STRATEGIC CHARGING OF SHARED FULLY-AUTOMATED ELECTRIC VEHICLE (SAEV) 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 fleet managers will need to account for charging times and range limitations of EV battery packs. This study investigates a variety of potential electric SAV (SAEV) fleet designs and charging strategies that relate to vehicle range decisions, battery state-of-charge buffers, charging station capacity choices, response times, and the ability of currently-charging vehicles to accept new trips. The agent-based transportation tool POLARIS is used to simulate over 36 SAEV management scenarios serving passenger travel across Illinois' Bloomington region, and a subset of the same for the Greater Chicago region. Results show a mixed fleet of short (100-mi) and long (250-mi) range SAEVs performs better than a homogenous short-range fleet, with lower empty vehicle miles traveled (eVMT), higher average vehicle occupancies, and lower idling time. Charging and service priority policies are both required, but at different times of the day to accommodate slow Level 2 chargers, but is not as important for DCFC charging stations. SAEVs can stay in place longer (1 hr versus 15 min) to keep eVMT low, but only if long-range SAEVs are in the fleet and the region is small. SAEVs in large regions are exposed to location-specific trip requests when idling in place, and need to have high average state of charge (SoC) across the fleet to serve all incoming requests. Homogenous fleets need careful prioritizing of charging over service for an acceptable multi-day operation when using a largely Level 2 charging station

network. Smart siting of EVCS and availability of fast chargers remain key to minimizing fleet size and keeping response times low.

Keywords: Shared autonomous electric vehicles; strategic charging; heterogenous fleet; agent-based simulation.

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 (GHGs) and consume 55% less energy than a gasoline-fueled alternative (Bauer et al., 2018). Beyond EVs' 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 Environmental Protection Agency, 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 and discharging 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 (eVMT)) while varying fleet composition. 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.

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 ridesourcing fleets.

Loeb et al. (2018) extended existing 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 use Bischoff et al.'s (2019) 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 an extension 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 next sub-sections characterize SAEV simulations by the decisions of when to send vehicles to charge, the SoC buffers, and the flexibility of vehicle states as it relates to charging.

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 (Winter et al., 2020). Without relocation strategies or SAEV cruising (similar to current TNCs), vehicles idle upon arriving at a traveler's destination. This may be at the destination or at a nearby parking lot (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. Although no one has yet examined the trade-off of this parameter with fleet size, previous models have checked if the battery level is sufficient in meeting a current transport request. 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.

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.

Electric Vehicle and Charging Parameters

In addition to sending vehicles to charge, the underlying assumption on charging behavior and battery parameters is important. EVs 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.

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)

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., 2018, 2018). 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.

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, 2020). 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. (2018)).

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, 2020), 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 behavior (de Souza et al., 2019).

The SAV module in POLARIS (Gurumurthy et al., 2020) is expanded on 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. Demand for SAVs is in turn subject to results from the mode-choice model, which identifies the preferred mode of travel considering household and individual preferences in addition to the fare, average wait times, and in-vehicle travel costs (featuring a time-varying and distance-varying component) of the trip. 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 decisions and repositioning strategies 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. Vehicle relocation, like vehicle assignment, is conducted by the operator to increase the spatial distribution of vehicles to minimize both wait times and eVMT caused by this action (de Souza et al., 2020) but is not explored here. DRS is allowed through the existing SAV module as highlighted in (Gurumurthy and Kockelman, 2020). 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.

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., 2020, 2020; Gurumurthy and Kockelman, 2020; 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 over and above the minimum SoC defined for an SAEV. 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 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 ranges to mimic bulk purchases of different models. Table 3 shows the distribution of ranges considered in each of the scenarios, using discrete ranges of either 100 miles or 250 miles for each of the SAEVs. The third 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). Since all ranges are assumed to be mile-equivalents of their battery capacities, SAEVs discharge battery as a direct function of distance traversed.

EV Charging Stations (EVCS)

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. 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 EVCS for use across all 36 scenarios.

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 and discharging behavior of batteries is ignored, and efficiency is assumed constant regardless of SoC since SAEVs are on average between the minimum and maximum thresholds that are preset and aim to improve efficiency. Additionally, this paper does not factor in charging station overhead time that arises from docking the vehicle (which could be near simultaneous with the help of mechanics and cleaners who will invariably need to service the vehicles). The linear charging rate is estimated using EPA data for 2019 BEVs (US Environmental Protection Agency, 2020). The average energy efficient EV uses 30kWh per 100 miles of driving distance. With automation increasing energy demands, one could expect to use more kWh per 100 miles of driving distance but advances in electric powertrain technology may counteract increased loads. To estimate the miles of range added per minute of charge, the charger speed (assumed 50 kW) is multiplied by 3.33 mi/kWh.

A queueing approach is followed at each EVCS and 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, in between the minimum and cutoff SoCs assumed. 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 (see Table 3 for a list of all model inputs).

For this study, EVCS were generated in a simulation run with all SR vehicles while prioritizing service and a 15-minute idle charging threshold to have enough stations across the region. A minimum of 5 plugs are assumed at an EVCS and a new station is generated when an existing EVCS is not within 2 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 2 mi Euclidean radius, a new station is generated. In summary, there are 3.6 vehicles per charger and a station density of 0.2 EVCS per square mile in Bloomington compared to 3.7 vehicles per charger and a station density of 0.12 EVCS per square mile in Chicago (**Error! Reference source not found.** a and b, respectively).

The intent of modeling strategic charging of SAEVs across two regions is not to compare results but to use a smaller region to highlight recommended technical and operational configurations of SAEV fleets from a total of 36 scenarios and to subsequently test the sensitivity of these configurations on a large-scale region with higher SAV demand and trip density that is likely to see a fleet of SAEVs first. The Bloomington network is comprised of 185 TAZs, 7,000 links, and 2,500 nodes across 74 square miles while the Chicago network has 1,961 TAZs, 31,900 links, and 19,400 nodes across 11,246 square miles. The population size of Bloomington is 120,000 versus nearly 11 million in Chicago. Since Chicago is a sprawling metropolitan region, only 50% of the population was sampled compared to 100% for Bloomington, with comparable fleet sizes of 1 SAEV per 100 residents of Bloomington and Chicago.

