# How Much Does Greater Trip Demand and Aggregation at Stops Improve Dynamic Ride-Sharing in Shared Autonomous Vehicle Systems?

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Word Count: 6,239 words + 2 tables x 250 words = 6,739 word equivalents (+ 7 figures)

Under review for presentation in the 100th Annual Meeting of the Transportation Research Board to be held virtually in January, 2020.

## ABSTRACT

Sharing vehicles and rides may become the norm with public use of fully-automated self-driving vehicles in the near future, assuming pandemic-related health concerns fade away. Dynamic ride-sharing (DRS) or pooling of trips can significantly improve system performance by lowering empty vehicle-miles traveled (eVMT) and increasing average vehicle occupancy (AVO). With several cities looking to promote efficient curb space use, especially with the use of pickup and drop-off locations (PUDOs), this study explores the advantages of PUDOs in improving DRS. A scenario analysis varying PUDO spacing and trip-demand density is undertaken for the case of Bloomington, Illinois using the agent-based simulator POLARIS. Results reveal that both PUDO spacing and trip-demand density help increase AVO (by up to 0.25 travelers per 4-seater SAV, on average) and decrease SAV VMT (by up to 20%) compared to the travel without DRS or stops. A quarter-mile PUDO spacing is recommended in downtown regions to keep walking trips short because longer walking trips may adversely impact demand. With 0.25 mi spacing, travelers walked less than 2 min, while the 0.5 mi spacing needed 3.5 min of walking. It is also important to prepare for queues at PUDOs at higher trip-densities that may add congestion without dedicated infrastructure.

***Keywords:*** *Shared autonomous vehicles, stop aggregation, dynamic ride-sharing, trip densities.*

## BACKGROUND

Transportation Network Companies (TNCs) like Uber (around the world), Lyft (in the U.S.), DiDi (in China), and Ola (in India, U.K., and Australia) have popularized shared mobility by providing cost-effective rides around the world. Pooled or shared rides that are matched real-time and en route further reduce operator costs by increasing average vehicle occupancy (by passengers). TNC services are helping lower personal vehicle registrations per capita across the US (Ward et al., 2019), and more dramatic reductions are expected (Fagnant and Kockelman, 2015; Quarles et al.,

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2019; Kim et al., 2020) in the future. Fully-automated or "autonomous" vehicles (AVs) are expected to lower TNC travel costs (Chen et al., 2016; Loeb and Kockelman, 2019; Becker et al., 2020). Consequently, operating costs are expected to be comparable to the bundled cost of owning and operating a personal vehicle (Walker and Johnson, 2016) and will lead to larger mode splits toward shared vehicles. Huang et al. (2019) estimated an increase in VMT of about 47% from demand shifts once shared AVs (SAVs) are available, after accounting for induced mode use. Availability of personal AVs, on the other hand, may increase household VMT by up to about 80%, according to Harb et al. (2018). Transit ridership may also be affected, with studies predicting transit being the key market for mode shifts to low-cost convenient SAVs (Hall et al., 2018; Reck and Axhausen, 2020; Gurumurthy et al., 2020b), and congestion will rise without a sustainable alternative to high-occupancy transit vehicles. Without ride-pooling or dynamic ride-sharing (DRS) among strangers, SAV use is likely to further increase congestion from added, unoccupied travel or empty vehicle-miles traveled (eVMT). If SAVs continue to operate like present-day TNCs combined with higher demand, curbside congestion from multiple pickups and drop-offs on busy downtown blocks is an additional concern.

Research on the use of single-occupant SAVs from across the world shows added eVMT in the range of 10-30% (Spieser et al., 2014; Fagnant et al., 2015; Bischoff and Maciejewski, 2016; Simoni et al., 2019; Gurumurthy et al., 2020a). DRS is one strategy to manage rising VMT if users are willing to share their ride (Agatz et al., 2011). Bilali et al. (2019) argue that detour time is important when it comes to a fleet's shareability since flexibility in detour times are a direct measure of flexibilities available in routes that help with trip matching. However, Lavieri and Bhat's (2019) stated preference survey results suggest that added delay from DRS detours en route is a key factor in Americans' unwillingness to share rides with those who do not share their origin and destination. Although these factors may seem to nullify the benefit of DRS, Hyland and Mahmassani's (2020) optimization of SAV operations with DRS illustrates how even slight flexibility in detours and delays can prove very useful at the network level. Various survey results suggest that travelers will be more willing to share rides in the future (Krueger et al., 2016; Stoiber et al., 2019; Gurumurthy and Kockelman, 2020).

Simulation studies have quantified the usefulness of DRS under different settings. Case studies in Austin, Texas have shown that a decrease in VMT can be observed with DRS when the trip densities are high (Fagnant and Kockelman, 2018), but tolling may be critical while also considering travel alternatives available to road users (Gurumurthy et al., 2019). Dense settings, such as New York City (Alonso-Mora et al., 2017) and Chengdu, China (Tu et al., 2019), especially benefit from DRS. Alonso-Mora et al. (2017) used the NYC taxi dataset to show that optimized DRS can serve these trips with one-sixth the fleet size and low response times. Similarly, Tu et al.'s (2019) DRS algorithm improved shareability from 7% to nearly 90% along with time savings of at least 10%. Diversifying the fleet to include more seats is another option that could work like a deviation from fixed-route transit. Martinez and Viegas (2017) achieved a 30% reduction in VMT by using a mixture of 4-, 8- and 16- seater SAVs in their simulation for Lisbon, Portugal. VMT savings largely stemmed from high average vehicle occupancy (AVO) for the fleet (greater than 4.0 with the 16-seater vehicles). Assuming that travelers do share their rides, fleet efficiency in catering to diverse demand and land use profiles is still a concern. Yan et al.'s (2020) Minneapolis-Saint Paul simulations show that an increase in trip density improves DRS, similar to Fagnant and Kockelman's (2018) results that lowered VMT thanks to higher demand for DRS.

