Shared Autonomous Vehicle Fleet Performance: Impacts of Trip Densities and Parking Limitations

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ABSTRACT

This study micro-simulates 2% and 5% of the region's 9.5 million daily person-trips and 20% of trips in the central Twin Cities with shared autonomous vehicles (SAVs) in the 7-county Minneapolis–Saint Paul region using MATSim to appreciate the effects of different trip-making densities and curb-use restrictions. Results suggest the average SAV in this region can serve at most 30 person-trips per day with less than 5 minutes average wait time, but generating 13% more vehicle-miles traveled (VMT). With dynamic ride-sharing (DRS), SAV VMT fell, on average, by 17% and empty VMT (eVMT) fell by 26%. Compared to idling-at-curb scenarios, parking-restricted scenariosgenerated 8% more VMT. Relying on 52 mi/gallon hybrid electric SAVs is estimated to lower travelers' energy use by 21% and reduce tailpipe emissions by 30%, assuming no new or longer trips. A 106 mi/gallon equivalent battery-electric fleet does much better by lowering energy use by 64%.

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Keywords: Shared Autonomous Vehicles; Dynamic Ride-Sharing; Agent-Based Modeling; Curb Parking; Empty Vehicle-Miles Traveled; Energy Analysis.

BACKGROUND

Autonomous vehicle (AV) technology has rapidly developed over the last decade. With AVs expected to be used in shared fleets, as shared AVs (SAVs), many researchers are working to optimize SAV strategies in the realms of operations and pricing, while minimizing negative urban and regional impacts, especially including traffic congestion and pollution .

Many AV benefits are anticipated since they can readily follow optimal routes to reach their destinations with self-adjustments in real-time (Claudel and Ratti, 2015). AVs may offer opportunities for dynamic allocation of lanes (if there is no median dividing opposing lanes) during peak periods and before entering bottlenecks by connecting to traffic management systems in real-time (Skinner and Bidwell, 2016). Such traffic management systems can reduce network congestion and the associated emissions and energy use (Ticoll, 2015; Taiebat et al., 2018). Driver error, including alcohol and drug use, use of mobile devices, fatigue and lack of driving knowledge or experience, is the predominant cause of traffic crashes (Eugensson et al., 2013). By eliminating driver error, AVs are expected to considerably improve motorized-travel safety (Rodoulis, 2014). SAVs are expected to further reduce travel costs (Chen and Kockelman, 2016; Fagnant and Kockelman, 2018; Lu et al., 2018; Simoni et al., 2019; Gurumurthy et al., 2019) and benefit long-distance travel (LaMondia et al., 2016; Perrine et al., 2018).

Improving ease of trip making adds vehicle miles traveled (VMT) to the network. Fagnant et al. (2014) used an agent-based model with a gridded representation of downtown Austin and 25 2-mi x 2-mi neighborhoods to evaluate different SAV relocation strategies. Average wait times in their 10 mi x 10 mi town fell and less than 0.5% of travelers waited more than five minutes. During peak periods, more than 97% of all SAVs were occupied, delivering high SAV utilization levels. They estimated each SAV could replace around 11 conventional vehicles if no travel outside the region was needed but added up to 10% more vehicle-miles traveled (VMT). Boesch et al. (2016) studied SAV operation for Zurich and found a similar replacement rate of 10 conventional vehicles with 1 SAV with a maximum waiting time of 10 min when more than 95% of trip requests were satisfied with 1 SAV for every 10 people simulated. Simoni et al. (2019) simulated AVs and SAVs across the City of Austin and estimated daily passenger-VMT increases of 16.2% for an AV-oriented scenario (where personal AVs are widely used) and 22.4% for an SAV-oriented scenario (where shared mobility is more prevalent). Gurumurthy et al. (2019) estimated empty travel (eVMT) by SAVs across the wider Austin region to vary from 3.8% to 18.9 % of total passenger-VMT. If SAVs are not permitted to wait at their most recent destination before responding to a new trip request, relocation will add more VMT.

Dynamic ride-sharing (DRS) in SAVs is likely to be an effective low-cost alternative for automobile travel. Jung et al. (2013) developed a shared-taxi algorithm by using hybrid simulated annealing to dynamically assign passenger requests efficiently. The simulation results revealed that the algorithm could minimize total travel times and maximize the total profit of a shared-taxi system. Fagnant et al. (2018) implemented anticipatory relocation similar to Jung et al. (2013) to strengthen the efficiency of their SAV fleets in Austin. The results showed that DRS decreased total average service time (from 15.0 to 14.7 minutes) and travel costs depending on different scenarios for SAV users. Furthermore, VMT decreased by over 8% with DRS, thereby lowering network congestion. With SAV services priced at $1.00 per mile for a non-shared trip, SAV fleet managers could earn a 19% annual (long-term) return on investing $70,000 per SAV initially. Hörl (2017) provided agent-based models for DRS in MATSim with congestion modeled endogenously, and showed that DRS use at least during peak times would lower congestion. Gurumurthy and Kockelman (2018) simulated SAVs with DRS in Orlando using AirSage's cellphone-based trip tables for over 30 days. Approximately 60% of single-person trips could be shared with other similar trips with less than 5 minutes of added travel time from sharing. Just 1 SAV per 22 person-trips could satisfy almost half the total demand in that region and could improve congestion.

The user choice in using an SAV for trip making is also important and is typically influenced by tolls and fares. Simoni et al. (2019) showed that SAV benefits are maximized only when pricing other modes with about 4% welfare gains in a variety of future alternatives. Kaddoura et al. (2020) introduced congestion pricing into their SAV simulations and analyzed the impact of different schemes on the market share of SAVs. The results show that the share of SAVs will decrease by about 16% when congestion pricing is applied to SAVs and conventional vehicles. Gurumurthy et al.'s (2019) simulation study showed better trip matching when trips in a personal vehicle were tolled, but did not allow for a choice to not share an SAV. Vosooghi et al. (2019) focused on the optimal DRS fare for 4-seater SAVs in France's Rouen Normandie metropolitan area. Offering shared rides at about 20% cheaper than a single-occupant ride was sufficient to attract users to pool their rides. Furthermore, fares lower than the 20% discount did not appear to increase SAV mode share. However, the study simulated relatively small fleet sizes from 2000 to 6000 with only about a 7.6% mode share. Hörl et al. (2019a) looked for the optimal SAV fleet size by studying dynamic prices. With mode choice, passengers chose whether to use an SAV according to estimated response times and fare. Their results showed that 1.2M trips could be satisfied with 25k SAVs at a fare of 0.27 EUR/km, which is 10% lower than the cheapest fare assessed for conventional vehicles in the France study.

The current literature states the importance of studying SAVs and fleet parameters as they may significantly impact future travel outcomes. Most studies, however, used a fixed sample for all analysis, and little is known regarding the extent of trip demand simulated on the fleet performance. Further, a significant restriction of most SAV studies is the assumption that vehicles are allowed to idle in place after completion of a trip, which may add some congestion from taking up a lane. This study microsimulates personal trip-making throughout the Minneapolis-St Paul (MSP) region of Minnesota, USA using a system of SAVs while considering varying trip densities, parking constraints, and fleet parameters. The simulations use the multi-agent travel-choice model MATSim (Horni et al., 2016) and MATSim's autonomous mobility-on-demand simulator (AMoDeus) developed by Ruch et al. (2018). Although mode choice is important from a user perspective, all trips are assumed to be made by an SAV here to gauge the service based on trip demand and fleet parking restrictions. The input files rely on network data from OpenStreetMap and 24-hour trip data from the region's metropolitan planning organization (MPO), called Minnesota Metropolitan Council. MATSim allows one to track individual travelers or "agents" throughout the day, between all activity sites. Metropolitan Council provided all travelers' itineraries, trip purposes, origins, and destinations, along with land use data by traffic analysis zone (TAZ). The SAV fleet size and starting locations are determined in a 24-hour initial simulation, so that a new SAV is generated whenever a traveler's wait time exceeds a desired window of 1 hour. In the subsequent 24-hr simulations, some travelers may wait longer, and the SAV fleet's response radius will expand until an SAV can be assigned. In other words, all travel demand will be met unless travelers cancel their SAV requests after waiting 1 hour. Finally, all SAVs are assumed to remain at the curb where they dropped off their passenger(s) in most scenarios, but several restricted-curb-parking scenarios are studied to allow inspection into the reality of congested curb settings and likely public policy responses to SAVs idling anywhere. The remaining paper describes details of the data set from OpenStreetMap and Minnesota Metropolitan Council, explains the methodology for disaggregation of trips and facilities, simulation scenario and principles of dynamic ride-sharing. Simulation results are presented before providing the paper's conclusions.

