Understanding the Impact of Trip Density and Demand on Shared Autonomous Vehicle Fleet Performance in the Minneapolis-Saint Paul Region

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ABSTRACT

Many well-known enterprises are road-testing fully-automated vehicles (AVs), including General Motors, Uber, Tesla, and Apple. Most AVs are expected to be used in shared AV (SAV) fleets initially, for daily trip-by-trip use, as an autonomous ride-sourcing service. SAVs will allow savings on vehicle ownership and maintenance costs, parking search and access times. This study micro-simulates passenger travel with SAVs throughout the Minneapolis–Saint Paul (MSP) region of Minnesota. The extended region includes 9.5 million trips across 7 counties, 2485 traffic analysis zones (TAZs), and about 42,000 roadway links. An agent-based toolkit, MATSim, allows tracking of individual travelers throughout the day and across their activity locations. Using supercomputers, this work simulated 180,000 person-trips and 450,000 person-trips (2% and 5% of the region's daily person-trips) and 480,000 person-trips for the Twin Cities (to understand the effect of trip densities) over a 24-hour weekday. Results suggest an average SAV in this region can serve at most 30 person-trips per day with less than 5 minutes of average wait time for travelers, thus replacing about 10 household vehicles but generating another 13% vehicle-miles traveled (VMT) each day. By enabling and encouraging active use of for dynamic ride-sharing (DRS), where strangers share rides, the SAV fleetwide VMT fell, on average, by 17% and empty VMT (eVMT) fell by 26%, as compared

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to scenarios without DRS. Interestingly, 81% and 84% of TAZs (in the AM and PM peak periods, respectively) have less than 6 minutes average wait times, suggesting that MSP residents will enjoy similar SAV service levels everywhere (though response times do rise during peak times of day). For the Twin Cities region, most eVMT emerges in the northern and southern sub-regions, rather than in the cities' central business districts (CBDs). The eVMT and wait times are relatively high during the AM and PM peak periods (6 am to 9 am and 3 pm to 6 pm) but fall significantly during the PM peak period if DRS is offered and actively used by travelers. When compared to idling-at-curb scenarios, the no-idling-on-busy-downtown-road-segment scenarios (using central SAV parking lots) generated 8% more VMT, while eVMT rose by 9 percentage points on average, across all four companion scenarios.

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

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.

Many AV impacts 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 is the predominant cause of traffic crashes, including alcohol and drug use, use of mobile devices, fatigue and lack of driving knowledge or experience (Eugensson et al., 2013). By avoiding this 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 impact 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). 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 VMT (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, such 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 SAVs 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 at 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 times from sharing. Only 1 SAV per 22 person-trips could satisfy almost half the total demand in that region and could improve congestion.

This study microsimulates personal trip-making throughout the Minneapolis-St Paul (MSP) region of Minnesota, USA using a system of SAVs. The simulations use the multi-agent travel-choice model MATSim (Horni et al., 2016) and MATSim's autonomous mobility-on-demand (AMoD) simulator developed by ETH Zurich and the Institute for Dynamic Systems and Control (Ruch et al., 2018). 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.

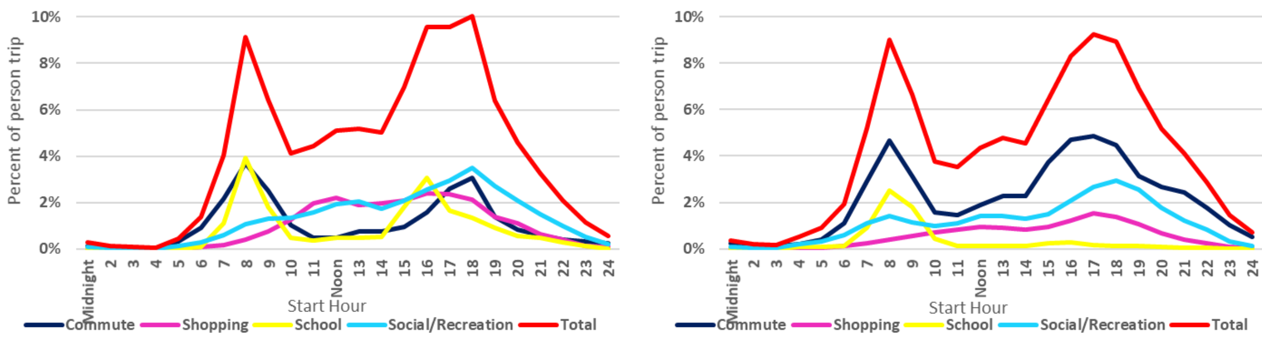
DATA SET

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. 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 11 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 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.