A structured approach to resolving the effect of trip density is absent in literature so far and is one of the paper's objectives.

Curbside congestion has not been a significant problem in the past. Regulated road access modes at large hubs such as railway stations and airports ensured that there was controlled use of curb space. Recent curbside congestion from airport pickups and drop-offs by TNCs has resulted in many airports using dedicated parking areas for TNC vehicles, which users must walk to. Dense cities like New York City and Washington, DC are facing this issue already with TNC vehicles crowding busy street curbsides, leading to unaccounted negative externalities from traffic hold up. Additionally, if no curbside parking or loading zones exist, TNC vehicles tend to park in the travel lane and put on their emergency hazards. This effectively closes down a lane of traffic. Curbside congestion may be alleviated by dedicating specific streets or areas as pickup-and-drop-off (PUDO) zones. Washington, DC piloted the implementation of PUDO zones for TNCs as early as 2017 and has since expanded its pilot program (District Department of Transportation, 2018). Houston and Boston recently followed suit in 2019 and 2020, respectively. Although these programs have been implemented, the network-wide benefits have not yet been quantified and there is little information on how they have affected TNC operation. The International Transport Forum (2018) conducted several microsimulations on the interaction of curb space and curb use, revealing insights into how cities must take over curb space after careful evaluation to make streets safer, and curbs more useful. Increased demand for SAVs in the future coupled with issues like eVMT and curbside congestion warrants a thorough study of the use of PUDO zones, and their influence on SAV operations.

In this study, an agent-based model called POLARIS (Auld et al., 2016) is used to study SAV operations and network benefits from the use of PUDO zones to aggregate trip requests. A case study of Bloomington, Illinois is conducted by varying trip demand, PUDO spacing, and fleet characteristics across several simulations. The next section discusses the methodology followed for the simulations, the algorithm behind deciding PUDO spacing, and an overview of fleet characteristics that are deemed essential to SAV operation. Results are tabulated and discussed next, and the paper concludes with inferences gleaned from this study.

## MODELING IN POLARIS

A large-scale agent-based modeling suite called POLARIS (Auld et al., 2016) is used in this study. POLARIS relies on transportation demand and supply models to synthesize and simulate person and freight travel across large regions such as the 20-county, 30M persons Chicago Metropolitan Area. Demand models include the population synthesizer that is sourced from ADAPTS (Auld and Mohammadian, 2009, 2012), and several mode and destination choice models. A time-dependent dynamic traffic assignment router (Verbas et al., 2018) is used to equilibrate traffic across the network to obtain a dynamic user equilibrium.

### SAV Operations

Gurumurthy et al.'s (2020c) SAV module was extended in this paper to include DRS and stop-based aggregation of incoming requests. The module provided functionality for simulating an on-demand service that operates similar to present-day TNCs. Demand for SAVs is expected to follow that of TNCs since the segment of population likely to travel in each of these modes largely overlap (Krueger et al., 2016; Haboucha et al., 2017; Lavieri et al., 2017; Stoiber et al., 2019). Unlike Gurumurthy et al. (2020c), the Bloomington application does not have a calibrated vehicle ownership model for a future of SAVs and only relied on fare and wait time impacts for predicting SAV demand. Therefore, all comparisons are with respect to SAV travel without DRS, as opposed to present-day travel. To facilitate computation, a zone-based assignment algorithm was adopted similar to Bischoff and Maciejewski (2016). POLARIS maintains a running list of idle (zero occupants and stationary) and in-use (moving or serving a request) vehicles by traffic analysis zones (TAZs). Requests were assigned based on the originating zone to an SAV in that zone or in a set of neighboring zones that are constructed as a function of maximum allowable response time.

The DRS algorithm implemented here is a heuristic to facilitate better use of empty seats in SAVs while limiting the delay experienced by each traveler in the SAV. The heuristic matched incoming requests to available vehicles that were either idling or performing a pickup, drop-off, or repositioning trip in the direction of the incoming request's destination. If SAVs were not idle or repositioning, this directionality was quantified as the angle between the Euclidian OD lines joining the ongoing and proposed trips based on available coordinates. If more than one occupant was riding the SAV, then the ongoing trip was based on who was scheduled to be dropped off next. This instantaneous match was supported by an approximate travel-time based sort of occupant destinations. Each time a dropoff was initiated, the SAV identifies the next nearest dropoff location and initiates that traveler's dropoff. This angle, in coordination with minimizing dropoff times, helped manage the extent of detours that may be allowed while maximizing pooled trips. A threshold for angle between these two Euclidian lines was provided as an input to the model. Additionally, each traveler's approximate delay (based on the estimated initial routing time without detours) was measured throughout their trip. If an SAV occupant experienced an instantaneous delay above a pre-defined threshold, new travelers are not added to the SAV. Two metrics for delay thresholds are used: absolute and percentage delays. Absolute delays or the magnitude of delays are important for short trips, where a 5-min trip can accommodate a 3-min delay (60% increase). However, a 30-min trip is likely able to accommodate more than 3 min of delay but no more than about 5% (or 6 min) of delay compared to its no-detour travel time. Following the example, both absolute and percentage delays are important since short trips are likely able to accommodate a larger percentage of delays while longer trips may need to adhere to a lower percentage of delay.

