USE OF SHARED AUTOMATED VEHICLES FOR FIRST-MILE LAST-MILE SERVICE: MICRO-SIMULATION OF RAIL-TRANSIT CONNECTIONS IN AUSTIN, TEXAS

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ABSTRACT

Fully-automated vehicles (AVs) coupled with ride-sharing and drivetrain electrification have the potential to provide sustainable transportation. The initial hype around AVs has subsided, with cities and vehicle manufacturers seeing low-speed shared AVs (SAVs) as a more practical mode for near-term AV deployments. SAVs may be an attractive way to experience first-mile last-mile (FMLM) connections to existing and future transit systems, replacing walk-to-transit, drive-to-transit, or even drive-only trips. Using the SUMO (Simulation of Urban MObility) toolkit, this paper tests this hypothesis by micro-simulating two fleets of SAVs providing FMLM ride-sharing service to 2.5% of central Austin's trip-makers along five stations of Austin's light-rail transit Red Line. The geofenced areas around several SAV-serviced stations are called Automated Mobility Districts (AMDs). With Red Line rail-service headways of 15 minutes, and 15 SAVs serving FMLM connections to and from each AMD, simulations suggest that 15.8% of the AMD travel demands would shift from drive-along to transit thanks to the convenient station-based FMLM SAV services. AMD-area VMT is predicted to rise 26% in 5 miles × 8 miles central Austin area with average vehicle occupancy falling 30% (from 1 to 0.7 persons), due to empty SAV driving (between riders). Private car VMT also falls in the AMD areas, possibly alleviating congestion along network links outside the AMD areas. Providing frequent transit service or enlarging SAV fleet sizes would significantly reduce passenger wait times, but coordination of train schedules and SAV fleet routing plans is important to achieve cost-effective and delay-minimizing on-demand service.

Keywords: Shared Automated Vehicles, First-Mile Last-Mile Service, Automated Mobility Districts, Microscopic Simulation

INTRODUCTION

In most U.S. cities, transit is a second or third or final mode choice, owing to two key reasons: Door-to-door travel times via transit far exceed those provided by ready alternatives, such as privately-owned automobile, owing primarily to transit access and egress times. Fixed schedules and fixed routes regularly make transit uncompetitive, compared to private vehicles or and ride-hailing options. However, transit generally enjoys a price advantage (thanks to heavy subsidies). For many decades, cities have grappled with falling transit ridership shares and rising congestion, with clear and complementary relationships between the two. While higher subsidies may increase transit ridership, the key to increase mode share of transit services lies in reducing door-to-door travel times. Since it is impossible (and inefficient) to provide transit service everywhere, providing efficient first-mile last-mile (FMLM) connections is an important option for expanding transit's catchment areas, lower access and egress times, and raising ridership.

Currently, modes such as walking, bicycling and scooters are being used by individuals for FMLM connections to transit. The most common FMLM mode is walking to the transit station (particularly to bus stops), with park-and-ride, kiss-and-ride (where a family member drops a household member off at the transit station), and TNC-and-ride, having meager mode shares. Each of these access-modes to transit have their own drawbacks. Park-and-ride is often time-consuming as a transit rider has to finding a parking space and walk to the station. While kiss-and-ride is convenient for the transit rider, it places drop-off and pick-up burden on a family member. TNC-and-ride sometimes beats the purpose of taking transit, as one has to pay for the TNC ride in addition to transit fares, and instead of using TNCs for FMLM, it might make sense to use TNCs for the entire length of the trip (particularly in ridesharing). Suffice to say that efficient FMLM connections to transit leave much to be desired.

It can be posited that emerging vehicle technologies could hold a key to increase efficiency in FMLM connections. Shared Automated Vehicles (SAVs) have all the necessary facets to overcome the drawbacks of the FMLM connections mentioned above. An FMLM connection by an SAV obviates the need to search for parking (making it better than park-and-ride). It unburdens the responsibility of a household member (or any driver for that matter) to drop-off and pick-up a transit rider (making it better than kiss-and-ride). Since the driver is out of the equation, service providers can offer SAV connections to transit at a reduced cost, or even as integrated into the transit fare (making it better than TNC-and-ride). Finally, current demonstrations of SAVs show that they run at speeds of 30 to 40 mph making them a faster alternative than walk-to, or bike-to transit.

This argument is bolstered by increasing interest in SAVs. The initial hype around AVs seems to have subsided, with AVs being identified in the 'trough of disillusionment' in the Gartner Hype Cycle (Ramsey, 2018). It is slowly being realized by cities and vehicle manufacturers alike that AVs are not going to replace privately owned automobiles overnight, and that the short term deployment of AVs will be in the form of SAVs in geofenced urban districts with high trip densities. Building on this idea, researchers at the National Renewable Energy Laboratory have coined the term Automated Mobility Districts (AMD), to define geofenced deployments of shared automated vehicles to realize the full benefits that AV technology can offer in the near term (Young, 2018; Zhu, 2018). Many small scale demonstrations in the U.S. and around the world corroborate the interest in SAVs and the concept of AMDs (Mcity, 2018; City of Arlington, 2017; Smart Columbus, 2019).

As AMDs require high trips density to ensure the success of SAVs (to achieve high occupancy), transit stations make the perfect use case for an AMD, as they see high densities of transit boarding and alighting throughout the day. This research effort therefore intends to quantify the impacts of deploying SAVs as FMLM connections to transit in geofenced regions. Microscopic simulation software SUMO (Simulation of Urban Mobility) is used in this study to investigate the deployment of SAV fleets serving multiple AMDs along the transit line between Austin downtown and Crestview station. First, a baseline scenario is simulated considering walk as the only access and egress mode to transit. The baseline scenario is compared with alternate scenarios that have SAVs serving as FMLM connections. The results from this study can help cities and transit authorities use SAV technology to its maximum benefit, and increase transit ridership.

