# DYNAMIC RIDE-SHARING IMPACTS OF GREATER TRIP DEMAND AND AGGREGATION AT STOPS IN SHARED AUTONOMOUS VEHICLE SYSTEMS

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## 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 ride-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 impacts of PUDOs on DRS rates and AVO values. Various PUDO spacings and trip-demand densities were studied, across the Bloomington, Illinois region, using the agent-based simulator POLARIS. Results reveal that greater PUDO spacing or distances between stops and higher levels of SAV use or trip demand increase AVO (by up to 0.2 travelers per 4-seater SAV, on average) and decrease SAV VMT (by up to 27%) compared to door-to-door SAV fleet operations without DRS or PUDOs. A quarter-mile PUDO spacing is recommended in downtown regions, similar to current transit stop spacing design, to keep walking trips short and demand relatively high. At 0.25 mi PUDO spacings (thoughtfully placed, using origin and destination clusters), travelers walked less than 5 min at either trip end, on average, while 0.5 mi spacings lead to about an additional 1 min of walking. More evenly distributed and large SAV demand can save up to 39% total VMT from DRS and stops. It is also important to prepare for queuing areas at PUDOs in settings of high trip densities, to limit curbside congestion.

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

## BACKGROUND

Ridehailing or Transportation Network Companies (TNCs) like Uber (offered almost globally), 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 to travelers around the world relative to taxis and other similar forms of shared transport. Pooled or shared rides that are matched real-time and en-route further reduce operator costs (per passenger-mile served) by increasing average vehicle occupancy

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or "AVO". TNC services are helping lower personal vehicle registrations per capita across the U.S., especially in rural states that are typically auto-centric (Ward et al., 2019), and more dramatic reductions are expected (Fagnant and Kockelman, 2015; Quarles et al., 2019; Kim et al., 2020). 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 should deliver larger mode splits toward shared-fleet 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., 2020c), and congestion will rise without a sustainable alternative to high-occupancy transit vehicles. Without ride-pooling or dynamic ride-sharing (DRS) among strangers while en route, 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 rides (Agatz et al., 2011). Bilali et al. (2019) argue that detour time is important when it comes to a fleet's shareability, since travelers' detour time flexibility relates directly to a DRS algorithm's routing flexibility, which is rather essential for high rates of trip-matching. However, added delay from DRS detours is considered a key factor in many travelers' unwillingness to share rides with those who do not share their origin and destination (Lavieri and Bhat (2019). 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 and total-system-cost levels. Various survey results also 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 how total VMT can fall - thanks to heavier use of DRS when trip densities are high (Fagnant and Kockelman, 2018), but road tolling may also be needed to shift users into shared fleets and shared rides (Zhao and Kockelman, 2018; Simoni et al., 2019; Gurumurthy et al., 2019). Dense settings, such as New York City (Alonso-Mora et al., 2017) and Chengdu, China (Tu et al., 2019), stand to benefit a great deal from DRS. Alonso-Mora et al. (2017) used the NYC taxi dataset to show how optimized DRS using 2,000 10-seater vehicles (15% of the taxi fleet) or 3,000 4-seater vehicles (22% of the taxi fleet) can serve these trips with 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 SAV fleet vehicles to include more seats is another option, that is less of a divergence from traditional, fixed-route, fixed-schedule transit systems. 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 fleet AVO values greater than 4.0 persons per vehicle (4.2 for 8-seater vehicles and 11.4 for 16-seater vehicles). Assuming that travelers do share their rides (with strangers), fleet efficiency in catering to diverse demand and land use profiles remains a concern. Yan et al.'s (2020) recent 7-county Minneapolis-Saint Paul simulations show how an increase in trip density improves DRS, and fleet response times average less than 5 minutes for calls across the region, across rural, suburban, and urban settings. A structured approach to resolving the effect of trip densities on ride-sharing rates, AVO, and fleet VMT is absent in literature so far and is therefore one of this paper's objectives.

Another objective has to do with curbside congestion, which has not been a significant problem in most settings, in the past. Regulated curb access at large hubs, such as railway stations and airports, has ensured reasonable flow of private vehicles, taxis and, more recently, TNC vehicles. Growing curbside congestion has resulted in many airports using dedicated parking areas for TNC vehicles, which users must walk to. Denser cities like New York City and Washington, DC, have busy street curbs, leading to adjacent-lane backups. 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 a curbside congestion alleviation measure as early as 2017 and has since expanded its pilot program (District Department of Transportation, 2018). Houston and Boston followed suit in 2019 and 2020, respectively (City of Houston, 2019; City of Boston, 2019). Although these programs have been implemented, the system-wide benefits of aggregating trips at specific locations have not yet been quantified and there is little information on how they have affected TNC operations and user walk and wait times. The International Transport Forum (2018) conducted several microsimulations on the interaction of curb space and curb use with PTV's VISSIM, revealing insights into how cities can better manage curb space, to make streets safer and curbs more useful. Increased demand for SAVs in the future, coupled with issues like eVMT and curbside congestion, warrants thorough study of PUDO zone use, and its influence on SAV operations.

