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**USING SHARED AUTOMATED VEHICLES
TO DELIVER PUBLIC TRANSPORT**

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TO DELIVER PUBLIC TRANSPORT**

by

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Abstract

Using Shared Automated Vehicles to Deliver Public Transport

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Shared automated vehicles (SAVs) will affect mode choice in several ways: door-to-door (D2D) services may be the most popular choice for SAV travelers, thanks to relatively low travel times and access costs, as well as ride-sharing opportunities to split costs. First-mile last-mile (FMLM) SAV services that connect travelers to transit stations (including airports) make use of existing transit investments while avoiding parking at or walking to and from those stations. Larger (and mid-size) SAVs may also replace traditional buses by adding frequency and lowering service costs on popular bus routes.

Motivated by SAVs' many potential benefits, this dissertation specifies traveler choices for different US settings, simulates fleets of SAVs in concert with other modes, and analyzes results for travelers, their networks, and their regions. This dissertation first *micro*-simulates operations of an SAV-based transit route to understand how traffic conditions and all travelers' costs (those in SAVs and in thousands of private vehicles) are affected by vehicle sizes, use of pull-out bays, and presence of signals along a 6.5-mile corridor. Using SUMO (Simulation of Urban MObility) software, results show that use of smaller, but more frequent SAVs lowers passenger wait times but can increase travel times for background travelers. Use of smaller SAVs does not significantly affect background traffic conditions due to their shorter dwell times (during passenger pickup and dropoff). Replacing 40-seat bus-type SAVs with 5- and 10-seat SAVs reduced total corridor transportation costs by 4% (reflecting all travelers' values of time,

plus vehicle operating and ownership costs), under various demand levels and SAV seat-occupancy factors.

The next microsimulation assigned and tracked SAVs delivering FMLM service to 5 commuter rail stations in central Austin neighborhoods. Thanks to SUMO, results include traveler mode choices, walk distances and routes, wait times, vehicle idling and bunching details, vis-à-vis train arrival times. With rail service headways of 15 minutes, simulations predict dramatic increases in train use (by roughly a factor of 10, at those stations). Variations in train headways and SAV fleet sizes illustrate how door-to-door travel remains the key predictor of travelers' mode choices. 4-seat SAVs perform similarly to 6-seat SAVs but cost less to provide. A dynamic ride-sharing (DRS) (vehicle-to-passenger assignment) algorithm tightly coordinated with train arrivals delivers 87% of travelers to their stations in time to catch the next train, while uncoordinated assignments deliver just 57% of travelers in time.

Finally, the POLARIS mesoscopic simulation is leveraged to integrate three SAV services across the 20-county Chicago region. When SAVs with DRS serve only D2D trips, at just \$0.50 per mile, with 1 SAV for every 40 residents, they attract 15% of trips (and ownership is predicted to fall from 0.66 to 0.37 household vehicles per capita), with a 15-minute average travel time and 4.6-mile average person-trip distance. Adding FMLM service (to about 54,000 train and bus stops) increases Chicagoans' transit mode split from 5.4% to 6.3%, with the same SAV fleet serving 12% more person-trip requests per day and driving 4.2% more SAV-miles traveled). Most FMLM person-trip distances are under 2 miles, with rail-station connections dominating (rather than those to bus stations). In terms of social welfare impacts (using normalized differences in logsums of mode and destination choice utilities), suburban area residents appear to benefit most from SAVs' arrival, followed by those in urban neighborhoods, especially for D2D trip-making. Overall, US communities and transit systems seem poised to benefit from SAV services.

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Chapter 1. Introduction

1.1 BACKGROUND AND MOTIVATION

Transportation has been evolving rapidly and will continue to develop as we move toward (fully-) automated vehicles (AVs). By freeing drivers' hands, AVs have the potential to bring benefits like crash reductions, shorter vehicle headways, optimized vehicle operations and traffic management, and lower emissions, along improved mobility for those unable or unwilling to drive (Greenblatt and Shaheen, 2015; Morando et al., 2018; Winkle, 2016). Since AVs drive themselves, former drivers will experience a reduced value of travel time (VOTT) en route and thus may not mind many longer-distance trips (LaMondia et al., 2016; Perrine et al., 2020).

In addition to automation technologies, shared mobility applications are moving forward. Transportation services and assets can be shared among users, either concurrently or one after another, delivering many cost and energy savings and greater system efficiency. By providing a variety of modes (ranging from buses and trains to shuttles and taxis, ride-hailing and car-sharing, bike-sharing and scooter-sharing, as well as van-based delivery services), shared mobility can enhance accessibility, reduce vehicle ownership, provide new ways to access goods and services, and increase multimodality. This dissertation is motivated by opportunities in shared mobility and automation of ground transport vehicles.

While public transit generally enjoys a price advantage thanks to heavy subsidies (Congressional Research Service, 2020), it is usually a second, third, or even final mode preference for passenger trips made in many U.S. cities. The percentage of U.S. workers commuting by transit was around 5 percent in 2019 (APTA, 2020). Increased automobile ownership, low gasoline prices, dynamic ride-sharing (DRS) options, and increasingly flexible work schedules are four reasons for recent drops in transit use (APTA, 2020). In general, door-to-door (D2D) travel times via transit far exceed those provided by ready alternatives (Federal Highway Administration, 2011), such as privately-owned automobiles. Fixed schedules and routes regularly make transit uncompetitive, compared to private vehicles and ride-hailing options. For many decades, U.S. and other cities have grappled with falling transit ridership shares and rising congestion, with clear and complementary relationships between the two.