The remainder of the paper is organized as follows. The next section presents a brief literature review on AV, SAV simulation studies, as well as mode choice literature. The following section discusses the simulation settings for the case study. The simulation procedure, along with a detailed description of the two-level nested mode choice model used in this study is presented in the methodology section. Results section presents the impacts of fleet size and transit service frequency on SAV-to-transit mode shares. The final section presents some concluding thoughts and directions for future research.

LITERATURE REVIEW

The effectiveness of FMLM connections to transit has been the subject of many research endeavors. Shaheen and Chan (2016) discussed the history of shared mobility within the context of the urban transportation with a specific focus on FMLM connections to public transit. Yap et al. (2015) conducted a stated preference survey in Delft, Netherlands to study the traveler's attitudes regarding automated vehicle as last-mile connection mode, finding that traveler's associate more disutility to in-vehicle time in an AV, compared to a manually driven vehicles, and that travelers' attitudes regarding sustainability is the most important determinant for choosing AVs.

Transit feeder systems have been investigated extensively, and many systems across the world are benefiting from it. Delhi Metro Rail Network runs efficiently to complement and supplement different other modes of transport in Delhi, India (Delhi Metro Rail Corporation Ltd., 2017). Over 170 buses are operated by two companies serving 32 bus routes, as feeders to the Delhi Metro. Ji et al. (2016) investigated the effects of personal demographics, trip characteristics, and station environments on public bicycle usage for rail transit access. Helen et al. (2019) developed a modeling framework to optimize the joint design of transit networks and SAV fleets using a bi-level mathematical programming formulation, with a transit network frequency setting problem formulation for the upper-level problem, and the lower-level problem of a dynamic combined mode choice in traveler assignment problem.

Agent-based and activity-based simulations are the most commonly used to investigate the impacts of the AV technology. Liu et al. (2017) conducted a large-scale micro-simulation of transportation patterns in a metropolitan area, relying on a system of shared autonomous vehicles, and concluded that foror travelers whose households do not own a human-driven vehicle, SAVs appear preferable for trips under 10 miles. Simulation of SAV fleet operations suggests that higher fare rates allow for greater vehicle replacement, which is due to travel demands shifting away from longer trip distances when fares rise. Dandl and Bogenberger (2018) compared the existing free-floating carsharing service with a hypothetical electric autonomous taxi (aTaxi) system which shares the same demand in the area of Munich. They found that one autonomous vehicle (3min to relocate) could substitute 2.2-3.7 conventional carsharing vehicles for maximal waiting times of 7.5 min and 10 min, while the level of service is insufficient for the maximal waiting time of 5 min.

However, transit is seldom involved in simulations as modeling complex interactions associated with transit movement (park-and-ride; walk-and-ride) is not easy. Some recent studies involve transit, but they do not consider the flexibility of incorporating the new automation technology. Alemi and Rodier (2017) investigated the potential market, cost-saving and VMT reductions as well as greenhouse gas emissions of the shift from driving alone to TNC and Bay Area Rapid Transit access services in San Francisco Bay Area. Two modes are considered in this work while walk-and-ride are not considered in the mode choice. Mo et al. (2017) investigated the mode choice of first-mile last-mile to/from mass rapid transit (MRT) in Singapore under the impacts of the built environment through the data analysis of 24 thousand samples from Household Interview Travel Survey. Residents in Singapore rely heavily on public transportation and car use accounts for only 0.98% of the trips.

Young et al. (2017) defined and Automated Mobility District as a campus sized deployment of shared automated electric shuttle fleet to serve FMLM connections, as well as short trips. The issues and benefits of AMDs are framed within the perspective of intra-district, inter-district and boundary issues. Based on the AMD concept, Zhu et al. (2018) simulated an AV fleet running on a fixed route to serve the demand in a hypothetical AMD network, using the SUMO platform. AMD toolkit developed by Zhu et al. (2018) is shown to be capable of simulating detailed vehicle movements for various operational configurations of AV shuttles, running fixed-route on-demand service across an AMD.

This paper applies the AMD toolkit (Young et al, 2017; Zhu et al., 2018) to the Austin transit network with multiple AMDs, focusing on the operations of SAVs as a FMLM solution to transit connectivity. This work extends the capabilities of the AMD toolkit by incorporating complex operations of the transit system, as well as the multidimensional interactions between pedestrians, SAVs, and transit.

DATASET

The road network data for Austin case study was obtained from OpenStreetMap (OSM) (Haklay and Weber, 2008), and imported into the SUMO simulation environment. Morning peak travel demand data for Austin city was obtained from 2030 scenario run of the Capital Area Metropolitan Planning Organization (CAMPO) model (CAMPO, 2010).

Capital Metro's Metro Rail Red Line Corridor provides a 32-mile commuter rail service that connects downtown Austin and Leander City in Texas Since 2010 (Figure 1). The Red Line's average daily ridership in January 2018 was 2,552 and is anticipated to reach 10,000 daily riders by 2025 with a 15-minute frequency between downtown and Kramer station (Capital Metro, 2018).