Table 3 Summary of Model Inputs

Region	**Bloomington**		**Chicago**	
DCFC EVCS				
Heuristic: x (plugs), y (miles), z (min)	5 plugs, 2 mi, 15 min		5 plugs, 2 mi, 15 min	
Number of Plugs	334		13,536	
Number of Stations	15		1,267	
Charger Speed (kW)	50		50	
Vehicle Range	**100-mi**	**250-mi**	**100-mi**	**250-mi**
Short-range (SR) only (%)	100%	0%	100%	0%
Long-range (LR) only (%)	0%	100%	0%	100%
Mixed-range (MR) (%)	50%	50%	50%	50%
Fleet Size (Vehicles)	1,191		49,768 (for 50%)	
People-to-SAEV Ratio	100:1		100:1	
Decision-to-Charge Parameters				
Minimum SoC (%)	20%		20%	
Minimum Absolute Range (mi)	30 mi		30 mi	
Minimum Idle Time (min)	15 min	60 min	15 min	

EV Charging Parameters					
Maximum SoC (%)	80%	85%	90%	85%	
Exit Charging Early	Yes		No	Yes	No
Base SAEV Assumptions					
Starting SoC (%)	Normal (μ = 70, σ = 5)			Normal (μ = 70, σ = 5)	
Vehicle Efficiency	30 kWh per 100 mi			30 kWh per 100 mi	

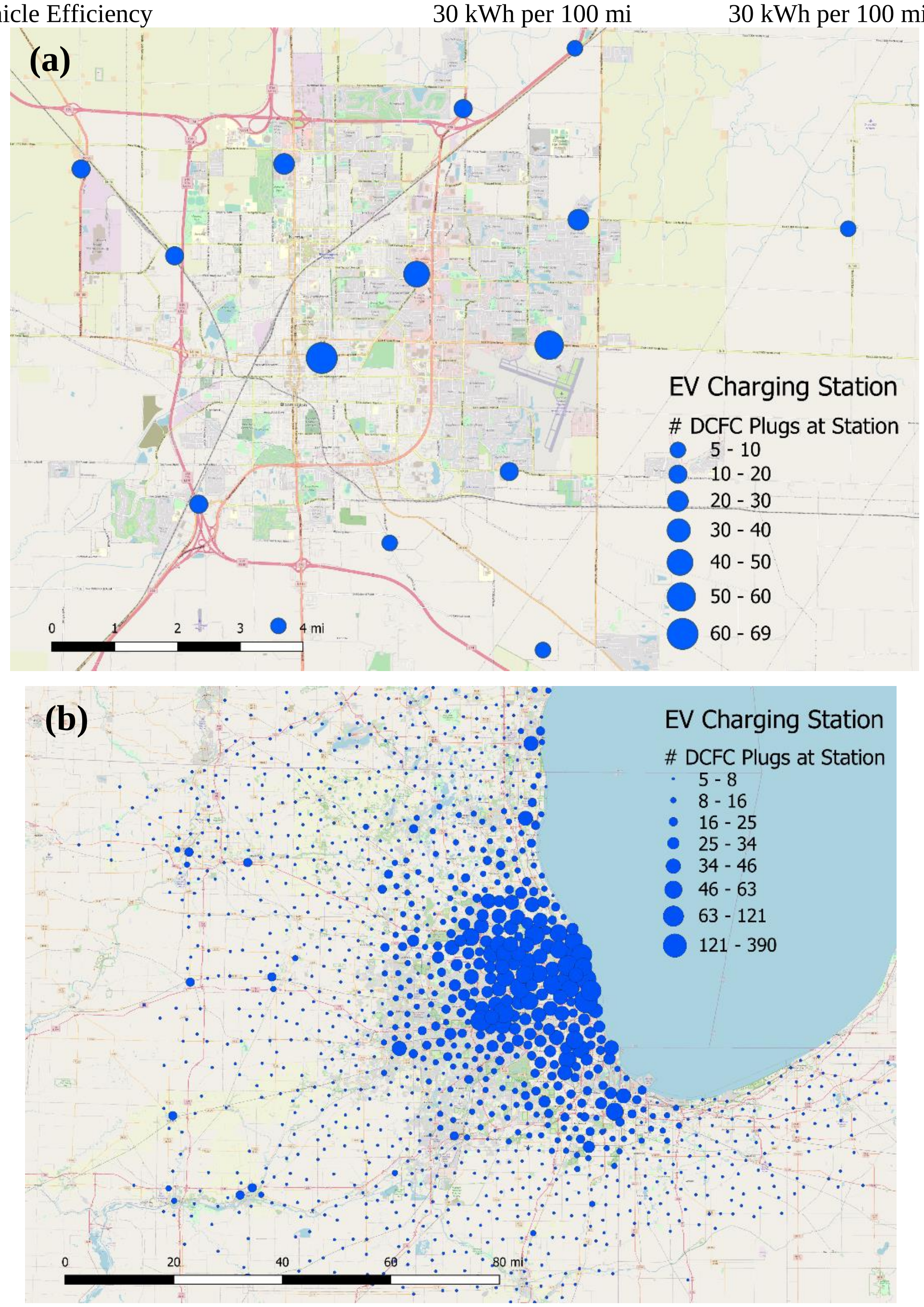

Figure 1 (a) Bloomington and **(b)** Chicago Road Networks with EVCS Locations and Sizing

RESULTS

Table 3 shows the EVCS network inputs and outputs alongside the fleet of SAEVs by range configuration with five additional categories of SAEV fleet specification, resulting in a set of 36 scenarios for Bloomington. Several charging strategies were studied here to identify key characteristics that improved fleet performance in terms of eVMT added, trips served per SAEV per day, and average number of trips to the charging station per SAEV per day. This process identified 6 additional scenarios to test for the Greater Chicago region: charging versus service priority, and policies across the three vehicle range fleet options. The results from this two-step process are presented below in two sub-sections.