Transit has been and will continuously be influenced by the emerging transportation and economic development trends. Shared AVs (SAVs), a fleet of AVs that can provide ride-hailing services, incorporate the advantages of shared mobility and automation technology, and are expected to have important impacts on future transit systems. SAV applications are growing, currently through pilot programs, partnerships, private sector involvement, and research by federal, state, and local agencies. By the end of 2019, there were more than ten AV shuttle pilot tests or demonstration projects in the U.S., in states like Texas, Florida, Michigan, and Colorado (Stocker and Shaheen, 2019). SAVs can provide D2D service, eclipsing public transit provision, or they can provide door-to-station/bus-stop service (and station-to-door service), thereby supporting transit operations - especially fixed investments in rail lines with dedicated rights of way.

SAVs' low per-mile costs should make them a popular choice in future transport systems. SAVs' D2D service is expected to cost less than \$0.50 per mile eventually, which is several times lower than what transportation network companies (TNCs) currently charge, and very competitive with privately owned, human-driven vehicles (Burns et al., 2013; Spieser et al., 2014). When capital costs and wait costs are included, Fagnant and Kockelman (2018) estimated that fares of \$1 per mile would generate generous returns on SAV fleet investments in many demand settings. Similarly, Bösch et al. (2018) predicted a \$0.50 per mile cost to provide DRS in SAVs and \$0.70 per mile for private SAV ride-hailing services. Simulating a fleet of shared automated all-electric vehicles (SAEVs) across the Austin region, Loeb and Kockelman, 2019 anticipated a cost of \$0.59 per passenger-occupied vehicle-mile, as compared to just \$0.45 per mile for hybrid-drivetrain SAVs. All estimates suggest significant cost savings for SAV fleet services over traditional transit, conventional ride-hailing, and ride-sharing services (e.g., Uber Pool and Lyft Line with human drivers). The National Transit Database (2019) indicates U.S. transit costs of \$1.40 per passenger-mile for bus and \$0.99 for light rail, with all passengers having to walk, bike, drive or get a ride to access and depart bus stops and transit stations. TNCs' ride-hailing services typically cost \$2 to \$3 or more per vehicle-mile, with pooled services costing closer to \$1.25 per passenger-mile (Bösch et al., 2018; Kessler, 2017).

Given SAVs' likely cost and service-quality differences, a key question is: how can we design and operate SAV fleets to improve on public transportation systems? The common

service types are expected to be door to door (D2D), SAV-based transit lines, and FMLM connections to transit stops and stations, as described below. Evaluation of these three is the basis for this dissertation.

1.1.1 Door-to-Door (D2D) Service

SAVs can provide D2D service like TNCs do, but with reduced labor costs and better control of vehicle assignments (to passengers) and routes. SAVs can offer both ride-hailing and ride-sharing services, and may increase average vehicle occupancy (AVO) to reduce regional vehicle-miles traveled (VMT) (Fagnant and Kockelman, 2018; Rodier et al., 2016) with efficient DRS. Improved safety from avoidance of human-driver errors can lower insurance costs, and cost-sharing across riders may make SAVs with DRS the most popular future travel mode (Clements and Kockelman, 2017).

Since D2D SAV services have been discussed simulated rather extensively by others (Alonso-González et al., 2020; Fagnant and Kockelman, 2018; Gurumurthy et al., 2020; Liu et al., 2017; Lokhandwala and Cai, 2018; Martinez and Viegas, 2017; Merlin, 2017; Snelder et al., 2019; Wadud et al., 2016), this dissertation looks to expanded SAV options, in replacing conventional buses and in accessing transit stations.

1.1.2 SAV-Based Transit Lines

SAVs can also serve as public transit vehicles, with fixed routes, stop locations, and frequencies. They can be a mixture of vehicle sizes, from a 4-seater (much like the common sedan, with ride-sharing en route) to 10-passenger vans, 20 passenger minibuses, and SAVs seating 40 or more (as full-size buses). Smaller SAVs can accelerate faster, are easier to maneuver (and park), and may cause less congestion and line-of-sight issues (for nearby travelers). When used in fixed-route service, smaller SAVs tend to skip stops because of fewer boardings and alightings. Larger SAVs may be more space-efficient (per person-mile traveled) but will have to stop more often (and for longer) at bus stops or stations, causing delays to riders and others in the corridor.

Comparing to the traditional transit service using 40-seat buses, a fleet of variably sized SAVs is likely to offer cost savings (by eliminating drivers' wages and lowering insurance costs) (Quarles et al., 2020), facilitate vehicle relocations and interlining (and idling) of services (across routes, by time of day and day of week, in much better synch with riders' demands, and independent of 8-hour work schedules for human drivers), and reduce vehicle headways/improve service frequency (via use of more, smaller/right-sized vehicles).

1.1.3 First-Mile Last-Mile (FMLM) Connections to Transit

Since it is impossible (and inefficient) to provide transit service everywhere, providing efficient FMLM connections is an important option for expanding transit catchment areas, lowering access and egress times, and raising transit ridership.

Transit riders often walk, drive, bike and scooter to make their FMLM connections to bus, train, and ferry stops; but each of these access modes to transit has its drawbacks. Park-and-ride journeys are often time-consuming, since a transit rider has to find a parking space and walk to the stop or station. While kiss-and-ride is convenient for the transit rider, it places drop-off and pick-up burdens on family members or friends. TNC-and-ride travelers have to pay for the TNC ride - in addition to transit fares. Suffice it to say, FMLM connections to transit systems are often problematic.

Emerging vehicle technologies may hold the key to competitive FMLM connections, helping increase transit system demand. SAV use obviates the need to walk or bike, find a ride, or search and pay for parking at transit stops.

1.1.4 Integrated Transit Services

An integrated SAV system can be any combination of service types mentioned above. Cost savings from eliminated drivers' wage makes it possible for transit operators to manage large fleets of SAVs, using different vehicle sizes. SAVs can switch to other types of service, at different times of day (including midnight pizza delivery, and mid-day parcel deliveries) and different days of the year, across locations (like high demand for rides during special events in nearby cities). An integrated system also enables more customer-pricing strategies (including

peak versus off-peak fares), making it easier for transit providers to avoid losses or subsidies, while promoting shared rides in relatively energy-efficient vehicles.