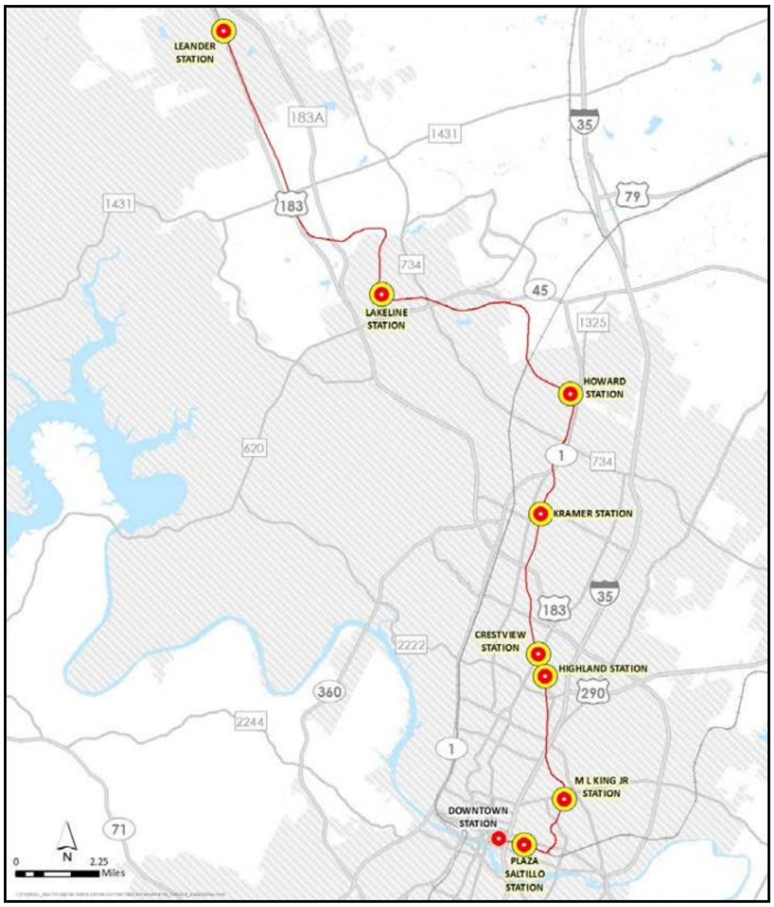
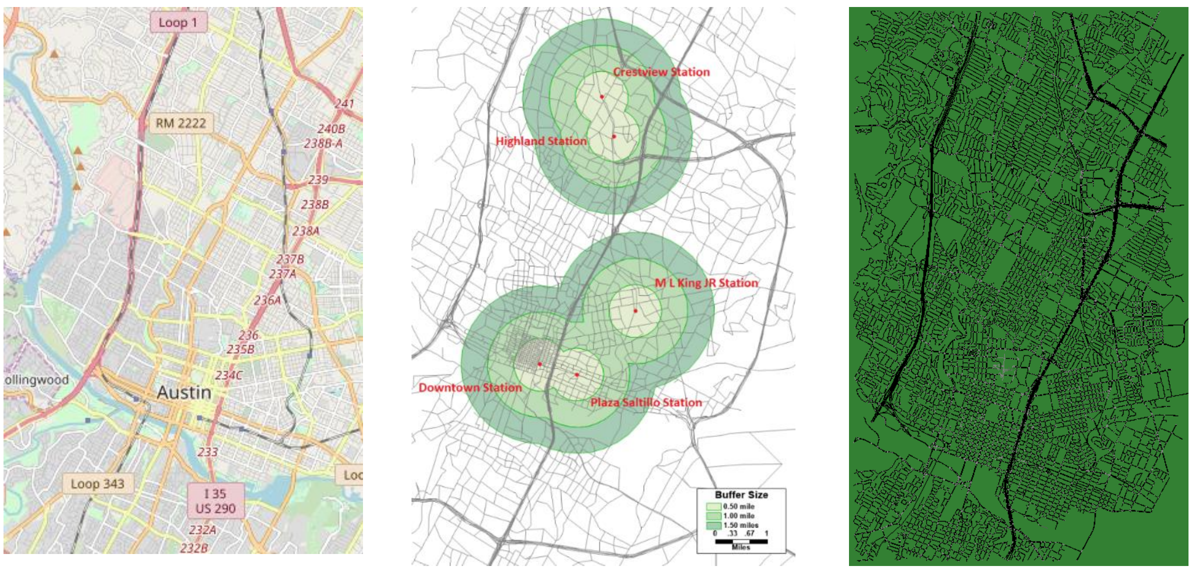


Figure 1. Current Red Transit Line in Austin (Capital Metro, 2018)

Austin Network

The year 2030 is considered for scenario runs in this analysis, with travel demand across a 5-mile × 8-mile square region in central Austin, and with a more frequent transit service between Crestview station and downtown Austin. Figure 2(a) shows the network obtained from OSM. The geographical extent of the study area is limited to five stations of the Red Line, owing to computational complexity of the microscopic simulation. Segments of Interstate-35 and Mopac freeways are included in the map to reflect a realistic route choice for road users. The network downloaded from OSM is cleaned and vetted so that there are no dead-end roads or invalid junctions. Signal settings for each intersection are left as default (provided by SUMO), with rail having a higher priority over vehicles running on the roadway. Reflecting real-world conditions, roadway vehicles will stop and let rail pass whenever the light rail approaches a shared intersection. Though rail connections are bi-directional in the real world, SUMO does not have the capability to simulated bi-directional railway lines. Therefore, two commuter rail lines are coded (one for each direction), with separate platforms created for the rail line in each direction. SAVs drop SAV-and-ride users at the curb nearest to the railway station, and the pedestrian will walk the rest of the way to get the platform of the commuter rail line.

AMDs are usually identified as neighborhoods or districts with high trip densities, such as a university campus, central business districts, or a military base (Young et al., 2017). In this study each 1.5 mile radial buffer from a station is considered as the operational extent of the SAV shuttle, and each AMD station comprises of 2-3 transit stops in total. Generally, 0.25 mile to 0.5 miles is seen as the walking distance to the transit stations (Nabors et al., 2008). Buffer size is limited to 1.5 miles in this study to avoid the overlap between AMDs, and also to improve the operational efficiency of SAVs. Each AMD has an SAV fleet that provides on-demand FMLM connections to transit trips in the corresponding AMD network. The two AMDs considered in this study are shown in Figure 2(b): The first AMD contains two stations: Crestview station and Highland station. The second AMD contains three stations: MLK station, Plaza Saltillo station and downtown station.



a) Network from OpenStreetMap　　b) Highway Network from CAMPO　　c) SUMO Simulation Network

Figure 2. Network and AMD Boundary

Travel Demand

Travel demand used in this study reflects the demand forecasted for year 2030 by CAMPO regional travel demand model. The CAMPO model has 2,252 traffic analysis zones (TAZ) covering Austin's six-county region. Travel demand between OD pairs from 246 zones is extracted from the CAMPO model for the purposes of this study. Since the network is obtained from OSM, a many-to-one association is established between the OSM links and the CAMPO TAZ boundaries. Based on CAMPO's OD trip table, each individual trip is reformatted into an edge-based OD table where the origin edge and destination edge are randomly selected from links associated with the corresponding TAZs. Morning peak period (6-9am) is used as the simulation horizon. Departure times from each TAZ were dispersed using a normal distribution across simulation time horizon. There are 42,125 trips generated across the 246 TAZ region from 6 am to 9 am. In this exercise, 1019 trips, which is a 2.5% sample of the morning peak trips are simulated to circumvent exhaustive run times of the microsimulation.

