Synergies Between Repositioning and Charging Strategies for Shared Autonomous Electric Vehicle Fleets

Matthew D. Dean[a], Krishna Murthy Gurumurthy[b], Felipe de Souza[b], Joshua Auld[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, United States

[b]Argonne National Laboratory, Energy Systems Division, 9700 S Cass Ave, Lemont, IL, 60439, United States

[*]Corresponding Author

Abstract

The emergence of on-demand shared autonomous electric vehicle (SAEV) service requires careful charging station planning and a joint charging and repositioning strategy to mitigate empty travel. This study couples charging and repositioning events as a means of improving service quality (rider wait times), reducing empty travel due to repositioning or charging, and improving fleet utilization (average daily trips per vehicle and charging queues). This synergy is explored for the Austin, Texas region using POLARIS, an agent-based model. On average, wait times were 39% lower, and 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 the fleet's percent empty travel on average by 1.6% relative to the scenario treating them as independent events (varies by charging station design). Sparser charging stations reduce investment costs, and operators can leverage this framework to keep average wait times down.

Keywords: Shared Autonomous Electric Vehicles, Repositioning, Charging, Charging Infrastructure, Agent-based Simulation, POLARIS

1. Introduction

The future of transportation may be electric, automated, and shared (the "3 revolutions") (Sperling, 2018). 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 (Narayanan et al., 2020). The latter is of particular interest to public transit agencies as on-demand SAEVs could replace low-usage fixed-route local buses, provide free transfers to line-haul services, and pass on savings from expensive paratransit services to expand mobility subsidies or reduce fare transit passes (Shaheen and Cohen, 2020). Sharing vehicles may lower parking demand, and if rides are shared (via dynamic ride-sharing), 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., non-motorized modes, outdoor dining, or green infrastructure) (González-González et al., 2020; ITF, 2018; Zhang et al., 2015). 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 (Becker et al., 2020; Bösch et al., 2018; Fulton et al., 2020; Johnson and Walker, 2016), affordable clean mobility may alleviate persistent transportation-related inequalities that burden low-income neighborhoods (Apte et al., 2019; Cohn et al., 2019; Niles and Pogodzinski, 2021; Wadud et al., 2016). On the other hand, potential gains in access are expected to add empty vehicle-miles traveled (VMT), which if left unregulated, could worsen congestion across cities (Fagnant et al., 2015; Fagnant and Kockelman, 2018; Gurumurthy et al., 2021a; Spieser et al., 2014). There is some evidence to suggest that ride-sourcing vehicles have already increased congestion in cities like San Francisco (Erhardt et al., 2019). And as a bridge technology, drivers of ride-sourcing platforms can incur significant deadheading (up to 26% of ride-sourcing mileage in one study (Wenzel et al., 2019), though others estimate a higher range of 36% to 45% when including ride-sourcing 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 carbon dioxide (CO_2) emissions per passenger-mile (SB-1014, 2018). At the street level, some municipalities have created dedicated zones for pick-up, drop-off, and other curbside activities (via dynamic use and pricing policies) to manage competing interests of this space by SAEVs and other modes (Gurumurthy and Kockelman, 2022; ITF, 2018; Litman, 2021; Marsden et al., 2020; Yan et al., 2020). 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 (i.e., wait times), but added travel drains the battery, thus increasing downtime at charging stations. Charging vehicles in advance of peak demand can increase the likelihood of a successful match by both aligning vehicle availability with demand and having sufficient range to complete most trips. Unlike present-day ride-sourcing platforms, future SAEVs will be governed by a central operator that has control over vehicle actions (e.g., repositioning, charging, maintenance, and pickup/drop-off). Since repositioning range-constrained vehicles both influences future charging actions and charging decisions influence vehicle availability, control strategies that coordinate charging and repositioning may improve operational efficiency and service quality. In this study, an optimization-based control strategy for charging and repositioning SAEVs is presented and compared to uncoordinated operational strategies. The strategy is presented numerically to derive intuition that is generalizable for any case study and then implemented in an agent-based simulation environment. In addition to comparing this novel control strategy to ones found in the literature, this paper explores asset utilization of different sizes of fleet-owned electric vehicle charging station networks.

As mentioned by Narayanan et al. (2020), using more realistic models tends to show lower benefits from on-demand shared vehicle service. Since early SAEV simulation studies (Chen et al., 2016; Loeb et al., 2018), advancements in activity-based agent-based models have allowed modelers to simulate background freight and inter-city travel within daily intra-city traffic, avoid down-sampling of populations (or at least model more than 50% of a metropolitan area's population), and incorporate finer link-level traffic behavior models. However, many improvements are necessary (e.g., full street networks, disaggregation of activity locations to addresses, trip party size distributions, complete multi-modal network mapping and integration). To better prepare for a world of SAEVs, a comparison of a joint charging and repositioning control strategy to prior strategies is warranted, given advancements in modeling techniques. If SAEV control strategies can reduce externalities and improve passenger service quality in theory but are applied to simplistic models then the benefits may be overstated. The first contribution of this study is a proposed joint charging and repositioning control strategy for SAEV fleets. The second contribution of this study is the application of this strategy to Austin, Texas, within a large-scale simulation environment to update estimates on SAEV service results from prior studies. It is also useful to compare this optimization-based strategy to others used in the literature to advance work in the realm of simulation-based fleet operations.

2. Background

Regulations to lessen added empty VMT by autonomous vehicles may target a certain type of travel. For example, this could include privately-owned autonomous vehicles cruising to avoid parking or SAEVs repositioning to neighborhoods with high demand, but without a pick-up request. In general, there are three sources of empty travel (Winter et al., 2020) for SAEV fleets:

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

The third category (repositioning VMT) 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 repositioning mileage is penalized (directly or indirectly), 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, often an hour-ahead (de Souza et al., 2020; Hörl et al., 2019). Since empty VMT 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 could fully charge during this process if they have at least half charge and a direct-current fast charger (DCFC) is available upon arrival.

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 (Alonso-Mora et al., 2017). Yet, even a 3% to 6% increase in empty VMT, as observed by another assignment strategy study using a fixed-trip dataset (Dandl et al., 2019), can shorten the range of SAEVs to serve passenger trips. As a consequence, there may be an increase in the number of rejected ride requests because more vehicles need to charge. This supply reduction effect may be more pronounced for a fleet of short-range vehicles (100-mi range or less). Even if DCFC chargers are used for SAEVs, a drop in the supply of vehicles may increase pick-up travel, reduce fleet operation revenue, and create a cycle of diminished average fleet state of charge (SOC). Though sophisticated optimal joint repositioning and charging models exist, computational complexity limits the scale and thus accessibility of applying such control models (Iacobucci et al., 2019). For this reason, simulation-based methods currently rely on heuristics or optimization-based control strategies that are applied at multiple time steps.

Previous agent-based simulations vary in percent empty VMT reported, as well as the increase in empty mileage with proactive repositioning strategies. Early SAEV work on a grid network with fixed demand 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% repositioning VMT (Chen et al., 2016). Although repositioning mileage was relatively small compared to total VMT, total empty travel across the four respective range and charger type scenarios in their study revealed that both repositioning and charging empty VMT were not insignificant (2.1% to 11.1%). With dynamic ride-sharing, repositioning mileage increased from an estimated 2.0% to 9.3%, but the average daily person-trips per vehicle also increased(Farhan and Chen, 2018).

Another study explored rebalancing shared autonomous vehicles (SAVs) to optimize relocating idling vehicles through a minimum cost flow problem (Vosooghi et al., 2019) within MATSim. The total empty VMT rose from 15% to 24% for one scenario; however, mode share also increased from 5.3% to 6.4%, confounding the increase in repositioning travel alone. Even with an overall increase in empty VMT, a shorter average waiting time of 25% to 35% led to a corresponding increase in mode share that could offset potential repositioning travel fees. If SAV fleets electrify, the authors found the share of empty VMT increases due to charging (18.3% and 22.8%, depending on the charging station siting algorithm). The authors note that charging without repositioning can result in less dispersed vehicles (Vosooghi et al., 2020). Similarly, Loeb et al. (2018) used MATSim to study charging infrastructure and range trade-offs and noted a range of empty VMT of 15.3% to 24.0%, though there was no repositioning strategy. In comparison to Chen et al. (2016) and Farhan and Chen (2018), Vosooghi et al. (2019, 2020) and Loeb et al. (2018) used a road network instead of a simplistic grid, which introduces congestion and improved travel time estimates. Though recent studies use more advanced modeling techniques, studies miss exploring operational trade-offs between repositioning and charging.

One study proposed an operations optimization framework that considered dispatch, repositioning, and charging trips from a fixed-trip dataset (Yi and Smart, 2021). They found that a DCFC network can reduce charging downtime by more than 5% compared to a mix of Level 2 and DCFC chargers, which corresponds to a 6% to 14% reduction in empty VMT. Increasing vehicle availability through reduced charge times allowed the SAEV operator to make better decisions. Relative to their vehicle-based heuristic dispatch strategy, central management increased trips met by 11%. Though they used a detailed road network with travel time estimates from OpenStreetMap, the study does not consider traffic congestion. Additionally, their SAEV service does not permit ride-sharing, which is understandable considering they propose an optimization-based method for repositioning vehicles to unmet requests as opposed to zones with insufficient supply.

Most SAEV fleet operation works are simulation-based approaches, with some proposing and studying optimization-based control strategies. Recent works from the operations research field have developed and numerically tested joint assignment, repositioning, and charging strategies for SAEV fleets. Given demand uncertainty and the sequential impacts of decisions over time, many of these mathematical models are intractable and require approximation methods to solve.

Al-Kanj et al. (2020) determined their optimal vehicle control strategy by learning a hierarchical aggregation of a value function (also called approximate dynamic programming or reinforcement learning). Their objective goal was to maximize total revenue while assuming the value function was linear with the number of vehicles, which ignored the diminishing value of an additional car. The authors suggest future work remedy this problem with a piecewise linear approximation. In a numerical case study for New Jersey, their strategy increased revenue per car by over 17% and increased the percentage of trips met from 74% to 95%. Kullman et al. (2021) used a deep reinforcement learning method to choose vehicle actions that optimizes fleet profit over the entire time horizon and compared their approach to a well-known repositioning strategy (Alonso-Mora et al., 2017). In a numerical experiment with the same Manhattan trip dataset as Yi and Smart (2021) used, Kullman et al.'s adaptable strategy increased the fleet's profit by 18% over a wait-and-see repositioning strategy (Alonso-Mora et al., 2017).

In summary, agent-based models that simulate repositioning strategies of SAEV fleets are, to the best of the author's knowledge, limited to three studies (Chen et al., 2016; Farhan and Chen, 2018; Yi and Smart, 2021), although several studies have explored repositioning of SAV fleets (Bauer et al., 2018; Bischoff and Maciejewski, 2016; de Souza et al., 2020; Fagnant and Kockelman, 2018, 2014; Hörl et al., 2019; Martinez and Viegas, 2017; Vosooghi et al., 2019; Winter et al., 2020). 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 (Yi and Smart, 2021).

Although repositioning and routing of SAEVs can be formulated as an extension of a *Green Vehicle Routing Problem*, *Dynamic Vehicle Routing Problem with Time Windows*, *Electric Vehicle Routing Problem*, or other intelligent assignment problems (see (Hörl et al., 2019) for further discussion), computationally efficient heuristic vehicle assignment and routing methods are adequate for large-scale regions. Using heuristic dispatch methods may even be advantageous for large regions with less than 40 average daily SAV trips per vehicle (Yi and Smart, 2021). A comparison of vehicle assignment and routing decisions is out of the scope of this work, which is on charging and repositioning decisions for SAEV fleets.

This study leverages POLARIS, an activity-based agent-based modeling framework, to simulate joint charging and repositioning decisions for a 100% synthesized Austin, Texas population. As mentioned by (Narayanan et al., 2020), using more realistic models tends to show lower benefits from SAV service. To better prepare for a world of SAEVs, a comparison of a joint charging and repositioning control strategy to prior strategies is warranted, given advancements in modeling techniques. Though we provide a numerical explanation of the strategy for generalizable intuition, findings from the case study of Austin, Texas, are used to compare with prior estimates of SAEV service (Chen et al., 2016; Loeb et al., 2018). This paper is organized as follows: Section 3 introduces heuristic and optimization-based charging and repositioning control strategies, including the proposed model. Section 4 introduces the POLARIS framework and the implementation of the case study for Austin. Results from the case study are presented in Section 5 and a discussion of the results are in Section 6. Finally, our conclusions and recommendations for SAEV fleet operators are in Section 7.

3. Modeling Framework

The charging and repositioning strategy developed in this study is an SAEV optimization-based control strategy. The strategy jointly considers charging and repositioning decisions at the same decision epoch, solved simultaneously, and explores the fleetwide benefits of this approach. The remainder of this section describes the model developed, alongside similar work and its shortcomings, and an example problem to illustrate the motivation for our implementation.

3.1 Optimization Framework for Charging and Repositioning

Existing repositioning strategies consider the balance between supply and demand but do not make optimal charging decisions (Chen et al., 2016; Farhan and Chen, 2018). Vehicle-level charging heuristics also often fail to account for possible queuing at charging stations by sending vehicles to the closest station or by assuming unlimited charging capacity (Chen et al., 2016; Farhan and Chen, 2018; Iacobucci et al., 2019; Yi and Smart, 2021). 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 charge vehicles. This creates an opportunity to observe the benefits of combining repositioning and charging decisions at a single time step.