1.2 OBJECTIVES

Motivated by the potential societal and individual mobility benefits of SAVs, this dissertation specifies, simulates, and analyzes travelers' behaviors and fleet operator decisions for a variety of SAV deployments, in a public transportation system.

Dissertation objectives include: (1) identifying relevant problems in SAV and transit operations, and finding research gaps in current studies, (2) developing simulation methods and evaluation strategies to investigate different SAV services in support of public transit, (3) quantifying the impacts of various SAV services on existing systems under different demand and supply conditions, (4) modeling and developing approaches for improving SAV operations and network performance, and (5) analyzing the relative operational efficiency and social benefits of SAV services in large-scale (wide-network) applications.

To meet these objectives, this dissertation conducts a comprehensive literature review of research that investigates public transit operations and their integration with SAVs. This review demonstrates the path from current transit systems to a future world supported by SAV fleets. It then develops simulations models to realistically mimic travelers' choices and vehicle operations, including people's driving, riding, walking, and waiting, as well as vehicles' idling, relocating, picking up, and dropping off of passengers. For the third objective, different simulation modules and model settings are assembled to predict new travel and traffic patterns under different SAV services, including SAV-based transit lines, FMLM connections to transit stations, and D2D services. To achieve the fourth objective, different fleet and vehicle sizes are applied with improved ride-sharing strategies with transit schedule coordination. Finally, simulation and measures of social welfare are used to evaluate new SAV services in large-scale applications across the Chicago region. As our world evolves toward automated transport systems, cities and regions can benefit from this dissertation's findings.

1.3 ORGANIZATION

This dissertation is organized as follows: Chapter 1 motivates the thesis topic, presents overarching goal and specific objectives, identifies key problems, and describes this work’s scientific contributions. Chapter 2 synthesizes existing SAV literature and identifies gaps in recent work on SAV services, with an eye toward transit services. Chapter 3 presents a microscopic model to illustrate SAV operations along a busy corridor, to analyze interactions among SAVs, transit passengers, and other (background) travelers/vehicles. Chapter 3 has been published as a paper in the *Journal of Advanced Transportation* (Huang et al., 2021a), and titled “SAV Operations on A Bus Line Corridor: Travel Demand, Service Frequency and Vehicle Size”, with co-authors Kara Kockelman and Long Truong. Chapters 4 and 5 also use microsimulation, to predict travel impacts and explore SAV operations in FMLM SAV service. Specifically, Chapter 4 quantifies the impacts of SAV serving FMLM rail-transit connections, with a focus on mode splits, network and fleet performance, and has been published in *Transportation Research Record* (Huang et al., 2021b), with co-authors Kara Kockelman, Venu Garikapati, Lei Zhu, and Stanley Young. Chapter 5 extends that work by enabling DRS in FMLM service, along with train-arrival coordination. Chapter 5’s associated paper is under the second-round review in *Computers, Environment and Urban Systems* (Huang et al., 2021c), with co-authors Kara Kockelman and Venu Garikapati. Chapter 6 integrates all SAV-based services, and has been presented at the 2021 Bridging Transportation Researchers (BTR) conference, with co-authors Kara Kockelman, Krishna Murthy Gurumurthy, and Omer Verbas. Finally, Chapter 7 concludes the dissertation and discusses areas of future research.

Chapter 2. Literature Review

2.1 SHARED AUTOMATED VEHICLES (SAVs)

This chapter discusses the state-of-art of SAV research, with a focus on different styles of service that SAVs can provide. SAV studies include papers that emphasize travel demand or transportation infrastructure, economics, policy, and/or the environment. Since AVs' are expected to improve safety and lane capacity (Chen et al., 2017; Milanés and Shladover, 2014; Morando et al., 2018), many papers have focused on smart management of vehicle control and signal timing, mobility impacts, and environmental benefits (Bichiou and Rakha, 2019; Chen and Kockelman, 2016; Childress et al., 2015; Fagnant and Kockelman, 2014; Jones and Leibowicz, 2019).

Anticipating travel behavior shifts is key to preparing communities for the advent of AVs. Researchers and others expect high demand for AV use, due to enhanced access for elderly, young, and disabled persons (Harper et al., 2016; Truong et al., 2017), on-demand services with no parking, driving or vehicle-ownership costs and maintenance hassles (Huang et al., 2020; LaMondia et al., 2016). Demand-side analyses are important (Fagnant and Kockelman, 2015; Gurumurthy and Kockelman, 2020b; Harper et al., 2016; Payre et al., 2014), but so are supply-side analyses, especially for fleet-style operations.

Fixed-route services for fleets of trains and buses are typically pre-scheduled. On-demand services originated from dial-a-ride (Wilson et al., 1971), but have become popular as ride-hailing services provided by TNCs. Chow et al. (2020) discussed fixed-route, flexible-route, and on-demand services as three classes of future public transit systems. The flexible-route service usually relies on a (largely) fixed-route, with flexibility in part of the route and/or stop locations. SAVs can be used in such systems, alongside D2D and other SAV services.

2.2 SAVs' DOOR-TO-DOOR ON-DEMAND SERVICE

Studies of SAVs are usually connected to the research in shared mobility, which SAV D2D service can offer by providing shared rides at low costs. As a result, vehicle ownership is also expected to fall (Menon et al., 2019). Numerous SAV studies focus on predicting the impacts of SAV introduction under various scenarios, including travel behavior changes, land-

use change, increased travel safety, environmental and economic benefits, and traffic impacts (Narayanan et al., 2020). Most current SAV studies focus on the D2D service, and only a handful have ventured into a discussion on SAVs in a multi-modal network. Zhao and Malikopoulos (2019) and Gurumurthy et al. (2019) have summarized recent research about SAV agent-based simulations, among which most studies do not involve public transit.