### Stop-Based Pickups and Dropoffs (PUDOs)

PUDO locations have been implemented here as a subset of locations used by all modes of travel in POLARIS. This simplification (as compared to designating specific streets or curb spaces for TNC pickups and drop-offs) should not affect aggregate or regional fleet analysis. PUDO zones were sampled using a hierarchical clustering algorithm for all possible origins and destinations in the software R. Hierarchical clustering created a dendrogram (i.e., a tree structure) of clusters with each location belonging to its own cluster downstream (at the base of the tree's root system). Moving upwards, locations were clustered based on proximity. With this type of agglomerative clustering, a predefined stop spacing $d_s$ was used to obtain the required set of stops that are no more than $d_s$ miles apart.

## DATASET AND SCENARIOS

In this paper, SAVs are simulated in the Bloomington region of the U.S. state of Illinois, to understand the effectiveness of aggregating SAV trips spatially by PUDO zones in boosting DRS. Bloomington is a small region, encompassing 74 square miles and home to about 120,000 residents. Its network has just 4,000 links and 2,500 nodes, which are 89 to 92% less than the comparable values for the Chicago region. The POLARIS activity-based model of tours and travel demand is quite behaviorally flexible and realistic, enabling certain traveler choices that other SAV simulations lack like the destination choice that has not been implemented in MATSim (Horni et al., 2016). The in-house population synthesizer also helps translate econometric models to agent-based input data. Trip demand across the Bloomington region can be conveniently scaled up or down in POLARIS, once there is a calibrated demand model. Yan et al.'s (2020) Minneapolis-Saint Paul region (and Twin Cities only) simulations using MATSim as the base code suggest that a large increase in trip density is needed to observe about 15% more shared trips. With this motivation, Bloomington's 100% demand scenario was scaled up by factors of 5 and 25 (500% and 2500%) in order to better detect the impact of SAV-trip-request density on DRS operations and AVOs. A 5x and 25x increase in trip-demand-density can easily congest links in the region and can confound with mode choices. So, a proportional increase in network capacity is also assumed here to focus attention on comparing regions with different densities.

Previous studies have established that DRS is also proportional to fleet size and availability (i.e., the ratio of travelers to SAVs), and is also a function of response time and maximum allowable delay (Gurumurthy et al., 2019; Yan et al., 2020). In order to separate these effects from that of using PUDOs, fleet size is calculated to maintain a constant requests-to-vehicles ratio in each scenario simulated, and response time (10 min) and allowable delay thresholds (5 min absolute delay and 5% added delay) are held constant across all scenarios. Additionally, the direct effect of having to walk longer distances to a PUDO zone is also tested. Table 1 highlights all possible values chosen for these variables.

**Table 1** Input Values Simulated as Separate Future Scenarios

| **Variable** | **Values** |
|---|---|
| Person-Trip Demand Levels Simulated | 1x, 5x & 25x all person-trips |
| Fleet Size | About 70 person-trips per SAV per day |
| Response Time Threshold | 10 min |
| Maximum Allowable Absolute Delay | 5 min |
| Maximum Allowable Percentage Delay | 5% of direct travel time |
| Maximum Trip Directionality for Pooling | 10 degrees |
| Pickup/Dropoff Location Spacings ($d_s$) | 0 mi, 0.25 mi & 0.5 mi |

Figure 1 shows the Bloomington region with all locations available as origins and destinations, and the two sets of stops used in this analysis. It is clear that the density even in the base demand case is likely to be high, and given that this region is only 74 sq. mi large, the fleet metrics for SAVs in this study are expected to be higher than observed in literature.

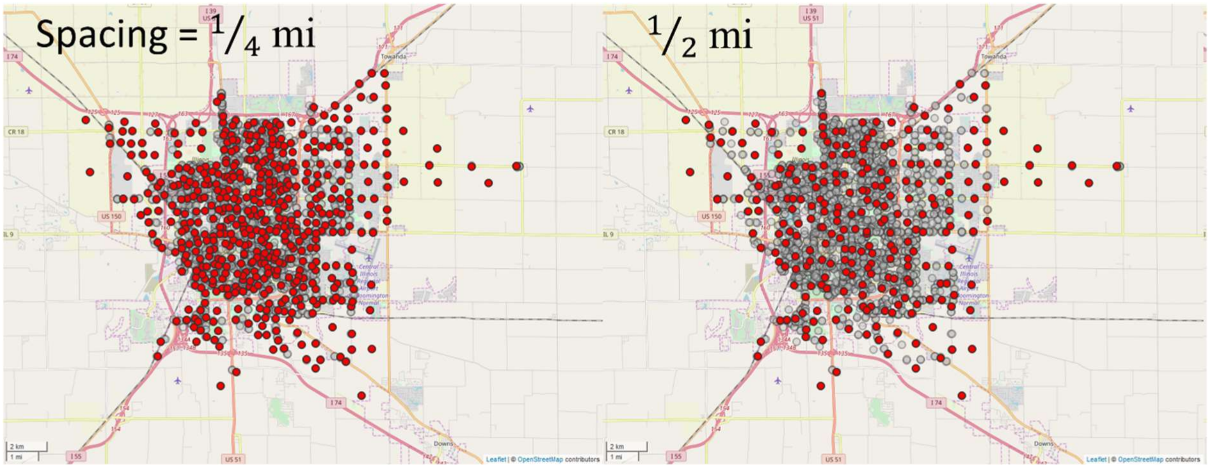


**Figure 1** Pickup and Dropoff Location Locations Chosen across Bloomington, Illinois in the $d_s$ = 0.25- and 0.5-mile PUDO Spacing Scenarios

