quality, regional greenhouse gas reduction, and access benefits, while possibly increasing urban congestion. Charging trips will add to empty travel (eVMT) and could magnify the spatiotemporal fleet imbalance of vehicles depending on charging station design and charging strategy. To this end, this study investigates the advantages of coupling charging events with repositioning as a means of improving operational efficiency (rider wait times), externalities (eVMT due to repositioning or charging), and operations (average daily trips per vehicle). This synergy is explored for the Austin, Texas region using POLARIS, an agent-based activity-based model. On average, wait times were 39% lower, and the average daily trips served per SAEV increased up to 6.4 (or 28%) compared to SAEV repositioning with heuristic charging. Coupling repositioning with charging decreased %eVMT on average by 1.6% relative to the scenario treating them as independent events (varies by charging station design). The advantage of this joint charging and repositioning optimization framework over heuristic charging and independent repositioning is pronounced in a depot-like charging station network. Joint optimization reduces average charging downtime, prioritizes charging in advance of peak periods, and quickly recovers fleet state of charge (SOC). Sparser charging stations reduce investment costs but also reduce trips served per vehicle. For regional fleet service, the joint optimization strategy is more effective than the independent baseline strategy at minimizing eVMT and lowering response times, particularly with sparser charging stations.

Keywords: Shared Autonomous Electric Vehicles, Repositioning, Charging, Agent-Based Simulation, POLARIS, Optimization

INTRODUCTION

The future of transportation may be electric, automated, and shared (the "3 revolutions") (*1*). Innovations around these dimensions may significantly impact urban form, energy use, and daily life. In a world where all three converge, households may rely on shared autonomous electric vehicles (SAEVs) to provide convenient door-to-door service or first-mile last-mile connections with line-haul public transit (*2*). Sharing vehicles may lower parking demand, and if trips are pooled (via dynamic ride-sharing [DRS]), congestion from low-occupancy vehicles may fall. Less demand for travel lanes and parking spaces may allow cities to reclaim land for other purposes (e.g., bikes/pedestrians, outdoor dining, or green infrastructure) (*3–5*). Since SAEVs offer lower per-mile costs relative to present-day ride-sourcing, due to automation replacing drivers and lower lifetime costs from an electric powertrain (*6–9*), affordable clean mobility may alleviate persistent transportation-related inequalities that burden low-income neighborhoods (*10–12*). On the other hand, potential gains in access are expected to add empty vehicle-miles traveled (eVMT), which, if left unregulated, could worsen congestion across cities (*13–16*). There is some evidence to suggest that ride-sourcing vehicles have already increased congestion in cities like San Francisco (*17*). And as a bridge technology, drivers of ride-sourcing platforms can incur significant deadheading (up to 26% of ride-sourcing VMT in one study (*18*), though others estimate a higher range of 36% to 45%) when including TNC driver trips to and from home.

In response to increases in urban congestion and ride-sourcing's environmental and air quality impacts, California developed the Clean Miles Standard, which will regulate a fleet's annual CO_2 emissions per passenger-mile (*19*). At the street level, some municipalities have created dedicated zones for pick-up, drop-off, and other curbside activities (e.g., dynamic use and pricing) to manage competing interests of this space by SAEVs and other modes (*4, 20–24*). The issue of vehicle emissions and curb access are examples of the larger issue at play across municipalities: how do transportation planners and policymakers regulate ride-sourcing externalities without stifling mobility innovation? A particular topic of interest is how to improve the operations of range-constrained SAEVs while reducing the externalities of deadheading given the impacts of ride-sourcing vehicles today.

While the public is interested in the benefits of SAEVs (e.g., low-cost, on-demand trips), fleet operators are interested in improving the service and energy efficiency of the vehicles. Repositioning vehicles may improve service quality but drains the battery, thus increasing the time spent charging. Charging vehicles in advance of peak travel times increases the likelihood of a successful match (defined as an SAEV responding to a ride request within a traveler's maximum waiting time) but removes vehicles from service and introduces additional eVMT. In this study, the trade-off between charging and repositioning SAEVs is jointly modeled at pre-defined time steps and evaluated using an agent-based model (ABM). Different operational policies, both from the literature and proposed herein, are assessed through the simulation to provide insights on how fleet operators may better serve demand while simultaneously mitigating added eVMT. Additionally, this paper explores asset utilization of different sizes of fleet-owned electric vehicle charging station (EVCS) networks. This study uses advancements in ABMs so that no down-sampling is required, realistic congestion is loaded onto detailed links, and activity schedules govern trips as opposed to historical taxi trip data.

Background

Regulations to lessen added eVMT by fully-automated vehicles (AVs) may target a certain type of eVMT. For example, this could include personally-owned AVs cruising to avoid parking or SAVs repositioning to neighborhoods with high demand, but without a pick-up request. In general, there are three sources of empty travel (*25*) for SAEV fleets:

- Empty pick-up mileage from vehicles assigned to a new, nearby ride request (pVMT).
- Empty charging mileage from vehicles driving to an assigned charging station (cVMT).
- Empty repositioning mileage from vehicles driving to an assigned location after its last trip (rVMT).

The third category (rVMT) is used to either find available parking or proactively relocate vehicles to balance anticipated demand with supply. Repositioning SAEVs is similar to how ride-sourcing drivers currently cruise to find new requests, often to areas of perceived demand from historical experience, but is different in that repositioning SAEVs is centralized and coordinated fleet-wide. Repositioning is critical for operators when SAEV demand results in many vehicles accumulating in low-demand areas while a dearth of vehicles is observed in high-demand areas. In cities where travel demand patterns are unidirectional in morning and evening peak hours, vehicles may require explicit repositioning policies to balance the supply of vehicles for off-peak periods. If rVMT is penalized, fleet operators will want to capture riders who are less price-sensitive (i.e., willing to accept an additional fee) or couple repositioning with charging trips to avoid a fee and lower total energy costs.

Overall, repositioning strategies seek to redress the spatiotemporal asymmetry of origins and destinations by balancing anticipated demand with supply at discrete time steps, t, often an hour-ahead (*26, 27*). Since eVMT rises with any repositioning strategy and the added travel distance lowers the available range for rides, coupling charging with repositioning may be advantageous for fleet operators. If vehicles are repositioned in advance of demand, they could travel to a charging station within their assigned zone and fully charge. This joint action eliminates the battery depletion aspect of repositioning and avoids large charging episodes during peak periods. Since only available vehicles (i.e., those idling or en route to their last drop-off) could be considered eligible for repositioning, even long-range vehicles (minimum range of 300 mi) could fully charge during this process if they have at least half charge and a fast charger is free upon arrival.

Previous agent-based simulations vary in percent eVMT reported, as well as the increase in eVMT with proactive repositioning strategies. Early SAEV work on a grid network found that a low-impact strategy of repositioning vehicles within a 2x2 square mi. zone to prevent an oversupply of vehicles in any smaller 0.5x0.5 square mi. block resulted in 1.4% to 6.1% rVMT (*28*). Although rVMT is relatively small compared to total VMT, total eVMT due to repositioning and charging across the four respective range and charger type scenarios in their study reveals this eVMT is not insignificant (2.1% to 11.1%). When DRS is introduced, rVMT increases to an estimated 2.0% to 9.3% but the average daily person-trips per vehicle also increases (*29*). Another study explored rebalancing SAVs to optimize locating idling vehicles through a minimum cost flow problem (*30*) using MATSim. The total eVMT rises from 15% to 24% for one scenario, however, mode share also increases from 5.3% to 6.4%, confounding the increase in rVMT alone. Even with an overall increase in empty travel, a shorter average waiting time of 25% to 35% leads to a corresponding increase in mode share that could offset potential rVMT fees.

A repositioning algorithm based on greedy assignment and solved through constrained optimization found that repositioning can lead to a 20% increase in the share of served SAV requests, similar to results using arcs (*31*). Yet, even a 3% to 6% increase in eVMT, as observed by another assignment strategy study using a fixed-trip dataset (*32*), can shorten the range of SAEVs to serve passenger trips. This in turn can potentially increase the number of rejected ride requests because of a supply issue caused by an increase in charging sessions per day, on average, especially for a fleet of short-range vehicles (100-mi range or less). Even if Level 3, or direct current fast charging (DCFC), chargers are used for SAEVs, a drop in the supply of vehicles may increase pVMT, reduce fleet operation revenue, and create a cycle of diminished average fleet state of charge (SOC). One study proposed an operations optimization framework that considered dispatch, repositioning, and charging trips from a fixed-trip dataset (*33*). They found that a DCFC network can reduce charging downtime by more than 5% compared to a mix of Level 2 and DCFC, which corresponds to a 6% to 14% reduction in eVMT. Increasing vehicle availability through reduced charge times allows the SAEV operator to make better decisions. In comparison to their vehicle-based heuristic dispatch strategy, central management can increase trips met by 11%.