SAV D2D service is expected to have an operating cost of less than \$0.50 per mile, which is lower than that of human-driven taxis and even personal human-driven vehicles (Burns et al., 2013; Spieser et al., 2014). When capital cost and wait cost are included, Fagnant and Kockelman (2018) estimated \$1.00 per mile for profit when assuming an operating cost of \$0.50 per mile. This aligns with Bösch et al.'s (2018) estimates when assuming \$0.50 per mile for DRS SAV service and \$0.70 for SAV ride-hailing service. The AVO of SAVs for D2D service can range from 1.13 to 3, depending on the type of DRS used (Gurumurthy and Kockelman, 2018; Hörl, 2017; Lokhandwala and Cai, 2018). Moreover, the average trip length is also anticipated to increase, up to 14% (Childress et al., 2015; Huang et al., 2020). The VMT change varies across the SAV D2D service region based on different assumptions, including cost, travel demand, fleet size, and settings of the DRS. Generally, the change can range from a 35% reduction in VMT to a 20% increase (Chen and Kockelman, 2016; Fagnant and Kockelman, 2018; Maciejewski and Bischoff, 2018). Vehicle replacement rate has also been investigated, showing that one SAV can replace up to 11 personal vehicle trips (Fagnant and Kockelman, 2018; Levin et al., 2017; Lokhandwala and Cai, 2018). In addition, Steck et al. (2018) estimated that the VOTT reduction for commuting drivers using SAVs compared to driving manually can be 18% in 2030 and 31% by 2050.

Narayanan et al. (2020) is the most recent literature review incorporating public transit as an essential factor when discussing the use of SAVs. More recently, studies have begun investigating SAVs' impacts on a multi-modal network to reflect a more reasonable real-world application. For example, Liu et al. (2017) simulated the use of SAVs in Austin's 6-county network, with a focus on travelers' mode choices. In a mixed traffic environment of private human-driven vehicles, public transit, and SAVs, the study analyzed the impacts of the SAV system on energy consumption and emissions under different SAV penetration rates and SAV rental fees. Results show the concern that SAVs are preferable for short-distance trips compared

to public transit for travelers who do not own a private vehicle, and extra VMT by SAVs could compromise environmental benefits. Snelder et al. (2019) explored the mobility impacts of SAVs in a mixed traffic environment, with a novel mode that captures demand elasticities and a combination of destination and mode choice model. In an SAV scenario, a large modal shift from all modes to SAVs was predicted, given low costs and low passengers' VOTT. Martinez and Viegas (2017) investigated two SAV service types around the city of Lisbon, Portugal. SAVs serving D2D competing with an autonomous minibus that replaces the current bus service was simulated in an agent-based model. Results indicate potential VMT and environmental impacts of SAV services, especially if introducing a market segmentation and the deployment of on-demand self-driving bus services. Merlin (2017) simulated SAVs and transit use for the relatively small Ann Arbor, Michigan network, with a focus on transit impacts. He estimated that SAVs will be preferred to buses, thanks to lower travel times and travel costs per day, alongside lower carbon emissions.

Some other literature investigates the relationship between SAVs and public transit through exploring the available modes in existing mode choice, by identifying the key benefits brought by automation technology (e.g. decreased VOTT and potential cost reduction). This method is also commonly seen in the mode choice input for agent-based simulations. For example, LaMondia et al. (2016) added AVs as a third alternative to a mode choice model between car and airplane. Results show that AVs tend to draw from the use of personal vehicles and airlines equally for travel of shorter than 500 miles, but airlines were estimated to remain preferred for longer distances. Another analysis was performed by Perrine et al. (2020) using long-distance travel data across the U.S., showing an airline revenue reduction varying from 53% when considering fully automated personal AVs to 61% under the SAV scenario. Although airlines are considered, congestion is not reflected in the analysis, as flights are modeled separately.

2.3 SAVS AS A COMPLEMENT TO EXISTING PUBLIC TRANSIT

Due to reduced parking needs, decreased vehicle ownership, cost and time efficiency, as well as the flexible on-demand service that SAVs can provide, instead of competing with public transit ridership, SAVs can also complement public transit service by increasing accessibility and

expanding the catchment area to public transit stations. 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, or neighborhoods with high trip densities (Hou et al., 2017; Zhu et al., 2018). By the end of Feb 2018, 17 active SAV pilots were active across eight states in the U.S. with eight of them serving passengers and nine in a testing-only phase (Stocker and Shaheen, 2019).

There can be two main ways for SAVs to serve as a complement to existing public transit. One is providing new fixed-route and fixed-stop transit services, while the other is offering FMLM service for transit station connections. Most of the studies about SAVs serving FMLM connections to transit emerged after the year 2016. Shaheen and Cohen (2018) noted that infill development brought by SAVs may increase public transportation ridership and even transform bus transit to rail transit in urban cores. Lenz and Fraedrich (2016) mentioned that AVs bring more possibilities in providing public transport services, even in suburban and rural areas.

Compared to the case when SAVs only provide D2D service, an integrated SAV fleet in a transit system is more complicated to model, as it involves multimodality in finding shortest paths across several combinations, in addition to seamlessly integrating it to an on-demand service for the first and last mile. Moreover, from a demand perspective, public transportation is often not the first choice for travel in most U.S. cities, and using SAVs for FMLM connections to existing public transit systems does not appear to be as attractive as a direct D2D service. Despite the modeling difficulties and the relatively low interest in FMLM use, there are still many studies that quantify SAV impacts when used for FMLM.

Yap et al. (2016) carefully surveyed traveler preferences for AVs in an integrated public system and predicted that AVs had the most potential for first-class train travelers using SAVs in their “last mile” (to a final destination). Abe (2021) investigated 2,300 Tokyo residents’ willingness to use SAVs for FMLM connections to urban rail transit. Those with station-access issues were most inclined to use SAVs in this way, as a substitute for feeder buses and personal cars, but not for cycling and walking (to and from urban train stations).

