SENSITIVTY OF CHARGING AND MAINTENANCE TRIPS OF SHARED FULLY-AUTOMATED ELECTRIC VEHICLE FLEETS IN A LARGE-SCALE MODEL

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ABSTRACT

Shared autonomous vehicles (SAVs) will likely emerge in many urban settings over the coming decade and may significantly impact passenger travel. SAV fleet managers, the public, and policymakers may be attracted to all-electric drivetrains' lower operating costs and environmental benefits but will need to account for charging times and range limitations of electric vehicle battery packs. Highly utilized fleets may also need periodic maintenance and cleaning. This study investigates a variety of potential electric SAV (SAEV) fleet designs and charging and maintenance strategies from the literature. The agent-based transportation tool, POLARIS, is used to simulate several scenarios serving passenger travel across Illinois' Greater Chicago region. Results show a mixed fleet of short (30 kWh) and long (90 kWh) range SAEVs performs better than a homogenous short-range fleet. SAEVs in large regions like Chicago need to have high average state of charge across the fleet to serve all incoming requests, necessitating careful downtime management. Investing in battery capacity helps to reduce empty travel and increase utilization. Leaving charging stations early to meet new demand requests, only helps long-range vehicles. When maintenance and cleaning trips are modeled, SAEVs outperform gasoline fueled vehicles because charging can take place at more locations and act as a passive rebalancing strategy.

Keywords: Shared autonomous electric vehicles; charging; maintenance; control heuristics; agent-based simulation.

1. BACKGROUND

Mobility-on-demand services provided by ridesourcing fleets or Transportation Network Companies (TNCs) can have negative or positive effects on urban congestion and emissions (Schaller, 2018; Balding et al., 2019; Union of Concerned Scientists, 2020). With autonomous vehicle (AV) deployments on the horizon, travelers may surrender their private vehicles (Menon et al., 2019) and rely increasingly on fleets of shared autonomous vehicles (SAVs) for their urban and interurban travel needs (Fagnant and Kockelman, 2014; Spieser et al., 2014; Fagnant and Kockelman, 2015; Bischoff and Maciejewski, 2016; Gurumurthy, 2018; Fagnant and Kockelman, 2018; Stocker and Shaheen, 2019). Electric SAV fleets (SAEVs) may even emit 73% less greenhouse gases and consume 55% less energy than a gasoline-fueled alternative (Bauer et al., 2018). Beyond electric vehicles' environmental benefits, lower operating and maintenance costs compounded by high utilization rates should provide savings of $0.05-$0.08/mi for electric SAVs relative to hybrid and internal combustion engine (ICE) powertrains (Bauer et al., 2018; US EPA, 2019), resulting in an estimated cost of $0.40/mi (Bösch et al., 2018; Loeb and Kockelman, 2019; Becker et al., 2020).

Most literature to date considers the tradeoff between increasing range and building a comprehensive network of EV charging stations (EVCS) in determining the minimum fleet size required. An increase in battery capacity increases range such that most trip requests are met without necessitating daytime charging, albeit at a higher upfront capital cost. In contrast, expanding EVCS availability through a higher density of spatially-distributed plugs lowers the range required of vehicles, although at higher land acquisition or leasing, capital, and operating costs (Huang and Kockelman, 2020). Through this dichotomous example, the sensitivity of assumed fleet parameters and strategies related to charging a fleet of SAEVs on service quality is ignored and left to confound results. Thus, this study examines the effect that operational and technical charging parameters have on level of service metrics (e.g., vehicle utilization, average wait times, and empty travel, or eVMT) while varying fleet composition. Additionally, the authors are not aware of any prior detailed simulation effort assessing the impact of maintenance and cleaning-only trips, which is another contribution of this work. The rest of this paper is organized as follows – existing literature is reviewed next and assumptions on fleet, EVCS and charging behavior for SAEVs are consolidated; the simulation framework is explained; the results from the sensitivity analysis are discussed, followed by recommendations for good forecasting practice in large-scale models, and then concluding remarks.

2. LITERATURE REVIEW

The first two simulation-based studies of SAEVs examined fleet costs and fleet size by varying battery range (short- and long-range, 80- and 200-mile, respectively) and charging station type (Level 2 and Level 3/Direct Current Fast Charging (DCFC), with a 30-minute and 4-hour maximum charge time, respectively) across a 100-mile x 100-mile gridded region based on Austin, Texas (Chen and Kockelman, 2016; Chen et al., 2016). Farhan and Chen (2018) extended this work by allowing dynamic ridesharing (DRS), showing that adding a second passenger to each vehicle substantially reduces the number of vehicles and charging stations required (by 55.7% and 32.2%, respectively). However, their model did not allow for real networks, actual land use patterns, or congestion feedback.

Bauer et al. (2018) developed an agent-based simulation of SAEVs in Manhattan using taxi-trip data to determine the trade-off between range and charger density under various charging speeds. A fleet of short-range (50-90 miles) vehicles accessing 11kW EVCS at a density of 66 chargers per square mile or 22 kW EVCS at a density of 44 chargers per square mile had the lowest operating costs. Bauer et al. (2019) extended this work to San Francisco and New York City, finding the operating cost of an EV fleet reaches cost parity with an ICE fleet at a 15% utilization level of 50kW chargers that are more sparsely distributed (3 chargers per square mile) for a 238-mile-ranged fleet. Their study differs from previous SAEV work by instituting a time-varying fleet size to model driver shifts in present-day TNCs.

Loeb et al. (2018) extended available SAV code (Bösch et al., 2016) in MATSim (Horni et al., 2016), an agent-based and activity-based travel demand model, to consider the constraints of EVs. A 5% random sample of trip demands was served entirely by SAEVs, and EVCS were generated like in Chen et al. (2016). Similarly, fleet size varied as a ratio of SAEVs to traveler (from 1:3 to 1:9) with the similar trade-offs in range and charge speeds as in Chen et al. (2016). Empty travel due to charging (cVMT) was 23.0% of total eVMT, partially because charging vehicles could serve new rides. Loeb and Kockelman (2019) then incorporated a response-time-based ridesharing-choice model for SAV users, leading to similar results. A comparison of battery range (60- versus 200-miles) and charging duration (30 versus 240 minutes) found that using long range vehicles with DCFC lowered average response times by 39% (from 8.4 to 5.1 minutes) and marginally lowered eVMT due to charging (1.3% to 1.1%).

Vosooghi et al. (2020) also used MATSim to study SAEV performance by varying charging infrastructure across the Rouen Normandie metropolitan region in France. They placed charging stations using distance- and coverage-based optimization schemes using estimated SAV demand from prior work (Vosooghi et al., 2019), varied the vehicle-to-plug ratio, and explored the performance of battery swapping stations. Vosooghi et al. (2020) also used Bischoff et al.'s (2019) electric vehicle (EV) extension in MATSim, which allows for charger queueing. Since vehicles are sent to the nearest charger without regard for current availability, upgrading EVCS to faster chargers (43kW instead of 22kW) reduced queue times by 64-95% depending upon the EVCS siting algorithm, which corresponds to a 2-19% increase in fleet utilization. Interestingly, upgrading to 43kW chargers was roughly equivalent to increasing the number of 22kW EVCS plugs by up to 67% from a baseline ratio of 1 charger to 4 SAEVs, revealing a distinct tradeoff between faster charging and the spatial plug density.

Zhang et al. (2020) leveraged a version of MATSim called BEAM (Sheppard et al., 2017) to site and size charging stations subject to service metrics and investigated the costs of various SAEV configurations (e.g., fleet size, vehicle range, and charger type) in the San Francisco Bay Area. Their findings reveal that the lowest-cost option was a fleet of short range (75-mile) vehicles accessing 50kW chargers. In contrast, Loeb and Kockelman (2019) found long range (200-mile) vehicles accessing these fast chargers to be the most profitable. In summary, a handful of studies have explored tradeoffs between charger speeds (more broadly categorized as Level 2 and 3) and range (short-range and long-range) by assuming exogenously-given SAV demands, no congestion feedbacks, and and/or simplified networks. Advancements in agent-based simulation tools, particularly since the development of MATSim, allowed for further trade-off work with the opportunity to model DRS.

More recently, Vosooghi et al. (2020) incorporated alternative modes and battery swapping stations to minimize charging times. Close examination of the literature reveals a highly variable set of assumptions about EV behaviors, with little to no common ground for comparison. Moreover, although some papers use MATSim, their underlying specifics such as congestion feedback or EVCS configuration (e.g., ratio of EVCSs to SAEVs, charger plugs per station, and power levels) are not apparent for an apples-to-apples comparison. Recognizing such differences, the sub-sections below characterize SAEV simulations by the decisions of when to send vehicles to charge, the state of charge (SOC) buffers, and the flexibility of vehicle states as it relates to charging.

2.1 Decision to Charge

Maximizing fleet utilization (i.e., trips per SAV per day) while minimizing eVMT can help increase operator profits. High utilization is made possible by ensuring available vehicles can service ride requests within a passenger's maximum allowable wait time and by proactively charging vehicles. Beyond this temporal aspect, fleet operators may wish to proactively reposition vehicles to locations of anticipated demand, albeit at a cost of eVMT (Dean et al., 2022; Winter et al., 2020). Without relocation strategies or SAEV cruising (like current TNCs), vehicles idle upon arriving at a traveler's destination. This may be at the destination or at a nearby parking lot (Fakhrmoosavi et al., 2022; Yan et al., 2020). Most models have SAEVs wait in place until they are assigned a new trip or at least one of the following charging conditions is met: a minimum battery level (e.g., 20% SOC), range is insufficient to meet the next trip request, or a minimum idle time (e.g., 30 min). Table 1 presents a review of relevant papers with charging decision parameters. The first condition, minimum battery SOC, is particularly problematic for undersized and short-range fleets – a high threshold represents a high opportunity cost for the operator by limiting the supply of vehicles that could serve an additional trip. It is clear from Table 1 that conditions to charge vary widely. Minimum SOC ranges from 5% to 35% and minimum idling time ranges from 5 min to 30 min. Moreover, studies with idle time charging decisions may have unnecessary charging trips from underutilized vehicles. Future work using this heuristic should add an additional check for low SOC.