In summary, ABMs that simulate repositioning strategies of SAEV fleets are, to the best of the author's knowledge, limited to three studies (*28, 29, 33*), although several ABM studies have explored repositioning of SAV fleets (*15, 25–27, 30, 34–37*). Moreover, only one study has integrated charging and repositioning decision-making, though they do this for a fixed-trip dataset in a simulation environment that does not have other modes or background congestion (*33*). This study jointly considers charging and repositioning decisions to both minimize eVMT and proactively charge vehicles during periods of low demand.

Although repositioning and routing of SAEVs can be formulated as a *Green Vehicle Routing Problem*, *Traveling Salesman*, or *Electric Vehicle Routing Problem*, or other intelligent assignment algorithms (see (*26*) for further discussion), computationally efficient heuristic vehicle assignment and routing methods provide reliable results for large-scale regions. Using heuristic dispatch methods is advantageous for large regions with less than 40 average daily SAV trips per vehicle (*33*). This study leverages POLARIS, an agent-based activity-based modeling framework, to simulate joint charging and repositioning decisions for a 100% synthesized Austin, Texas population. As mentioned by (*2*), using more realistic models tends to show lower benefits from SAV service. To better prepare for a world of SAEVs, it is critical to update prior findings given advancements in modeling techniques. To this end, this study provides better estimates on SAEV service in Austin, Texas, while providing other researchers a benchmark on how to optimally manage repositioning and charging trips.

MODELING FRAMEWORK

The ABM tool called POLARIS (*38*) is used to investigate the synergies of optimized charging and repositioning of SAEV fleets. POLARIS uses demand models to simulate agents' weekday activities across a region for a single day. These models are estimated from data provided by the region's Metropolitan Planning Organization (MPO) and the U.S. Census Bureau according to the ADAPTS modeling framework (*39, 40*). For example, daily activities are subject to near-term scheduling constraints like synthesized person- and household-level attributes and long-term residential and vehicle self-selection choices. A time-dependent dynamic traffic assignment router (*41*) routes vehicles whose experienced travel time is an outcome of a mesoscopic traffic flow model based on the link transmission model (*42*). This results in finer link-level traffic behavior than queue-based algorithm approaches (*43*). POLARIS was chosen over other tools since it can simulate 100% of a large-scale region's population and read in time-dependent background traffic, such as freight and other external travel. In developing a model of the region's travel behavior and traffic, trips were not fixed (frequency, departure time, and mode chosen) but the population was fixed (workplace choice, vehicle ownership, households) to understand how different SAEV scenarios can change outcomes in a competitive, dynamic world. This can add complexity in interpreting results but leads to a more realistic analysis given that operational changes can influence the percent of trips met and subsequent demand.

This study makes use of baseline SAEV functionality in POLARIS to assess the performance of the proposed optimization-based repositioning strategy for SAEVs. Since the fleet operator's goal is to provide a high-quality service at low operating costs, vehicle assignment, charging decisions, and repositioning strategies are centrally coordinated. As a summary, Table 1 shows all the assumptions made.

The EVCS network inherently influences charging downtime, energy use, and operating costs. Better utilization of chargers through optimal charging strategies may even allow operators to have a sparser network. A heuristic to site and size stations was adopted from Gurumurthy et al. (*45*), which generates a new station for vehicles based on density parameters and additional plugs based on queue time limits. Since the algorithm sites stations based on demand and arguably oversupplies plugs under the sub-optimal baseline heuristic control of charging, it was compared to two networks where the number of plugs is scaled and where select stations are eliminated. This is done to reflect how stations with fewer plugs may be able to avoid electrical upgrades, assuming sufficient residual capacity. Additionally, eliminating smaller stations in the network can avoid land acquisition costs, which increasingly become a larger portion of the total cost with decreasing plug count.

SAEV REPOSITIONING STRATEGIES

A repositioning strategy for SAVs (*27*) is adapted to consider the new logistical challenges of an electrified fleet. EVs are both range constrained and have substantial charging times, requiring careful coordination with the repositioning goal of improving service quality for riders. The fleet operator must check each vehicle before repositioning to ensure sufficient charge to reach the desired zone and serve the expected demand. Location and availability of chargers can also be factored into this decision so that vehicles arrive at an assigned charging station in a TAZ and recharge before expected demand picks up. With EVCS queuing modeled in POLARIS, assigning vehicles to available chargers smartly in the region can help minimize downtime, leading to higher average SOC throughout the day.

With most proactive repositioning strategies, the purpose is customer-centric: vehicles in low-demand zones are moved to high-demand zones with the goal of meeting latent demand and shortening wait times. Since not all zones receiving vehicles have chargers, any coupling of the two activities should weigh the loss in SOC from traveling to the destination and the goal of balancing supply with demand. To this end, an optimization-based strategy is employed with an

TABLE 1 Assumptions in POLARIS' SAEV Module

Type	Description
Assignment	The operator assigns vehicles to riders using a computationally-efficient, zone-based assignment (*35, 44*) by matching ride requests to SAEVs in the same or nearby zones, thereby reducing overall pVMT and ensuring adequately low response times. This is supported by Hörl et al.'s study that revealed their adopted load-balancing heuristic (*35*) has lower wait times during peak times than their alternative optimized Global Euclidean Bipartite Matching algorithm (*26*). The operator truncates an array of neighboring zones according to pre-defined maximum wait times using free-flow travel times. This array is used to ensure that if an agent chooses an SAEV within the utility-maximizing mode choice model, an available SAEV will likely serve the trip within a reasonable window. The operator also dispatches the longest-idling vehicles first within a zone (if there are multiple available vehicles), to maximize vehicle utilization (*44*).
DRS	DRS is centrally coordinated to ensure that matching new riders to existing trips does not exceed vehicle capacity or delay travelers past a maximum allowable delay both in absolute (min) and relative travel time (% more than expected) (*23*). Rides are matched using a heuristic that uses directions between the vehicle's final destination in its sequence of trips and the new request's destination. The angle threshold between these trips for matching is set to 10°. Once a match is made, all current pick-ups and drop-offs are reordered using a sequential search through an R-tree that respects the traveler pick-up constraint (cannot drop-off a traveler before picking them up). Like other ABMs, two or more travelers cannot yet request a shared ride together (like pooled ride-sourcing trips).
Charging Heuristics	Baseline charging rules are defined and tracked by both the fleet operator and SAEVs (*45*). The operator ensures SAEVs have sufficient range to complete currently assigned ride requests before adding a new request to the vehicle's to-serve list. The SAEV, in turn, checks its state of charge (SOC) at the end of each tour so that it can charge if below a threshold. SAEVs can also proactively charge if idling for longer than an allowable threshold. Once a charging decision is met, the operator uses an R-tree search to find the nearest charging station based on downtime (so that distance and queue time are factored into charging station assignment).
Charging SAEVs	Electricity consumption follows a link-based regression model using real-world EV data, whereas charging follows a linear rate based on maximum power output of the charger. SAEVs and private EVs do not share charging infrastructure. The operator does not allow charging vehicles to unplug early and serve ride requests. In a world of eVMT fees and battery-draining repositioning, service priority policies may only be wise for unique circumstances like special events (e.g., concert or stadium traffic), but POLARIS does not model these special trip generators. Thus, "service priority" charging is not permitted.
Supply-Demand	The operator keeps track of the supply and demand for SAEVs by traffic analysis zone (TAZ) for repositioning. A vector of feasible repositioning TAZs are computed based on zones having an abundance or dearth of vehicles, relative to requests for baseline repositioning (*27, 46*). Demand models and subsequent trips within the region are for a typical weekday. As a result, daily (and seasonal/special event) trends that are observed with ride-sourcing data are not observed in weekday travel demand simulations.

objective to maximize the fleet average SOC, subject to a zone-based demand-to-supply inequality constraint. As the coupled repositioning and charging action both fulfills the goal of meeting unmet demand and increasing SOC, a natural preference can develop over repositioning when plugs are available. The following subsection outlines the optimization-based coupling approach and how setting variables to zero can lead to baseline charging and repositioning strategies.