The repositioning strategy for SAVs by de Souza et al. (2020) is adapted to consider the new logistical challenges of an electrified fleet. Electric vehicles are both range constrained and have substantial charging times, requiring careful coordination with any repositioning strategy of distributing idle vehicles to meet anticipated demand so that service quality improves. The fleet operator must check each idle vehicle before repositioning to ensure sufficient charge to reach the desired zone and serve the expected demand. Location and availability of chargers can also factor into decision-making so that vehicles arrive at an assigned charging station in a zone and recharge before expected demand increases. Assigning vehicles to available chargers as opposed to charging stations can help minimize downtime (or conversely increase vehicle availability). If charging is prioritized when there is little to no supply deficit, then vehicles are more likely to be available during peak travel periods and serve more trip requests.

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 expected future 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 to create optimal charging and repositioning decisions for idle vehicles. In this framework, the repositioning decisions are obtained by solving a Linear Programming problem at every control time step. Following previous work, the region is split into an arbitrary set of zones, and the input data are defined based on these zones. In this work, the region's traffic analysis zones are used, but any other zone definition can be used. The following nomenclature for this strategy is defined in Table 1 and explained below. Although this work does not employ any sophisticated demand prediction model or multi-step model predictive control, the control strategy projects the prevailing demand one step ahead (e.g., 15 minutes) and acts to avoid expected supply deficits in the future. Therefore, the control strategy, which acts in anticipation of future problems, can be considered proactive.

Table 1: Model nomenclature for repositioning and charging control strategy

Type	Name	Description
Endogenous Variable	s_j	Supply of vehicles in zone *j*
	$z_j(i)$	Vehicle *i* idles in zone *j* or en route to zone *j* as the final destination (binary)
	δ_j	Slack variable for zone *j* to guarantee a non-negative supply deficit
	C_j	Available capacity of charging station(s) in zone *j*
	SOC_i	State of charge of vehicle *i*
Exogenous Variable	f_j	Expected demand in zone *j*
	t_{ij}	Zone-to-zone travel time estimate for vehicle *i* moving from its current zone to destination zone *j*
	v_i	Binary variable based on the vehicle's SOC (1 when $SOC_i > SOC^{min}$, indicating vehicle i is available).
Decision Variables	x_{ij}	Vehicle *i* repositions to zone *j* (binary)
	a_{ij}	Vehicle *i* goes to a charging station in zone *j* (binary)
Parameters	SOC^{max}	Maximum state of charge (cutoff for charging vehicles)
	SOC^{min}	Minimum state of charge
	α	Weight for charging trips
	β	Weight for slack variable
Sets	I	Set of vehicles $i \in I$
	I_j	Set of vehicles at zone *j*, $I_j \subseteq I$
	Z	Set of zones $j \in Z$

Note: The expected demand may also be an endogenous variable if reactive – but for each independent control step it is still considered exogenous.

The fundamental zonal variables, expected demand and current supply, are denoted as f_j and s_j, respectively. The supply s_j is computed based on the current state of each vehicle $i \in I$ ($s_j = \sum_{i \in I} z_j(i)$) where $z_j(i) = 1$ if the vehicle i is idling in zone j or currently performing a set of operations which will eventually end in zone j (i.e., last dropoff in zone j or charging or repositioning in zone j); $z_j(i) = 0$ otherwise. The expected demand f_j is assumed to be an integer number and can be obtained through historical counts or any appropriate estimation method. The zonal variable $\delta_j > 0$ $(j \in J)$ denotes the slack variables for supply deficit at zone j. This variable was not present in de Souza et al. (2020) but in other work (Dandl et al., 2019), and the role is discussed further below.

The time-varying zone-to-zone travel time skim matrix, TT_{OD}, where $O \in Z, D \in Z$, is assumed to be given or pre-computed for every pair. For simplicity, we denote t_{ij} as the travel time for vehicle i to travel to zone j. Note that t_{ij} is the element that is returned from TT_{OD} by knowing the origin zone O of vehicle i and the destination zone D. These assumptions and definitions are the same as de Souza et al. (2020). However, repositioning decisions are now taken for each vehicle as opposed to zone aggregated decisions. Here, the binary variable x_{ij} indicates if vehicle i will reposition to zone j with x_{ij} defined for each idle vehicle $i \in I_j$ and for every zone j.

For the charging decisions, it is necessary to track the SOC of each vehicle. At any given time, the SOC for vehicle SOC_i ranges from 0% to 100%. A minimum threshold SOC^{min} is set to the minimum desired operational SOC for vehicles, which should be higher than absolute low SOC settings used in charging heuristics. If not, the fleet may be balancing supply and demand with vehicles that are not capable of serving future requests because repositioning drained the battery. A binary constant v_i takes the value 1 when $SOC_i > SOC^{min}$, indicating vehicle i is available for repositioning. Effectively, setting v_i to 0 makes vehicle i more likely to go charge. Since v_i is a constant known before each time step, it is not a binary decision variable. The supply of unused charging stations (i.e., plugs) at zone j is denoted as C_j.

The binary decision variable a_{ij} denotes whether vehicle i will move and then charge in zone j and is defined for each idle vehicle $i \in I$ and for all zones $j \in J$. Charging decisions need to consider the availability of chargers. To that end, the number of vehicles charging at zone *j* cannot exceed the current charger availability at that zone: $\sum_{i \in I} a_{ij} \leq C_j,\ j \in Z$. To permit some queuing at stations, all stations can allow up to 30% of the number of available plugs (hence total available capacity is 1.3 times the available plug count). Since this constant need not be applied in all case studies, it is left out of the constraint.

Given these variables, it is easy to develop constraints for the optimization problem. The decision variables associated for each vehicle *i* must respect that each vehicle can perform at most one operation: $0 \leq \sum_{j \in Z}\left(x_{ij} + a_{ij}\right) \leq 1,\ i \in I$, which considering that x_{ij} and a_{ij} are binary, enforces that only one element associated with vehicle *i* can be assigned the value of 1.

The movement of an idle vehicle to or from zone *j* impacts vehicle availability of that zone. Accounting for vehicles entering and leaving the zone can be thought of as a mass balance problem that ensures vehicle supply for a given zone is greater than or equal to expected demand: $\sum_{i \in I}\left(x_{ij} v_i + a_{ij}\right) - \sum_{i \in I_j}(a_{ji} + x_{ji}) v_i + \delta_j \geq f_j - s_j,\ j \in Z$, where I_j is the set of idle vehicles at zone *j*. Recall that v_i is a binary constant that depends on the SOC of vehicle *i*, meaning that a vehicle moving to zone *j* with low SOC does not count towards the destination zone's supply. Effectively, x_{ij} is eliminated for vehicles with $v_i = 0$. This constraint also includes the slack variable for supply deficit, δ_j. If there is a current supply deficit, this constraint is satisfied either by repositioning vehicles to zone *j* or by relying on the slack variable. The operator desires to have the value of all slack variables be 0, meaning the expected demand and supply is balanced for all zones. However, this situation may not be possible in periods of high demand (i.e., high f_j) and low supply (i.e., low s_j). In that case, the slack variables prevent an infeasible problem without additional changes to the problem inputs (i.e., reducing the demand as needed). The use of slack variables is a new addition to previous repositioning work.

The optimization problem cast as a minimization problem has an objective function that aligns with the three key goals of the strategy: (i) reduce total travel from decisions, (ii) keep idle vehicles with sufficient SOC, and (iii) avoid underserving zones. The objective function J is as follows:

$$J = \sum_{i\in I, j\in Z} t_{ij}\left(x_{ij} + a_{ij}\right) - \alpha \sum_{i\in I, j\in Z} a_{ij}(SOC^{max} - SOC_i) + \beta \sum_{j\in Z} \delta_j \tag{1}$$

The first term in the objective function weights the travel time and since it is positive it attempts to reduce the travel time cost of each repositioning or charging vehicle. Travel times are taken from a time-dependent zone skim matrix, but could include travel time estimate from each vehicle i's current location to desired repositioning destination in zone j. The second term in the objective function weights the increase of SOC which would follow from a vehicle moving to a charging station in zone j (i.e., $a_{ij} = 1$). Note the minus sign for a minimization problem rewards vehicles that charge so long as $\alpha > 0$, with a higher benefit applying for vehicles with a low SOC. Finally, the third term in the objective function penalize supply deficits so long as $\beta > 0$.

Considering the objective is in units of travel time (α and β have suitable units to transform the second and third terms into time units), we can derive trade-offs between the second and third terms with the first. Regarding charging benefits, ignoring the supply deficit, a charging trip for vehicle i to zone j would lead to negative or zero cost when $t_{ij} \leq \alpha(SOC^{max} - SOC_i)$. Considering the linearity in this relationship, $\alpha = \frac{t_{ij}}{SOC^{max} - SOC_i}$ is the minimum charging increment per unit time that is accepted for performing a charging decision. Not that this reasoning can be made since the vehicle does at most one operation (i.e., if $a_{ij} = 1$, then $a_{ik} = 0 \quad \forall\, k \neq j\ and\ x_{ij} = 0 \quad \forall j$. The benefit of this approach is that all else constant, if only one vehicle is to go charge in zone *j* the best vehicle to send is the one with the lowest current SOC, since that increases the likelihood of the fleet fulfilling ride requests in the future.

A similar analysis can be done to explore the time tradeoff between travel time cost and meeting supply deficit with a slack variable. Any repositioning between vehicle *i* to zone *j* reduces the δ_j of zone *j* by one unit. Therefore, β is the maximum travel time an idle vehicle will travel to a zone with a supply deficit. If $t_{ij} > \beta$ then it becomes less costly to incur a unit increase in the third term ($\beta\delta_j$) instead of repositioning a vehicle ($t_{ij}x_{ij}$).

Note, other studies may include charging as a constraint or an added term in the objective function multiplied by a large constant *M* (Iacobucci et al., 2021). Since most objective functions minimize costs (or maximize profit), the optimal solution may avoid charging until forced through a minimum SOC or increasing charging as much as possible at the end of an optimization time step. Including time-varying electricity prices or opportunity costs (i.e., penalty for charging a vehicle during peak hours instead of being available) could help to opportunistically charge vehicles. Instead, our strategy will charge vehicles with low SOC if nearby a charging station and the supply of vehicles is greater or equal to the expected future demand.

The multiple terms in the objective function are weighted with non-zero parameters α and β, which prioritize charging vehicles and repositioning vehicles to minimize the reliance on the slack variable, respectively. Parameter values were adjusted through several iterations until two distinct outcomes were achieved, namely: demand prioritization (DP) and charging prioritization

(CP). The objective with these two scenarios is also meant to speak to the sensitivity of the optimization to charging and repositioning trips.

3.1.1 *Optimization Problem Formulation*

Combining the constraints and the objective function, the problem is formulated as:

$$P: \min_{a_{ij}, x_{ij}, \delta_j} J$$

$$J = \sum_{i\in I, j\in Z} t_{ij}\left(x_{ij} + a_{ij}\right) - \alpha \sum_{i\in I, j\in Z} a_{ij}(SOC^{max} - SOC_i) + \beta \sum_{j\in Z} \delta_j$$

s.t.

$$0 \leq \sum_{j\in J}\left(x_{ij} + a_{ij}\right) \leq 1, \qquad i \in I$$

$$\sum_{i\in I} a_{ij} \leq C_j, \qquad j \in Z$$

$$\sum_{i\in I}\left(x_{ij}v_i + a_{ij}\right) - \sum_{i\in I_j}(a_{ji} + x_{ji})v_i + \delta_j \geq f_j - s_j, \qquad j \in Z$$

$$x_{ij} \in \{0,1\}, \qquad i \in I, j \in Z$$

$$a_{ij} \in \{0,1\}, \qquad i \in I, j \in Z$$

$$0 \leq \delta_j, \qquad j \in Z \qquad (2)$$

which is a Mixed Integer Linear Programming (MILP) since x_{ij} and a_{ij} are binary variables. Nevertheless, this problem can be efficiently solved due to its inherent properties and variable elimination. The following combinations of variables can be eliminated:

1) all x_{ij} vehicles with $SOC < SOC^{min}$ and therefore $v_i = 0$, since $x_{ij} = 1$ would reposition a vehicle without the destination zone increasing supply by one unit;
2) all x_{ij} with $t_{ij} > \beta$ since it is more beneficial to incur an increase in slack to meet the demand-to-supply constraint than it would to reposition a vehicle (note there is no variable elimination for $\beta \rightarrow \infty$);
3) similarly, all a_{ij} such that $t_{ij} - \alpha(SOC^{max} - SOC_i) > \beta$.

With elimination of these variables, the constant v_i only appears with the term a_{ij} in the demand-to-supply balance constraint. Nevertheless, the key factor to efficiently solve the optimization problem is to eliminate the binary variables. We exploit the total unimodularity property of the constraint matrix, which occurs when the right-hand sides of inequality constraints are integer variables and proves the solution is integral numbers. This property has been exploited in (de Souza et al., 2020; Hyland and Mahmassani, 2018). Absent a formal proof, numerical analysis on a large number of instances of varying sizes (Walter and Truemper, 2013) demonstrates the problem has totally unimodular constraints for $v_i = 1 \, \forall i$ (i.e., only vehicles that count as supply, otherwise they are ignored). This means that the binary decision variable constraints on the problem can be replaced with:

$$0 \leq x_{ij} \leq 1, \qquad i \in I, j \in Z$$

$$0 \leq a_{ij} \leq 1, \qquad i \in I, j \in Z \qquad (3)$$

Thus, this problem can be solved through Linear Programming, provided that f_j and s_j are also integers. The problem may not be totally unimodular in the case there are vehicles with low SOC. Based on numerical experiments, in all cases, the solver yields integral numbers for the solution. If there is a case where this is not true, the problem could be solved by setting $v_i = 1$ for all vehicles in that case.