Table 1 Summary of SAEV Decision-to-Charge Conditions

Variable	Study	Parameter or Condition
Minimum battery threshold (SOC)	Iacobucci et al. (2018a)	35%[a]
	Iacobucci et al. (2019)	20%
	Bauer et al. (2019)	20%
	Lokhandwala and Cai (2020)	20%
	Vosooghi et al. (2020)	20%
	Zhang et al. (2020)	10%
	Loeb et al. (2018)	5%
	Loeb and Kockelman (2019)	5%
Insufficient vehicle range	Chen et al. (2016)	To complete trip request
	Loeb and Kockelman (2019)	To complete trip request and below 80% SOC
	Bauer et al. (2019)	To complete trip request and reach nearest charger with capacity[b]
	Vosooghi et al. (2020)	To complete trip request and reach nearest charger
Minimum idle time	Loeb et al. (2018)	30 min
	Bauer et al. (2019)	15 min and driving time to nearest charger[c]
	Iacobucci et al. (2018a)	5 min

[a] Vehicles are sent to charging stations once 35% SOC is met, however, vehicles can still accept requests before this threshold is met, unless the estimated range will lead to a 20% or lower SOC at its destination.
[b] Bauer et al. (2019), like Bauer et al. (2018), includes charger capacity and will assign vehicles to chargers that have available plugs. In contrast, Vosooghi et al. (2020) sends vehicles to the closest charger regardless of current occupancy, but forces queuing until a spot becomes available.
[c] Bauer et al. (2019) set the idling threshold to equal the time a vehicle could have driven to the closest station and charged for 15 minutes.

2.2 Electric Vehicle and Charging Parameters

In addition to sending vehicles to charge, the underlying assumption on charging behavior and battery parameters is important. Electric vehicles charge nonlinearly and charging efficiency is not constant during charging, especially at the extremes of the battery level. While charging and discharging rates are governed by C-rates (Collin et al., 2019), large-scale models have assumed either a constant rate bounded by minimum and maximum SOC or a two-step process to simplify constant voltage constant current (e.g., Loeb et al., 2018). The buffers that limit the designed capacity of a battery (often 10-20%) help to prevent enhanced battery degradation because of higher charging stress at the boundaries of SOC (Argue, 2019). Table 2 summarizes charging parameters that are unique to EVs in SAEV simulation literature, including maximum SOC, charging speeds, and charger sizing. The variation in charging cutoff is lower than the lower bounds on decisions to charge described in the previous section. Most studies assume a maximum SOC threshold between 80-90%, but this can also depend on the type of charger used. Charging speeds range from 7kW to 50kW and assume homogenous charger type such that results correspond to a specific charger level. Vosooghi et al. (2020), on the other hand, is the only known study to use a mixture of charger types. The ratio of vehicles-to-plugs varies typically from 1.9 to 32.5 as does the underlying number of plugs per station (e.g., 60 plugs per station in Vosooghi et al. (2020) versus 1 plug per station in Chen et al. (2016), respectively), often subject to charger speed, fleet range, and spatial characteristics of the region studied.

As electricity consumption (or battery discharge) is a function of the vehicle's auxiliary power demands, like on-board computers and climate-control, and the vehicle's trajectory across different transportation facilities, reasonably accurate and precise discharge models can strengthen the validity of SAEV simulation results. Demir et al. (2014) categorized energy discharge models as factor-based, macroscopic, or microscopic, as used in Basso et al.'s (2019) EV routing problem. The factor model is the most simplistic and assumes a uniform energy discharge in kWh/mi (e.g., 0.25 kWh/mi). Thus, the total energy consumption for a trip is the sum of energy discharged from the battery along each link on the route (Bauer et al., 2018; Iacobucci et al., 2018a, 2018b; Moawad et al., 2021). Vosooghi et al. (2020) implemented an energy consumption model to calculate battery discharge, which does not appear to have visible effects on fleet performance – eVMT in the range of 18.3-22.8% matches other studies but an average wait time between 13.2 and 13.9 minutes is high – however, this is likely a result of no maximum allowable wait time or relocation strategy.

Table 2 Electric Vehicle Charging Parameters, as Assumed in the SAEV Literature

Variable	Study	Parameter or Condition [unit if unclear]
Maximum SOC	Iacobucci et al. (2019)	90%
	Zhang et al. (2020)	85%
	Farhan and Chen (2018)	80%
	Iacobucci et al. (2018a)	80%
	Chen et al. (2016)	80% for Level 3 Charging, 100% otherwise
	Loeb et al. (2018)	80% for Level 3 Charging, 100% otherwise
	Zhang and Chen (2020)	80% for Level 3 Charging, 100% otherwise
	Vosooghi et al. (2020)	80% for Level 3 Charging, 100% otherwise
Charging Speeds	Chen et al. (2016)	30, 240 min
	Loeb and Kockelman (2019)	30, 240 min
	Loeb et al. (2018)	30, 240 min
	Farhan and Chen (2018)	45, 240 min
	Bauer et al. (2018)	7, 11, 22, and 50kW
	Bauer et al. (2019)	7.7, 22, and 50kW
	Iacobucci et al. (2018a)	10kW
	Iacobucci et al. (2018b)	10kW
	Iacobucci et al. (2019)	20, 50kW
	Vosooghi et al. (2020)	22kW, 43kW
Vehicles-to-plugs	Chen et al. (2016)	1.9, 2.4, 2.5, 13.3[a]
	Bauer et al. (2018)	2.8 – 3.3, 6.5, 32.5[a]
	Vosooghi et al. (2020)	4.17[b]

[a] As reported in Vosooghi et al. (2020)
[b] Estimated using information in Vosooghi et al. (2020)

2.3 Flexibility of Vehicle Charging States

Bauer et al. (2019), Loeb et al. (2018), and Zhang and Chen (2020) permitted charging vehicles to serve ride requests (i.e., service priority policy), but under different conditions. The first allowed any vehicle to accept a request, resulting in many short-charging episodes. The second sent only the highest SOC vehicles if SAEVs within the response time and minimum SOC thresholds were not available. The third permitted only vehicles above 80% SOC to accept requests. Having the flexibility to increase supply given periods of high demand is important for fleet operators, but some cities may not be willing to accept additional eVMT due to short-charge periods, particularly in the short-term when AVs may not provide congestion relief (Litman, 2021). Under current thresholds and relocation schemes in the literature, the operator forgoes the opportunity to concurrently assign vehicles to charging stations in zones with predicted demand, thereby minimizing eVMT. Li et al. (2019) allowed for relocating EVs to charge at a waypoint if the required relocation distance exceeded the estimated battery range. However, they did not permit vehicles exiting this waypoint charging station to serve nearby trips if local demand was exceptionally high, but rather had vehicles continue onto their existing relocation destination. Additionally, vehicles sent to an EVCS either because of a minimum idling or SOC threshold do not have the flexibility to serve new transport requests. In the future, fleet operators may wish to assign new trip requests to vehicles already en route to charge due to idling if the detour does not cause the SOC to fall below the minimum value (similar to the flexibility in the minimum SOC of 35% in Iacobucci et al. (2018a)).

2.4 Maintenance and Cleaning Trips

Vehicle maintenance and cleaning trips are absent in simulation studies, though analytical cost models do parse out the scaled per-mile variable costs from these trips (Becker et al., 2020; Bösch et al., 2018). Unlike present-day TNC vehicles, drivers will not be present to clean vehicles between trips. This means that vehicles must drive to centralized service depots where technicians can clean or perform routine maintenance for vehicles. Depending on the frequency of cleaning, one study estimates the cleaning alone takes up 29% of operating costs (Bösch et al., 2018). Even if cleaning is performed every 40 trips, which may not be enough to lower hygiene anxiety post-pandemic (Curtale et al., 2021), cleaning costs will constitute at least one-quarter to one-third of operating costs, especially in high-income countries (Becker et al., 2020).

3. SIMULATION FRAMEWORK

This study uses POLARIS, an agent-based modeling tool designed for large-scale transportation networks (Auld et al., 2016) that has the capability to model TNCs (Gurumurthy et al., 2020), SAVs (Gurumurthy and Kockelman, 2022), and now SAEVs. Since individual agents can be tracked real-time, including vehicle trajectories at the link level, post-processing the outputs helps illuminate how SAEV parameter assumptions can impact fleet and network operations. In POLARIS, travel decisions are made to align with an agent's daily schedule, subject to near and long-term constraints (e.g., workplace choice and vehicle ownership). Like MATSim, dynamic traffic assignment is able to capture congestion effects (Verbas et al., 2018; Auld et al., 2019) but POLARIS differs slightly in its use of a mesoscopic traffic flow model which captures greater link-level traffic flow behavior (de Souza et al., 2019) but at a mesoscopic scale. Figure 1 captures the overview of the POLARIS architecture as used in this study which consists of the typical steps involved in an agent-based activity-based model. POLARIS' novelty arises in being able to capture 100% of a region's synthetic population. A typical day's travel demand resulting from one POLARIS run is used to lock in each agent's trip choices (e.g., departure time, mode choice, destination choice) so that the results shown in this study reflect the outcome of operational changes and not any underlying change in demand. TNC fleet operations in this fixed demand setting continue to operate as an on-demand service. If the passenger cannot be picked up within their maximum allowable wait time, then the trip is artificially simulated with a ghost TNC vehicle.

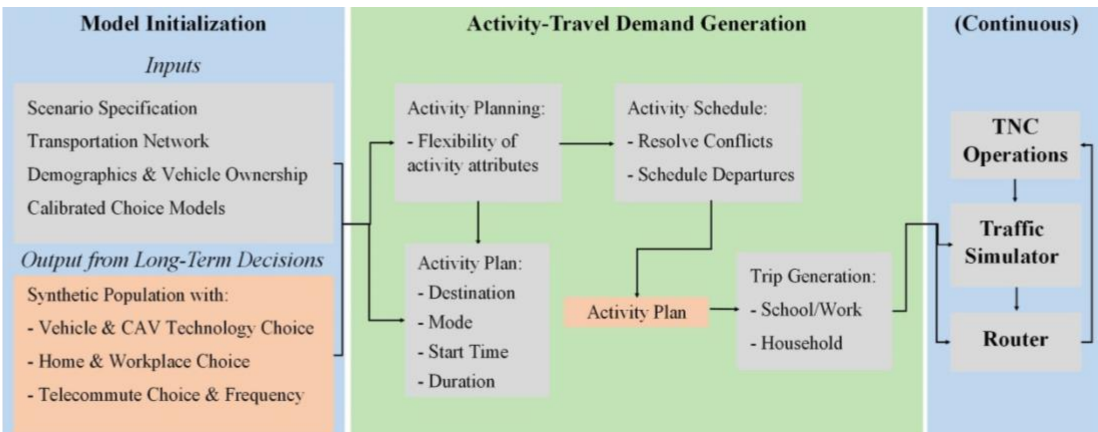


Figure 1 Simplified Overview of the POLARIS Architecture

The SAV module in POLARIS (Gurumurthy et al., 2020) is expanded here to allow for range-constrained EVs. Although some travelers are more environmentally conscientious than others, the demand for SAEVs is expected to mimic that for an SAV. The fleet operator's goal is to provide a high-quality service at low operating costs to ensure a sound return on investment. Ride requests, trip matching, charging and maintenance decisions are centrally monitored to this end. The operator assigns vehicles to riders by a zone-based assignment (Bischoff and Maciejewski, 2016; Gurumurthy et al., 2020) to ensure nearby vehicles serve nearby rides, which reduces overall eVMT and ensures low response times. Although this is not a nearest-neighbor assignment, since available vehicles are aggregated at the zone level for operators, the relative size of the traffic analysis zones (TAZs) in locations with high SAV use is small enough to yield an acceptable sub-optimal solution. Once this initial assignment is made, the vehicle makes routing choices to minimize travel times and records trip information like distance, time, and empty travel at the path level. DRS is allowed through the existing SAV module as highlighted in (Gurumurthy and Kockelman, 2022). A heuristic to DRS matching is followed where trips are matched to vehicles en route depending on seat availability and the directionality of the trip being served with respect to the new trip that may be added to the tour. DRS introduces new parameters such as controlling for maximum allowable delay (both as a percentage of solo travel time and absolute value), degree of directionality, and maximum seats in the vehicle.