This work studies SAV operations and network benefits from use of PUDO "stops" or zones to aggregate person-trip ends (much like bus stops). The Bloomington, Illinois network is used with a variety of trip-making intensities (or land use densities), PUDO spacing, and fleet operational attributes (like single-occupant and shared rides). The next section discusses the simulation assumptions used, the algorithm behind PUDO locations, and an overview of fleet characteristics. This is followed by discussion of results and inferences gleaned from this work.

## 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, 30-million 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, and each link follows a mesoscopic traffic flow model (de Souza et al., 2019) that provides reliable link-level speeds depending on congestion.

### SAV Operations

Gurumurthy et al.'s (2020b) 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. 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, or drop-off trip in the direction of the incoming request's destination. Idling SAVs were automatically matched to minimize wait time for assignment. If an SAV was not idle, a measure of directionality was calculated as the angle between the Euclidian OD lines joining the ongoing and proposed trips using XY coordinates. A threshold for angle between these two Euclidian lines was provided as an input to the model. If the ongoing trip was picking up or dropping off another traveler near the new request, the requirement was waived. If more than one occupant was riding the SAV, then the ongoing trip was based on the current SAV task (either a pickup or a dropoff).

This instantaneous match was supported by a Euclidian distance-based constrained shortest path across all assigned pickups and drop-offs. Each time a new traveler was added to the traveling party, an R-tree implementation was used to construct the ordering of pickups and drop-offs that minimized total distance while taking into account whether travelers were picked up before they are dropped off. During this process, 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. Smart matching through directionality constraints, delay checking and a heuristic for the constrained shortest path helped manage the extent of detours that may be allowed while maximizing pooled trips.

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. (2020b), 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. The activity scheduler in POLARIS is currently not sophisticated enough to jointly route multiple travelers in high-occupancy trips. Travelers driving a vehicle are routed on the network, and those riding in a personal vehicle driven by another member of the household is artificially simulated (i.e., taking into account travel time, but not the vehicle trajectory). The outcome of travelers' activity schedule is also that all trips choosing to use an SAV/TNC is currently single-party trips. In reality, travelers choosing to use these services typically do so as multiple-traveler parties. Results stemming from this assumption make the results more conservative. However, all travelers opting to use the fleet are assumed to be willing to share (irrespective of the final routing outcome). Therefore, these opposing objectives balance out some of the fleet impacts to a certain extent.

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

PUDO locations have been implemented here as a subset of activity locations that exists in and used by all modes of travel in POLARIS. Activity locations are only used as origins and destinations (and not as nodes in the network), and form a critical component that helps the POLARIS router route trips. Location data is generated from underlying building and employment information and make up the most frequently visited addresses in the region. Since these locations are already used by traveler agents in POLARIS, travelers can walk to and from a location (like when travelers get out of their car, or deboard a bus). PUDOs forming a subset of these locations are, therefore, accessible and make for a great choice for PUDO locations. 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 groups of stops that are no more than $d_s$ miles apart. By sampling centrally from these groups, the resulting set of stops used are stabled and are used throughout this analysis. Since, PUDOs are envisioned here to improve a fleet's DRS potential, SAVs serve trips from and to PUDOs, and then idle at these locations until a new request is matched. Since the locations used in POLARIS comes from underlying buildings data and networks from the appropriate Metropolitan Planning Organization (MPO), there is a higher degree of aggregation in the periphery of the regions simulated. Requests that have origins and destinations more than 1 mi away are allowed to be picked up and dropped off without having the traveler walk to a PUDO. In this case, SAVs may idle in suburban links, and away from congested roads.

## 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 and 92% less than the comparable values for the Chicago region, respectively. 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. This meant that 5 or 25 times the population of Bloomington, planned activities and made trips in the same region. 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 for certain scenarios to focus attention on comparing regions with different densities. Another set of scenarios are evaluated when artificially aligning traveler preference toward SAV fleets to understand the other extreme mode share, and consequent network impacts. In these scenarios, the personal auto modes are not available for travelers to use, and they rely only on SAVs, non-motorized, and transit modes to meet their travel needs. In the future, vehicle ownership is likely never to reach this extreme (of zero vehicles per household) with high value of travel time travelers preferring personal modes for convenience and privacy, but studies like Menon et al. (2019) have showed that reduced vehicle ownership, especially in urban centers of large regions, is the expected preference. The ordered probit model outlined in Menon et al. for vehicle disposal was also incorporated into POLARIS, similar to prior work in POLARIS (Gurumurthy et al., 2020b, 2021) to use with the 5x and 25x scenarios, to stress test the fleet in light of boosted demand.