## RESULTS

Twelve scenarios were simulated in this study in an attempt to isolate fleet operation effects that are of interest. The base case for Bloomington consists of three simulations with varying trip densities and without offering DRS. Base case results highlight the small share of person-trips for SAVs and transit at about 7% and 4%, respectively, in auto-centric Bloomington. It is important to note that these SAV trips were modeled similar to current-day TNC demand. Fleet size was scaled up proportional to the demand simulated to retain constant mode splits, and each SAV, on average, made 65 person-trips per day, traveling about 430 mi per SAV per day. The heuristic employed minimized response times to about 5 min, with a linearly decreasing trend as trip density increased exponentially. Percent eVMT also fell by 2.5% (to 31.5%) and then 5% (to 29%) in the 5x and 25x demand-density scenarios relative to the starting eVMT value of 34%.

Employing DRS increased SAV mode shares by 1% (from 7% to 8%) and marginally lowered system VMT. There was a 2% reduction in SAV VMT with DRS and with current Bloomington person-trip densities, but was notably higher for higher trip densities with a reduction of about 8%. All scenarios apart from the base case mentioned above maintained the SAV availability (SAV vehicles proportional to SAV trips) with each SAV serving about 70 person-trips per SAV per day. Figure 2 shows the mode shares observed across all scenarios for Bloomington when DRS was used. Ideally, the impact of walking to a PUDO zone is likely to affect travelers' willingness to choose SAVs, but this was not factored into the mode choice. Compared to the base case without DRS, percent eVMT dropped significantly, by about 15%, thanks to bundling rides together, and the greater availability of SAVs to serve requests. Overall response times rose marginally when using DRS, likely owing to having to detour from an existing trip. But those response times fall with increasing trip density.

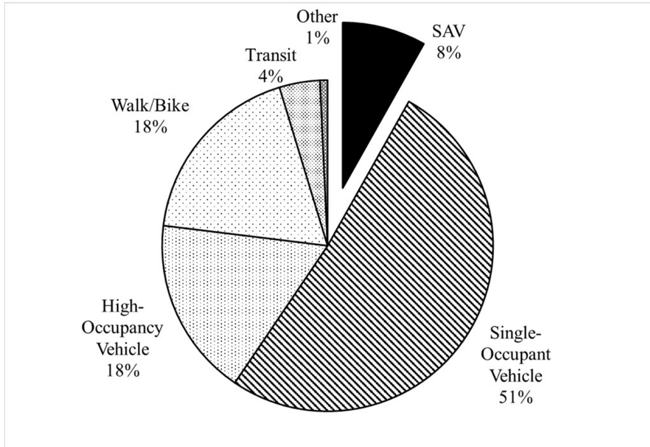


**Figure 2** Trip Modal Shares across Scenarios Simulated for Bloomington

Table 2 documents scenario-specific fleet metrics such as the average SAV idling time over a 24 hr day, person-trips served per SAV per day, average fleet VMT per SAV per day and the average travel time while choosing the SAV mode to travel. All metrics shown here for Bloomington, Illinois are higher than typically found in shared fleet studies and is likely attributed to the small 74 sq. mi region. Average trip length in Bloomington is about one-third that of NHTS' U.S. average of 12 mi but may be skewed right from long and frequent trips in megaregions. On average, SAVs for the fixed demand-to-supply ratio stay idle about half the day, irrespective of stop aggregation and DRS. About 10 more person-trips are made per SAV per day owing to the use of DRS. Stop aggregation helps improve fleet utilization without DRS but the direction of effect is not apparent when pooling is allowed. Average VMT per SAV over the 24 hr day falls when the fleet is serving multiple passengers simultaneously as expected, as more SAVs are available to serve requests across the region which lowers eVMT. There is further reduction in average VMT with stops since the residual is converted to walking trips. The use of DRS, on average, increases travel times by 70-100% but the 24 hr average is biased high. The increase in average travel time is exacerbated in the 5x and 25x demand scenarios and is likely a result of bad matching (use of similar matching parameters in the heuristic used) even though a higher demand is available for matching. A trip-level percent change in travel time is the actual delay. With synthesized populations and some randomness, it is hard to provide such a metric using POLARIS when comparing trip-level travel times between scenarios. A histogram of experienced travel times is provided in Figure 6 instead.