METHODOLOGY

Simulation of Urban Mobility Toolkit

The simulation exercise in this effort is carried out using SUMO, which is an open-source, microscopic, and multimodal traffic simulation toolkit (Krajzewicz et al., 2012). Using SUMO, it is possible to carry out micro-simulations of multimodal vehicles considering effects of traffic signals, vehicle routes and driving behavior models. Multimodal microscopic functions make SUMO a tool that can explicitly model the interactions among pedestrians, SAVs and transit, e.g. access and egress of transit use, getting on and off the SAV, and ride-sharing mechanism for on-demand services.

TraCI (Traffic Control Interface) is a toolkit in SUMO that allows to retrieve values of simulated objects and to manipulate their behavior "on-line" (Krajzewicz et al, 2008). On-demand services in SUMO can be implemented through TraCI by retrieving the information of on-demand requests and then dispatching vehicles to serve the demand. On-demand service has been tested on a small AMD (1,364 edges and 570 nodes) in Greenville, SC, with about 300 trips served by a single capacity vehicle fleet of four vehicles providing on-demand service and two vehicles running fixed route (Zhu, et al., 2017). This builds on previous efforts by Zhu et al. (2017) by incorporating interactions between pedestrians, SAVs, and transit, and by implementing SAVs as a FMLM connection to a larger transit line.

The SUMO simulation routine starts with importing travel demand and road network information into the software. Demand data includes trips by mode (derived from the OD trip table as describe above), and network data comprises of all the roadway links, transit lines, curbs, and platforms. For this simulation study, travelers are given a choice spectrum comprising of four modes namely walking, private automobile (also referred to as the car), walk-and-ride transit, and SAV-and-ride transit. It is important to note here that the shares for various modes are determined based on characteristics of the modes (wait-time, in-vehicle travel time etc.). For the preliminary analysis presented in this paper, routes for walk, car and walk-and-ride modes are determined based on shortest-paths measured by free-flow travel time in SUMO. During the simulation, pedestrians, and private vehicle drivers follow the routes assigned by SUMO, while interacting with other modes in the simulation. Origin station, and destination station are defined for the walk-and-ride and SAV-and-ride users at mode choice stage, but more detailed interactions between SAV, transit and SAV-and-rides users are modeled in TraCI. Transit is coded as a high capacity commuter rail running from Crestview station to downtown, and back to its origin. The commuter rail runs with a frequency of 15 minutes, and a stop time of 30 seconds at each station.

Vehicles and persons are evaluated and simulated second by second, in the SUMO simulation. Pedestrian and car mode users follow the assigned route plan, while SAV-and-ride users make a request and wait for the shuttle to pick them up (at their origin location or the transit station). Dynamic-ride sharing (DRS) is not considered in this effort. So, vehicles evaluate requests from passengers and generate a plan that picks up all the passengers and drops them off based on their trip request times. An SAV-and-ride user's trip consists of the following segments: making an on-demand request at the origin, getting on and off an SAV, walking to transit station, waiting to the origin transit station and taking transit to destination station, walking out of the station and making another on-demand request, getting on and off SAV, and walking to the final destination. For the analysis presented in this paper, mode of access and egress is assumed as the same, meaning that walking from origin location to transit station, and taking an SAV at destination station is not allowed. The authors acknowledge that this is an important limitation, and plan to address this in future research efforts. Access-, and egress-walking distance is limited within one mile around the station, and SAV fleets serve only in the AMDs designated to them (i.e., SAVs designated to serve FMLM connections for the Downtown-Plaza-ML King Jr AMD, will not honor trip requests from the Crestview-Highland station AMD). At the end of the simulation routine, SUMO outputs second-by-second vehicle traces, as well as ride-sharing plans, which help in computing performance metrics for various modes used in the simulation.

Mode Choice

The mode choice decisions in this simulation are modeled at the trip level, using a nested logit model (Ben-Akiva and Lerman, 1985). SUMO generated network travel times, and wait time information is used to calculate mode shares. A two-level nested logit model is used, considering walk-and-ride and SAV-and-ride nested under transit mode, which is compared with walk and drive at the same level (shown in Figure 3). Parameters, and their coefficients in the mode choice model are adapted from relevant literature (Liu et al., 2017, Chen and Kockelman, 2016; Wen et al., 2018). In-vehicle travel time (IVTT) for car mode is set as $17.67 per hour, following Liu et al (2017). Out-of-vehicle travel time (OVTT), comprising of wait and walk times, is assumed to be twice as much as IVTT. The same OVTT value is used for all modes, knowing that different modes will have different configurations of wait and walk times. For example, walk mode will not have any wait time associated with it as an individual simply walks from origin to destination. Car mode is assumed to provide door-to-door connectivity. Therefore, it does not have wait and walk time components. For SAV-to-ride, the OVTT parameter consists of wait time (for SAV at the origin), walking and waiting time for transit, as well as walking and waiting (for SAV at the transit station). Operating cost of car is assumed to be 60 cents per mile, whereas transit fares has a $2 flat fee (Liu et al., 2017). Constants for car utility (-15.3) and walking distance coefficient (-1.2) are obtained from Wen et al. (2018).

