ON- AND OFF-STREET PARKING STRATEGIES AND OUTCOMES FOR SHARED AUTONOMOUS VEHICLE FLEET OPERATIONS

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ABSTRACT

As global demand for ride-hailing services rises, there is an increased urgency to study shared autonomous vehicle (SAV) fleets and their impacts on regional travel. Most SAV studies assume fleet vehicles idle in-place after trip completion, which severely limits understanding the impacts of new parking demand on the expected supply and demand balance. Parking spots are a premium commodity, especially in dense downtown settings, so this study examines the service impacts of SAVs parking in legal on- or off-street locations when idle across the 6-county Austin region (with nearly 2M travelers). Using an agent-based activity-based travel demand model with dynamic traffic simulation, two restricted-parking scenarios for SAVs were simulated, with and without personal vehicle parking. SAVs either found the nearest available parking spot or one with the least-cost option (via a tradeoff of on parking fees and distance-based costs). Using a supply of 8,400 aggregated parking locations in Austin, this study simulated fleet performance with different trip demands, with SAV fares of $1 per mile plus a $1 fixed pickup fee with dynamic ridesharing permitted. Parking costs averaged less than $4 per day (per SAV) using the nearest parking search strategy. Such low parking costs are thanks to the region's provision of mostly free parking. Requiring parking raised traveler wait times (by about 1 min, on average). Requiring SAVs park off-street increases parking costs for personal vehicle drivers by 22% as SAVs occupy some free parking spaces, especially in the most probable least cost parking search strategy.

Keywords: Shared Autonomous Vehicles, Off-street Parking, On-street Parking, Parking Demand, Agent-based Modeling

INTRODUCTION

The demand for ride-hailing services (like Lyft, Uber, and Didi) is rising as they compete with other modes. In 2017, 2.6 billion passengers used ride-hailing in the US, which is 37% higher than the prior year's value (Schaller 2018). These companies provide the option to share rides with a stranger. Ridesharing or pooling helps lower the number of low-occupancy private vehicles and allows operators to provide a discount on ride-hailing fares (Wenzel et al., 2019). Fleets of shared, fully automated, or "autonomous" vehicles (SAVs) can facilitate dynamic ridesharing (DRS) by lowering ride-hailing costs and relying on central-fleet management algorithms (Fagnant and Kockelman 2014, 2015). SAVs offering ridesharing among strangers are already operating in San Francisco (via Cruise), Las Vegas (via Motional), and Phoenix (via Waymo). While SAVs may enhance mobility options for many - while addressing some congestion and emissions issues (Xia et al. 2021, Alessandrini et al. 2015, Parkin et al. 2018, Fagnant and Kockelman 2014, Lee and Kockelman 2019, Loeb and Kockelman 2019), they can contribute to traffic and create curb congestion in dense settings (where trip starts and ends are concentrated, as in a central business district [CBD], for example) (Gurumurthy and Kockelman 2022, Hunter et al. 2022, Yan et al. 2020).

To lower users' wait time, the fleet size for ridesharing or ride-hailing could be increased. Gao et al. (2022) found an increase in fleet size would impose additional fuel cost and empty vehicle-miles travelled (eVMT), if these vehicles cruise (or aimlessly idle) on streets until routed to the next passenger. According to Schaller (2017), the number of ride-sourcing vehicles and trips in New York City from 2013 to 2017 increased by 59% and 15%, respectively. In the same period, the number of idle vehicles increased by 81% and ride-sourcing drivers spent more than 40% of their time empty and cruising for passengers, which increased VMT by 36%. The same trends are expected to happen for ridesharing using SAVs if appropriate policies are not used to manage the empty VMT. A congestion charge or a cap on fleet size are the policies that are being used to address these concerns in ride-sourcing services (NYCTLC 2019, NYCTLC et al. 2019) currently. Gao et al. (2022) suggested forcing these vehicles to park as the best strategy to control their extra VMT and eVMT. They proposed a shared parking model for ridesharing that coordinates vehicle-to-passenger and vehicle-to-garage pairings. They found that the parking enforcement increased passenger demand by 5.3% (from 115 per min to 121 per min for the San Francisco network) and increased ride-sharing revenue by 22% (from $29,664/h to $36,240/h). Their study focused only on ridesharing using conventional cars and does not consider SAVs, which may be centrally coordinated.

Millard-Ball (2019) stated that AVs' and SAVs' parking decisions are driven economically, meaning that companies may prefer cruising if they find parking costly. On the other hand, free curbside parking locations are limited, especially in large urban areas, such as Manhattan, NY, which highlights the importance of considering metered curbside and off-street parking locations. Off-street parking spaces can be used more efficiently with SAVs as these vehicles can park back-to-back in multiple rows assuming communication capabilities between vehicles, rather than in two separate rows in current parking structures. Nourinejad et al. (2017) focused on AVs' optimal car-park layout and observed that their optimal AV parking structure can reduce the required parking space by 87%. In addition, previous studies introduced AVs and SAVs as a solution to the parking space problem. Okeke (2020) simulated demand with 2,181 parking slots on the University of the West of England, Frenchay campus and investigated the impacts of different market shares of AVs and SAVs on free parking spaces when forcing these vehicles to park far from the high parking demand area. While this study observed an increase in the available parking spaces for conventional cars, it did not investigate the impact of this strategy on the increased VMT and eVMT. They also applied their strategy for a small campus network with an area of 80 acres and 23 accessible carparks.

