STRATEGIC CHARGING OF SHARED FULLY-AUTOMATED ELECTRIC VEHICLE (SAEV) FLEETS

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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 SAEV fleet managers will need to account for charging times and range limitations of EV battery packs. This study investigates a variety of potential SAEV fleet design 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. Results show a mixed fleet of short (100-mi) and long (250-mi) range SAEVs performs better than a homogenous 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. 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. Homogenous fleets need careful prioritizing of charging over service for

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an acceptable multi-day operation. 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 gas (GHG) and consume 58% 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 a 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 are 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, and then followed by recommendations for good forecasting practice in large-scale models, and concluding remarks.

LITERATURE REVIEW

The first simulation-based studies on 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), 30-min and 4-hour maximum charge times respectively) across a 100-mile x 100-mile gridded city 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 (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 EVCSs were generated like 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 from 8.4 to 5.1 minutes and marginally improved 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 place charging stations based on two distance- and coverage-based optimization schemes using estimated SAV demand (Vosooghi et al., 2019), vary the vehicle-to-outlet ratio, and explore 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) reduces 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 outlets by up to 67% from a baseline ratio of 1 charger to 4 SAEVs.

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). 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. System performance have largely varied across study thanks to key decisions concerning SAEVs. The next sub-sections characterizes SAEV simulation literature by the framework's decisions to send vehicles to charge, the SoC buffer, and the flexibility of vehicle states as it relates to charging.

Decision to Charge

Vehicles wait in place until 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., 60 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 meet an additional trip. Although no one has 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 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 is 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. A simplification in large-scale analyses is a linear charging rate constrained by minimum and maximum SoC. 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. 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 7 kW to 50 kW and assume homogenous charger type such that results correspond to a specific charger level. The ratio of vehicles-to-plugs varies typically from 1.9 to 32.5 as does the underlying number of plugs per station, 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)

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, the operator forgoes the opportunity to concurrently assign vehicles to charging stations in zones with predicted demand, thereby minimizing eVMT. 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)).

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. The SAEV module is used in this paper understand the sensitivity of charging strategies on fleet operation. 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).

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, 2020; Vosooghi et al., 2020). Thus, the current four-seater battery electric vehicles (BEVs) available in the U.S. having advertised 84 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 pickups and dropoffs) 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. If the SoC or available range falls below the minimum threshold that is pre-defined, 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 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 which aim to improve efficiency. The linear charging rate is estimated using EPA data for 2019 BEVs (EPA, 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, EVCSs were generated in a simulation run with all SR vehicles while prioritizing service and a 30-minute idle charging threshold to have a enough stations across the region for the 15-min idle input used for scenario testing. A minimum of 5 plugs are assumed at an EVCS, and is created when an existing EVCS is not within 15 mi (50% of the minimum absolute threshold assumed). A new plug is generated when vehicles wait longer than 15 min (50% of the average charging time using a DCFC). In summary, there are 6.4 vehicles per charger and a station density of 0.35 EVCS per square mile (Figure 1).

Table 3 Summary of Model Inputs

DCFC EVCS	**Total**		
Heuristic: x (plugs), y (miles), z (min)	5 plugs, 15 mi, 15 min		
Number of Plugs	225		
Number of Stations	26		
Present Charger Speed (kW)	50		
Vehicle Range	**100-mi**	**250-mi**	**TOTAL**
Short-range (SR) only (%)	100%	0%	
Long-range (LR) only (%)	0%	100%	1440 SAEVs
Mixed-range (MR) (%)	50%	50%	
Decision-to-Charge Parameters			
Minimum SoC (%)	20%		
Minimum Absolute Range (mi)	30 mi		
Minimum Idle Time (min)	15 min	60 min	
EV Charging Parameters			
Maximum SoC (%)	80%	85%	90%
Exit Charging Early	Yes	No	
Base SAEV Assumptions			
Starting SoC (%)	N(70,5)		
Vehicle Efficiency	30 kWh per 100 mi		

