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

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ABSTRACT

Sharing vehicles and rides is set to 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 unoccupied miles (empty VMT) 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 and eliminating negative externalities that arise from queues forming at these PUDOs. 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 tip-demand density help increase AVO (by up to 0.25, on average) and decrease empty VMT (by up to 4%). A quarter-mile PUDO spacing is recommended in downtown regions to keep walking trips short because longer walking trips may adversely impact demand. 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., 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).

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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) estimate an increase in VMT of about 40% VMT from demand shifts once SAVs are available, after accounting for induced mode use. High reliance on shared AVs (SAVs) may have some negative effects. Without ride-pooling or dynamic ride-sharing (DRS) among strangers, SAV use is likely to increase congestion from added, unoccupied travel or empty vehicle-miles traveled (eVMT). Another negative consequence is curbside congestion from many SAV pickups and drop-offs on busy downtown blocks.

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., 2020). DRS is a proven strategy to manage rising VMT given that 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 as a detour is a direct measure of flexibility in route. However, Lavieri and Bhat (2019) show from their stated preference survey that added delay from detours is the primary detriment to willingness to share a ride. 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; Gurumurthy and Kockelman, 2020; Stoiber et al., 2019).

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 objectives of this paper.

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. More recently, the disruption caused by TNCs was most noticeable at airport curbsides around the world and many airports have now moved to using dedicated locations for TNCs. 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. 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 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 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

An existing module for SAVs (Gurumurthy et al., 2020) was extended in this paper to include DRS and stop-based aggregation of incoming requests. The module provides functionality for simulating an on-demand service that operates similar to present-day TNCs. To facilitate computation, a zone-based assignment algorithm is 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 are 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. Repositioning is also modeled based on these zone lists with a linear program to minimize unoccupied travel (de Souza et al., 2020).

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 attempts to match incoming requests to available vehicles that are either idling or performing a pickup, drop-off, or

† https://ddot.dc.gov/release/mayor-bowser-and-ddot-announce-pick-updrop-zone-pilot-program-expansion
‡ https://www.itf-oecd.org/shared-use-city-managing-curb-0

repositioning trip in the direction of the incoming request's destination. This directionality is quantified as the angle between the lines joining the current and proposed trips based on available coordinates. This angle is a succinct proxy for the extent of detours that may be allowed while maximizing pooled trips, and a threshold is provided as an input to the model. Additionally, each traveler's approximate delay (based on the estimated initial routing time without detours) is measured throughout their trip to avoid new travelers from being added to the SAV when any traveler experiences a delay beyond the predefined absolute delay or the predefined percentage delay while en route. Both absolute and percentage delays are important since short trips are sensitive to percentage delays while longer trips are sensitive to absolute delays.

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 are sampled using a hierarchical clustering algorithm for all possible origins and destinations in the software R. Hierarchical clustering creates 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 are clustered based on proximity. With this type of agglomerative clustering, a predefined stop spacing d_s is 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 or an order of magnitude smaller in size compared to Chicago. The POLARIS activity-based model of tours and travel demand is quite behaviorally flexible and realistic, enabling certain behavioral choices that other SAV simulations lack like the destination choice that has not been implemented in popular models testing SAVs like 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. 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., number of people having access to one SAV), 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 and allowable delay thresholds 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 trips/day per SAV
Response Time Threshold	10 minutes
Allowable Absolute Delay	10 min (maximum)
Allowable Percentage Delay	15% of direct travel time
Pickup/Dropoff Location Spacings	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.