Coupled Repositioning & Charging

Existing repositioning strategies consider the balance between supply and demand but rely on simple threshold charging decisions. Vehicle-level heuristics often fail to account for possible queuing at charging stations by sending vehicles to the closest station or assume unlimited charging capacity. Even with a centrally-managed trade-off between distance to the charger and time spent queuing the heuristic still does not answer the question of when to best proactively charge vehicles. This creates an opportunity to observe the benefits of combining repositioning and charging decisions at a single time step. The formulation detailed here takes into account supply, demand, charging locations, plug availability, and every vehicle's SOC. This scenario of optimizing for both SOC and a balance in supply and demand is then compared to a baseline repositioning strategy that is derived by setting certain decision variables to zero. The optimization formulation is shown in Equations 1-6:

$$\min_{a_{ij,r},x_{ij,r},\delta_{ij,r}} J = \sum_{i\in\mathscr{I},j\in\mathscr{Z}} t_{ij,r}\left(x_{ij,r}+a_{ij,r}\right) - \sum_{i\in\mathscr{I},j\in\mathscr{Z}} \alpha a_{ij,r}\left(SOC^{\max}-SOC_{i,r}\right) + \beta\sum_{j\in\mathscr{Z}}\delta_{j,r}, \quad \forall r\in R \tag{1}$$

$$s.t. \quad 0 \leq x_{ij,r} \leq 1, \quad i\in\mathscr{I}, j\in\mathscr{Z} \tag{2}$$

$$0 \leq a_{ij,r} \leq 1, \quad i\in\mathscr{I}, j\in\mathscr{Z} \tag{3}$$

$$0 \leq \sum_{j\in\mathscr{Z}} x_{ij,r}+a_{ij,r} \leq 1, \qquad i\in\mathscr{I} \tag{4}$$

$$\sum_{i\in\mathscr{I}} a_{ij,r} \leq C_j, \quad j\in\mathscr{Z} \tag{5}$$

$$f_{j,r}+\delta_{j,r} \geq s_{j,r} + \left(\sum_{i\in\mathscr{I}} a_{ij,r}+x_{ij,r}\right) - \left(\sum_{i\in\mathscr{I}_j} a_{ij,r}+x_{ij,r}\right)v_i, \quad j\in\mathscr{Z} \tag{6}$$

where for each zone, j, the supply of vehicles, s_j, accounts for: (i) vehicles idling at that zone j with SOC higher than $SOC^{\min}$, and (ii) non-idle vehicles that are expected to idle at zone j (i.e., drop-off in which the last customer is at zone j, repositioning to zone j, or repositioning to and then charging at zone j). The minimum supply at zone j is f_j, which is adjusted in agreement with the expected demand for each zone. The slack variable, δ_j, indicates the unmet demand at zone j. In addition, the availability capacity of the EVCS in zone j is denoted as C_j. To permit some queuing at stations, all stations can allow up to 30% of the number of plugs (hence total available capacity is 1.3 times plug count).

With respect to variables associated with each vehicle, $\mathscr{I}_j$ is the set of idle vehicles currently in zone j. For each vehicle $i \in \mathscr{I}$ the binary variable $x_{i,j}$ takes the value 1 if the vehicle i will perform a repositioning trip to zone j, and 0 otherwise. Likewise, $a_{i,j}$ represents whether the vehicle i will perform a repositioning trip and then charge at zone j. For each idle vehicle, the current SOC is denoted as SOC_i. Since each vehicle can undertake only one operation at a time, the sum of $x_{i,j}$ and $a_{i,j}$ cannot exceed one. Finally, the goal is to keep the supply in each zone higher than the estimated demand f_j. The variable $v_{i,j}$ is an indicator variable that takes value of 1 if vehicle i has $SOC_i \geq SOC^{\min}$. The current supply s_j must balance with the vehicles coming to and leaving from zone j. In cases where it is not possible to serve all zones, the variable δ_j has the supply deficit at that zone.

The objective function J attempts to reduce travel cost, increase charging, and ensure enough supply in each zone with parameters α and β to be specified. The value of α weights the priority for charging and β the priority for serving demand. Parameter values were adjusted through several iterations until two distinct outcomes were achieved, namely: demand prioritization (DP) through repositioning and charging prioritization (CP) through coupled charging whenever possible. The objective with these two scenarios is also meant to speak to the sensitivity of the optimization to charging and repositioning trips. The model formulation permits different demand horizon windows, from which to estimate the expected zonal demand, f_j. The demand window times a scaling parameter is equal to the repositioning time step, r, so that modelers can vary the sensitivity of f_j to the demand horizon window.

For example, a modeler may wish to consider the previous hour's zonal demand but prioritize repositioning at every 15-minutes to obtain better estimates for the expected demand. As SAEV operations occur every second, the shorter the repositioning step the better fleet information the operator receives. For example, the operator would update its record of charging station availability to know whether the station can accept more vehicles. However, better demand forecasts are necessary with shorter time steps, which comes from historical ridership data and a willingness of SAV riders to inform operators of their departure times in advance (which is only available for select ride-sourcing platforms, see Lyft's Wait & Save).

Due to the particular structure of the problem, the Mixed Integer Linear Programming Eq. (1) can be solved as a Linear Programming and, therefore, with reduced computational cost. The inequality constraint Eq. (4) is unimodular (*46, 47*) and, therefore, the solutions are always at the corners of that constraint (i.e., either 0 or 1) and the solutions will be integer as long the upper and lower bounds are also integer. This means that the solution of the problem always yields an integer value of $a_{i,j}$ and $x_{i,j}$.

APPLICATION IN AUSTIN, TEXAS

The proposed formulation presented above is evaluated for a fleet of SAEVs serving trips in Austin, Texas, and compared to baseline strategies. The fleet was constrained to both a six-county metropolitan region and a smaller geofenced region extending from the central business district (CBD). The geofenced region reflects the expectation that initial SAEV operations may be restricted to areas with high trip density (e.g., the CBD, government complexes, universities, mixed-use developments, airports). The six-county region represents the long-term future of SAEV operations and is simultaneously used to rigorously evaluate the proposed joint optimization framework for a large-scale region.

The Austin metropolitan region encompasses close to 5,300 square miles of land, and the transportation system is represented with about 2,160 TAZs, 16,100 links, and 10,400 nodes. The smaller geofenced region (60.3 sq mi) covers about 400 TAZs, 3,500 links, and 2,170 nodes. The fleet size was set at 15,000 vehicles and 2,220 vehicles (almost 1 SAEV per 125 residents) for the two analysis regions, both with 300-mi range vehicles. Figure 1 shows a layout of the two service areas and the roadway network. Figure 2 maps the EVCS locations (100% heuristic-sited) since the alternative is a scaled-down network.