DATA SET

Travel demand data was obtained for the MSP region from the local MPO in the form of trips with aggregated origins and destinations at the TAZ level. This data was generated using activity-based models for the year 2015. The MSP network was extracted from OpenStreetMap for the 19 counties in the region and cleaned using MATSim's network simplification code. The network spans seven counties in the MSP region with 42,485 directed road links and 20,746 nodes. It also contains coordinates of nodes and basic information for each link, such as connected nodes, length, free speed, capacity, number of lanes, and available travel modes.

Nearly 9.5 M person-trips made on a typical weekday (when school is in session) were provided by Metropolitan Council, and each trip is identified by a person ID, a household ID, the person type, trip mode, trip purpose, origin TAZ, destination TAZ, trip distance, departure time and arrival time. The person types include a child, non-working adult, senior, part-time worker, full- time worker or an adult student. The trip purposes include school, work, university, meal, shopping, personal business and social recreation. There are seven trip modes observed, including drive alone, shared rides, walk, walk to transit, park-and-ride, bike and school bus. This study assumes that all demand is satisfied by using SAVs for a corner-case future. Therefore, the selected mode for each trip that was provided in the dataset is not used. External trips and truck trips are also not included in this dataset or in this work's SAV fleet assignments, since they come from far away or require large vehicles, and Metropolitan Council did not have departure times or tours for them. As a result, the congestion levels in these simulations are optimistic and, in reality, would lengthen travel times and perhaps extend many SAV response times.

METHODOLOGY

Temporal and Spatial Disaggregation

Trip start and end times in the dataset are provided in rather coarse 30-minute bins, and their origins and destinations are aggregated by TAZ. There are just 48 half-hour bins in a day and 2485 TAZs across this 6364 square-mile region. For effective agent-based simulation of SAV fleet operations across tens of thousands of roadway links, with updates every second on vehicle assignments and position, much higher temporal and spatial resolution is needed. Further, computational restrictions on the supercomputer used for these simulations necessitated that the trips from only 7 counties in the MPO (Anoka, Carver, Dakota, Hennepin, Ramsey, Scott and Washington counties) which are located in the center of Minnesota were used. Trips in the dataset that ended in the other 12 MSP-area counties were discarded. Spatial and temporal disaggregation was done similar to Gurumurthy and Kockelman (2018), with an output of one-minute resolution on departure times and a uniform distribution in space for home locations within the TAZ.

Instead of spreading all non-home trip ends uniformly across TAZs, five types of non-home sites were created to provide some natural within-TAZ aggregation of jobs and businesses. Sites for individual work, shopping, social contact, and school activities tend to be clustered in larger buildings, rather than smaller, often-separated dwelling units. To help avoid many unrealistic, crossed paths by travelers and unrealistic or wasted routings, and enhance opportunities for DRS, these 5 trip-end site types were created. Their locations are randomly generated in each TAZ. The numbers of sites in a TAZ is determined by the magnitude of trip-ends (e.g. 1 new work location per 2000 work trip ends). Each TAZ has at least 5 trip-end sites for 5 types if there are less than 2000 trip ends.

SAV Operations, Simulation, and Dynamic Ride-Sharing

MATSim is an activity-based, extendable, multi-agent simulation framework implemented in Java (Horni et al, 2016) and is used in this study. It contains microscopic modeling of traffic and an adaptive co-evolutionary algorithm for convergence. A set of travel itineraries for each simulated agent, containing detailed spatial and temporal information, a network file and activity locations are provided as inputs. The objective is to maximize the utility of each agent by using a co-evolutionary algorithm for departure time and mode replanning. Dynamic traffic assignment (DTA) with a queue-based approach is the core network-assignment framework, and this uses an improved Dijkstra's algorithm for shortest path calculation (Rieter et al., 2014). There are five stages in the execution of MATSim: initial demand is fed into the tool (occurs only once), mobility simulation using DTA is performed, executed itineraries are scored, and replanning is done to maximize this utility. After reaching convergence, results of the final set of itineraries are analyzed. All trips are assumed to be made by SAVs, so the mode planning aspect of MATSim is not utilized. However, agents are allowed to shift their departure times to accommodate anticipated response times of SAVs. This is carried out using an in-built algorithm that switches activity duration, and consequently, departure times, randomly between iterations. As is standard in most MATSim studies, a maximum of 30 min is set for the activity duration perturbation, and travelers are penalized for deviations from the preferred departure times that were initially provided to the simulation. Horni et al. (2016) provide thorough references to using and modifying the MATSim parameters.

The DRS code used in this study is adapted from Ruch et al. (2018) and uses algorithms from Fagnant et al. (2015). In MATSim, the dynamic vehicle routing problem (DVRP) module (Maciejewski et al., 2017) is implemented for SAV simulation and allows for dynamic and demand-responsive vehicle dispatch, similar to taxi operation. Vehicle dispatch is generally initiated the moment an agent wishes to depart using such a mode. All SAV trips are assumed eligible to be matched for DRS. A least-cost path algorithm in MATSim is used in the code for optimizing collocation and determining aggregated trips for SAVs within acceptable distances for pickup. Fagnant et al.'s (2015) DRS matching constraints are used here and can be summarized as follows: Constraint 1: Passengers' trip duration increases less than 20%. Constraint 2: The existing passengers' remaining trip time increases less than 40%. Constraint 3: The total in-vehicle trip time for second or subsequent trips increases by less than the maximum of 20% of the total trip without ridesharing, or by 3 minutes. Constraint 4: Second or subsequent travelers will wait up to a maximum of 10 minutes. Constraint 5: Total planned trip time to serve all passengers is less than the sum of remaining time to serve the current trips, time to serve the new trip, and drop-off time, if not pooled.

Parking Strategy

The underlying parking strategy for SAVs in MATSim is based on the AMoDeus. In most previous simulation studies, SAVs are removed from the network and assigned to fake links that are not in the congestible network after a passenger is dropped off. In reality, vehicles will remain on the roads when the travelers arrive at their destinations and impact capacity on the link. They will not be allowed to remain there on the curbside. Many popular destinations in the region could have long queues of SAVs picking up or dropping off passengers, creating excessive curb space use and lane-level congestion. To account for this, parking lots were created on the links that had at least 400 trip origins and destinations per curb-link per day to allow SAVs to exit the roadway while remaining close to trip hotspots until they receive a new trip assignment. Each parking lot in a scenario is assumed to have equal capacity that totals to accommodate 80% of the fleet. During the simulation, parking requests are processed every 5 seconds. After a trip is completed, the empty SAV will locate the two nearest parking lots while checking for parking availability in these lots. If there is space available, the SAV can wait in the parking lot instead of idling by the curbside. If both parking lots are full, an available parking lot in the region less than 0.5 mi away is assigned to the SAV to improve operations elsewhere, since the current location has enough idle SAVs for good service. Once a parking destination is decided, the SAV will follow the best route to the parking lot. If no parking lot is assigned, then the SAVs are assumed to be far away from busy streets and are allowed to park on the curbside. Figure 1 shows the parking strategy along with DRS choices that are followed when requests come through to the operator.