3.1 SAEV Module

Previous SAV work has shown an average daily VMT between 230-430 miles per SAV depending on the assumed parameters and region simulated (Farhan and Chen, 2018; Loeb et al., 2018; Simoni et al., 2019; de Souza et al., 2020a, 2020b; Gurumurthy and Kockelman, 2022; Vosooghi et al., 2020). Thus, the current four-seater battery electric vehicles (BEVs) available in the U.S. advertising 84 mile to 373 mile ranges would need to recharge at least once a day if used intensively, as expected for shared fleets (EVAdoption, 2019). To prevent stranding vehicles, the fleet operator checks vehicle range and SOC at different levels of the vehicle-to-request assignment. In addition to finding the closest SAEV for trip assignment using a zone-based list (Bischoff and Maciejewski, 2016; Gurumurthy et al., 2020), the operator verifies the vehicle meets a minimum pre-defined SOC and range (say, 20% and 30 miles) before allowing the pick-up so that there is sufficient range remaining to allow the SAEV to go charge. DRS trips are added en route and do not follow an aggregate matching strategy so checks at the beginning and end of a tour (chained trips representing pick-ups and drop-offs) are not sufficient. The vehicle continuously updates the available range, and the minimum SOC and range requirement are verified before executing the next trip in the tour. When an additional DRS rider is set to join a vehicle, the remaining required range is estimated using Euclidean distances between planned pick-ups and drop-offs. If the SOC or available range falls below the minimum threshold that is pre-defined, or is not sufficient to complete existing trips, additional trips are not accepted so that the vehicle can recharge at the end of the tour. This also maximizes sharing, as permitting by other parameters, with the vehicle preparing to charge while completing previously assigned trips.

SAEV battery capacity (or "range") is another input and the module allows for a homogenous fleet with a single range, or a mixed-range (MR) fleet denoted as a discrete distribution of specific battery capacities to mimic bulk purchases of different models. The MR scenario is a unique contribution in simulating a combined fleet of both short (SR) and long-range (LR) vehicles. Also, these vehicles are expected to have a distribution of initial SOC to reflect a continuous multi-day operation when testing only one 24-hour period. All simulations start with the battery level normally distributed with a mean of 70% and standard deviation of 5%, which allows for some variability compared to a fixed 70% for Iacobucci et al. (2019) and 100% for Zhang et al. (2020). Battery consumption is estimated not on mile-equivalents with link lengths, but rather through a machine learning (ML) model developed by combining POLARIS trajectory outputs with EV consumption estimates from Autonomie (Moawad et al. 2022). Interested readers are referred to that paper for more details.

Maintenance checks to clean sensors, download software, and update hardware are necessary but have been neglected in the literature. Service trips will increase eVMT, repositioning vehicles to central depots for maintenance may increase passenger wait times and these trips can drain the battery, especially for low-range vehicles. Trips may be scheduled in advance for all vehicles, subject to crew scheduling and available service bays, or done through a decentralized heuristic. Service trips in this paper are assumed to follow a uniform distribution and take the same amount of time. Depots are co-located with a few charging stations, such that during routine maintenance trips the SAEVs can also utilize service bay chargers. This allows for investments in any electrical upgrades for charging stations to also be extended to service depots. When an SAEV receives a maintenance trip request from the operator, it fulfills its trips before driving to the nearest depot. In addition to nearly once-daily maintenance trips, which could be less frequent, the modeler can require short cleaning trips after every *n* trips. Although the SAEV may not require cleaning before the maintenance trip if riders are financially responsible for their mess, the COVID-19 pandemic has heightened rider's expectation of routine cleanings (PricewaterhouseCoopers, 2021). By requiring cleanings after many consecutive trips, rider's satisfaction with the service may increase. During cleaning-only trips, staff may choose to wash the vehicle and thus charging is not permitted.

Figure 2 is the flowchart that conveys the relationship between charging and serving trips once a vehicle has completed any trip. The middle box ("Idle") indicates that vehicles wait in place between trip requests after arriving at a trip's destination. In this study, SAEVs do not have to drive to the nearest parking lot to wait for vehicle assignments. Once the vehicle is idle after arriving at a destination, there are a series of checks to ensure that vehicles perform routine charging and maintenance trips. As a heuristic, the order of checks reflects the prioritization of trips. The first check tries to guarantee that vehicles can go to a service depot for routine vehicle maintenance. If the simulation is not yet at the vehicle's assigned service hour the next check is whether the vehicle has completed *n* consecutive trips. This ensures that vehicles that are highly-utilized are sanitized. If a service trip (for maintenance or cleaning) is required, the vehicle finds the nearest service depot by Euclidean distance and travels to the assigned location. The next two checks determine if an idle vehicle should charge. While the first will send a vehicle to go charge if below a minimum SOC, the second is a passive charging policy of charging underutilized vehicles. If the operator decides to charge vehicles using idle thresholds, the vehicle will start counting the time it sits idle before finding a charging station. To avoid unnecessary charging of idle vehicles with high range, only idle vehicles below a certain SOC will advance to the second idle time check.

The charging station selection process is not as simple as selecting the nearest location. There is a search process of the nearest five locations to find the station with the lowest charging trip downtime. This calculation takes in the previous quarter hour's average queue time and the estimated time spent charging. The latter considers the current SOC, the estimated consumption of traveling to the charging station, and the time spent charging to the cutoff level. If no plugs are available, the SAEV will queue until the vehicle starts charging. At every charging time step, the vehicle will assess its current SOC, and, if the operator enables service priority, determines if the vehicle has a minimum SOC of 60% to serve demand that no other SAEV can meet. The SAEV stops charging at the cutoff level and exits the EVCS to idle for the next assignment.

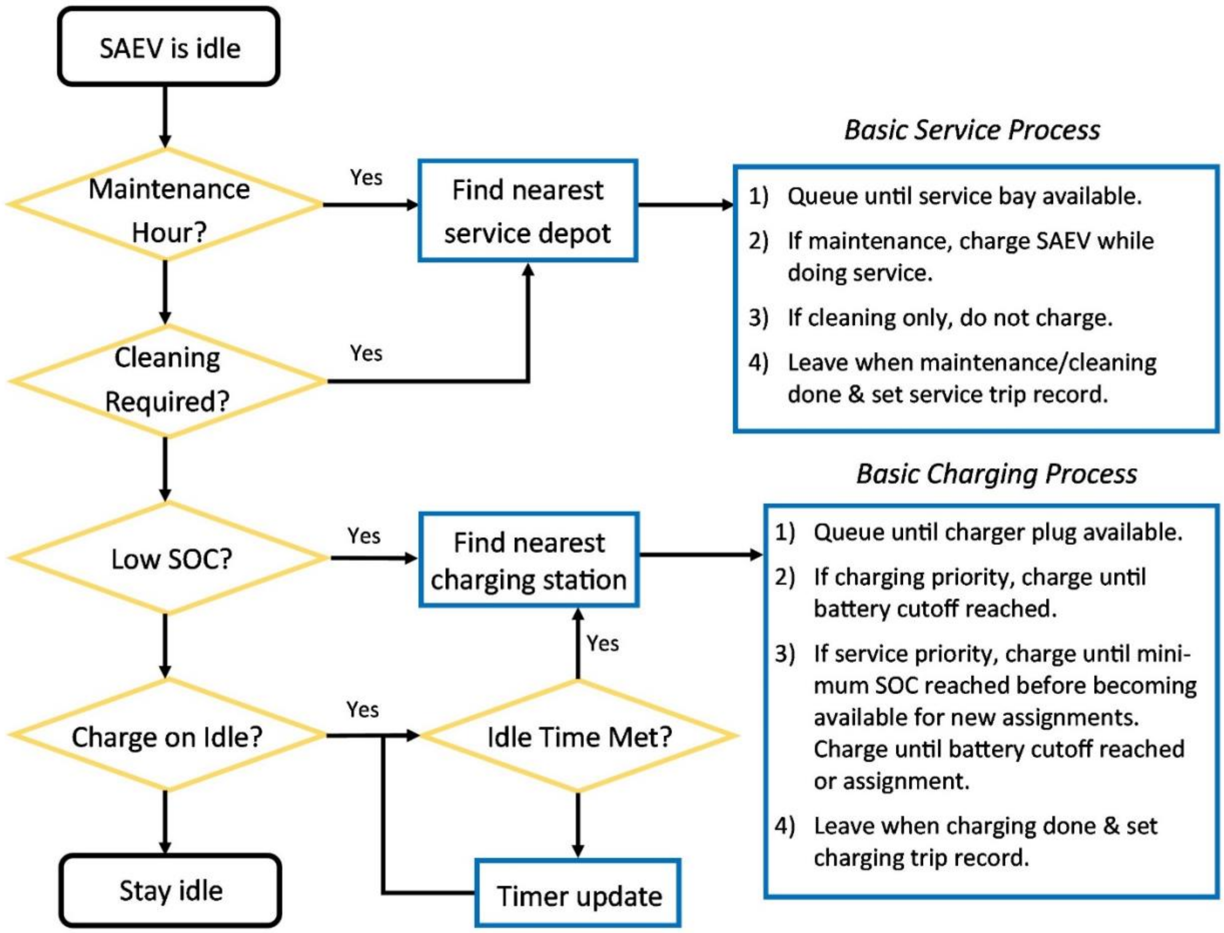


Figure 2 Flowchart for SAEV End-of-Trip Charging and Maintenance Decisions

Before an idle SAEV is assigned to a pick-up request, the operator first checks to see if the vehicle has sufficient range to drive to the pick-up trip and drop-off the passenger and not drop below the minimum battery thresholds. Under DRS, the process is similar but requires more range checks. DRS already has checks to ensure adding an additional passenger does not exceed total and marginal delay and the direction of the pick-up request is in the same direction as the ongoing route. Simulating SAEVs needs an additional range check to ensure that the vehicle range of the added detours does not diminish range past the minimum battery thresholds. This process can be computationally intensive if actual routing distances are queried from the POLARIS router, so the Euclidean distances for ordered pick-up and drop-off trips are calculated and a multiplicative factor of 2 is applied to provide a conservative range reduction estimate. If the approximated range exceeds the available range or if it would trigger the minimum battery threshold, the vehicle becomes unavailable to new requests.