Bloomington Region

The base case of SAVs without range or charging constraints was also simulated with the same fleet size (1,191 SAVs) for comparing the SAEV operation to that of SAVs. DRS-enabled SAVs were able to serve 50.7 person-trips per SAV per day adding about 19.1% eVMT thanks to a revenue-trip average vehicle occupancy (AVO) of about 1.69. This constituted 10% in mode share for the small region of Bloomington. Without range constraints, SAVs, on average, traveled 292.5 mi per SAV per day, idling about 62.1% of the day. The added downtime due to charging and subsequent spatial imbalance of SAEVs responding from an EVCS will likely alter charging VMT (cVMT) and lower demand. Hence, the drop in demand from this base scenario is of interest.

The results of 36 SAEV-specific scenarios are summarized here, under the broad categories of the fleet distribution: SR, LR, and MR. Charging speeds assumed here imply about 30 and 75 minutes of charging for SR and LR vehicles, respectively, and this may leave some SAEVs unable to serve trips at peak periods of the day. A fleet size of 1,191 SAEVs was assumed here and the demand served was compared to that of the unconstrained base case.

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

Table 4 highlights the effect of charging strategy on the SAEV fleet performance when assuming a homogenous fleetwide range of 100-miles (SR), 250-miles (LR), and a 50-50 combination of the two ranges (MR), revealing that range and flexible charging policies have the largest effect on fleet performance, particularly in daily trips served per SAEV and unoccupied travel. The magnitude of difference in average trips served compared to an SAV fleet is low for an LR fleet, but worthy of investigation for SR and MR fleets. It is important to remember that the small Bloomington region has shorter than average trip lengths. The spatial and temporal distributions that affect trips served may see larger differences in large regions, as observed in the next sub-section.

Table 4 Fleet Range Composition on SAEV Fleet Performance

Range	Min. Idle Time	Max. SoC	Charging (C) / Service (S) Priority	% Empty VMT	% Charging VMT	Avg. Daily Person-Trips per SAEV	Avg. Daily Charging Trips per Charging SAEV	Avg. Time Spent at EVCS (in hr)	% Demand Change
SR (100 mi)	15 min	80%	C	23.4	3.6	48.8	5.4	1.3	-3.8
			S	23.5	3.9	49.0	5.8	1.4	-3.4
		85%	C	23.3	3.5	48.9	5.3	1.4	-3.6

			S	23.3	3.7	48.7	5.7	1.5	-3.9
		90%	C	22.9	3.4	49.1	5.1	1.5	-3.2
			S	23.3	3.7	48.9	5.6	1.5	-3.5
	60 min	80%	C	23.1	3.2	48.6	4.8	1.3	-4.3
			S	23.2	3.4	48.7	5.2	1.3	-4.1
		85%	C	22.9	3.1	49.2	4.6	1.3	-3.1
			S	23.0	3.3	48.9	5.1	1.3	-3.7
		90%	C	22.7	2.9	48.3	4.4	1.3	-4.9
			S	22.9	3.2	48.6	4.9	1.4	-4.2
LR (250 mi)	15 min	80%	C	21.9	2.5	50.0	3.7	2.0	-1.4
			S	21.6	2.7	50.6	3.8	2.1	-0.4
		85%	C	21.6	2.4	50.2	3.7	2.1	-1.2
			S	21.6	2.6	50.2	3.7	2.1	-1.0
		90%	C	21.5	2.4	50.4	3.6	2.3	-0.6
			S	21.5	2.4	50.7	3.7	2.2	0.0
	60 min	80%	C	21.1	1.9	49.9	2.8	1.5	-1.7
			S	21.1	2.0	50.2	2.9	1.5	-1.0
		85%	C	21.1	1.8	50.0	2.8	1.7	-1.4
			S	21.1	1.9	49.1	2.7	1.4	-3.0
		90%	C	20.8	1.8	50.1	2.6	1.7	-1.4
			S	20.8	1.9	50.2	2.8	1.6	-1.0
MR (50% 100 mi, 50% 250 mi)	15 min	80%	C	22.3	3.0	49.8	4.5	1.6	-1.8
			S	22.4	3.1	49.4	4.7	1.7	-2.6
		85%	C	22.2	2.9	49.3	4.3	1.6	-2.6
			S	22.4	3.1	50.0	4.6	1.8	-1.4
		90%	C	22.2	2.9	49.8	4.2	1.8	-1.7
			S	22.4	3.0	49.5	4.4	2.0	-2.6
	60 min	80%	C	22.1	2.5	49.4	3.8	1.4	-2.6
			S	22.0	2.6	48.8	3.9	1.3	-3.8
		85%	C	21.9	2.4	49.6	3.6	1.5	-2.1
			S	21.9	2.5	49.3	3.9	1.5	-2.8
		90%	C	21.6	2.3	49.7	3.5	1.6	-2.1
			S	21.7	2.5	49.6	3.8	1.6	-2.3

Compared to a similar-sized SAV fleet, demand for an SR SAEV fleet drops by 3-5%, a result due in part to vehicles spending on average about 1.4 hours of the day at an EVCS. This average time increases by about 10 minutes if SAEVs are permitted to serve additional trips when they reach an adequate SoC of 60% because vehicles, on average, require an additional 0.4 charging trips per day. The flexibility to serve trips marginally improves the average number of trips served per SAEV per day for lower battery cutoffs and when a 60-minute idling threshold is used. Percent eVMT is about 2-3% higher than the SAV scenario and can be directly attributed to the additional charging trips made by SAEVs, and, the potentially longer pick-up trips because of bunching at an EVCS. VMT from charging trips (cVMT) is around the 1.8% to 3.9% mark. Requiring a higher cutoff of SoC before unplugging from the charger has little to no effect on average time spent at an EVCS, as expected, since DCFC chargers' charge time is proportional to the battery capacity. Longer idling times before sending an SAEV increases the supply of vehicles to meet new rides, but surprisingly demand falls, likely from the low average SoC, and, thus, range.

Long-range SAEVs perform marginally better, serving on average 1.3 more trips per SAEV per day than the SR counterpart. LR vehicles have 2 fewer daily charging sessions, lowering cVMT to 1.8-2.7%, consequently lowering %eVMT. If service priority policy is implemented, the average time at an EVCS drops by 3.3%, subsequently increasing the number of average daily trips by 0.6 to 1.3. A high idle (60-min) and service priority policy lowered %eVMT relative to a high idle and charging priority policy for all battery cutoffs while increasing the average daily trips per SAEV. Interestingly, the low idle, 80% battery cutoff, service priority policy almost served as many trips as a fleet of SAVs, while the 85% and 90% thresholds did not show a similar trend. The low idle and 80% battery cutoff recharges vehicles in periods and areas of low demand while the service priority policy allows for flexibility in balancing supply and demand without repositioning policies.