Liang et al. (2016) presented two integer programming models to investigate the service area selection and trip acceptance criteria of an SAV system for first/last mile transport that

maximizes the profit of the SAV operator, near a train station in the city of Delft, Netherlands. Fleet size is also shown to be important to the profitability of the system due to the service capacity and the cost of fleet ownership. Pinto et al. (2019) presented a bi-level model solving the proper fleet size of SAVs and the most efficient transit frequency for 20,920 transit vehicle trips within a 16,819 traffic analysis zones (TAZs) Chicago region (city of Evanston and a five-mile buffer area). The heuristic solution procedure involves solving the upper-level problem using a nonlinear programming solver and solving the lower-level problem using an iterative agent-based assignment-simulation approach. Two bus types and 15 train types are simulated, and four modes are involved: walk, transit, SAVs, and SAVs plus transit. Results indicate significant traveler benefits, in terms of improved average traveler wait times compared to the initial transit network design.

Simulations are typically the preferred tool and can reflect vehicle operations and road congestion well. Zachariah et al. (2014) synthesized the New Jersey trip data and simulated a ride-sharing system of SAVs providing FMLM service to train stations. Authors noted that train stations will have a substantial potential for sharing rides, especially during peak hours, and taking advantage of these spatial and temporal peaks in ride-sharing demand are likely key to an optimized ride-sharing system. Vakayil et al., (2017) simulated a multi-modal transit system that integrates a FMLM service with mass-transit services, considering transit frequency, transfer costs, and vehicle relocation. Results indicated up to a 50% reduction in congestion and vehicular emissions thanks to FMLM service. Gurumurthy et al. (2020) compared an SAV fleet's FMLM service to a D2D service across the Austin, Texas region through a 5% sample simulated in MATsim (Multi-Agent Transport Simulation) and pricing decisions turned to be the key to mode splits and traffic impacts. Shen et al. (2018) simulated Singapore's mass-transit system (just 4.6 square miles) during morning peak hours, and estimated that such services will enhance system efficiency, using fewer road resources and being financially sustainable. Wen et al. (2018) investigated the opportunities between AVs and public transit in a major European city using static-travel time agent-based simulation. They simulated scenarios with various fleet sizes, vehicle capacities (up to 4), fare schemes, and hailing strategies for the connections to the transit station. A nested logit mode choice model was presented, considering bus, rail, park and ride, and AV and ride nested under transit mode. They estimated that 560 vehicles are enough to

accommodate the travel demand in the city if sharing is not available, but the fleet size can be reduced to lower than 200 if an SAV can be shared by 4 people.

Electrified fleets work even better overall. Farhan et al. (2018) showed how SAEVs can complement existing public transit services. Results showed great potential for leveraging SAEVs to increase transit catchment area, but reduced demand for park and ride infrastructure. The simulated SAEV fleet could reduce system-wide VMT by 37% through ride-sharing and fast charging, which also effectively decreases the fleet size and wait time. Scheltes and de Almeida Correia (2017) studied the use of SAEVs serving last-mile ride-hailing service of a train line segment in Delft. Even with the high preference for non-motorized modes in the Netherlands, they concluded that the SAEV system can compete with walking but not with cycling. Their simulated SAEV system was able to reduce average passenger travel time and waiting time, especially when pre-booking was allowed.

Table 2-1 shows the summary of the 11 most recent papers that integrate SAVs into public transit while serving as an FMLM tool. Applications were tested on real networks, from a 13-node network to a large city network. Simulation methods take a leading role, due to the complexity and difficulty in modeling the problem in an analytical form. 4-seat SAVs are the most tested, although SAVs can have 5 or more seats, considering no drivers, or up to 10 or more seats in vehicles, like shared minibuses or minivans. Vehicles that have one seat typically cannot be regarded as serving shared rides, rather as car sharing. Half of the listed studies consider large demand levels, but only two studies have congestion involved. Congestion can be modeled in many ways, but the computation burden can be raised dramatically with the growth in network size. Therefore, most of the studies ignore the real congestion impact, while only presenting VMT estimates. Moreover, only two studies touch on the use of EVs. The battery capacity of EVs results in the need for charging, which is more practical but also increases the scope of the problem. The charging station location decisions bring more uncertainty to modeling and make it challenging to demonstrate.

Table 2-1. Literature summary for FMLM service with SAV

Articles	Location	Type	Network size	Max Vehicle Size
Zachariah et al., 2014	New Jersey	simulation	state level	5 seats
Liang et al., 2016	Delft, Netherlands	optimization	500 × 500 m	1 seat
Yap et al., 2016	Netherlands	survey	N/A	N/A
Scheltes and de Almeida Correia, 2017	Delft, Netherlands	simulation	13 nodes	1 seat
Vakayil et al., 2017	Washington DC	simulation	city level	10 seats
Shen et al., 2018	Singapore	simulation	12 × 12 km	4 seats
Wen et al., 2018	A major European city	simulation	15 × 10 km	4 seats
Farhan et al., 2018	Seattle	simulation	7.5 × 6 mi	4 seats
Pinto et al., 2019	Chicago metropolitan	optimization	64,083 links	N/A
Gurumurthy, Kockelman, et al., 2020	Austin, Texas	simulation	city level	4 seats
Abe, 2021	Tokyo metropolitan	survey	N/A	N/A

Table 2-1. Literature summary for FMLM service with SAVs (cont.)