**Table 2** Fleet Performance across Different Stop Spacing and Demand Scenarios

| Demand | Stop Spacing | DRS? | Avg. Idle Time (in hr) | Avg. Trips per SAV per day | Avg. SAV VMT per day | Avg. Access and Egress Time | Avg. Travel Times (including wait and walk) |
|---|---|---|---|---|---|---|---|
| **Base** | No PUDO | No | 10.4 | 64.4 | 428.3 | 0 min | 8.2 min |
| **5x** | | | 10.3 | 68.0 | 439.1 | 0 | 8.2 |
| **25x** | | | 10.2 | 70.0 | 438.3 | 0 | 8.2 |
| **Base** | No PUDO | Yes | 10.7 | 73.0 | 422.5 | 0 | 14.6 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0.25 mi | | 11.3 | 73.8 | 403.7 | 1.9 | 15.9 |
| | 0.5 mi | | 11.9 | 72.6 | 383.3 | 3.3 | 16.7 |
| **5x** | No PUDO | | 10.5 | 71.8 | 412.0 | 0 | 16.6 |
| | 0.25 mi | | 11.0 | 71.8 | 392.0 | 1.9 | 18.1 |
| | 0.5 mi | | 11.5 | 70.5 | 370.9 | 3.3 | 18.6 |
| **25x** | No PUDO | | 10.4 | 69.9 | 398.2 | 0 | 19.3 |
| | 0.25 mi | | 10.8 | 70.5 | 381.1 | 1.9 | 20.2 |
| | 0.5 mi | | 11.2 | 68.7 | 360.3 | 3.3 | 20.2 |

Figure 3 shows the comparison of AVO and percent eVMT as a function of trip density and assumed PUDO zone spacing. Even with trip density as currently observed, an AVO of 1.8 is attained while counting single-party requests only, and this increases with increases in trip density. The choice of PUDO spacing also has a similar effect on AVO. The effect size of stop spacing on AVO decreases with higher demand. It is important to keep in mind that travelers may be unwilling to walk the extra mile, so the AVO increase estimated here is reliant on travelers' willingness to walk to a PUDO location, as well as to share a ride. Greater eVMT reductions are observed as trip density increases, since the probability of finding a traveler increases throughout the region. This decrease is further aided by the use of PUDO locations but only marginally. Although the magnitude of difference is 1 or 2 percent points, the 1.3M trips served under 25x trip density sees considerable benefit in congestion mitigation. SAVs are able to serve more trips with a smaller impact on congestion with DRS and the use of PUDO zones.

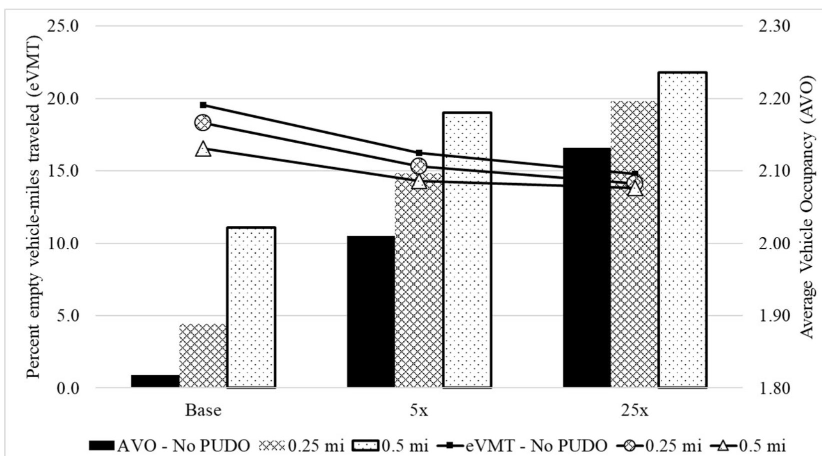


**Figure 3** Effect of Demand and Stops on Percent eVMT and AVO

The use stops increased total VMT savings by an additional 0.5% with current Bloomington demand irrespective of spacing. This corresponded to about 6% to 10% savings in SAV VMT even when mode shares are only 8%. Figure 4 shows total VMT and the corresponding SAV VMT for the nine trip density and stop spacing scenarios. Larger trip-demand density allowed for better trip matching and results in SAV VMT savings of up to 18%. The constant mode share assumption through these scenarios meant that the effective savings in total VMT only improved by about 1% more than savings in the current trip-density scenario. If mode share is not a significant concern, better utilization of a smaller fleet in the higher trip-density scenarios may be sufficient to achieve similar VMT savings. However, there would be a drop in SAV demand if maximum response thresholds were not relaxed. Two smaller fleet sizes were tested to reveal that VMT savings can be higher (up to two times) with fleet sizes cut by a third, but stops no longer help boost VMT savings. Benefits of aggregation is offset by serving half as many trips. Smaller fleets have lower idle time and skew average travel times high by likely trying to bundle and serve more trips. This result may be specific to the small region of Bloomington with relatively short trip distances of 4 mi compared to the NHTS' 12 mi U.S. average. Larger regions may not have trips ready to be bundled at all times of day or in all directions of travel.