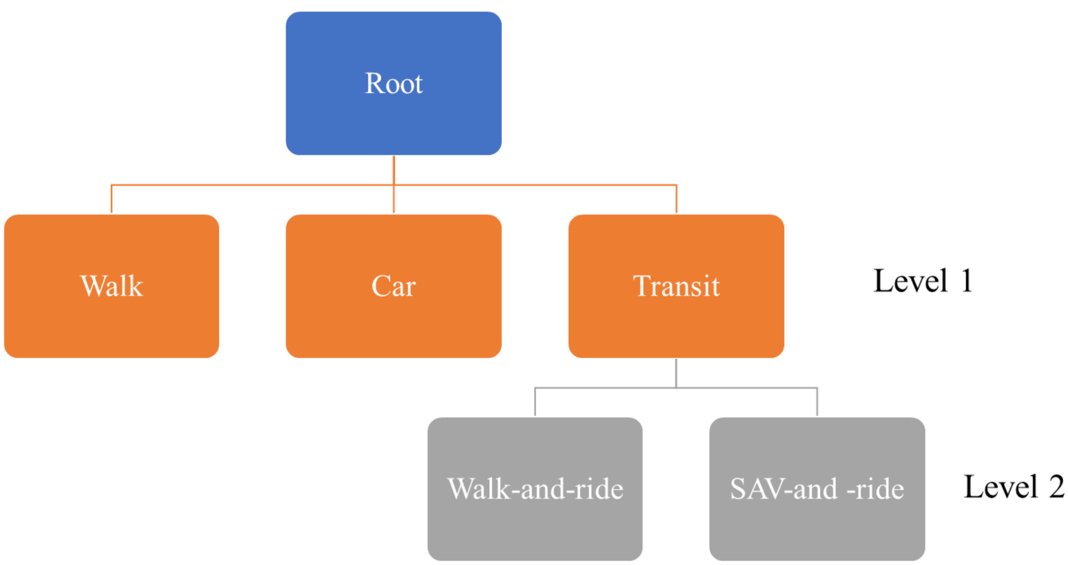


Figure 3. Two-Level Mode Choice Structure

Assuming a walking speed of 3.1 mph, the utility of walking mode is:

$$V_{walk} = -1.2 \times d_{walk} - 35.34 \times t_{walk}$$

After obtaining the driving distance and free-flow travel time from the network, the utility of car mode is:

$$V_{car} = -15.3 - 0.6 \times d_{driving} - 17.67 \times t_{driving}$$

Value of IVTT for both modes nested under transit is assumed to be half of car (Liu et al., 2017). The nesting coefficient for the transit nest is set as 0.7 based on mode choice component of the CAMPO travel demand model (Brinckerhoff, 2012). Average waiting time and walking time (both access and egress to both transit and SAV) are assumed to be 2.5 minutes (Brinckerhoff, 2012). Therefore, $t_{access_{walk}} = t_{egress_{walk}} = t_{FM-waiting_{SAV}} = t_{LM-waiting_{SAV}} = t_{waiting} = 2.5$, which means the access and egress walking time to/from transit, first-mile (FM) and last-mile (FM) waiting time for SAV, and waiting time for train are assumed to be the same.

The calculation of the utility function for transit mode is a bit more involved compared to that of other modes. First, the transit stations closest to a trip's origin and destination locations are identified. If both these stations are identified to be the same (reflecting the 'short' travel time of the trip), transit mode is precluded from the choice set. Since SAV operates within a designated AMD, the SAV-and-ride mode is not considered as a feasible mode, if distance from a trip's origin location to a transit station is greater than 1.5 miles, which is the radius of AMD. For walk-and-ride mode, if the distance to access-, or egress-station is greater than 1 mile, walk-and-ride mode is taken out from the available mode set, since distance threshold for walk mode is set at one mile. The transit travel distance is computed as the railway distance between platform centroid points of the boarding and alighting stations. Average speeds of urban rail systems in the U.S. are observed to be between 19 mph to 38 across the U.S. (Light Rail Progress, 2001). So, the speed of transit mode is set to be 32 mph, and is not affected by congestion on the roadway.

After obtaining the locations of the origin and destination stations, the FM and LM distance ($d_{FM_{SAV}}$ and $d_{LM_{SAV}}$), as well as FM and LM travel time $\left(t_{FM_{SAV}}\right.$ and $\left.t_{LM_{SAV}}\right)$, utility of walk-and-ride mode can be computed using:

$$V_{w\&r} = -2 - 8.84 \times t_{rail} - 35.34 \times (t_{access_{walk}} + t_{egress_{walk}}) - 35.34 \times t_{waiting}$$

And the utility of SAV-and-ride comes out to be:

$$\begin{aligned} V_{SAV\&r} = -2 - 8.84 \times t_{rail} - 1 \times \left(d_{FM_{SAV}} + d_{LM_{SAV}}\right) - 8.84 \times \left(t_{FM_{SAV}} + t_{LM_{SAV}}\right) \\ - 35.34 \times (t_{FM-waiting_{SAV}} + t_{LM-waiting_{SAV}} + t_{waiting}) \end{aligned}$$

Therefore, the utility of transit is:

$$V_{transit} = 0.7 \times \log\left(\exp\left(\frac{V_{w\&r}}{0.7}\right) + \exp\left(\frac{V_{SAV\&r}}{0.7}\right)\right)$$

Based on the utility equations shown above, mode shares are computed for all modes. Following this step, route plans are generated for all modes except SAV-and-ride.

Real-time Simulation Control

Since the routes for walk only mode, car, walk-and-ride modes are generated apriori to the real-time simulation, and the real-time simulation control will primarily focus on passenger, and SAV movements for the transit riders choosing SAV-and-ride option. At each time step (i.e., every one second), SAV-and ride transit users are tagged with different flags so that the controller can obtain, and react to a riders' current status, and location. SAV ride requests from passengers are evaluated every 300 seconds. Armed with information of passengers' pick-up and drop-off locations, routing plans are generated for each vehicle in the SAV fleet to pick-up and drop-off passengers based on the order of their trip request. A naïve logic implemented in the preliminary analysis, and will be enhanced with dynamic ride sharing (DRS) functionalities (such as enroute passenger pickup) in future research.