The optimization problem, through variable elimination, has interesting special cases. If there are no charging decisions (i.e., $a_{ij} = 0 \, \forall i \in I$) the problem reduces to a repositioning strategy. Removing the slack variables and charging decisions, this problem becomes nearly equivalent to the baseline repositioning strategy, which is shown in the Appendix. Similarly, the problem becomes a model for charging decisions if repositioning is ignored. Since the model formulation allows for the flexibility of dialing the tradeoff between these features, it allows for a study of the synergies between these strategies.

As mentioned previously, the problem is solved at a decision-making time step that is subject to modeler judgment. 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). This study assumes a time step of 15 minutes to react to zonal demand, which is estimated based on trip requests made in the prior 15 minutes.

3.2 Simple Numerical Example of Joint Charging and Repositioning Strategy

As a simple example, Equation (2) is applied to a fictitious town with four zones, two charging stations, and a fleet size of five SAEVs. Figure 1 shows the zones labeled 1-4 clockwise from the top left. Charging stations are represented as lightning bolts and both zones 2 and 4 have a single charging connection. At some decision-making time step there are three vehicles (black) that are idle. Three vehicles are not counted towards available supply s_j: the red vehicle picking up a passenger in zone 1 and a green vehicle charging in zone 2. Vehicle 4 in zone 3 has insufficient SOC for repositioning and is not counted as supply at origin and potential destination zones. If this vehicle charges, it will be counted as an additional supply unit at the destination zone. Based on the prior quarter-hour, the expected demand for the city is f_j = {1,0,1,0}. This means that only zone 1 has a supply deficit while the remaining zones either have sufficient supply or both supply and demand are zero. At present, there are four plausible choices (though more exist):

1) do not reposition or charge any idle vehicles and rely on a slack variable to satisfy the first constraint.
2) reposition vehicle 2 to zone 1 to reduce the supply deficit.
3) reposition vehicle 2 to zone 1 to reduce the supply deficit and assign vehicle 5 to the charging station in zone 4.
4) reposition vehicle 5 to zone 1 to reduce the supply deficit.

If the travel time for vehicle 2 to zone 1 (choice 2) is less than the travel time for vehicle 5 to zone 1 (choice 4), then the least-cost option between the two choices is to reposition vehicle 2 to zone 1. However, there is a trade-off between minimizing the travel time cost in the objective function to satisfy the zonal supply and demand constraint and relying on a slack variable for zone 1 (choice 1). If the parameter β is greater than the travel time cost for vehicle 2 repositioning to zone 1, then the lowest objective value between these two choices is found in repositioning vehicle 2. The last comparison to make is between choice 2 and choice 3. Choice 3 would increase the travel time cost by assigning vehicle 5 to the available charging station in zone 4 but could lower the objective value if the product of α and the SOC increase from charging the vehicle is greater than the travel time cost. Provided that the zone-to-zone travel times for vehicle 2 is $t_{2j} = \{2,0,3,5\}$ and vehicle 5 is $t_{5j} = \{6,2,0,2\}$, the weight parameter for charging is $\alpha = 10$, the SOC increase for vehicle 5 is 0.40, and the weight parameter for slack is $\beta = 20$, the objective values of the four choices are: 20, 2, 0, and 6. Hence, the optimization-based control strategy would pursue choice 3. The benefit of this choice is that users of this SAEV in zone 1 will experience lower wait times, the anticipated supply deficit is minimized at this time step without relying on a slack variable, and a vehicle can charge 40% of its battery during an off-peak period. Additionally, by assigning charging vehicles to charging stations with available capacity, the strategy minimizes charging downtime and resulted in zone 4 having a vehicle, albeit an unavailable SAEV. If the parameter for charging were less, say $\alpha = 2$, then the best strategy would be choice 2, since the reward for charging is not greater than the travel time cost for charging. Thus, the trade-off between charging is sensitive to the SOC increase and the travel time cost. The operator would be wise to not send a vehicle to a charging station if $\alpha \leq (\triangle\, SOC)^{-1} * tt_{ij}$ and not reposition a vehicle if $\beta \leq tt_{ij}$ (for a single vehicle decision).

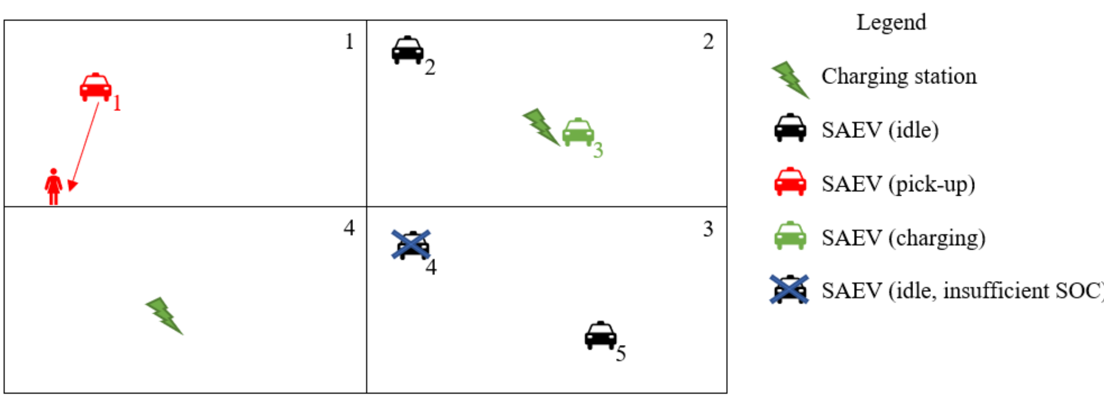

Figure 1: Illustration of a numerical example of the proposed charging and repositioning strategy

4. Case Study

4.1 POLARIS simulation environment

The activity-based agent-based modeling tool called POLARIS (Auld et al., 2016) is used to investigate the optimization-based control strategy for charging and repositioning SAEV fleets for a large-scale region to derive insights for fleet operators and transportation planners alike. Although the control strategy is transferable to any simulator, POLARIS was chosen due to advancements in simulation modeling and to compare with baseline charging and repositioning strategies from prior studies (de Souza et al., 2020; Gurumurthy et al., 2021b). The simulation environment 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 and the United States Census Bureau according to the ADAPTS modeling framework (Auld and Mohammadian, 2012, 2009). Interested readers should refer to the appendix for data on the calibration of these econometric models. 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 (Verbas et al., 2018) routes vehicles whose experienced travel time is an outcome of a mesoscopic traffic flow model based on the link transmission model (de Souza et al., 2019). This results in finer link-level traffic behavior than queue-based algorithm approaches (Horni et al., 2016). The region's population is not down sampled and time-dependent background traffic, such as freight and other external travel, is added to links to add increased realism. 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 variation 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. The following subsections detail the modeling assumptions for SAEV operations and fleet-owned charging stations within POLARIS.

4.1.1 Assignment and Dynamic Ride-sharing

The operator assigns vehicles to riders using a computationally-efficient, zone-based assignment (Bischoff and Maciejewski, 2016; Gurumurthy, 2020) by matching ride requests to SAEVs in the same or nearby zones, thereby reducing overall pick-up VMT and ensuring adequately low response times. This is supported by Hörl et al.'s study that revealed their adopted load-balancing heuristic (Bischoff and Maciejewski, 2016) has lower wait times during peak times than their alternative optimized Global Euclidean Bipartite Matching algorithm (Hörl et al., 2019).

The operator truncates an array of neighboring zones for each zone 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 (Gurumurthy, 2020).

Once pick-up time is limited to a threshold, delays from sharing a ride need to be taken into consideration. Dynamic ride-sharing 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 (minutes) and relative travel time (percent more than expected) (Gurumurthy and Kockelman, 2022). 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 spatial sequential search (i.e., a spatial R-tree architecture) that respects the traveler pick-up constraint (cannot drop-off a traveler before picking them up). In short, the assigned vehicle finds the nearest pickup or dropoff location (out of all scheduled and newly assigned locations) by shortest Euclidean path. Like other agent-based models, two or more travelers cannot yet request a shared ride together (like multi-party ride-sourcing trips).

4.1.2 Electric Vehicle Consumption and Charging Station Modules

Baseline charging rules are defined and tracked by both the fleet operator and SAEVs (Gurumurthy et al., 2021b). Electricity consumption and charging takes a factor-based approach (i.e., available range of vehicles decreases by vehicle-miles traveled and increases by a linear charging rate). 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 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 made, the operator finds the nearest charging station based on downtime (so that distance and queue time are factored into charging station assignment). SAEVs and private electric vehicles do not share charging infrastructure. The operator does not allow charging vehicles to unplug early and serve ride requests.

The charging station 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 (Gurumurthy et al., 2021b), 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 infrastructure 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.

4.2 Austin, Texas Simulation Inputs and Scenarios

The proposed control strategy in section 3.1.1 is evaluated for a fleet of SAEVs serving trips in Austin, Texas, and compared to baseline strategies (section 3.1). The fleet was constrained to both a 6-county metropolitan region and a smaller geofenced region extending from the central business district. Though both service areas geofence SAEVs, this study considers the 6-county metropolitan region as the largest possible service area for both SAEV and non-SAEV intra-city trips. For simplicity, the central city geofence is abbreviated to "geofenced region." The geofenced region reflects the expectation that initial SAEV operations may be restricted to areas with high trip density (e.g., the central business district, government complexes, universities, mixed-use developments, airports). The 6-county metropolitan 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 abstracted to 2,160 zones, 16,100 links, and 10,400 nodes. The smaller geofenced region (60.3 sq mi) covers about 400 zones, 3,500 links, and 2,170 nodes. The fleet size was exogenously 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. This aligns with literature of vehicle-to-resident ratios and the goal that SAEVs should have sufficient to cover average daily VMT before needing to charge from a near empty SOC. Figure 2 shows a layout of the two service areas and the roadway network.

All scenarios used a 2015 roadway model that aggregates local roads and includes centroid connectors from the region's metropolitan planning organization. The synthetic population was estimated from year 2018 United States Census Bureau's American Community Survey Public Use Microdata Sample (United States Census Bureau, 2018). Appropriate mode choice models (e.g., nested multinomial logit) were developed from the 2016-2017 Austin household travel survey (provided by the region's metropolitan planning organization). Taxi and ride-sourcing vehicles in the survey were estimated as SAEVs in the mode choice model, with assumed fare components ($0.50/mile and $0.25/minute) and a value of travel time savings parameter (25%) to reduce the disutility of traveling in an on-demand, door-to-door autonomous vehicle. Since taxi and ride-sourcing vehicles were underrepresented in the household travel 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 (Becker et al., 2020; Compostella et al., 2021). In addition, the vehicle ownership reduction model in Menon et al. (2019) is adapted to present a future base case where approximately decennial vehicle ownership choices are influenced by SAVs. As 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. Table D.1 in the appendix shows levels of household vehicle ownership before and after this model is applied for the synthetic Austin population.

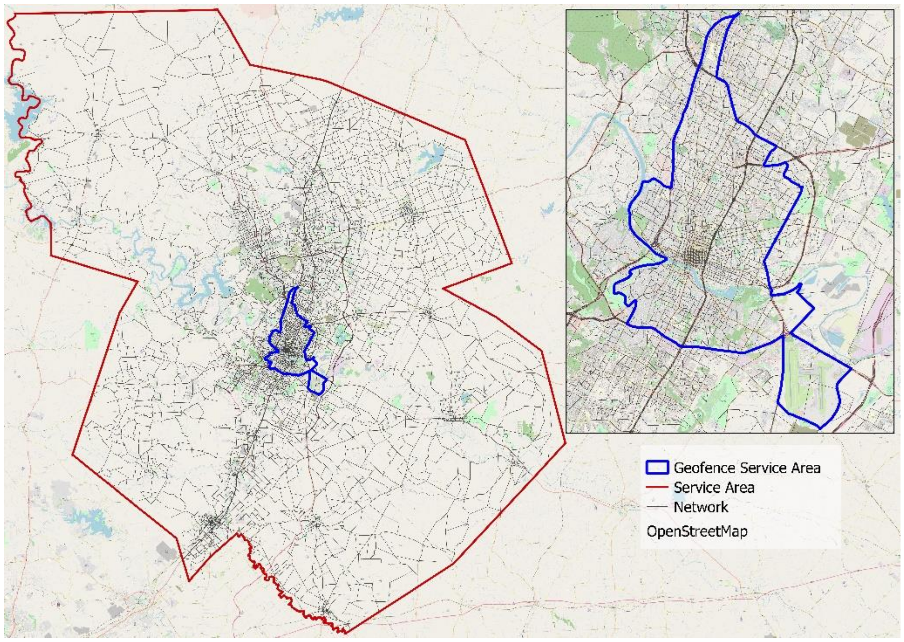

Figure 2: Overview of Austin, Texas service areas and roadway network

Three fleet-owned charging station 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 on a warm start run. If an SAEV queues at a charging station for longer than 15 minutes, an additional plug is generated. This siting process is done with 100-mi vehicles and the baseline charging heuristic. Short-range vehicles were used to provide sufficient charging capacity during peak hours, albeit the set-up lowers utilization of fleet charging equipment. Figure 3 maps the charging station locations (100% heuristic-sited) since the alternative is a scaled-down network.