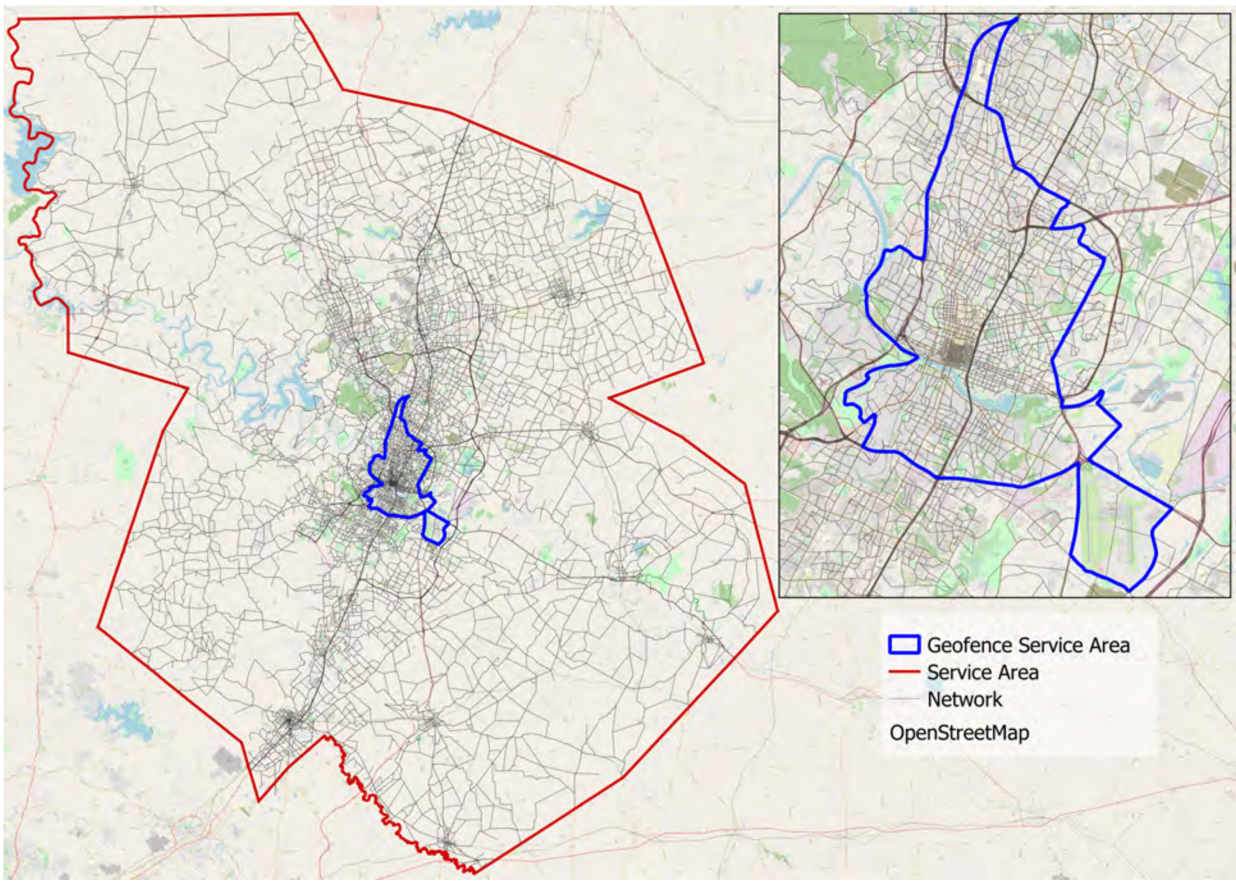

FIGURE 1 Overview of Austin, Texas service areas and network

All scenarios used a 2015 roadway network and a synthetic population estimated from year 2018 Census Bureau's American Community Survey (ACS) Public Use Microdata Sample (PUMS) (*48*). Appropriate mode choice models (e.g., nested multinomial logit) were developed from the 2016-2017 Austin household travel survey (provided by the region's MPO), with SAEVs offered as a taxi/ride-sourcing vehicle type with assumed fare components ($0.50/mile and $0.25/minute) and value of travel time savings (25%) parameter. Since SAEVs are assumed to be similar to present-day taxi/ride-sourcing vehicles, which was underrepresented in the survey, the alternative specific constants for this mode were scaled up by 50% to reflect the belief that this mode will be more attractive in the future due to sharing behavior and more experience with on-demand ride-sourcing. The cost estimates come from prior work in this field (*6, 49*). In addition, the vehicle ownership reduction model in Menon et al. is adapted to present a future base case where approximately decennial vehicle ownership choices are influenced by SAVs (*50*). As

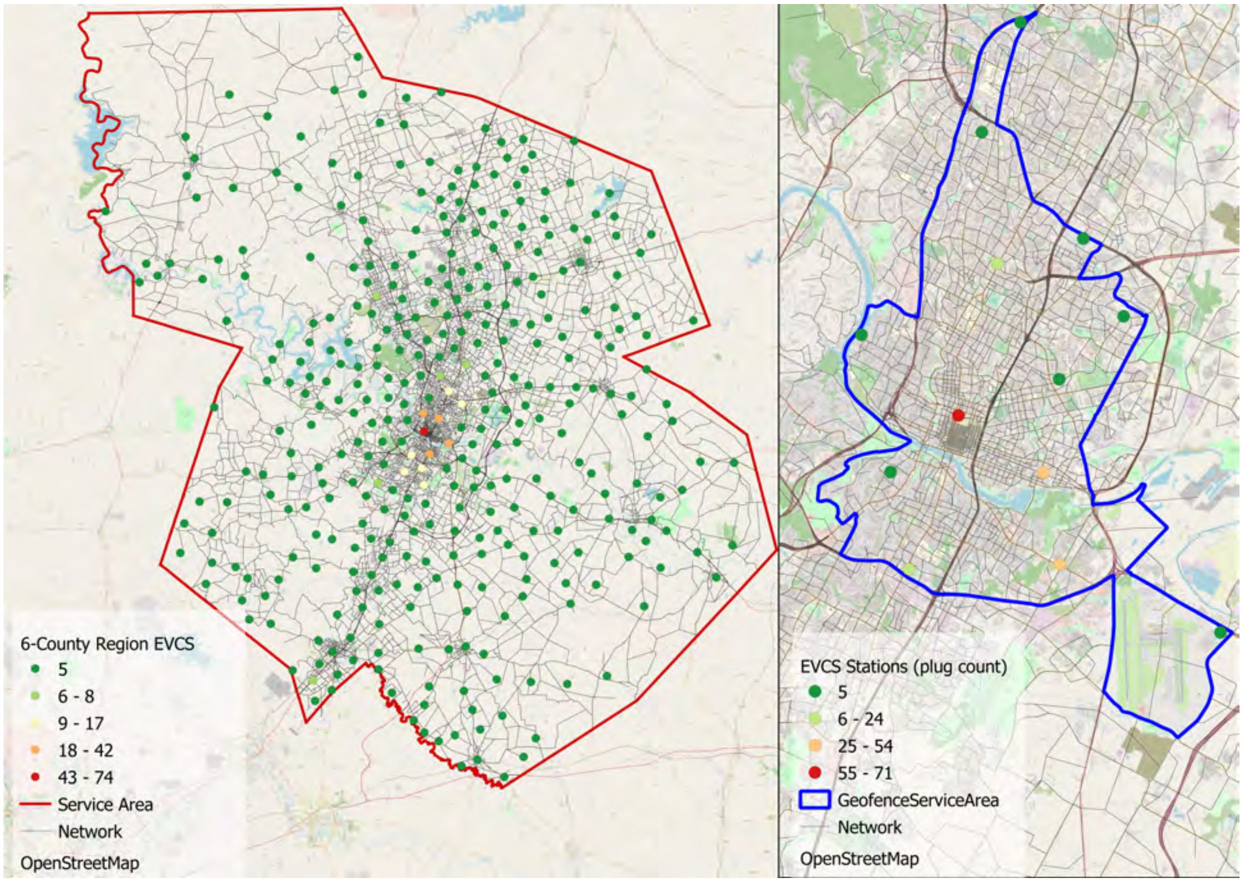

FIGURE 2 EVCS heuristic-sited scenario in Austin, Texas' 6-county and core area geofence

a result of these forecasting assumptions, the mode choice model results in an SAEV mode share of 6.3% for rule-based charging and no-repositioning scenario (versus 2.4% with the present-day mode choice model) in the 6-county region.

Three fleet-owned EVCS networks were used: a densely distributed heuristic ("distributed"), scaled-down version by eliminating 50% of plugs at each station ("scaled 50%"), and scaled-down by eliminating 75% of plugs at each station and further removing 50% of 1-plug stations ("depot-like"). The heuristic sites a 50kW charging station with 5 plugs if a station is not within 2 Euclidean miles from a vehicle sent to charge. If an SAEV queues at an EVCS for longer than 15 minutes, an additional plug is generated. This siting process is done once with 100-mi vehicles and the generated charging stations used in subsequent scenarios. Short-range vehicles were used to provide sufficient charging capacity during peak hours, albeit the set-up lowers utilization of fleet charging equipment. The advantage of three EVCS networks is that it allows for a discussion on the spatial-temporal utilization of chargers and the appropriateness of using high-density, small stations for the zone-based optimization framework.

The first operational strategy is the baseline scenario of rule-based charging without repositioning (Base). The second strategy uses the proposed SAEV framework but does not allow for repositioning to understand the effect of this framework on charging trips (OC). The third strategy sought to fulfill more trip requests and lower passenger wait times by allowing repositioning but uses rule-based charging (Base-Repo). The proposed SAEV coupled repositioning strategy was compared to the baseline SAEV repositioning strategy. By changing the relative weight of charging or repositioning, three outcome strategies were developed to understand the contribution of each activity to service quality. These three strategies can be adopted by operators (perhaps even by the time of day), and are assessed by performance metrics and implications for the fleet (e.g., VMT charges, downtime, charging costs). The fourth strategy sought to mitigate repositioning effects and charging trip downtime by optimizing the two events jointly with a higher focus on demand (DP). The fifth strategy examined the trade-off between the two events with a higher priority for charging (CP). The sixth strategy attempted to blend the need for repositioning and coupled charging, or "joint" (J).