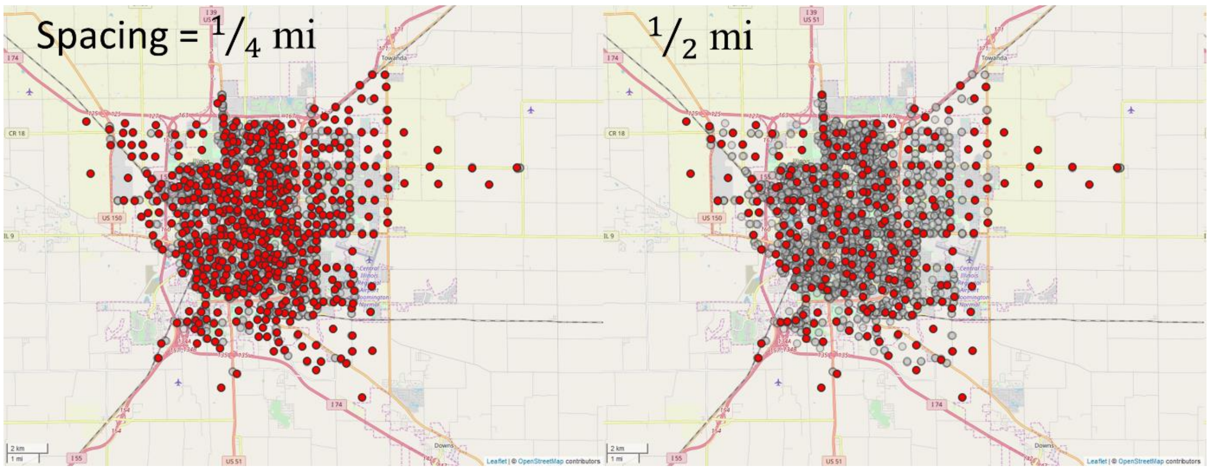

Figure 1 Pickup and Dropoff Location Locations Chosen across Bloomington, Illinois in the 0.25- and 0.5-mile PUDO Spacing Scenarios

RESULTS

About 12 scenarios were simulated in this study in an attempt to isolate fleet operation effects that are of interest. The base case for Bloomington comprised of three simulations with varying trip densities without offering DRS. Base case results highlight the small share of trips for SAVs and transit at about 7% and 4%, respectively, in auto-centric Bloomington. Fleet size was scaled up proportional to the demand simulated to retain constant mode splits, and each SAV, on average, made 65 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% and then 5% in the 5x and 25x demand-density scenarios relative to the starting eVMT value of 34%.

Employing DRS increased SAV mode shares by 1% and marginally lowered system VMT. There was a 2% reduction in SAV VMT without DRS and with current Bloomington person-trip densities, but showed promise at 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 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.

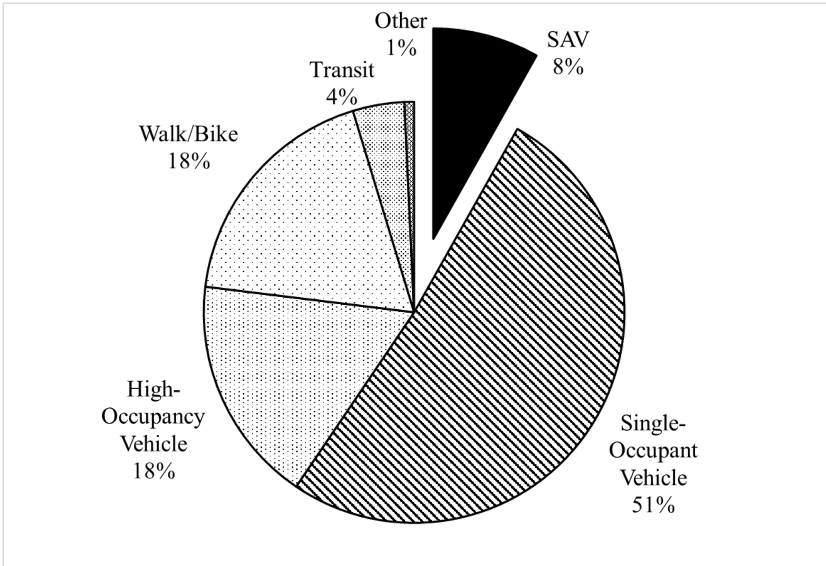

Figure 2 Trip Modal Shares across Scenarios Simulated for Bloomington

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, a large AVO of 2.0 is attained, and this increases with increases in trip density. The choice of PUDO spacing also has a similar effect on AVO. 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. 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.