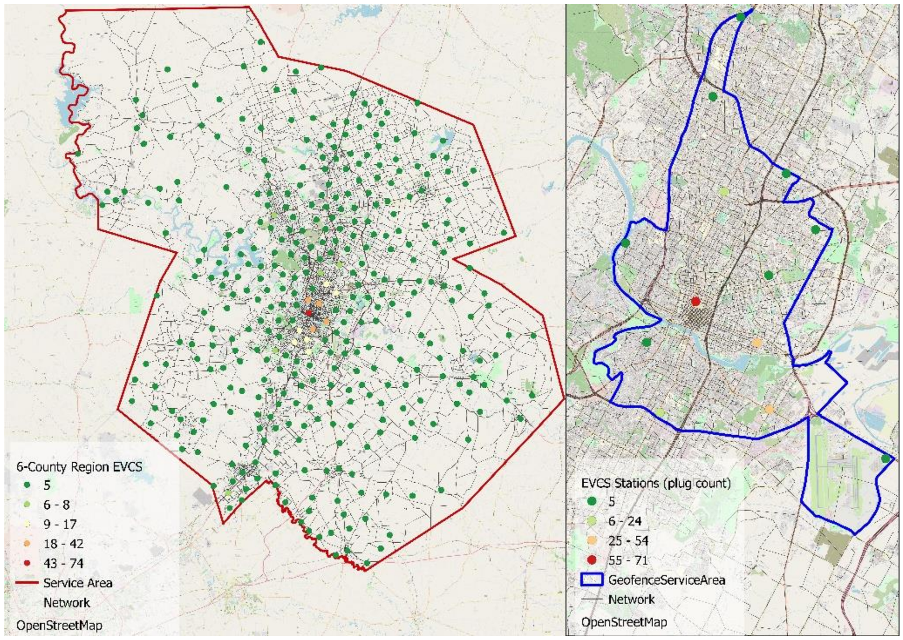

Figure 3: Charging station heuristic-sited scenario in Austin, Texas' 6-county and core area geofence

The second charging station network assumes a uniform scaling factor of 0.5 at each station to reduce the count of plugs. An additional scenario was performed to create a sparser network that resembles a depot-like charging station business model, with each reduction rounding down to the nearest whole plug. The advantage of three charging station 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. See the appendix for a plug and station count comparison between charging station networks.

The first operational strategy is the baseline scenario of rule-based charging without repositioning ("Base") (Gurumurthy et al., 2021b). 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 SAV-based repositioning ("BaseRepo") (de Souza et al., 2020). The proposed SAEV charging and repositioning control strategy was compared to the baseline SAV repositioning strategy. By changing the relative weight of charging or repositioning parameters, three control strategies were developed to understand the contribution of each activity to performance metrics and implications for the fleet (e.g., empty VMT, downtime). Though the entire 24-hour simulation uses constant weights, fleet operators may change parameter values by the time of day. 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"). See Table E.1 in the appendix for the weights used in this study. As mentioned in section 3.1, a higher value for β would encourage more repositioning trips, up to the travel time trade-off, and a higher value for α would encourage more charging trips, up to the product of travel time and inverse SOC change trade-off.

5. Results

Thirty-six scenarios were run (three charging station 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 heuristic charging and no repositioning. Zone-based repositioning was added to minimize supply deficits, which should lower wait time. Next, the proposed framework was leveraged to optimize charging trips to compare results against heuristics commonly used in agent-based models. Two optimization-based joint repositioning and charging scenarios were developed to emphasize joint repositioning and charging decision-making, respectively (with a third trying to find a balance between the two). Table 2 shows the results from the geofenced core area service, followed by the 6-county metropolitan 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, percent empty VMT (%eVMT), percent repositioning VMT (%rVMT), and percent charging VMT (%cVMT).

Table 2: Core area geofence (60.3 square miles) fleet performance

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

Simulations were all performed using Texas Advanced Computing Center supercomputers with most scenarios taking less than two 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 (de Souza et al., 2020). For reference, a 6-county charge priority simulation (using 15-minute repositioning-charging time steps) takes 47 minutes longer than the heuristic charging scenario, which itself takes 64 minutes. The time to solve the joint recharging-repositioning optimization problem can take 7 to 21 seconds for each decision epoch, depending on the number of idle vehicles. Pre-processing times in creating the matrix of inputs to the solver are not included here but are also a function of demand. See Table F.1 in the Appendix for the time to solve the problem for the 6-county region during the evening peak demand.

Table 3: Metropolitan 6-county region (5,300 square miles) fleet performance

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

The goal of repositioning is to better match supply and demand. Figure 4 plots average wait times (i.e., match wait time plus pick-up wait time) over the 24-h simulation across all operational scenarios for the regional service area with the original heuristic-sited charging station network. Similarly, centrally coordinated charging and joint charging and repositioning should reduce empty VMT while increasing fleet average SOC. Figure 5 plots fleet average SOC throughout the 24-h simulation for the regional service area, assuming the same charging station network. The joint strategies can keep higher average SOC over the 24 hours period. Apart from the demand priority case, they are also faster to recover higher SOC following the morning and evening peaks. During special events (with disproportionate demand compared to historical data), the higher fleet SOC will enable a more resilient response.

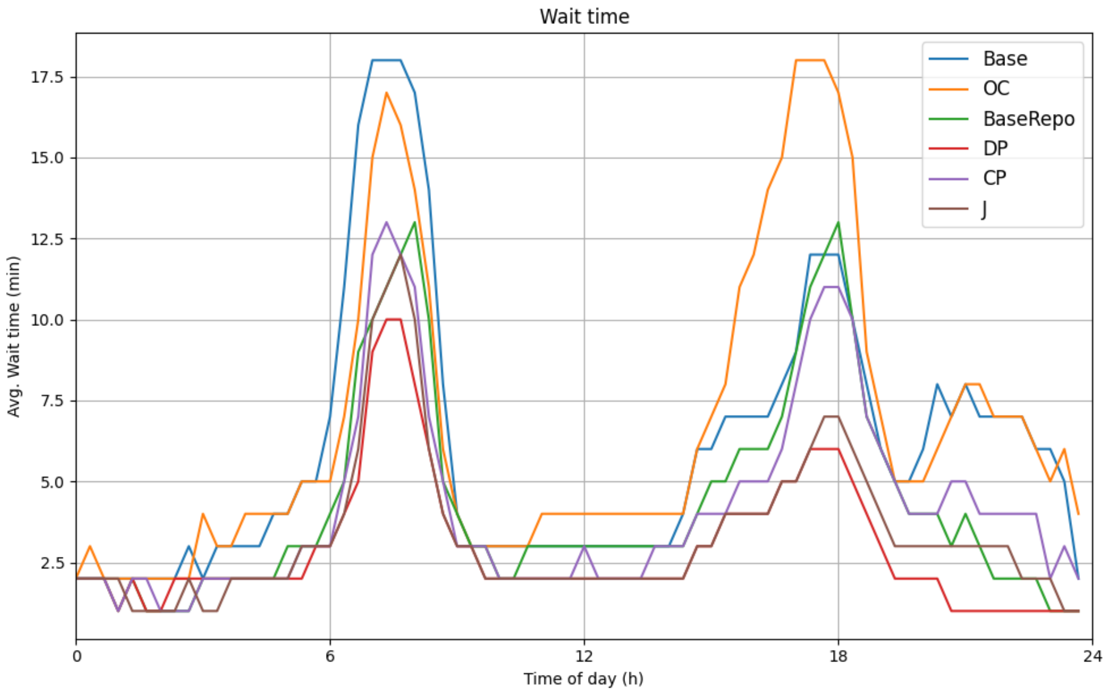

Figure 4: Average wait times by operational scenario (6-county service with distributed charging station network)

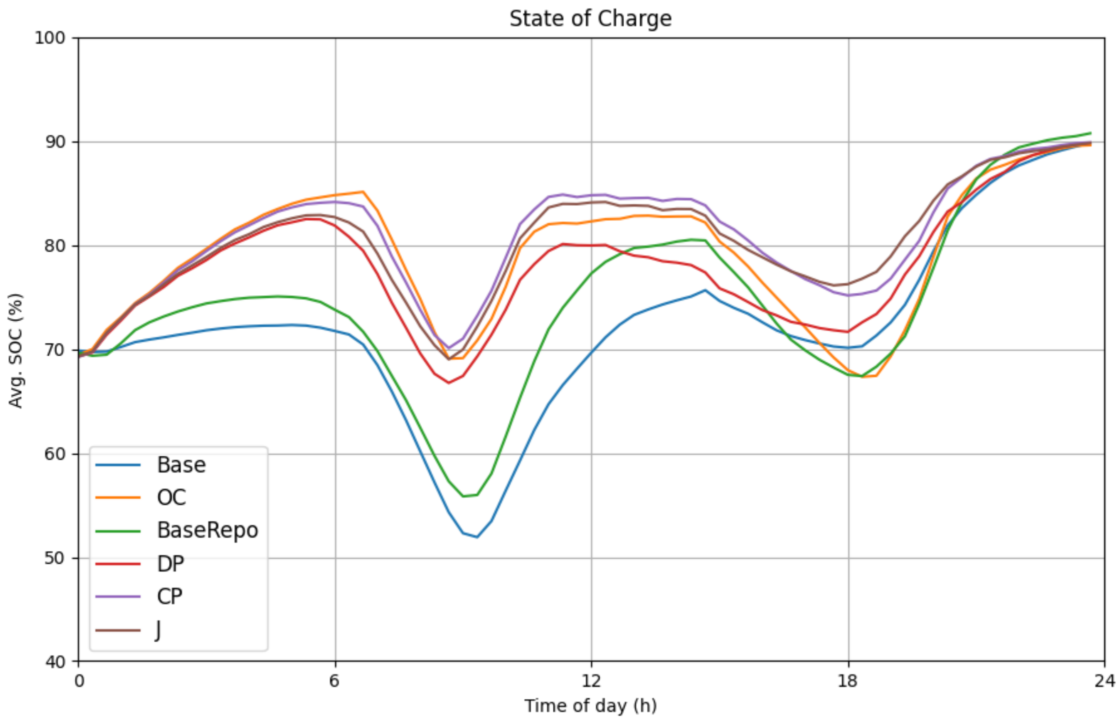

Figure 5: Average SOC by time of day by operational scenario (6-county service with distributed charging station network)

It is clear from both the tables and the plots that the joint optimization-based control strategies increase total served SAEV demand 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 served demand from base repositioning on average by 2.8% and 3.9% for the distributed and scaled 50% charging station designs, respectively. The SAV-based repositioning strategy with heuristic charging (BaseRepo) can be greedy in rebalancing vehicles to meet demand in smaller regions, like the downtown core 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 dynamic ride-sharing but fewer idle vehicles that can pick-up a passenger for a new tour. There is some difficulty in keeping wait times low for the optimization scenarios, except for demand priority (DP). This suggests that the repositioning strategy to minimize supply deficit would benefit from a predictive estimate on minimum supply instead of relying on the prior quarter hour demand. The charging priority (CP) scenario seems to perform the best in raising fleet SOC throughout the day but can increase average wait times by two minutes compared to demand priority.

6. Discussion

6.1 Service Area and Charging Station Networks

The geofenced service area, which covers points of interest in Austin (e.g., the central business district, 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 regions and small zones, unlike (Chen et al., 2016)). For example, adding SAV-based repositioning decreased average wait times by 57% to 75% within the 60.3 square mile core geofence. Moreover, while using the previous 15-minute demand as a predictor for future demand is fine, operators will likely use an ensemble approach with ridership history and other data sources. At first glance, repositioning may want to be avoided in the downtown since SAEVs can exacerbate congestion (through an average of 31.1% unoccupied VMT), like present-day ride-sourcing fleets (Wenzel et al., 2019). However, Table 2 results show lower percent empty VMT (an average of 20.3 %eVMT) with almost all control strategies and charging station networks relative to SAV-based repositioning with heuristic charging. Without repositioning, the average SAEV misses up to an additional 11% daily trips. Coupling repositioning and charging into a single control strategy in the core geofence helps to lessen the societal cost of added mileage and at a lower expense per passenger traveled (i.e., the ratio of percent empty VMT to daily trips per vehicle). This ratio can explain the efficiency of a fleet's control strategy. If repositioning increases average daily trips per vehicle without increasing the percent empty VMT this inefficiency ratio will become smaller. If percent empty VMT increases at a rate that is more than half the increase in daily trips per vehicle, then the inefficiency ratio becomes greater. For a depot-like charging network, the inefficiency ratio for baseline repositioning is 0.70 versus 0.43 for the three joint optimization-based strategies. A large magnitude difference is observed for the two other charging station types.

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 6 shows the average wait times for SAEVs across all zones 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 7. The median zonal wait time for joint optimization is reduced by 1.2 minutes in both the AM and PM relative to baseline repositioning. The downtown core, unsurprisingly, is where the lowest wait times can be found while higher wait times are found in the outskirts of the region. 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.