Results

Thirty-six scenarios were run (three EVCS networks, two service networks, and six operational strategies). The base operational scenario is a fleet of SAEVs operating in Austin (6-County and geofenced region) using rule-based charging without repositioning. Zone-based repositioning was added to try and capture unmet demand and lower wait times. Next, the proposed framework was leveraged to optimize charging trips to compare results against heuristics commonly used in ABMs. Two optimization-based joint repositioning and charging scenarios were developed to emphasize repositioning and charging activities, respectively (with a third mixing the two). Table 2 shows the results from the geofenced SAEV service, followed by the 6-County region in Table 3. Each table reports the results from the three charging station networks and six operational methods with respect to the following metrics: average pick-up wait times, average daily trips served per SAEV, %eVMT, %rVMT, and %cVMT.

TABLE 2 Core area geofence (60.3 sq mi) fleet performance

EVCS	Operational Strategy	Avg Wait Time (min)	Avg Daily Trips	%eVMT	%rVMT	%cVMT
Distributed	Base	5.93	43.36	21.49	-	8.07
Distributed	OC	6.48	44.69	19.02	-	4.30
Distributed	Base-Repo	2.57	46.66	31.98	8.55	10.03
Distributed	DP	2.68	43.49	25.53	12.23	4.98
Distributed	CP	5.00	45.10	19.08	2.23	4.58
Distributed	J	3.76	43.89	19.83	4.59	4.85
Scaled 50%	Base	9.47	41.71	25.57	-	8.08
Scaled 50%	OC	6.07	44.40	18.42	-	4.31
Scaled 50%	Base-Repo	3.18	46.09	29.87	11.42	9.93
Scaled 50%	DP	2.70	43.51	24.25	11.85	3.88
Scaled 50%	CP	4.77	44.65	18.81	2.27	4.57
Scaled 50%	J	3.43	43.35	19.75	4.94	4.72
Depot-like	Base	10.18	39.29	26.87	-	8.64
Depot-like	OC	5.61	43.54	16.75	-	3.12
Depot-like	Base-Repo	2.57	46.66	31.39	13.00	10.53
Depot-like	DP	3.06	43.65	21.19	9.99	2.11
Depot-like	CP	4.69	43.58	17.07	2.02	2.90
Depot-like	J	4.01	43.47	17.30	3.60	2.55

Keys: Distributed = Original heuristic-sited network, Scaled 50% = Scaled down plug count, Depot-like = Removal of 50% 1-plug stations from 75% scaled-down network, Base = Rule-based Charging Only, Base-Repo = Base + SAV-based Repositioning, OC = Optimized Charging Only, DP = Demand Priority, CP = Charge Priority, and J = Joint Charging & Repositioning

TABLE 3 6-County region fleet performance

EVCS	Operational Strategy	Avg Wait Time (min)	Avg Daily Trips	%eVMT	%rVMT	%cVMT
Distributed	Base	8.77	28.26	20.55	-	7.11
Distributed	OC	9.83	31.28	21.50	-	7.74
Distributed	Base-Repo	6.90	31.87	26.01	7.07	8.43
Distributed	DP	5.00	31.94	29.05	12.91	7.16
Distributed	CP	6.57	32.04	23.99	5.21	8.42
Distributed	J	5.50	31.57	25.69	8.56	7.57
Scaled 50%	Base	10.34	28.07	20.82	-	6.52
Scaled 50%	OC	10.05	30.01	22.31	-	8.45
Scaled 50%	Base-Repo	9.83	31.70	25.61	5.82	7.19
Scaled 50%	DP	5.24	31.70	28.92	12.85	6.97
Scaled 50%	CP	7.79	31.02	24.64	4.81	8.60
Scaled 50%	J	6.18	31.21	25.77	8.19	7.74
Depot-like	Base	13.94	22.50	23.32	-	6.53
Depot-like	OC	10.66	27.74	19.36	-	4.52
Depot-like	Base-Repo	15.56	22.64	28.04	4.38	7.43
Depot-like	DP	9.04	29.04	23.86	6.99	4.28
Depot-like	CP	9.32	28.54	21.03	3.35	4.47
Depot-like	J	9.04	29.04	22.08	4.92	4.34

Simulations were all performed using Texas Advanced Computing Center (TACC) supercomputers with most scenarios taking less than 2 hours, depending on the number of variables and the optimization solver (CPLEX or GLPK) used. CPLEX was used for the proposed optimization framework due to improved computational performance while GLPK was used for the base repositioning scenario that came from (*46*). For reference, a 6-County joint charge priority simulation (using 15-minute repositioning-charging time steps) takes 47 minutes longer than the heuristic charging scenario, which takes 64 minutes.

The goal of repositioning is to better match supply and demand. Figure 3 plots average response times (i.e., match wait time + pick-up wait time) over the 24-h simulation across all operational scenarios for the regional service area with the original heuristic-sited EVCS network. Similarly, centrally managing charging and simultaneously charging and repositioning should reduce eVMT while increasing fleet average SOC. Figure 4 plots fleet average SOC throughout the 24-h simulation for the regional service area, assuming the same charging station network. It is clear from both the tables and the plots that the joint optimization scenarios increase total SAEV demand served for the 6-County region but not necessarily for the geofenced service area. For the sprawling Austin region, the joint optimization scenarios (OC, DP, CP, and J) can increase total demand from Base-Repo on average by 2.8% and 3.9% for the distributed and scaled 50% charging station design, respectively. The SAV-based repositioning strategy with heuristic charging (Base-Repo) can be greedy in rebalancing vehicles to meet demand in smaller regions, like the geofence here, and where chargers are abundant such that charging downtime and charging station locations are not as important. With increased demand, there are more opportunities for DRS but fewer 'idle' vehicles that can pick-up a passenger for a new tour. There is some difficulty in keeping response times low for the optimization scenarios, except for demand priority (DP). The charging priority (CP) scenario seems to perform the best in raising fleet SOC throughout the day but can increase average response times by two minutes compared to DP. However, all strategies leveraging the proposed optimization framework, including optimal charge (OC), increase SOC during off-peak hours at a faster rate than existing strategies when there is less demand for vehicles. Even during special events (with disproportionate demand compared to historical data), the higher fleet SOC will enable a more resilient response.

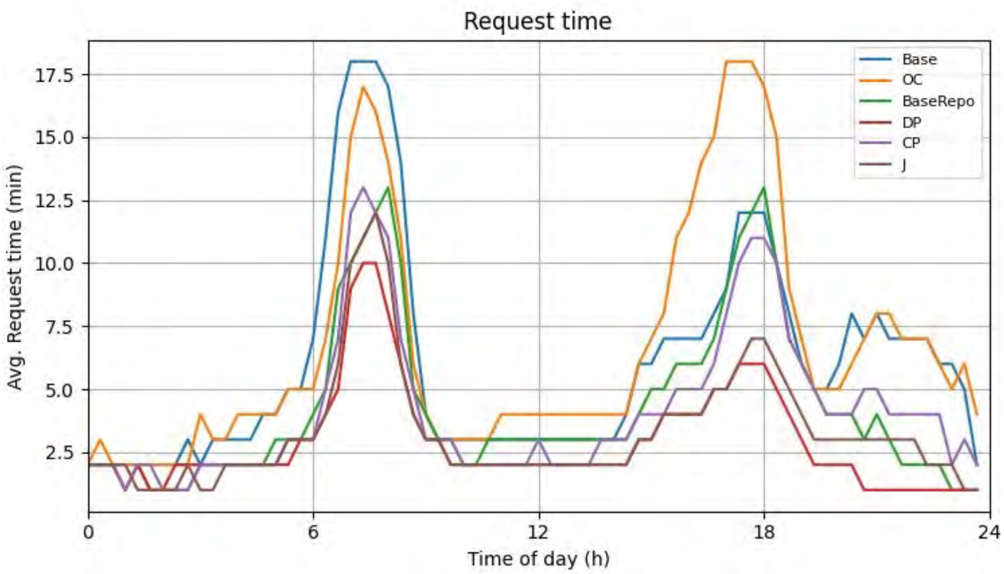

FIGURE 3 Average request times by operational scenario (regional service with distributed EVCS network)

