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, by combining car-sharing and taxi services. SAVs will allow savings on parking time and cost, as well as vehicle maintenance and storage. 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 3.5 million residents, 1.8 million jobs, 19 counties, 3030 traffic analysis zones (TAZs), and about 57,000 roadway links (obtained using OpenStreetMap). An agent-based toolkit, MATSim, allows tracking of individual travelers throughout the day and across their activity locations. In this study, more than 450,000 person-trips are simulated for the entire region, as well as just the Twin Cities over a 24-hour application. Results suggest that SAVs in this region can serve at most 30 person-trips per day with less than 5 minutes of average wait time, thus replacing about 10 household vehicles (assuming no one needs to leave the region) but generating another 13 percent vehicle-miles traveled (VMT), adding congestion to the network. By implementing dynamic ride-sharing (DRS), where strangers share SAV rides, fleet's VMT falls, on average, by 17% and its empty VMT (eVMT) falls 52%. Various energy and emissions savings are also expected, when energy-efficient SAVs are used, as compared to the typical US household vehicle.

Keywords: Shared autonomous vehicles, agent-based simulation, dynamic ride-sharing, Minneapolis-St Paul.

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 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 offer opportunities for dynamic allocation of lanes during peak periods andr before entering traffic bottlenecks by connecting to traffic management systems in real-time (WSP/ Parsons Brinckerhoff and Farrells 2016). Such traffic management systems can reduce network congestion and the associated emissions and energy use (Ticoll, 2015). Human error while driving is the dominant cause of traffic crashes in developed countries, 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 (Hars 2010; Rodoulis 2014). SAVs are also expected to reduce travel costs (Chen and Kockelman, 2015; Liu et al., 2016; Fagnant and Kockelman, 2018; Simoni et al., 2019; Gurumurthy et al., 2019), impact long-distance travel, and increase trip-making by the disabled and young.

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. Bhat (2016) made a comparison of current taxi implementation and dynamic ride-sharing scheme through New York City Area. It confirmed DRS has a significantly higher average vehicle occupancy than non-ride-sharing schemes. 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. This value would increase to 80% if waiting time or travel time increased to 15 and 30 minutes. With the 1 SAV per 22 person-trips, SAVs could satisfy almost half of total demand in that region for improving congested traffic condition.

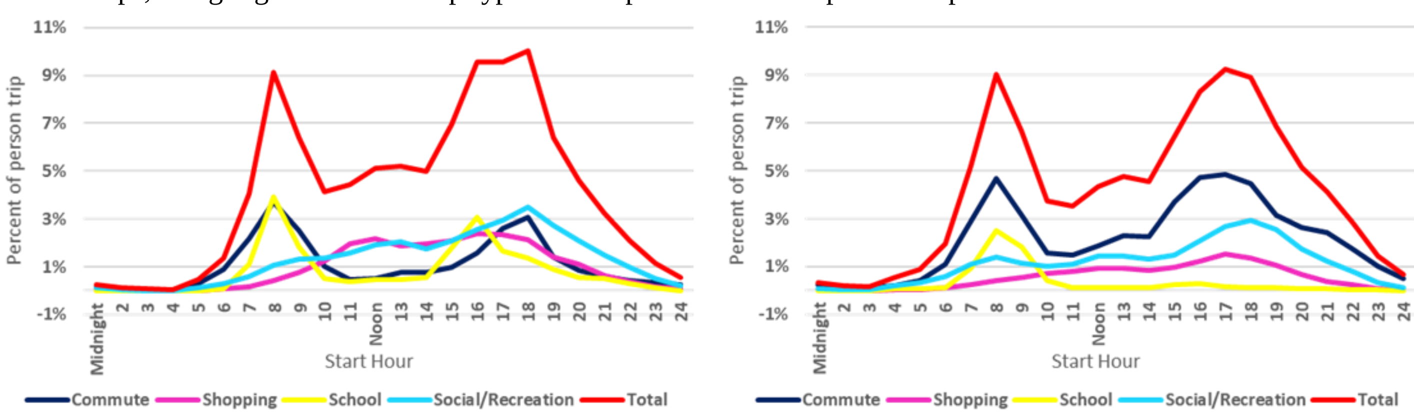
This study simulated SAV fleets across the MSP region in Minnesota with DRS. The simulations use the multi-agent travel-choice model MATSim (www.matsim.org).The input files based on network data from OpenStreetMap and 24-hour trips data from Minnesota Metropolitan Council, to model real transportation flow in this region. 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. There are 3030 TAZs across the state of Minnesota, as well as the highway network, containing around 364,000 links and 148,000 nodes.