City centers typically have complex rules governing curb use. Some blocks may allow for unlimited free parking, others have time limits, whereas the remaining blocks require a permit or hourly charge. Previous modeling of SAV parking policies and assignment strategies has mostly simplified the problem by focusing on a few centralized parking structures or depots instead of using existing paid or free curbside parking. For example, Yan et al. (2020) modeled SAVs in the Minneapolis-Saint Paul metro. They compared scenarios where SAVs simply idled in place after completing their trips versus requiring them to find and park at the nearest synthesized garage (estimated based on trip starts and ends). Their analysis found that VMT increased by 8% and eVMT increased by 9% when SAVs were redirected to parking locations after dropping off all their passengers This applied to the scenarios with and without DRS enabled. A limitation of Yan et al. (2020) is that they modeled only 2-5% of the region's estimated person-trips due to the limitations imposed by MATSim, another travel demand simulator. Furthermore, in their parking implementation, SAVs assigned to a parking location were locked and not available to serve passengers while enroute to the parking spot. Levin et al. (2020) investigated the impact of zone-specific parking fee on AVs' repositioning and cruising behavior and optimized parking fee and space over the Sioux Falls network. Their results showed that optimizing parking fee significantly impacted the repositioning behavior (total number of repositioning trips decreased by 6.5%) and decreased AVs' eVMT (eVMT reduced by 18.5%). They assumed parking data and cost due to the lack of available data.

Zhang et al. (2015) modeled on-street curbside parking demand and minimized overall parking cost (fuel cost to move to parking plus parking fee) to investigate the impacts of cruising on VMT. They used a simple MATLAB grid-based model and simulated a small fraction of the total trips in the City of Atlanta, Georgia.. Their results showed that DRS can reduce required parking land by 4.5% in Atlanta at 5% SAV market share. Charging parking in congested areas move the parking demand from downtown to adjacent neighborhoods. Finally, Bischoff et al. (2018) used MATSim to model AV parking in Berlin. They used three parking search methods: cruising without parking restrictions, choosing from designated AV parking sites similar to Yan (2019), and a random search method where AVs randomly turn at intersections until they find available parking adjacent to their links.

Contributions

The current study expands upon previous studies by applying parking search to SAVs that behave very differently from private vehicles and have access to features such as DRS. In addition, this study adds two additional SAV parking strategies: one where SAVs know current parking availability and head directly to the closest available spot, and another where parking-related costs to the fleet operator are minimized. Private vehicles park in the nearest available parking space. An agent-based activity-based simulator called POLARIS is extended and used in this study for the parking strategy. This robust tool allows for simulating a 100% of the Austin area of around 1.9 million residents with features such as SAVs, dynamic traffic assignment, and DRS. This study adds novelty by simulating real-world parking locations, and simulates fleet choices across a large urban area, to understand the impacts of requiring off-street parking on the SAV fleet's eVMT, response times, costs, and other performance metrics.

The remainder of this paper is organized as follows: The next section elaborates on the parking strategy implemented in POLARIS to consider on- and off-street parking locations and to avoid SAVs' idling in place on the street. Then, the specifications of the Austin 6-county network and datasets used to simulate parking locations on this network are explained. Finally, the SAV operations, parking costs, and users' wait time are compared for different SAV fleet and parking search scenarios in the results section followed by conclusions and limitations of this study.

DATASETS USED

To simulate parking locations, the City of Austin's geographic information system (GIS) database of on-street parking locations (Austin Transportation Department, 2021) was used. This data was processed with context gleaned from Google Street View to fill in the gaps in on-street parking in the CBD. An index of off-street lots and parking garages with their respective capacities were then compiled from datasets provided by the Texas Facilities Commission and the Downtown Austin Alliance. Finally, since an exact accounting of parking on all streets in the region would be impractical and unnecessary, OpenStreetMap data was downloaded to provide a rough estimate of on-street parking across the rest of the six-county metro area. A total of 8,425 on- and off-street parking lots, with 550,799 available spaces, were generated for this network, as shown in Figure 1. Dense zones have about 5.4 lots per acre, while those at the periphery may have only one parking lot but there is always one within at the most 5 miles of an origin (which is mostly true only in the periphery of the network). Figure 2 illustrates the spatial distribution of parking lots, their spaces, and population density for all zones across the Austin 6-county network. Parking lots are denser in the populated area (i.e., in the CBD), while available spaces on the periphery are high given the larger area of those zones. The average and median distance of addresses to their closest parking lot are 0.29 and 0.20 miles, respectively.