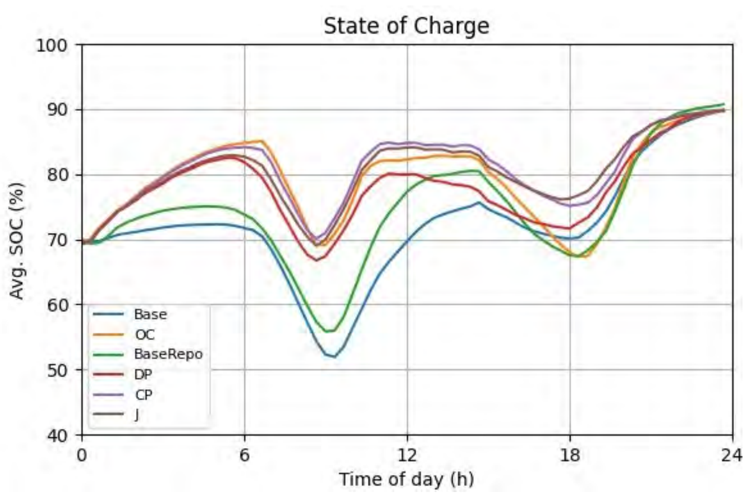

FIGURE 4 Average request times by operational scenario (regional service with distributed EVCS network)

DISCUSSION

Service Area and EVCS Networks

The geofenced service area, which covers points of interest in the City (e.g., the CBD, University of Texas at Austin, mixed-used developments, and the commercial airport), is likely to see SAEV service first. The model results indicate that zone-based repositioning can substantially improve service response even in small areas and using small zones, unlike (*28*). Moreover, while using the previous 15-minute demand as a predictor for future demand is fine, operators would use an ensemble approach with ridership history and other data sources. At first glance, repositioning may want to be avoided in the downtown else SAEVs exacerbate congestion, however, the results show lower %eVMT with almost all approaches and EVCS networks. Without repositioning, the average SAEV misses up to an additional 11% daily trips. Coupling repositioning and charging in this area helps to reduce the added mileage and at a lower expense per passenger traveled (see the ratio of %eVMT to daily trips per vehicle).

In comparison, the larger 6-county service area may represent the long-term future of SAEV service where vehicles cover sprawling metros. Repositioning is essential in reducing the spatiotemporal mismatch of supply and demand. Figure 5 shows the average wait times for SAEVs across all TAZs during the morning and evening SAEV peak hours (7-8 am and 3-4 pm, respectively) for the scenario of baseline repositioning. When joint optimization (J) is introduced with well-distributed charging stations, the spatiotemporal mismatch is better addressed, see Figure 6. The downtown core, unsurprisingly, has the lowest request time while TAZs in the outskirts of the region have higher request times. Although agents have a maximum wait time of 15 minutes, if a vehicle is initially assigned to them but is delayed (due to an unexpected range constraint, for example), the agent will have longer pick-up times.

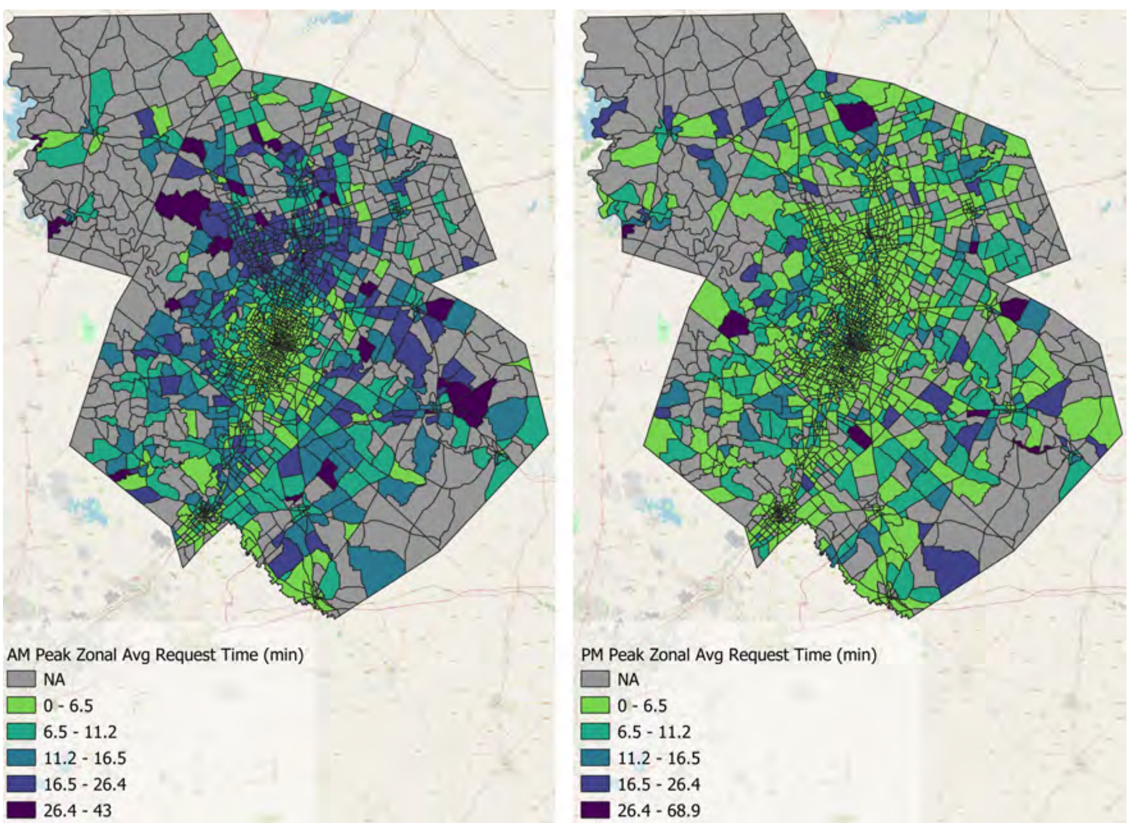

FIGURE 5 Average request times by zone during AM and PM peak hour for base repositioning with heuristic charging using distributed EVCS network

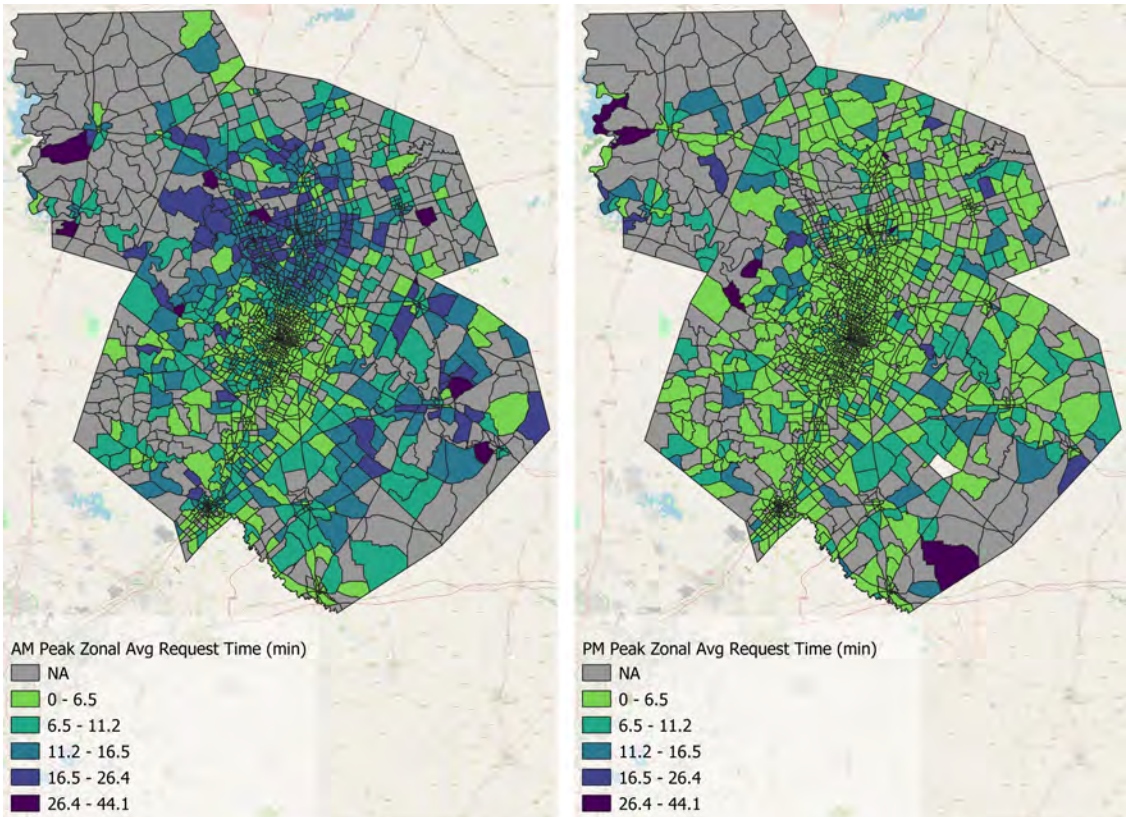

FIGURE 6 Average request times by zone during AM and PM peak hour for joint optimization using distributed EVCS network