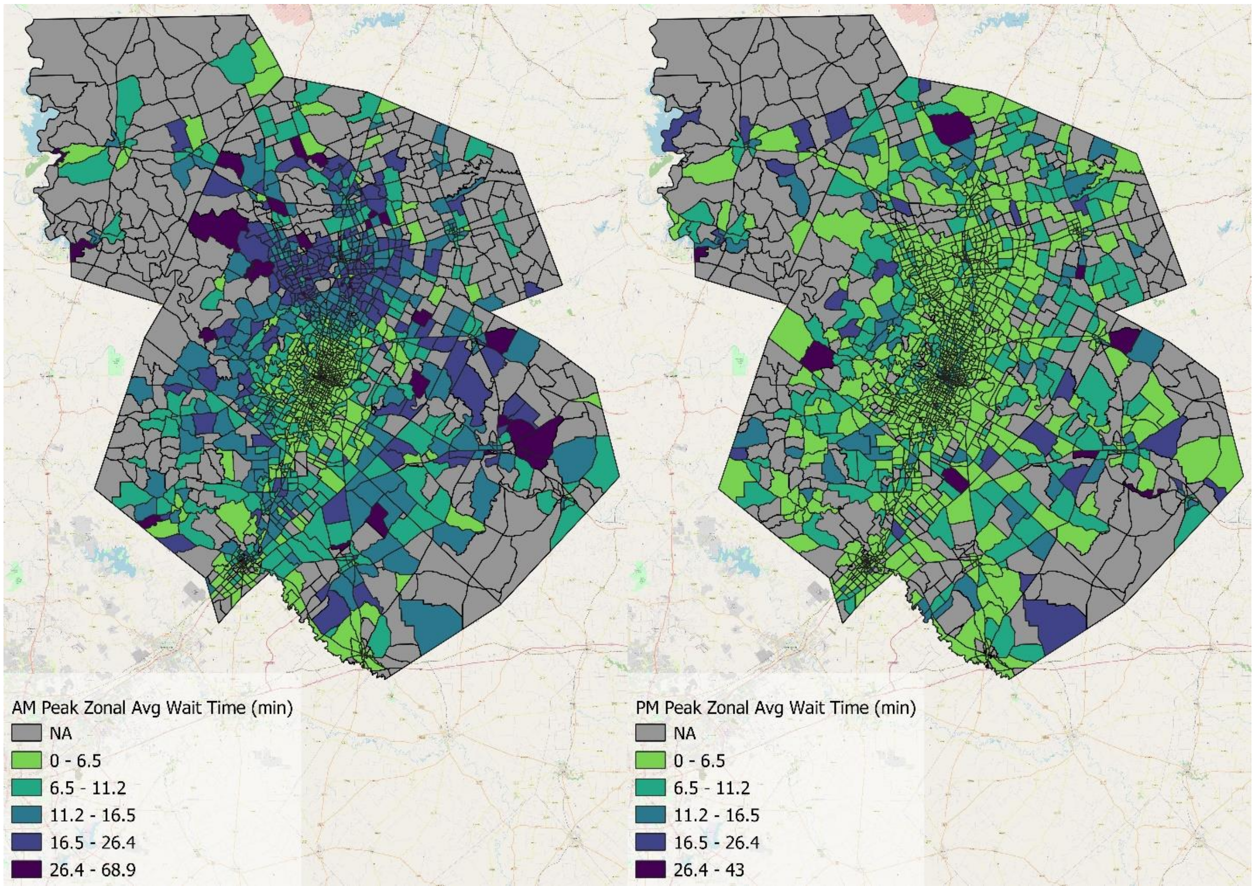

Figure 6: Average wait times by zone during AM and PM peak hour for base repositioning with heuristic charging using a distributed charging station network

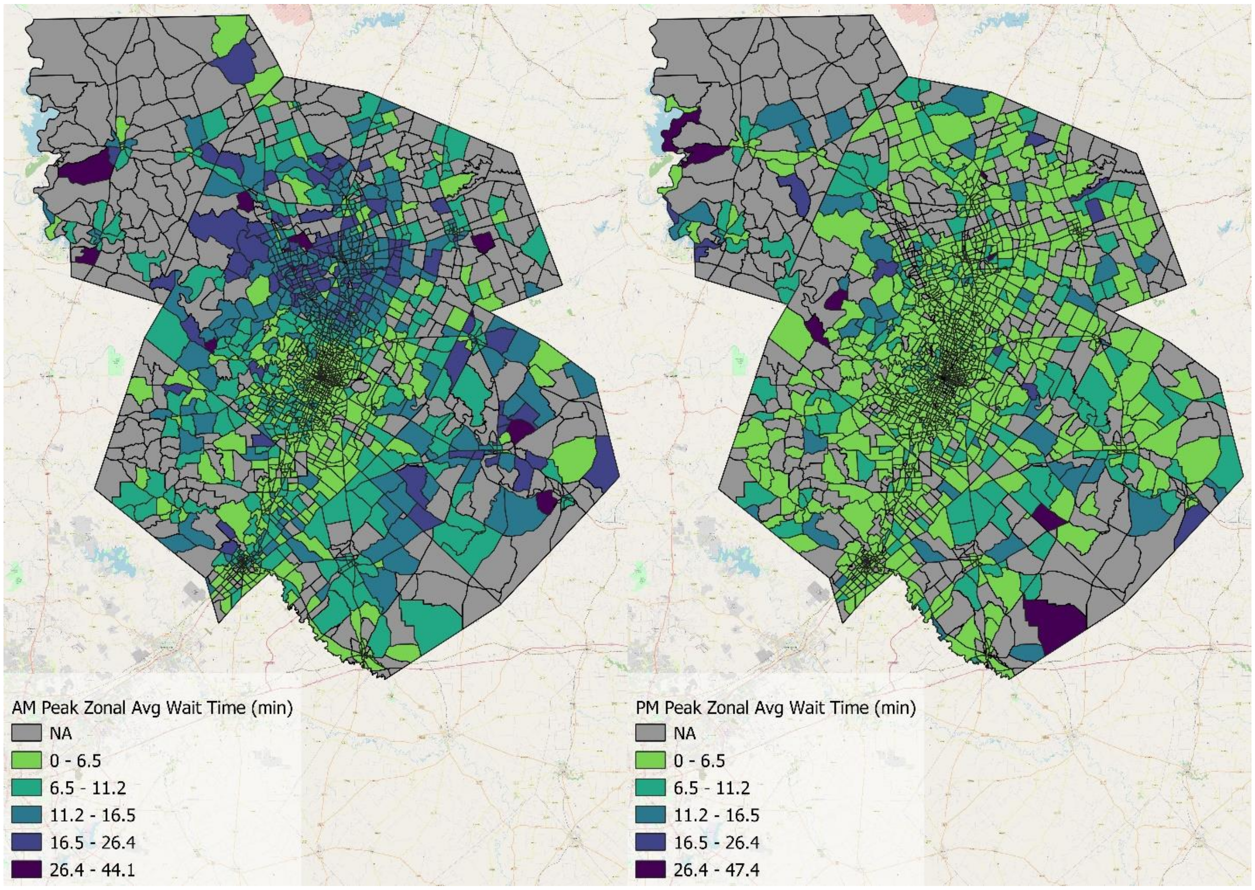

Figure 7: Average wait times by zone during AM and PM peak hour for joint optimization using a distributed charging station network

In the core geofence service area, a depot-like charging station 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 percent empty VMT, which affects downtime, charging costs, and perhaps in the future empty travel 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 charging station network may be wiser because it provides distributed 1-plug stations to reduce empty travel (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 results in less demand served. Heuristic charging station siting algorithms may consider moving away from strict siting rules and instead use distance from the city center to increase the probability of generating a 1-plug station over a depot.

6.2 Optimal Charging

Leveraging the proposed optimization framework to consider only charging leads can improve fleet average SOC during the off-peak hours (e.g., a difference of more than 10% SOC by 6 AM and again at noon), enabling the fleet to meet more trips throughout the day than the base case with no repositioning. The percent charging VMT (cVMT) can increase for the 6-county region (up to an additional 1.9 %cVMT) but vehicle utilization increases by an additional 1.9 riders per day. Table 2 indicates that base repositioning increases average daily trips per vehicle (+4.57, on average) and lowers average response times (-65.9%) but adds substantial percent empty VMT in this smaller geofence (+6.4). On the other hand, optimal charging (OC) sufficiently redistributes vehicles around (additional 1.33 to 4.25 average daily trips per SAEV) and keeps percent charging VMT down (%cVMT can fall by a magnitude of 7.41). If the depot-like network is preferred for a geofenced service area, the optimal charging policy may have similar average of 43.5 daily trips per vehicle as other joint repositioning and charging strategies. However, for a regional service, optimal charging is insufficient in repositioning vehicles, especially in the PM peak (see Figure 4).

6.3 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 charging priority (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 supply deficit). 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 8 shows boxplots for time spent at a charging station (queue plus charging) versus just charging across the day for the base and charging priority policy using a distributed charging network. Baseline charging does not prioritize an increase in SOC during the morning (see also Figure 5) and must charge throughout the day to recover after the AM peak. In comparison, charging priority has larger charging downtime in the early morning to prepare for the AM peak. Additionally, the optimization-based charging strategy can charge as many vehicles as available plugs at charging stations. In contrast, the base charging heuristic can send vehicles to a charging station irrespective of the queue time. This can explain the difference in downtime durations between the two plots (outliers often exceed 3.5 hours after noon for base versus a handful of outliers exceeding 1.5 hours during the early morning hours). Similar patterns are found with a scaled 50% charging station network (Figure 9). This charging station network has fewer plugs which increases vehicle downtime during the day for both base and charging priority scenarios. There is more charging during the morning to midday hours with charging priority because of fewer charging opportunities.

The distributed and 50% scaled-down charging station 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 10 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 charging priority scenarios for a distributed charging station network across the 6-county 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 charging priority 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. Although the charging priority policy does not seek to lower electricity costs (including demand charges), it appears to have this effect.

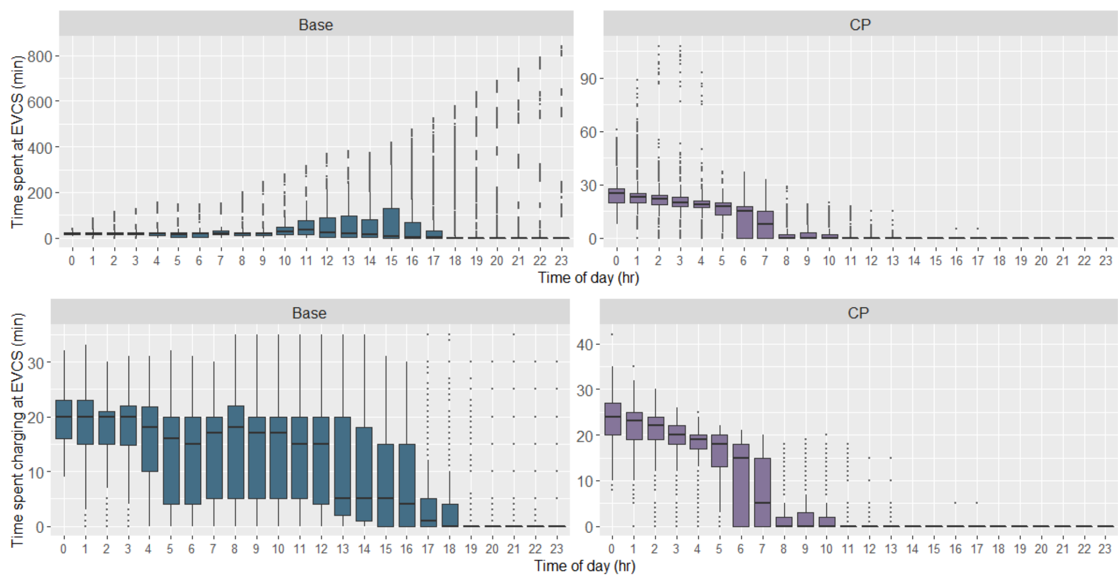

Figure 8: Boxplot of downtime charging for the base and charge priority scenarios with a 6-county service area and distributed charging station network (note: scale differences)

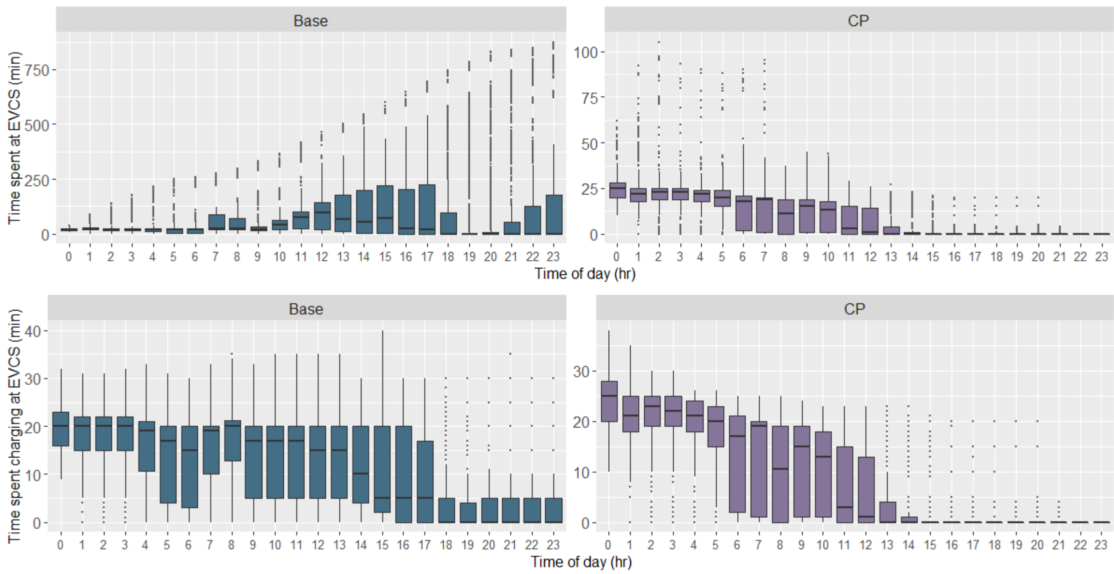

Figure 9: Boxplot of downtime charging for the base and charge priority scenarios with a 6-county service area and 50% scaled-down charging station network (note: scale differences)