Nearly 11 M trips were provided by the MPO, 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. Person types were classified as a child, non-working adult, senior, part-time worker, full- time worker or an adult student. Trip purposes included school, work, university, meal, shopping, personal business and social recreation. There were 7 trip modes observed, such as drive alone, shared ride, walk to transit, park-and-ride, bike and school bus. This study assumes that all demand is satisfied by using SAVs, so the mode from the dataset was not used. External trips and truck trips are not included in this dataset.

Figure 1 shows the comparison of departure time distributions between the MSP data set and the U.S. 2017 National Household Travel Survey (NHTS). An average individual in the MSP region makes about 4.4 person-trips on a weekday (versus 3.4 person-trips per day for the average American). The daily person-trips per household in the MSP region is 8.9 on a weekday (versus 8.6 person-trips per day for the average American household). The daily person-miles traveled (PMT) in MSP is around 34.3 per person while the daily PMT per person from NHTS is 39.0 miles. The time-of-day comparison reveals that the commute trips in MSP are significantly higher for the AM and PM peak, largely owing to the absence of weekend trips in the MSP dataset. The relatively flat curves of non-commute trips in MSP region, especially shopping trips, is highlighted. School trip-types have a pronounced AM peak as expected.



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

The trip data from Minnesota Metropolitan Council was classified into 30-minute bins for start and end times, and their origins and destinations were grouped by TAZs. For an effective agent-based simulation of SAVs, higher temporal and spatial resolution was necessary. Additionally, the departure time of these trips was not always in the 30-minute bin in reality, since trips in the region can start many minutes in advance or can end many minutes later, so temporal disaggregation needed to be done in adjoining bins.

One-minute bins were used here for obtaining detailed departure and arrival times for each agent. Departure times were disaggregated by adding a random number from the uniform distribution with mean 0 and standard deviation 15. This was done so that the trips occurring at the previous 30 minutes bin and plus a random value from -15 minutes to +15 minutes (Gurumurthy and Kockelman, 2018). Once a departure time was adjusted for these spatially disaggregated trips, according to the specific highway skim file from Minnesota Metropolitan Council for time of day (AM peak, midday, PM peak and night), the arrival time for each trip can be assigned. Finally, the original 24-hour data set with 30-minute bins were disaggregated into smooth, one-minute bin trip data, which is more temporally detailed and realistic for departure and arrival time patterns.

Trip origins and destinations were disaggregated using a Python code and an ArcGIS package to generate specific coordinates for each person's home. Home locations were generated for each home-based trip uniformly in a TAZ, and close to a link for smoothening the simulation process. Similarly, activity locations for activities other than home were needed for this study, instead of the generated origin and destination coordinates for each trip. The aggregated activity locations in each TAZ is more natural and realistic for simulation than individual origin and destination coordinates for each trip. Most trips typically end in office locations, campuses or shopping markets, so these are able to be serve as virtual stop stations for the trips departing from these locations after activity completion.

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.