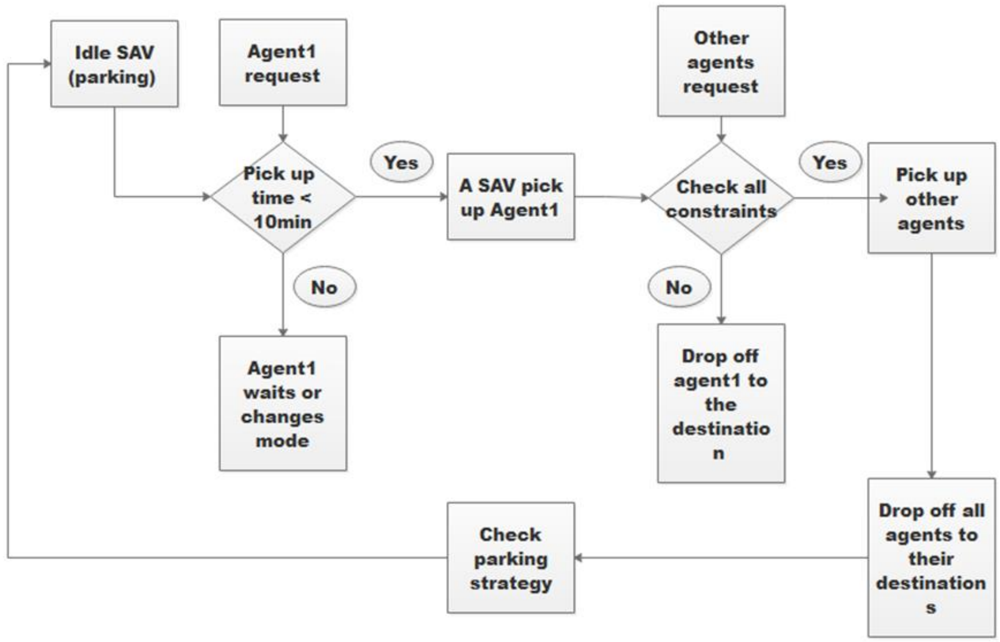


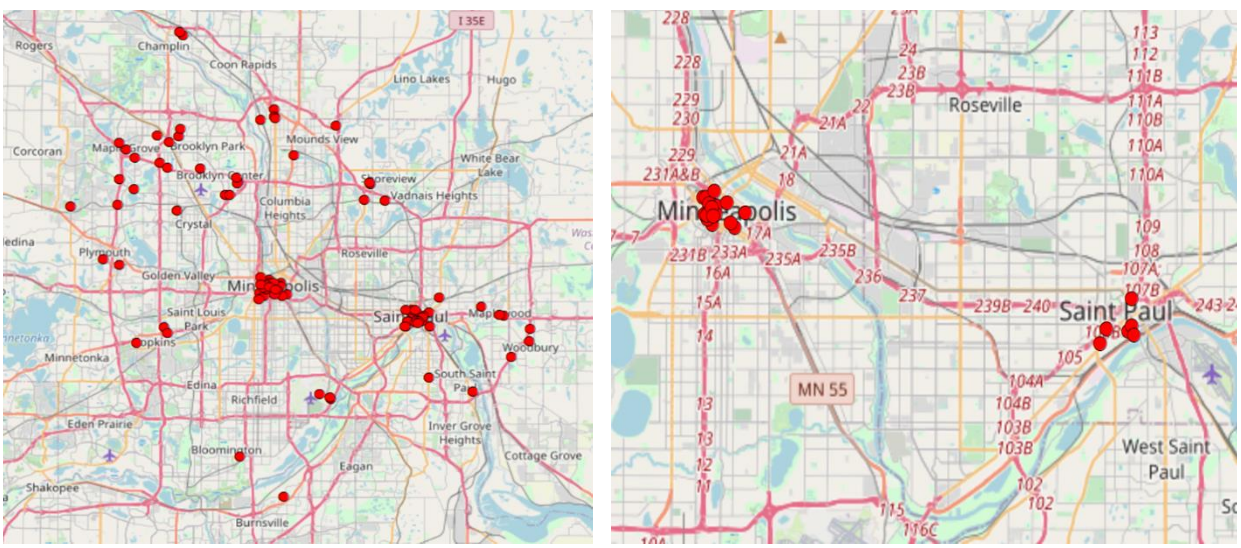
Figure 1 Flowchart for parking and dynamic ride-sharing strategies used

Simulation Scenarios

Two broad scenarios are considered in this study: when SAVs are allowed to park on curbs assuming no impact on traffic flow even if these lanes may be blocked in reality, and when explicitly considering parking availability in lots that are placed throughout the region based on conditions described above. For each of these broad scenarios, travel demand is varied as a sample of trips simulated along with certain fleet parameters as discussed next.

For scenarios with curb parking permitted everywhere, the 7-county SAV-fleet simulations were run with various fleet sizes to appreciate the variation in system performance metrics such as wait times and mode preference. The 22 different scenarios' results are compared here. Using the full 7-county region, this work simulated about 180,000 and 457,000 person trips (2% and 5% of the region's total 9.5 million person trips) over a 24-hour period. For the Twin Cities scenario, about 487,000 person trips were simulated from the dataset to identify the impact of increasing trip densities in a smaller geofenced region. A base scenario was studied as the business-as-usual (BAU) case by simply simulating the travel demand obtained from the local MPO by using the mode associated with the trip in the dataset without enabling SAV use. The agent itineraries, network, and activity locations were processed to obtain the BAU metrics for VMT. The travel times observed in the BAU case were compared to that in the dataset to calibrate the flow and storage capacities of links in MATSim for realistic sample simulation. Flow and capacities can either be assumed directly proportional to the sample simulated (i.e., 0.5 factor if 50% sample is simulated), but for small samples, this factor needs to be scaled non-linearly. Horni et al. (2016) suggest proportional flow factor scaling, but non-linear scaling ($s^{0.75}$, if s is sample proportion) for storage to account for small samples needing higher than proportional storage to queue in links. This was iteratively changed in small steps after this initial factor, and MATSim travel times for trips were compared to corresponding trips from the dataset for calibration. Some scenarios were simulated without DRS, meaning each SAV could only serve only one agent at a time. Fleet sizes were also varied for different scenarios to understand how fleet size affects trip patterns. Fleet sizes may have the greatest impact on VMT/eVMT, idle time, and travel delay since size is directly proportional to time to arrive at the requests' origin. Furthermore, the simulation of the Twin Cities area (Minneapolis and Saint Paul), which has a higher population and trip density, is more valuable for SAV operation in the near future compared to simulations of the large 7-county area.

For the scenarios with curb parking restricted, parking lots were positioned in this study to analyze the impact of parking on SAV operations. Different numbers of parking lots were used for scenarios with the seven counties and the Twin Cities, since areas of simulation can significantly affect the available parking lots. For the aforementioned regions, 106 and 28 parking lots were created, respectively. Although the Twin Cities area is only 1/26th that of the seven counties, the Twin Cities region contributes about 30% of total trips since Minneapolis is the most populous city in the state, and Saint Paul is the state capital. It is obvious that the Twin Cities should have many parking lots to balance the SAVs. Figure 2 shows the parking lot generation across the seven counties and Twin Cities. SAVs search for the nearest parking lot that is less than 0.5 miles away. If none exist, the SAV parks curbside.



a. 7 Counties **b.** Twin Cities

Figure 2 SAV Parking Lot Locations (Source: ArcGIS + OpenStreetMap)

RESULTS

Scenarios with Curb Parking Permitted Everywhere

The results suggest that an SAV in the MSP region can serve about 30 person trips per day, on average; thus replacing about 10 household vehicles (assuming no one needs to leave the region), but generates an additional 13% VMT per day and adds congestion to the network. Those using

DRS spend time waiting for other passengers to enter or exit SAVs, which often go out of the way to pick up and drop off others, effectively increasing the average trip duration (from request to drop-off) by 34% per day.

Fleet size affects the success rate for matching, and this in turn affects how many shared rides are observed. Furthermore, travel times in the network can also impact average wait time. Table 1 shows the results in terms of scenarios and fleet sizes. SAV fleet sizes are represented as the number of travelers per SAV per day in order to illustrate the influence of fleet sizes across scenarios with different sample sizes, and to scale well with the population. The simulation results include eVMT, percent of DRS trips, SAV runtime, average vehicle occupancy (AVO), and average wait time.

2% trips in the 7-counties

For the scenarios where 2% of the total trips are simulated, the average VMT and eVMT go up without DRS and increased demand per SAV per day (reduced fleet size), causing a surge in the operation time of each SAV. The average waiting time for individuals in several scenarios ranges from 2.5 minutes to 13.7 minutes. For scenarios with DRS, 6–33% of the simulated trips are shared. Smaller SAV fleets increase the proportion of the DRS trips due to the lower availability of SAVs, leading to better utilization through sharing. The long response times of 35 min to 40 min are observed with the lowest SAV availability condition (15 travelers /SAV/day). Under this particular condition, the results show an exorbitant share of DRS trip (up to 43.4%) and AVO (up to 1.80), which seem appealing for congestion mitigation, but come at the expense of waiting time. A larger fleet can solve this problem. The average VMT and eVMT decline sharply since SAVs can respond to multiple trips at the same time with DRS and choose the most economical route to pick up passengers. The values of AVO are relatively low, since 2% of the total trips represents a low trip density. The average waiting time becomes slightly longer due to the decreased SAV fleet size. As the number of travelers per SAV per day rises from 10 to 15, there is an increase in the average waiting time per trip from 11 min to 40 min, as SAVs cannot satisfy all demands at the same time; consequently, some SAVs have to first finish serving some requests and then come back for the remaining ones. However, since those scenarios involved 2% of the total trips across the 7 counties, the spatial dispersion resulted in 6% unserved trips per day. In order to avoid this impact, it is recommended that areas with higher population density be targeted in a region.

