AGENT-BASED SIMULATION FOR SHARED AUTONOMOUS VEHICLE USE ACROSS THE MINNEAPOLIS-SAINT PAUL REGION

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ABSTRACT

Many well-known enterprises are road-testing fully-automated vehicles (AVs), including General Motors, Waymo, 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-hailing service. SAVs will allow savings on vehicle ownership and maintenance costs, parking search time, and parking access times. This study micro-simulates passenger travel throughout the Minneapolis–Saint Paul (MSP) region of Minnesota, when relying on a system of SAVs. The extended region includes 9.5 million trips, 7 counties, 2485 traffic analysis zones (TAZs), and about 42,000 roadway links (obtained using OpenStreetMap). 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 9.2 million daily person-trips) and 480,000 person-trips for the Twin Cities over a 24-hour weekday. Results suggest that the 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 (assuming no one needs to leave the region) but generating another 13 % vehicle-miles traveled (VMT) each day, thereby adding some congestion to the network. By enabling and encouraging active use of for dynamic ride-sharing (DRS), where strangers share rides together, the SAV fleetwide VMT fell, on average, by 17% and empty VMT (eVMT) fell by 26%, as compared to scenarios without DRS. Interestingly, the 81% and 84% of TAZs with less than 6 minutes average wait times (in the AM and PM peak periods, respectively) are uniformly distributed over this large, 7-county region, 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’ CBDs. 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.

Keywords: Self-driving Vehicles; Shared Autonomous Vehicles; Dynamic Ride-Sharing; Travel Demand Modeling; 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. For example, AVs 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). Human error while driving is the dominant 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 such mistakes, AVs are expected to considerably improve motorized-travel safety (Rodoulis, 2014). SAVs are also expected to reduce travel costs (Chen and Kockelman, 2016; Fagnant and Kockelman, 2018; Lu et al., 2018; Gurumurthy et al., 2019; Simoni et al., 2019) and impact long-distance travel (Perrine et al., 2018; LaMondia et al., 2016).

With added travel comes added 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). Fagnant et al. (2014) used an agent-based model with a gridded representation of Austin streets and 25 2-mile by 2-mile 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 their 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). Gurumurthy et al. (2019) simulated 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 sit at their most recent destination, before responding to a new trip call, such relocation will add new VMT.

Dynamic ride-sharing (DRS) is considered as an effective mode alternative for users to access available automobiles with lower cost. 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 can maximize the system efficiency of dynamic ride-sharing. Fagnant et al. (2018) improved the algorithm from Jung et al. (2013) to strengthen the efficiency of anticipatory SAV relocation and simulated SAVs fleets in Austin. The results showed DRS decreased total 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, which means the congestions of the network was improved. With SAV services at $1.00 per mile of a non-shared trip, SAVs operation companies can earn a 19% annual (long-term) return on investment with $70,000 per SAV. Hörl (2017) provided agent-based models for DRS in MATSim while models also generated dataset of people and detailed trips information for dynamic traffic simulation. Gurumurthy and Kockelman (2018) simulated SAVs with DRS in Orlando using MATLAB. This simulation used data set from AirSage’s cellphone-based trip tables for over 30 days. Approximately 60% of single trips were willing to be shared with other individual trips with less than 5 minutes added travel times from sharing. With the 1 SAV per 22 person-trips, SAVs could satisfy almost half of total demand in that region for improving congested traffic condition.

This study microsimulates personal trip-making throughout the Minneapolis-St Paul (MSP) region of Minnesota State, USA using a system of SAVs. The simulations use the multi-agent travel-choice model
MATSim (www.matsim.org). The input files rely on network data from OpenStreetMap and 24-hour trip-making data from the region’s metropolitan planning organization, called Metropolitan Council. The agent-based MATSim toolkit allows one to track individual travelers or “agents” throughout the day, between all addresses or 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 demands will be met unless travelers cancel their SAV requests after waiting 1 hour. Finally, all SAVs are assumed to be able to remain at the curb where they dropped off their passenger(s) in most scenarios, but several restricted-curb-parking scenarios allow one to appreciate 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 analyses are presented before providing the paper’s conclusions.

DATA SET

Travel demand data was obtained for the MSP region from the local metropolitan planning organization (MPO), Minnesota Metropolitan Council, 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 and cleaned for the 19 counties in the region. The network file includes 7 counties of the Minnesota state with 42,485 directed road links and 20,746 nodes. It also contains coordinates of nodes and basic information of each link, such as connected nodes, length, free speed, capacity, number of lanes and available travel modes nodes.