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 (Bilali et al., 2019; 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 25% 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 Density 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 | 25% 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.

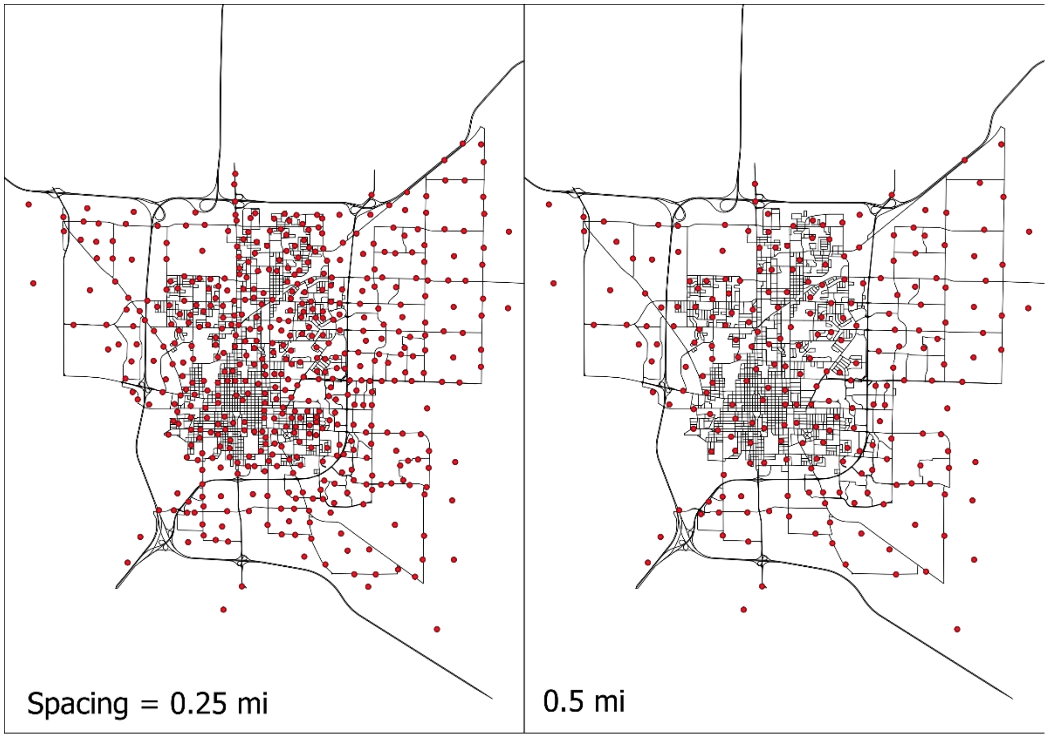


**Figure 1** Pickup and Dropoff Location Locations Chosen across Bloomington, Illinois in the $d_s$ = 0.25- and 0.5-mile PUDO Spacing Scenarios

## RESULTS

Two sets of results are presented in this study as explained above. First, the effect of trip-end density in conjunction with the different stop spacing was tested. Results regarding effects on empty VMT, total and fleet VMT, delay, and other fleet metrics are presented and discussed. Second, the case with an artificially inflated mode share for SAVs is highlighted to draw conclusions on preferential traveler impacts on fleet use and impact on the network.

### Effect of Density

Twelve scenarios were simulated 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 8% 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 56 person-trips per day, traveling about 319 mi per SAV per day. The heuristic employed minimized response times to about 3.7 min, with a linearly decreasing trend as trip density increased exponentially. Percent eVMT also fell by 3.6% (to 32.5%) and then 2.5% (to 30%) in the 5x and 25x demand-density scenarios relative to the starting eVMT value of 36.1%.

Employing DRS increased SAV mode shares by 2% (from 8% to 10%), or, in other words, was able to meet demand that could not be met without DRS, and lowered system VMT by 3-7%. There was a 9.4% 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 up to 20.3%. 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 average mode shares observed across all scenarios for Bloomington when DRS was used. The impact of walking to a PUDO zone is likely to affect travelers' willingness to choose SAVs, and was iteratively fed back into the mode choice, so the results presented are for a converged run of travelers' choice preferences. Compared to the base case without DRS, percent eVMT dropped significantly, by about 12%, thanks to bundling rides together, and the greater availability of SAVs to serve requests. Overall response times dropped marginally when using DRS, likely owing to traveler pickups along existing trips. The response times fall more with increasing trip density.