5% trips in the 7-counties

The scenarios where 5% of the total trips are simulated have a larger trip density across seven counties, leading to only 1.3% of simulated trips being unserved. Compared to the results from the 2% trip simulations, the VMT from the scenarios without DRS relatively increases, and this is likely from the addition of 3% of trips with longer travel lengths. However, the eVMT decreases with this increase in trip density. For scenarios with 5, 10 and 15 travelers per available SAV per day, the DRS trip proportions in 5% trip simulations increase by an average of 15%. These increases are based on increased opportunities for DRS trip matching, which lead to a decline in eVMT. More trips are served in the scenarios using a 5% sample, and the average wait time is shorter. With the same SAV availability per day, individuals from both samples have similar waiting times. However, fewer trips are unmet in the scenario with 5% trips due to a better trip request demand to SAV availability ratio at many times of day. Each SAV would face more requests during a day, which would lead to more trips served and a shorter average wait time. With a smaller fleet, the values of AVO increase dramatically. The highest AVO achieved is 1.84 and is obtained with a small fleet serving 15 travelers per SAV per day, but it also yields the longest average wait time per trip of 32.3 minutes in the SAV-undersupplied setting. An average SAV is expected to serve about 30 trips per day (Fagnant et al., 2015; Loeb and Kockelman, 2019; Loeb et al., 2018). Besides varying SAV availability as 5, 10, and 15 travelers per SAV, this study also simulates a standalone scenario with 7 travelers per SAV per day, which represents 28 trips per day. Figure 3 shows the histogram of wait times of the scenario with and without DRS. About 62% of trip wait times are less than 5 minutes, most are 1–2 minutes. Although 55% of trips experienced wait times of less than 5 minutes without DRS, more trips (68%) were served with low wait times under 5 minutes with DRS, especially those trips that previously had more than 11 minutes of wait time.

Table 1 Key Findings from 22 Simulation Scenarios

Region and Trip #	DRS?	Travelers per SAV per Day	VMT per SAV per Day (mi/day)	Empty VMT (%)	SAV Run Time per Day (hr.)	Trips as DRS per Day (%)	Trips per SAV per Day	AVO (person)	Avg Wait Time per Trip (min.)	Unmet trips (%)
7-counties, 2% of total trips	No DRS	5	175	12.7	9.4	--	19.0	1	3.7	5.7
		10	406	24.8	11.4	--	37.9	1	11.0	5.7
		15	557	22.3	18	--	55.4	1	39.9	6.9
	Yes DRS	5	170	11.7	8.4	5.9	19.0	1.03	4.0	5.7
		10	378	22.8	11	15.7	37.9	1.23	10.7	5.8
		15	526	22.2	16.5	43.4	34.3	1.80	34.5	6.5
7-counties, 5% of total trips	No DRS	5	173	14.1	8.9	--	20.2	1	2.5	0.3
		7	277	18.1	10.5	--	28.0	1	4.9	0.6
		10	432	25.2	12.5	--	40.0	1	13.7	0.6
		15	559	23.0	14.5	--	54.6	1	36.1	3.0
	Yes DRS	5	174	10	8.4	12.4	20.0	1.14	3.7	0.5
		7	254	14.5	9.6	20.3	28.0	1.23	4.6	0.5
		10	261	19.7	10.9	26.3	40.0	1.41	9.7	0.5
		15	514	20.0	15.3	42.5	59.3	1.84	32.3	1.8
Twin Cities 20% of total trips	No DRS	5	117	9.5	4.3	--	15.9	1	2.5	1.5
		7	170	13.0	6.1	--	22.3	1	3.2	1.5
		10	253	17.0	6.1	--	31.8	1	3.9	1.5
		15	414	23.4	7.9	--	47.8	1	11.9	1.6
	Yes DRS	5	109	7.2	4	20.7	15.9	1.28	2.9	0.1
		7	156	10.0	4.6	25.2	22.3	1.32	3.6	0.2
		10	227	13.3	5.9	30.4	31.8	1.56	3.6	0.5
		15	347	17.4	7.2	38.8	47.8	1.63	7.1	1.5

Spatial and temporal analyses (5% of trips in the 7-counties)

Figure 4 shows average wait times during AM peak and PM peak across TAZs in the seven counties. About 81% and 84% of TAZs having less than 6-minute wait times are distributed evenly during AM peak and PM peak, respectively, and only 1% of TAZs are served with wait times more than

10 minutes. These figures show uniform wait times across the region and suggest residents of this region could get similar SAV service level everywhere.

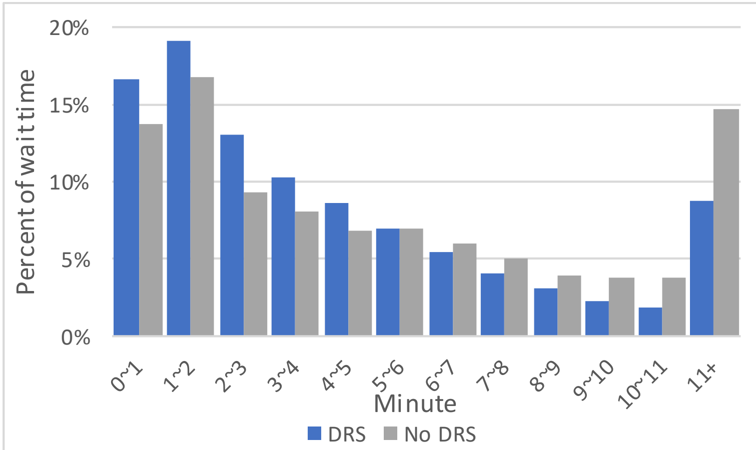
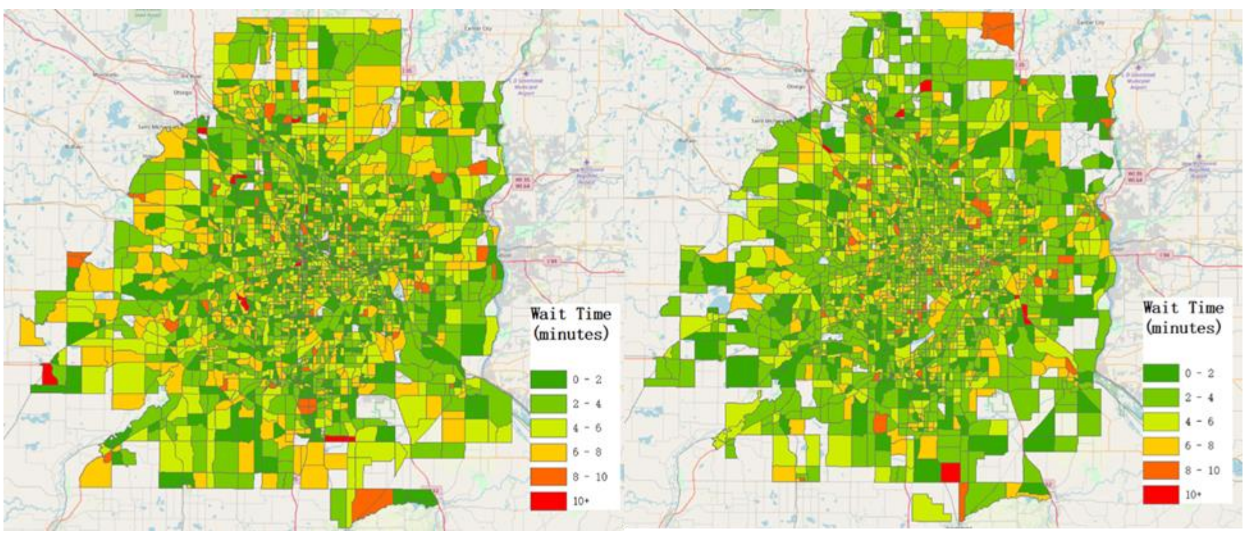


