

1 **STRATEGIC CHARGING OF SHARED FULLY-AUTOMATED ELECTRIC VEHICLE**  
2 **(SAEV) FLEETS IN A LARGE-SCALE MODEL**

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24 **ABSTRACT**

25 Shared autonomous vehicles (SAVs) will likely emerge in many urban settings over the coming  
26 decade and may significantly impact passenger travel. SAV fleet managers, the public, and  
27 policymakers may be attracted to all-electric drivetrains' lower operating costs and environmental  
28 benefits, but fleet managers will need to account for charging times and range limitations of EV  
29 battery packs. This study investigates a variety of potential electric SAV (SAEV) fleet designs and  
30 charging strategies that relate to vehicle range decisions, battery state-of-charge buffers, charging  
31 station capacity choices, response times, and the ability of currently-charging vehicles to accept  
32 new trips. The agent-based transportation tool POLARIS is used to simulate over 36 SAEV  
33 management scenarios serving passenger travel across Illinois' Bloomington region, and a subset  
34 of the same for the Greater Chicago region. Results show a mixed fleet of short (100-mi) and long  
35 (250-mi) range SAEVs performs better than a homogenous short-range fleet, with lower empty  
36 vehicle miles traveled (eVMT), higher average vehicle occupancies, and lower idling time.  
37 Charging and service priority policies are both required, but at different times of the day to  
38 accommodate slow Level 2 chargers, but is not as important for DCFC charging stations. SAEVs  
39 can stay in place longer (1 hr versus 15 min) to keep eVMT low, but only if long-range SAEVs  
40 are in the fleet and the region is small. SAEVs in large regions are exposed to location-specific  
41 trip requests when idling in place, and need to have high average state of charge (SoC) across the

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1 fleet to serve all incoming requests. Homogenous fleets need careful prioritizing of charging over  
2 service for an acceptable multi-day operation when using a largely Level 2 charging station  
3 network. Smart siting of EVCS and availability of fast chargers remain key to minimizing fleet  
4 size and keeping response times low.

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

## 7 **BACKGROUND**

8 Mobility-on-demand services provided by ridesourcing fleets or transportation network companies  
9 (TNCs) can have negative or positive effects on urban congestion and emissions (Schaller, 2018;  
10 Balding et al., 2019; Union of Concerned Scientists, 2020). With autonomous vehicle (AV)  
11 deployments on the horizon, travelers may surrender their private vehicles (Menon et al., 2019)  
12 and rely increasingly on fleets of shared autonomous vehicles (SAVs) for their urban and  
13 interurban travel needs (Fagnant and Kockelman, 2014; Spiesser et al., 2014; Fagnant and  
14 Kockelman, 2015; Bischoff and Maciejewski, 2016; Gurumurthy, 2018; Fagnant and Kockelman,  
15 2018; Stocker and Shaheen, 2019). Electric SAV fleets (SAEVs) may even emit 73% less  
16 greenhouse gases (GHGs) and consume 55% less energy than a gasoline-fueled alternative (Bauer  
17 et al., 2018). Beyond EVs' environmental benefits, lower operating and maintenance costs  
18 compounded by high utilization rates should provide savings of \$0.05-\$0.08/mi for electric SAVs  
19 relative to hybrid and internal combustion engine (ICE) powertrains (Bauer et al., 2018; US  
20 Environmental Protection Agency, 2019), resulting in an estimated cost of \$0.40/mi (Bösch et al.,  
21 2018; Loeb and Kockelman, 2019; Becker et al., 2020).

22 Most literature to date considers the tradeoff between increasing range and building a  
23 comprehensive network of EV charging stations (EVCS) in determining the minimum fleet size  
24 required. An increase in battery capacity increases range such that most trip requests are met  
25 without necessitating daytime charging, albeit at a higher upfront capital cost. In contrast,  
26 expanding EVCS availability through a higher density of spatially-distributed plugs lowers the  
27 range required of vehicles, although at higher land acquisition or leasing, capital, and operating  
28 costs (Huang and Kockelman, 2020). Through this dichotomous example, the sensitivity of  
29 assumed fleet parameters and strategies related to charging and discharging a fleet of SAEVs on  
30 service quality is ignored and left to confound results. Thus, this study examines the effect that  
31 operational and technical charging parameters have on level of service metrics (e.g., vehicle  
32 utilization, average wait times, and empty travel (eVMT)) while varying fleet composition. The  
33 rest of this paper is organized as follows – existing literature is reviewed next and assumptions on  
34 fleet, EVCS and charging behavior for SAEVs are consolidated; the simulation framework is  
35 explained; the results from the sensitivity analysis are discussed, followed by recommendations  
36 for good forecasting practice in large-scale models, and then concluding remarks.

## 37 **LITERATURE REVIEW**

38 The first two simulation-based studies of SAEVs examined fleet costs and fleet size by varying  
39 battery range (short- and long-range, 80- and 200-mile, respectively) and charging station type  
40 (Level 2 and Level 3/direct current fast charging (DCFC), with a 30-minute and 4-hour maximum  
41 charge times, respectively) across a 100-mile x 100-mile gridded region based on Austin, Texas  
42 (Chen and Kockelman, 2016; Chen et al., 2016). Farhan and Chen (2018) extended this work by  
43 allowing dynamic ridesharing (DRS), showing that adding a second passenger to each vehicle

1 substantially reduces the number of vehicles and charging stations required (by 55.7% and 32.2%,  
2 respectively). However, their model did not allow for real networks, actual land use patterns, or  
3 congestion feedback.

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

13 Loeb et al. (2018) extended existing SAV code (Bösch et al., 2016) in MATSim (Horni et al.,  
14 2016), an agent-based and activity-based travel demand model, to consider the constraints of EVs.  
15 A 5% random sample of trip demands was served entirely by SAEVs, and EVCS were generated  
16 like in Chen et al. (2016). Similarly, fleet size varied as a ratio of SAEVs to traveler (from 1:3 to  
17 1:9) with the similar trade-offs in range and charge speeds as in Chen et al. (2016). Empty travel  
18 due to charging (cVMT) was 23.0% of total eVMT, partially because charging vehicles could serve  
19 new rides. Loeb and Kockelman (2019) then incorporated a response-time-based ridesharing-  
20 choice model for SAV users, leading to similar results. A comparison of battery range (60- versus  
21 200-miles) and charging duration (30 versus 240 minutes) found that using long range vehicles  
22 with DCFC lowered average response times by 39% (from 8.4 to 5.1 minutes) and marginally  
23 lowered eVMT due to charging (1.3% to 1.1%).