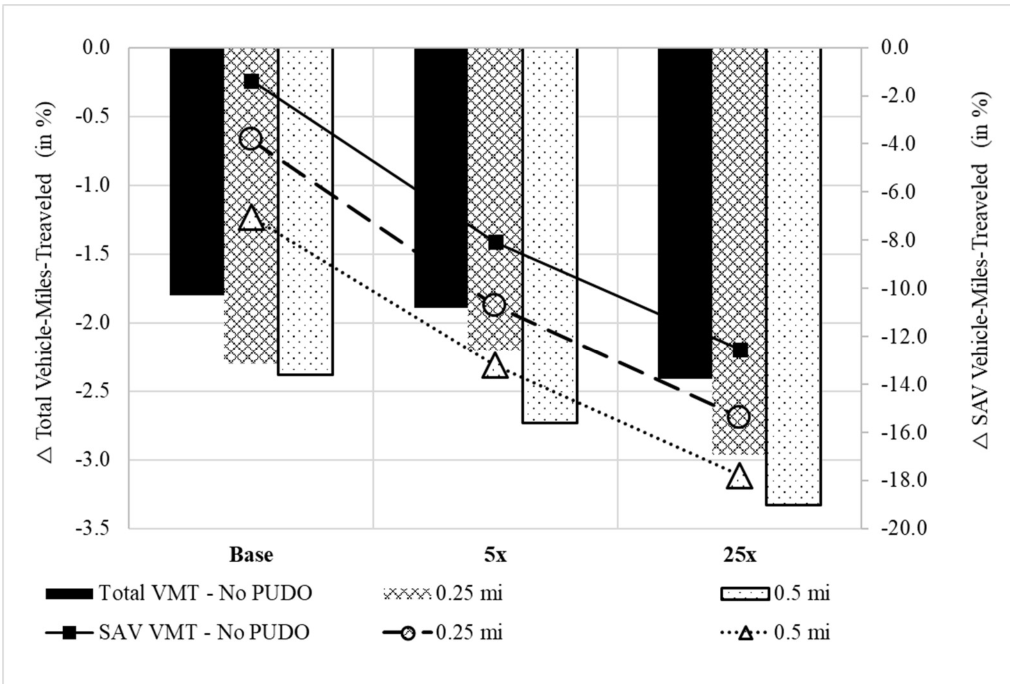


**Figure 4** Changes in Total Vehicle-Miles Traveled and SAV Vehicle-Miles Traveled

Stops and demand improve AVO over an average travel day, but the significance of stop-based aggregation of trips is best highlighted in Figure 5. Even a quarter-mile stop spacing increases aggregation during the mid-day off-peak, with hourly AVO increasing from 1.2 to 1.5, and is likely the sole contributor to higher daily AVO in a given scenario. For an adequate ratio of trip requests to SAVs, peak-time DRS is expected to be maximum, as allowed by spatio-temporal trip collocation, acceptable delays and vehicle-capacity restrictions. If stop-based pickup and dropoff is selectively enforced in the off-peak, the overall fleet performance improves from better seat utilization. This may be the ideal trade-off between expecting travelers to walk to stops throughout the day, which adds delay and deters demand, and no stop aggregation, where VMT savings are not optimally (or even sub-optimally) high. It is also important to note that all AVO values mentioned here are for single-party requests. VMT savings will remain more or less the same with multi-person parties who may have shared the ride, but the reported AVO will be higher for such a service.

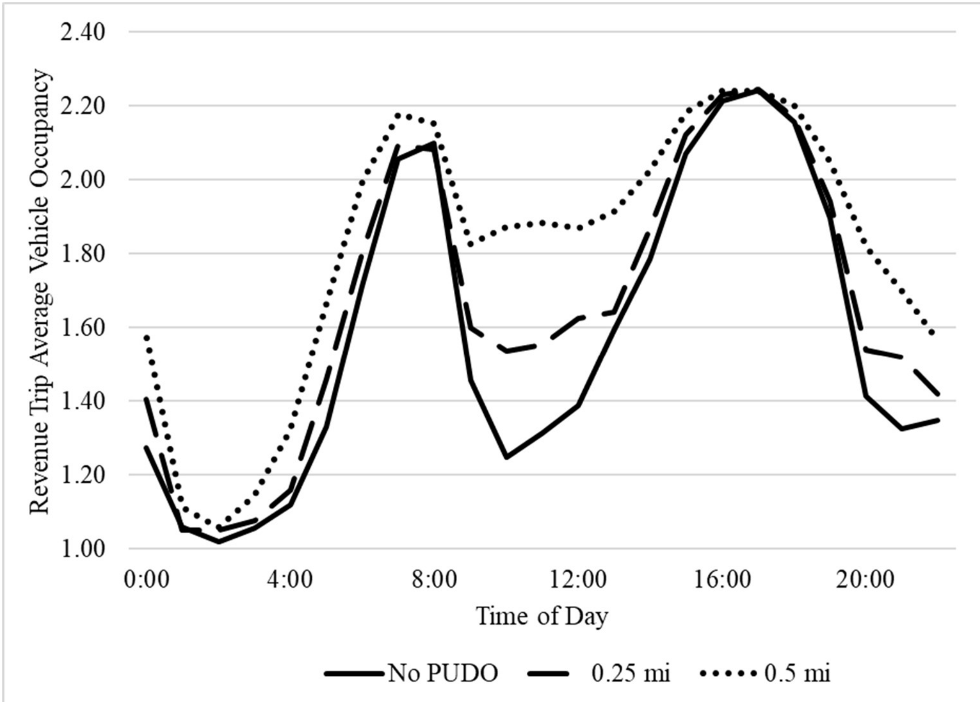


**Figure 5** Impact of Stop Aggregation on Temporal Distribution of AVO for Base Demand

Reductions in system and fleet VMT come at the cost of travelers incurring delays while sharing rides. Figure 6 illustrates the total time spent walking to a stop (depending on the scenario) and traveling to a destination when traveling by an SAV. Proportion of trips made under 10 min without DRS was nearly twice as much when rides are shared. Binned travel times show a spillover effect with trips incurring about 5 additional minutes of travel time. Time spent walking to and waiting at a stop, which is about 2 to 3 min, moves trip travel times by another bin. An average 5-10 min added time may be acceptable for most non-emergency trip types, given the expected low cost of SAV travel. Extreme bins with travel times longer than 30 min are only seen with DRS. This is expected with some travelers penalized more than others depending on the origin-destination pair and the time of day, but may also be an artifact of the heuristic employed here. Large VMT savings allowing for better traffic flow along with subsidized shared rides can make the service attractive with optimized matching algorithms.