Since maintenance and cleaning actions will likely require human technicians and cannot be fully automated like self-docking (or wireless) charging, there are fewer service depots. Relative to charging, maintenance and cleaning trips should have significantly more empty travel. To counteract the expected increase in empty travel, a convenience-based maintenance check can stop DRS if the vehicle's destination is very close to a service depot and schedule maintenance at the end of a trip. Figure 3 presents the logic of DRS and convenience-based service checks within a vehicle scheduling function.

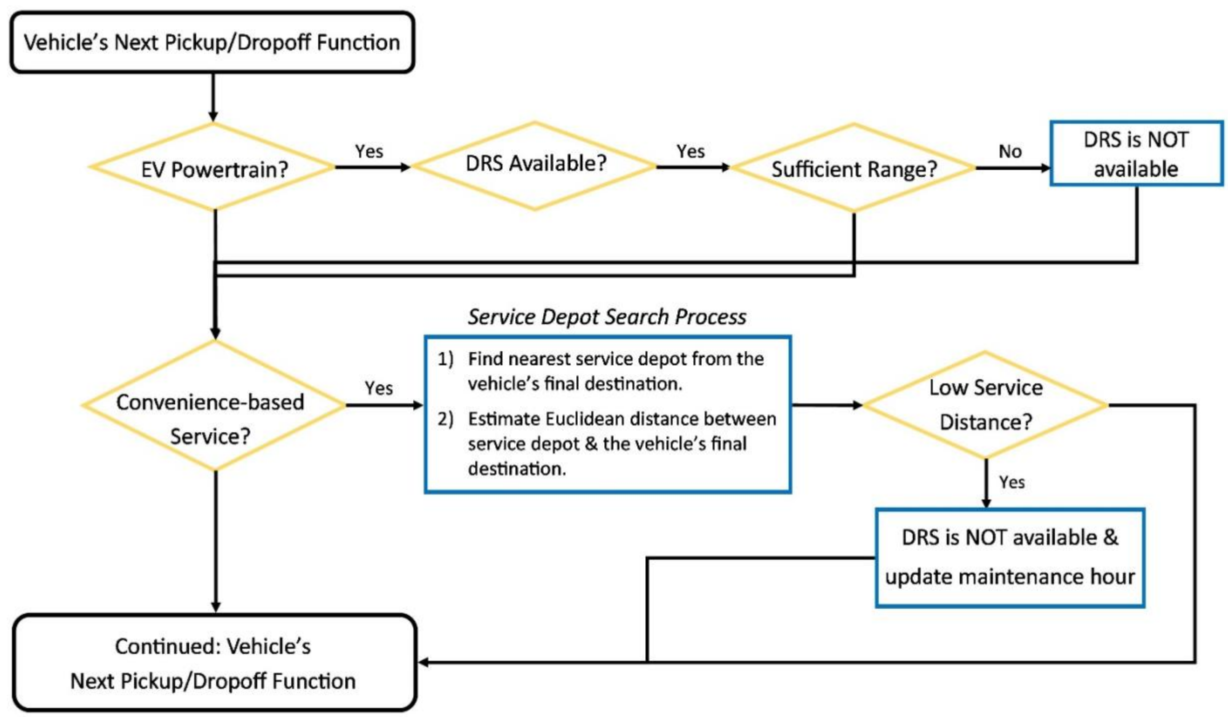


Figure 3 Flowchart for SAEV Mid-Tour Charging and Maintenance Decisions

3.2 EV Charging Stations (EVCS) & Depot Locations

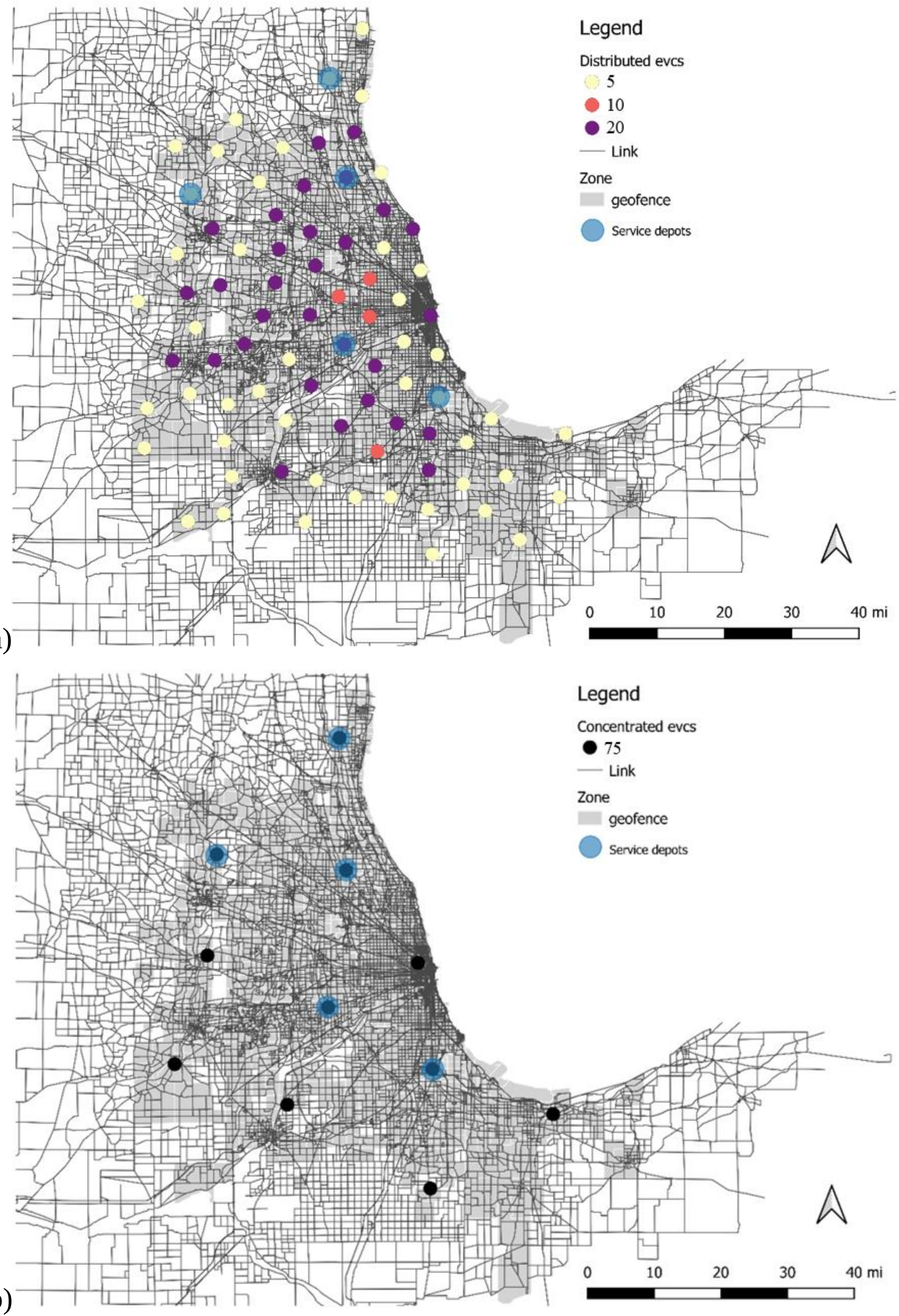
The SAEVs utilize a network of fleet-owned DCFC stations, designed based on recommendations from the literature (i.e., station density and vehicle-to-plug ratio). Previous work has resorted to heuristics to site charging stations to prevent stranding vehicles or using historical SAV demand (Chen et al., 2016; Loeb et al., 2018; Loeb and Kockelman, 2019; Vosooghi et al., 2020). Likewise, a new station with a default x plugs is created if there is not one within y miles of the vehicle once the decision to charge is met. If an SAEV queues at an EVCS longer than z minutes, a new plug is added (while ensuring that the capacity limit v is respected). If the SAEV does not have sufficient range to meet a charger in the generation phase, a new EVCS is generated. This heuristic was used to generate two distinct EVCS networks – one that has more stations with fewer plugs ("distributed") and one that increases spacing and base number of plugs ("concentrated").

The EV charging model is based on the vehicle's battery capacity and the charger speed. Although battery charging could be modeled by a constant-current constant-voltage model, the vehicles are assumed to charge at a constant linear rate. Furthermore, numerous studies find degradation in battery capacity after many charging cycles (see Han et al., (2014)), but like Iacobucci (2018) and Sheppard et al. (2019), capacity fade is not incorporated into the model. Detailed charging behavior of batteries is ignored, and efficiency is assumed constant regardless of SOC since SAEVs are between the minimum and maximum thresholds that are preset to retain efficiency. Additionally, this paper does not factor in charging station overhead time that arises from docking the vehicle, but a queueing approach is followed at each EVCS where SAEVs wait at the charging station for the next available plug. The SAEVs that are queuing are assumed to find space at the charging station and do not create network spillbacks. The SAEV operator can stop an SAEV from charging if needed, given that its SOC at that instant is above a threshold. A 60% threshold is used in this study when overriding a charging session. Charging priority and charging override are both tested to evaluate which strategy helps improve SAEV fleet performance.

3.3 Case Study of Chicago, Illinois

For this study, EVCS were generated in a simulation run with all LR (90 kWh) vehicles while prioritizing charging and a 30-minute idle charging threshold to minimize investment costs across the region. An initial dry run generates the two EVCS networks that are used for the scenarios (e.g., distributed and concentrated). A minimum of *x* plugs is assumed at an EVCS and a new station is generated when an existing EVCS is not within *y* mi for both cases to cover the sprawling region of Chicago sufficiently. To prevent stranding vehicles, if at the end of a tour an SAEV had insufficient range to meet the nearest EVCS, regardless of whether one existed within a *y* mi Euclidean radius, a new station is generated. This results in a ratio of about 36 vehicles per plug for a fleet set at a ratio of 1 SAEV per 150 people. The station density for these fleet-owned charging stations, which are located exclusively within the service area (or geofence), is 32.7 square miles per EVCS for the distributed network and 237.82 square miles per EVCS for the concentrated network. Figure 4 shows a map of the Chicago metro with the service area, links, and two charging station networks. Table 3 shows the SAEV, EVCS, and depot modeling assumptions used in this paper

The intent of comparing the charging strategies with a combination of battery capacity and charging station densities is to situate the results in this study with that in the literature. The metropolitan network has 1,961 TAZs, 31,900 links, and 19,400 nodes across 11,246 square miles, of which the fleet operates in nearly a quarter of the area (23.5%), catering to 80% of the region's population. In additional to nearly 15.46 million daily person-trips from a 50% synthesized population, the Chicago region has significant freight traffic, which makes up 7.5% of daily VMT.