The 5,300 square mile 6-county region's network contains 16,059 road links, 10,435 nodes, and 39,638 origins and destinations, and contains roughly 93% of all addresses (with the final 7% being in low-density residential settings, very close to coded links and addresses). The entire 1.9 million population of Austin's 6-county region was simulated. POLARIS, an agent-based model developed by Argonne National Lab, can micro-simulate SAV operations across in complex/realistic network for a wide region (Auld et al., 2016; Gurumurthy et al., 2020. Like MATSim and other agent-based models, POLARIS lets users track individual vehicles and travelers across roadways, walkways, and bikeway links linked to specific destinations (typically individual addresses). This gives far more detailed results than zone-based demand models. Travel demand for scenario runs were created using calibrated travel demand choice models for a synthetic population in POLARIS.

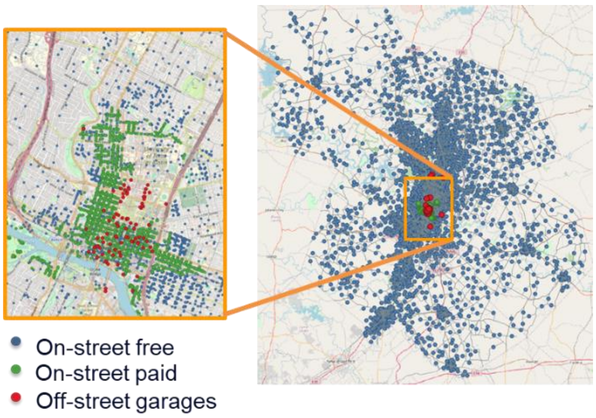

Figure 1. On-street and Off-street Parking Lots for SAV Use, as Simulated across the 6-County Austin, Texas Region

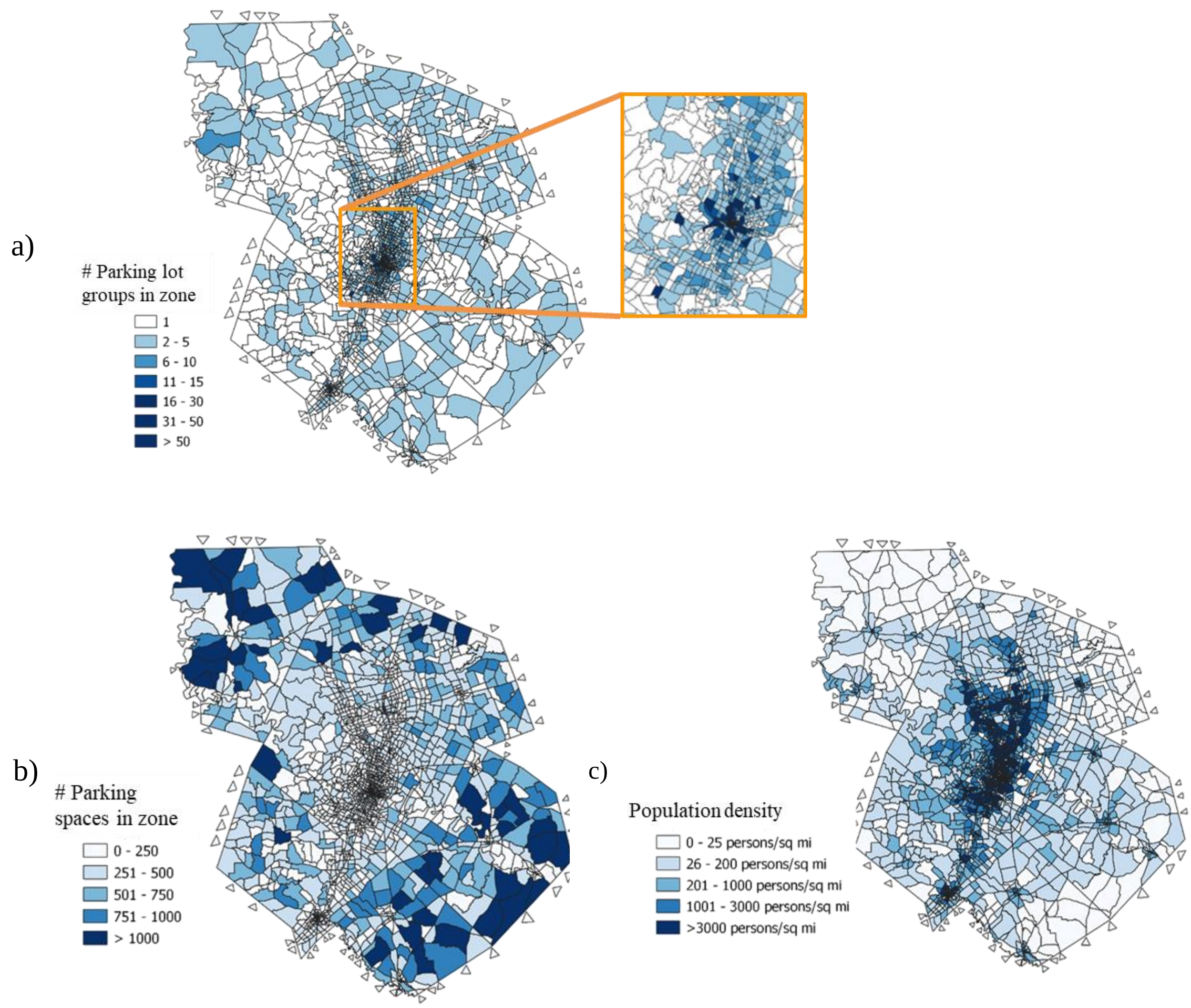

Figure 2. Spatial Distribution of Parking Lots (a), Available Parking Spaces (b), and Population Density (c)