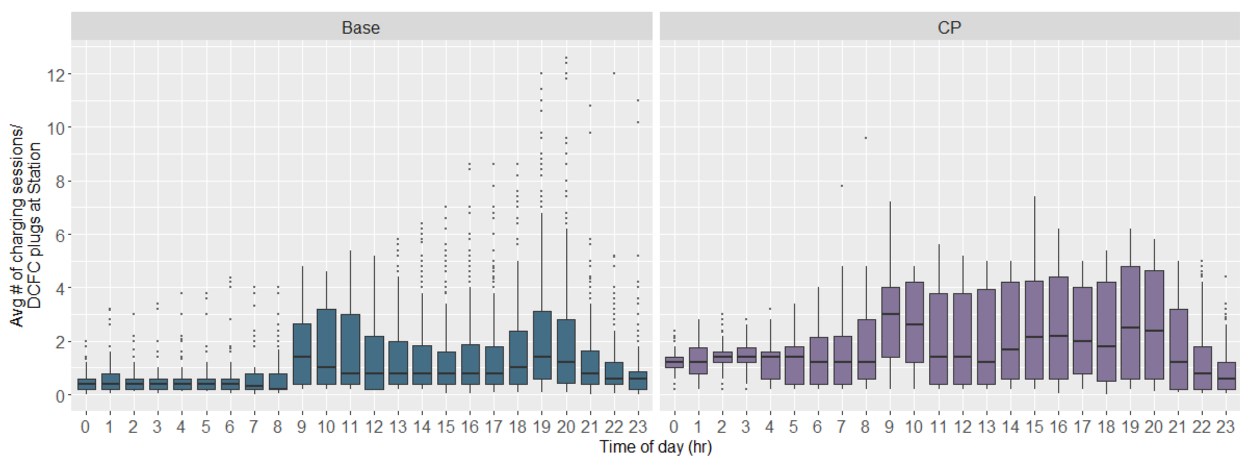

Figure 10: Boxplot of average hourly ratio of charging sessions to plugs in a station for 6-county service and distributed charging station network

6.4 Repositioning with Baseline Charging

The repositioning scenario with baseline charging (BaseRepo) demonstrates why fleet operators will likely pursue repositioning, even at the expense of added empty travel 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 percent empty VMT, which is equivalent to an additional 0.5 deadhead miles per rider). In a downtown geofenced service area, up to 6.2% more trips can be served with an uncoupled repositioning and charging strategy. Though the simulation allows for trip rejections due to a wait time limit, this is not recorded to compare the change in service rate. For example, a joint assignment and repositioning algorithm suggested by Alonso-Mora et al. showed a 20% increase in the service rate when the operator repositions idle vehicles (Alonso-Mora et al., 2017). Still, fleet operators would be wise to adopt a control strategy that optimize charging and repositioning trips at the same decision-making time step to ensure sufficient fleet supply for repositioning. Additionally, coupling charging with repositioning may address the empty travel dilemma (Dandl et al., 2019), which is that a 3%-6% rise in empty travel shortens range and could lower demand.

6.5 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 empty VMT (2%-41%) due to additional travel. However, a depot-like charging station network with charging priority policy for the 6-county region reduced percent empty travel by nearly 10% while increasing served 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 empty travel is penalized, this scenario suggests the best possible path forward.

The control strategy studied here decides the best repositioning and charging decisions at each decision epoch given the same set of available vehicles. Future work may study a sequential policy rather than a simultaneous optimization-based policy to understand whether the same results are achievable. However, a constrained second optimization may not lead to the best possible outcome. If the fleet size is scaled down, perhaps due to maintenance, and demand does not change, then there should be fewer idle vehicles. Depending on the priority for repositioning or charging, the sequential order may lead to the second problem having very few vehicle-to-zone choice combinations. A worse outcome may result, especially if the first problem consistently leaves few options for the second problem (i.e., a biased outcome due to prioritization). If the supply of available vehicles is not an issue, modelers could minimize prioritization bias in two ways:

1) If repositioning is solved first, a modeler could replace the travel time-based threshold for zones with a SOC-based threshold to prevent severe SOC loss.
2) If charging is solved first, a modeler could continue to prioritize low-SOC vehicles up to a ceiling on the number of vehicles sent to charge. The cap could be a ratio instead of a number so that the repositioning problem always has available vehicles.

6.6 Updates on prior Austin SAEV Simulations

Differences in city residential and jobs densities, mode splits, and existing transportation infrastructure makes it difficult to compare simulation results across cities. For this reason, the results from this study are compared to Loeb and Kockelman (2019) and Loeb et al. (2018). While previous work and this paper simulated the same 6-county region, no down sampling of the population is required. Prior work simulated 5% of the region’s population (with an SAEV mode share of 2%). Additionally, this work includes background external traffic (e.g., interstate freight and passenger travel). Other differences apply, including the ratio of SAEVs to agents – this study adopts a ratio of 1 SAEV per 125 agents while Loeb and Kockelman (2019) use a ratio of 1 SAEV per 10 residents (for a reduced fleet scenario). Our depot-like charging station scenario has 188 stations while Loeb and Kockelman (2019) site 155 stations and only 5 stations in Loeb et al. (2018).

Table 4 compares performance metrics of this study to these past studies based in Austin. Previous heuristics may be biased low for average wait times and biased high for average daily trips, particularly for the ratio of SAEVs to residents and low mode split. A substantial difference exists in empty travel between the two prior studies and this study supports the empty travel reported from the earlier study (Loeb et al., 2018). Finally, Loeb and Kockelman (2019) report an average vehicle occupancy of 1.60. This study finds a revenue miles-weighted average vehicle occupancy of 1.65 to 1.79, depending on the operational strategy for the depot-like charging station network. Even though activity generation, and subsequently trip generation, is for single-person trips in POLARIS, assuming all riders are willing to share reveals consistently high vehicle occupancies.

Table 4: Comparison of Austin, Texas 6-county region (5,300 square miles) fleet performance results by study

Study	Operational Strategy	Avg Wait Time (min)	Avg Daily Trips	%eVMT	%rVMT	%cVMT
Loeb et al. (2018)	Base ("Long Range SAEV Fast Charge, Reduced Fleet")	9.50	26.8	22.3	NA	6.45
Loeb and Kockelman (2019)	Base ("Long Range SAEV Fast Charge, Reduced Fleet")	9.20	35.1	8.62	NA	1.27
Present Study	Base	13.94	22.50	23.32	NA	6.53
	Optimal Charge	10.66	27.74	19.36	NA	4.52
	Base Repositioning	15.56	22.64	28.04	4.38	7.43
	Demand Priority	9.04	29.04	23.86	6.99	4.28
	Charge Priority	9.32	28.54	21.03	3.35	4.47
	Joint	9.04	29.04	22.08	4.92	4.34

Note: The present study results are with a depot-like charging station to align more closely with number of stations in Loeb and Kockelman (2019). See the preceding text for an explanation of study differences. NA = not applicable.

6.7 Limitations

The 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 present in weekday travel demand simulations. Additionally, the study relied on data inputs from the region's metropolitan planning organization, including the road network that is less than full lane miles. An internal comparison between the model network and the OpenStreetMap network suggests there is a 53% reduction in center lane miles, assuming a 2-lane rule. However, many roads in the OpenStreetMap network have a 0.5 lane value, so using this network would require data manipulation to fix errors (which may change the estimate on the percent reduction in center lane miles).

The household travel survey used to create a mode choice model does not include trips made by tourists, who would not be sampled in the household travel survey and may rely more heavily on ride-sourcing vehicles than other modes. Additionally, we made modeling adjustments to the estimated mode choice model to adjust utility values in the era of on-demand SAEV service. Although there have been advances in activity-based agent-based models, these limitations can be addressed in future work to provide increased realism.

Future work could include time-varying weights instead of creating distinct operational scenarios that apply for the entire simulated travel period. For example, increasing β before and during peak traffic would further incentivize the operator to reposition vehicles to zones experiencing a supply deficit instead of using slack variables to balance demand and supply. Similarly, increasing α during off-peak travel hours or low-cost electricity periods could spur more opportunistic charging. The latter is more useful in utility regions that charge time-of-use electricity rates.

7. Conclusion

This study develops an optimization-based control strategy for charging and repositioning for a fleet of SAEVs and integrates it within a large-scale agent-based simulation. The framework is evaluated against heuristic charging and SAV-based repositioning strategies found in the literature to understand its operational performance and externalities. A set of six SAEV charging and/or repositioning control strategies are tested across three charging station network designs and two service 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 core geofenced region, central coordination of SAEV charging as opposed to vehicle-level heuristic 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 metropolitan region, a centrally coordinated charging-only strategy is not enough to rebalance vehicles, and a joint repositioning and charging control strategy is required.
- Joint charging and repositioning can reduce added congestion on roadways (21% less percent empty VMT), increase served demand (28% more daily trips per SAEV), and reduce wait time (by up to 41%), assuming 6-county metropolitan service area with a depot-like charging station network.
- The joint charging and repositioning strategy is most advantageous in the PM peak period, where demand is spatially and temporally spread out. By aligning charging in advance of expected demand, when there is little to no supply deficit, the fleet can increase vehicle availability for this evening peak period.
- Centrally coordinated charging decisions better utilizes fleet-owned charging infrastructure, and the joint charging and repositioning control strategy can serve more average daily trips per vehicle at a sparser charging station network than the baseline charging strategy with a distributed charging station network.
- Joint charging and repositioning decision-making that is constrained by charging station availability has the benefit of spreading out charging demand 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-based repositioning control, the increase in percent empty VMT and particularly

percent charging VMT 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 charging station supply (i.e., transition to SAEVs), which should be considered in detail in future work. However, fleet operators would be wise to adopt a joint charging and repositioning decision-making control strategy, 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 the average daily trips per SAEV increases (resulting in lower direct electricity costs). Additional scenarios could be an optimization module that solves for the optimal fleet size, subject to demand that changes based on fare scenarios, wait times, and dynamic ride-sharing detour delays.

CRediT authorship contribution statement

Matthew D. Dean: Conceptualization, Methodology, Writing - Original Draft, Review & Editing, Visualization. Krishna Murthy Gurumurthy: Conceptualization, Methodology, Software, Writing - Review & Editing. Felipe de Souza: Conceptualization, Methodology, Software, Writing - Review & Editing. Joshua Auld: Resources, Software, Supervision. Kara M. Kockelman: Supervision and Writing - Review & Editing.

Declaration of competing interest

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

Acknowledgements

This material is also based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1610403. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. The work done in this paper was sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The U.S. Government retains for itself, and others acting on its behalf, a paid-up nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government. The authors acknowledge the Texas Advanced Computing Center (TACC) at The University of Texas at Austin for providing HPC and database resources that have contributed to the research results reported within this paper. The authors thank the reviewers for their feedback that greatly improved the article.

Appendix

A. Baseline Repositioning Problem Formulation

The existing repositioning strategy from de Souza et al. (2020) is presented here:

$$P: \min_{x_{ij}} J$$

$$J = \sum_{i \in I, j \in Z} t_{ij} x_{ij}$$

s.t.

$$0 \leq x_{ij} \leq 1, \qquad i \in I, j \in Z$$

$$0 \leq \sum_{j \in Z} x_{ij} \leq 1, \qquad i \in I$$

$$\sum_{i \in I} x_{ij} - \sum_{i \in I_j} x_{ji} \geq f_j - s_j, \qquad j \in Z \qquad \text{(A.1)}$$

Defining variable $y_{zj} = \sum_{i \in Z(i)} x_{ij}$, problem A.1 can be equivalently formulated in terms of the sum:

$$P: \min_{y_{zj}} J$$

$$J = \sum_{z \in Z, j \in Z} t_{zj} y_{zj}$$

s.t.

$$0 \leq y_{ij} \leq |Z(i)|, \qquad i \in Z, j \in Z$$

$$0 \leq \sum_{j \in Z} y_{ij} \leq |Z(i)|, \qquad i \in I$$

$$\sum_{z \in Z} y_{zj} - \sum_{z \in I_j} y_{zj} \geq f_j - s_j, \qquad j \in Z \qquad \text{(A.2)}$$

where $|Z(i)|$ refers to the number of elements on the set $Z(i)$ (i.e., the number of idle vehicles at zone *j*).

B. Austin Model Calibration

The POLARIS model for the Austin metropolitan region was developed using various econometric models calibrated using data from both the region's metropolitan planning organization and the United States Census Bureau. The following plots (Figures B.1-B.4) show the count of hourly trip departures by time of day, count of trips by activity type, mode choice by trip purpose, and trip distance by activity type. The plots compare simulated POLARIS data and the observed data made available to the authors for this study.

Activity plans for agents are representative of a typical weekday before the COVID-19 pandemic. The model’s time-dependent travel time matrices were obtained through convergence to minimize the gap between experienced and routed travel times under dynamic traffic assignment. Within the context of mode choice models, agents make activity plans (including mode choice planning) right before the travel day starts. The mode choice model uses time-dependent travel estimates for planning. If the agent has a change in their activity schedule, skim travel time estimates are ignored, and within-the-simulation travel time estimates from the router are used. Wait times for SAEVs can be included in the mode choice model but were not built into the mode choice model for this region. Future work may consider new mode choice specifications for this region by using a feedback loop of zonal wait times or experienced zone-to-zone travel delay with dynamic ride-sharing (for a willingness to share model).

Fleet size is out of the scope of this study, though should be optimized since vehicle costs are expected to remain the largest share of total SAEV cost (Luke et al., 2021). Optimization of fleet size within a profit maximization problem is ignored in this study. A replacement rate strategy of sizing fleet proportional to residents of the geofence is used (e.g., 1 SAEV per 125 residents). The literature shows a range of fleet size proportion either to populations or to total trips served.