(a)

(b)

Figure 4 Chicago Road Networks with EVCS Locations (a – Distributed, b – Concentrated) and Sizing by Plug Count

Table 3 Summary of Model Inputs

DCFC EVCS	**Distributed**		**Concentrated**
Heuristic: v (capacity), x (plugs), y (miles), z (min)	40 plugs, 1 plugs, 5 mi, 15 min		150 plugs, 10 plugs, 15 mi, 15 min
Number of Plugs	870		825
Number of Stations	80		11
Charger Speed (kW)	50		50
Battery Capacity	**30 kWh**		**90 kWh**
Short-range (SR) only (%)	100%		0%
Long-range (LR) only (%)	0%		100%
Mixed-range (MR) (%)	50%		50%
Fleet Size			
Fleet Size (Vehicles)	28,578		
People-to-SAEV Ratio	150:1		
Decision-to-Charge Parameters			
Minimum SOC (%)	15%		
Minimum Absolute Range (mi)	30 mi		
Maximum Idle Check SOC (%)	40%		
Minimum Idle Time (min)	15 min		60 min
EV Charging Parameters			
Maximum SOC (%)	95%		
Service Priority Minimum SOC (%)	60%		
Exit Charging Early	Yes	No	
Base SAEV Assumptions			
Starting SOC (%)	Normal (μ = 70, σ = 5)		
Vehicle Efficiency	30 kWh per 100 mi		
Depot Assumptions			
Number of Depots	5		
Number of Service Bays/Depot	50		
Maintenance Duration (min)	30 min		
Cleaning Duration (min)	5 min		
Cleaning Trip Frequency (n^{th} trip)	10 trips		
Convenience-Based Service Distance	2 mi		

4. RESULTS

Table 3 also shows the EVCS network inputs and outputs alongside the fleet of SAEVs by range configuration with additional categories of SAEV fleet specification, resulting in a set of 24 all-electric SAV scenarios for the Greater Chicago region. The effect of minimum range or battery cut-off was seen as negligible for a smaller case study not described here, so only charging versus service priority and low versus high idle time strategies were studied. The tables below report key characteristics that are of interest to the operator, planner, and users: median wait times, percent empty travel (and the breakdown by ongoing operation), trips served per SAV per day, and average wait time at charging stations if a vehicle had to wait. The focus here is on the effect of charging versus service priority, when to charge a vehicle based on idle time, the three vehicle range fleet options, and EVCS network design.

After generating baseline demand for SAV service in Chicago with a sufficiently large fleet size (i.e., 50,000 vehicles), this resulting trip table was used in all operational scenarios to understand the impact of operational decisions. As expected, a fleet size that is 40% smaller than what was used to generate demand for this mode cannot serve all trip requests. This is similar to how travelers check expected wait times on the TNC app of their choice and decide against taking a trip or this mode. Although this demand reduction is high, it is likely because the distribution of trips (spatially and temporally) in Chicago's service area of 2,616 square miles is not concentrated enough. If a fleet of mostly gasoline-powered SAVs are subjected to service requirements, then the sparser depot locations negatively impact performance and there could be a 20% reduction in demand from the no-service baseline. As there are more charging locations than service stations, the all-electric fleet tends to serve more trip requests then the conventionally fueled SAV fleet.

Vehicle utilization, the service region's sprawl, and average number of trips can explain the expected average daily VMT per vehicle. Each vehicle has an average of 9-12 person-trips per day, though the maximum person-trips for a vehicle ranges from 49 to 62. To compensate for low utilization in exurban and suburban neighborhoods, the operator could increase the fare price, which may help to offset the higher empty travel costs between pickup locations. The average vehicle sits idle 43% of the day (or 10.3 hours) across all 24 SAEV scenarios. In the future, vehicles could serve as delivery vehicles between distribution centers and retail storefronts when not serving passengers, which could increase vehicle utilization and revenue-generating opportunities. Other trips that contribute to total VMT are maintenance trips (24% of SAEVs do either convenience-based or are available at the assigned maintenance hour), cleaning trips (31%), and charging trips (percent of fleet vehicles charging depends on range). Overall, this region can expect about 125 miles per vehicle per day, with some driving considerably more.

The average trip's travel time within the fleet's service area is around 35 minutes, which suggests that individuals are utilizing this service for non-leisure trips, which tend to be longer in duration and distance. Additionally, the average vehicle occupancy over revenue miles is 1.61 across all 24 SAEV and 2 SAV scenarios, thanks to the assumption that all riders are willing to share a vehicle up to a 5 minute or 5% detour in travel time, whichever is less. For a sprawling region like Chicago, this occupancy rate indicates the potential for congestion relief and energy savings if riders are incentivized to share.

4.1 Fleet Range Composition (Short-Range, Long-Range, and Mixed-Range)

An increase in battery capacity (i.e., vehicle range), and all else constant, only helps to reduce the likelihood of needing to charge vehicles, given an average VMT per vehicle of 125 miles. The SR fleet and fleet with a 50-50 combination of two ranges (MR), unsurprisingly, will have more charging trips. Only about 28% of LR vehicles need to charge during the day while 54% of MR vehicles and 74% of SR vehicles must charge, which is why the share of charging VMT to total empty VMT is about three times less for LR vehicles than SR vehicles. As a result, SR fleets give up an average of 2 trips per vehicle per day. In this case study, that results in not serving about 57,000 trips.

As charging is a type of rebalancing, an increase in charging trips may lead to a spatial imbalance of idle vehicles to passenger pick-up locations. Fortunately, there is no evidence that SR fleets have higher median wait times than LR fleets. Charging downtime is another critical aspect that should influence fleet range composition decisions. Although there are some vehicles (and chargers) rated at a maximum charge power of 250 kW, the investment and operating costs (through electricity demand charges) may nudge operators to invest in the more common 50 kW chargers. Assuming there are 50 kW chargers and a linear charge rate, a 30-kWh vehicle with some SOC buffers can charge in less than 30 minutes. In contrast, a 90-kWh vehicle charging from a low SOC constraint could charge for more than 90 minutes. If there are too few charging plugs, one would expect the queue time for LR vehicles to take longer than SR vehicles. This should only hold for regions where the average daily mileage forces vehicles to go charge. Since nearly 3 in 4 SR vehicles must charge, the average wait time (when a queue is present) is 14 to 24 minutes longer than shown with a LR fleet.

Fleet range may even affect whether vehicles can perform routine maintenance. In a fleet of SR vehicles, 21% to 23% visit a depot for routine maintenance while 26% of LR vehicles do maintenance. A plausible explanation for this difference is that the SR vehicle hits the low SOC constraint while checking whether new passengers can be added to an existing trip tour, forcing the vehicle to go charge and missing the reserved service hour because of long wait times at the charging station. If vehicles can charge during 30 minutes of routine maintenance, as assumed, this stands to benefit the 1 in 5 SR vehicles (or 1 in 4 for LR fleets) that perform a service trip.

A mixed fleet of SR and LR SAEVs performs better than a complete SR fleet but worse than the LR fleet in certain service metrics like average trips served, percent eVMT and average charging queue times. The MR fleet inherits high daily charging trips from an SR fleet but also fewer charging trips from an LR fleet, resulting in more balanced charging episodes. This fleet composition scenario suggests that if fleets start with cheaper SR vehicles and wait for next-generation battery technology to mature and lower in price, that the transition to an all-LR vehicle fleet is promising (i.e., higher vehicle utilization, less time spent queueing at charging stations).

Table 4 SAEV Fleet Performance in Chicago for a Distributed EVCS

Range	HI (60 min)/ LI (15 min)	CP / SP	Median Wait Time (min)	Avg. Daily Person-Trips per SAV	Avg. Daily SAV VMT	Revenue -Trip AVO	% eVMT	% cVMT (in eVMT)	% mVMT (in eVMT)	Avg. Daily Charging Trips per SAEV	Avg. Wait Time at EVCS, if waited (in min)	% Demand Change
Gasoline-powered SAV (***no service***)	-	-	6.8 min	13.8 trips/day	140 mi	1.57 pax	29.3%	0.0%	0.0%	-	-	-
Gasoline-powered SAV	-	-	7.1	11.0	125	1.60	35.2%	0.0%	23.0%	-	-	-20.15%
LR (90 kWh)	LI	SP	7.1	12.2	136	1.59	34.9%	5.7%	20.5%	0.30	109	-11.3%
		CP	7.2	11.9	134	1.59	34.7%	5.4%	5.3%	0.28	112	-13.5%
	HI	SP	7.1	12.2	135	1.59	34.8%	5.2%	15.1%	0.28	118	-11.9%
		CP	7.0	12.0	133	1.60	34.5%	4.9%	15.1%	0.26	134	-12.8%
SR (30 kWh)	LI	SP	7.0	10.3	120	1.62	35.8%	15.8%	16.1%	0.75	126	-25.8%
		CP	7.1	10.3	121	1.62	35.9%	15.5%	15.8%	0.74	136	-25.3%
	HI	SP	7.1	10.3	122	1.62	35.5%	14.9%	12.2%	0.72	142	-25.7%
		CP	7.0	10.4	120	1.62	35.8%	14.8%	12.0%	0.73	143	-25.0%
MR (30 kWh & 90 kWh)	LI	SP	7.0	11.6	131	1.61	35.5%	10.4%	11.5%	0.54	93	-16.2%
		CP	7.1	11.7	133	1.60	35.7%	10.3%	11.3%	0.54	98	-15.3%
	HI	SP	7.0	11.6	131	1.60	35.4%	10.0%	13.9%	0.53	98	-15.8%
		CP	7.1	11.5	130	1.60	35.5%	10.2%	14.3%	0.52	102	-16.9%

Abbreviations: LR = Long Range, SR = Short Range, MR = Mixed Range, HI = High Idle, LI = Low Idle, CP = Charging Priority, SP = Service Priority, Pax = Passengers.