Figure 3 Temporal Distribution of Wait Times Across 7 Counties

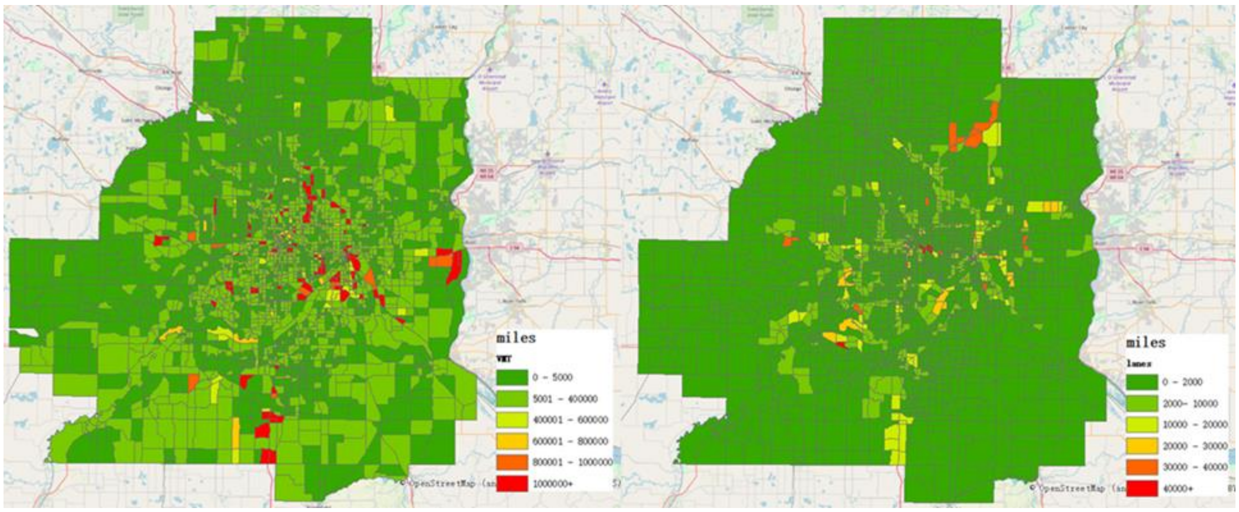


a. AM Peak **b.** PM Peak

Figure 4 Spatial Distribution of Wait Times Across 7 Counties (assuming 7 travelers per SAV per day)

This study also considered the spatio-temporal analyses of VMT and eVMT across the 7 counties. VMT and eVMT were extracted from the output by link and time of day. In order to make the comparison more intuitive, Figure 5 shows VMT and eVMT distributions across TAZs. As expected, most SAV VMT and eVMT occurs on freeways and highways across the MSP region, especially on the highway around the Twin Cities (of Minneapolis and Saint Paul). The TAZs with the most VMT are scattered around the downtown areas of the Twin Cities, since the two cities' central business districts (CBDs) have the highest trip-end densities. The eVMT distribution is similar to the VMT distribution. For example, Columbia Heights (in northern Minneapolis) and

West Saint Paul (in southern Saint Paul) generate the most eVMT and VMT around the Twin Cities, since they have relatively few and dispersed trip ends. Since most VMT and eVMT are generated on freeways, it would be better if these SAVs arrived at the pick-up locations using secondary roads to reduce congestion on freeways. However, the consequent increase in wait times needs to be kept low. Many drivers may prefer direct routes using highways and freeways even if congested rather than using secondary roads, but a centrally-controlled SAV fleet may perform better with smarter route choice..



a. VMT **b.** eVMT

Figure 5 Distributions of VMT and eVMT across 7 Counties' TAZs

20% trips in Twin Cities

Results for the Twin Cities show that VMT is significantly less compared to the 7-county region since the Twin Cities are much smaller than the 7 counties and there is a higher chance of trip matches for DRS. The smaller area also yielded a smaller percentage of eVMT per day. With similar numbers of simulated trips (456,800 trips in 7 counties and 487,000 trips in Twin Cities), the simulated trips in scenarios with 7 counties had longer travel distances and lower trip density. Lower trip density results in a higher percentage of eVMT because of the wide distribution of the trips. Thus, a high percentage of eVMT and long-distance trips may lead to more SAV run time per day. The proportion of DRS trips per day in Twin Cities increases from 20.7% to 38.8%, which is the highest average value among all the corresponding scenarios. It is important to note that the number of trips per SAV per day is different between the 7-county and Twin Cities scenarios for the same number of travelers per SAV. For each traveler, the trips made in the Twin Cities exclude those outside. Although the number of travelers per SAV is the same and total simulated trips used is similar in these scenarios, the simulations for the Twin Cities had more traveler agents and a larger SAV fleet. Therefore, the number of trips per SAV per day in the Twin Cities was less than the number of trips per SAV per day in the 7-county scenario. This could have had a negative impact on AVO. However, according to the results of the scenarios with 5, 7, and 10 travelers per available SAV per day, the values of AVO in Twin Cities are, on average, greater than the values of AVO in the 7 counties because more trips may be shared in a smaller area. The average wait times with DRS are lower than those without DRS across all simulated scenarios, and indicate that DRS reduces wait times. Agents find it difficult to find an idle SAV unless they are willing to wait until the SAVs drop other individuals and return for them, and DRS can reduce wait times under these circumstances. Among all scenarios, a smaller SAV fleet only slightly impacts average wait times in the Twin Cities owing to shorter pickup distances and wait times in this area. With a larger trip density, the negative impact of a small SAV fleet will be balanced with DRS trips, thereby increasing the AVO. Compared to Levin et al.'s (2017) simulation results for Austin under mixed SAV and private vehicle fleets, the AVO from the Twin Cities scenario is lower. While both studies' SAVs serve about 31 person-trips per day, Levin et al. focused only on Austin's CBD, where much shorter trips and higher trip densities resulted in better trip matching opportunities and thus a higher AVO. In the Twin Cities scenarios, two entire cities and the neighborhoods between them were served, which is much more realistic a scenario.

Spatial and temporal analyses (20% trips in Twin Cities)

Figure 6 shows the eVMT observed on one day across the Twin Cities. For the scenario without DRS, the AM peak and PM peak, which have numerous requests, are the significant sections of eVMT distribution, and SAVs cannot satisfy those demands at the same time. Since DRS is not provided in this situation, SAVs can serve no more than one trip at a time. As a result, more eVMT is generated from low SAV utilization. When DRS is available, the eVMT shrinks because SAVs can serve multiple agents at one time, and more SAVs are available at any given time. This plays a significant role in lowering eVMT during the PM peak because more agents during this time of day have nearby origins, especially in CBDs. Commuters leave work around the same time so there are more opportunities for DRS trip matching. Although eVMT also decreases during the AM peak with DRS, it only declines by 3% as compared to about 13% during the PM peak. The trips during the AM peak have the opposite characteristic. During the AM peak, more agents share similar destinations but have different origins. Due to sparsely distributed origins, SAVs cannot match many DRS trips, and centralized destinations can also concentrate SAV availability. This imbalance may lead to SAVs generating more eVMT to respond to subsequent requests. Figure 7 shows the distribution of response times, which has similar trends to Figure 5, owing to the characteristic discussed above.

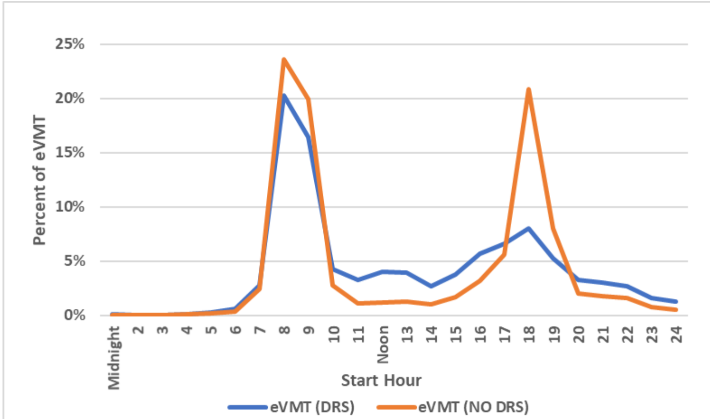


Figure 6 Distribution of eVMT with Start Time of Trip (base on 1-hour bin)

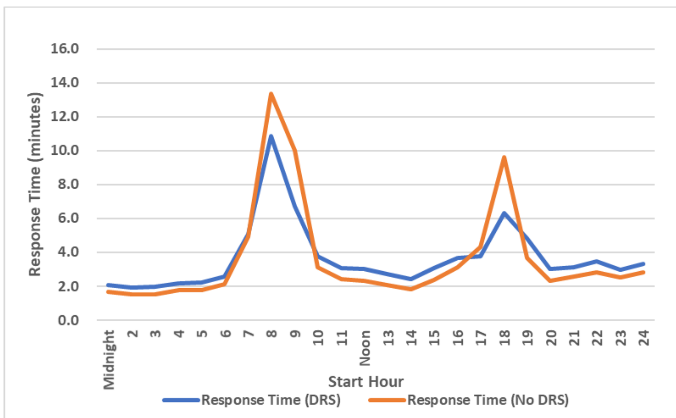


Figure 7 Distribution of Response Time with Trip Start Time (using1-hour bins, 7 travelers per SAV per day)

Added VMT from detours in a DRS trip can cause congestion in the simulation network as compared to agents driving a private vehicle if matching is not optimized. Figure 8 shows the added detour VMT of a day across the Twin Cities. As discussed above, DRS trips were mainly distributed during the PM peak. Hence, about 30% of the added detour VMT in a day was generated during this period, while only 10% added detour VMT was generated during the AM peak. The average detour VMT during the PM peak was 0.4 miles per trip, while the average detour VMT during the AM peak was 0.7 miles per trip because the origins of agents were sparsely distributed during the AM peak.

