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

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ABSTRACT
The demand for ridehailing services (like Lyft, Uber, and Didi) is rising as they compete with other modes. Most SAV studies assume that vehicles are allowed to idle in place after completion of a trip, which should add congestion by taking up a lane, but is frequently not modeled. This study focuses on the SAV fleet impacts of allowing parking on street versus requiring off-street idling, between serving trips, across the 6-county Austin region (with nearly 2M travelers). Using POLARIS, an agent-based activity-based travel demand forecaster, two off-street-parking-required scenarios were compared to a scenario where vehicles can idle on the street (after drop-off, until being assigned a new passenger). In the first scenario, SAVs simply move to the nearest available parking lot. The second parking strategy sends the SAV to a lot based on the tradeoff of price and distance costs. Over 8,400 parking lots were simulated for different fleet sizes, with SAV fares of $1 fixed pickup cost plus $1 per rider-occupied network-mile, and dynamic ridesharing permitted in half the simulations. Dynamic ride-sharing increased average travel time (from 14.6-14.9 min to 21.9-23.2 min, across different scenarios) and average users’ wait time (from 5.3-5.7 min to 6.8-8.0 min) while decreasing the share of empty vehicle-miles travelled (from 21.4-22.5% to 12.2-13.6%). The average vehicle occupancy in scenarios with ridesharing also increased from 1 person to 1.33-1.40 persons per vehicle. The total parking cost and parking time is also significantly lower with ridesharing capability (i.e., $2.04/veh-$2.86/veh) relative to without ridesharing (i.e., $3.74/veh-$4.80/veh). Parking demand also decreased from 11.4-17.9 per vehicle to 6.6-9.1 with ride-sharing capability in the nearest parking search strategy as ride-sharing increased trip chaining.

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

INTRODUCTION
The demand for ridehailing services (like Lyft, Uber, and Didi) is rising as they compete with other modes. In 2017, 2.6 billion passengers used ridehailing in the US, which is 37% higher than the prior year’s value (Schaller 2018). These companies provided the option to share rides with strangers before the COVID-19 pandemic. Ridesharing or “carpooling” helps lower the number of low-occupancy private vehicles along with ride-hailing fares (Wenzel et al., 2019). Fleets of shared, fully automated, or “autonomous” vehicles (SAVs) can facilitate dynamic ridesharing (DRS) by lowering ridehailing 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/or emissions issues (Xia et al. 2021, Alessandrinia et al. 2015, Parkin et al. 2018, Fagnant and Kockelman 2014, Lee and Kockelman 2019, Loeb and Kockelman 2019), they can add traffic and create curb congestion in busy settings (where trip starts and ends are high, as with a central business district, 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), as 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 proper policies or regulations are not used to lower their 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). Gao et al. (2022) suggested parking capability for these vehicles as the best strategy to control their extra vehicle-miles travelled (VMT) and eVMT. They proposed a shared parking model for ridesharing that coordinates vehicle-passenger and vehicle-garage matchings. They found that the parking implementation increased passenger demand by 5.27% (from 115 per min to 121 per min for the San Francisco network) and increased ride-sharing revenue by 22.17% (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, the curbside free 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 in multiple rows behind each other, rather than only two 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 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 by forcing these vehicles to park far from the high demand parking 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 very small campus network.

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 tended to simplify 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 area. They compared scenarios where SAVs simply idled in place after completing their trips versus obliging them to find the nearest garage to park in. 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 the MATSim software implementation. In addition, 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 Sioux Falls network. Their results showed that optimizing parking fee significantly impacts the repositioning behavior (total number of repositioning trips decreased from 169,790 to 158,870) and decreases AVs’ eVMT (eVMT reduced from 1,834,223 mi 1,494,467 mi). They conducted this analysis on a small network and assumed parking data and cost due to the lack of available data.
Zhang et al. (2015) modeled on-street curbside parking demand minimizing 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 their study region. 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, 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. While this is a robust method of parking search that mirrors the way human drivers cruise for parking, the current study expands upon it 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 seeks to add two additional 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. The POLARIS travel modelling software is updated in this study for the parking strategy. This robust tool allows for simulating 100% of the Austin area with around 2 million population with features such as SAVs, dynamic traffic assignment, and DRS. This study strives to simulate real-world parking locations and choices by an SAV fleet across a large urban area, in order to appreciate the impacts of requiring off-street parking capability on the SAV fleet’s eVMT, response times, costs, and other performance metrics.

The reminder of this paper is organized as follows. The next section elaborates on the parking strategy implementation in the POLARIS traffic simulator to consider on- and off-street parking locations and to avoid SAVs’ idling in place on 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 with and without DRS in the application and results section followed by conclusions and limitations of this study.