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

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

1 particularly since the development of MATSim, allowed for further trade-off work with the  
 2 opportunity to model DRS. More recently, Vosooghi et al. (2020) incorporated alternative modes  
 3 and battery swapping stations to minimize charging times. Close examination of the literature  
 4 reveals a highly variable set of assumptions about EV behaviors, with little to no common ground  
 5 for comparison. Moreover, although some papers use MATSim, their underlying specifics such  
 6 as congestion feedback or EVCS configuration (e.g., ratio of EVCSs to SAEVs, charger plugs per  
 7 station, and power levels) are not apparent for an apples-to-apples comparison. Recognizing such  
 8 differences, the next sub-sections characterize SAEV simulations by the decisions of when to send  
 9 vehicles to charge, the SoC buffers, and the flexibility of vehicle states as it relates to charging.

## 10 **Decision to Charge**

11 Maximizing fleet utilization (i.e., trips per SAV per day) while minimizing eVMT can help  
 12 increase operator profits. High utilization is made possible by ensuring available vehicles can  
 13 service ride requests within a passenger’s maximum allowable wait time and by proactively  
 14 charging vehicles. Beyond this temporal aspect, fleet operators may wish to proactively reposition  
 15 vehicles to locations of anticipated demand, albeit at a cost of eVMT (Winter et al., 2020). Without  
 16 relocation strategies or SAEV cruising (similar to current TNCs), vehicles idle upon arriving at a  
 17 traveler’s destination. This may be at the destination or at a nearby parking lot (Yan et al., 2020).  
 18 Most models have SAEVs wait in place until they are assigned a new trip or at least one of the  
 19 following charging conditions is met: a minimum battery level (e.g., 20% SoC), range is  
 20 insufficient to meet the next trip request, or a minimum idle time (e.g., 30 min). Table 1 presents  
 21 a review of relevant papers with charging decision parameters. The first condition, minimum  
 22 battery SoC, is particularly problematic for undersized and short-range fleets – a high threshold  
 23 represents a high opportunity cost for the operator by limiting the supply of vehicles that could  
 24 serve an additional trip. Although no one has yet examined the trade-off of this parameter with  
 25 fleet size, previous models have checked if the battery level is sufficient in meeting a current  
 26 transport request. It is clear from Table 1 that conditions to charge vary widely. Minimum SoC  
 27 ranges from 5% to 35% and minimum idling time ranges from 5 min to 30 min.

28 **Table 1** Summary of SAEV Decision-to-Charge Conditions

Variable	Study	Parameter or Condition
Minimum battery threshold (SoC)	Iacobucci et al. (2018a)	35% <sup>a</sup>
	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%
Insufficient vehicle range	Loeb and Kockelman (2019)	5%
	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 <sup>b</sup>
Minimum idle time	Vosooghi et al. (2020)	To complete trip request and reach nearest charger
	Loeb et al. (2018)	30 min
	Bauer et al. (2019)	15 min and driving time to nearest charger <sup>c</sup>
	Iacobucci et al. (2018a)	5 min

29 <sup>a</sup> Vehicles are sent to charging stations once 35% SoC is met, however, vehicles can still accept requests before this  
 30 threshold is met, unless the estimated range will lead to a 20% or lower SoC at its destination.

<sup>b</sup> 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.

<sup>c</sup> 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.

## 6 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 <sup>a</sup>
	Bauer et al. (2018)	2.8 – 3.3, 6.5, 32.5 <sup>a</sup>
	Vosooghi et al. (2020)	4.17 <sup>b</sup>

<sup>a</sup> As reported in Vosooghi et al. (2020)

<sup>b</sup> 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., 2018a, 2018c). 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. (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. 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).

1 The SAV module in POLARIS (Gurumurthy et al., 2020) is expanded on here, to allow for range-  
2 constrained EVs. Although some travelers are more environmentally conscientious than others,  
3 the demand for SAEVs is expected to mimic that for an SAV. Demand for SAVs is in turn subject  
4 to results from the mode-choice model, which identifies the preferred mode of travel considering  
5 household and individual preferences in addition to the fare, average wait times, and in-vehicle  
6 travel costs (featuring a time-varying and distance-varying component) of the trip. The fleet  
7 operator's goal is to provide a high-quality service at low operating costs to ensure a sound return  
8 on investment. Ride requests, trip matching, charging decisions and repositioning strategies are  
9 centrally monitored to this end. The operator assigns vehicles to riders by a zone-based assignment  
10 (Bischoff and Maciejewski, 2016; Gurumurthy et al., 2020) to ensure nearby vehicles serve nearby  
11 rides, which reduces overall eVMT and ensures low response times. Although this is not a nearest-  
12 neighbor assignment, since available vehicles are aggregated at the zone level for operators, the  
13 relative size of the traffic analysis zones (TAZs) in locations with high SAV use is small enough  
14 to yield an acceptable sub-optimal solution. Once this initial assignment is made, the vehicle makes  
15 routing choices to minimize travel times and records trip information like distance, time, and  
16 empty travel at the path level. Vehicle relocation, like vehicle assignment, is conducted by the  
17 operator to increase the spatial distribution of vehicles to minimize both wait times and eVMT  
18 caused by this action (de Souza et al., 2020a) but is not explored here. DRS is allowed through the  
19 existing SAV module as highlighted in (Gurumurthy and Kockelman, 2020). A heuristic to DRS  
20 matching is followed where trips are matched to vehicles en route depending on seat availability  
21 and the directionality of the trip being served with respect to the new trip that may be added to the  
22 tour. DRS introduces new parameters such as controlling for maximum allowable delay (both as a  
23 percentage of solo travel time and absolute value), degree of directionality, and maximum seats in  
24 the vehicle.

## 25 **SAEV Module**

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

1 of the tour. This also maximizes sharing, as permitting by other parameters, with the vehicle  
2 preparing to charge while completing previously assigned trips.

3 SAEV range is another input and the module allows for a homogenous fleet with a single range or  
4 a mixed-range (MR) fleet denoted as a discrete distribution of specific ranges to mimic bulk  
5 purchases of different models.

6  
7 Table 3 shows the distribution of ranges considered in each of the scenarios, using discrete ranges  
8 of either 100 miles or 250 miles for each of the SAEVs. The third scenario is a unique contribution  
9 in simulating a combined fleet of both short (SR) and long-range (LR) vehicles. Also, these  
10 vehicles are expected to have a distribution of initial SoC to reflect a continuous multi-day  
11 operation when testing only one 24-hour period. All simulations start with the battery level  
12 normally distributed with a mean of 70% and standard deviation of 5%, which allows for some  
13 variability compared to a fixed 70% for Iacobucci et al. (2019) and 100% for Zhang et al. (2020).  
14 Since all ranges are assumed to be mile-equivalents of their battery capacities, SAEVs discharge  
15 battery as a direct function of distance traversed.