Figure 1 shows departure time choices for person-trips by trip purpose in the MSP dataset and in the 2017 NHTS dataset for the U.S. It appears that all trip types in Figure 1 have both AM and PM peaks excepting MSP's school and shop trips, which are low and flat (and perhaps too low and flat to be realistic) across all afternoon hours. The NHTS data set also suggests more shopping trip departures across most times of day, with more of a mid-day peaking pattern. The NHTS social/recreation trips exhibit mid-day and PM peaks.

On average, MSP travelers make 4.4 person-trips per weekday versus just 3.4 person-trips/day in the NHTS data set. Such trip-generation differences are striking and suggest that either the NHTS respondents are under-reporting or that the MSP data is biased high. Daily person-miles traveled (PMT) in the MSP data for a typical weekday is around 34.3 miles, versus 39.0 miles/weekday/person in the NHTS data set, suggesting that MSP person-trips are relatively short.



a. Time of day from 2017 NHTS **b.** Time of day from MSP data set

Figure 1 Distribution of Person Trips by Trip Purpose Based on 1-hour Bins

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 are 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 (as shown in Figure 2) were used. Trips in the dataset that ended in the other 12 MSP-area counties were discarded.

One-minute bins were used here for obtaining the detailed departure and arrival times for each agent. The departure times were disaggregated by first spreading all binned trips' start times across the 30 minutes uniformly, and then adding a random number from a uniform distribution with a mean 0 and standard deviation of 15 minutes to help smooth trip-rate transitions across all the 30-minute bin endpoints, as discussed in Gurumurthy and Kockelman (2018). Once a departure time was adjusted for these spatially disaggregated trips, departure times could be estimated using the Met Council's highway travel-time base values (for each of the four broad times of day: AM peak, midday, PM peak and night). Home-based trip origins and destinations were disaggregated using Python code and an ArcGIS package to generate specific coordinates for each person's home location, uniformly spread (in 2D space) across the associated TAZ, and then associated with the closest OSM roadway link, to ensure each home site is accessible.

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 are determined by the numbers 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 the trip ends are less than 2000.

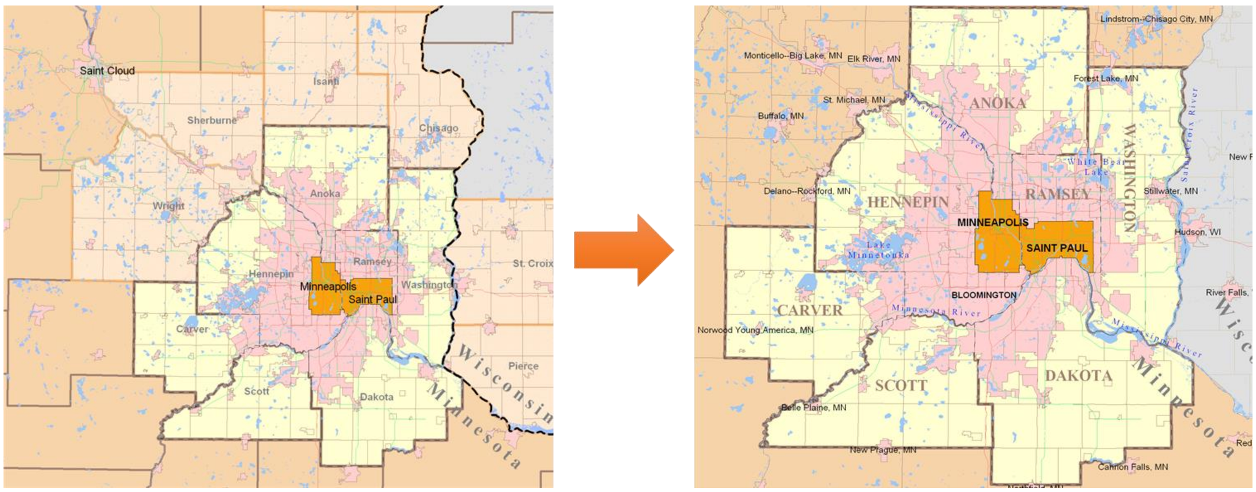


Figure 2 Moving from 19 County Trip Data to 7 Counties for the Modeled MSP Region

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 itinerary 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 (Rieser 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. The DRS code used in this study is adapted from Claudio 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 of10 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. 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.