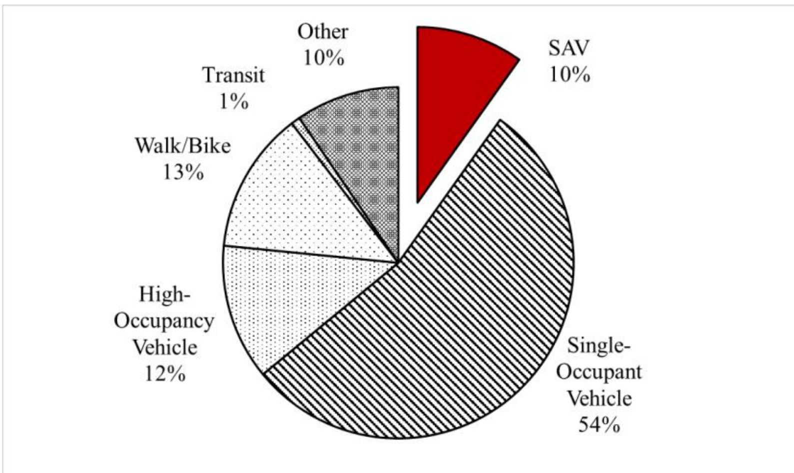


**Figure 2** Trip Modal Shares across Varying-Density-Focused Scenarios Simulated with DRS for Bloomington

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 relatively 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 two-thirds the day, irrespective of stop aggregation and DRS. A smaller fleet can be used intensively to lower idling time and improve average person-trips served per SAV, but this comes at the cost of higher response times. Fleet vehicles idling about 60-65% was found to be the right balance between meeting existing demand, and with low response times. About 10 more person-trips are made per SAV per day owing to the use of DRS, but this gap unsurprisingly narrows with increase in density. Stop aggregation allows the fleet to idle up to 8% more highlighting better fleet utilization. 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 by lowering eVMT. There is further reduction in average VMT with stops since the residual is converted to traveler walking trips. The use of DRS, on average, increases travel times by 50-100% but the 24 hr average is biased high. The increase in average travel time is higher in the 5x and 25x demand scenarios even though a higher demand is available for matching. Although the absolute comparison in travel times reveals large differences, the percentage allowable delay based on travel times helps restrict experienced travel times within acceptable values as shown later. A cumulative probability distribution of experienced travel times is provided in Figure 6.

**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. Walk Time | Avg. Travel Times (including wait and walk) |
|---|---|---|---|---|---|---|---|
| **Base** | No PUDO | No | 14.7 | 55.7 | 319.3 | 0.0 | 6.3 |
| **5x** | | | 12.7 | 69.2 | 409.5 | | 6.5 |
| **25x** | | | 12.9 | 70.3 | 401.7 | | 6.5 |
| **Base** | No PUDO | Yes | 15.6 | 65.4 | 289.2 | 0.0 | 9.8 |
| | 0.25 mi | | 16.1 | 62.3 | 268.0 | 4.8 | 12.9 |
| | 0.5 mi | | 16.7 | 58.7 | 248.1 | 5.6 | 14.4 |
| **5x** | No PUDO | | 14.4 | 76.1 | 340.7 | 0.0 | 11.1 |
| | 0.25 mi | | 15.0 | 62.3 | 314.4 | 4.2 | 13.8 |
| | 0.5 mi | | 15.5 | 70.2 | 296.2 | 5.4 | 15.6 |
| **25x** | No PUDO | | 14.9 | 74.7 | 320.1 | 0.0 | 11.6 |
| | 0.25 mi | | 15.1 | 73.2 | 310.6 | 4.2 | 14.2 |
| | 0.5 mi | | 15.8 | 69.2 | 285.1 | 5.4 | 15.9 |

Figure 3 shows the total travel distance-weighted 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 1.7 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 but remains marginal across all densities. It is important to keep in mind that travelers may be unwilling to walk the extra mile, so the AVO increase estimated here is from travelers who were willing to walk to a PUDO location (assuming similar weights in the mode choice as in-vehicle travel time), 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. However, higher stop spacing counteracts some of the eVMT likely from using circuitous routes to get to a stop in light of queuing. Although the magnitude of difference in eVMT is 2 or 3 percent points, extrapolating this to 1.4M trips served under the 25x trip density sees considerable benefit in congestion mitigation. In other words, the fleet may have needed 2% or more VMT to satisfy these trips without use of PUDOs provided at 0.25 mi. SAVs are able to serve more trips with a smaller impact on congestion with DRS and the use of thoughtfully-sited PUDO zones.