The various stages in SAV-and-ride operation are described in detail below. The terms transit rider, user, and SAV-and-ride user are used interchangeably in the description.

Stage 0: Initialization. Information regarding origin edge, first-mile SAV pick-up edge, first-mile SAV drop-off edge, and origin transit station is identified for each SAV-and-ride user. At this stage, an SAV-and-ride user commences walking to the network edge where they will be picked up.

Stage 1: SAV-and-ride user arrives at first-mile departure location (mid-way point of the pick-up roadway link) and waits for a ride. Any SAV-and-ride user arriving at a departure location will be assigned with an SAV at the next vehicle re-plan step (i.e., the next 300 second time bin).

Stage 2: SAV-and-ride user boards the vehicle and the vehicle proceeds to pick up the next user assigned to it. In the event that all the seats on the SAV are occupied or when there are no more passenger pick-up requests (in a given time step), then the SAV heads to drop-off the passengers.

Stage 3: When the SAV has picked up all assigned SAV-and-ride transit users, the users' stage will be changed to stage 3. The SAV will drop off all the passengers at their designated station locations.

Stage 4: SAV-and-ride user is dropped off at the transit station and commences walking to the origin transit station platform. There is a walking leg involved here since transit riders cannot be dropped by the SAVs directly on the transit platform.

Stage 5: SAV-and-ride user arrives at the origin station and waits for the train. Once a user reaches this stage, the rest of his/her journey will be identified and cached, including destination transit station, last-mile SAV pick-up edge, last-mile SAV drop-off edge and final destination edge.

Stage 6: Once the train arrives at the station, the rider will board the train.

Stage 7: The SAV-and-ride user is dropped off at the destination station and walks to location where he/she will be picked up by an SAV.

Stage 8 - 11: These stages represent the SAV routing logic for the last mile, as described in steps 1-3.

Stage 12: SAV-and-ride user arrived at the final destination edge.

The SAVs are controlled using TraCI module in SUMO, constantly reacting to the status of the SAV-and-ride transit users. Maximum vehicle speed of SAVs is set at 45 mph, considering most automated shuttles currently being demonstrated see top speeds around 40 miles or so. Various stages in SAVs operations are described below:

Stage 0: Initialization. SAVs are placed at random locations in their designated AMDs.

Stage 1: Idling. Before receiving a request (evaluated 300 seconds), SAVs are parked, and wait for a trip request.

Stage 2: Routing and running. Once a routing plan is generated for an SAV to pick-up and drop-off riders, it will proceed to the first pick-up point. Each SAV will first pick-up all the passengers assigned to it on a trip, and then drop-off the passengers in the sequence they were picked up.

Stage 3: Re-distribute. After an SAV has finished dropping off all passengers, it is re-located to a nearby location on the network where it can park itself and wait for the next trip request (reflecting a real-world situation where ride hail drivers often relocate themselves to a location in anticipation of future trip demand) .

AUSTIN APPLICATION RESULTS

For the Austin case study, baseline scenario considers only considers walk, drive, and walk-and-ride modes as the modal alternatives. Transit in the baseline (as well as FMLM) scenario is assumed to be running between Crestview station and downtown Austin with a frequency of 15 minutes. FMLM scenarios are tested with each AMD served by a fleet of fifteen SAVs serving the SAV-and-ride users. A cost of $1 per mile is assumed as the fare for the SAV (Liu et al., 2017). Table 1 shows the mode share results for baseline scenario as well as FMLM scenario. Both scenarios are run with 2.5% of the total travel demand for the defined region.

A transit survey conducted in Austin in 2011 shows a total of 1,755 daily transit trips for the rail line across all stops (Brinckerhoff, 2012). Since this paper considers 2.5% of total demand, the analysis would capture 44 trips spread across all the 9 stations. Further assuming that these boardings are distributed uniformly across all stations, 24 daily transit trips would be captured in five stations investigated (among 9 stations that have been built currently) in this paper, across the whole day. Therefore, 8 trips during AM peak for walk-and-ride mode align reasonably well with the 2011 field observation. Both baseline scenario and FMLM scenario see the same number of walk-and-ride trips. The one-mile constraint on walk to transit constraint might be playing a part in keeping the mode share for walk-and-ride constant. SAV-and-ride mode gains a large mode share (of 161 trips) from car and a small mode share (of 8 trips) from walk. The reasons for this could be cost-, and time-effectiveness of SAV mode, compared with car and walk modes respectively. Although SAV modes gain mode share, it is observed that the average vehicle occupancy (AVO) of all vehicles for the FMLM simulation dropped to 0.7 from 1 in the baseline. The primary reason for this is the empty vehicle travel encumbered by SAVs both in traveling to pick up the first passenger, as well as in relocating after dropping off the last passenger. Empty vehicle travel accounts for 36% of SAV VMT (and 24% of total VMT), which is in close alignment with deadhead miles quantified using real-world TNC data (Henao and Marshall, 2018; Fagnant et al., 2015). The naïve ride-matching and routing logic used for preliminary analysis can also be a reason for the high SAV VMT observed here. Based on this logic, SAVs always pick-up passengers in the order of their requests, and drop-off in the order of their pick-ups (as opposed to geographical proximity to the shuttle location). A positive result from the deployment of SAVs in AMDs is that car VMT has seen a reduction of 23.5% (from 2,827 to 2,162). This could reduce congestion on the highway and increase travel speeds, but could lead to increased congestion at local places around transit station. Future efforts will investigate the feedback of from mode choice model on network performance.