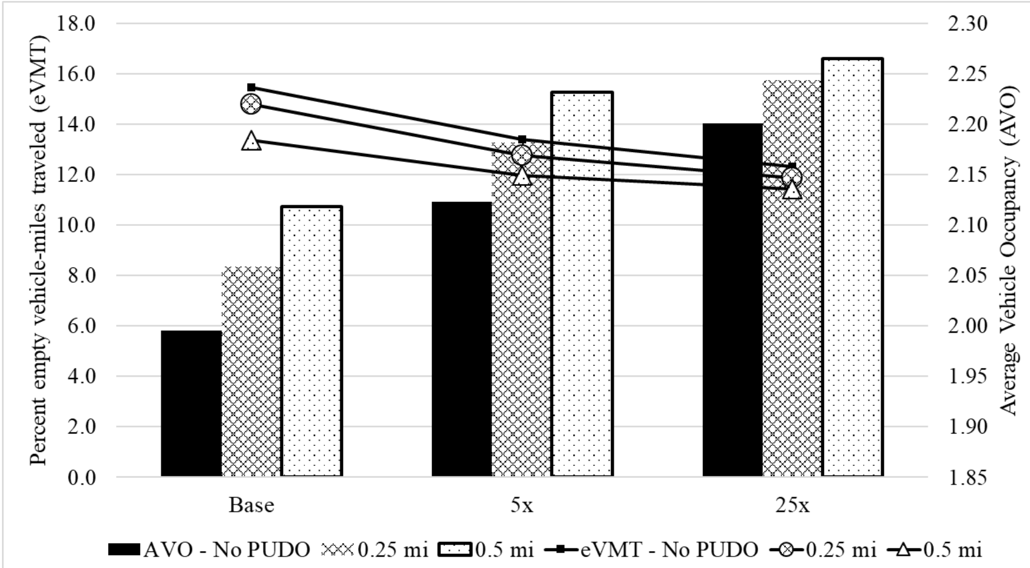

Figure 3 Effect of demand and stops on percent eVMT and AVO

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 yet, this queue-forming behavior can be seen from average trip clustering in the different times of day. Figure 4 compares the 15-min queues forming at PUDOs in the 5x and 25x trip density scenarios when PUDO spacing was 0.25 mi. Passenger queues roughly translating to the 2.0 AVO implies that at least 50% of queue length in SAVs would be arriving at the PUDOs in a given 15-min time period. 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 queues may outweigh congestion savings from eVMT reduction. PUDO spacing greater than 0.5 mi may create bottlenecks. Careful PUDO location planning will be required for current demand and dedicated infrastructure will be a necessity going forward.