PARKING STRATEGY MODEL

In the real-world, many ride-hailed vehicles (or SAVs) cannot simply idle in place after dropping off passengers and should find a more suitable place to park and wait for a new assignment. In far-flung rural and suburban parts of Austin and most other U.S. settings, parking is free and in ample supply. In dense downtowns, however, it is often restricted and priced. The strategy developed here requires SAVs to seek the closest or lowest (total) cost parking spots when starting to idle after completing a trip. The parking search strategy starts after an SAV drop-off. Two different parking search objectives are adopted in this study: first, finding the closest parking space using Euclidean distances, and second, minimizing a combination of the expected parking cost and the cost to drive to the parking location. This second objective could be expanded in the future to include parameters like proximity to SAV trip demand and extra penalties for egress from multi-story parking garages when going to serve the next trip. The basic format used in the scenarios for this study is as follows:

$$\min\,(C_p t + C_r d)\ \text{ s.t. } d < d_m \tag{1}$$

where C_p is the hourly parking fare in each parking location, which was gathered as a part of the data collection, and t is the time parked. C_r represents the cost of an SAV traveling one mi to park, d is the distance to the parking lot (in miles), and d_m is the maximum parking distance that is allowed. The parking finder reads in several scenario settings and a maximum search distance prevents extreme distances (to find a parking spot). Figure 3 summarizes the parking search process.

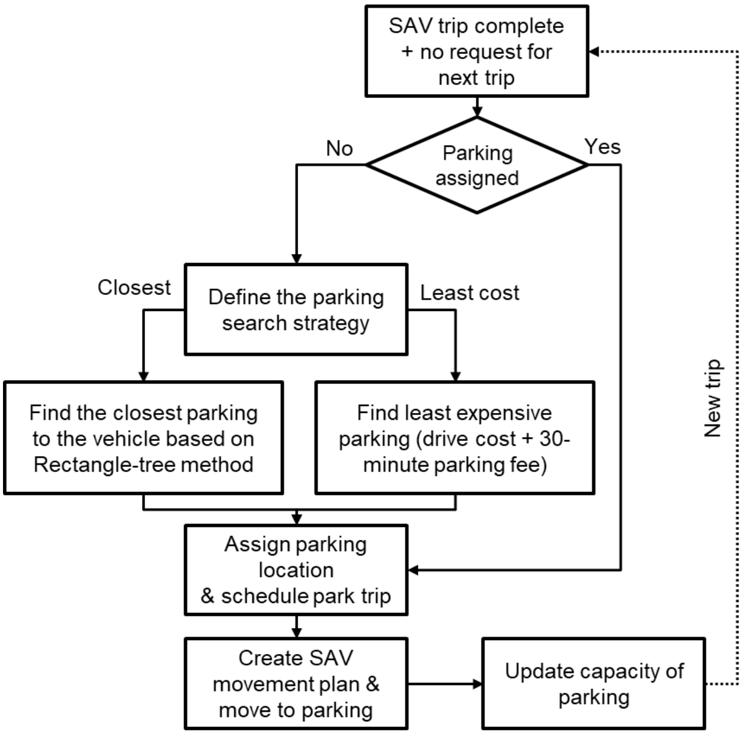

Figure 3. Parking Search Program Logic for SAVs

The cost of SAV travel per mile is another key parameter, with the default set to $1/mile here. This is reflective of a composite cost for fuel, depreciation, and maintenance, and thanks to the absence of human drivers. A final input parameter is the expected time per parked position (in hours). This value is multiplied by each parking lot's cost per hour (per SAV) (defined in the data collection) and used in the cost-minimization scenario. Once all these values have been initialized, the current coordinates of the SAV searching for parking are found, and POLARIS begins iterating through possible parking spaces when a parking request is made. At the start of each simulation run, a list of available parking spots at each parking location is initialized to the total number of spaces. During a parking request, the model checks if a parking space is indeed available. When each vehicle parks and or "unparks," parking lot capacity is updated. Next, the chosen parking ID is fed into the parking trip scheduler. This signals the SAV to start its parking trip.