Articles	DRS	Large Scale (> 1 m trips)	Congestion	Electric Vehicle	Transit Type	FM or LM
Zachariah et al., 2014	✓	✓	✗	✗	rail	FM/LM
Liang et al., 2016	✗	✗	✗	✗	rail	LM
Yap et al., 2016	✗	N/A	N/A	✗	rail	FM
Scheltes and de Almeida Correia, 2017	✗	✗	✗	✓	rail	LM
Vakayil et al., 2017	✓	✓	✗	✗	metro	FM/LM
Shen et al., 2018	✓	✓	✗	✗	metro	FM/LM
Wen et al., 2018	✓	✗	✗	✗	rail	FM/LM
Farhan et al., 2018	✓	✓	✗	✓	rail	FM/LM
Pinto et al., 2019	✓	✗	✓	✗	bus & rail	FM/LM
Gurumurthy et al., 2020	✓	✓	✓	✗	bus & rail	FM/LM
Abe, 2021	✗	N/A	N/A	✗	urban rail	FM/LM

While FMLM connection has shown promise in improving traveler wait times and travel times, new SAV-based transit lines leveraging SAVs can also be useful to an ailing public transit system. Although large-size SAVs may require more mature technologies of automation, the existing 40-seat conventional buses may eventually be replaced with SAV fleets. Instead of providing on-demand service, such SAV fleets will aim to serve large transit demands by offering rapid transit with fixed routes, stops, and schedules. Stocker and Shaheen (2019) mentioned that large-size SAVs, which are more likely to accommodate 20 or more passengers, can be operated through business-owned vehicles, or a hybrid fleet owned by both businesses and individuals. The service can be offered based on fixed schedules and routes, with more potential for demand-based flexibility (Stocker and Shaheen, 2017). Automation technologies like cooperative adaptive cruise control (CACC), lane-keeping, precision parking, and self-

relocation are going to make SAV transit efficient and safe, and the potential capacity for exclusive bus lanes may increase over 50% (Lazarus et al., 2018).

FMLM connections by themselves may improve the attractiveness of rail systems and some bus lines, while transit lines based on high-frequency, self-driving minibuses or SAVs can also increase transit ridership. Current studies of SAV-based transit focus mainly on acceptance (Bernhard et al., 2020; Nordhoff et al., 2019), so planning and operational insights are still lacking. For example, Mirnig et al. (2020) surveyed and concluded that the functionalities of booking and reserving spots in an automated bus will have more impacts on vulnerable populations (like the disabled and aged). Bernhard et al. (2020) explored 942 participants' willingness to use self-driving minibuses in Mainz, Germany, and found respondents to be most concerned about system safety and environmental benefits. Moorthy et al. (2017) compared costs of conventional public transit to a hypothetical SAV system for transit between Ann Arbor and Detroit's Wayne County Airport, with simplified network and operating assumptions. They estimated that SAVs could provide up to 37% energy savings, depending on vehicle powertrain and ridership parameters. They neglected vehicle stopping and routing, for thousands or millions of origin-destination pairs, which is what real systems will seek to address.

Only a handful of papers have discussed an integrated transit system with SAV-based transit (Gurumurthy et al., 2019; Harb et al., 2021; Narayanan et al., 2020; Zhao and Malikopoulos, 2020). A thorough investigation of multi-service SAV operations in an integrated system is warranted and is the prime motivation for this dissertation.

2.4 MODELING METHODS

The simulation is the most commonly used method to uncover SAVs' operational strategies for any type of service. Specifically, studies are conducted around fleet sizing decisions (Fagnant et al., 2015; Maciejewski and Bischoff, 2018; Spieser et al., 2014; Vazifeh et al., 2018; Burns et al., 2013) along with efforts on ride-sharing mechanisms (Fagnant and Kockelman, 2018; Hyland and Mahmassani, 2018; Maciejewski et al., 2017), EVs involving decisions of charging station locations (Loeb et al., 2018; Loeb and Kockelman, 2019; Chen et al., 2016; Zhang and Chen, 2020) and environmental effects (Martinez and Viegas, 2017; Fagnant and Kockelman, 2014; Greenblatt and Shaheen, 2015).

Different scopes of simulations have been leveraged by existing studies to reflect different levels of network performance. Meso- and Micro- scope simulations perform better at collecting information at individual or agent levels, including detailed person and vehicle trajectory, while the information from a microscopic simulation can be more precise in simulation timestep resolution. Most of the simulation software are mesoscopic, such as MATsim (Axhausen, 2016), POLARIS (Auld et al., 2016), and ActivitySim (Gali et al., 2008), and the application can usually be citywide or larger, like Austin (Fagnant et al., 2015), Chicago (Gurumurthy et al., 2020), Zurich (Boesch et al., 2016) and Lisbon (Martinez and Viegas, 2017). SUMO (Lopez et al., 2018) and VISSIM (Rahman et al., 2019) are popular microscopic simulation tools that can simulate more detailed traffic flow (Alazzawi et al., 2018; Zhu et al., 2018) but the computation burden usually does not allow for large-scale network simulation. Macroscopic models can usually simulate statewide or nationwide networks, but can only zoom into the level of vehicle routes instead of trajectories. Example applications include the impacts of AVs on long-distance travel and freight travel (LaMondia et al., 2016; Perrine et al., 2020).

Analytical modeling and optimization also contribute to SAV predictions, including SAVs' assignment (Hyland and Mahmassani, 2018), distribution, parking, relocation (de Souza et al., 2020), and charging strategies for SAEVs (Iacobucci et al., 2019). Compared to simulations, optimization models provide a more rigorous relationship between variables of interest but unavoidably request proper approximations or simplifications of some related functions. Since many vehicle and human features need to be captured, the optimization models tend to function more as a submodule in a simulation environment targeting one other objective, (e.g., planning, strategic or operational purpose) (de Souza et al., 2020; Pinto et al., 2020).