### 16 **EV Charging Stations (EVCS)**

17 The SAEVs utilize a network of fleet-owned DCFC stations, designed based on recommendations  
18 from the literature (i.e., station density and vehicle-to-plug ratio). Previous work has resorted to  
19 heuristics to site charging stations to prevent stranding vehicles or using historical SAV demand  
20 (Chen et al., 2016; Loeb et al., 2018; Loeb and Kockelman, 2019; Vosooghi et al., 2020).  
21 Likewise, a new station with a default  $x$  plugs is created if there is not one within  $y$  miles of the  
22 vehicle once the decision to charge is met. If an SAEV queues at an EVCS longer than  $z$  minutes,  
23 a new plug is added. If the SAEV does not have sufficient range to meet a charger in the generation  
24 phase, a new EVCS is generated. This heuristic was used to generate EVCS for use across all 36  
25 scenarios.

26 The EV charging model is based on the vehicle's battery capacity and the charger speed. Although  
27 battery charging could be modeled by a constant-current constant-voltage model, the vehicles are  
28 assumed to charge at a constant linear rate. Furthermore, numerous studies find degradation in  
29 battery capacity after many charging cycles (see Han et al., (2014)), but like Iacobucci (2018) and  
30 Sheppard et al. (2019), capacity fade is not incorporated into the model. Detailed charging and  
31 discharging behavior of batteries is ignored, and efficiency is assumed constant regardless of SoC  
32 since SAEVs are on average between the minimum and maximum thresholds that are preset and  
33 aim to improve efficiency. Additionally, this paper does not factor in charging station overhead  
34 time that arises from docking the vehicle (which could be near simultaneous with the help of  
35 mechanics and cleaners who will invariably need to service the vehicles). The linear charging rate  
36 is estimated using EPA data for 2019 BEVs (US Environmental Protection Agency, 2020). The  
37 average energy efficient EV uses 30kWh per 100 miles of driving distance. With automation  
38 increasing energy demands, one could expect to use more kWh per 100 miles of driving distance  
39 but advances in electric powertrain technology may counteract increased loads. To estimate the  
40 miles of range added per minute of charge, the charger speed (assumed 50 kW) is multiplied by  
41 3.33 mi/kWh.

42 A queueing approach is followed at each EVCS and SAEVs wait at the charging station for the  
43 next available plug. The SAEVs that are queueing are assumed to find space at the charging station  
44 and do not create network spillbacks. The SAEV operator can stop an SAEV from charging if



1 needed, given that its SoC at that instant is above a threshold, in between the minimum and cutoff  
 2 SoCs assumed. A 60% threshold is used in this study when overriding a charging session. Charging  
 3 priority and charging override are both tested to evaluate which strategy helps improve SAEV fleet  
 4 performance (see Table 3 for a list of all model inputs).

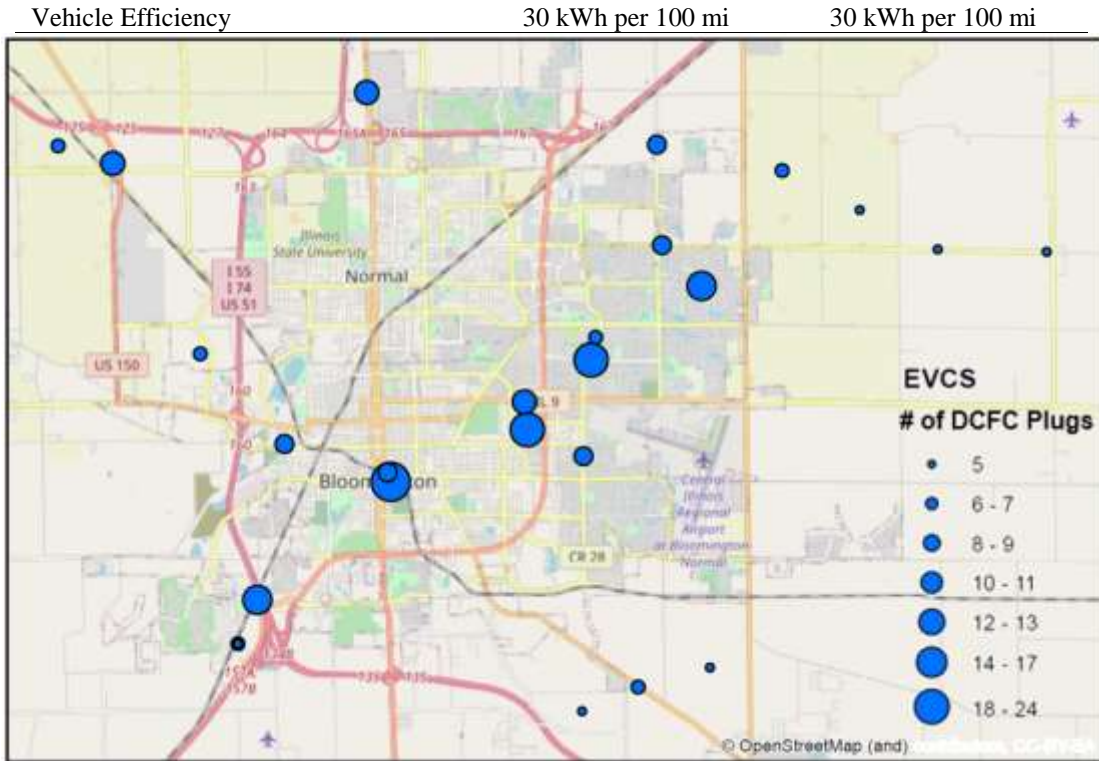
5 For this study, EVCS were generated in a simulation run with all SR vehicles while prioritizing  
 6 service and a 30-minute idle charging threshold to have enough stations across the region. A  
 7 minimum of 5 plugs are assumed at an EVCS and a new station is generated when an existing  
 8 EVCS is not within 15 mi for the case of Bloomington (50% of the minimum absolute threshold  
 9 assumed). In contrast, a 2 mi threshold was used for Chicago to cover the sprawling region  
 10 sufficiently. To prevent stranding vehicles, if at the end of a tour an SAEV had insufficient range  
 11 to meet the nearest EVCS, regardless of whether one existed within a 15 mi (or 2 mi) Euclidean  
 12 radius, a new station is generated. In summary, there are 6.4 vehicles per charger and a station  
 13 density of 0.35 EVCS per square mile in Bloomington compared to 12.0 vehicles per charger and  
 14 a station density of 0.74 EVCS per square mile in Chicago (Figure 1 a and b, respectively).

15 The intent of modeling strategic charging of SAEVs across two regions is not to compare results  
 16 but to use a smaller region to highlight recommended technical and operational configurations of  
 17 SAEV fleets from a total of 36 scenarios and to subsequently test the sensitivity of these  
 18 configurations on a large-scale region with higher SAV demand and trip density that is likely to  
 19 see a fleet of SAEVs first. The Bloomington network is comprised of 185 TAZs, 7,000 links, and  
 20 2,500 nodes across 74 square miles while the Chicago network has 1,961 TAZs, 31,900 links, and  
 21 19,400 nodes across 11,246 square miles. The population size of Bloomington is 120,000 versus  
 22 nearly 11 million in Chicago. Since Chicago is a sprawling metropolitan region, only 50% of the  
 23 population was sampled compared to 100% for Bloomington. The ratio of residents to fleet size  
 24 was lower for Chicago – 50 people per SAEV, compared to about 82 per SAEV in Bloomington.