While traveling on the network, the SAV is routed using the dynamic traffic assignment (DTA) methods employed by POLARIS. However, enroute switches can be triggered at any time to pick up new travelers (in which case the current parking trip is canceled, and a pickup trip is created to route the SAV to the user's location). If a parking event does happen, then the parking data (e.g., lot ID, vehicle ID, parking price per hour, and parking durations) are added to the record, and then combined with other parking records (to provide a register of all parking sessions for the SAV fleet over the course of the day). This can be used to determine the fleet's total parking cost, time spent parked, and - most importantly - where vehicles park.

To better reflect real-world parking supply conditions, all personal vehicles are also allowed to park using the nearest parking search strategy. Drivers of private vehicles evaluate parking urgency (depending on proximity to a non-home destination) and parking availability on or nearby the current link while they are moving on the network close to their destination. If the agent finds an empty parking space near the final destination, they park, and the parking location's capacity is updated (Figure 4).

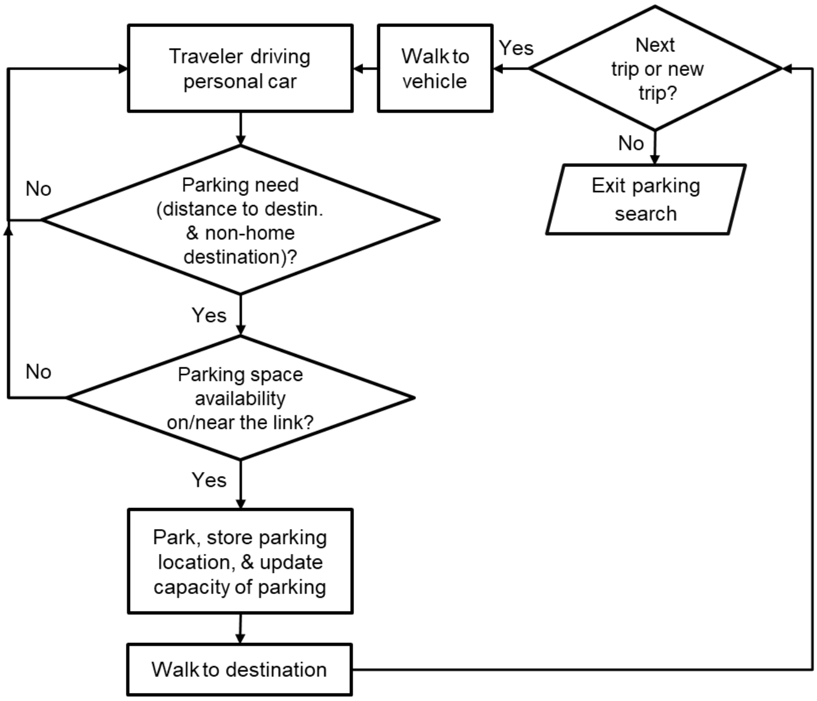

Figure 4. Parking Search Program Logic for Private Vehicles

MODEL AND SCENARIOS

Two restricted parking configurations were tested for SAV service and compared with a scenario where SAVs were allowed to simply idle after drop-offs. These scenarios restrict parking to legal, known parking locations. In the first restricted parking scenario, which is useful in areas with high curb demand and good parking information such as the CBD and surrounding regions, SAVs must move to the nearest parking location with available spaces considering the parking supply minus occupied spaces by other vehicles. In the second parking scenario, more cost-related parameters are used in the parking search model to find a lot that minimizes price and distance. The same cost per mile to operate the SAV to pickup/drop-off users ($1/mile in the scenarios of this paper) was used, and the parking option with the lowest combination of hourly price and cost of driving was selected to park. The minimum cost of half an hour of parking was used even though the average idle time is lower than the minimum amount of paid parking time. The maximum distance that an SAV can go to park is assumed to be 6 miles. SAVs are only allowed to serve trips starting in the Travis County geofence, which has the highest demand in the Austin network. This geofence includes the City of Austin (except for a small section in Williamson County) and some of its suburbs, such as Pflugerville, Manor, and Bee Caves.

This study simulates SAV trips in a geofence as the fleet is mostly profitable in high-density demand areas. These two restricted SAV parking search strategies were compared with the scenarios without parking restrictions for SAVs for different SAV fleet sizes. SAV fleet size of 5,000, 10,000, and 15,000, which provides 1 SAV for 100 to 300 residents, were compared to show the parking functionality for different SAV fleet sizes. Rideshare cost was also assumed to be $1 upfront plus a cost per mile of $1/mile. Human-driven vehicles (HVs) are simulated across the entire 6-county Austin network and park at designated on-street and off-street locations if their destinations are in the urban core where free street parking is limited. This paper first simulates two fixed demand scenarios (i.e., reading demand from database) to compare SAV operations with and without restricted parking (Table 1). Then, to compare two SAV parking search strategies and the personal vehicle parking, simulations without fixed demand were run and parking-related operations were compared (Table 2).