Other than simulation and optimization models, surveys have also been conducted to explore people's views on SAVs concerning public transportation, although most of the surveys are conducted emphasizing perspectives on willingness to pay, willingness to share rides, adoption rate by demographic and land use pattern, instead of public transportation (Bansal et al., 2016; Bansal and Kockelman, 2017; Hohenberger et al., 2016; Lavieri and Bhat, 2019; Krueger et al., 2016). Pakusch et al. (2018) conducted a stated preference survey in Germany, collecting opinions of preference among traditional private car, personal AV, traditional shared car, SAV, and public transport. Results suggest that the preferred travel mode remains to be private cars,

either traditional or automated. There will be reduced use of public transportation, with 7% shifted to AVs and 9% shifted to SAVs. Similar results are also found in Wadud et al., (2016): SAVs may divert passengers from transit systems due to D2D service. Haboucha et al. (2017) used public transit attitude as a latent factor to investigate people's preference for SAVs. They predicted that the SAV adoption rate can be at most 70%, even if the service is provided free, and individuals who never use public transit are less likely to use an SAV. Bansal et al. (2016) suggested that 41% of Texans are not yet ready to use SAVs but 7.3% hope to rely entirely on SAVs even at \$1.00 per mile.

2.5 SUMMARY

To sum up, there have been extensive studies conducted about SAVs during the past decade. Many of them are public transportation-related, but FMLM studies, as well as SAV-based transits, are lacking. This is due to more interest in SAV's D2D services, and the large problem scope of multimodal modeling and simulations, the involvement of various stakeholders, and the modeling challenges. Regarding this, simulation has been leading this kind of research, with mostly heuristic methods pursuing optimized objectives. In addition, congestion is seldom considered in current SAV FMLM studies, which also tend to overlook the standpoint from an integration of different SAV services. This shows the limitations of many existing SAV applications. To fill the gaps of current studies on SAVs, this dissertation starts with the effort of quantifying the impacts of each SAV service, follows up with cost analysis and operational suggestions, and further explores how an integrated SAV service system can function in a multimodal transportation system.

Chapter 3. Shared Automated Vehicle Operations on New Transit Corridors

3.1 OVERVIEW

By eliminating drivers' wages and self-relocating, SAVs may eventually operate in a traditional transit corridor, replacing conventional transit vehicles, and have frequent interactions with riders and other vehicles sharing the same right of way. Seeking the best SAV size for a transit corridor not only relates to the riders but is also important to the service provider. Riders would like to experience less waiting time and onboard time with fewer stops and rerouting, while SAV operators would like to maximize profit or social welfare.

This chapter microsimulates SAVs' operation in a 6.5 mile-corridor setting to understand how traffic reacts to, and how riders and system costs are affected by vehicle sizes and performance attributes for SAV-based transit. The detailed microscopic model captures multifaceted ride and vehicle behavior, including bus bunching, SAVs waiting for approaching passengers, and skipping stops at full capacity. Various scenarios are tested, including different road congestion status, adding traffic signals for the corridor, and adding parking bays for SAVs' stops.

This chapter is organized as follows. The next section demonstrates the methodologies of the detailed proposed simulation model for the SAV-transit service. After introducing the setups of the scenario, results and analyses are presented, followed by discussions of the application. The last section concludes this chapter.

3.2 MICROSIMULATION DESCRIPTION

3.2.1 SUMO Simulation Setup

This chapter uses SUMO (Simulation of Urban MObility) software, which is capable of microsimulating interactions among different travel modes (Krajzewicz et al., 2012), to investigate how vehicle size and attributes of such SAV-based transit affect traffic, transit riders, and system costs. The detailed manipulations are achieved through TraCI (Traffic Control

Interface), a toolkit in SUMO that allows retrieving real-time values of simulated objects, which can conduct user-defined behavior “on-line” through Python scripts.

The simulation network setup in this study is a 6.5-mile, 2-lane, straight corridor with no traffic signals. This corridor has a lane width of 11.6 ft and a speed limit of 30 mph based on recommended designing practices from the American Public Transportation Association (Barr et al., 2020). As also suggested in previous studies, SAV stops are evenly placed (every quarter mile) along the corridor (Walker, 2012) at the middle point of a road segment. Two types of vehicles, namely SAVs and conventional vehicles (referred to as background flow in the following context), can travel in both lanes. SAVs are inserted into the corridor to serve riders with a fixed schedule (i.e. a fixed frequency) and run a fixed route to the end of the corridor, with stops at the stations. A Poisson distributed background flow of conventional cars with a mean departure rate is assumed. The base case scenario will test a departure rate of 0.7 vehicles per second, which is approximately 1260 vphpl (vehicle per hour per lane), to reflect a common flow rate on a 30-mph corridor (Barr et al., 2020). Due to curbside stops, SAVs obstruct the vehicles behind when serving passengers at stops. Scenarios that have parking bays and added traffic signals for SAVs are also tested in a later context. With a high dispatching rate (frequency) of SAVs, “bus bunching” can be observed, as SAVs can overtake previously dispatched SAVs.

Travel demand in this chapter refers to SAV riders/passengers, who walk on the road (access or egress the SAV stops), wait for SAVs, and ride in SAVs. Other active modes are ignored here because they would not affect the operations of SAVs or conventional vehicles, although there may be taxis, which will stop and pick-up/drop-off passengers, and scooters/bicycles, which potentially slow down the traffic. Passengers are uniformly generated at random along the corridor, arriving with a uniform distribution in a 3-hr period of peak time. Since the distance between two consecutive stations is 1/4 miles, passengers who have origins and destinations between two consecutive stations probably give up taking transit. Therefore, only those passengers who have a trip distance longer than 1/3 miles are considered rational SAV users and randomly generated along the corridor. These riders walk to the nearest stop, get on the next available SAV and get off at the stop closest to his/her destination. An SAV that has not reached its capacity will stop at a stop where new riders are waiting or where current riders want to alight. Further, an SAV waits for passengers approaching the stop if this SAV has

stopped at the station and the passenger can walk to catch this SAV in 10 seconds. After a rider gets off the SAV, he/she walks to the destination location and then disappears from the simulator. Figure 3-1 shows an illustration of the bus line corridor. One passenger is shown to be waiting at the stop, while the SAV has just arrived at that stop, causing the following vehicles to brake.