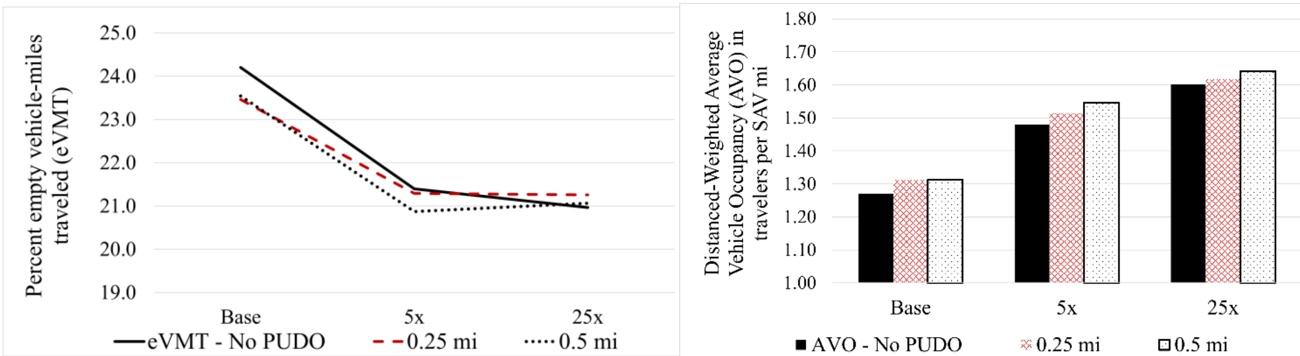


**Figure 3** Effect of Demand and Stops on Percent eVMT and AVO

The use of 0.25 mi-spaced stops increased total VMT savings by an additional 2% with current Bloomington demand irrespective of spacing. This corresponded to about 15% to 23% savings in SAV VMT even when mode shares are only 10%. 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 28%. The constant mode share assumption through these scenarios meant that the effective savings in total VMT only improved by about 5% 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 at the cost of not meeting trip requests. The 25x scenario shows a large spike in VMT added when stops are provided at 0.5 mi spacing. This may point toward a larger fleet requirement or more seats on the SAV to manage all the demand that is focused at fewer stops. 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.

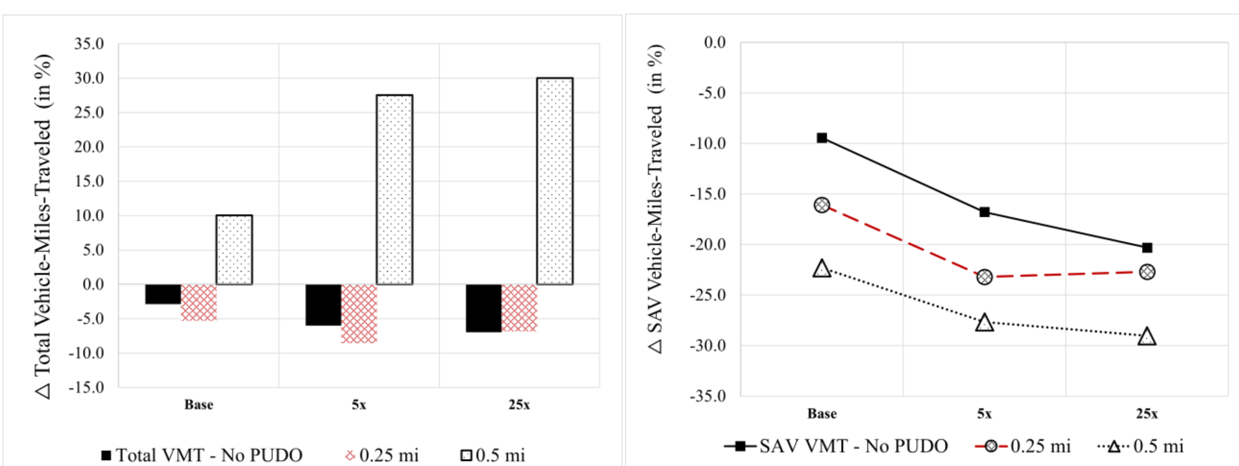


**Figure 4** Changes in Total Vehicle-Miles Traveled and SAV Vehicle-Miles Traveled

Stops and demand-density improve AVO over an average travel day, but the significance of stop-based aggregation of trips is best highlighted in the first subplot of Figure 5. Even a quarter-mile stop spacing increases aggregation during the mid-day off-peak, with hourly distance-weighted AVO increasing from 0.90 to 1.10, and is likely the dominant contributor to higher daily AVO in a given scenario. The improvement from a value less than 1 to greater than 1 also speaks to improving the efficiency of the fleet by lowering empty travel. 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. The second subplot in Figure 5 shows the AVO trend with 5x trip-density. Increase in density provides for three AVO peaks where the transition between AM peak and midday peak is the only valley, before quickly recovering to a high of 1.75. As evident, AVO also remains higher than 1.40 throughout the day starting from AM peak highlighting best use of the SAV fleet at most hours in the day. If this sharing peaks throughout the day, like in 25x (not shown), it may point towards the requirement of a larger fleet to maintain low eVMT but at the cost of higher idling time (and parking space use). 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.