APPLICATION AND RESULTS

Table 1 shows SAV operation details for different fleet-size scenarios when using the minimum-distance (to closest parking lot) strategy compared to idling in-place scenario. To compare these two scenarios, traffic was first simulated without restricted parking for 5000 SAVs. Demand was then fixed to compare SAV operations for different fleet sizes with and without restricted parking. The results suggest that restricted parking implementation increases users' wait times (from 3.0-4.7 min to 3.9-6.3 min). SAV profit becomes smaller with restricted parking scenarios due to parking costs and smaller trips served. Idle time falls slightly from 8.9 hours (5000 fleet size) to 18.1 hours (15,000 fleet size) per day per SAV to 8.3 to 17.7 hours and AVO falls from 1.59-1.97 to 1.62-1.87 after restricted parking implementation.

As expected, vehicle utilization and idle time are inversely related. The larger the fleet, the fewer trips are served per vehicle on average (since there is less than 1 SAV for every 100 person-trips in the simulation). On the other hand, increasing SAV fleet size decreased the average users' wait time (from 5 to 3 minutes with unrestricted parking and from 6 to 4 minutes with restricted parking). By having a higher fleet size, average SAVs' daily revenue fell from almost $500 to $200, and AVO with DRS option fell from 1.90 to 1.60 persons per SAV. Note that more than 99.8% of all person-trips requested in all scenarios were met during the simulation horizon in less than 10 minutes waiting time. The SAV mode share within the geofence was 25% with and without restricted parking in two fleet size scenarios (i.e., 10,000 and 15,000 SAVs). Increasing SAVs fleet size increased the SAV mode share from 20% (with restricted parking) and 23% (unrestricted parking) to 25%.

Table 1. SAV Operations with and without Restricted Parking with a Fixed Demand

	Unrestricted Parking			SAV Parking Restricted		
SAV Fleet Size:	5000	10,000	15,000	5000	10,000	15,000
Profit per day per SAV ($)	$353	163	113	$342	149	101
Wait time for users, avg. (min)	4.7 min	3.1	3.0	6.3 min	4.3	3.9
SAV trips/vehicle/day	77 trips	43	30	65 trips	43	30
AVO (per revenue-mile)	1.97 occupants	1.64	1.59	1.87 occupants	1.66	1.62
Idle time per day (hr/vehicle)	8.9 hr	15.4 hr	18.1 hr	8.3 hr	14.6 hr	17.7 hr
SAV mode share in geofence (%)	23%	25%	25%	20%	25%	25%
%Empty VMT (%eVMT)	17.6%	12.5%	11.9%	13.6%	14.3%	14.4%
Demand (person-trips per day)	386,887 trips	433,057	434,439	322,805 trips	431,357	433,673
Avg travelled distance (mi)	8.72 mi	7.82	7.73	11.19 mi	8.51	8.32
Avg travel time (min)	18.3 min	15.9	15.6	20.6 min	17.2	16.7

Table 2 shows fleet parking costs, times, and number of trips for two SAV parking search strategies, as well as the nearest parking strategy for private vehicles (with idling in-place for SAVs). The number of parking trips by private vehicles is higher when SAVs do not park on off-street and on-street parking spaces, probably due to more spaces available for HVs. Restricted parking implementation for SAVs slightly increase the parking fee for private vehicles as SAVs occupy some free parking spaces across the network, especially in the least-cost parking search strategy. However, due to the availability of free parking spaces across the Austin 6-county region, parking fee is still negligible ($0.55 per parking trip of private vehicles without SAV restricted parking vs $0.65 per parking trip with SAV restricted parking). SAVs park in off-street parking spaces on average 5 hours per day where the average parking duration is half an hour. All vehicles' average parking duration is 4 hours per parking trip, which falls to 3 hours per parking trip after implementation of restricted SAV parking search strategies, as average parking duration of SAVs is half an hour. Parking costs using the least-cost parking search strategy were less than $3 per day for all SAV fleet scenarios and less than $4 using the nearest parking search strategy for SAVs. Use of free parking location, with a marginal tradeoff for distance, did not increase the empty VMT (14% for both SAV parking search strategies) and average idle time of vehicles (8 to 16 minutes for both SAV parking search strategies).

Table 2. Parking Costs and Counts for Different Parking Scenarios

Scenario:	Closest Parking for all Vehicles			Min Cost for SAVs and Closest Parking for HVs			Unrestricted SAV Parking		
SAV Fleet Size:	5000	10,000	15,000	5000	10,000	15000	5000	10,000	15,000
SAVs									
#Parking Stops per SAV per day	15.80 stops	18.83	15.72	15.80	18.86	15.63	-	-	-
$Parking per SAV/day	$2.46	$2.31	$3.49	$1.52	$1.60	$2.28	-	-	-
HVs									
Parking Fee per HV Parking Stop ($)	$0.68	$0.57	$0.59	$0.69	$0.57	$0.72	$0.60	$0.47	$0.46
# HV Parking Events	181,602 stops	155,547	143,739	182,794	155,732	144,107	185,094	174,091	172,624

Note: Additional mobility metrics are shown in the "restricted" column in Table 1.