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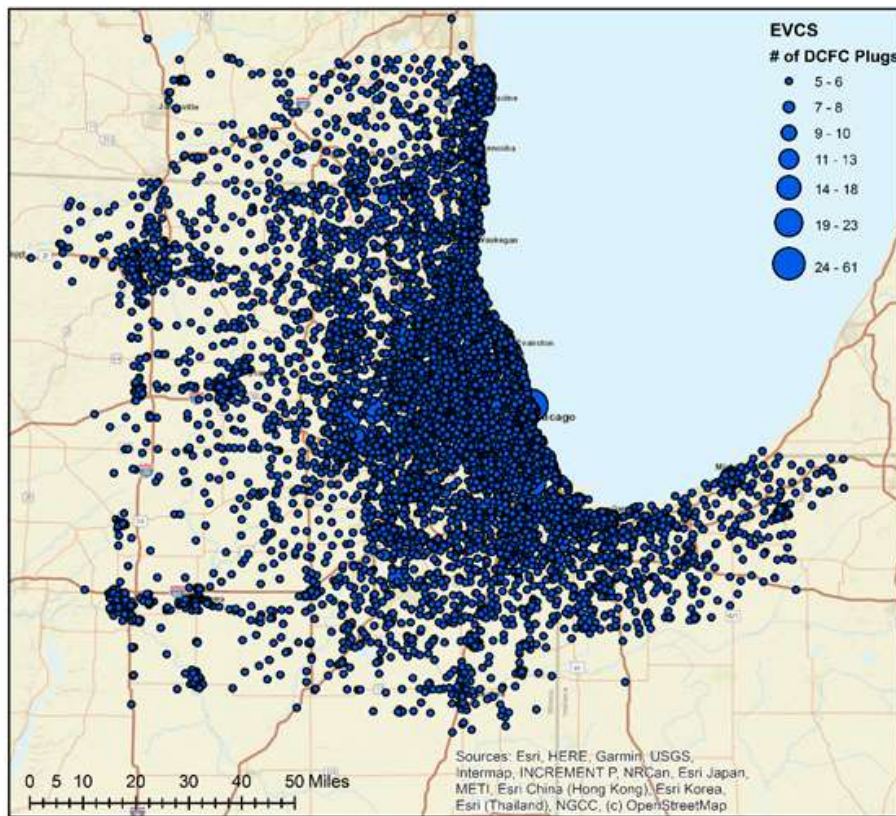
**Table 3** Summary of Model Inputs

<b>Region</b>	<b>Bloomington</b>		<b>Chicago</b>	
<b>DCFC EVCS</b>				
<i>Heuristic: x (plugs), y (miles), z (min)</i>	5 plugs, 15 mi, 15 min		5 plugs, 2 mi, 15 min	
<i>Number of Plugs</i>	225		42,329	
<i>Number of Stations</i>	26		8,269	
<i>Present Charger Speed (kW)</i>	50		50	
<b>Vehicle Range</b>				
	<b>100-mi</b>	<b>250-mi</b>	<b>100-mi</b>	<b>250-mi</b>
<i>Short-range (SR) only (%)</i>	100%	0%	100%	0%
<i>Long-range (LR) only (%)</i>	0%	100%	0%	100%
<i>Mixed-range (MR) (%)</i>	50%	50%	50%	50%
<i>Fleet Size (Vehicles)</i>	1440		99,536 (for 50%)	
<i>People-to-SAEV Ratio</i>	82:1		50:1	
<b>Decision-to-Charge Parameters</b>				
Minimum SoC (%)	20%		20%	
Minimum Absolute Range (mi)	30 mi		30 mi	
Minimum Idle Time (min)	15 min	60 min	15 min	
<b>EV Charging Parameters</b>				
Maximum SoC (%)	80%	85%	90%	85%
Exit Charging Early	Yes	No	Yes	No
<b>Base SAEV Assumptions</b>				
Starting SoC (%)	Normal ( $\mu = 70$ , $\sigma = 5$ )		Normal ( $\mu = 70$ , $\sigma = 5$ )	



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3

**Figure 1a** Bloomington road network with EVCS locations



4

1 **Figure 1b** Chicago road network with EVCS locations

2 **RESULTS**

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

11 **Bloomington Region**

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

20 The results of 36 SAEV-specific scenarios are summarized here, under the broad categories of the  
 21 fleet distribution: SR, LR, and MR. Charging speeds assumed here imply about 30 and 75 minutes  
 22 of charging for SR and LR vehicles, respectively, and this may leave some SAEVs unable to serve  
 23 trips at peak periods of the day. A fleet size of 1440 SAEVs was assumed here and the demand  
 24 served was compared to that of the unconstrained base case.

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

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

34 **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	5.2	4.4	-6.0
			S	22.4	4.2	40.9	5.8	4.3	-5.7
		85%	C	22.2	3.6	40.5	5.0	4.2	-6.3
			S	22.3	4.0	41.2	5.6	4.5	-5.9

	60 min	90%	C	22.3	3.6	40.8	4.8	4.5	-5.8
		80%	S	22.2	4.0	40.9	5.6	5.0	-5.3
			C	22.5	3.4	40.1	4.5	4.3	-7.0
		85%	S	22.2	3.9	40.6	5.2	4.2	-6.3
	C		22.1	3.2	40.9	4.3	4.2	-5.8	
	90%	S	22.1	3.8	40.3	5.0	4.5	-6.7	
		C	21.9	3.1	40.4	4.2	4.2	-6.7	
	S	22.1	3.8	40.5	4.9	4.4	-6.6		
LR (250 mi)	15 min	80%	C	21.1	2.5	41.9	3.7	3.9	-3.0
			S	21.0	2.6	43.1	4.1	3.7	-0.7
		85%	C	21.2	2.4	42.0	3.6	4.1	-3.1
			S	20.9	2.6	42.9	4.0	4.3	-0.9
		90%	C	21.1	2.3	42.2	3.5	4.5	-2.8
			S	20.9	2.6	43.0	3.9	4.6	-1.3
	60 min	80%	C	20.5	1.8	42.0	2.8	3.2	-3.0
			S	20.5	1.9	42.6	3.1	3.1	-1.5
		85%	C	20.6	1.8	41.6	2.6	3.3	-3.9
			S	20.5	2.0	42.6	3.0	3.3	-1.5
		90%	C	20.5	1.7	41.4	2.5	3.7	-4.1
			S	20.4	2.0	42.7	3.0	3.0	-1.2
MR (50% 100 mi, 50% 250 mi)	15 min	80%	C	21.6	3.1	42.1	4.5	4.1	-3.2
			S	21.7	3.4	41.9	4.9	3.9	-3.0
		85%	C	21.7	3.1	42.1	4.3	4.1	-2.5
			S	21.6	3.3	42.3	4.9	4.2	-2.0
		90%	C	21.7	3.0	41.8	4.2	4.5	-3.4
			S	21.5	3.2	41.9	4.6	4.1	-2.8
	60 min	80%	C	21.5	2.6	41.3	3.6	3.3	-4.4
			S	21.2	2.9	41.7	4.1	3.6	-3.6
		85%	C	21.2	2.4	41.8	3.5	3.3	-3.7
			S	21.1	2.8	42.2	4.1	3.4	-2.2
		90%	C	21.0	2.4	41.9	3.5	3.5	-3.4
			S	21.1	2.7	42.6	3.9	3.7	-2.4