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, and eVMT and average charging times are better than an SR fleet and worse than an LR fleet. The mixed range fleet inherits high daily charging trips from an SR fleet but also high charging durations from an LR fleet, resulting in more balanced charging episodes. Average daily trips served is around 48.8-50.0 per SAEV, compared to 49.1-50.7 per LR SAEV. The scenario with the highest daily trips was a low idle, 85% SoC cutoff, and service priority configuration and was similar to the best scenario for LR fleets (low idle, 90% cutoff and service priority). The total demand served in comparison to an SAV fleet continued to be about 1.4 to 3.8% lower. This is better than a 100% SR fleet and is likely economical as larger batteries are expected to cost more.

Charger Priority versus Service Priority

A service priority policy also increases average trips per SAEV per day while reducing average time spent at charging stations (for LR and MR fleets), thereby creating more demand for this mode. A downside to this operational flexibility is the extended low SoC of the fleet that remains depressed following the morning peak period as seen in Figure 2. SAEV fleets have the lowest SoC in the evening across all scenarios, as expected, and a combined service priority and high idle policy may lead to odd charging behavior over several days if the average fleet SoC is lower than at the start of the day. There is a clear tradeoff between meeting increased SAV demand at the morning peak period through service priority and high idle policies and sacrificing lower SoC for the remainder of the day. The operator should consider a time-dependent strategy that implements charger priority after the morning peak period and service priority during the peak hours, especially since the demand for SAVs is generally more acute during these periods. Although the average SoC is not logged at midnight, the trend is clear that the maximum 5% deficit will be recouped. The assumption of 70% average SoC is valid, and having up to 60 min idle times should not influence multi-day operations.

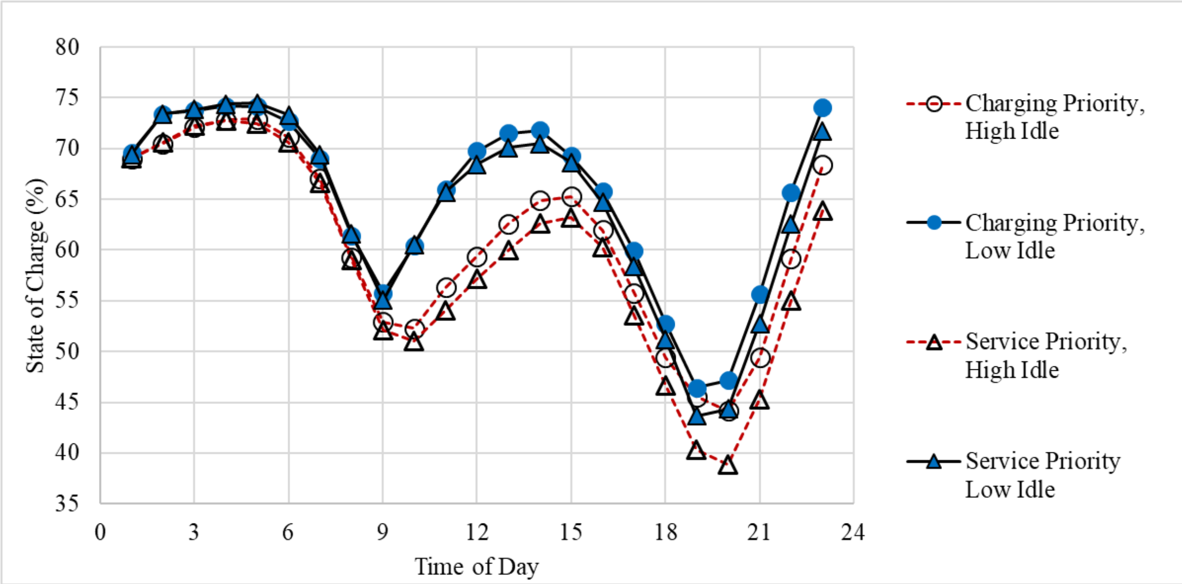

Figure 2 Fleet State of Charge by Time of Day, a LR 85% SoC Cutoff Scenario

Fleet Utilization

Figure highlights the fleet's utilization across different scenarios as a function of %eVMT and % idling time. SAEV range and charging-versus-service priority show the differences in utilization quite well. Compared to the SR and mixed fleet, the LR fleet has the lowest %eVMT as a direct consequence of having enough range to serve trips. The high idling percentage in a day with charging priority is rooted in average charge times and reduction in SAEV demand compared to the base SAV scenario. Allowing SAEVs to prioritize service improves user pick-up times, but at the cost of needing to charge multiple times throughout the day. The mixed fleet has relatively low %eVMT and % idling time and benefits more from the 50% LR SAEVs than the SR SAEVs in the fleet since SR vehicles may be adding more %cVMT for multiple charging trips in a day as shown in Figure 4. Although the mixed fleet has 50% each of SR and LR vehicles, the performance may be seen as a weighted average of the two ranges. Figure 4 shows that the mixed fleet under service priority can provide daily SAV trips near that of long-range fleets prioritizing charging, albeit at marginally higher %cVMT.