Figure 4 illustrates parking demand of all vehicles (Figure 4a) and SAVs (Figure 4b) and SAV trip requests distribution over the network for the 10,000-fleet with DRS and nearest parking strategy. SAV trip requests and parking demand are in the Travis County geofence, as these vehicles were limited to serve in this area in the simulations of this study. Other vehicles have trips across the entire 6-county Austin network, so their parking requests were distributed across the entire network (Figure 4a). As expected, SAVs' parking demand is more focused in the areas with higher trip requests, including the CBD. Figure 2 shows parking supply also follows parking demand, providing sufficient parking space for all SAVs in this study. Therefore, parking supply should match population density and trip requests, which was the case in this study, to accommodate different fleets across the network.

Figure 5 illustrates the temporal distributions of parking demand for SAVs and all vehicles (i.e., SAVs and private vehicles) and trip requests over the simulation time. This figure is drawn based on the results of the 10,000-SAV fleet scenario with the closest parking search strategy for all vehicles. The highest number of SAV requests happens around 7:30-7:45 AM and 5-

5:15 PM, while the highest SAV parking demand occurs around noon and 7:30:7:45 PM (with a temporal shift relative to the number of trip requests as vehicles are busy serving travelers at AM and PM peak periods). The peak parking demand for all vehicles, including non-SAVs, occurs at 7:45-8 AM.

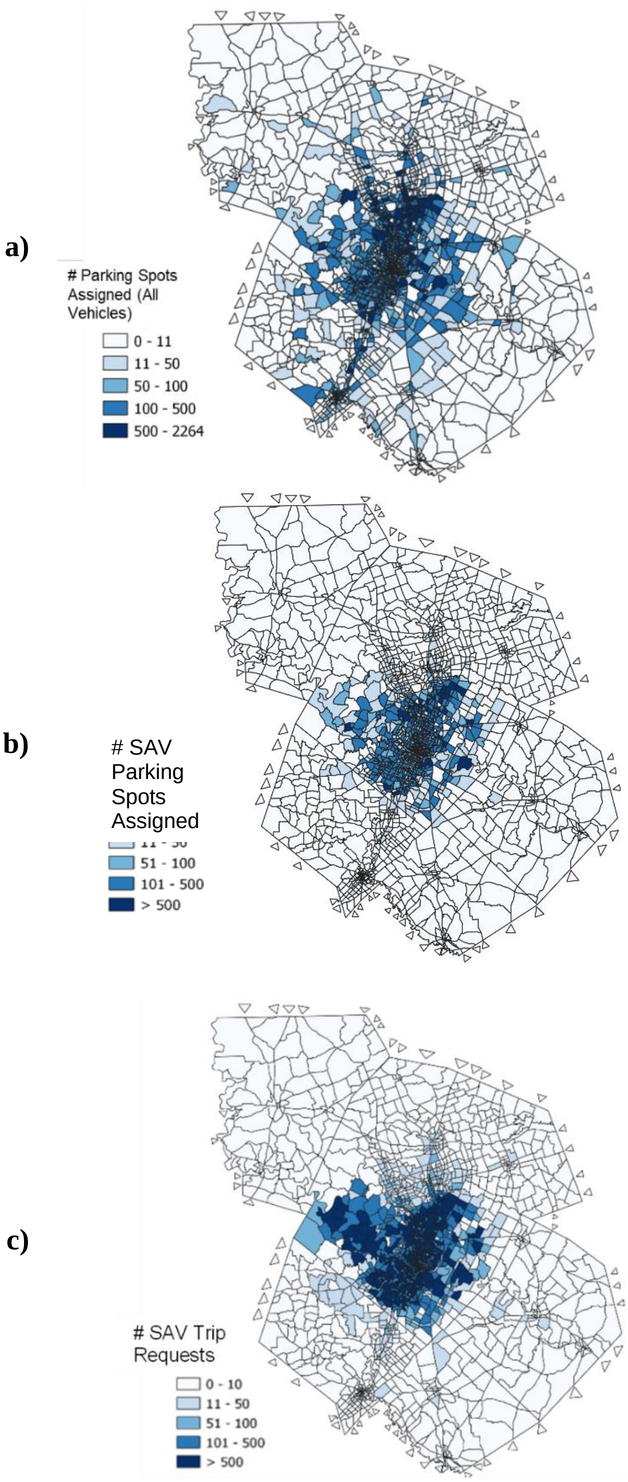

Figure 4. Spatial Distribution of All Vehicles' Parking Events (a), SAV Parking Events (b) and SAV Trip Requests (c)

a)

b)