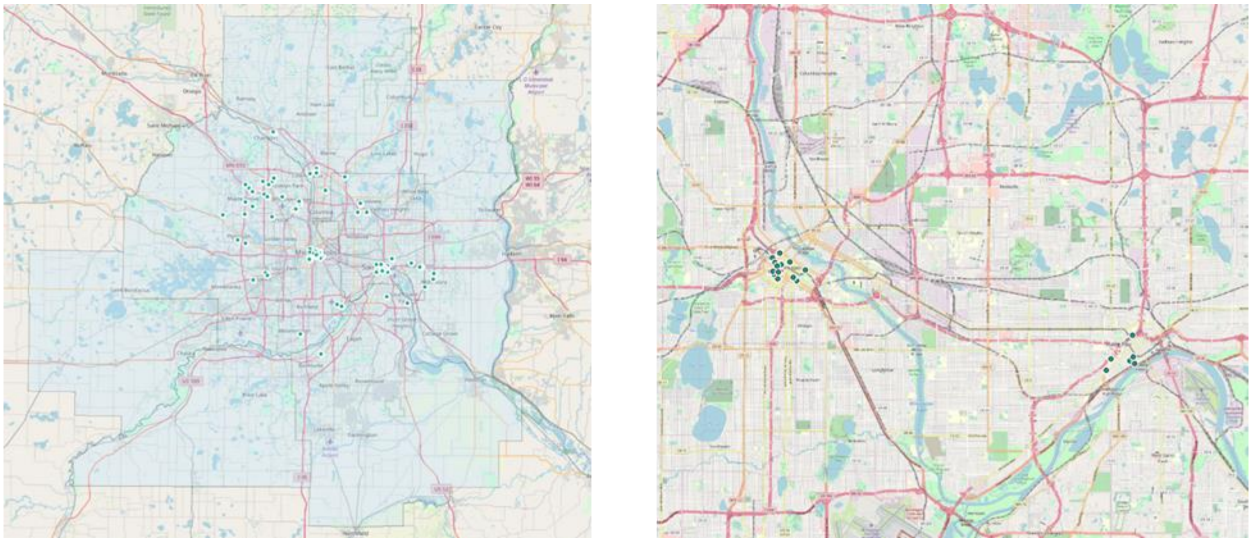
Parking Strategy

The underlying parking strategy for SAVs in MATSim is based on the AMoD package. Originally, SAVs are removed from the network and assigned to fake links that are not in the congestable 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 and 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 with at least 400 trip origins and destinations per curb per day to allow SAVs to exit the roadway until they have received a new trip assignment. During the simulation, parking requests are satisfied every 5 seconds. After a trip is completed, the empty SAV will locate the nearest or second nearest links with parking lots while checking for parking availability in the lot. If both parking lots are full, the SAV will randomly choose an available parking lot in the region 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.

Simulation Scenarios

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 and457,000 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. 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 MATSim parameters such as flow and storage capacities of links for realistic sample simulation. Some scenarios were simulated without DRS, which means each SAV can 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 number 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 more parking lots to balance the SAVs. Figure 3 shows the parking lots generation across the seven counties and Twin Cities. SAVs searched for the nearest parking lots if the distance between the SAVs and nearest parking lots was less than 0.5 miles.



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

Figure 3 SAV Parking Lot Locations

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 another 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.

For 2% of the total trips scenarios, 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, which is consistent with the actual waiting time of Uber or Lyft. For scenarios with DRS, 6–33% of the simulated trips are shared. Smaller SAV fleets increases the proportion of the DRS trips from the lower availability of SAVs, leading to better utilization through sharing. 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.

The simulations with 5% trips 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 increase, 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 less. With the same SAV availability per day, individuals from both samples of total trips have similar waiting times. However, with the increased fleet size in the scenario with 5% trips, the demand also increases temporally and spatially, leading to a decrease in unmet trips. Each SAV would face more requests during a day, which will 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 4 shows the histogram of wait times of the scenario with and without DRS. About 62% of trip wait times are less than 5 minutes, mainly of 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 20 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
	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

Figure 5 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, 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.