1

## 2 Short-Range SAEVs

3 Compared to a similar-sized SAV fleet, demand for an SR SAEV fleet drops by 5-7%, a result due  
4 in part to vehicles spending on average about 4.4 hours of the day at an EVCS. This average time  
5 increases by about 12 minutes if SAEVs are permitted to serve additional trips when they reach an  
6 adequate SoC of 60% because vehicles, on average, require an additional 0.6 charging trips per  
7 day. The flexibility to serve trips marginally improves the average number of trips served per  
8 SAEV per day for lower battery cutoffs and when a 60-minute idling threshold is used. Percent  
9 eVMT is about 2-3% higher than the SAV scenario and can be directly attributed to the additional  
10 charging trips made by SAEVs, and, the potentially longer pick-up trips because of bunching at an  
11 EVCS. VMT from charging trips (cVMT) is around the 3-4% mark. Requiring a higher cutoff of  
12 SoC before unplugging from the charger has little to no effect on average time spent at an EVCS,  
13 as expected, since DCFC chargers' charge time is proportional to the battery capacity. Longer  
14 idling times before sending an SAEV increases the supply of vehicles to meet new rides, but  
15 surprisingly demand falls, likely from the low range.

1 Long-Range SAEVs

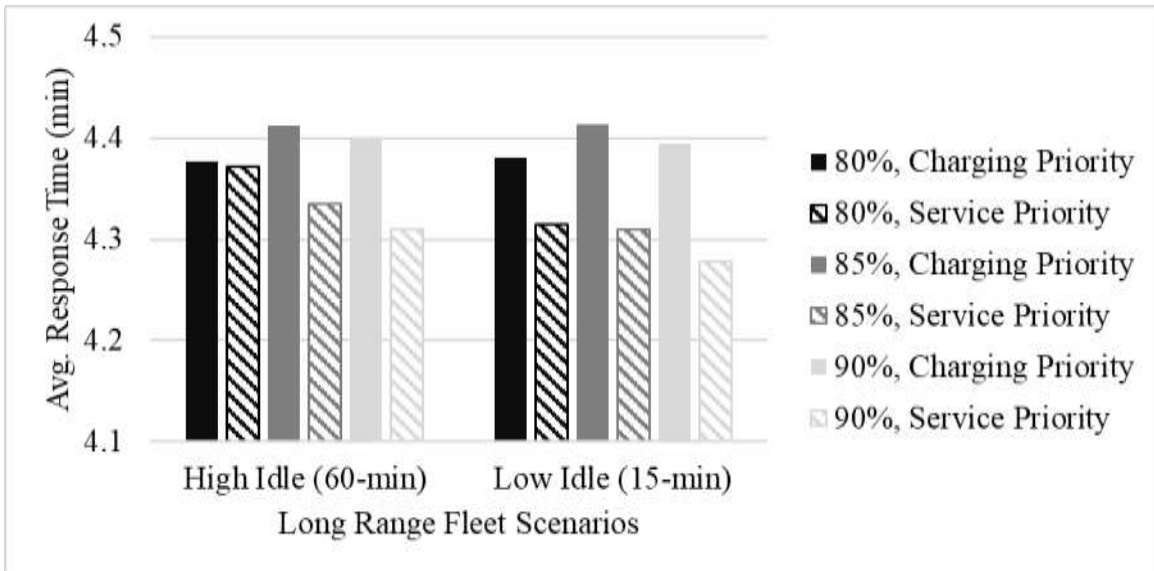
2 Long-range SAEVs perform marginally better, serving on average 1.6 more trips per SAEV per  
3 day than the SR counterpart. LR vehicles have 2 fewer daily charging sessions, lowering cVMT  
4 to 1.7-2.6%, consequently lowering %eVMT. If service priority policy is implemented, the average  
5 time at an EVCS drops by 3.3%, subsequently increasing the number of average daily trips by 0.6  
6 to 1.3. A high idle (60-min) and service priority policy lowered %eVMT relative to a high idle and  
7 charging priority policy for all battery cutoffs while increasing the average daily trips per SAEV.  
8 Interestingly, the low idle, 80% battery cutoff, service priority policy almost served as many trips  
9 as a fleet of SAVs, while the 85% and 90% thresholds did not show a similar trend. The low idle  
10 and 80% battery cutoff recharges vehicles in periods and areas of low demand while the service  
11 priority policy allows for flexibility in balancing supply and demand without repositioning  
12 policies. However, the efficacy of this policy is unclear.

13 Mixed-Range SAEVs

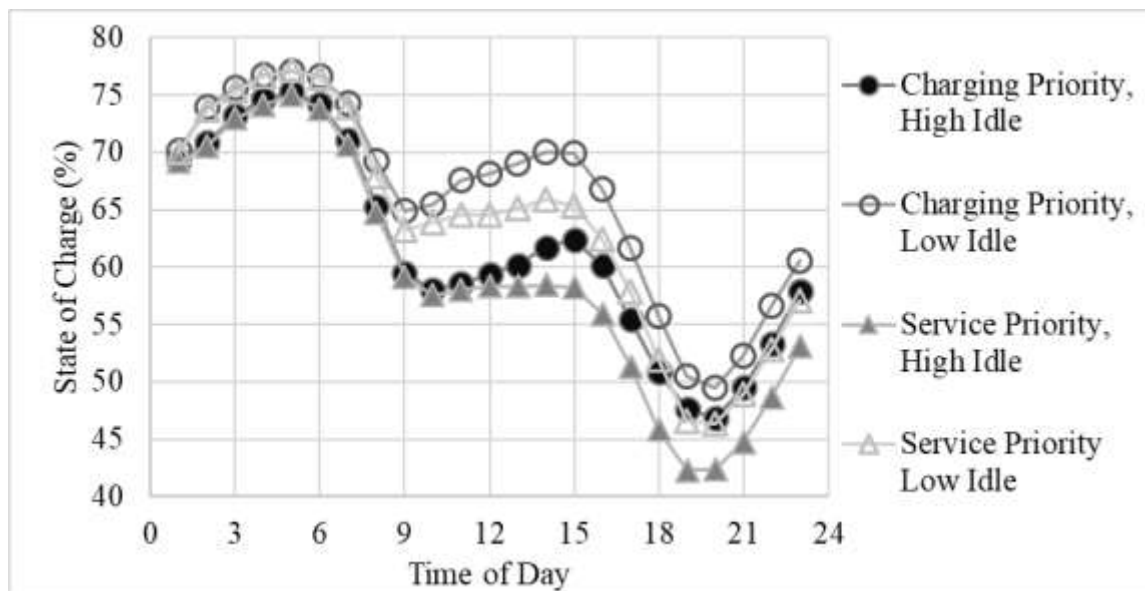
14 A mixed fleet of SR and LR SAEVs performs better than a complete SR fleet but worse than the  
15 LR fleet in certain service metrics like average trips served, but eVMT and average charging times  
16 are better than an SR fleet and worse than an LR fleet. The mixed range fleet inherits high daily  
17 charging trips from an SR fleet but also high charging durations from an LR fleet, resulting in  
18 more balanced charging episodes. Average daily trips served is around 41.3-42.6 per SAEV,  
19 compared to 41.4-43.1 per LR SAEV. The scenario with the highest daily trips was a high idle,  
20 90% SoC cutoff, and service priority configuration and was a contrast to the best scenario for LR  
21 fleets (low idle, 80% cutoff and service priority). The total demand served in comparison to an  
22 SAV fleet continued to be about 2.0 to 4.8% lower. This is better than a 100% SR fleet and is  
23 likely economical as larger batteries are expected to cost more.