Five of the seven trip types (classified based on trip origins and destinations) described in the previous section was used in this study as activity locations, which are: home, work, shopping, education and leisure. Figure 2 shows an example itinerary for an agent which includes activities, mode and detailed spatial and temporal information to carry out a day's activities. The itinerary for each agent is usually a round-trip, which means that the agent starts and ends the day in the same location, typically home.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  </plan>
</person>
```


FIGURE 2 Example of an Agent's Plan

In a MATSim simulation, SAVs are generated in iteration zero according to how the input trip demands are spatially dispersed. SAVs are then able to respond to agents' requests based on their travel plan. The DRS contribution from Hörl (2017) is used here with some modifications. 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 it allows for dynamically demand-responsive vehicle dispatch, similar to taxi operation. Vehicle dispatch is generally started 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 find aggregated trips for SAVs within acceptable distances for pickup. The DRS matching constraints used here could be summarized as follows (Fagnant et al., 2015):

- Constraint 1: Passengers' trip duration increases should less than 20%.
- Constraint 2: Passengers' remaining trip time increases should less than 40%.
- Constraint 3: Second or later's total trip time grows by ≤ 20% total trip without ridesharing, or 3 minutes.
- Constraint 4: Second or later 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.

Simulation Scenarios

Travel in the MSP region was studied at varying levels of trip density. Figure 3 shows the two scenarios based on spatial extent studied here, with one covering the entire 19-county region, and the other covering the 7-county twin-city region. In the study, MATSim runs were performed on the Texas Advanced Computing Center's (TACC's) Wrangler supercomputer, to simulate scenarios for 24 hours.

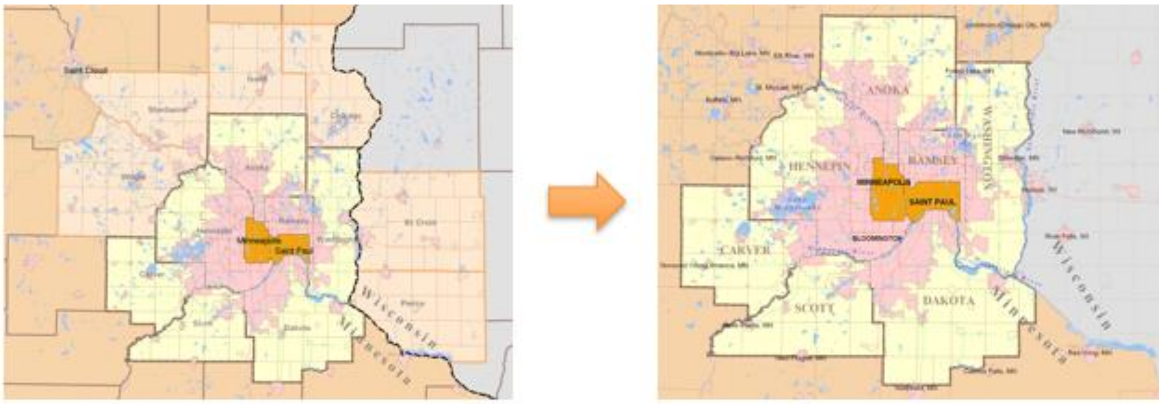

FIGURE 3 Simulation area for scenarios using 19- and 7-counties

Twenty different scenarios simulated here are compared using their performance metrics. For simulations in the 7-county region, this work simulated 456,800 person-trips (5% of the region's 9.2 million total person-trips) over a 24-hour period. For the Twin Cities scenario, about 487,000 person-trips from dataset were simulated. 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 MPO, without enabling SAV use. The agent itineraries, network, and activity locations were processed to obtain BAU metrics on VMT Samples of 2% and 5% of total trips are used rather than the full population owing to large runtimes. The results of the BAU case were calibrated using the dataset travel times by modifying flow and storage capacities of links for realistic sample simulation. Personal AVs and SAVs are two trends for AV usage. On the one hand, with technologies developing, the costs of AVs will decrease and may be affordable one day. On the other hand, transportation network companies have already tested SAVs. SAVs are more suitable from a business model point of view for these companies and the cost of operation of SAVs will be relatively lower than personal AVs. SAVs are implemented as the only transportation mode in this scenario used in this study. That is, regardless of trip modes information in the data set, all trips were satisfied by using SAVs. Based on the results of 5% of total trips simulation, some scenarios were simulated without DRS, which means each SAV can only service one agent a time. Fleet sizes also were changed for different scenarios to understand how trip patterns are sensitive to size. 