DATA SETS 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, and Google Street View was performed to fill in the gaps in on-street parking in the central business district. Next, an index of off-street lots and parking garages with their respective capacities was compiled. Finally, since an exact accounting of parking on all streets in the region would be impractical and unnecessary, OpenStreetMap data were downloaded to provide a rough estimate of on-street parking across the rest of the six-county metro area. 8,425 on- and off-street parking lots were generated for this network, as shown in Figure 1. The most densely lotted zones have about 5.4 lots per acre, while those at the periphery may have zero parking lot. The 6-county region’s network contains 16,059 road links, 10,435 nodes, and 39,638 possible 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).
Figure 1. On-street and off-street parking lots for SAV use, as simulated across the 6-county Austin, Texas region

The entire 1.9 million population of Austin 6-county region was simulated in this study. This was done using the POLARIS travel demand modeling software. POLARIS is an agent-based model developed by Argonne National labs and can micro-simulate SAV operations across in complex/realistic network for a wide region (de Souza et al., 2019). Similar to MATSim and other agent-based models, POLARIS lets users track individual vehicles and travelers across roadways, walkways, and bikeway links to specific destinations (typically individual addresses). This gives far more detailed results than zone-based demand models. The current Austin-area network has 16,059 road links, 10,435 nodes, and 39,638 possible destinations, based on the Capital Area Metropolitan Planning Organization (CAMPO) 2015 roadway network. The region’s 1,885,993 persons were synthetically generated using the US Census Bureau’s 2018 American Community Survey (ACS) Public Use Microdata Sample (PUMS) and iterative proportional fitting (IPF) method. The mode choice model was previously calibrated using the 2016-2017 Austin-area household travel survey (Dean et al. 2022).

**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 program developed here seeks the closest or lowest (total) cost parking spots for idle SAVs. 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 as the crow flies, 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 upon 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 their next trip. The basic format used in the scenarios for this study is as follows:

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

(1)

where $C_p$ is the hourly parking cost in each parking location and $t$ is the minimum time parked, $C_r$ represents the cost per mile of ridesharing, $d$ is the distance to the parking lot (in miles), and $d_m$
is the maximum parking distance that the search is conducted within. The parking finder reads in several scenario settings and a maximum search distance prevents extreme distances (to find a parking spot). By setting this value to a distance and only including parking information in certain parts of the simulated region, this ensures that SAVs must find parking in those specified areas. If the SAV finds itself in a setting with ample parking (like a suburban neighborhood) but none explicitly included in the code, it will simply idle in place. Figure 2 summarizes the parking search process.

![Parking Search Program Logic Diagram](image)

Figure 2. Parking Search Program Logic

SAV travel cost per mile is another key parameter, with the default set to $0.50/mile. This is reflective of a composite cost for fuel, depreciation, and maintenance. 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) and used in the cost-minimization scenario. Its default value is 30 minutes. However, an initial model run delivers a more accurate parking session duration (reflecting that scenario’s fleet size, demand, and other factors that affect SAVs’ parked/idle time).

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. First, the model checks if that parking space is indeed available. At the start of each run, a list of available parking spots at each parking location is initialized to equal the total number of spaces. When each vehicle parks and or “unparks”, parking lot capacity is updated. Among the parking locations with available space, the nearest or the least expensive parking space is found (depending on the selected parking search strategy/scenario used). Next, the chosen parking ID is fed into the parking trip scheduler. This calls several functions common to starting any type of SAV trip in POLARIS. First, the idle structure, which keeps track of the number of idle SAVs in each zone, is updated to reflect that the SAV that is going to park is no longer idling in the departure zone. Then, the link
adjacent to the parking destination is pulled from the parking database and set as the destination link. A movement plan connecting the current link and destination link is created, and the SAV is pushed onto the network.

While traveling on the network, the SAV is routed using the dynamic traffic assignment (DTA) methods employed by POLARIS. However, it can be redirected 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). Parking 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). Using this, one can determine the fleet’s total parking fees paid, time spent parked, and - most importantly - where vehicles park.

MODEL AND SCENARIOS

Two parking configurations were tested for SAV service and compared with a scenario that SAVs were allowed to simply idle after drop-offs. In the first 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. Because there was no readily available parking information, parking supply was randomly generated throughout the model region, treating the entire area as if it were a CBD. In the second parking scenario, a more advanced parking search model was used that finds a list of the 50 closest spaces and sends the SAV to the parking location with the best combination of 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 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. It is possible that SAV operators could negotiate with garage owners or the city to pay for the exact time they stay parked which would lead to lower parking costs, which is beyond the scope of this initial parking search algorithm.