24 Charger Priority versus Service Priority

25 The flexibility to interrupt charging and send SAEVs to serve new requests tends to improve  
26 average response times marginally. Figure 2 shows this effect for LR fleets while controlling for  
27 battery cutoff and minimum idling policies. These response time differences are expected to  
28 increase for large regions. A service priority policy also increases average trips per SAEV per day  
29 while reducing average time spent at charging stations (for LR and MR fleets), thereby creating  
30 more demand for this mode. A downside to this operational flexibility is the extended low SoC of  
31 the fleet that remains depressed following the morning peak period as seen in Figure 3. SAEV  
32 fleets have the lowest SoC in the evening across all scenarios, as expected, and a combined service  
33 priority and high idle policy may lead to odd charging behavior over several days if the average  
34 fleet SoC is lower than at the start of the day. There is a clear tradeoff between meeting increased  
35 SAV demand at the morning peak period through service priority and high idle policies and  
36 sacrificing lower SoC for the remainder of the day. The operator should consider a time-dependent  
37 strategy that implements charger priority after the morning peak period and service priority during  
38 the peak hours, especially since the demand for SAVs is generally more acute during these periods.  
39 Although the average SoC is not logged at midnight, the trend is clear that there may be a 5-15%  
40 difference to catch up on if the assumption of 70% average SoC needs to hold, so prioritizing  
41 charging and service can have a significant effect on multi-day operation.



**Figure 2** Effect of flexible discharge policies on average wait times

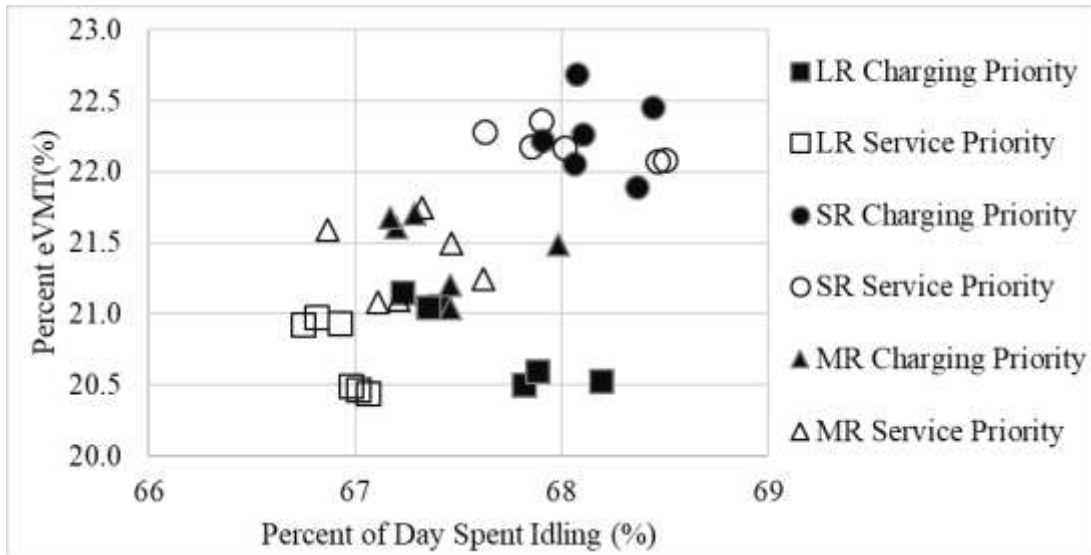


**Figure 3** Fleet state of charge by time of day, a LR 85% SoC cutoff scenario

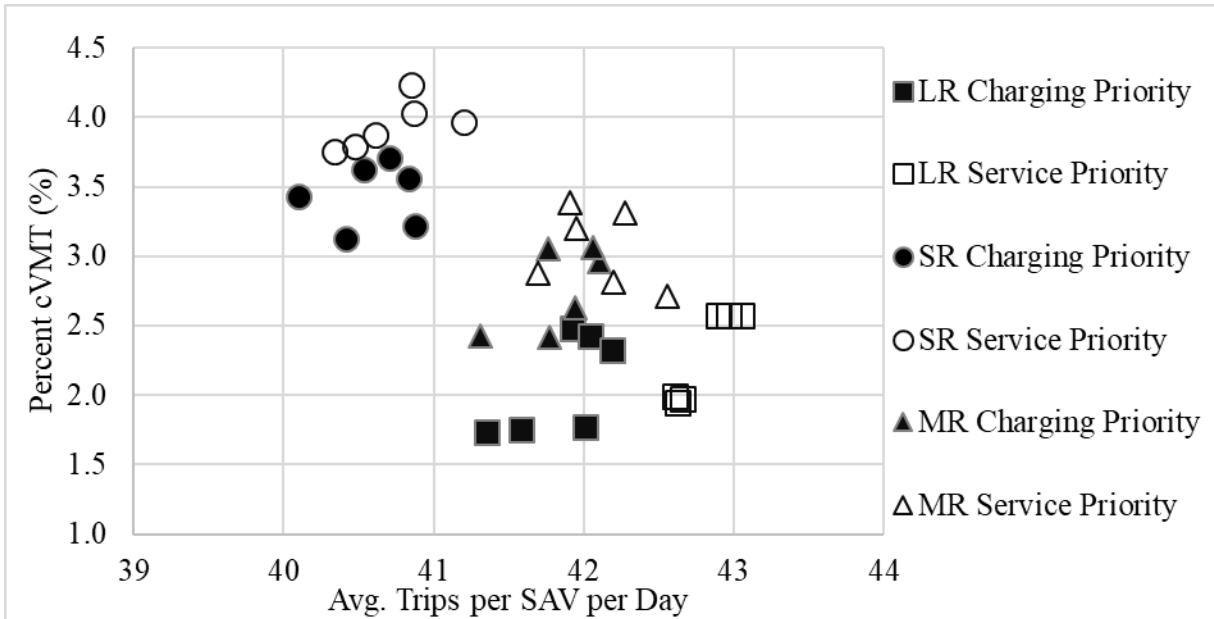
*Fleet Utilization*

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 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 benefit more from the 50% LR SAEVs than the SR SAEVs in the