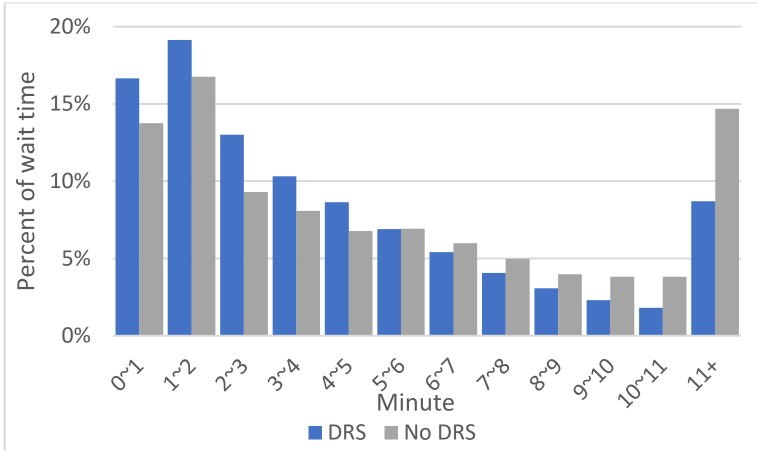
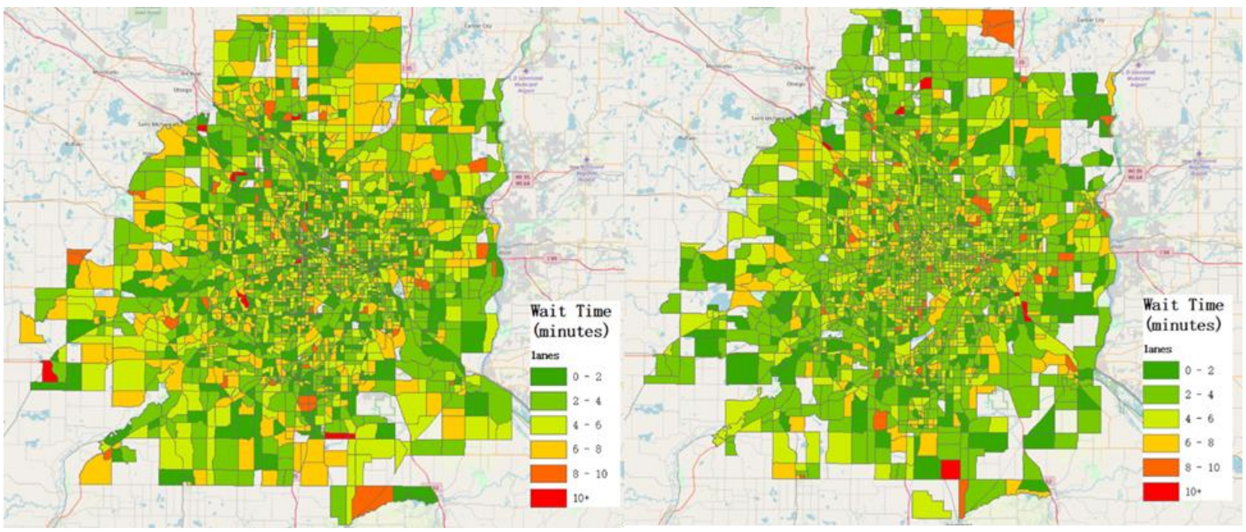