Nearly 11 M person-trips for a typical weekday (when school is in session) were provided by Metropolitan Council, with each trip 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 are classified as 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 7 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. Therefore, the dataset’s selected modes were 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 this thesis’ simulations lack some expected congestion that 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 data set and in the U.S.’s 2017 NHTS. 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. NHTS social/recreation trips exhibit mid-day and PM peaks.

On average, MSP travelers make 4.36 person-trips per weekday versus just 3.37 trips/day in the NHTS data set. Such trip-generation differences are striking and suggest that NHTS respondents are under-reporting or MSP data are 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.

![Graph](https://via.placeholder.com/150)

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

**METHODOLOGY**

**Temporal and Spatial Disaggregation**

Metropolitan Council person-trip start and end times are provided in rather coarse 30-minute bins, and their origins and destinations are grouped into/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. To respect Texas Advanced Computing Center Wrangler supercomputer run-time restrictions (of 48 hours), only conditions in the MPO’s 7 counties (Anoka, Carver, Dakota, Hennepin, Ramsey, Scott and Washington counties), located in the center of Minnesota State (as shown in Figure 2) were used, rather than trips that ended in another 12 MSP-area counties that the Metro Council also provided (since they like to keep track of 7-county residents’ movements in a halo region around their model region).

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 “skim” values (for each of 4 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, 5 types of non-home “facilities” or 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 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 (Simoni et al., 2019). Based on the module, all SAV trips are 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 should less than 20%. Constraint 2: The former Passengers’ remaining trip time increases should less than 40%. Constraint 3: The total trip time for second or subsequent trips increases by ≤ 20% of the total trip without ridesharing, or by 3 minutes. Constraint 4: Second or subsequent travelers will wait up to 10 minutes. Constraint 5: Total planned trip time to serve all passengers ≤ remaining time to serve the current trips + time to serve the new trip + drop-off time, if not pooled. Constraint 5: Total planned trip time to serve all passengers ≤ remaining time to serve the current trips + time to serve the new trip + drop-off time, if not pooled.
Simulation Scenarios

7-county SAV-fleet simulations were run with various fleet sizes to appreciate the variation in system performance metrics. The 22 different scenarios’ results are compared here. Using the full, 7-county region, this work simulated 456,800 person trips (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. Different fleet sizes are used to understand wait time and mode preference. A base scenario was studied as the business-as-usual (BAU) case by simply simulating the travel demand obtained from the local metropolitan planning organization (MPO) without enabling SAV use. The agent itineraries, network, and activity locations were processed to obtain the BAU metrics for VMT. Samples of 2%, and 5% of the total trips are used rather than the full population given the long runtimes. The results of the BAU case were calibrated using the dataset travel times by modifying the flow and storage capacities of links for realistic sample simulation. Personal AVs and SAVs are 2 trends in AV usage. On the one hand, with the development of technologies, the costs of AVs will decrease and may become affordable one day. On the other hand, transportation network companies have already tested SAVs. SAVs are more suitable for these companies from a business model point of view, and the cost of operation of SAVs will be relatively lower than personal AVs. SAVs are implemented as the only transportation mode in the scenario used in this study. That is, regardless of trip modes information in the dataset, all trips were satisfied by using SAVs. Based on the results of 5% of the total trips simulation, some scenarios were simulated without DRS, which means each SAV can only service one agent a time. Fleet sizes were also altered 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 SAVs need to spend more or less time to arrive at the start location. 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 foreseeable future compared to simulations of the large 7-county area. Since the simulations across the Twin Cities only consider the trips with both their origins and destinations within the Twin Cities area, extracting those trips from 5% of total trips will decrease the population and trip density compared to scenarios with the 7-county region. In order to balance this influence, 20% of trips within the Twin Cities are simulated.

RESULTS

The results suggest that an SAV in the MSP region can serve about 30 person trips per day, on average; thus, this replaces about 6 or 7 household vehicles (assuming no one needs to leave the region) but generates another 20% 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 by 34% per day.