1 fleet since SR vehicles may be adding more %cVMT for multiple charging trips in a day as shown  
 2 in Figure 5. Although the mixed fleet has 50% each of SR and LR vehicles, the performance may  
 3 be seen as a weighted average of the two ranges. Figure 5 shows that the mixed fleet under service  
 4 priority can provide daily SAV trips near that of long-range fleets prioritizing charging, albeit at  
 5 marginally higher %cVMT.



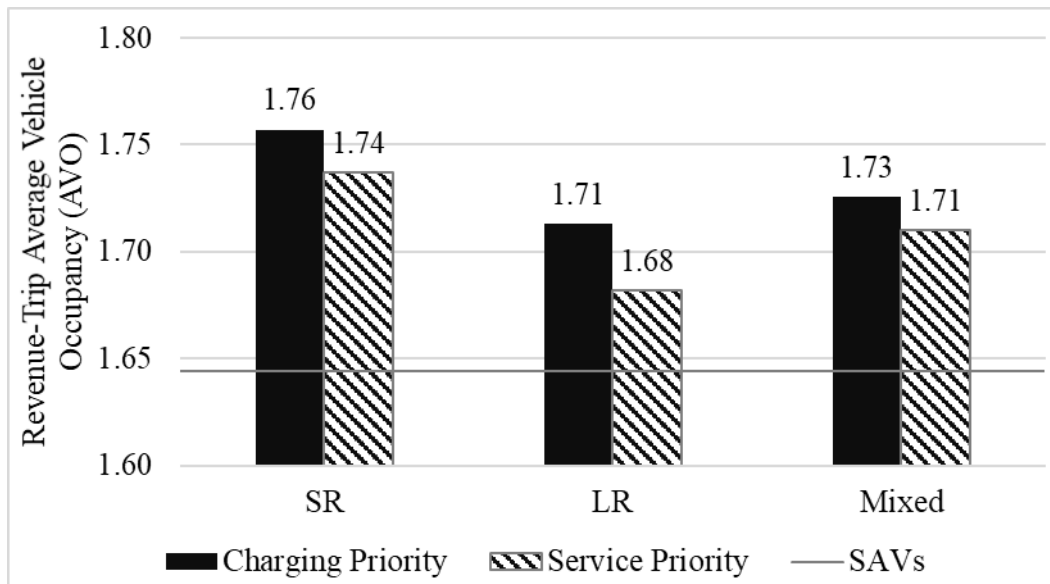
6 **Figure 4** Fleet utilization as a function of percent empty VMT and percent idling time



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

1 *Dynamic Ride-Sharing*

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



16

17

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

18

**Chicago Region**

19 The 36 scenarios with Bloomington helped narrow down the effect of certain charging parameters  
 20 such as maximum idle time before sending an SAEV to charge, and the preferred maximum SoC  
 21 cutoff while charging. Six scenarios were run for a 50% sample of Chicago owing to the 7-hour  
 22 runtime for each scenario. As previously mentioned, 1 SAEV for Chicago served 50 residents in  
 23 the region, leading to a slightly elevated fleet size compared the fleet for Bloomington to account  
 24 for sprawl. Table 5 shows fleet metrics such as %eVMT, %cVMT, AVO, average daily trips per  
 25 SAEV, average time spent at an EVCS, and the % change in demand owing to range constraints.  
 26 The case study of Chicago is interesting since the region exhibits urban sprawl, as well as a high  
 27 density of SAV trips in the city center, higher than most sprawling metropolitan regions. This  
 28 sprawl meant that SAVs served about 22.1 person-trips per day, on average, or half as much as a  
 29 vehicle in the Bloomington fleet. Each SAV traveled over 150 mi per day and transported about



1 1.7 travelers per revenue trip. SAVs add about 12% eVMT assuming there is no need to refuel for  
 2 gasoline. This is lower than the %eVMT added by the Bloomington fleet, and can be attributed to  
 3 the slightly smaller per capita fleet size.

4 Similar sized fleets of range-constrained SAEVs serve fewer daily trips (about 20 person-trips per  
 5 day per SAEV) across all range configurations as expected, and the person-trips difference was  
 6 traded for an approximately equal number of charging trips per day. Chicago’s SAEV fleet  
 7 performs as expected across all metrics except AVO and % demand change. Time spent at an  
 8 EVCS in a day, on average, is consistent across fleet ranges, and this reflects the equilibrium  
 9 between the number of charging trips and charging time based on range. SR fleet vehicles need to  
 10 make 1 more charging trip per day, on average, compared to an LR fleet vehicle, whereas the MR  
 11 fleet vehicles exhibit an intermediate average number of charging trips per SAEV per day thanks  
 12 to the mixture. The AVO of the SAEV fleet decreased compared to an SAV fleet, since the  
 13 downtime of charging SAEVs temporarily lowered supply such that available SAEVs could not  
 14 sufficiently compensate. This also, unexpectedly, lead to a decrease in demand, nearly 10%, from  
 15 range constraints. Varying regional extents impact SAV and SAEV fleet performance differently.  
 16 While some operational characteristics, such as maximum SoC, minimum idle time, and fleet  
 17 range composition impact fleet performance consistently across different regions, fleet size and  
 18 operational behavior differ.