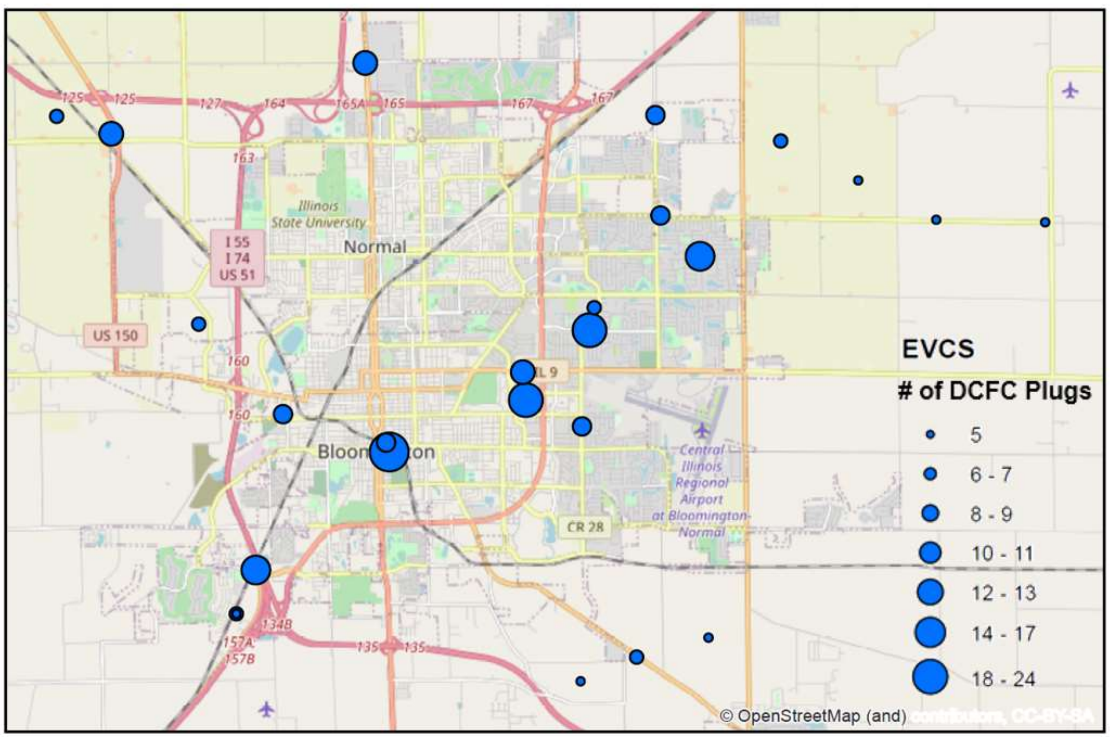

Figure 1 Bloomington road network with EVCS locations

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. 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. The base case of SAVs without range or charging constraints was also simulated with the same fleet size (1440 SAVs) for comparing the SAEV operation to that of SAVs. DRS-enabled SAVs were able to serve between 43.4 trips per SAV per day adding about 18.9% eVMT thanks to a revenue-trip average vehicle occupancy (AVO) of about 1.64. This constituted 10% in mode share for the small region of Bloomington. Without range constraints, SAVs, on average, traveled between 246.8 mi per SAV per day, idling about 67% of the day. The added downtime due to charging and subsequent spatial imbalance of SAEVs responding from an EVCS will likely increase response time and lower demand, hence, the drop in demand from these two base scenarios is of interest.

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. Although the magnitude difference in average trips served is low here, 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.

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 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	22.7	3.7	40.7	5.0	4.4	-6.1
			S	22.4	4.2	40.9	5.6	4.3	-5.6
		85%	C	22.2	3.6	40.5	4.8	4.2	-6.4
			S	22.3	4.0	41.2	5.4	4.5	-5.9
		90%	C	22.3	3.6	40.8	4.6	4.5	-6.0
			S	22.2	4.0	40.9	5.3	5.0	-5.4
	60 min	80%	C	22.5	3.4	40.1	4.3	4.3	-7.2
			S	22.2	3.9	40.6	5.0	4.2	-6.5
		85%	C	22.1	3.2	40.9	4.2	4.2	-6.0
			S	22.1	3.8	40.3	4.7	4.5	-6.8
		90%	C	21.9	3.1	40.4	4.0	4.2	-6.7
			S	22.1	3.8	40.5	4.7	4.4	-6.8
LR (250 mi)	15 min	80%	C	21.1	2.5	41.9	3.3	3.9	-3.0
			S	21.0	2.6	43.1	3.7	3.7	-0.8
		85%	C	21.2	2.4	42.0	3.2	4.1	-3.1
			S	20.9	2.6	42.9	3.6	4.3	-1.1
		90%	C	21.1	2.3	42.2	3.1	4.5	-2.9
			S	20.9	2.6	43.0	3.5	4.6	-1.5