Table 1. Comparison results of base case and FMLM served by SAVs

	Mode Share				Average vehicle occupancy	Vehicle-miles traveled			
	Car	SAV&Ride	Walk&Ride	Walk		Car	SAV	Empty	Total
Base	70.83%	0.00%	0.79%	28.39%	1.0	2,827	0	0	2,827
	721 trips	0	8	289					
FMLM	55.01%	16.60%	0.79%	27.60%	0.7	2,162	1,516	851	3,554
	560 trips	169	8	281					

After exploring the impacts of implementing SAVs as a modal alternative to car, and walk-and-ride modes, sensitivity analysis exercises were carried to understand the impact of fleet size and transit frequency on the performance of the SAV mode. FMLM scenario presented above has a transit frequency of 15 minutes and two fleet sizes of 15 vehicles in the two AMDs. Building on this, scenarios were developed to test the performance of SAV-to-ride mode, based on transit frequencies of 5 min, 10 min, 15 min and 20 min, and increasing SAV fleet size from 5 to 20 vehicles (in increments of 5 vehicles). With a more frequent transit service, FMLM service performance was observed to be quite stable, but waiting time for transit saw a significant reduction, as expected. The average travel time for FMLM (SAV service to-, or from- the transit station) is around 30 minutes, which is longer than one would normally expect. An intelligent ride-sharing mechanism, possibly a DRS, would help reduce the access-, and egress-times for SAV-and ride mode. Contrary to sensitivity on transit frequency, transit performances are stable with changes in SAV fleet size. A larger fleet size would lead to lower average vehicle occupancy but also less wait time, as the need for sharing trips reduces with increasing fleet size. Analyses such as these can help determine the optimal operational characteristics for FMLM deployments to weigh SAV performance against investment decisions.

Table 2. Sensitivity analysis on transit frequency and fleet size.

Scenarios		SAV (average value of FM and LM)				Transit		
		Average vehicle occupancy	Waiting time (minutes per person)	Total travel time (wait + onboard + walk) (minutes per person)	Distance (miles per trip)	Waiting time (minutes per person)	Total travel time (wait + onboard + walk) (minutes per person)	Distance (miles per trip)
Frequency (minutes)	5	0.69	5.87	30.31	1.29	2.93	29.56	2.02
	10	0.70	5.87	28.81	1.40	5.49	32.32	2.02
	15	0.69	5.77	27.16	1.43	6.99	33.62	2.02
	20	0.65	5.25	28.26	1.23	10.55	37.18	2.02
Fleet size (vehicle number in each AMD)	5	0.93	11.01	51.74	1.05	6.99	33.62	2.02
	10	0.79	7.48	35.13	1.32	6.99	33.62	2.02
	15	0.69	5.77	27.16	1.43	6.99	33.62	2.02
	20	0.66	5.29	24.27	1.32	6.99	33.62	2.02

CONCLUSION

Extending the concept of deploying shared automated vehicles in geofenced regions with a high trip density (labeled as an Automated Mobility District, or an AMD), this paper explores the idea of using shared automated vehicles (SAVs) to provide first mile last mile (FMLM) connectivity to transit in AMDs. Although there are some mesoscopic agent-based simulations on transit, transit operations are oversimplified and FMLM service is rarely investigated. This paper makes one of the first attempts at understanding the scope for adopting SAVs for FMLM connections using the microscopic simulation tool SUMO. This paper not only models detailed transit operations (such as stopping duration, schedule, shared intersections by railway and roadway, and railway flatform for getting on and off), but also makes a foray into incorporating operational logic associated with deploying SAVs for FMLM connections to transit. Outputs from the microsimulation represent second by second passenger and vehicle movements, which can be used to obtain accurate estimates of VMT, energy and fuel consumptions, and performance metrics for the SAV mode (e.g. ride-sharing time, walking time and waiting time). Furthermore, this paper extends the AMD concept to a larger network with multiple AMDs at the same time. With increasing interest from cities in SAV technology as an urban mobility solution, AMD deployments (where SAVs are used to provide on-demand service) can be anticipated in the near future.

A case study analysis was conducted where fleets of SAVs provide FMLM service to Austin's Red transit line around central Austin area. Travel demand data from Austin's CAMPO model is used for this analysis, and a 2.5% percent of the travel demand for the region is considered for the microscopic simulation analysis. An open source microscopic simulation tool (SUMO), was augmented with a nested-logit mode choice model to conduct the analysis. With SAV fleet serving FM or LM requests in their designated AMDs, it was observed that 15.8% of the travel demand would shift from car mode to SAV-and-ride mode. Though SAV-and-ride mode gains mode shares from car, and walk-and-ride modes, it was observed that systemwide VMT would increase (and average occupancy would decrease) with the implementation of SAVs, owing primarily to the empty vehicle travel of SAVs. The empty VMT from SAVs accounts for 36% of SAVs' VMT and 24% of total VMT in the system. This calls the need for developing deadhead minimization routines, to reduce empty VMT from SAVs, and AVs. From the scenario analysis exercises, it was seen that frequent transit service would significantly reduce the passenger waiting time at the station, but it would not improve the performance of SAV fleet. Increasing SAV fleet size on the other hand would reduce wait time for SAV pick-ups as expected.

While this paper makes an initial attempt at simulating SAVs as an FMLM connection to transit, a few shortcomings remain to be addressed. It was observed that the naïve ride-matching and routing logic implemented in this study led to increased empty vehicle travel in the systems. Immediate efforts will focus on enhancing operational logic with features such as dynamic ride sharing and deadhead minimization. Access-, and egress-legs to transit were enforced to be the same in the simulation for simplicity. This will be relaxed in the next iteration, as transit riders in all likeliness can take an SAV to access a transit station, but walk to the final destination for the egress-leg of the trip. The results presented in this paper consider 2.5 % of the demand for the region of interest, owing to computational complexity of the micro-simulation. Solutions will be explored to simulate 100% of the AMD's travel demand using advanced computing resources.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Y. Huang, K. Kockelman, V. Garikapati, L. Zhu; data collection: Y. Huang; analysis and interpretation of results: Y. Huang; draft manuscript preparation: Y. Huang, K. Kockelman, V. Garikapati, L. Zhu, S. Young. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

Alemi, F. and Rodier, C., 2016. Simulation of Ridesourcing Using Agent-Based Demand and Supply Regional Models: Potential Market Demand for First-Mile Transit Travel and Reduction in Vehicle Miles Traveled in the San Francisco Bay Area (No. NCST-20161200).