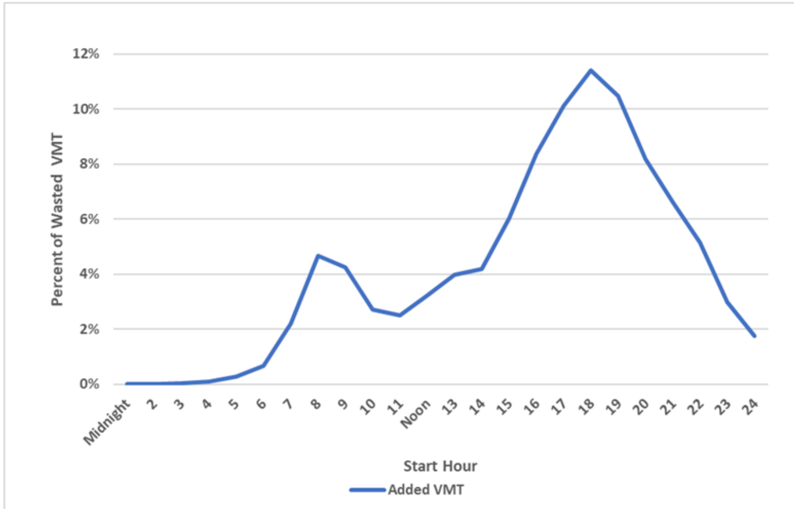


Figure 8 Distribution of Detour VMT with Start Time of Trip (using 1-hour bins)

Parking demand reductions from using a shared fleet

Change in parking demand was approximated for all scenarios simulated with respect to the sample's base fleet assuming each person uniquely listed in the database used their own vehicle. Figure 9 shows the reduction in parking demand aggregated over different fleet sizes and DRS assumptions for the three samples simulated. The pattern of parking reduction over the working day is similar when observing the larger 7 counties even though the number of trips made is more than doubled. However, the fleet size was also proportionally increased, so SAV utilization may not have improved with the increase in trips. A larger reduction in parking demand of 80% was observed in the Twin Cities as opposed to a 60% reduction for the 7-counties region for a comparable number of trips made. This is likely from a larger number of trips ending downtown. These calculations do not take into account parking at home at the beginning and end of the day. Irrespective of travelers' decisions to own vehicles in the future, a larger demand for parking will exist in the night time from most SAVs idling due to no trip demand.

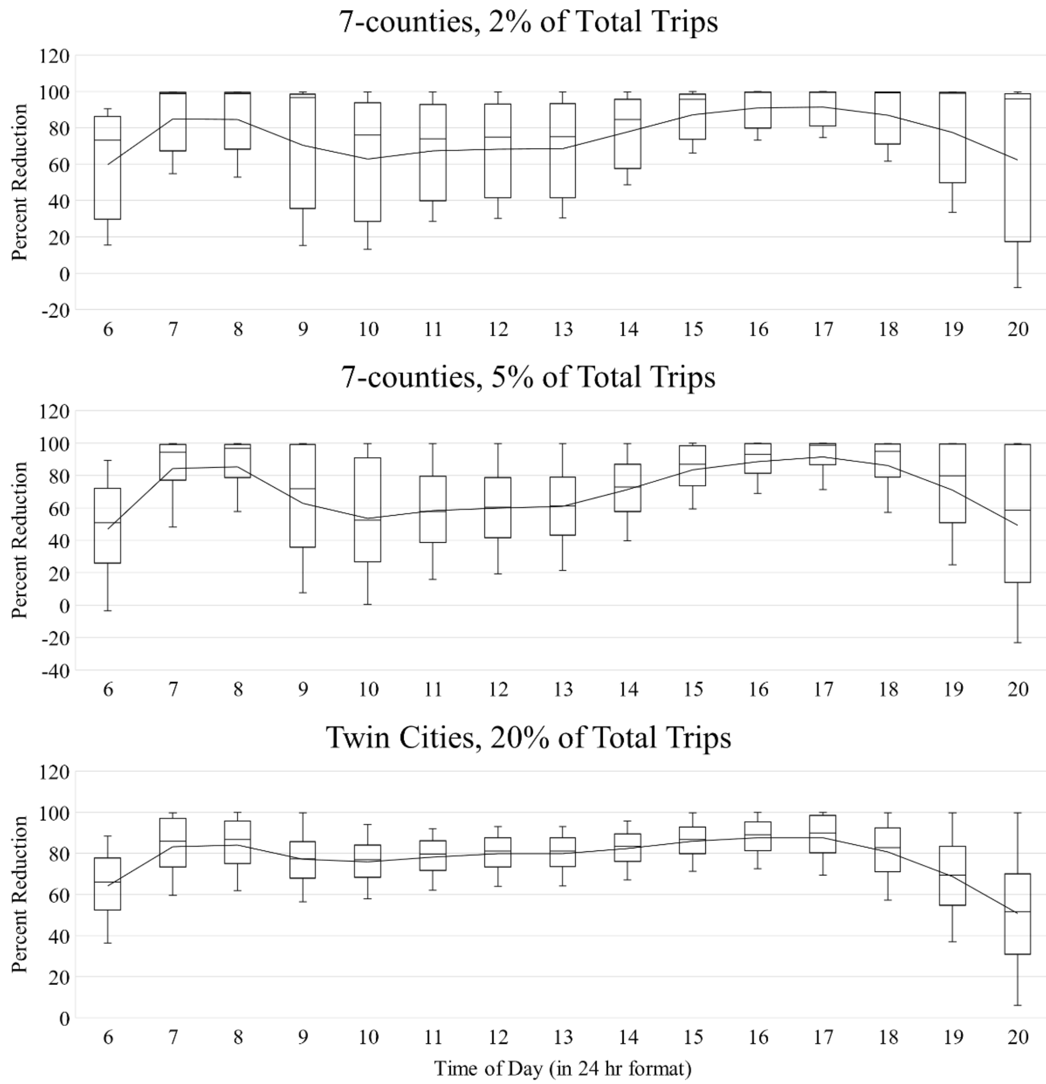


Figure 9 Aggregated Reductions in Parking Demand by Time of Day

Scenarios with Curb Parking Restricted

Table 2 shows the comparison of SAV performances between scenarios with curb parking permitted everywhere versus restricted curb parking. The comparison of the parking strategies was based on 7 travelers per SAV per day after testing. For the 7 counties, implementing restricted curb parking generated 8% more VMT, on average, since SAVs always headed to the nearest parking lots after they dropped off the last passenger. About a 7% increase in eVMT was observed due to this restriction. Since those parking lots were chosen based on links with the most origins and destinations, the parking trips for SAVs can be considered as an optimized relocation. SAVs reposition to parking lots with more trip densities which means that the SAV may have more opportunities to respond to future requests and may reduce the average wait time. However, since SAVs could not respond to requests during parking trips, the average wait time was actually 10%

higher than the average wait time for the scenarios with curb parking permitted everywhere. This inability also reduced the number of DRS trips by 5% with restricted curb parking. These added parking trips also increased SAV operation time by 15%. There is a slight increase in the value of AVO which is counterintuitive compared to the decreased number of DRS trips. This may be from repositioning to locations that have more common trip destinations.

The size of the simulated regions could influence the performance of relocation for parking. For the Twin Cities scenario, benefits included 47% less average SAV runtime per day, 5% more DRS trips, 7% more AVO, and 23% less average wait time. These results indicated that considering a geofenced area may decrease the negative impacts of parking trips, since it will be easier for SAVs to finish their shorter parking trips and be ready for passenger requests. However, the average parking VMT per vehicle increased as compared to that from the 7 counties scenario, as the Twin Cities had a lower parking lot density than the 7 counties.