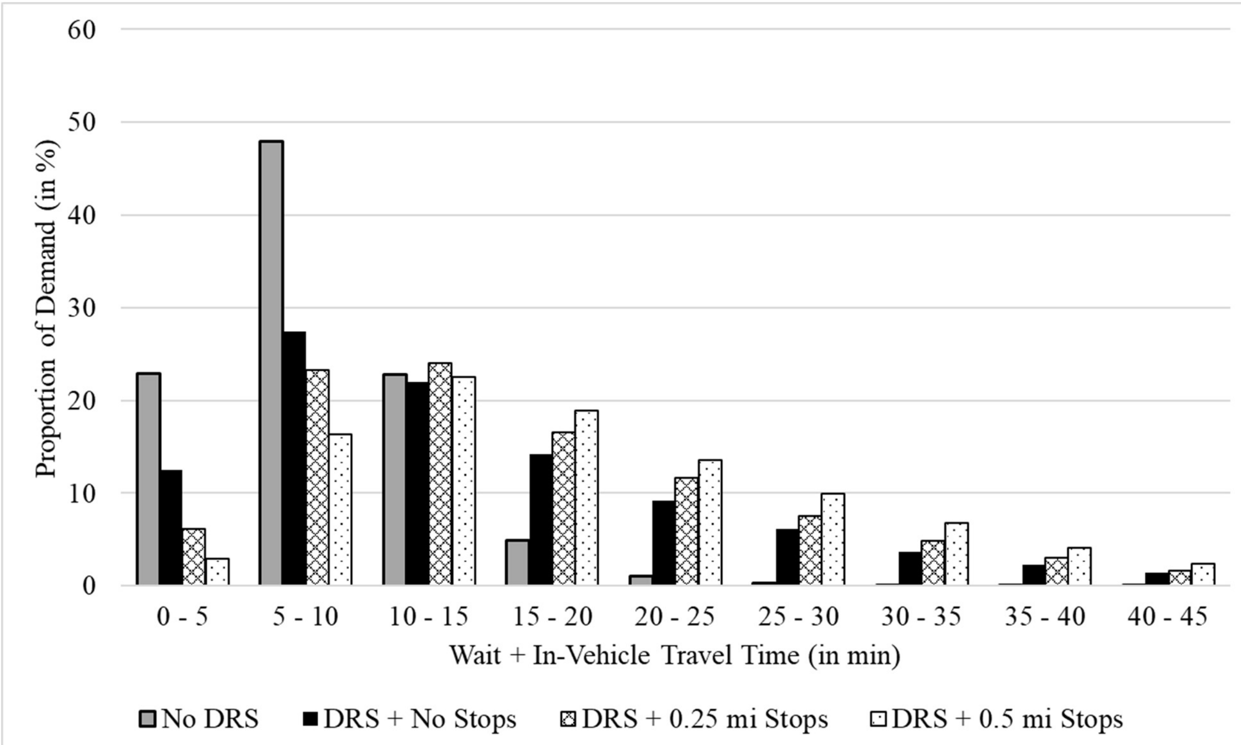


**Figure 6** Histogram of Wait, Walk and Travel Times while using an SAV
*Note:* Bins with less than 1% demand are not shown.

Increased trip densities of 5x and 25x the current density improve certain fleet metrics but can add congestion on links with these PUDOs. Although queues forming because of aggregating pickup trips is not modeled into POLARIS on the congestible network yet, this queue-forming and curb-encroaching behavior can be seen from average trip clustering in different times of day. Figure 7 compares the 15-min traveler arrivals at PUDOs in the 5x and 25x trip density scenarios when PUDO spacing was 0.25 mi. With AVOs ranging 1.8-2.2 per SAV, at least 100 SAVs would be arriving at the PUDOs in the peak 15-min time period. Off-road infrastructure to sustain about 12-16 SAVs arriving every minute at PUDO zones does not currently exist but MPOs need to be planning for such situations in a future of SAVs. These SAVs taking up curb space may outweigh congestion savings from eVMT reduction if they are not able to leave the main roadway quickly. PUDO spacing greater than 0.5 mi may create bottlenecks. Careful PUDO location planning will be required for current demand and dedicated off-road infrastructure will be a necessity going forward.