Different SAV fleet sizes affect the matching success rate that affects how many shared rides are observed. Furthermore, travel times of the networks and average wait time can also be impacted. Table 4.1 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 populations. eVMT shows the negative effect of an SAV fleet. It is generated when an SAV receives a request and comes to the passenger who called the SAV. Unlike the conventional vehicle, eVMT cannot be avoided with SAV implementation. A low eVMT entails the high efficiency of using SAVs and can also help reduce congestion in the network, along with emissions. The SAV runtime represents the average working period of an SAV in 24 hours. AVO is the average vehicle occupancy for evaluating the effect of DRS in the network. The average wait time is another significant result of the efficiency of DRS from the traveler agents’ point of view. The vehicle replacement rate represents the productivity of SAV implementation. Each conventional vehicle performs 3.05 trips per day, on average,
as per the NHTS data (Fagnant and Kockelman, 2016). The average number of served trips per
conventional vehicle divided by the average value of served trips per SAV per day is the vehicle
replacement rate. Revenue is the sum of the traveling expenses in a 24-hour simulation.

For 2% of the total trips scenarios without DRS, coupled with the growth of travelers per SAV per day
(reduced fleet size), the average VMT and eVMT go up, 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 DRS ones. With smaller SAV fleets, the proportion of the DRS trips increases
due to the fact that the lower availability of SAV prompts individuals to opt for DRS trips. The average
VMT and eVMT decline sharply since the DRS can respond to multiple trips at the same time and choose
the most economical route to pick up passengers. The values of AVO are relatively low, since there is a
low trip density of 2% across the 7 counties. 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 minutes to 40 minutes, as SAVs cannot satisfy all
demands at the same time; consequently, some SAVs have to first finish some orders and then come back
for the rest. 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 a
higher population density be taken as a target parameter in a region.

The simulations with 5% trips have a larger trip density across 7 counties, leading to only 1.3% of
simulated trips being unserved. Compared to the results from the same scenarios for 2% trip simulations,
the VMT from the scenarios without DRS relatively increase, which is considered to be caused by the
addition of 3% of trips with longer travel lengths; moreover, the eVMT decreases. This can be explained
by the comparison of the DRS-trip proportion between 2% and 5% sample simulations. For scenarios
with travelers per SAV per day as 5, 10 and 15, the DRS trip proportions in 5% trip simulations increase
by an average of 15%. Those increases are based on more opportunities for DRS trip matching, which
lead to the decline in eVMT. The served trips in the scenarios using a 5% sample are more, and the
average wait time is less. With the same travelers per SAV per day, individuals from the scenarios with
different percentage of total trips face an equal probability of getting an SAV at the same time. However,
with the increased fleet size in the scenario with 5% trips, the temporal travelers per SAV per day also
increase. Each SAV would face more requests during a day, which will lead to more served trips and a
shorter average wait time. With a smaller SAV fleet size, 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. The
SAV is expected to serve about 30 trips per day (Fagnant et al., 2015; Loeb and Kockelman, 2019; Loeb
et al., 2018). Besides travelers per SAV per day as 5, 10 and 15, this study also simulates a scenario with 7
travelers per SAV per day, which represents 28 trips per day according to simulation results. 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, mainly of 1–2 minutes. Compared to the 55% of trips with 0–5 minutes of wait
time in the scenario without DRS, DRS can bring down the wait time of 68% of trips to less than 5
minutes. DRS reduces wait times significantly, especially for the trips with long wait times. The wait
times for about 40% of trips that have a wait time of more than 11 minutes is reduced by DRS.
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### TABLE 1. Key Findings from 20 Simulation Scenarios

<table>
<thead>
<tr>
<th>Region and Trip #</th>
<th>DRS?</th>
<th>Travelers per SAV per Day</th>
<th>VMT per SAV per Day (mi/day)</th>
<th>Empty VMT (%)</th>
<th>SAV Run Time per Day (hr.)</th>
<th>%Trips as DRS per Day</th>
<th>Trips per SAV per Day</th>
<th>AVO (person)</th>
<th>Avg Wait Time per Trip (min.)</th>
<th>Unmet trips (%)</th>
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<tbody>
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<td>7-counties, 2% of total trips</td>
<td>No DRS</td>
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<td>175</td>
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<td>3.7</td>
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<td>117</td>
<td>9.5%</td>
<td>4.3</td>
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<td>15.9</td>
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<td>7.2</td>
<td>38.8%</td>
<td>47.8</td>
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<td>1.5</td>
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*Figure 4 shows average wait times during AM peak and PM peak across TAZs in 7 counties. 81% and 84% of TAZs with less than 6 minutes wait times are widely distributed during AM peak and PM peak, while only 1% of TAZs served by more than 10 minutes wait times. These figures show uniform wait times across the region and suggest residents of this region could get similar SAVs service level everywhere.*
The Twin Cities area in the MSP region is chosen to study the SAV operation. Compared with the results in the scenario of 7 counties, simulated VMT in the scenario of Twin Cities is significantly less, since the Twin Cities are much smaller than the 7 counties and the higher number of opportunities for DRS trips match the more concentrated trips of the area. 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 density. Lower density may result in a high 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 noted that the number of trips per SAV per day is different in the 7-county scenarios and Twin Cities scenarios for the same number of travelers per SAV. For each traveler, the simulated trips in Twin Cities excluded those outside the Twin Cities. Although the
same number of travelers per SAV and similar total simulated trips were used in these scenarios, the Twin
Cities scenarios had more traveler agents and a larger SAV fleet. Therefore, the number of trips per SAV
per day in Twin Cities scenarios is less than the number of trips per SAV per day in the 7-county
scenarios. This could have a negative impact on AVO. However, according to the results of the scenarios
with 5, 7, and 10 travelers per 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 DRS trips may be generated in a small area. The
average wait times of simulations with DRS are lower than those of simulations without DRS. This
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, which will take up too much time. DRS
can reduce the wait times in such situations. Among all scenarios, with decreased a SAV fleet size, there is
a small impact on average wait times in scenarios across Twin Cities. This can justify why smaller areas
relatively reduce the distance between SAVs and agents. With a larger trip density, the negative impact of
a decreased SAV fleet size will incur more DRS trips. Thus, the values of AVO will also go up.