In the geofenced service area, a depot-like EVCS network is preferred over distributed or scaled-down version because the average wait time is only 15-34 seconds longer across these joint scenarios, representing a minor opportunity cost for deferred investment in charging stations. At the same time, this charging station network exhibits lower %eVMT, which affects downtime, charging costs, and perhaps in the future eVMT fees. Since trip ends and stations are centralized, the distance between stations is not as important as in a sprawling region. In the larger service area, the scaled-down EVCS network may be wiser because it provides distributed 1-plug stations to reduce eVMT (and offer coupled charging-repositioning benefits), reduces investment costs, and still has low average charging times versus a depot-like network which concentrates charging and also results in less demand served. Heuristic EVCS siting algorithms may consider moving away from strict siting rules and using distance from the city center as a means to increase the probability of generating a 1-plug station over a depot hub.

Optimal Charging

Leveraging the proposed optimization framework to consider only charging leads to improved fleet average SOC during off-peak hours, enabling the fleet to meet more trips throughout the day than the base case with no repositioning. The %cVMT only marginally increases for the 6-County region, while for the geofenced service area there is a decrease in %cVMT. Table 2 indicates that base repositioning increases average daily trips per vehicle and lowers average response times but adds substantial %eVMT. On the other hand, OC sufficiently redistributes vehicles around (additional 1.33 to 4.25 average daily trips per SAEV), lowers average wait times, and keeps %cVMT down. If the depot-like network is preferred for a geofenced service area, the OC policy can even have more trips per vehicle than other repositioning strategies. However, for a regional service, OC is unlikely to be sufficient in repositioning vehicles, especially in the PM peak (see Figure 3).

Charger Downtime and Utilization

All scenarios charge a vehicle if the available range drops below a minimum threshold, which is largely unavoidable for SAEVs with consecutive trips. In comparison to the baseline charging scenario where charging is controlled through 'idling gap-outs,' the CP optimization strategy prioritizes charging when it increases the value to the fleet (i.e., increase in SOC is greater than travel time cost and any unmet demand). There are already advantages for riders and the network with this strategy, but fleet operators will also want to know how this impacts charger utilization. Figure 7 shows boxplots for time spent at an EVCS (queue + charging) versus just charging across the day for the base and CP policy using a distributed charging network. Baseline charging does not prioritize an increase in SOC during the morning (see also Figure 4) and has to charge throughout the day to recover after the AM peak. In comparison, CP has larger charging downtime in the early morning to prepare for the AM peak.

Similar patterns are found with a scaled 50% EVCS network (Figure 8, but with fewer plugs, there is higher vehicle downtime during the day for both base and CP scenarios. There is more charging during the morning to midday hours with CP, likely because of fewer repositioning to charging opportunities due to a queuing constraint.

The distributed and 50% scaled-down EVCS networks are oversized for the long-range vehicles used in this analysis but benefit the fleet with smaller queues and more coupled charging-repositioning opportunities. Figure 9 plots the ratio of charging sessions per plug at a station averaged across all stations during each hour of the day for the base and CP scenarios for a distributed EVCS network across the region. A ratio greater than 1.0 indicates that there were more charging sessions than the number of plugs, likely indicating at or near average station capacity (since not all charging sessions take an hour and not all plugs may be used). The boxplot shows that the ratio of demand to supply for each hour of the day is consistently concentrated at or above 1.0 for the CP policy. However, some stations in the base scenario have high utilization rates. While higher utilization of chargers makes the investment in chargers worthwhile, it can suggest that fleet operators may be exposed to high electricity demand charges. The CP policy does not seek to lower electricity costs (including demand charges) but appears to have this effect.

Repositioning with Baseline Charging

The repositioning scenario with baseline charging demonstrates why fleet operators will likely pursue repositioning, even at the expense of added eVMT for other travelers. The 6-County region especially needs repositioning to attract more riders to SAEVs (up to an 8.2% increase in demand for a 26.6% increase in %eVMT - or an additional 0.5 deadhead miles per rider). This is less demand than the algorithm suggested by (*31*) (20% increase in demand with repositioning). Still,

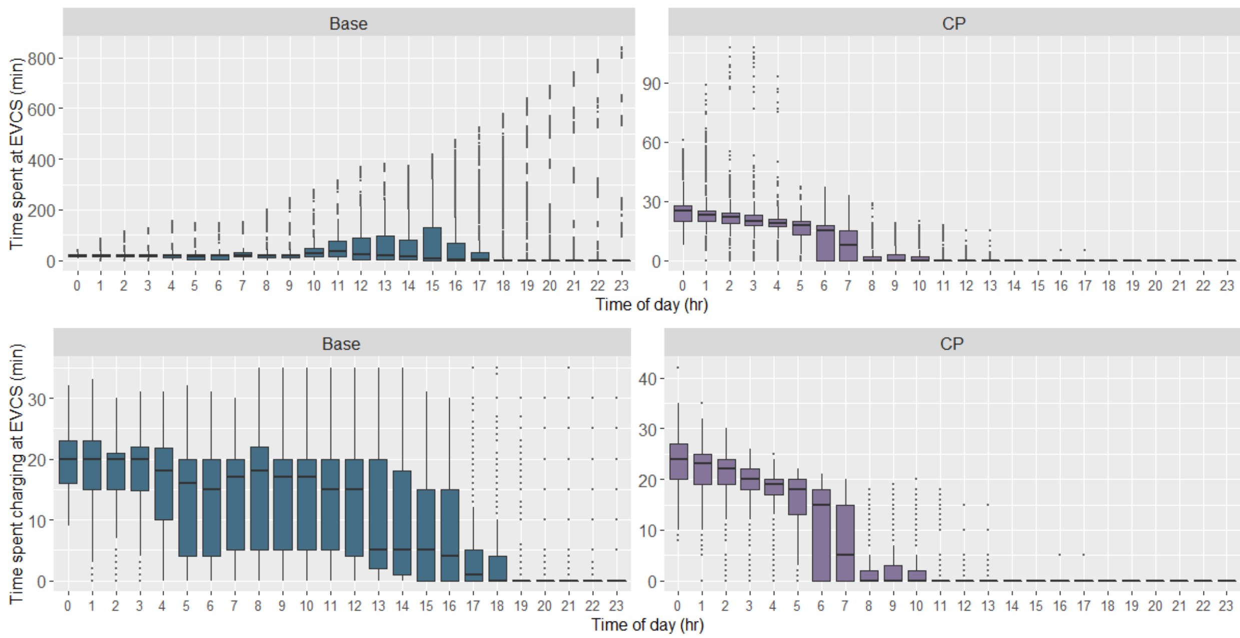

FIGURE 7 Boxplot of downtime charging for the base and charge priority scenarios with a regional service and distributed EVCS network