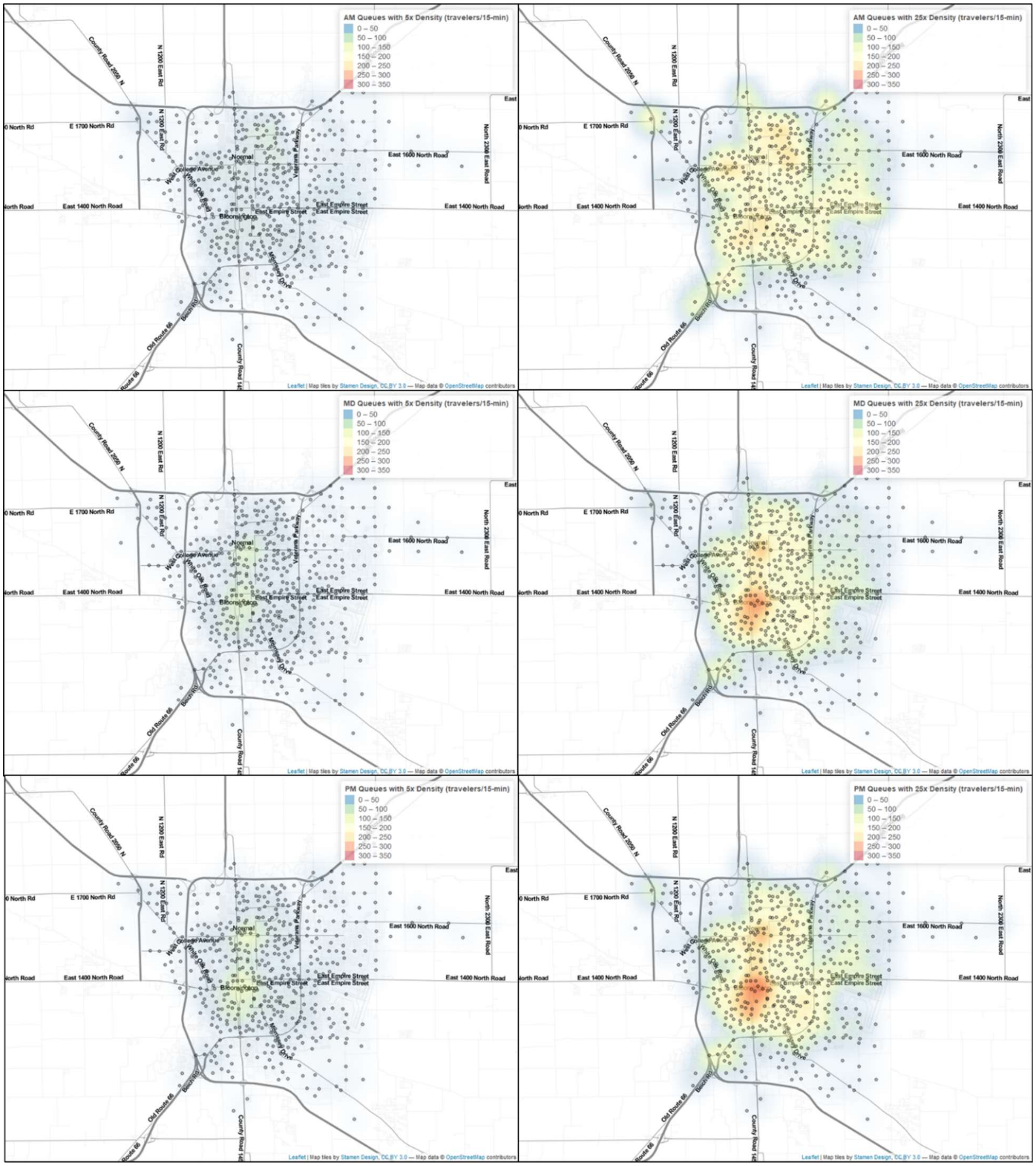


**Figure 7** Queues forming in the AM (6 – 10am), MD (10am – 4pm), and PM (4pm – 8pm) for 5x and 25x Density and 0.25 mi Spacing

## CONCLUSIONS

The use of DRS in SAVs is important to lower their negative impacts on the network. This study focused on how trip density and PUDO zone spacing impacts DRS trip matching and fleet operation. Twelve scenario simulations reveal that the use of PUDO zones does contribute to improving trip matching, and, thereby, AVO. The magnitude of improvement in AVO is effective when trip densities are relatively low and the consequent SAV VMT savings can result in considerable time savings. Further, regions with higher trip densities stand to benefit more, over and above the positive effect of stop aggregation. System VMT savings purely from using PUDO zones are less than 1%, which undermines the benefits of an increased AVO marginally. Larger mode shares of SAVs, and perhaps operating more freely, in a large network may enjoy greater benefits but this effect was purposefully isolated to focus on PUDO zones. A non-uniform enforcement of stops both spatially and temporally is expected to help the system as a whole (attractive mode for users, as well as congestion relief).

The use of PUDO zones is shown to be useful in boosting DRS for different regions. However, some limitations of this study are important to resolve for better quantification of results. First, the PUDO zones are identified based on physical location without reflecting the distribution of trip origins and destinations, since they are highly correlated with spacing decisions. Future work can try to incorporate the use of sophisticated algorithms like those used by Wan et al. (2015) to identify PUDO hotspots. Walking time is not yet endogenous to mode choice in this model and this may lower SAV demand. There also needs to be a limit on the number of vehicles that simultaneously use a PUDO zone thanks to physical space restrictions in the real world. PUDOs without dedicated infrastructure may not be able to serve more than 5 travelers arriving in a 15-min interval without adversely impacting surrounding travel times from blocking capacity, and the consequent queue spillbacks.

## ACKNOWLEDGMENTS

This paper and the work described were sponsored by the U.S. Department of Energy Vehicle Technologies Office under the Systems and Modeling for Accelerated Research in Transportation Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems Program. David Anderson, a Department of Energy Office of Energy Efficiency and Renewable Energy manager, played an important role in establishing the project concept, advancing implementation, and providing ongoing guidance. The authors would also like to thank Felipe Augusto de Souza for his help with code development and testing, and Maizy Jeong for editing and submission assistance.

## AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: K.M. Gurumurthy, K.M. Kockelman; analysis and interpretation of results: K.M. Gurumurthy; draft manuscript preparation: K.M. Gurumurthy, K.M. Kockelman. All authors reviewed the results and approved the final version of the manuscript.

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