	60 min	80%	C	20.5	1.8	42.0	2.5	3.2	-3.0
			S	20.5	1.9	42.6	2.8	3.1	-1.6
		85%	C	20.6	1.8	41.6	2.4	3.3	-4.2
			S	20.5	2.0	42.6	2.7	3.3	-1.6
		90%	C	20.5	1.7	41.4	2.3	3.7	-3.9
			S	20.4	2.0	42.7	2.7	3.0	-1.4
MR (50% 100 mi, 50% 250 mi)	15 min	80%	C	21.6	3.1	42.1	4.2	4.1	-3.4
			S	21.7	3.4	41.9	4.5	3.9	-3.1
		85%	C	21.7	3.1	42.1	4.0	4.1	-3.0
			S	21.6	3.3	42.3	4.5	4.2	-2.0
		90%	C	21.7	3.0	41.8	3.8	4.5	-3.6
			S	21.5	3.2	41.9	4.3	4.1	-2.6
	60 min	80%	C	21.5	2.6	41.3	3.4	3.3	-4.8
			S	21.2	2.9	41.7	3.8	3.6	-3.6
		85%	C	21.2	2.4	41.8	3.3	3.3	-3.5
			S	21.1	2.8	42.2	3.8	3.4	-2.4
		90%	C	21.0	2.4	41.9	3.2	3.5	-3.4
			S	21.1	2.7	42.6	3.6	3.7	-2.6

Short-Range SAEVs

Compared to a similar-sized SAV fleet, demand for an SR SAEV fleet drops by 5-7%, a result due in part to vehicles spending on average about 4.4 hours of the day at an EVCS. This average time increases by about 12 minutes if SAEVs are permitted to serve additional trips when they reach an adequate SoC of 60% because vehicles, on average, require an additional 0.6 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 pickup trips because of bunching at an EVCS. VMT from charging trips (cVMT) is around the 3-4% 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 range.

Long-Range SAEVs

Long-range SAEVs perform marginally better, serving on average 1.6 more trips per SAEV per day than the SR counterpart. LR vehicles have 2 fewer daily charging sessions, lowering cVMT to 1.7-2.6%, consequently lowering %eVMT. If service priority policy is implemented the average time at an EVCS drops by 3.3%, subsequently increasing the 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. However, the efficacy of this policy is unclear.

Mixed-Range SAEVs

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, but 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 a SR fleet but also high charging durations from a LR fleet, resulting in more balanced charging episodes. Average daily trips served is around 41.3-42.6 per SAEV, compared to 41.4-43.1 per LR SAEV. The scenario with the highest daily trips was a high idle, 90% SoC cutoff, and service priority configuration and was a contrast to the best scenario for LR fleets (low idle, 80% cutoff and service priority). The total demand served in comparison to an SAV fleet continued to be lower, at about 2.0-4.8% lower. This is better than 100% SR fleet and is likely economical as larger batteries are expected to cost more.

Charger Priority versus Service Priority

The flexibility to interrupt charging and send SAEVs to serve new requests tends to improve average response times marginally. Figure 2 shows this effect for LR fleets while controlling for battery cutoff and minimum idling policies. These response time differences are expected to increase for large regions. 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 3. Fleets have the lowest fleet average 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 there may be a 5-15% difference to catch up on if the assumption of 70% average SoC needs to hold, so prioritizing charging and service can have a significant effect on multi-day operation.