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) that has 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 balancing 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, replacing about 6 or 7 household vehicles (assuming no one needs to leave the region) but generating another 20 percent VMT, and adding congestion to the network. Those using DRS spend time waiting for other passengers to enter or exit SAVs, which often go out of their way to pick-up & drop-off others, which increases the average-trip duration by 34%.

Different SAV fleet sizes affect the matching success rate affecting how many shared rides are observed. Furthermore, travel times of the networks and average wait time can also be impacted. Table 1 shows results by scenario and fleet sizes. SAV fleet sizes are shown as the number of travelers per SAV in order to illustrate the influence of fleet sizes across scenarios with different population. Empty VMT (eVMT) shows the negative *effect* of an SAV fleet. It is generated when a SAV receives a request and comes to the passenger who called the SAV. Unlike the conventional vehicle, eVMT cannot be avoided with SAV implementation. Low eVMT means high efficiency of using SAV and it also can help reduce congestion of the network, in addition to emissions. SAV run time represents the average working period of SAV in 24 hours. AVO is the average vehicle occupancy for evaluating the effect of DRS in the network. Average wait time is another significant result for efficiency of DRS from agents' point of view. Vehicle replacement rate represents the productivity of SAV implementation. Each conventional vehicle performs 3.05 trips per day, on average, from NHTS data (Fagnant and Kockelman, 2016). The average number dividing the average value of served trips per SAV is vehicle replacement rate. Revenue is the sum of the travelling expenses in 24 hours simulation.

For 2% of the total trips scenarios without DRS, coupled with the growth of travelers per SAV (reduced fleet size), the average VMT and eVMT go up, causing the 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, based on the costs mentioned at the beginning of this section, 6%-33% of the simulated trips are DRS ones. With smaller SAV fleets, the proportion of DRS trips enlarges, due to the fact that the lower availability of SAV prompts individuals to prefer DRS trips. The average VMT and eVMT decline sharply since 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 travelers per SAV rise from 10 to 15, there is an increase in average waiting time from 11 minutes to 40 minutes since SAVs cannot satisfy all demands at the same time; consequently, some SAVs have to finish some orders first 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 29% unserved trips. In order to avoid this impact, higher population density is recommended as a target parameter in a region.

TABLE 1 Key Findings from 20 Simulation Scenarios

Region & Trip #	**DRS?**	**Travelers per SAV**	**VMT per SAV per day**	**Empty VMT (%)**	**SAV Run Time per Day**	**%Trips as DRS**	**Trips per Day per SAV**	**AVO**	**Avg Wait Time (min.)**	**Unmet trips (%)**
7-counties	No DRS	5	175 mi/day	12.7%	9.4 hr	--	19.0trips	1 person	3.7 min	29.0%
		10	406	24.8%	11.4	--	37.9	1	11.0	29.1
		15	557	22.3%	18	--	55.4	1	39.9	30.8

, 2% of total trips	**Yes DRS**	5	170	11.7%	8.4	5.9%	19.0	1.03	4.0	23.3
		10	378	22.8%	11	15.7%	37.9	1.23	10.7	23.2
		15	526	22.2%	16.5	43.40%	34.3	1.20	34.5	30.0
7-counties, 5% of total trips	No DRS	5	173	14.1%	8.9	--	10.2	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