19  
 20

**Table 5 SAEV Fleet Performance in Chicago**

Range	Charging (C) / Service (S) Priority	Avg. SAV VMT per day	% Empty VMT	% Charging VMT	Avg. Daily Trips per SAEV per day	AVO	Avg. Daily Charging Trips per SAEV per Day	Avg. Time Spent at EVCS (in hr)	% Demand Change
Gasoline-powered SAV	-	150.9 mi	11.8%	-	22.1	1.66	-	-	-
SR (100 mi)	C	135.0	16.3	1.3	20.1	1.33	2.4	1.6	-9.2
	S	133.8	16.4	1.5	20.2	1.26	2.8	1.6	-8.5
LR (250 mi)	C	135.1	14.0	0.8	20.0	1.52	1.4	1.7	-9.7
	S	135.3	14.2	0.9	20.1	1.47	1.5	1.7	-8.9
MR (50% 100 mi, 50% 250 mi)	C	135.3	15.2	1.1	19.9	1.43	1.9	1.6	-9.7
	S	133.9	15.3	1.2	20.0	1.37	2.2	1.6	-9.4

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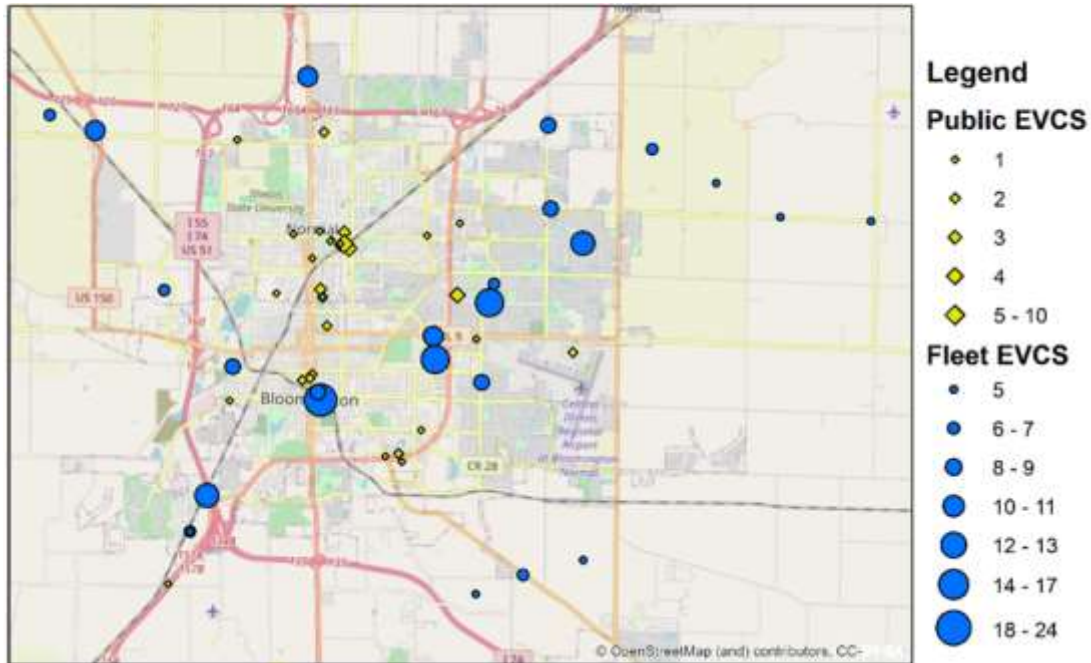
**22 Utilizing existing EVCS versus siting depot-owned fast charging EVCS**

23 In addition to modeling a mixed-range (MR) fleet of vehicles to determine the tradeoffs between  
 24 procuring more affordable SR vehicles and accessing the range benefits of LR vehicles (e.g., fewer  
 25 charging trips per day increasing vehicle utilization), this study explored whether existing public

1 charging stations could support a future fleet of SAEVs. Certainly, the transition to electric  
2 mobility will drive the growth of and demand for public charging infrastructure. Private EVCS  
3 networks (e.g., Tesla, ChargePoint, EVgo) may opt to retrofit their stations with self-docking plugs  
4 or wireless charging for AV compatibility to increase utilization, especially during non-business  
5 hours. Then, the spatial distribution of current charging infrastructure and charger types will likely  
6 impact future fleet operation in the form of added cVMT and, perhaps, increased response times,  
7 given that existing infrastructure has predominately concentrated at civic buildings, large retail  
8 developments, and universities. The impact of using the existing EVCS infrastructure (as of 2017)  
9 was compared to the private DCFC EVCS generated for SAEVs.

10 Figure 7 shows the spatial distribution of the existing EVCS infrastructure compared to  
11 fleet-owned DCFC, sited according to a heuristic strategy. The public network has 33 stations with  
12 a total of 62 plugs. All stations have L2 plugs, except one with 5 additional DCFC plugs, and  
13 another with one additional L1 plug. The fleet-owned network has 26 stations with a total of 225  
14 plugs. Although there are fewer stations, the cord count increases by 263% and all plugs are DCFC.  
15 A direct result of this set up is the decrease in average time spent queuing for an available plug at  
16 a charging station, between 36% and 45% depending on range configuration, but with a  
17 comparable percentage of cVMT. The lower average charging duration increased the supply of  
18 available vehicles and reduced passenger wait times by 78-81%. Since response times are  
19 improved due to a greater supply of sufficiently-charged SAEVs when relying on an all-DCFC  
20 network, the average daily trips per short range SAEV increased by 306% (or from 10.0 to 40.7  
21 average trips per SAEV). Even LR fleets had a noticeable 115% improvement (from 19.7 to 42.4  
22 average trips per SAEV). The tradeoff between modifying existing charging stations to meet fleets  
23 of on-demand SAEVs is clear. Relative to a fleet of gasoline-powered SAVs, demand for SAEVs  
24 falls, on average, by 76.7% for SR, 54.2% for LR, and 63.1% for MR fleet configurations when  
25 SAEVs use existing charging stations. Using a dedicated DCFC EVCS network for SAEVs lowers  
26 demand only by 2.3-6.3% across all range configurations.

27  
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29



**FIGURE 7** Comparison of public and fleet-owned EVCS in Bloomington

(Note: scale of marker is different)

## 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 fleet experienced a marginal increase in %eVMT compared to an SAV fleet (+2%), and MR (+0.5%) and LR (+1.5%) SAEV fleets. The SR and MR fleets in Chicago, on the other hand, saw larger increases in %eVMT compared to the SAV fleet (at 11.8%), as well as the LR SAEV fleet (at 14%), 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

1 studies are sufficient from an operational perspective, but the low minimum idling thresholds (15-  
2 minutes and shorter) will add eVMT while also presenting an opportunity cost of serving  
3 additional new trips.

4 The use of EVCS capacity and queuing adds realism that some prior models missed. Even with  
5 DCFC stations, vehicles in an SAEV fleet designed for small regions can expect to spend 3-5 hours  
6 a day charging, whereas SAEVs operating in a large region, like Chicago, will have a nearly  
7 individualized plug access from siting EVCS across the region, as opposed to a primarily central-  
8 placement of EVCS in Bloomington. The results indicate a near 1:1 relationship between an  
9 increase in the ratio of SAEVs per charger and the expected decrease in time spent at a charging  
10 station per day. Demand reductions seen from a comparable SAV fleet is expected, but the  
11 magnitude is rooted in the fleet composition, regional extent, and charging strategies studied here.  
12 Larger regions need more SAEVs per capita for adequate service (trips and response time), but  
13 may serve 10% fewer trips due to long trip lengths. Smaller regions see smaller reductions in  
14 demand, since the constrained fleet (fraction of vehicles not charging) can still access all trip  
15 requests and maximize seat use assuming travelers are comfortable sharing rides.

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

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