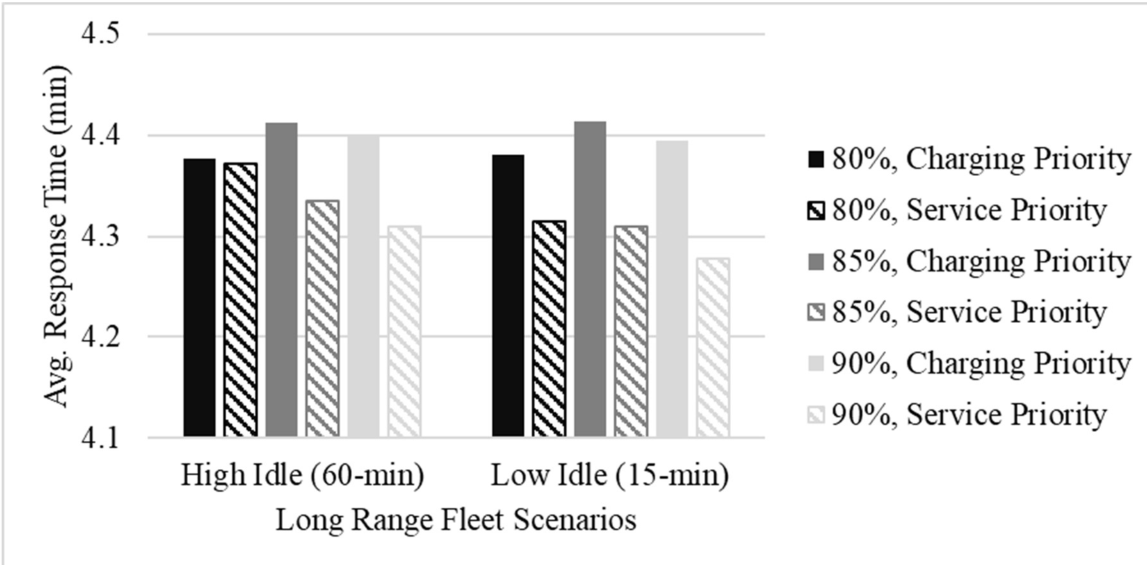

Figure 2 Effect of flexible discharge policies on average wait times

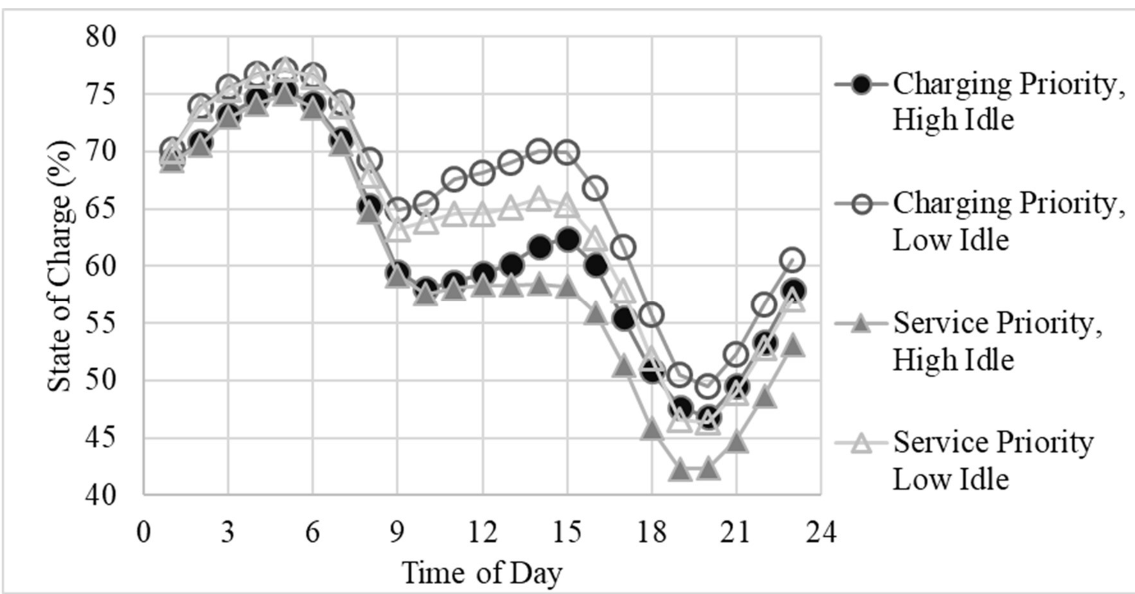

Figure 3 Fleet state of charge by time of day, a LR 85% SoC cutoff scenario

Fleet Utilization

Figure 4 highlights the fleet's utilization across different scenarios as a function of % eVMT and % idling time. SAEV range and charging-versus-service priority shows 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 to the base SAV scenario. Allowing SAEVs to prioritize service improves user pickup 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 seems to benefit more from the 50% LR SAEVs than the extra %cVMT that the SR SAEVs may be adding for multiple charging trips in a day as shown in Figure

5. 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 5 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.