The simulations with 5 percent trips have a larger trip density across 7 counties, leading to only 1.3% of simulated trips being unserved. Compared with the results from the same scenarios for 2 percent trips simulations, the VMTs from the scenarios without DRS relatively increase, which is considered to be caused by adding 3% of trips with longer travel lengths, and the eVMT decreases. This can be explained by the comparison of DRS-trip proportion between 2 percent and 5 percent sample simulations. For scenarios with travelers per SAV as 5, 10 and 15, the DRS trip proportions in 5 percent trips simulations increase by 5% on average. 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 percent sample are more, and average wait time is less. With the same travelers per SAV, individuals from the scenarios with different percentage of the total trips face an equal probability to get a SAV at the same time. But with increased fleet size in the scenario with 5 percent trips, the temporal travelers per SAV also increase. Each SAV would face more requests during a day, which will lead to more served trips and shorter average wait time. With 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. But it also brings the longest average wait time as 32.3 min in the SAV-undersupplied situation. 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 as 5, 10 and 15, this study also simulates a scenario with 7 travelers per SAV which represents 28 trips per day. Figure 4 shows the histogram of wait times of the scenario with and without DRS. About 62% of trips' wait times are less than

5 minutes, mainly between 1 min and 2 min. Compared to the 55% of trips with 0~5 minutes of wait times of the scenario without DRS, DRS can make 68% of trips with wait times less than 5 min. DRS reduces wait times significantly especially for the trips with a long wait time. About 40% of trips with more than 11 minutes of wait times are reduced by DRS.

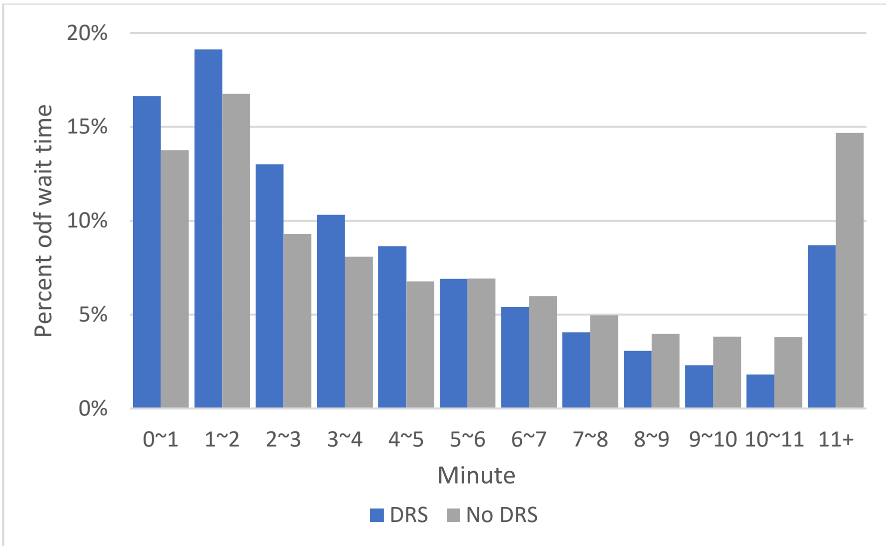

FIGURE 4 Wait Times Histogram across 7 Counties

Twin cities in MSP region are 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 Twin cities are much smaller than 7 counties and more opportunities for DRS trip match more concentrated trips in Twin cities. The proportion of DRS trips in Twin cities increases from 20.7% to 38.8% which is the highest average values among all corresponding scenarios. It also can explain why the scenarios in Twin cities have the shortest eVMT. The average wait times of simulations with DRS are lower than those of simulations without DRS. It indicates that DRS reduces the wait times. Agents find it hard to find an idle SAV unless they are willing to wait for them until SAVs drop other individuals and come back, which will cost too much time. DRS can reduce the wait times in such situations. Among all scenarios, with decreased SAV fleet size, there is a small impact on average wait times in scenarios across Twin Cities. This can be explained why smaller areas relatively reduce the distance between SAVs and agents. With a larger trip density, the negative impact of decreased SAV fleet size will induce more DRS trips. Thus, the values of AVO will also go up.

Figure 5 shows the eVMT of a day across Twin Cities. For the scenario without DRS, AM peak and PM peak with a lot of requests are the main parts of eVMT distribution and SAVs cannot satisfy those demands at one time. Since DRS is not provided in this situation, SAVs can only serve no more than one trip. As a result, more eVMT is generated from “coming back” processes. But when DRS is available, the eVMT will shrink because SAVs can serve multiple agents at one time and “coming back” processes will be reduced. It 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 central business districts (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 AM peak with DRS, it only declines by 3% compared with about 13% during PM peak. Those trips during AM peak have opposite attributes. During 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 make SAVs generate more eVMT to response further requests.