Table 5 SAEV Fleet Performance in Chicago for a Concentrated EVCS

Range	HI (60 min)/ LI (15 min)	CP / SP	Median Wait Time (min)	Avg. Daily Person-Trips per SAV	Avg. Daily SAV VMT	Revenue-Trip AVO	% eVMT	% cVMT (in eVMT)	% mVMT (in eVMT)	Avg. Daily Charging Trips per SAEV	Avg. Wait Time at EVCS, if waited (in min)	% Demand Change
Gasoline-powered SAV (***no service***)	-	-	6.8 min	13.8 trips/day	140 mi	1.57 pax	29.3%	0.0%	0.0%	-	-	-
Gasoline-powered SAV	-	-	7.1	11.0	125	1.60	35.2%	0.0%	23.0%	-	-	-20.15%
LR (90 kWh)	LI	SP	7.3	12.0	136	1.60	37.5%	16.3%	13.6%	0.28	61	-13.4%
		CP	7.2	11.9	134	1.60	37.5%	16.9%	13.5%	0.29	60	-14.1%
	HI	SP	7.2	11.9	135	1.60	37.3%	16.1%	13.7%	0.28	71	-13.7%
		CP	7.2	11.8	134	1.60	37.0%	15.8%	13.7%	0.27	59	-14.5%
SR (30 kWh)	LI	SP	7.0	9.0	121	1.64	43.9%	43.9%	9.0%	0.77	84	-34.7%
		CP	6.9	8.9	119	1.64	43.6%	43.5%	9.2%	0.74	73	-35.5%
	HI	SP	6.9	8.8	118	1.63	43.7%	43.5%	9.2%	0.74	76	-36.0%
		CP	7.0	8.8	119	1.64	43.2%	43.2%	9.1%	0.73	74	-36.0%
MR (30 kWh & 90 kWh)	LI	SP	7.0	8.9	120	1.64	43.6%	43.7%	9.2%	0.76	75	-35.4%
		CP	7.0	8.9	120	1.64	43.8%	43.7%	9.0%	0.76	82	-35.2%
	HI	SP	6.9	8.9	119	1.63	43.5%	43.4%	9.1%	0.74	78	-35.8%
		CP	7.0	10.8	131	1.62	40.4%	29.3%	11.8%	0.54	119	-21.5%

Abbreviations: LR = Long Range, SR = Short Range, MR = Mixed Range, HI = High Idle, LI = Low Idle, CP = Charging Priority, SP = Service Priority, Pax = Passengers.

4.2 Charger Priority versus Service Priority

The service priority policy allows for unassigned trip requests to be served by a charging vehicle that has at least 60% SOC. The trade-off here is that interrupting charging and subsequent back-to-back trip assignments may lead to another charging trip. The SP charging policy results in more trips served and LR fleets stand to benefit the most. LR vehicles that have an interrupted charge will still have more remaining capacity (nearly double that of a SR vehicle) and can meet more trips before having to charge again. To understand whether there is a long-term difference in fleet average SOC, Figure 5 plots the hourly difference in this measure. Note, a positive value indicates that the equivalent CP scenario results in a higher fleet SOC than SP. Line dashing is used to highlight the difference in idle charging decisions times (dashed = low idle, solid = high idle). The color explains the difference in charging station networks (orange = concentrated, green = distributed) and the shading distinguishes the range of vehicles (darker = long range, lighter = short range). The mixed range fleet includes a filled in marker to further differentiate between SR and LR charging strategies.

There is largely no difference in fleet average SOC until more vehicles move in the network and initiate the end-of-trip decision process, which coincides with the morning peak. Charging to the maximum SOC should result in positive values for all time steps and this plot shows that most scenarios are at or above 0. LR fleets with a low idle threshold for charging has a consistently higher average fleet SOC at the end of the day for CP than SP. The greater the battery capacity, the higher the average fleet SOC when vehicles are forced to charge until the maximum cutoff level. Since idle vehicles can only charge once below 40% SOC, vehicles with larger batteries will skew fleet average SOC if forced to charge longer, and when given more opportunities to charge (via a low idle threshold). In contrast, SR vehicles tend to have better battery performance with a SP policy for a distributed charging station network. Fortunately, the results show there is no wide variation in fleet average SOC (greater than 2% by the end of the day). If need be, SP could be restricted to peak hours to fulfill more ride requests while CP is implemented after the evening peak to raise SOC at the end of the day.

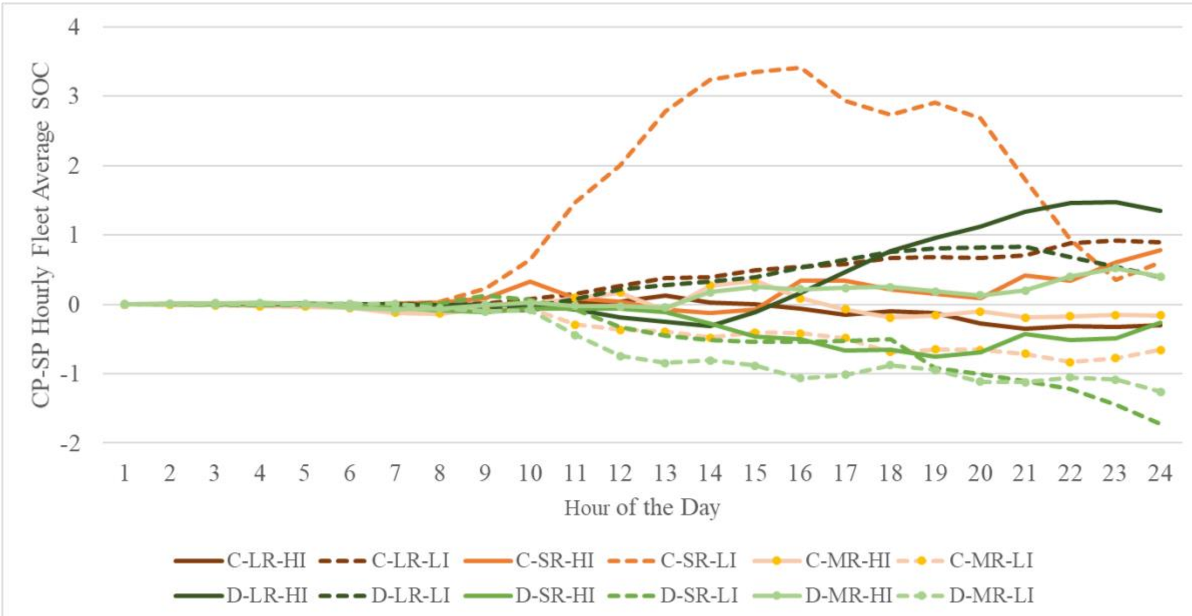


Figure 5 Difference in Fleet State of Charge by Time of Day Between Charging and Service Priority Policies

4.3 Charging Station Density

This study used two charging station archetypes, a distributed and concentrated station network. The distributed charging network had 40 locations with a total of 870 plugs while the concentrated station had 11 locations and 825 plugs. Although the average daily VMT had no discernable difference, the percent of empty travel increased for the concentrated charging station network (an added 3% for LR vehicles and 8% for SR vehicles). If SR vehicles are adopted, the increasing number of charging trips and percent of vehicles charging will lead to a greater increase in percent of daily VMT going to charging. Although the operator would have far less land acquisition/leasing costs with a concentrated station network, each SR vehicle gives up 1.4 trips per day and the LR vehicle an additional 0.2 trips per day. This may appear small, but relative to conventionally fueled no-service SAVs, the SR fleet faces a 35% reduction in trips served with sparser charging stations versus 25% with more locations. A fairer comparison between powertrains reveals a 19% reduction in trips served versus a 6% reduction from SR vehicles on sparser and denser charging station networks, respectively. If a fleet transitions from a SR fleet to a LR fleet (i.e., a MR fleet), then the act of rebalancing vehicles via charging, albeit less frequently than an entire SR fleet, allows for more passengers served. However, this assumption may only hold if the number of charging stations is greater than service depots, as in this study.

The concentrated station network has less wait time (between 55 and 65 min) when counting only vehicles in the queue. Since the wait time estimation is reactive and may not reflect an increase in wait time from vehicles yet to arrive, a concentrated network with more plugs appears to solve this issue. However, a more accurate wait time algorithm could remedy this problem and help realize the benefit of distributed stations.

Figure 6 plots a distribution of the fleet average SOC by time of day. The image shows a clear difference between the station types with a concentrated network (orange lines) increasing SOC faster after the morning peak hours. Since our study only simulated a 24-hour period, the rate of SOC increase was linearized for the early morning hours of the next day, since average SOC at the beginning of the day remains more or less constant. Assuming the rate holds, only SR fleets using a concentrated charging station network would recoup the fleet average SOC. This is in large part because the charge on idle heuristic requires a SOC less than 40%, which most SR vehicles should meet after the morning peak, and that the concentrated network has less queue time, allowing vehicles to charge faster. Since distributed stations have systematically lower fleet average SOC, fleets could improve the decision-making rule of selecting charging stations or simply add more chargers. Finally, LR fleets using a concentrated charging station network have near similar fleet average SOC profiles after 6 pm as fleets accessing distributed charging stations. While this combination would less infrastructure cost and increases the number of trips served (albeit at an upfront cost for 90kWh batteries) it comes at a cost of high charging downtime.

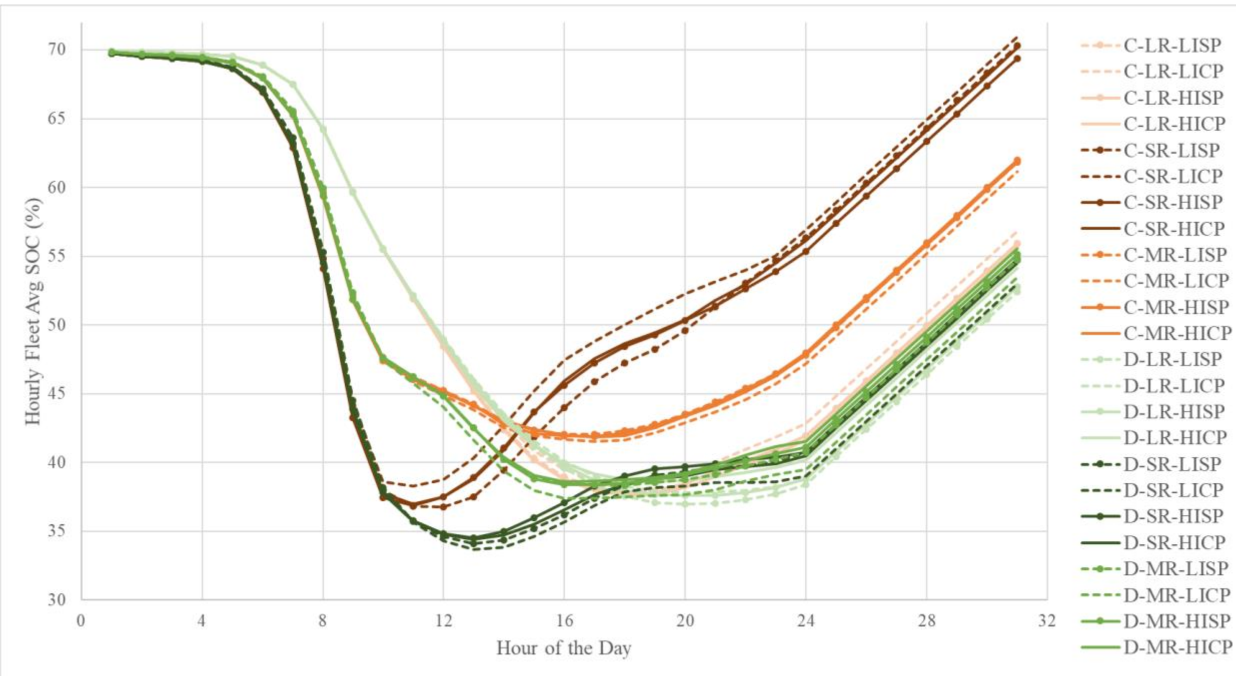


Figure 6 Difference in Fleet State of Charge by Time of Day Across All Policies

4.4 Fleet Utilization

Figure 7 highlights the fleet's utilization across different scenarios as a function of percent eVMT and percent idling time. The circles highlight the effect of range and charging infrastructure on these two metrics. If vehicle battery prices do not fall and the investment in charging stations is constrained, the first generation of SAEV fleets will likely use SR vehicles and a concentrated charging station network (orange circle with the dotted line in the figure). This study shows an additional 5% congestion impact, as measured in percent empty travel, from using SR vehicles over LR vehicles with this charging station network. If the fleet invests more in distributed charging stations, then the congestion impact could be greatly reduced, even more than increasing battery capacity. However, LR vehicles serve more trips per day than SR vehicles and helps to explain the difference in average idle time. Increasing vehicle range can help mitigate the impact of charging station design on percent empty travel, since these vehicles charge less often. Lastly, fleets using concentrated charging stations have far less variation in percent empty travel and percent of the day spent idling even after accounting for the differences in idle times and charging versus service priorities (see spread within the circles).