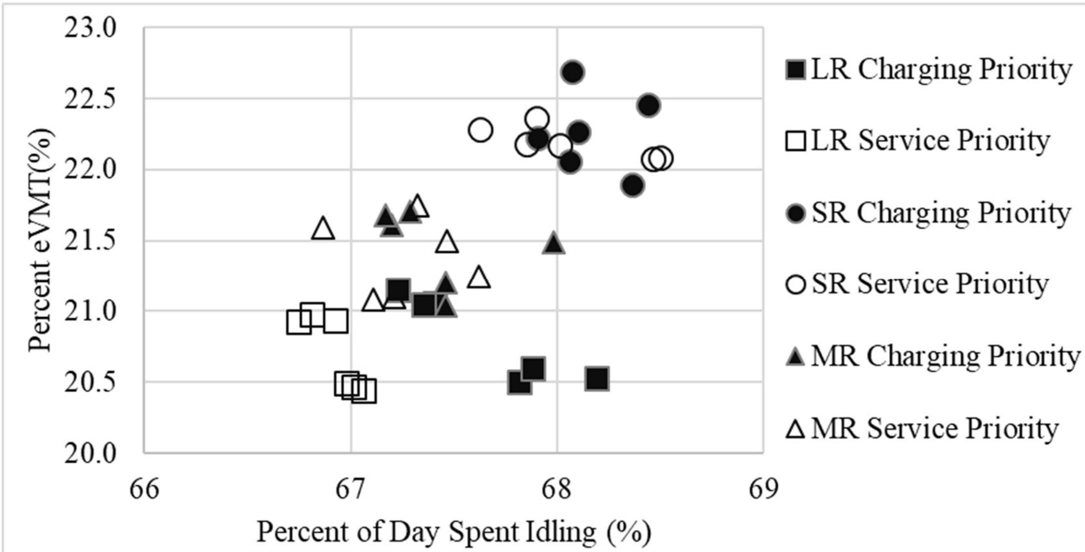

Figure 4 Fleet utilization as a function of percent empty VMT and percent idling time

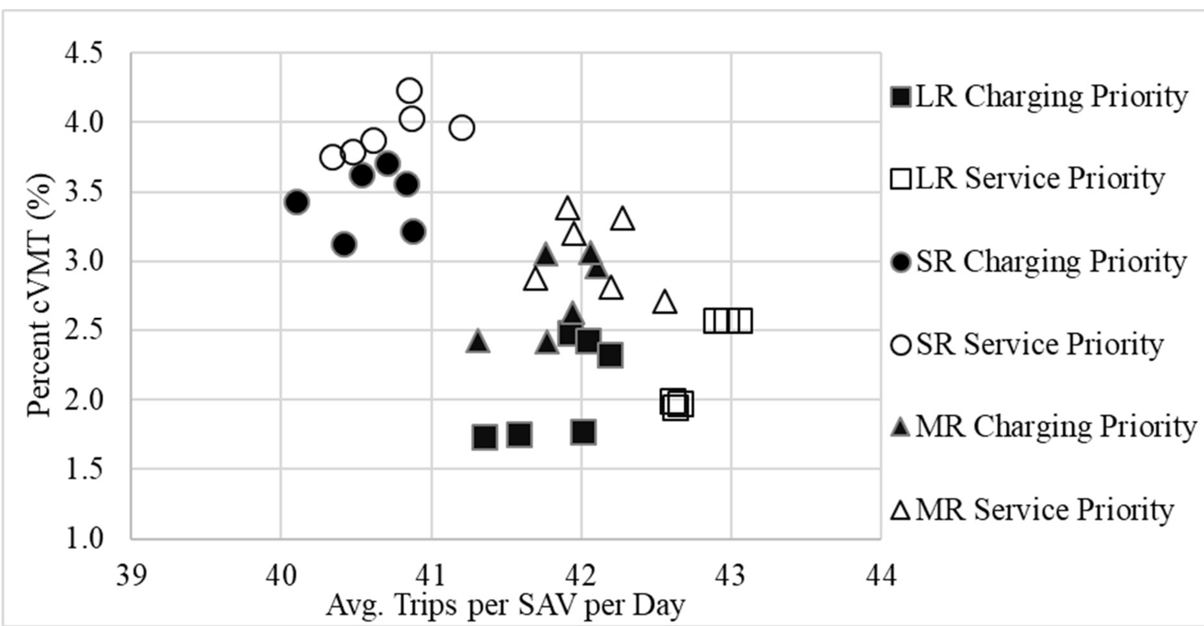

Figure 5 Fleet utilization as a function of daily trips per SAEV and percent charging VMT