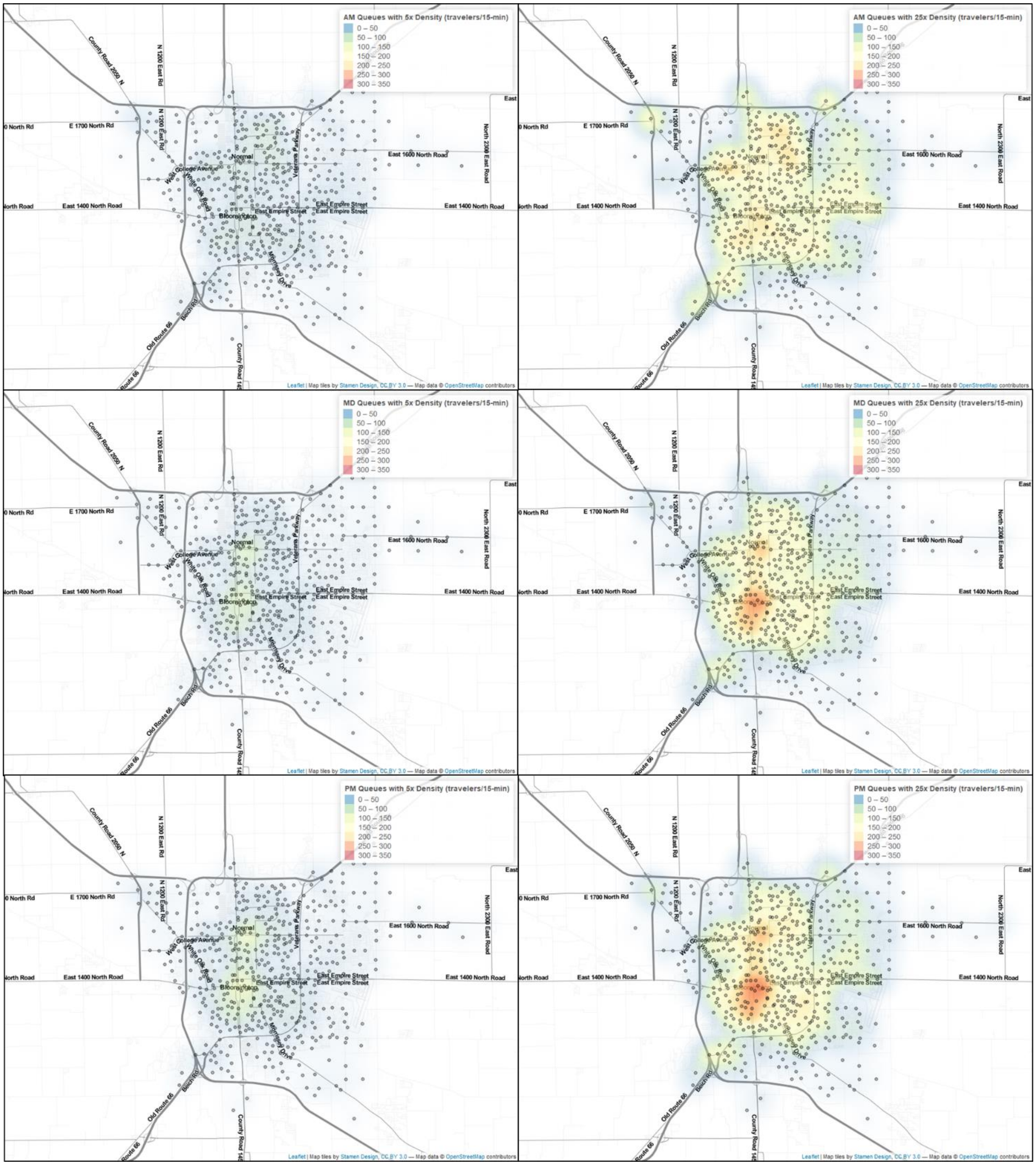

Figure 4 Queues forming in the AM (6 – 10am), MD (10am – 4pm), and PM (4pm – 8pm) for 5x and 25x Density and 0.25 mi Spacing

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 impact DRS and fleet operation. About 12 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 low but this is also associated with SAV VMT savings that can result in considerable time savings. Further, regions with higher trip densities stand to benefit more, over and above the positive effect of increasing trip demand. System VMT savings purely from using PUDO zones are less than 1%, which lowers the benefits of an increased AVO marginally. Larger mode shares of SAVs may operate more freely in the network and enjoy greater benefits but this effect was purposefully isolated to focus on PUDO zones.

The use of PUDO zones is shown to be useful in aiding 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, which may lower SAV demand. There also needs to be a limit on the number of vehicles that simultaneously use a PUDO zone, due, thanks to physical space restrictions in the real world. PUDOs without dedicated infrastructure may not be able to serve more than 5 trips in a 15-min interval without adversely impacting surrounding travel times.

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