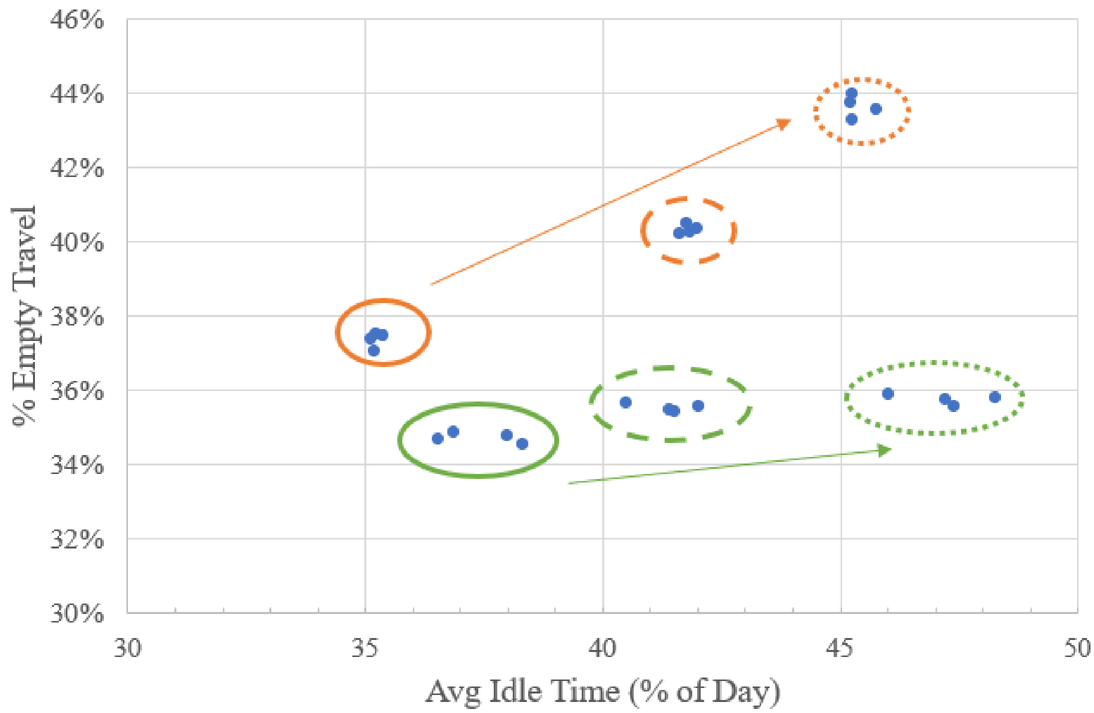


Figure 7 Fleet Utilization as a Function of Percent Empty VMT and Percent Idling Time
(Note: Orange = Concentrated, Green = Distributed, Sold Line = LR, Dashed Line = MR, Dotted Line = SR)

CONCLUSIONS

The use of EVs is slowly catching up and the future of shared vehicles is better off with an electric powertrain to minimize the carbon footprint of transportation. SAEV fleet operations are studied in detail here, through a variety of fleet compositions and charging strategies. Over 24 scenarios were simulated for the Greater Chicago, IL region using the agent-based tool POLARIS to learn the impact of fleet choice and charging strategy on fleet performance and system impact.

The decision to use an SR, LR or MR fleet is important to manage the added congestion through eVMT. Irrespective of whether charging or service is prioritized, the all-electric SR fleet experienced a marginal increase in percent empty travel compared to an SAV fleet (+3.6%) versus +2.5% for LR SAEV fleets. When comparing SAEVs to SAVs, there are two distinctions to be made. If studies do not model routine maintenance or periodic cleaning trips, say after the n^{th}

consecutive trip, then the reference SAV case may be underestimating average percent empty travel by 16.7% (i.e., there is a magnitude difference of 5.9% %eVMT). Assuming that service depot locations are sparser than charging stations, since charging could be performed autonomously with wireless charging or self-docking technology, switching powertrains to battery electric vehicles could help reduce the impact of maintenance trips on fleet performance. Moreover, some maintenance checks can be performed while a vehicle is charging, which can recoup lost energy from the vehicle traveling to the service depot. In fact, this study found that LR vehicles serve more trips than SAV fleets when adding these service trips.

Prioritizing service over charging is useful in improving the average daily trips served per SAEV and should be pursued, so long as operators ensure that vehicles with at least 60% SOC are released. Service priority makes the most sense at peak times of day and using a low idle threshold for charging can help recoup fleet state of charge during off-peak periods faster. Since this study had a relatively high utilization rate of vehicles temporally (i.e., vehicles were idle about 10 hours of the day on average), a higher idle time for charging resulted in only marginally longer wait times and lower SOC.

The use of charging station capacity and queuing adds realism that some prior models missed. Even with 50kW charging outlets, SAEV vehicles may wait between 1 to 2 hours if there's a queue. This is in part due to relying on charging heuristics, however strategic, to schedule charging trips after a vehicle finishes a tour. If instead vehicles could decide to charge during the early morning hours, in advance of demand, the fleet could reduce charging wait times and perhaps serve more trips in the case of SR vehicles. Additionally, the SOC at the end of one day did not exceed the starting SOC distribution for this case study. New research could assume a starting SOC range of 60% to 65% instead of the 70-100% assumptions in the literature.

Demand reductions seen from an SAV fleet with no service is expected, but the magnitude is rooted in the fleet composition, charging station design, and finally in charging strategies studied here. Larger regions may need more SAEVs per capita for adequate service (trips and response time), but the average daily trips per vehicle would likely decrease. Constraining the service area of these fleets to areas with a higher concentration of trip requests can help increase vehicle utilization. Additionally, if SAV fares were adjusted to recoup the costs of longer travel lengths to pick-up locations or if per-mile/per-minute prices were higher in regions with lower demand, then perhaps the fleet could justify the less than ideal average daily vehicle utilization rate.

This simulation study comes with a limitation arising from the use of heuristics that helps study large samples of demand. While the approach is reasonable, optimal solutions are preferred in many cases, and the tradeoff arises between modeling travel demand behaviorally well versus making distributional assumptions to focus on optimizing an objective function. Studies like Shi et al. (2019) and Al-Kanj et al. (2020) have shown the value add from optimizing operations, but incorporating it into a demand model that tracks all forms of travel is not yet done and will likely be done in due time.

ABBREVIATIONS

AV	Autonomous Vehicle

cVMT	Charging Vehicle-miles Traveled
DCFC	Direct Current Fast Charging
DRS	Dynamic Ride-sharing
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
eVMT	Empty Vehicle-miles Traveled
ICE	Internal Combustion Engine
SAEV	Shared Autonomous Electric Vehicle
SAV	Shared Autonomous Vehicle
SOC	State of Charge
TAZ	Traffic Analysis Zone
TNC	Transportation Network Company
VMT	Vehicle-miles Traveled

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REFERENCES

Al-Kanj L, Nascimento J, Powell WB. Approximate dynamic programming for planning a ride-hailing system using autonomous fleets of electric vehicles. Eur J Oper Res 2020;284:1088–106. https://doi.org/10.1016/j.ejor.2020.01.033.

Argue C. What can 6,000 electric vehicles tell us about EV battery health? Geotab 2019. https://www.geotab.com/blog/ev-battery-health/ (accessed May 4, 2020).

Auld J, Hope M, Ley H, Sokolov V, Xu B, Zhang K. POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations. Transp Res Part C Emerg Technol 2016;64:101–16. https://doi.org/10.1016/j.trc.2015.07.017.

Auld J, Verbas O, Stinson M. Agent-Based Dynamic Traffic Assignment with Information Mixing. Procedia Comput Sci 2019;151:864–9. https://doi.org/10.1016/j.procs.2019.04.119.

Balding M, Whinery T, Leshner E, Womeldorff E, Fehr & Peers. Estimated Percent of Total Driving by Lyft and Uber In Six Major US Regions, September 2018. Fehr & Peers; 2019.

Basso R, Kulcsár B, Egardt B, Lindroth P, Sanchez-Diaz I. Energy consumption estimation integrated into the Electric Vehicle Routing Problem. Transp Res Part Transp Environ 2019;69:141–67. https://doi.org/10.1016/j.trd.2019.01.006.

Bauer GS, Greenblatt JB, Gerke BF. Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. Environ Sci Technol 2018;52:4920–8. https://doi.org/10.1021/acs.est.7b04732.

Bauer GS, Phadke A, Greenblatt JB, Rajagopal D. Electrifying urban ridesourcing fleets at no added cost through efficient use of charging infrastructure. Transp Res Part C Emerg Technol 2019;105:385–404. https://doi.org/10.1016/j.trc.2019.05.041.

Becker H, Becker F, Abe R, Bekhor S, Belgiawan PF, Compostella J, et al. Impact of vehicle automation and electric propulsion on production costs for mobility services worldwide. Transp Res Part Policy Pract 2020;138:105–26. https://doi.org/10.1016/j.tra.2020.04.021.

Bischoff J, Maciejewski M. Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin. Procedia Comput Sci 2016;83:237–44. https://doi.org/10.1016/j.procs.2016.04.121.

Bischoff J, Márquez-Fernández FJ, Domingues-Olavarría G, Maciejewski M, Nagel K. Impacts of vehicle fleet electrification in Sweden – a simulation-based assessment of long-distance trips. 2019 6th Int. Conf. Models Technol. Intell. Transp. Syst. MT-ITS, 2019, p. 1–7. https://doi.org/10.1109/MTITS.2019.8883384.