Figure 4 Temporal Distribution of Wait Times Across 7 Counties

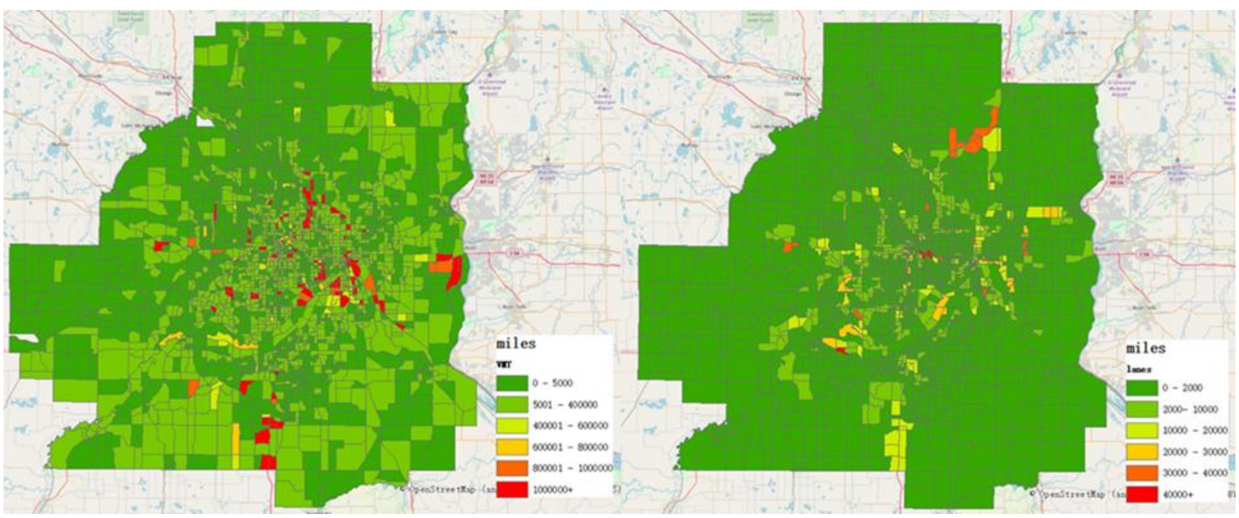


a. AM Peak **b.** PM Peak

Figure 5 Spatial Distribution of Wait Times Across 7 Counties (assuming 7 travelers per SAV per day)

Results for the Twin Cities show that VMT is significantly lesser 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 less 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 excludes those outside. Although the number of travelers per SAV is the same and total simulated trips used 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 indicates 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 lower 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.

This study also considered the spatial and temporal analyses of VMT and eVMT across 7 counties. An extension code was created to extract VMT and eVMT by link and time of day. In order to make the comparison more intuitive, Figure 6 shows VMT and eVMT distributions across TAZs, respectively. As expected, most SAV VMT and eVMT occur on freeways and highways across the MSP region, especially the highway around the Twin Cities (of Minneapolis and Saint Paul). The TAZs with the most VMT were 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 Twin Cities, since they have a 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 need to be kept low. Many drivers prefer to wait on highways rather than using idle secondary roads, but centrally-controlled SAVs may perform better with smart route choice.



a.VMT **b.** eVMT

Figure 6 Distributions of VMT and eVMT across 7 Counties' TAZs

Figure 7 shows the eVMT observed on one day across 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. 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. Meanwhile, 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 8 shows the distributions of response time, which have the similar trends with Figure 6 owing to the characteristic discussed above.

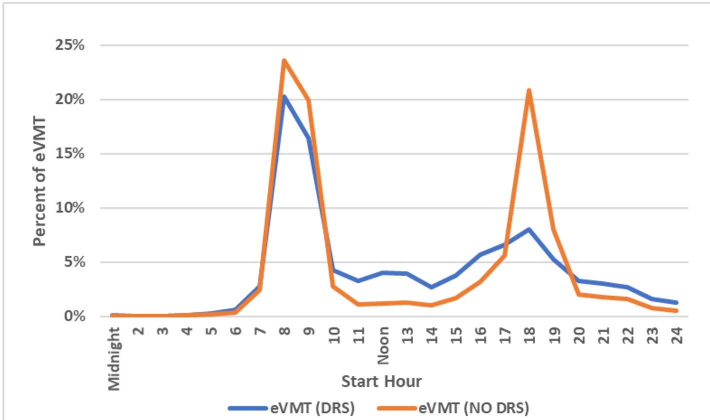


Figure 7 Distribution of eVMT with Start Time of Trip (base on 1-hour bin)