For example, Vosooghi et al. (2020) recommend 1 SAEV per 16 residents from a prior study that used a range of 1:8 up to 1:25 (Vosooghi et al., 2019). In contrast, Yi and Smart (2021) tested a range from 1:150 up to 1:200 and Gurumurthy et al. (2021b) used 1:100. If the control strategy can improve fleet efficiency, then it is plausible to study a fleet replacement ratio of 1 SAEV per 125 residents over prior work using smaller ratios.

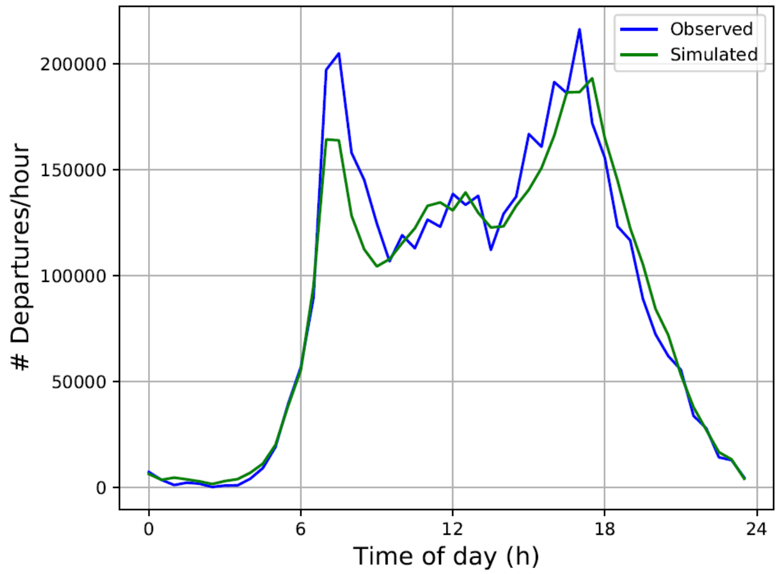

Figure B.1: Distribution of trip departures by hour

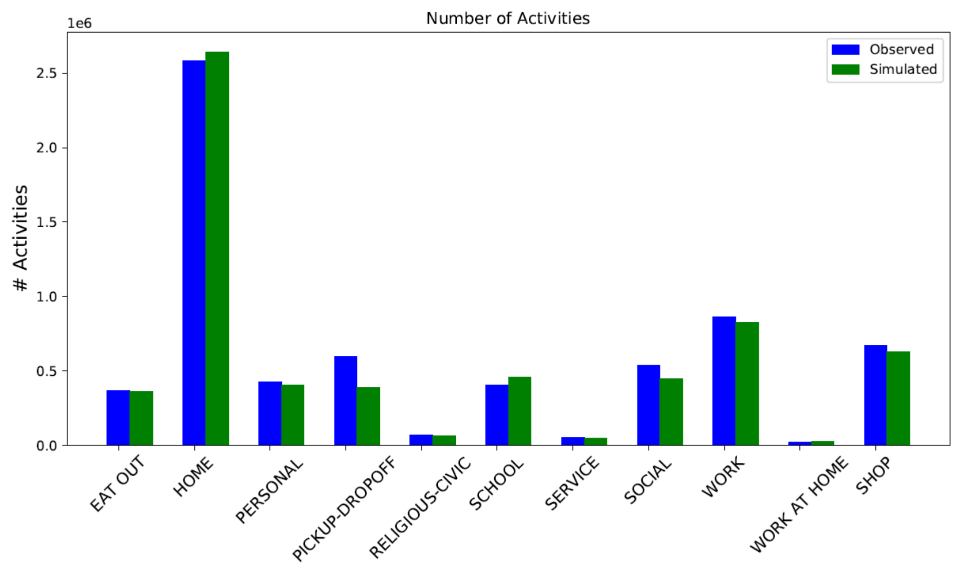

Figure B.2: Trip counts by activity type

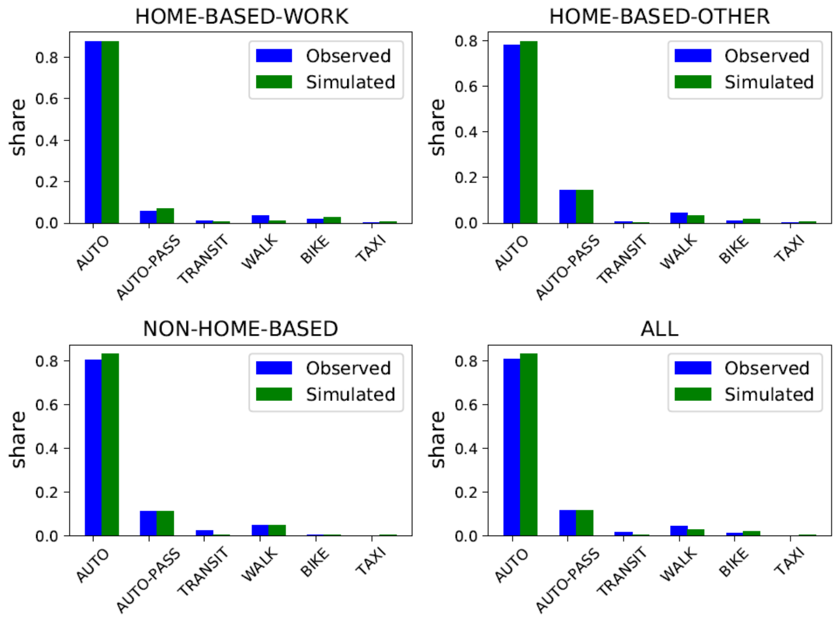

Figure B.3: Distribution of mode choice by trip purpose

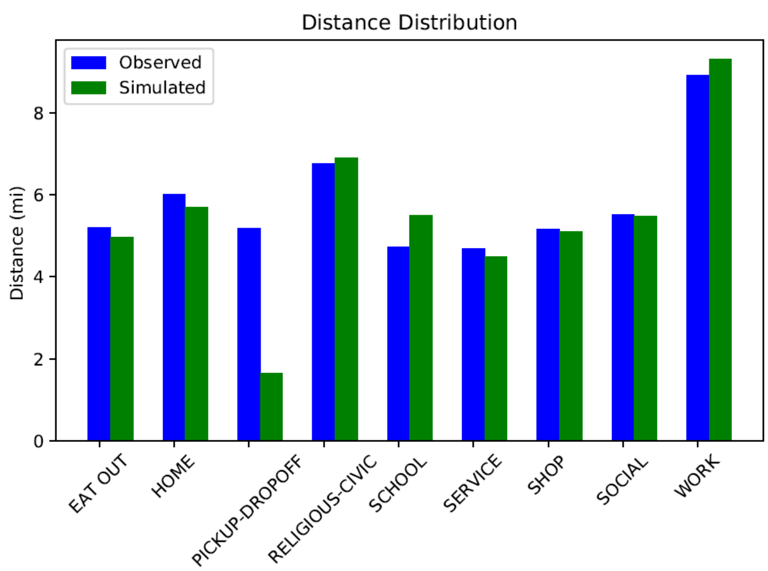

Figure B.4: Average trip distance by activity type

C. Charging Station Configuration

The scaling of the heuristic-sited charging station was done to examine the performance of the optimization framework more rigorously. The 75% reduction scenario of plugs per station is shown in Figure C.1. The green dots are stations with more than 1 plug (i.e., charging hubs). The yellow dots contain include those green stations and 50% of the 1-plug stations (i.e., mix of central depots and distributed chargers). By randomly removing the other half (red dots), there is some clustering of stations in suburban parts of the region. The resulting charging station configuration is summarized in Table C.1 by station count and total number of plugs.

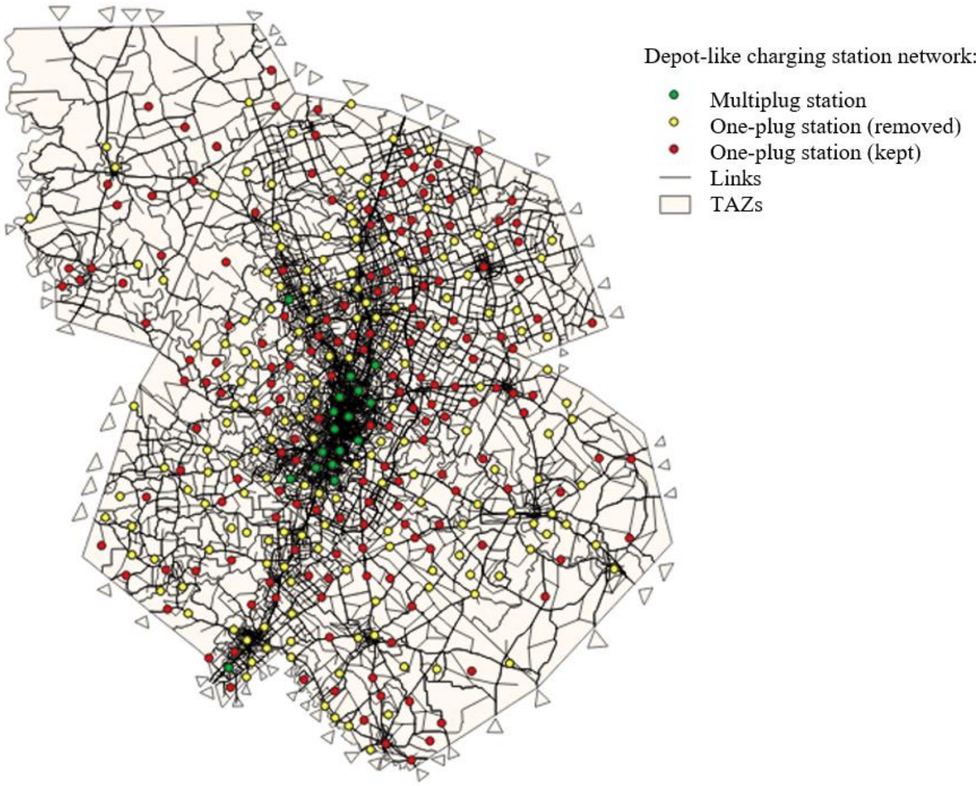

Figure C.1: Depot-like charging station network creation

Table C.1: Charging station configuration results by service area: plug count (station count)

Charging Station	Geofence Region (60.3 sq mi)	6-county Region (5,300 sq mi)
Distributed	244 (13)	2045 (359)
Scaled 50%	127 (13)	1197 (359)
Depot-like	56 (9)	257 (188)

D. Vehicle Disposal Model Outcome

Table D.1 lists the distribution of households by the number of vehicles they own. The leftmost column indicates the vehicle ownership distribution of the synthetic population that was derived from data on existing household ownership from the United States Census Bureau. The rightmost column indicates a scenario of future vehicle ownership where households let go of their vehicle(s) and rely on other modes of transportation, including on-demand SAEVs. This distribution is derived from two adapted random parameters ordered probit econometric models: one for single-vehicle households and one for multi-vehicle households (Menon et al., 2019). The first change this study made was in lowering the multi-vehicle and single-vehicle household's threshold parameters for relinquishing a vehicle, which increases the probability of vehicle disposal. The second change was in adjusting triangular distribution parameters (i.e., lower limit, upper limit, and mode).

Table D.1: Effect of vehicle disposal model

Household Vehicles	Baseline Vehicle Ownership	Future Vehicle Ownership
0	8.46	20.43
1	32.53	37.43
2	41.30	29.92
3	12.42	8.39
4	3.80	2.76
5 or more	1.49	1.08

Note: Future vehicle ownership case is a hypothetical based upon a model adopted from the literature. The authors used this model to simulate a future where residents increasingly rely on a system of on-demand SAEVs.

E. SAEV Framework Weights

Table E.1 lists the weights used in the SAEV Framework (Equation (2)) for the two service regions by strategy type.

Table E.1: SAEV framework weight parameters

Operational Strategy	6-county (5,300 sq mi) region		Core area geofence (60.3 sq mi) region	
	Alpha	Beta	Alpha	Beta
Optimal Charge	100.0	0	50.0	0
Joint	85.0	750	45.0	300
Demand Priority	80.0	2000	40.0	1000
Charge Priority	100.0	500	50.0	200

F. Computational Solver Times

Table F.1 lists the time to solve the problem for the 6-County region in this study for a 2-hour portion of the evening peak period, as indicated from Figure B.1.

Table F.1: Computational solve time for the 6-County region

Charging Station	Operational Policy	2-Hour Evening Peak by Quarter-Hours								
		4:00 PM	4:15 PM	4:30 PM	4:45 PM	5:00 PM	5:15 PM	5:30 PM	5:45 PM	6:00 PM
Distributed	Optimal Charge	7	3	3	3	6	2	2	2	6
	Joint	9	4	4	5	9	4	4	4	9
	Demand Priority	13	7	6	7	13	6	6	6	14
	Charge Priority	8	4	3	4	10	4	4	4	10
Scaled 50%	Optimal Charge	7	3	3	3	6	3	3	3	8
	Joint	11	4	4	6	10	5	5	4	3
	Demand Priority	13	6	5	6	10	6	5	6	15
	Charge Priority	8	4	4	4	8	4	3	4	7
Depot-like	Optimal Charge	2	0	0	0	0	0	0	0	0
	Joint	1	0	0	0	0	0	0	0	0
	Demand Priority	0	0	0	0	0	0	0	0	0
	Charge Priority	1	0	0	0	0	0	0	0	0

References

Al-Kanj, L., Nascimento, J., Powell, W.B., 2020. Approximate dynamic programming for planning a ride-hailing system using autonomous fleets of electric vehicles. European Journal of Operational Research 284, 1088–1106. https://doi.org/10.1016/j.ejor.2020.01.033

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. PNAS 114, 462–467. https://doi.org/10.1073/pnas.1611675114

Apte, J.S., Chambliss, S.E., Tessum, C.W., Marshall, J.D., 2019. A Method to Prioritize Sources for Reducing High PM2.5 Exposures in Environmental Justice Communities in California. California Air Resources Board and the California Environmental Protection Agency, Sacramento, CA.