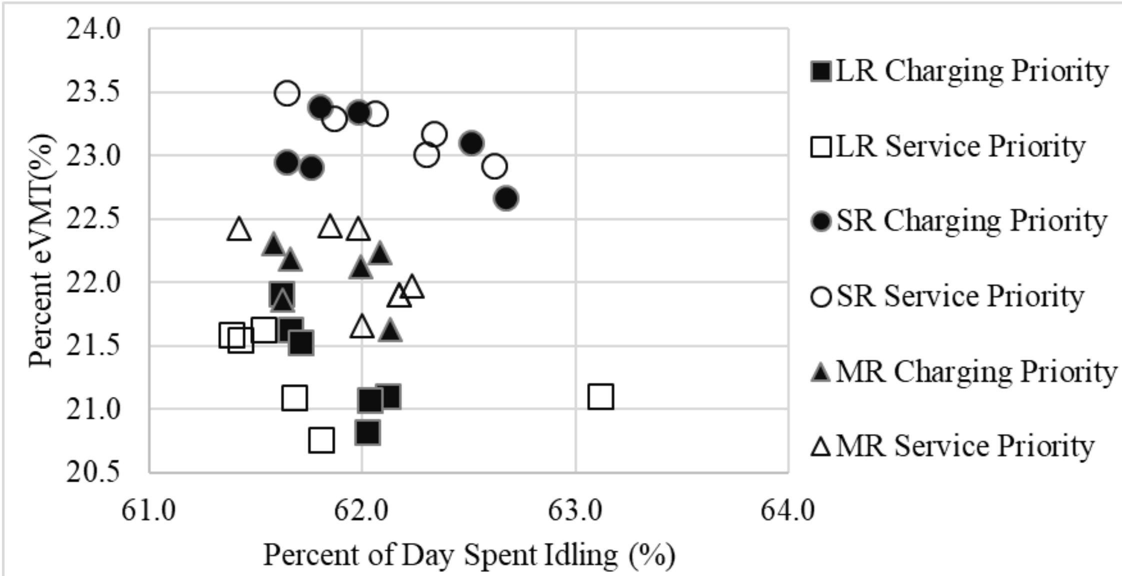

Figure 3 Fleet Utilization as a Function of Percent Empty VMT and Percent Idling Time

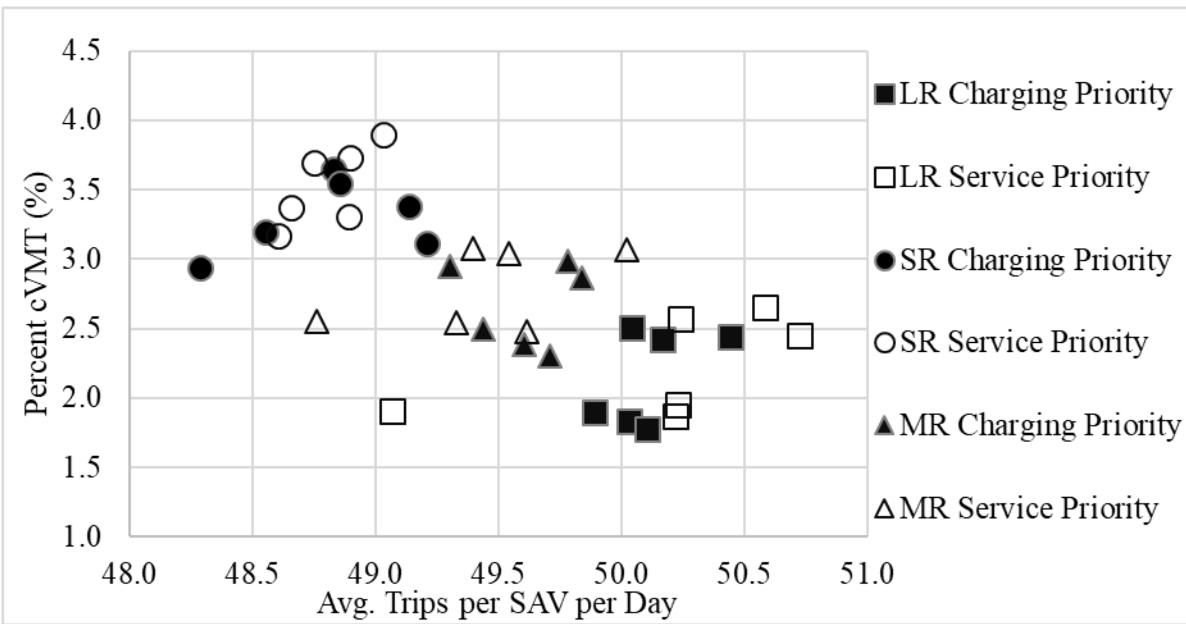

Figure 4 Fleet Utilization as a Function of Daily Trips per SAEV and Percent Charging VMT

Dynamic Ride-Sharing

There was no effect of the choice of fleet composition and charger-versus-service priority on the revenue-trip AVO for the case of Bloomington when considering 1 SAEV available every 100 residents. Minimum idle time and SoC cutoffs did not increase or decrease AVO significantly. A smaller fleet serving trips in Bloomington may have characterized a marked difference in range and priorities. With average idling time in the day at 62%, the chosen fleet size may have been ideally sufficient for balancing trip requests and response times. Average response times per request were around 4.3 min and comparable to a similarly-sized SAV fleet.

Chicago Region

The 36 scenarios with Bloomington helped narrow down the effect of certain charging parameters such as maximum idle time before sending an SAEV to charge, and the preferred maximum SoC cutoff while charging. Six scenarios were run for a 50% sample of Chicago owing to the 7-hour runtime for each scenario. Table 5 shows fleet metrics such as %eVMT, %cVMT, AVO, average daily trips per SAEV, average time spent at an EVCS, and the % change in demand owing to range constraints. The case study of Chicago is interesting since the region exhibits urban sprawl, as well as a high density of SAV trips in the city center, higher than most sprawling metropolitan regions. This sprawl meant that SAVs served about 22.9 person-trips per day, on average, or less than half as much as a vehicle in the Bloomington fleet. Each SAV traveled over 318.8 mi per day and transported about 1.59 travelers per revenue-trip. SAVs add about 11.2% eVMT assuming there is no need to refuel for gasoline. This is lower than the %eVMT added by the Bloomington fleet, and can be attributed to the slightly smaller per capita fleet size.