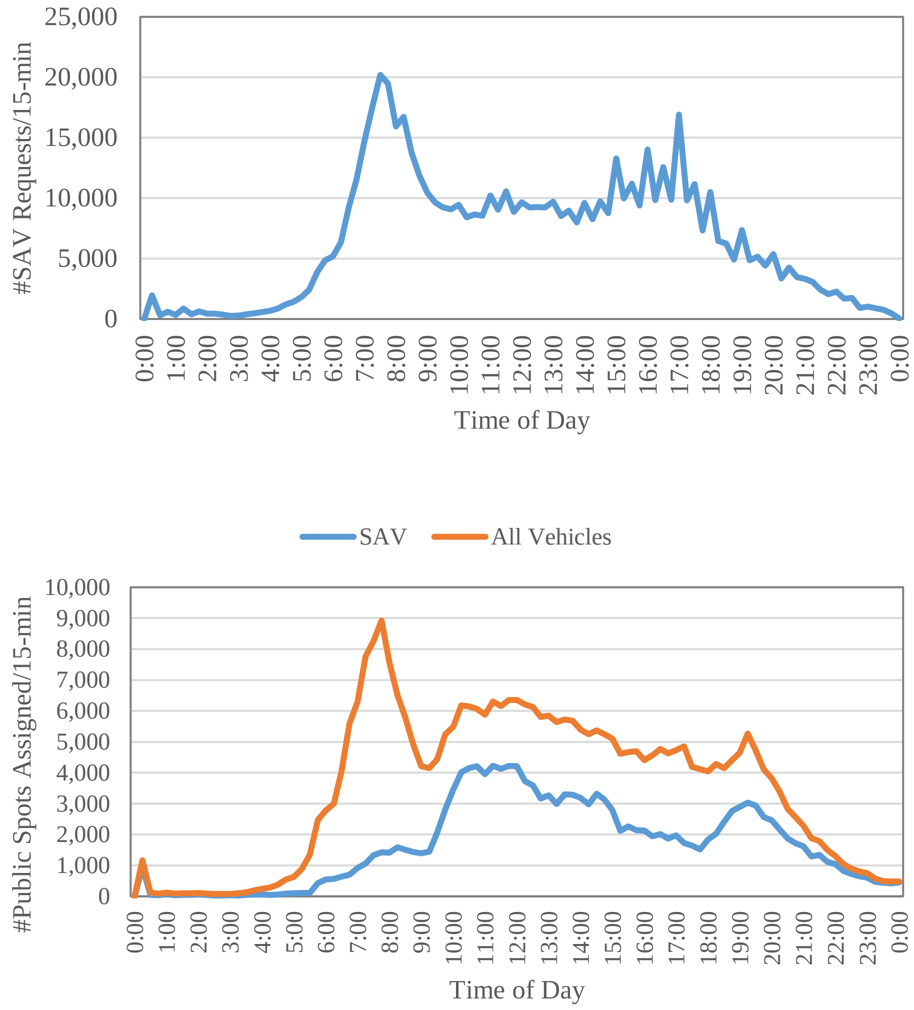

Figure 5. Temporal Distribution of SAV Trip Requests (a) and Parking Spots Assigned (b)

CONCLUSIONS

This study examines the impacts of moving SAVs to park at permitted on-street (free and metered) and off-street spots while idling. Using POLARIS, an agent-based simulator, two restricted-parking scenarios were compared to scenarios without SAV parking restrictions (where SAVs can idle in place between trip assignments) with and without private vehicle parking. In the first scenario, SAVs move to the nearest available spot, and the second scenario sends SAVs to sites offering the best combination of parking fees (which are highest in central Austin) and distance traveled (which incurs vehicle operating costs). These parking policies were tested with SAVs serving the Travis County (the county with the highest demand in the entire 6-county Austin region). Private vehicles are simulated across the entire 6-county region with 8,452 aggregated parking sites and 5,300 square-miles of land.

Results of different fleet sizes and parking search strategies (including idling in place) were compared. Results suggest that parking costs will average less than $4 per day (per SAV) with the nearest parking search strategy and $3 per day using the least cost parking search strategy. All SAVs parking in free spots adds negligible VMT while offering the least expensive parking strategy. Parking restrictions increase traveler wait times (from about 4 to 5 minutes) and empty VMT (from about 12% to 14% of SAV-fleet VMT). As expected, idle-SAV parking demand is higher in areas with more trip requests, including the region's CBD. SAV profit is smaller when vehicles are sent to on-street or off-street parking locations, due to the parking costs and smaller trips served. Allowing SAVs to park increases the average parking fee paid by other vehicles by 22% ($0.45-$0.60 to $0.57-$0.72 per HV parking event). However, the fee is small due to the high availability of free parking spaces in Austin. All SAVs parking in the least cost parking adds negligible VMT while offering the least expensive parking strategy. Parking prices can be used as a planning strategy to shift personal vehicle drivers to sharing rides and reduce traffic congestion due to parking searches.

In general, SAV movements to permitted parking spots should be considered in future fleet simulations, since vehicles sitting idle at drop-off points may not be permitted or acceptable in many busy (and many residential) settings. This analysis had some limitations, which can be addressed in future research. For example, the mode choice models used in this study had a small taxi/SAV trip sample, leading to a low probability of choosing this mode. The mode choice models were modified to address this issue, but real-world data should be used in future research for this purpose. In addition, similar to carsharing vendors, SAVs may buy spaces in the CBD to have dedicated staging areas, which should be considered in the future research.

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AUTHOR CONTRIBUTIONS

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

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