Table 2 SAV Performance Compared With and Without Curb Parking for 1:7 SAV Availability

	Curb Parking	VMT per SAV per day per day	Empty VMT (%)	SAV Run Time per Day	%Trips as DRS	Trips per Day per SAV per day	AVO	Avg Wait Time (min.)
7-counties	Allowed	254 mi	14.5%	9.6	20.3%	28	1.23	4.6
	Constrained	272	20.1	10.1	19.6	28	1.24	5.2
Twin Cities	Allowed	156	10.0	4.6	25.3	22	1.32	3.6
	Constrained	170	18.2	5.8	24.9	22	1.32	4.0

Parking lot utilization

Parking lots were generated for these simulations based on the road segments in the region that had origin and destination trip densities larger than 400 trip-ends per curb-link per day. Since the capacity of these parking lots was assumed to accommodate a maximum of 80% of the fleet simulated, the temporal utilization of all parking lots can inform planners of daily usage levels when shifting to trip-making largely by SAV fleets, and at different densities (a proxy here for SAV mode shares). Figure 10 shows the temporal aggregate parking utilization for the 7-counties and Twin Cities scenarios, and the consistent trend appears to be correlated with SAV demand at different times of day. Both scenarios have SAV fleets serving about the same number of trips but at different densities. Parking lots in the Twin Cities are nearly five times larger than lots spread out in the 7-counties scenario. Even with smaller lots, a consistently higher parking utilization is observed for the denser Twin Cities region. This is as expected since higher trip densities correspond to efficient fleet usage, and more SAVs are idle at trip-end hotspots in the Twin Cities. However, Figure 10 is not reflective of SAVs parked by the curb in neighborhoods that do not have high-density trip ends, and, by design, parking lots.

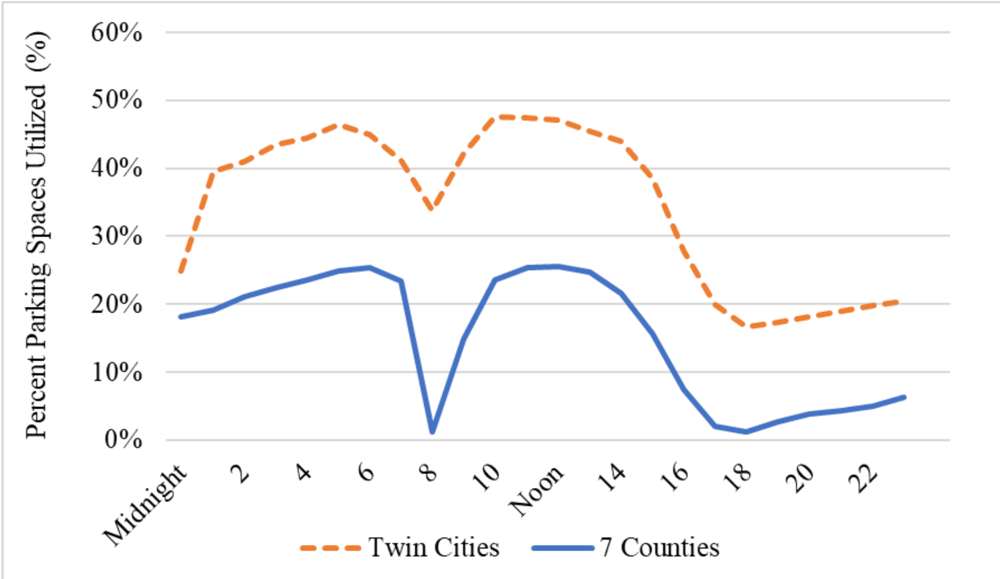


Figure 10 Parking Lot Utilization by Time of Day

Figure 11 shows the proportion of SAVs in parking lots and parked on the curbside. The proportion of vehicles parked on the curbside is higher in the off-peak times for the 7-county region, since the larger extent of the region provides locations away from busy streets to park at the curb and not impact traffic patterns. More vehicles also seem to be in use during peak times in the lower-density 7-county setting to allow pickups to occur across the region. In the Twin Cities setting, parking lots contain a higher proportion of idling SAVs right after the morning peak, likely from trips flowing into the two downtowns. SAVs operating in large metro regions may need minimal parking lot capacity owing to space availability in other parts of the region. However, allowing SAVs to reposition to such locations does add VMT, and, consequently, some congestion. In denser settings, with SAVs operating only within city boundaries, parking lot infrastructure will help alleviate congestion. Going forward, parking consideration needs to be assumed in future simulation studies corresponding to the setting simulated, or forecasters may underestimate the congestion expected.

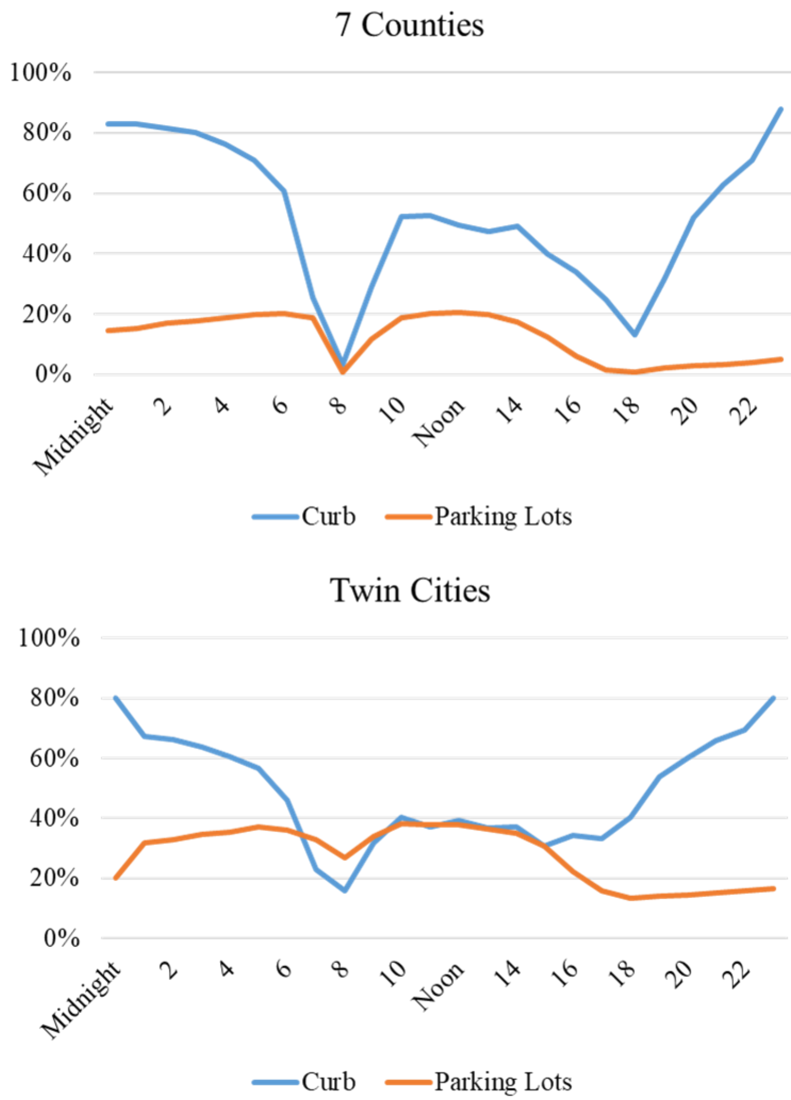


Figure 11 SAVs in Lots and Curbside in 7 Counties and Twin Cities

ENERGY AND EMISSIONS ANALYSIS

An energy and emission analysis is warranted to determine the initial estimates for feasibility and consequences for the environment. Energy and emission coefficients were taken from a report on emission factors for greenhouse gas inventories (EPA, 2014) and Chester and Horvath's (2009) conventional gasoline vehicle inventory estimates, as shown in Table 3. The factors of emission species evaluated here are sulfur dioxide (SO_2), carbon monoxide (CO), oxides of nitrogen (NO_x), volatile organic compounds (VOCs), particulate matter that is 10 micrometers or less in diameter (PM10), and greenhouse gases (GHGs) including carbon dioxide (CO_2) and methane (CH_4). The coefficients used here do not include pickup trucks and SUVs. This analysis assumed that SAV operation had no influence on trip demand, although people may make more and longer trips using SAVs if generalized costs fall in comparison with conventional vehicle travel. This analysis also included the energy and emissions of SAEVs if they operated in the MSP region instead of SAVs. SAEVs were assumed to be charged at home and only once per day. Except GHGs, all the coefficients of factors are based on vehicle operation (in use), startup emissions, manufacture, maintenance, and vehicle parking. Three specific vehicle kinds, namely internal combustion engine (ICE) vehicles, hybrid electric vehicles (HEVs), and battery electric vehicles (BEVs), were used here to represent sedans, SAVs, and SAEVs. Their miles per gallon (MPG) ratings, taken from EPA (2019), are shown in Table 4.