Similar sized fleets of range-constrained SAEVs serve fewer daily trips (about 20 person-trips per day per SAEV) across all range configurations as expected, and the person-trips difference was traded for an approximately equal number of charging trips per day. Chicago's SAEV fleet performs as expected across all metrics except AVO and % demand change. Time spent at an EVCS in a day, on average, is consistent across fleet ranges, and this reflects the equilibrium between the number of charging trips and charging time based on range. SR fleet vehicles need to make 2 more charging trip per day, on average, compared to an LR fleet vehicle, whereas the MR fleet vehicles exhibit an intermediate average number of charging trips per SAEV per day thanks to the mixture. The AVO of the SAEV fleet decreased compared to an SAV fleet, since the downtime of charging SAEVs temporarily lowered supply such that available SAEVs could not sufficiently compensate. This also, unexpectedly, led to a decrease in demand, nearly 8%, from range constraints. Varying regional extents impact SAV and SAEV fleet performance differently. While some operational characteristics, such as maximum SoC, minimum idle time, and fleet range composition impact fleet performance consistently across different regions, fleet size and operational behavior differ.

Table 5 SAEV Fleet Performance in Chicago

Range	Charging (C) / Service (S) Priority	Avg. SAV VMT per day	% Empty VMT	% Charging VMT	Avg. Daily Person-Trips per SAEV per day	Revenue-Trip AVO	Avg. Daily Charging Trips per SAEV per Day	Avg. Time Spent at EVCS (in hr)	% Demand Change
Gasoline-powered SAV	-	318.8	11.2	-	22.1	1.59	-	-	-
SR (100 mi)	C	289.6	15.4	2.7	20.7	1.47	4.8	1.4	-6.3
	S	283.7	15.7	2.9	20.5	1.42	5.1	1.5	-7.1
LR (250 mi)	C	292.3	13.1	1.6	20.4	1.60	2.8	1.9	-7.6
	S	293.0	13.1	1.7	20.5	1.57	3.0	2.0	-7.1
MR (50% 100 mi, 50% 250 mi)	C	289.9	14.2	2.1	20.4	1.54	3.8	1.6	-7.6
	S	287.0	14.3	2.3	20.3	1.50	4.1	1.7	-7.8

Utilizing Existing EVCS Versus Siting Depot-Owned DCFC EVCS

In addition to modeling a mixed-range (MR) fleet of vehicles to determine the tradeoffs between procuring more affordable SR vehicles and accessing the range benefits of LR vehicles (e.g., fewer charging trips per day increasing vehicle utilization), this study explored whether existing public charging stations could support a future fleet of SAEVs. Certainly, the transition to electric mobility will drive the growth of and demand for public charging infrastructure. Private EVCS networks (e.g., Tesla, ChargePoint, EVgo) may opt to retrofit their stations with self-docking plugs or wireless charging for AV compatibility to increase utilization, especially during non-business hours. Then, the spatial distribution of current charging infrastructure and charger types will likely impact future fleet operation in the form of added cVMT and, perhaps, increase response times, given that existing infrastructure has predominately concentrated at civic buildings, large retail developments, and universities. The impact of using the existing EVCS infrastructure (as of 2017) was compared to the private DCFC EVCS generated for SAEVs.

Figure 5 shows the spatial distribution of the existing EVCS infrastructure compared to fleet-owned DCFC, sited according to a heuristic strategy. The public network has 33 stations with a total of 62 plugs. All stations have L2 plugs, except one with 5 additional DCFC plugs, and another with one additional L1 plug. The fleet-owned network has 26 stations with a total of 225 plugs. Although there are fewer stations, the cord count increases by 263% and all plugs are DCFC. A direct result of this set up is the decrease in average time spent queuing for an available plug at a charging station, between 36% and 45% depending on range configuration, but with a comparable percentage of cVMT. The lower average charging duration increased the supply of available vehicles and reduced passenger wait times by 78-81%. Since response times are improved due to a greater supply of sufficiently-charged SAEVs when relying on an all-DCFC network, the average daily trips per short range SAEV increased by 306% (or from 10.0 to 40.7 average trips per SAEV). Even LR fleets had a noticeable 115% improvement (from 19.7 to 42.4 average trips per SAEV). The tradeoff between modifying existing charging stations to meet fleets of on-demand SAEVs is clear. Relative to a fleet of gasoline-powered SAVs, demand for SAEVs falls, on average, by 76.7% for SR, 54.2% for LR, and 63.1% for MR fleet configurations when SAEVs use existing charging stations. Using a dedicated DCFC EVCS network for SAEVs lowers demand only by 2.3-6.3% across all range configurations.

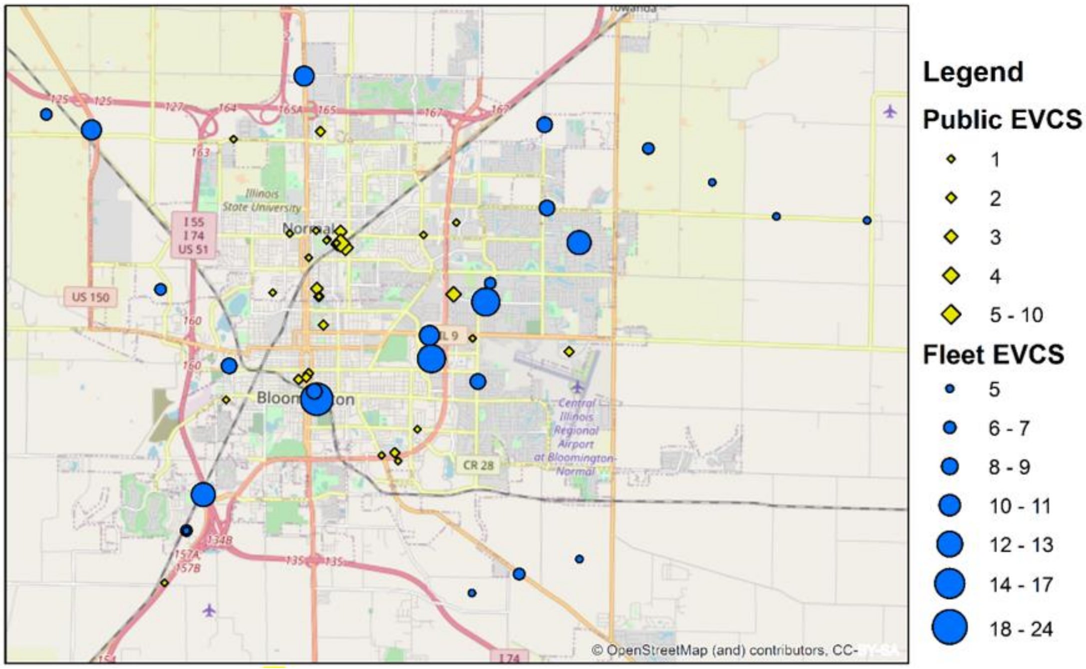

Figure 5 Comparison of Public and Fleet-Owned EVCS in Bloomington
(Note: Marker scales differ)

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 36 scenarios were simulated for Bloomington, IL and 6 scenarios for Chicago, IL using the agent-based tool POLARIS to learn the impact of fleet choice and charging strategy on fleet performance and system impact, in two distinct regions.