These two parking search strategies were compared with the scenarios without parking capability for different SAV fleet size, rideshare cost, and DRS scenarios. SAV fleet size of 20,000, 25,000, 30,000, and 35,000 were compared to show the parking functionality for different SAV fleet sizes. Rideshare cost was also assumed to be $1/mile upfront plus a cost per mile of $1/mile. All these scenarios are compared with and without DRS capability to show the impact of ridesharing on SAV operations, users’ wait time, and parking costs. Thus, the total of 48 scenarios are simulated and compared in this study.

APPLICATION AND RESULTS

Table 1 shows SAV operation details (including fleet parking costs, per SAV) for different SAV fare and fleet-size scenarios when using the minimum-distance (to closest parking lot) strategy. As expected, total person-trips requested and served, idle times, and SAV mode shares rise with fleet size (since there is less than 1 SAV for every 115 person-trips in the simulation, even when using the largest [35,000] fleet size). On the other hand, increasing SAV fleet size decreased the average users’ wait time, average SAVs’ revenue, and average vehicle occupancy (AVO) with DRS option. Note that more than 99.8% of all person-trips requested in almost all scenarios were met during the simulation horizon in less than 10 minutes waiting time. The results also suggest that dynamic ride-sharing increased average travel time (from 14.6-14.9 min to 21.9-23.1 min, across different scenarios) and average users’ wait time (from 5.3-5.7 min to 6.8-8.0
while decreasing the share of empty VMT (from 21.4-22.5% to 12.2-13.6%). The AVO in scenarios with DRS also increased from 1 person to 1.33-1.40 persons per vehicle. The total parking cost and parking time is also significantly lower with DRS capability (i.e., $2.04/veh-$2.86/veh) relative to without DRS (i.e., $3.74/veh-$4.80/veh). Parking demand also decreased from 378,028-400,117 to 181,844-229,839 with ride-sharing capability in the nearest parking search strategy as DRS increased trip chaining.

Table 2 shows the same SAV operations and parking costs for the least cost parking strategy. Comparing the results with and without DRS for different ride-sharing costs, the same trends as the minimum distance parking strategy were observed in this parking strategy. The parking costs using the least cost parking search strategy were zero for all scenarios with and without DRS, meaning that SAVs were all parked in free on-street parking locations rather than off-street garages or on-street metered parking locations (as is the case for the nearest distance parking search). Use of free parking location, with a marginal tradeoff for distance, did not increase the empty VMT and average idle time of vehicles. In both parking search strategies without DRS relative to the scenario without parking, average vehicles’ idle time decreased up to 11% (15-18 hr to 14-18 hr), share of empty VMT from total VMT increased up to 54% (14.80-17.54% to 21.64-23.02%), and average wait time increased up to 21% (4.58-4.83 min to 5.37-5.80 min). DRS also reduced parking demand by more than 50% (12-19 per veh to 7-9 per veh) in different scenarios. Although parking strategy increased users’ wait time and SAVs’ share of empty VMT relative to the scenarios with vehicles idle in place after drop-offs (not realistic), these values would be significantly lower compared to letting vehicles cruise around the network while idling.

Table 1. SAV operations and parking costs for the nearest distance parking search strategy

<table>
<thead>
<tr>
<th>SAV Fleet Size</th>
<th>w/o DRS</th>
<th>w DRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg travel time (min)</td>
<td>14.6 min</td>
<td>23.1 min</td>
</tr>
<tr>
<td>Demand (person-trips per day)</td>
<td>545,987</td>
<td>678,608</td>
</tr>
<tr>
<td>Revenue per day per vehicle ($)</td>
<td>$267.95</td>
<td>$370.46</td>
</tr>
<tr>
<td>AVO (weighted by revenue distance)</td>
<td>1.00 persons</td>
<td>1.40 persons</td>
</tr>
<tr>
<td>Avg idle time per day per vehicle (hr)</td>
<td>14.8 hr</td>
<td>13.4 hr</td>
</tr>
<tr>
<td>#Person-trips per SAV/day</td>
<td>27.3</td>
<td>33.9</td>
</tr>
<tr>
<td>SAV mode share (%)</td>
<td>14.4%</td>
<td>17.3%</td>
</tr>
<tr>
<td>%eVMT</td>
<td>22.5%</td>
<td>12.2%</td>
</tr>
<tr>
<td>Avg users’ wait time including pickup time (min)</td>
<td>5.7 min</td>
<td>8.0 min</td>
</tr>
<tr>
<td>Avg daily parking cost ($/SAV/day)</td>
<td>$3.74</td>
<td>$2.04</td>
</tr>
<tr>
<td>#Parking episodes per SAV per day</td>
<td>18.90</td>
<td>9.1</td>
</tr>
</tbody>
</table>

* Parking costs reported here exclude the costs of parking before the first trips
Table 2. SAV operations for the least cost parking search strategy