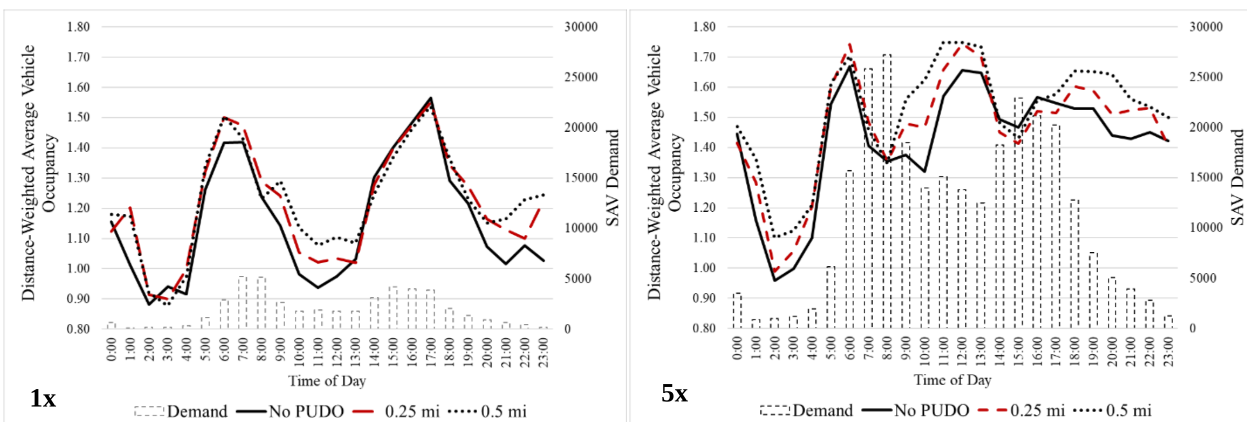


**Figure 5** Impact of Stop Aggregation on Temporal Distribution of AVO for 1x and 5x Demand

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 or from a stop, waiting for an SAV, and, subsequently, time spent in an SAV. Proportion of trips made under 10 min without DRS was nearly 20% more as when rides are shared. Time spent walking to and waiting at a stop, which is about 4 to 5 min, increases trip travel times slightly. 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 but are less than 5% of all trips. This is expected with some travelers penalized more than others depending on the origin-destination pair and the time of day. Large VMT savings allowing for better traffic flow along with subsidized shared rides can make the service attractive with optimized matching algorithms.