Ben-Akiva, M.E., Lerman, S.R. and Lerman, S.R., 1985. *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Brinckerhoff, P., 2012. CAMPO Mode Choice Model: Calibration / Validation Report. Alliance Transportation Group. Retrieved from https://capmetro.org/pc/docs/CAMPOModelCalibrationValidationReport_2012.pdf

Capital Metro, 2018, Red Line Short-Term Investments. Retrieved from: https://www.capmetro.org/uploadedFiles/New2016/ProjectConnect/Resources/Project_Background/Corridors_and_Services/Red_Line_Short-Term_Flipbook_032818.pdf

Capital Area Metropolitan Planning Organization (CAMPO), 2010. CAMPO 2035 Regional Transportation Plan. Retrieved from: https://47kzwj6dn1447gy9z7do16an-wpengine.netdna-ssl.com/wp-content/uploads/2018/03/CAMPO_2035_Plan_Adopted_May_242010wMods.pdf

Chen, T.D. and Kockelman, K.M., 2016. Management of a shared autonomous electric vehicle fleet: Implications of pricing schemes. *Transportation Research Record*, *2572*(1), pp.37-46.

City of Arlington, 2017. Milo Pilot Program Closeout Report. Retrieved from: https://www.arlingtontx.gov/UserFiles/Servers/Server_14481062/File/City%20Hall/Depts/Office%20of%20Strategic%20Initiatives/Transportation%20Planning/Milo_Closeout_Report.pdf.

Dandl, F. and Bogenberger, K., 2018. Comparing future autonomous electric taxis with an existing free-floating carsharing system. *IEEE Transactions on Intelligent Transportation Systems*, (99), pp. 1-11.

Delhi Metro Rail Corporation Ltd., 2017. Retrieved from http://www.delhimetrorail.com/feederbus.aspx

Fagnant, D.J., Kockelman, K.M. and Bansal, P., 2015. Operations of shared autonomous vehicle fleet for Austin, Texas, market. *Transportation Research Record*, *2563*(1), pp.98-106.

Haklay, M. and Weber, P., 2008. Openstreetmap: User-generated street maps. *IEEE Pervasive Computing*, *7*(4), pp. 12-18.

Henao, A. and Marshall, W.E., 2018. The impact of ride-hailing on vehicle miles traveled. *Transportation*, pp.1-22.

Hou, Y., Young, S.E., Garikapati, V., Chen, Y. and Zhu, L., 2018. *Initial Assessment and Modeling Framework Development for Automated Mobility Districts* (No. NREL/CP-5400-68290). National Renewable Energy Lab. (NREL), Golden, CO (United States).

Ji, Y., Fan, Y., Ermagun, A., Cao, X., Wang, W. and Das, K., 2017. Public bicycle as a feeder mode to rail transit in China: The role of gender, age, income, trip purpose, and bicycle theft experience. *International Journal of Sustainable Transportation*, *11*(4), pp. 308-317.

Krajzewicz, D., Erdmann, J., Behrisch, M. and Bieker, L., 2012. Recent development and applications of SUMO-Simulation of Urban MObility. *International Journal on Advances in Systems and Measurements*, *5*(3&4).

Liu, J., Kockelman, K.M., Boesch, P.M. and Ciari, F., 2017. Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. *Transportation*, *44*(6), pp. 1261-1278.

Light Rail Progress, 2001. Light Rail Schedule Speed – Faster Than Bus, Competitive with Car. Retrieved from https://www.lightrailnow.org/myths/m_lrt012.htm.

Mo, B., Shen, Y. and Zhao, J., 2018. Impact of built environment on first-and last-mile travel mode choice. *Transportation research record*, *2672*(6), pp. 40-51.

Mcity, University of Michigan, 2018. Mcity Driverless Shuttle - A Case Study. Retrieved from https://mcity.umich.edu/wp-content/uploads/2018/09/mcity-driverless-shuttle-case-study.pdf

Nabors, D., Schneider, R., Leven, D., Lieberman, K. and Mitchell, C., 2008. *Pedestrian Safety Guide for Transit Agencies* (No. FHWA-SA-07-017). United States. Federal Highway Administration.

Pinto, H.K., Hyland, M.F., Mahmassani, H.S. and Verbas, I.Ö., 2019. Joint design of multimodal transit networks and shared autonomous mobility fleets. *Transportation Research Part C: Emerging Technologies*.

Ramsey, 2018. Autonomous Vehicles Fall into The Trough of Disillusionment ... But That's Good. Forbes. Retrieved from https://www.forbes.com/sites/enroute/2018/08/14/autonomous-vehicles-fall-into-the-trough-of-disillusionment-but-thats-good/#69d493177b5a

SAE International, 2018. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. Retrieved from: https://www.sae.org/standards/content/j3016_201806/

Shaheen, S. and Chan, N., 2016. Mobility and the sharing economy: Potential to facilitate the first-and last-mile public transit connections. *Built Environment*, *42*(4), pp. 573-588.

Smart Columbus, 2019. Self-Driving Shuttles. Retrieved from: https://smart.columbus.gov/projects/self-driving-shuttles.

Wen, J., Chen, Y.X., Nassir, N. and Zhao, J., 2018. Transit-oriented autonomous vehicle operation with integrated demand-supply interaction. *Transportation Research Part C: Emerging Technologies*, *97*, pp. 216-234.

Yap, M.D., Correia, G. and Van Arem, B., 2016. Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A: Policy and Practice*, *94*, pp. 1-16.

Zhu, L., Garikapati, V., Chen, Y., Hou, Y., Aziz, H.A. and Young, S., 2018. Quantifying the Mobility and Energy Benefits of Automated Mobility Districts Using Microscopic Traffic Simulation. In *International Conference on Transportation and Development* (p. 98).