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 Bloomington fleet experienced a marginal increase in %eVMT compared to an SAV fleet (+4%), and MR (+1%) and LR (+2%) SAEV fleets. The SR and MR fleets in Chicago saw larger increases in %eVMT compared to the SAV fleet (at 11.2%), as well as the LR SAEV fleet (at 13%), as the average trip length in the region is about 3 times longer than Bloomington's, and trips served by SAEVs are twice as long between the two regions. The use of a mixed fleet may be helpful in the short term to maximize the number of trips served while keeping added %eVMT at a nominal value. This is also true when there is limited EVCS infrastructure available, unlike gas stations on nearly every other block. Prioritizing service over charging is useful in improving the average daily trips served per SAEV but this may keep the SoC low, on average, throughout the day. Service priority makes the most sense at peak times of day while simultaneously prioritizing charging during the off-peak periods ensures better average SoC. Yet, sprawling regions may not benefit from time-dependent charging and service priority policies, as each SAEV is exposed to a smaller number of trips that it can service, so the tradeoff between charging or prioritizing service is not critical. Battery cutoff levels to prevent battery degradation long-term exhibited marginal effects on fleet performance, as did minimum idling policies designed to proactively send vehicles to charge at low-demand periods. Maximum SoC assumptions between 80-85% used in current studies are sufficient from an operational perspective, but the low minimum idling thresholds (15-minutes and shorter) will add eVMT while also presenting an opportunity cost of serving additional new trips.

The use of EVCS capacity and queuing adds realism that some prior models missed. Even with DCFC stations, vehicles in an SAEV fleet designed for small regions can expect to spend up to 2 hours a day charging, whereas SAEVs operating in a large region, like Chicago, will have a nearly individualized plug access from siting EVCS across the region, as opposed to a primarily central-placement of EVCS in Bloomington. The results indicate a near 1:1 relationship between an increase in the ratio of SAEVs per charger and the expected decrease in time spent at a charging station per day. Demand reductions seen from a comparable SAV fleet is expected, but the magnitude is rooted in the fleet composition, regional extent, and charging strategies studied here. Larger regions need more SAEVs per capita for adequate service (trips and response time), but may serve 10% fewer trips due to long trip lengths. Smaller regions see smaller reductions in demand, since the constrained fleet (fraction of vehicles not charging) can still access all trip requests and maximize seat use assuming travelers are comfortable sharing rides.

The use of current EVCS infrastructure and plug availability in Bloomington throws light on the importance of these charging strategies near-term, if current infrastructure is to play a part in an SAEV fleet. The use of predominantly Level 2 plugs at most existing charging stations poses a significant constraint on fleet performance of SAEVs not only due to queue times, but also for longer charging episodes, as the average Level 2 charging time is about 1.5-2.0 hours, or 4 times as long as an average DCFC charging episode. Charging priority was found most important only in this setting owing to the long charge times, and can be an important strategy in the next decade, especially when applied at off-peak times of day. The extent to which strategic siting and sizing of EVCS infrastructure and fleet size methods are pursued may affect supply-side configuration results, perhaps, only the relative differences. The contribution of a mixed range fleet demonstrates the possibility to achieve low %eVMT and low idling time nearly on par with an LR-only fleet, at a substantially lower price (due to high costs of batteries at present).

Limitations and Future Work

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 arisis between modeling travel demand behaviorally well versus making distributional assumptions in order 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 possible and will likely be done in due time. Another limitation arises from the continuous improvement of EV battery ranges. Although prior work has introduced SR vehicles (max 100 miles), advancements in battery chemistry and pack architecture suggest future research should operate under the assumption that current LR vehicles (max 250 miles) will be the minimum range offered in most EV brands (Bloomberg New Energy Finance (BNEF), 2020). Further, fleet operators will want to maximize uptime to meet revenue-generating opportunities and will select battery capacities that meet expected daily mileage and duty cycles. The LR fleet in the Chicago case study had about 3.0 charging trips per vehicle in a day, on average. Either expected range should increase to reduce charging trips to once daily, or modelers should unlock additional range by relaxing SoC buffers. Recent real-world battery degradation data suggests that battery degradation may be no more than 5% of original capacity for advanced packs (Lambert, 2018), which would be attractive to SAEV fleet operators that expect high annual mileage.

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AUTHOR CONTRIBUTION STATEMENT

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

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. Eur. J. Oper. Res. 284, 1088–1106. https://doi.org/10.1016/j.ejor.2020.01.033

Argue, C., 2019. What can 6,000 electric vehicles tell us about EV battery health? [WWW Document]. Geotab. URL https://www.geotab.com/blog/ev-battery-health/ (accessed 5.4.20).

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. Transp. Res. Part C Emerg. Technol. 64, 101–116. https://doi.org/10.1016/j.trc.2015.07.017

Auld, J., Verbas, O., Stinson, M., 2019. Agent-Based Dynamic Traffic Assignment with Information Mixing. Procedia Comput. Sci., The 10th International Conference on Ambient Systems, Networks and Technologies (ANT 2019) / The 2nd International Conference on Emerging Data and Industry 4.0 (EDI40 2019) / Affiliated Workshops 151, 864–869. https://doi.org/10.1016/j.procs.2019.04.119

Balding, M., Whinery, T., Leshner, E., Womeldorff, E., Fehr & Peers, 2019. Estimated Percent of Total Driving by Lyft and Uber In Six Major US Regions, September 2018 (No. SF19-1016). Fehr & Peers.