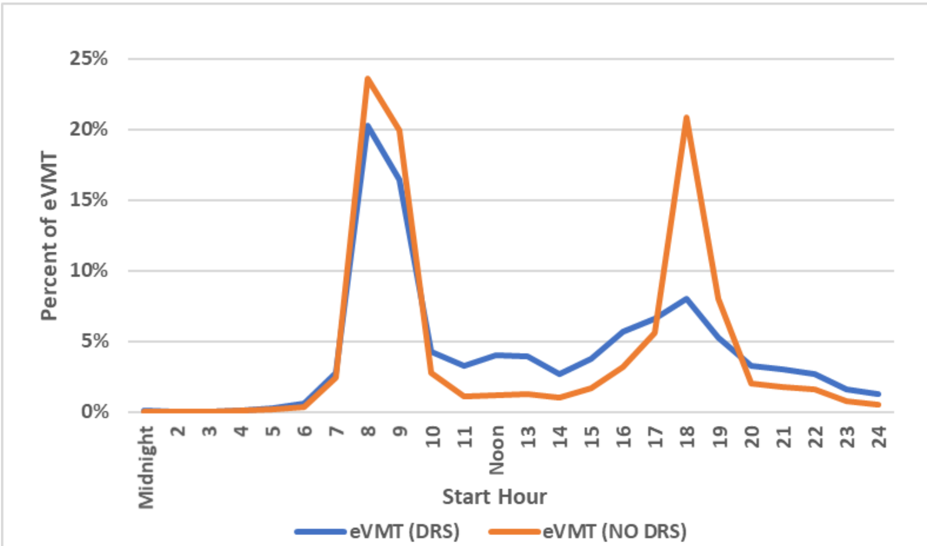

FIGURE 5 Distribution of eVMT with Start Time of Trip (Base on 1-hour bin)

Wasted VMT means extra VMT for each agent from a DRS trip, which can cause congestion in the simulation network compared with each agent's trip duration if the agent drives a private vehicle. This value also indicates the wasted VMT of SAV. Figure 6 shows the wasted VMT of a day across Twin Cities. As discussed above, DRS trips are mainly seen in PM peak. So, about 30% of wasted VMT in a day is generated during this period while only 10% of wasted VMT is generated during AM peak. But the average wasted VMT during PM peak is 0.4 mi per trip while during AM peak the figure is 0.7 because origins of agents are widely distributed during AM peak.

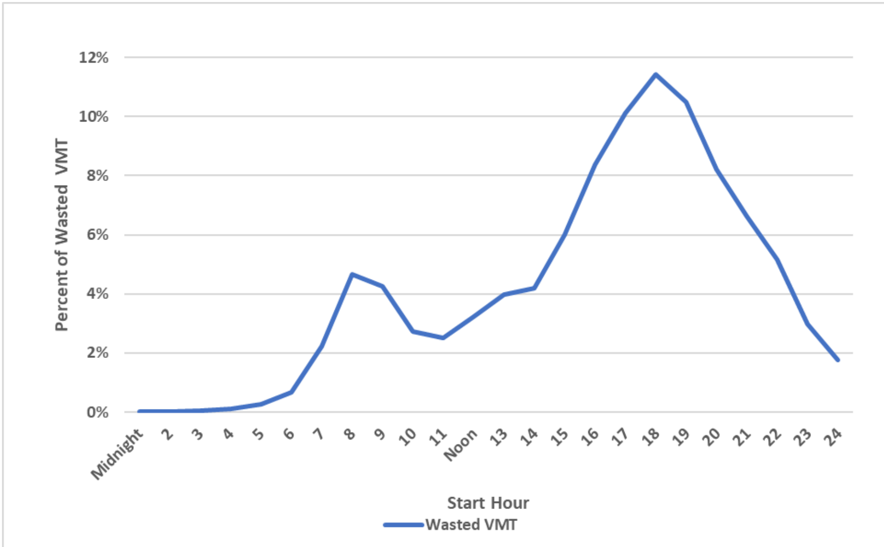

FIGURE 6 Distribution of Wasted Time with Start Time of Trip (using 1-hour bins)

CONCLUSIONS

This work simulated and then evaluated the performance of SAV fleet vehicles serving requests across the MSP region. The work uses MATSim code and compares SAV fleet operations for different levels of trip demand and geofenced regions. Significant operational differences were found across different SAV fleet sizes (in terms of SAVs per traveler) serving different densities of demand, with and without DRS enabled. With an average of 7 travelers per SAV across the region's 7 counties, vehicles served an average of 28 person-trips per day with less than 5 min average wait time across travelers. Among those simulation scenarios, average empty VMT accounted for 7.2% to 25.2% of fleet VMT, with each SAV working 4 to 16.5 hours per day. Using the same fleet size and demand levels, but allowing for DRS among strangers whose trips have meaningful overlap in space and time of day, average response times fell 10%.

This work notes how SAVs may perform somewhat better in settings with higher trip-making densities (like the Twin Cities themselves), rather than across large regions containing many suburbs and exurban areas, thanks to higher vehicle occupancies (AVOs) and more shared rides (DRS), but average wait times remain very competitive across this large, low-density region, and do not appear to vary much by location. Interestingly, eVMT rates are highest on links in areas/neighborhoods with low trip-making density. It would be valuable to have mode and destination choices be endogenous here, but such behavioral changes are still difficult to predict. It also would be valuable to be able to run the supercomputers for weeks at a time, to simulate higher demand levels for larger regions. Regardless, the results of SAV applications in this new US setting, keeping track of eVMT and average wait times by zones across the 7-county region, with and without DRS, offer valuable new information. Performance metrics used here will be useful to track in other settings, and should be helpful to planners, policymakers, fleet manufacturers, and ridehailing app developers. A further look at opportunities for credit-based congestion pricing strategies, to moderate excessive AV use, along with different vehicle sizes (and consolidated pickup and dropoff locations) will also be valuable.

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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