Dynamic Ride-Sharing

Figure 6 shows the effect of the choice of fleet composition and charger-versus-service priority on the revenue-trip AVO. Minimum idle time and SoC cutoffs did not increase or decrease AVO significantly so the AVO averaged across scenarios are highlighted in Figure 6. Prioritizing charging resulted in a small increase in AVO, and, interestingly higher than SAVs, even though the demand was only slightly lower. This largely stems from the variably constrained fleet size due to charging requirements during the day while incoming trip requests remained more or less the same. Service priority reduced AVO to 1.68-1.74, which is quite comparable, but the poorer performance is likely from inadequate charge when the SAEV exits an EVCS lowering the number of chained trips before the SAEV had to go charge again. The SR fleets are expected to need more charging trips than an LR fleet, so the absence of available SAEVs is seen to help improve AVO under service priority policy. The mixed fleet does better than the LR fleet in this case, as the SR vehicles may be charging while the LR vehicles are available for better DRS trip matching. These results are interesting from an operator perspective but depend finally on user willingness to share rides with a stranger as assumed to be true for all users here.

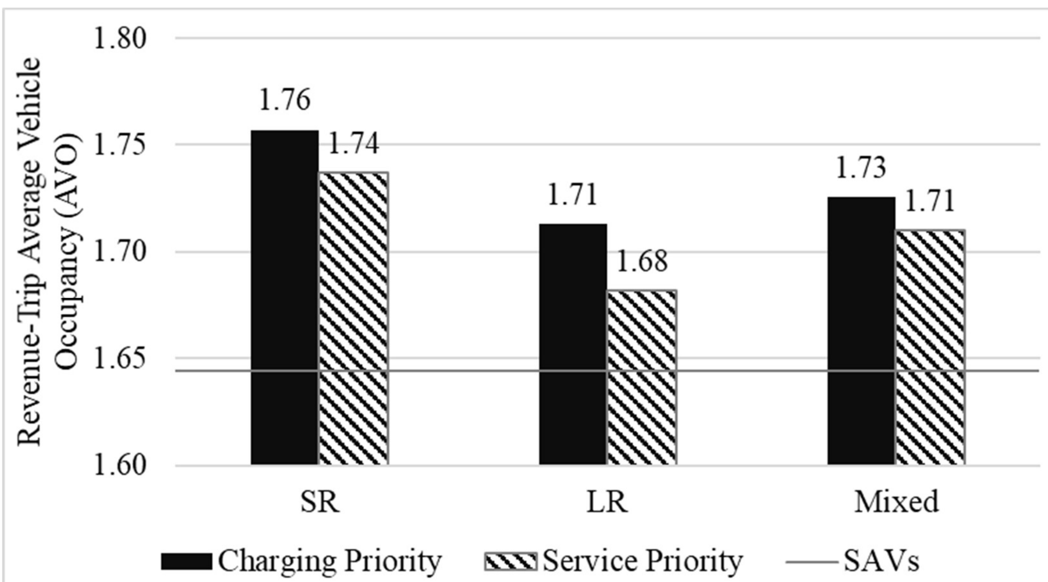

Figure 6 Effect of charging strategy on average vehicle occupancy (AVO)

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 here thoroughly through a variety of fleet compositions and charging strategies. Over 36 scenarios are simulated 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 a SR, LR or mixed-range (MR) fleet is important to manage the added congestion through eVMT. Irrespective of whether charging or service is prioritized, an SR fleet adds about 1.8-3.4% more eVMT than a MR or LR fleet. A larger region like Chicago may see higher %eVMT for the same assumed fleet ranges as the average trip length in the region is about 3 times longer than Bloomington's. The use of a mixed fleet may be helpful in the short term to maximize 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 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 most sense at peak times of day while simultaneously prioritizing charging at the off-peaks would ensure better average SoC. 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. Current maximum SoC assumptions between 80-85% is sufficient, but the low minimum idling thresholds (15-minutes and shorter) will add eVMT and present 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, a vehicle can expect to spend 3-5 hours a day charging. Demand reductions seen from a comparable SAV fleet is expected, but the magnitude is rooted in the fleet composition and charging strategies studied here. 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 LR-only fleet, at a substantially lower price (due to high costs in batteries at present).

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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.

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