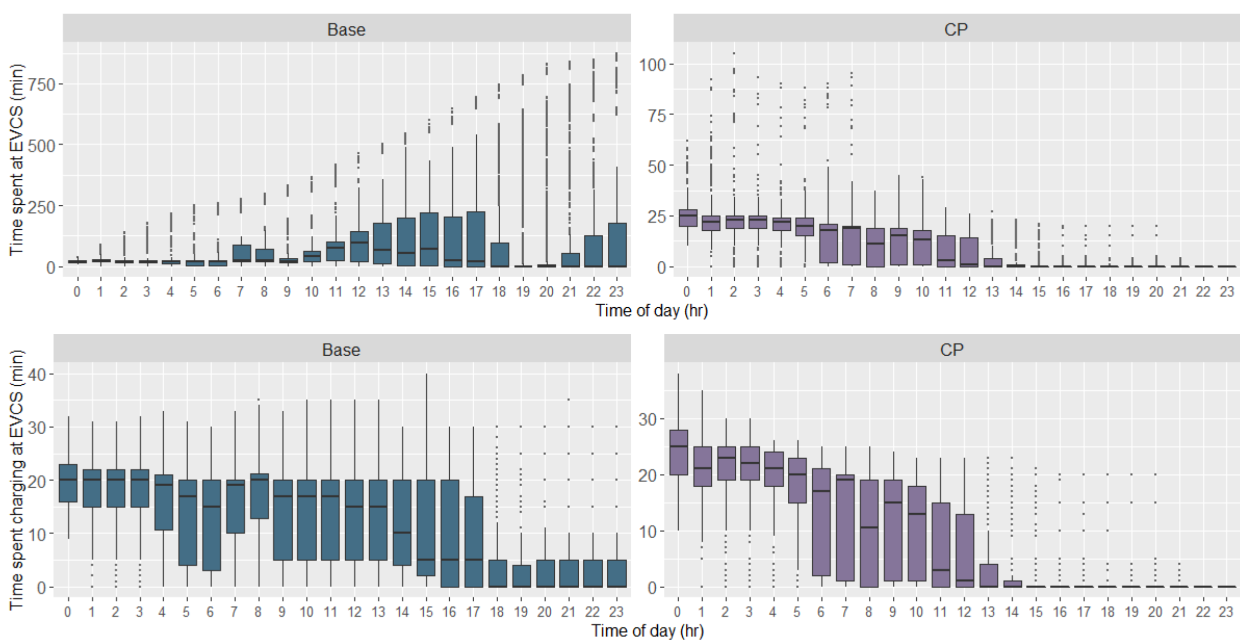

FIGURE 8 Boxplot of downtime charging for the base and charge priority scenarios with a regional service and scaled 50% EVCS network

fleet operators would be wise to also optimize charging trips to ensure sufficient fleet supply for repositioning. Additionally, coupling charging with repositioning may address the eVMT dilemma found by (*32*), which is that a 3%-6% rise in eVMT shortens range and could lower demand.

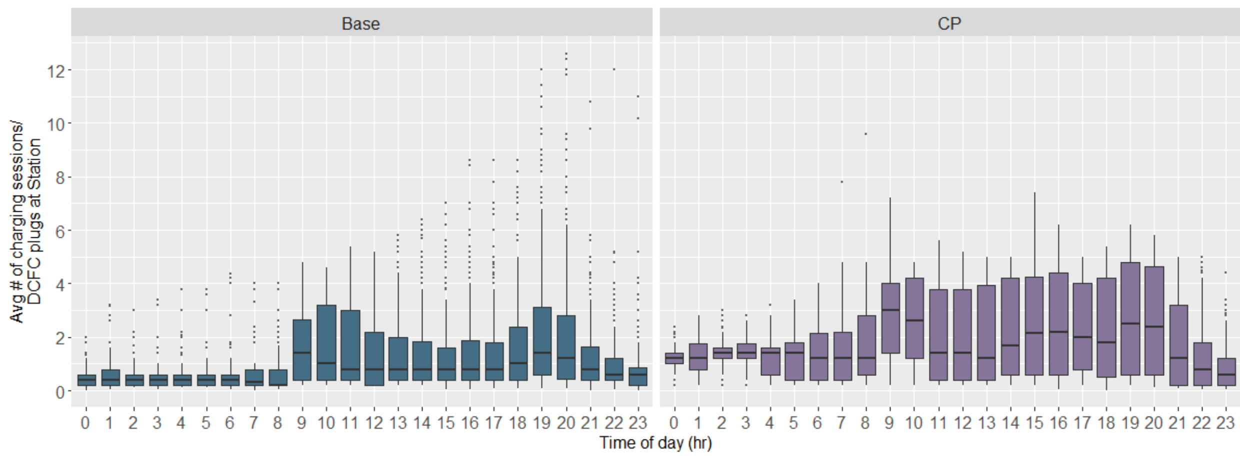

FIGURE 9 Boxplot of average hourly ratio of charging sessions to plugs by EVCS for regional service and distributed EVCS network

Joint Optimization of Charging and Repositioning

The coupled framework aligning charging with repositioning trips reduced the idle time of vehicles overall by both increasing demand (9%-28%) and eVMT (2%-41%) due to additional travel. However, a depot-like EVCS network with CP policy for the 6-County region reduced %eVMT by nearly 10% while increasing demand by 26%, suggesting it is possible to serve additional riders while negating externalities like empty travel.

The average fleet SOC throughout the day was higher than the two previous baseline scenarios, further suggesting that charging downtime does not have to be detrimental if timed appropriately. Coupling the two events reveals synergies that fleet operators can exploit to increase revenue-generating opportunities. The repositioning scenarios result in a more balanced fleet than having no repositioning strategy, but the coupled strategy increases fleet SOC and increases the likelihood of capturing more demand at later peak hours. If eVMT is penalized, this scenario suggests the best possible path forward.

CONCLUSION

This study develops a framework to jointly study charging and repositioning decisions for a fleet of SAEVs within a large-scale agent-based simulation. The framework is evaluated against rule-based charging and zone-based repositioning strategies found in the literature in terms of operational performance and externalities. A set of six SAEV management strategies are tested across three EVCS network designs and two geofenced regions to show how sprawl and charging station design can influence results. The results of all thirty-six scenarios lead to several key findings:

- Without repositioning in a geofenced region, centrally-managed charging of SAEVs as opposed to rule-based charging can reduce average wait times (from 10.2 min to 5.6 min), lead to higher demand served (an increase in 4.3 daily SAEV trips), and could allow for a reduced fleet size at the same level of service as the baseline.
- However, once a fleet serves a larger region, an optimal charging policy is not enough to reposition vehicles, and a joint repositioning and charging policy is required.

- The joint charging and repositioning strategy is most advantageous in the evening peak period, where demand is spatially and temporally spread out. Aligning charging in advance of expected demand prepares the fleet for this evening peak period.
- Joint charging and repositioning can reduce added congestion on roadways by coupling charging trips with repositioning trips (21% less %eVMT, 28% more daily trips per SAEV, and 41% less wait time), assuming 6-county regional service with a depot-like EVCS network.
- Centrally-managed charging decisions leads to better management of fleet-owned charging equipment, and with the joint operational (J) scenario the fleet can serve more daily trips per vehicle at a depot-like EVCS network (75% reduction in plugs at heuristic-sited stations + 50% 1-plug stations removed) than the baseline heuristic (Base) scenario with a distributed EVCS network.
- Coupled charging and repositioning trip optimization has the benefit of spreading out charger utilization both spatially and temporally, leading to expected benefits for the distribution grid in reduced peak load and the operator in reduced demand charges.
- Geofenced SAEV service can still benefit from zone-based repositioning, and using the proposed framework for coupled charging improves upon heuristic charging (across all key metrics). Although average daily trips per vehicle may be higher with heuristic charging and SAV repositioning strategies, the increase in %eVMT and particularly %cVMT is problematic for cities already experiencing significant travel delays.

This study forecasts future SAEV demand and the impact of optimal repositioning-charging on meeting demand. It does not consider the temporal evolution of SAEV demand and EVCS supply (i.e., transition to SAEVs), which should be considered in detail in future work. However, fleet operators would be wise to jointly couple charging with repositioning, as done in this study, to improve response times, reduce externalities, and improve ridership volumes per vehicle.

If electricity costs are incorporated into this objective function to minimize total operational costs (e.g., opportunity and electricity), then the frequency of charging would likely decrease. However, the objective function studied results in fewer charging trips per day even though average daily trips per SAEV increases (resulting in lower direct electricity costs). Similarly, the objective function does not seek to minimize response times directly but comes as a result of managing fleet availability both spatially and temporally through repositioning and charging decisions.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Dean, M.D., Gurumurthy, K.M., and de Souza, F.; data collection: Dean, M.D., Gurumurthy, K.M., de Souza, F., and Auld, J.; analysis and interpretation of results: Dean, M.D., Gurumurthy, K.M., and de Souza, F., and Kockelman, K.M.; draft manuscript preparation: Dean, M.D., Gurumurthy, K.M., de Souza, F., and Kockelman, K.M. All authors reviewed the results and approved the final version of the manuscript.

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