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, along with the links. In order to make the
comparison more intuitive, Figures 5 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. eVMT distribution is similar to 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. Like vehicles in reality,
more drivers prefer to wait on highways rather than use idle secondary roads. But program controlled
SAVs may perform better in this situation.

![Figure 5](image.png)

**FIGURE 5. Distributions of VMT and eVMT across 7 Counties’ TAZs**

Figure 6 shows the eVMT of a day across Twin Cities. For the scenario without DRS, the AM peak and
PM peak, which have numerous requests, are the main parts 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 due to the “coming back” processes. But when
DRS is available, the eVMT will shrink because SAVs can serve multiple agents at one time, thus
reducing the “coming back” processes. This obviously plays a role in the eVMT during the PM peak
because more agents in this span share the same or close origins, especially in CBDs. Commuters need to
go off work from their companies or other workplaces 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 opposite
attributes. During the AM peak, more agents share the same or close destinations but with different
origins. Due to widely distributed origins, SAVs cannot match many DRS trips, and centralized
destinations can also centralize SAVs locations. This imbalance may lead to SAVs generating more eVMT
to respond to subsequent requests. Figure 7 shows the distributions of response time, which have the
similar trends with Figure 6 since the same reasons as discussed above.

![Figure 6](image_url)

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

![Figure 7](image_url)

**Figure 7.** Distribution of Response Time with Trip Start Time (using 1-hour bins, 7 travelers per SAV per day)

Added VMT means extra VMT for each agent from a DRS trip, which can cause congestion in the
simulation network as compared to each agent’s trip duration if the agent drives a private vehicle. This
value also indicates the added VMT of SAVs. Figure 8 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. But 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 widely
distributed during the AM peak.

![FIGURE 8. Distribution of Wasted Time with Start Time of Trip (using 1-hour bins)](image)

**CONCLUSIONS**

This work simulated and then evaluated the performance of an SAV fleet serving requests across the MSP
region. The work uses MATSim code and compares the SAV fleet operations for different levels of trip
demand and geofenced regions. 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, with each SAV working 4 to 18 hours per day, with 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, resulting in the most use & least use hours per day per SAV. Using the same fleet size
and demand levels but allowing for DRS among strangers whose trips have meaningful overlap (in terms
of routes or locations traveled and departure times), the same SAV fleets’ average response times fell 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 Twin Cities-only geofenced fleet achieved, on average,
25% more DRS trips, and 19% shorter (average) wait times.

This study also evaluated variations in SAV VMT and eVMT values across the 7-county region’s 2485
TAZs. Most SAV VMT and eVMT are generated on freeways and highways across the MSP region,
especially the highway around the Twin Cities (of Minneapolis and Saint Paul). eVMT distribution is
similar to VMT distribution. 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.
SAVs’ eVMT was mainly distributed in the areas that had a relatively low trip-end density and quite
dispersed geographically while high-VMT TAZs were scattered around the downtown areas of the Twin Cities. 81% and 84% of TAZs with less than 6 minutes wait times are widely distributed during AM peak and PM peak. The study shows uniform wait times across the region and suggests residents of this region could get similar SAVs service level everywhere.

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 very 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 complicated and/or slowed down the code too much to be used here (maxing out the UT Austin 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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