Auld, J., Hope, M., Ley, H., Sokolov, V., Xu, B., Zhang, K., 2016. POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations. Transportation Research Part C: Emerging Technologies 64, 101–116. https://doi.org/10.1016/j.trc.2015.07.017

Auld, J., Mohammadian, A., 2012. Activity planning processes in the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model. Transportation Research Part A: Policy and Practice 46, 1386–1403. https://doi.org/10.1016/j.tra.2012.05.017

Auld, J., Mohammadian, A., 2009. Framework for the development of the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model. Transportation Letters 1, 245–255. https://doi.org/10.3328/TL.2009.01.03.245-255

Bauer, G.S., Greenblatt, J.B., Gerke, B.F., 2018. Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. Environ. Sci. Technol. 52, 4920–4928. https://doi.org/10.1021/acs.est.7b04732

Becker, H., Becker, F., Abe, R., Bekhor, S., Belgiawan, P.F., Compostella, J., Frazzoli, E., Fulton, L.M., Guggisberg Bicudo, D., Murthy Gurumurthy, K., Hensher, D.A., Joubert, J.W., Kockelman, K.M., Kröger, L., Le Vine, S., Malik, J., Marczuk, K., Ashari Nasution, R., Rich, J., Papu Carrone, A., Shen, D., Shiftan, Y., Tirachini, A., Wong, Y.Z., Zhang, M., Bösch, P.M., Axhausen, K.W., 2020. Impact of vehicle automation and electric propulsion on production costs for mobility services worldwide. Transportation Research Part A: Policy and Practice 138, 105–126. https://doi.org/10.1016/j.tra.2020.04.021

Bischoff, J., Maciejewski, M., 2016. Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin. Procedia Computer Science 83, 237–244. https://doi.org/10.1016/j.procs.2016.04.121

Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transport Policy 64, 76–91. https://doi.org/10.1016/j.tranpol.2017.09.005

Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. Transportation Research Part A: Policy and Practice 94, 243–254. https://doi.org/10.1016/j.tra.2016.08.020

Cohn, J., Ezike, R., Martin, J., Donkor, K., Ridgway, M., Balding, M., 2019. Examining the Equity Impacts of Autonomous Vehicles: A Travel Demand Model Approach. Transportation Research Record 2673, 23–35. https://doi.org/10.1177/0361198119836971

Compostella, J., Fulton, L.M., De Kleine, R., Chul Kim, H., Wallington, T.J., Brown, A.L., 2021. Travel time costs in the near- (circa 2020) and long-term 2030–2035) for automated, electrified, and shared mobility in the United States. Transport Policy 105, 153–165. https://doi.org/10.1016/j.tranpol.2020.12.014

Dandl, F., Hyland, M., Bogenberger, K., Mahmassani, H.S., 2019. Evaluating the impact of spatio-temporal demand forecast aggregation on the operational performance of shared autonomous mobility fleets. Transportation. https://doi.org/10.1007/s11116-019-10007-9

de Souza, F., Gurumurthy, K.M., Auld, J., Kockelman, K.M., 2020. An Optimization-Based Strategy for Shared Autonomous Vehicle Fleet Repositioning. Presented at the 6th International Conference on Vehicle Technology and Intelligent Transport Systems, Prague, Czech Republic, p. 7.

de Souza, F., Verbas, O., Auld, J., 2019. Mesoscopic Traffic Flow Model for Agent-Based Simulation. Procedia Computer Science 151, 858–863. https://doi.org/10.1016/j.procs.2019.04.118

Erhardt, G.D., Roy, S., Cooper, D., Sana, B., Chen, M., Castiglione, J., 2019. Do transportation network companies decrease or increase congestion? Science Advances 5. https://doi.org/10.1126/sciadv.aau2670

Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 45, 143–158. https://doi.org/10.1007/s11116-016-9729-z

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transportation Research Part C: Emerging Technologies 40, 1–13. https://doi.org/10.1016/j.trc.2013.12.001

Fagnant, D.J., Kockelman, K.M., Bansal, P., 2015. Operations of Shared Autonomous Vehicle Fleet for Austin, Texas, Market. Transportation Research Record: Journal of the Transportation Research Board 2536, 98–106. https://doi.org/10.3141/2536-12

Farhan, J., Chen, T.D., 2018. Impact of ridesharing on operational efficiency of shared autonomous electric vehicle fleet. Transportation Research Part C: Emerging Technologies 93, 310–321. https://doi.org/10.1016/j.trc.2018.04.022

Fulton, L., Brown, A., Compostella, J., 2020. Generalized Costs of Travel by Solo and Pooled Ridesourcing vs. Privately Owned Vehicles, and Policy Implications (No. UC-ITS-2018-14). Institute of Transportation Studies, Davis, Davis, CA.

González-González, E., Nogués, S., Stead, D., 2020. Parking futures: Preparing European cities for the advent of automated vehicles. Land Use Policy 91, 104010. https://doi.org/10.1016/j.landusepol.2019.05.029

Gurumurthy, K.M., 2020. Integrating Supply and Demand Perspectives for a Large-Scale Simulation of Shared Autonomous Vehicles. Transportation Research Record 2674, 12. https://doi.org/10.1177/0361198120921157

Gurumurthy, K.M., Auld, J., Kockelman, K., 2021a. A system of shared autonomous vehicles for Chicago: Understanding the effects of geofencing the service. Journal of Transport and Land Use 14, 933–948. https://doi.org/10.5198/jtlu.2021.1926

Gurumurthy, K.M., Dean, M.D., Kockelman, K.M., 2021b. Strategic Charging of Shared Fully-Automated Electric Vehicles. Presented at the 100th Annual Meeting of the Transportation Research Board, Washington, D.C.

Gurumurthy, K.M., Kockelman, K.M., 2022. Dynamic ride-sharing impacts of greater trip demand and aggregation at stops in shared autonomous vehicle systems. Transportation Research Part A: Policy and Practice 160, 114–125. https://doi.org/10.1016/j.tra.2022.03.032

Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K.W., 2019. Fleet operational policies for automated mobility: A simulation assessment for Zurich. Transportation Research Part C: Emerging Technologies 102, 20–31. https://doi.org/10.1016/j.trc.2019.02.020

Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity Press. https://doi.org/10.5334/baw

Hyland, M., Mahmassani, H.S., 2018. Dynamic autonomous vehicle fleet operations: Optimization-based strategies to assign AVs to immediate traveler demand requests. Transportation Research Part C: Emerging Technologies 92, 278–297. https://doi.org/10.1016/j.trc.2018.05.003

Iacobucci, R., Bruno, R., Schmöcker, J.-D., 2021. An Integrated Optimisation-Simulation Framework for Scalable Smart Charging and Relocation of Shared Autonomous Electric Vehicles. Energies 14, 3633. https://doi.org/10.3390/en14123633

Iacobucci, R., McLellan, B., Tezuka, T., 2019. Optimization of shared autonomous electric vehicles operations with charge scheduling and vehicle-to-grid. Transportation Research Part C: Emerging Technologies 100, 34–52. https://doi.org/10.1016/j.trc.2019.01.011

ITF, 2018. The Shared-Use City: Managing the Curb. OECD-ITF Corporate Partnership, Paris, France.

Johnson, C., Walker, J., 2016. Peak Car Ownership: The Market Opportunity of Electric Automated Mobility Services. Rocky Mountain Institute.

Kullman, N., Cousineau, M., Goodson, J., Mendoza, J., 2021. Dynamic Ridehailing with Electric Vehicles. Transportation Science 37. https://doi.org/10.1287/trsc.2021.1042

Litman, T., 2021. Autonomous Vehicle Implementation Predictions: Implications for Transport Planning. Victoria Transport Policy Institute, Victoria, Canada.

Loeb, B., Kockelman, K.M., 2019. Fleet performance and cost evaluation of a shared autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. Transportation Research Part A: Policy and Practice 121, 374–385. https://doi.org/10.1016/j.tra.2019.01.025

Loeb, B., Kockelman, K.M., Liu, J., 2018. Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions. Transportation Research Part C: Emerging Technologies 89, 222–233. https://doi.org/10.1016/j.trc.2018.01.019

Luke, J., Salazar, M., Rajagopal, R., Pavone, M., 2021. Joint Optimization of Autonomous Electric Vehicle Fleet Operations and Charging Station Siting. arXiv:2107.00165 [cs, eess].

Marsden, G., Docherty, I., Dowling, R., 2020. Parking futures: Curbside management in the era of 'new mobility' services in British and Australian cities. Land Use Policy 91, 104012. https://doi.org/10.1016/j.landusepol.2019.05.031

Martinez, L.M., Viegas, J.M., 2017. Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. International Journal of Transportation Science and Technology, Connected and Automated Vehicles: Effects on Traffic, Mobility and Urban Design 6, 13–27. https://doi.org/10.1016/j.ijtst.2017.05.005

Menon, N., Barbour, N., Zhang, Y., Pinjari, A.R., Mannering, F., 2019. Shared autonomous vehicles and their potential impacts on household vehicle ownership: An exploratory empirical assessment. International Journal of Sustainable Transportation 13, 111–122. https://doi.org/10.1080/15568318.2018.1443178

Narayanan, S., Chaniotakis, E., Antoniou, C., 2020. Shared autonomous vehicle services: A comprehensive review. Transportation Research Part C: Emerging Technologies 111, 255–293. https://doi.org/10.1016/j.trc.2019.12.008

Niles, J.S., Pogodzinski, J.M., 2021. Steps to Supplement Park-and-Ride Public Transit Access with Ride-and-Ride Shuttles (Final Report No. 21–19). Mineta Transportation Institute, San Jose, California. https://doi.org/10.31979/mti.2021.1950

SB-1014, 2018. Bill Text - SB-1014 California Clean Miles Standard and Incentive Program: zero-emission vehicles. [WWW Document]. URL https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB1014 (accessed 2.25.21).

Shaheen, S., Cohen, A., 2020. Chapter 3 - Mobility on demand (MOD) and mobility as a service (MaaS): early understanding of shared mobility impacts and public transit partnerships, in: Antoniou, C., Efthymiou, D., Chaniotakis, E. (Eds.), Demand for Emerging Transportation Systems. Elsevier, pp. 37–59. https://doi.org/10.1016/B978-0-12-815018-4.00003-6

Sperling, D., 2018. Three Revolutions: Steering Automated, Shared, and Electric Vehicles to a Better Future. Island Press, Washington, D.C.

Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., Pavone, M., 2014. Toward a Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand Systems: A Case Study in Singapore, in: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation, Lecture Notes in Mobility. Springer International Publishing, Cham, pp. 229–245. https://doi.org/10.1007/978-3-319-05990-7_20

United States Census Bureau, 2018. 2018 American Community Survey 1-Year Public Use Microdata Samples [SAS data file]. Washington, D.C.

Verbas, Ö., Auld, J., Ley, H., Weimer, R., Driscoll, S., 2018. Time-Dependent Intermodal A* Algorithm: Methodology and Implementation on a Large-Scale Network. Transportation Research Record 2672, 219–230. https://doi.org/10.1177/0361198118796402

Vosooghi, R., Puchinger, J., Bischoff, J., Jankovic, M., Vouillon, A., 2020. Shared autonomous electric vehicle service performance: Assessing the impact of charging infrastructure. Transportation Research Part D: Transport and Environment 81, 102283. https://doi.org/10.1016/j.trd.2020.102283

Vosooghi, R., Puchinger, J., Jankovic, M., Vouillon, A., 2019. Shared autonomous vehicle simulation and service design. Transportation Research Part C: Emerging Technologies 107, 15–33. https://doi.org/10.1016/j.trc.2019.08.006

Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transportation Research Part A: Policy and Practice 86, 1–18. https://doi.org/10.1016/j.tra.2015.12.001

Walter, M., Truemper, K., 2013. Implementation of a unimodularity test. Math. Prog. Comp. 5, 57–73. https://doi.org/10.1007/s12532-012-0048-x

Wenzel, T., Rames, C., Kontou, E., Henao, A., 2019. Travel and energy implications of ridesourcing service in Austin, Texas. Transportation Research Part D: Transport and Environment 70, 18–34. https://doi.org/10.1016/j.trd.2019.03.005

Winter, K., Cats, O., Martens, K., van Arem, B., 2020. Relocating shared automated vehicles under parking constraints: assessing the impact of different strategies for on-street parking. Transportation. https://doi.org/10.1007/s11116-020-10116-w

Yan, H., Kockelman, K.M., Gurumurthy, K.M., 2020. Shared autonomous vehicle fleet performance: Impacts of trip densities and parking limitations. Transportation Research Part D: Transport and Environment 89, 102577. https://doi.org/10.1016/j.trd.2020.102577

Yi, Z., Smart, J., 2021. A framework for integrated dispatching and charging management of an autonomous electric vehicle ride-hailing fleet. Transportation Research Part D: Transport and Environment 95, 102822. https://doi.org/10.1016/j.trd.2021.102822

Zhang, W., Guhathakurta, S., Fang, J., Zhang, G., 2015. Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. Sustainable Cities and Society 19, 34–45. https://doi.org/10.1016/j.scs.2015.07.006