<table>
<thead>
<tr>
<th>Ridesharing</th>
<th>w/o DRS</th>
<th>w DRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAV Fleet Size</td>
<td>20,000</td>
<td>25,000</td>
</tr>
<tr>
<td>Avg travel time (min)</td>
<td>14.6 min</td>
<td>14.7 min</td>
</tr>
<tr>
<td>Demand (person-trips per day)</td>
<td>544,159</td>
<td>569,198</td>
</tr>
<tr>
<td>Revenue per day per vehicle ($)</td>
<td>273.37</td>
<td>225.13</td>
</tr>
<tr>
<td>AVO (weighted by revenue distance)</td>
<td>1.00 persons</td>
<td>1.00 persons</td>
</tr>
<tr>
<td>Avg idle time per day per vehicle (hr)</td>
<td>14.8 hr</td>
<td>16.3 hr</td>
</tr>
<tr>
<td>#Person-trips per SAV/day</td>
<td>27.2</td>
<td>22.8</td>
</tr>
<tr>
<td>SAV mode share (%)</td>
<td>14.4%</td>
<td>14.9%</td>
</tr>
<tr>
<td>%eVMT</td>
<td>22.5%</td>
<td>22.0%</td>
</tr>
<tr>
<td>Avg users’ wait time including pickup time (min)</td>
<td>5.7 min</td>
<td>5.5 min</td>
</tr>
<tr>
<td>Avg daily parking cost ($/SAV/day)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>#Parking episodes per SAV per day</td>
<td>17.9</td>
<td>15.5</td>
</tr>
</tbody>
</table>

SUMMARY AND CONCLUSION

This study focuses on allowing SAVs to park on existing on-street (free and metered) and off-street parking locations while idling. The parking simulation was performed in POLARIS traffic simulator. Two parking configurations were tested in this study and compared with a scenario without parking (i.e., vehicles stay idle on place after drop-off until the next pickup). In the first parking scenario, SAVs move to the nearest available parking location. The second parking search scenario finds a list of the 50 closest spaces and sends the SAV to the parking location with the best combination of price and distance, including the cost of moving to the parking location and the parking fee.

These parking configurations were tested for the Austin 6-county network with around 5,300 sq-mi of land and 1.89M population. The simulations were run for 100% of travel demands on a typical weekday. To simulate parking locations, the GIS database by Austin Transportation Department (2021) was used to define on-street parking locations across the city of Austin. In addition, an index of off-street lots and parking garages with their respective capacities was compiled. Finally, OpenStreetMap data was used to provide a rough estimate of on-street parking in the rest of the six-county Austin metro area. Every road classified as tertiary or residential on the site was divided into 5-meter segments to conservatively calculate the supply of parking provided about every 10 meters on each side of the road on local streets. The total of 8,452 parking locations were simulated across the network.

Different scenarios for fleet size, SAV fare, and parking search strategy were compared with and without DRS option. The results showed that average travel time were up to 57% higher with the DRS option in both parking search strategies while the average occupancy of vehicles was up to 43% higher with the DRS option relative to the scenarios without DRS. The DRS option also
decreased the percentage of empty VMT up to 47% of VMT in different fleet size and ride-share cost scenarios.

The comparison of SAV operations and parking results for different parking search strategies also showed that SAVs were sent to free parking locations in the minimum cost parking search strategy, while the cost of parking was between $37,360 (20K SAVs and 50¢/mile rideshare fee with DRS) and $187,634 (35K SAVs and 50¢/mile rideshare fee without DRS) to park SAVs within pickup and drop-offs in the minimum distance parking search strategy. AVs’ ability to reposition and skip parking costs is mentioned as their major benefits for SAVs. Thus, the nearest parking strategy might not be a feasible option to force SAVs to use, unless supporting policies or regulations exist.

Overall, SAV parking allocation should be considered in the SAV simulations as forcing vehicle to be idle on their locations adds to the traffic congestion by taking up a lane. In addition, moving vehicles across the network after drop-offs significantly increases empty VMT, which highlights the importance of parking allocation. 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. This study also assumes that only SAVs park and they do not yet have to compete with private vehicles for spaces. It is possible that parking spots could be scaled down, e.g., reducing the capacity of all parking locations by 90% to ensure there is still some restriction on the ability of SAVs to find parking, but there was no reliable parameter that could be decided upon to by which to reduce parking. In the future, the better alternative would be to have all vehicles park at the end of the trip, which would necessitate the acquisition of better data on free off-street parking such as that found at grocery stores, schools, or restaurants.

REFERENCES


Austin Transportation Department – Parking Enterprise Division, (2021). Parking Inventory. https://services.arcgis.com/0L95CJ0VTaxqcmED/ArcGIS/rest/services/Parking_Inventory/FeatureServer.


Dean M, Gurumurthy, K. M., de Souza, F. D., Auld, J, Kockelman, K. M., Synergies between charging and repositioning strategies for shared autonomous electric vehicle fleets. Presented at