Table 3 Energy and Emission Assumptions for Conventional Gasoline Vehicle

Energy and Emissions Species	Running Emissions per mile	Startup Emissions	Manufacture	Maintenance	Parking
Energy use (kj/mi)	4,800	0	550	210	79
SO_2 (mg/mi)	21	0	110	45	19
CO (mg/mi)	11,000	7300	560	180	28
NO_x (mg/mi)	850	170	110	41	34
VOC (mg/mi)	310	350	110	52	27
PM10 (mg/mi)	110	0	30	0	14
CO_2 (mg/mi)	357,000				
CH_4 (mg/mi)	173				

Table 4 Fuel Economy of Three Vehicle Types

	ICE conventional vehicle and SAV	Hybrid SAV	SAEV
Make + Model	Ford Focus	Toyota Prius (HEV)	Chevrolet Bolt (BEV)
Fuel Economy	31 mi/gal	52 mi/gal	106 mi/gal

This study assumed 1 hour for engines to cool down similar to Kang and Recker (2009). In total, 68% of U.S. vehicle trips (with internal combustion engines) are cold starts. From MSP simulation results, 10% of vehicle trips are considered cold start trips for the 7-county region and 7% are considered cold start trips for the Twin Cities. In order to make comparisons intuitively, all the analyses were based on PMT. The average PMT of a passenger in an ICE vehicle across the U.S. was taken from NHTS 2017. Using MSP simulation results, a comparison of the energy and emissions for different vehicles is presented in Figure 12. Compared to an ICE vehicle, ICE SAVs could save 13% of energy and emissions. HEV SAVs could save 20% of energy and reduce emissions by 30%, while BEV SAVs could decrease energy use by 64% and emissions by 68%. A spatial analysis of passenger vehicles' PM10 emissions is also interesting to pursue to note the concentration of emissions in the region. PM10 concentrations mirror the VMT seen in Figure 5 in this study. However, passenger travel is not a key source of PM10 for any US region because passenger vehicles in the US are typically not diesel or coal-fired.

The costs of the emissions were also analyzed for advanced evaluation. The results indicate that energy use and emissions per HEV SAV and BEV SAV per day were significantly less than those of conventional gasoline vehicles, since HEV SAVs and BEV SAVs satisfy more demands. The costs savings are not as great as the energy use and emissions savings, since the electricity generated in power plants may create more emissions. The emissions of SAEVs should be carefully evaluated in further studies.

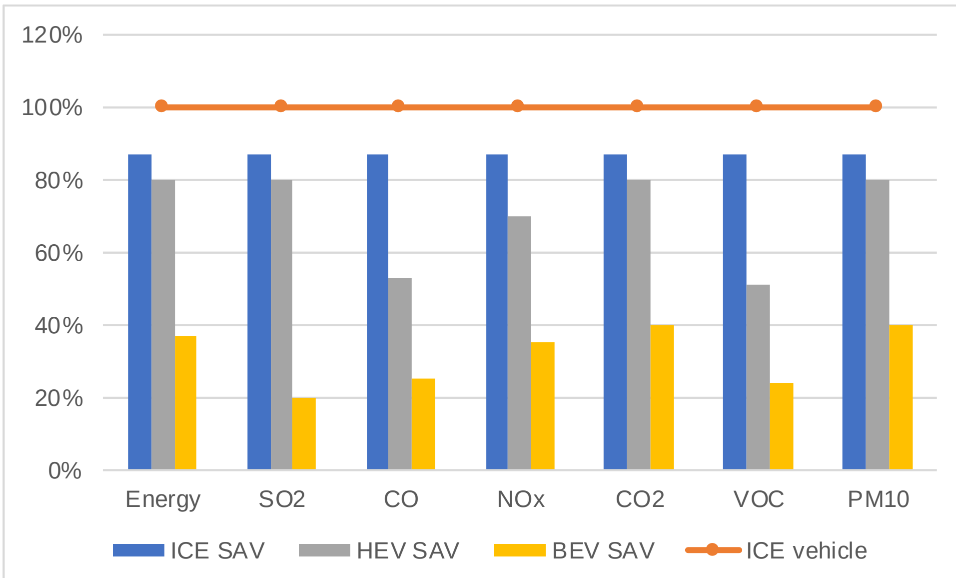


Figure 12 Energy and Emissions per PMT, by Vehicle Type

CONCLUSIONS

This work simulated and then evaluated the performance of an SAV fleet serving requests across the MSP region to quantify the effects of trip density and SAV demand on performance using MATSim. Significant operational differences were found for different SAV fleet sizes (in terms of SAVs per traveler) serving different densities of demand (i.e., different percentage shares of all trips), with and without DRS enabled. With an average of 7 travelers per SAV per day across the region's 7 counties, vehicles served an average of 28 person trips per day with an average wait time of less than 5 minutes. Among all simulation scenarios, eVMT averaged 7.2% to 25.2% of the SAV's fleet total VMT, with each SAV working 4 to 18 hours per day. The DRS scenario with 5 travelers per SAV per day in the Twin Cities and the no DRS scenario with 2% of total trips and 15 travelers per SAV per day in the 7 counties resulted in the best and worst SAV use scenarios, respectively. Using the same fleet size and demand levels while allowing for DRS among strangers whose trips have meaningful overlap (in terms of routes or locations traveled and departure times) helped lower the average response times by 10% (from an average of 5 minutes to 4.5 minutes, for example). This work also finds that SAVs may perform better in regions with a high population density and trip density with shorter trip lengths (i.e. 19% shorter trip lengths than the national average) rather than a large region containing many suburban and rural areas. Trip-making density is also important to consider for future simulation studies since it rather directly impacts SAV fleet performance. Relative to the large, 7-county service area, the fleet restricted to the Twin Cities achieved, on average, 25% more DRS trips, and 19% shorter (average) wait times. Parking demand was inevitably reduced by serving the trips with a smaller fleet compared to personally-owned vehicles. Parking demand in large downtowns like the MSP region may become 10% of what is observed now. Adding a realistic limitation on curbside parking resulted in 5% more DRS trips, 7% higher AVO values, and 23% less wait time, on average.

Energy and emissions implications were also studied for the SAV fleet in the MSP region while taking into account curbside parking restrictions on busy streets. Alternative drivetrain energy estimates reveal that HEV SAVs may reduce the fleet's energy demands by 21% and different emission species by 20% - 53%, while BEV SAVs save 64% in energy use and lower emissions by 60% - 80% for different species. Thus, HEV SAVs and BEV SAVs may save 31% and 25% of emission costs, respectively. These estimates are on the lower end of the estimated range by Lee and Kockelman (2019), likely due to parking restrictions in the Twin Cities. This work suggests that more careful consideration of SAVs' parking needs is important for future studies to provide a more accurate and less optimistic estimate of energy savings.

Limitations of this study include the absence of external trips and commercial vehicle trips (i.e. about 16% of traffic), which contribute to VMT and congestion. Another limitation is that SAVs headed to parking lots are not available for incoming requests until they finish parking, thus resulting in conservative estimates of how SAV fleets facing curb-parking restrictions would actually fare. It also would be useful for the simulations to equilibrate new destination and mode choices endogenously, when choosing departure times and routes, and to sample all travelers rather than subsets for the larger (county-wide and region-wide) services areas; but such behaviors slowed down the code to be used here (maxing out the supercomputers' 48-hour run-time windows permitted). More optimization techniques can be used for vehicle assignments to travelers (Ruch et al., 2020), fleet sizing (Horl et al., 2019b), proactive SAV relocations (Bischoff and Maciejewski, 2020), peak-hour SAV pricing, congestion pricing of all trips on congested links, and so forth. Regardless, this study's results should prove helpful in anticipating future fleet operations across regions in the U.S. and elsewhere, enabling better decision-making by SAV fleet managers, regional policymakers, and the public at large. The metrics documented here can serve as a meaningful reference for decision-making during SAV implementation by local and federal authorities.

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