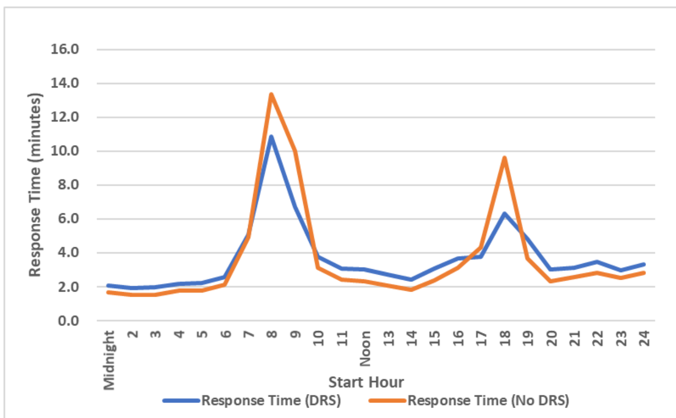


Figure 8 Distribution of Response Time with Trip Start Time (using1-hour bins, 7 travelers per SAV per day)

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 9 shows the added 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 VMT in a day was generated during this period, while only 10% added VMT was generated during the AM peak. The average added VMT during the PM peak was 0.4 miles per trip, while the average added VMT during the AM peak was 0.7 miles per trip because the origins of agents were sparsely distributed during the AM peak.

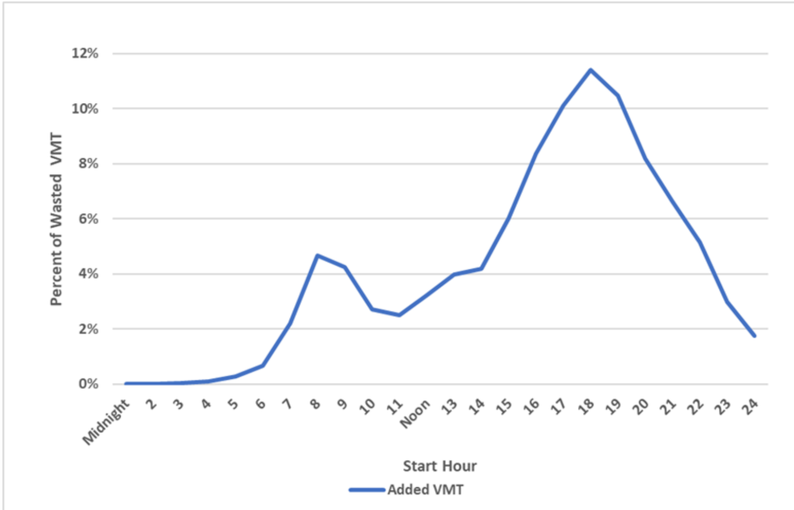


Figure 9 Distribution of Wasted VMT with Start Time of Trip (using 1-hour bins)

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 7 counties, restricted curb parking implemented generated 8% more VMT, on average, since SAVs always headed to the nearest parking lots after they dropped off the last passenger. About 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 entails that it 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 higher by 10% 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. It 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 scenarios, as the Twin Cities had 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

CONCLUSIONS

This work simulated and then evaluated the performance of an SAV fleet serving requests across the MSP region to quantify effect 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 22 simulation scenarios, eVMT averaged 7.2% to 25.2% of the SAV's fleet total VMT, and with each SAV working 4 to 18 hours per day. The DRS scenario with 5 travelers per SAV per day in Twin Cities and the no DRS scenario with 2% of total trip and 15 travelers per SAV per day in 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, on average) rather than a large region containing many suburban and rural areas. 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.

To avoid congesting busy streets across the region with SAVs idling in between drop-offs and pickup calls, relocation impacts to nearby parking lots on busy streets (i.e., links with at least 400 trip origins and destinations per curb per day) were compared to results for scenarios where curb parking is permitted everywhere. Scenarios that required off-street parking lot use for SAVs ending trips on busy links (roughly 0.02% of all street-miles in the MSP network) generated 8% more VMT and 7% more operational time on average, along with 5% fewer DRS (ride-sharing) trips for those scenarios. These curb-use constraints had a noticeable effect on operations. For the Twin Cities geofenced scenario (with just 273 square miles of SAV service area), compared to 7 counties scenario with curb parking restricted. parking lots used to protect busy streets actually resulted in 5% more DRS trips, 7% higher AVO values, and 23% less wait time, on average.

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. 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, fleet sizing, proactive SAV relocations, 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.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm the contribution to the paper as follows: study conception and design: Yan, H., Kockelman, K., and Gurumurthy, K.M.; Data and results analyses: Yan, H., Kockelman, K., and Gurumurthy. K.M.; Draft manuscript preparation: Yan, H., Kockelman, K., and Gurumurthy, K.M. All authors reviewed the results and approved the final version of the manuscript.

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