Bösch PM, Becker F, Becker H, Axhausen KW. Cost-based analysis of autonomous mobility services. Transp Policy 2018;64:76–91. https://doi.org/10.1016/j.tranpol.2017.09.005.

Bösch PM, Ciari F, Axhausen KW. Autonomous Vehicle Fleet Sizes Required to Serve Different Levels of Demand. Transp Res Rec 2016;2542:111–9. https://doi.org/10.3141/2542-13.

Chen TD, Kockelman KM. Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes. Transp Res Rec J Transp Res Board 2016;2572:37–46. https://doi.org/10.3141/2572-05.

Chen TD, Kockelman KM, Hanna JP. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. Transp Res Part Policy Pract 2016;94:243–54. https://doi.org/10.1016/j.tra.2016.08.020.

Collin R, Miao Y, Yokochi A, Enjeti P, von Jouanne A. Advanced Electric Vehicle Fast-Charging Technologies. Energies 2019;12:1839. https://doi.org/10.3390/en12101839.

Curtale R, Liao F, van der Waerden P. User acceptance of electric car-sharing services: The case of the Netherlands. Transp Res Part Policy Pract 2021;149:266–82. https://doi.org/10.1016/j.tra.2021.05.006.

Dean MD, Gurumurthy KM, de Souza F, Auld J, Kockelman KM. Synergies Between Repositioning and Charging Strategies for Shared Autonomous Electric Vehicle Fleets, Washington, D.C.: 2022.

Demir E, Bektaş T, Laporte G. A review of recent research on green road freight transportation. Eur J Oper Res 2014;237:775–93. https://doi.org/10.1016/j.ejor.2013.12.033.

EVAdoption. BEV Models Currently Available in the US – EVAdoption 2019. https://evadoption.com/ev-models/bev-models-currently-available-in-the-us/ (accessed June 11, 2020).

Fagnant DJ, Kockelman K. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp Res Part Policy Pract 2015;77:167–81. https://doi.org/10.1016/j.tra.2015.04.003.

Fagnant DJ, Kockelman KM. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 2018;45:143–58. https://doi.org/10.1007/s11116-016-9729-z.

Fagnant DJ, Kockelman KM. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transp Res Part C Emerg Technol 2014;40:1–13. https://doi.org/10.1016/j.trc.2013.12.001.

Fakhrmoosavi F, Hunter CB, Kockelman KM, Gurumurthy KM, Dean MD. On- and Off-Street Parking Strategies and Outcomes for Shared Autonomous Vehicle Fleet Operations 2022.

Farhan J, Chen TD. Impact of ridesharing on operational efficiency of shared autonomous electric vehicle fleet. Transp Res Part C Emerg Technol 2018;93:310–21. https://doi.org/10.1016/j.trc.2018.04.022.

Gurumurthy KM, Kockelman KM. Dynamic ride-sharing impacts of greater trip demand and aggregation at stops in shared autonomous vehicle systems. Transp Res Part Policy Pract 2022;160:114–25. https://doi.org/10.1016/j.tra.2022.03.032.

Gurumurthy KM, de Souza F, Enam A, Auld J. Integrating Supply and Demand Perspectives for a Large-Scale Simulation of Shared Autonomous Vehicles. Transp Res Rec 2020:0361198120921157. https://doi.org/10.1177/0361198120921157.

Han X, Ouyang M, Lu L, Li J. A comparative study of commercial lithium ion battery cycle life in electric vehicle: Capacity loss estimation. J Power Sources 2014;268:658–69. https://doi.org/10.1016/j.jpowsour.2014.06.111.

Horni A, Nagel K, Axhausen KW, editors. The Multi-Agent Transport Simulation MATSim. Ubiquity Press; 2016. https://doi.org/10.5334/baw.

Huang Y, Kockelman KM. Electric vehicle charging station locations: Elastic demand, station congestion, and network equilibrium. Transp Res Part Transp Environ 2020;78:102179. https://doi.org/10.1016/j.trd.2019.11.008.

Iacobucci R. Shared Autonomous Electric Vehicles: Potential for Power Grid Integration. Kyoto University, 2018.

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

Iacobucci R, McLellan B, Tezuka T. Modeling shared autonomous electric vehicles: Potential for transport and power grid integration. Energy 2018a;158:148–63. https://doi.org/10.1016/j.energy.2018.06.024.

Iacobucci R, McLellan B, Tezuka T. The Synergies of Shared Autonomous Electric Vehicles with Renewable Energy in a Virtual Power Plant and Microgrid. Energies 2018b;11:2016. https://doi.org/10.3390/en11082016.

Iacobucci R, McLellan B, Tezuka T. The Synergies of Shared Autonomous Electric Vehicles with Renewable Energy in a Virtual Power Plant and Microgrid. Energies 2018c;11:2016. https://doi.org/10.3390/en11082016.

Li L, Lin D, Pantelidis T, Chow J, Jabari SE. An Agent-based Simulation for Shared Automated Electric Vehicles with Vehicle Relocation*. 2019 IEEE Intell. Transp. Syst. Conf. ITSC, Auckland, New Zealand: IEEE; 2019, p. 3308–13. https://doi.org/10.1109/ITSC.2019.8917253.

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

Loeb B, Kockelman KM. Fleet performance and cost evaluation of a shared autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. Transp Res Part Policy Pract 2019;121:374–85. https://doi.org/10.1016/j.tra.2019.01.025.

Loeb B, Kockelman KM, Liu J. Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions. Transp Res Part C Emerg Technol 2018;89:222–33. https://doi.org/10.1016/j.trc.2018.01.019.

Lokhandwala M, Cai H. Siting charging stations for electric vehicle adoption in shared autonomous fleets. Transp Res Part Transp Environ 2020;80:102231. https://doi.org/10.1016/j.trd.2020.102231.

Menon N, Barbour N, Zhang Y, Pinjari AR, Mannering F. Shared autonomous vehicles and their potential impacts on household vehicle ownership: An exploratory empirical assessment. Int J Sustain Transp 2019;13:111–22. https://doi.org/10.1080/15568318.2018.1443178.

Moawad A, Li Z, Pancorbo I, Gurumurthy KM, Freyermuth V, Islam E, et al. A Real-Time Energy and Cost Efficient Vehicle Route Assignment Neural Recommender System. ArXiv:211010887 2021.

PricewaterhouseCoopers. How to restore confidence in travel during an uncertain time. Consum Mark 2021. https://www.pwc.com/us/en/industries/consumer-markets/library/how-to-restore-confidence-in-travel-during-covid-19.html (accessed October 28, 2021).

Schaller B. The New Automobility: Lyft, Uber and the Future of American Cities. Schaller Consulting; 2018.

Sheppard C, Waraich R, Campbell A, Pozdnukov A, Gopal AR. Modeling plug-in electric vehicle charging demand with BEAM: the framework for behavior energy autonomy mobility. Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States); 2017. https://doi.org/10.2172/1398472.

Sheppard CJR, Bauer GS, Gerke BF, Greenblatt JB, Jenn AT, Gopal AR. Joint Optimization Scheme for the Planning and Operations of Shared Autonomous Electric Vehicle Fleets Serving Mobility on Demand. Transp Res Rec 2019;2673:579–97. https://doi.org/10.1177/0361198119838270.

Shi J, Gao Y, Wang W, Yu N, Ioannou PA. Operating Electric Vehicle Fleet for Ride-Hailing Services With Reinforcement Learning. IEEE Trans Intell Transp Syst 2019:1–13. https://doi.org/10.1109/TITS.2019.2947408.

Simoni MD, Kockelman KM, Gurumurthy KM, Bischoff J. Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios. Transp Res Part C Emerg Technol 2019;98:167–85. https://doi.org/10.1016/j.trc.2018.11.002.

de Souza F, Gurumurthy KM, Auld J, Kockelman KM. A Repositioning Method for Shared Autonomous Vehicles Operation. Procedia Comput Sci 2020a;170:791–8. https://doi.org/10.1016/j.procs.2020.03.154.

de Souza F, Gurumurthy KM, Auld J, Kockelman KM. An Optimization-Based Strategy for Shared Autonomous Vehicle Fleet Repositioning, Prague, Czech Republic: 2020b, p. 7.

de Souza F, Verbas O, Auld J. Mesoscopic Traffic Flow Model for Agent-Based Simulation. Procedia Comput Sci 2019;151:858–63. https://doi.org/10.1016/j.procs.2019.04.118.

Spieser K, Treleaven K, Zhang R, Frazzoli E, Morton D, Pavone M. 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, editors. Road Veh. Autom., Cham: Springer International Publishing; 2014, p. 229–45. https://doi.org/10.1007/978-3-319-05990-7_20.

Stocker A, Shaheen S. Shared Automated Vehicle (SAV) Pilots and Automated Vehicle Policy in the U.S.: Current and Future Developments. In: Meyer G, Beiker S, editors. Road Veh. Autom. 5, Springer International Publishing; 2019, p. 131–47.

Union of Concerned Scientists. Ride-Hailing’s Climate Risks: Steering a Growing Industry toward a Clean Transportation Future. Cambridge, MA: Union of Concerned Scientists; 2020.

US EPA. Fast Facts on Transportation Greenhouse Gas Emissions. Green Veh Guide 2019. https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions (accessed April 17, 2020).

Verbas Ö, Auld J, Ley H, Weimer R, Driscoll S. Time-Dependent Intermodal A* Algorithm: Methodology and Implementation on a Large-Scale Network. Transp Res Rec 2018;2672:219–30. https://doi.org/10.1177/0361198118796402.

Vosooghi R, Puchinger J, Bischoff J, Jankovic M, Vouillon A. Shared autonomous electric vehicle service performance: Assessing the impact of charging infrastructure. Transp Res Part Transp Environ 2020;81:102283. https://doi.org/10.1016/j.trd.2020.102283.

Vosooghi R, Puchinger J, Jankovic M, Vouillon A. Shared autonomous vehicle simulation and service design. Transp Res Part C Emerg Technol 2019;107:15–33. https://doi.org/10.1016/j.trc.2019.08.006.

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

Yan H, Kockelman KM, Gurumurthy KM. Shared autonomous vehicle fleet performance: Impacts of trip densities and parking limitations. Transp Res Part Transp Environ 2020;89:102577. https://doi.org/10.1016/j.trd.2020.102577.

Zhang H, Sheppard CJR, Lipman TE, Zeng T, Moura SJ. Charging infrastructure demands of shared-use autonomous electric vehicles in urban areas. Transp Res Part Transp Environ 2020;78:102210. https://doi.org/10.1016/j.trd.2019.102210.

Zhang TZ, Chen TD. Smart charging management for shared autonomous electric vehicle fleets: A Puget Sound case study. Transp Res Part Transp Environ 2020;78:102184. https://doi.org/10.1016/j.trd.2019.11.013.