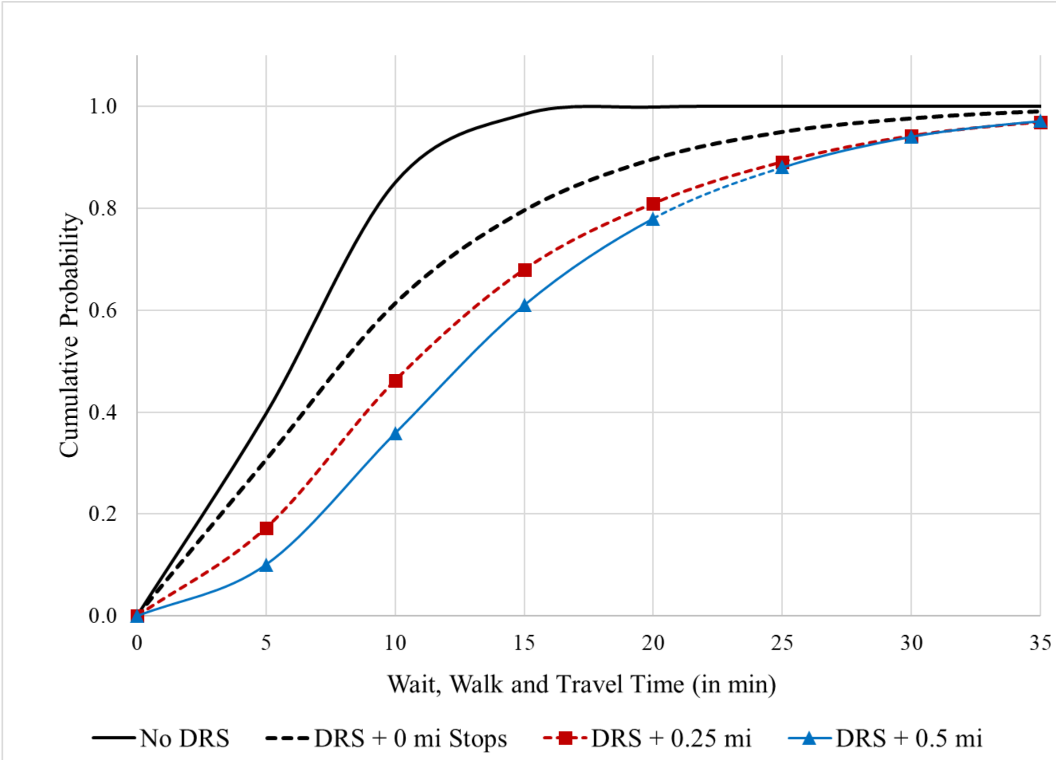


**Figure 6** Cumulative Probability Distribution of Wait, Walk and Travel Times while using an SAV

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 at 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 1.2-1.6 per SAV, at least 150 SAVs would be arriving at the PUDOs in the peak 15-min time period. Off-road infrastructure to sustain about 10 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 or equal to 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.