Basso, R., Kulcsár, B., Egardt, B., Lindroth, P., Sanchez-Diaz, I., 2019. Energy consumption estimation integrated into the Electric Vehicle Routing Problem. Transp. Res. Part Transp. Environ. 69, 141–167. https://doi.org/10.1016/j.trd.2019.01.006

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

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

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. Transp. Res. Part Policy Pract. 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 Comput. Sci. 83, 237–244. https://doi.org/10.1016/j.procs.2016.04.121

Bischoff, J., Márquez-Fernández, F.J., Domingues-Olavarría, G., Maciejewski, M., Nagel, K., 2019. Impacts of vehicle fleet electrification in Sweden – a simulation-based assessment of long-distance trips, in: 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS). Presented at the 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), pp. 1–7. https://doi.org/10.1109/MTITS.2019.8883384

Bloomberg New Energy Finance (BNEF), 2020. BNEF Electric Vehicle Outlook Report 2020.

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

Bösch, P.M., Ciari, F., Axhausen, K.W., 2016. Autonomous Vehicle Fleet Sizes Required to Serve Different Levels of Demand. Transp. Res. Rec. 2542, 111–119. https://doi.org/10.3141/2542-13

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

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

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

de Souza, F., Gurumurthy, K.M., Auld, J., Kockelman, K.M., 2020. A Repositioning Method for Shared Autonomous Vehicles Operation. Procedia Comput. Sci. 170, 791–798. https://doi.org/10.1016/j.procs.2020.03.154

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 Comput. Sci. 151, 858–863. https://doi.org/10.1016/j.procs.2019.04.118

Demir, E., Bektaş, T., Laporte, G., 2014. A review of recent research on green road freight transportation. Eur. J. Oper. Res. 237, 775–793. https://doi.org/10.1016/j.ejor.2013.12.033

EVAdoption, 2019. BEV Models Currently Available in the US – EVAdoption [WWW Document]. URL https://evadoption.com/ev-models/bev-models-currently-available-in-the-us/ (accessed 6.11.20).

Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. Part Policy Pract. 77, 167–181. https://doi.org/10.1016/j.tra.2015.04.003

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. Transp. Res. Part C Emerg. Technol. 40, 1–13. https://doi.org/10.1016/j.trc.2013.12.001

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

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

Gurumurthy, K.M., Kockelman, K.M., 2020. How Much Does Greater Trip Demand and Aggregation at Stops Improve Dynamic Ride-Sharing in Shared Autonomous Vehicle Systems? Presented at the 2nd Bridging Transportation Researchers, p. 12.

Han, X., Ouyang, M., Lu, L., Li, J., 2014. A comparative study of commercial lithium ion battery cycle life in electric vehicle: Capacity loss estimation. J. Power Sources 268, 658–669. https://doi.org/10.1016/j.jpowsour.2014.06.111

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

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

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

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

Iacobucci, R., McLellan, B., Tezuka, T., 2018. Modeling shared autonomous electric vehicles: Potential for transport and power grid integration. Energy 158, 148–163. https://doi.org/10.1016/j.energy.2018.06.024

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

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

Lambert, F., 2018. Tesla battery degradation at less than 10% after over 160,000 miles, according to latest data. Electrek. URL https://electrek.co/2018/04/14/tesla-battery-degradation-data/ (accessed 11.5.20).

Li, L., Lin, D., Pantelidis, T., Chow, J., Jabari, S.E., 2019. An Agent-based Simulation for Shared Automated Electric Vehicles with Vehicle Relocation*, in: 2019 IEEE Intelligent Transportation Systems Conference (ITSC). Presented at the 2019 IEEE Intelligent Transportation Systems Conference - ITSC, IEEE, Auckland, New Zealand, pp. 3308–3313. https://doi.org/10.1109/ITSC.2019.8917253

Litman, T., 2020. Autonomous Vehicle Implementation Predictions: Implications for Transport Planning.

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. Transp. Res. Part Policy Pract. 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. Transp. Res. Part C Emerg. Technol. 89, 222–233. https://doi.org/10.1016/j.trc.2018.01.019

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

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. Int. J. Sustain. Transp. 13, 111–122. https://doi.org/10.1080/15568318.2018.1443178

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

Sheppard, C., Waraich, R., Campbell, A., Pozdnukov, A., Gopal, A.R., 2017. 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). https://doi.org/10.2172/1398472

Sheppard, C.J.R., Bauer, G.S., Gerke, B.F., Greenblatt, J.B., Jenn, A.T., Gopal, A.R., 2019. Joint Optimization Scheme for the Planning and Operations of Shared Autonomous Electric Vehicle Fleets Serving Mobility on Demand. Transp. Res. Rec. 2673, 579–597. https://doi.org/10.1177/0361198119838270

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

Simoni, M.D., Kockelman, K.M., Gurumurthy, K.M., Bischoff, J., 2019. Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios. Transp. Res. Part C Emerg. Technol. 98, 167–185. https://doi.org/10.1016/j.trc.2018.11.002

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

Stocker, A., Shaheen, S., 2019. Shared Automated Vehicle (SAV) Pilots and Automated Vehicle Policy in the U.S.: Current and Future Developments, in: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation 5, Lecture Notes in Mobility. Springer International Publishing, pp. 131–147.

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

US Environmental Protection Agency, 2020. Fuel Economy of New All-Electric Vehicles [WWW Document]. New -Electr. Veh. URL https://www.fueleconomy.gov/feg/PowerSearch.do?action=alts&path=3&year1=2019&year2=2021&vtype=Electric&srchtyp=newAfv (accessed 6.11.20).

US Environmental Protection Agency, 2019. Fast Facts on Transportation Greenhouse Gas Emissions [WWW Document]. Green Veh. Guide. URL https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions (accessed 4.17.20).

Verbas, Ö., Auld, J., Ley, H., Weimer, R., Driscoll, S., 2018. Time-Dependent Intermodal A* Algorithm: Methodology and Implementation on a Large-Scale Network. Transp. Res. Rec. 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. Transp. Res. Part Transp. Environ. 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. Transp. Res. Part C Emerg. Technol. 107, 15–33. https://doi.org/10.1016/j.trc.2019.08.006

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. Understanding the Impact of Trip Density and Demand on Shared Autonomous Vehicle Fleet Performance in the Minneapolis-Saint Paul Region 20.

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

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