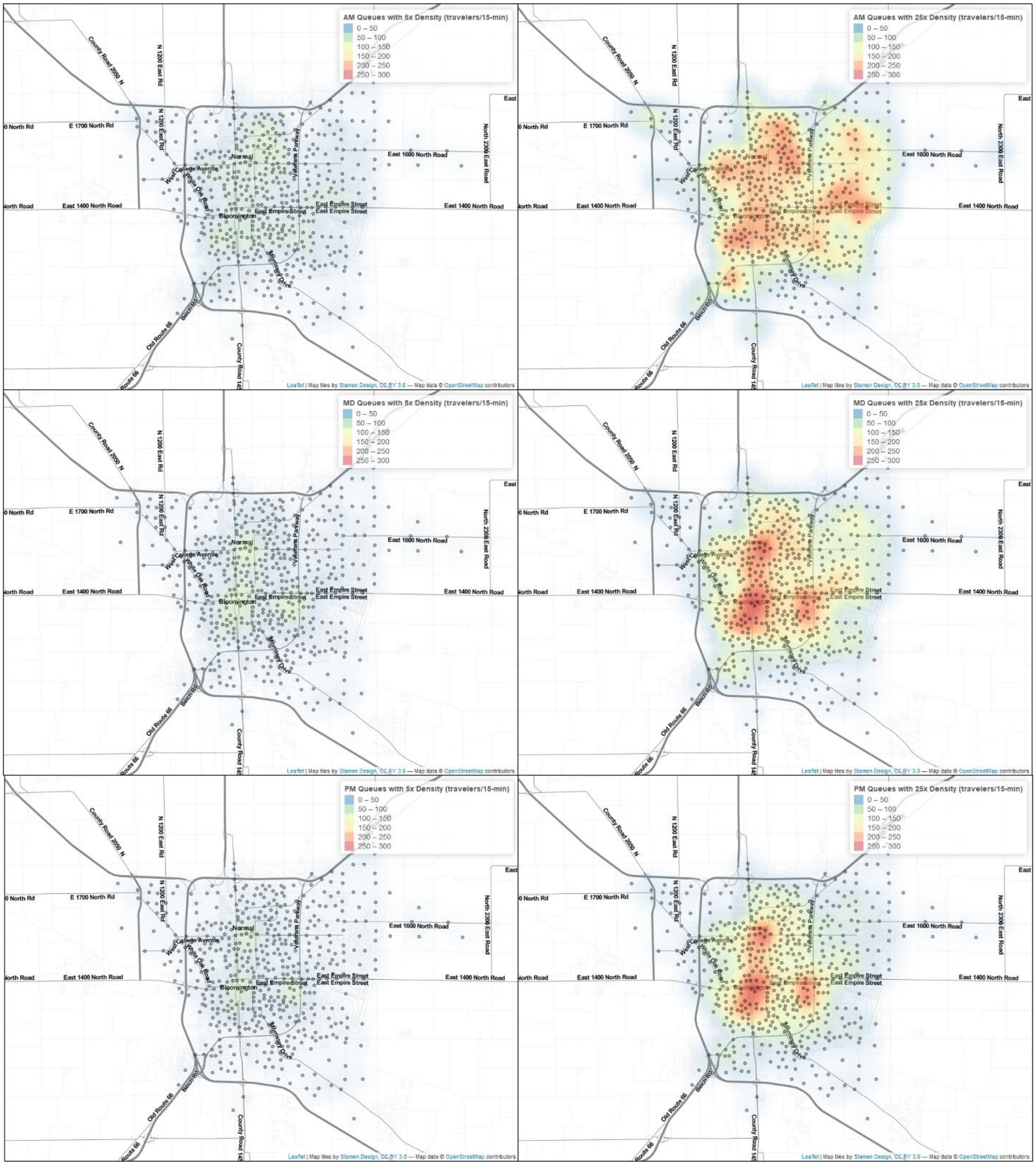


**Figure 7** Queues forming in the AM (6 – 10am), MD (10am – 4pm), and PM (4pm – 8pm) for 5x and 25x Density and 0.25 mi Spacing

## Effect of Demand

Four additional scenarios were run to observe the effect of SAV mode share on the network. Table 3 shows the fleet-level metrics and network effects for an SAV-reliant City arising from the artificial change in mode preferences (while allowing for non-motorized and transit modes to operate). SAV mode shares in these scenarios are around 60%, with the remaining share split almost equally between walk/bike and other modes (like schoolbus trips). Transit shares are low in the base scenario runs (less than 1%) and drop to almost 0% showing the trip attraction toward SAVs. More reliable transit like in Chicago or NYC may retain some mode share (as evidenced by Gurumurthy et al. (2021)). In order to maintain some comparison with simulation runs above, and to be able to meet increased demand in this 1x density scenario, fleet size for the four scenarios presented here were identical to the 5x trip-density runs above. Idling time across the fleet remained similar to the base trip density scenario, but rose by about 4% when DRS was turned on. There was more idling when comparing to the 5x density scenario that emulates sparser pickup and dropoff locations from mimicking base density travelers, and this corresponds to higher fleet utilization, meaning that a smaller fleet will be able to serve the City within similar response times. Average person-trips per SAV per day was found much lower owing to the same reason, but still at a high average daily person-trips per SAV compared to most other studies looking at larger regions. With an SAV-focused demand, trip-density distribution is more even in these scenarios, and was evident with the considerable drop in average SAV VMT through the 24 hr day. Average travel times were marginally higher than other scenarios. This is because of the difference arising from average travel distances when comparing only between SAV riders versus all travelers (who now use SAVs). Average walking time falls by half a minute owing to stops being more accessible on average. AVO is also considerably high by 0.2 travelers per mi from this even distribution of trip origins and endings. The highlight of these sets of scenarios is the large potential for lowering total VMT when using SAVs. Even without DRS, total VMT dropped by 6% from travelers using SAVs as opposed to driving their personal vehicles or being chauffeured by family. With DRS this VMT savings is much higher at 24% and use of stops continue to improve savings by up to a total of 40% in savings.

**Table 3** Fleet Metrics and Network Impacts for a SAV-Reliant City

| Stop Spacing | DRS? | Avg. Idle Time (in hr) | Avg. Trips per SAV per day | Avg. SAV VMT per day | Avg. Walk Time | Avg. Travel Times (including wait and walk) | % Change in Total VMT | Distance-Weighted Average Vehicle Occupancy |
|---|---|---|---|---|---|---|---|---|
| No PUDO | No | 14.7 hr | 53.8 | 329.6 | 0.0 | 6.8 min | -6.2% | 0.67 |
| | Yes | 16.6 | 56.5 | 259.4 | 0.0 | 11.5 | -24.0 | 1.49 |
| 0.25 mi | | 17.1 | 54.7 | 241.5 | 4.3 | 14.1 | -27.4 | 1.53 |
| 0.5 mi | | 17.3 | 53.2 | 232.6 | 5.4 | 16.0 | -39.8 | 1.55 |

## 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 trip-density focused 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 4%, 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 recommended stop spacing of a quarter mile closely resembled that used presently by transit planners, but PUDOs are able to be placed more flexibly outside of specific corridors to improve access area compared to a typical transit route's catchment area. Four additional mode share-focused scenarios revealed the potential for SAV fleets and stops in improving regional travel thanks to demand for SAVs being more evenly spread out. VMT savings of up to 39% is achievable but is reliant on travelers choosing shared mobility, and being willing to walk and share rides with strangers.

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. 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.

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## AUTHOR CONTRIBUTIONS

**Krishna Murthy Gurumurthy**: Conceptualization, Methodology, Software, Formal analysis, Writing- Original draft preparation. **Kara M. Kockelman**: Conceptualization, Validation, Writing- Reviewing and Editing.

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