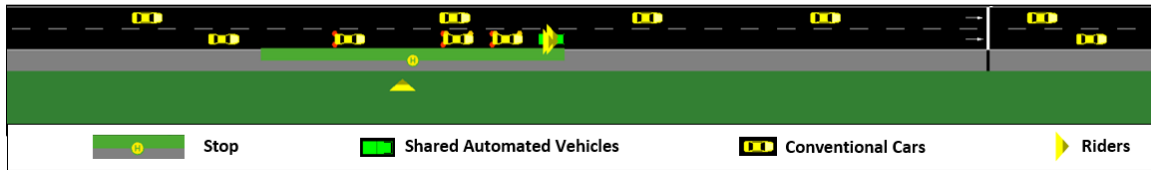


Figure 3-1. Bus line simulation demonstration

3.2.2 Simulation Framework

Figure 3-2 shows the simulation design details, by demonstrating the whole simulation flow and how vehicles and riders interact in the simulator. Road network and bus stop information are read first, including the edge lengths, as well as the length and position of the SAV stops. Travel demand is then processed to obtain the start location of the journey, departure station, arrival station, and destination location of the itinerary. After that, the simulation starts, and the itinerary of riders is processed by the simulator at time 0. Beginning at the first step of the simulation, background flow comes into the corridor and SAVs depart from the start point of the corridor based on the fixed headway. During every step of the simulation, which is every 0.5 seconds, the status of riders and SAVs are tracked and updated. Riders' status is tracked to inform SAVs (e.g. whether riders are catching the SAV, waiting at the bus station, or already on board) so they can react accordingly. The status and locations of SAVs are also tracked, to determine whether the SAVs need to stop at the next station. The designed simulation also checks whether riders need to get off at the next station. If no one is getting off, it then checks whether passengers are waiting at the next station and if there are available seats on board. When the SAV is dwelling at a stop, it keeps checking whether a rider can catch the SAV in 10 seconds and will then let those people get on the SAV. After the SAV leaves the station, it sets future stops for all new riders' destination stations. SAV and rider status and locations are checked

every timestep until the simulation reaches the time horizon. The output includes both passenger and vehicle information, such as vehicles' and riders' travel time and waiting time, background vehicle speed, and AVO.

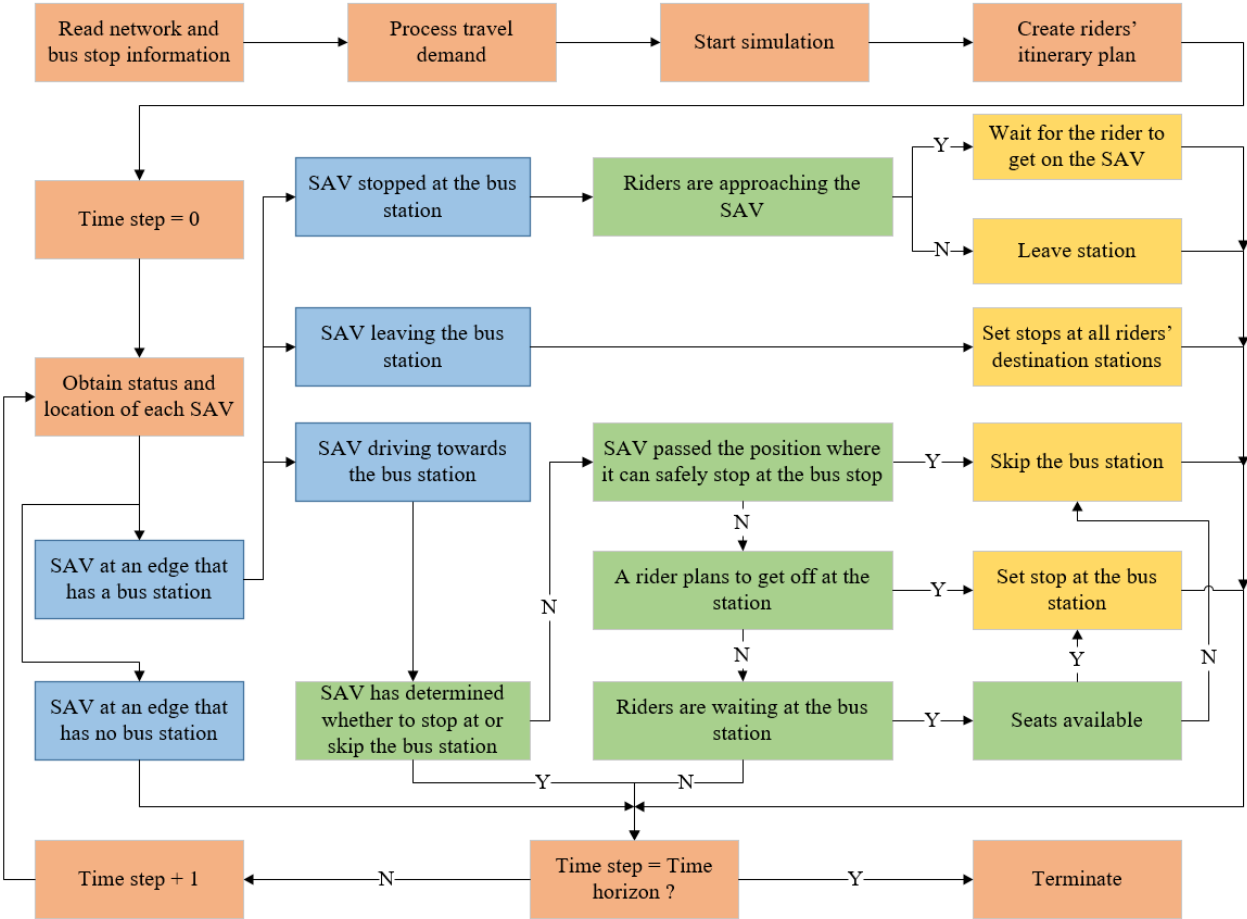


Figure 3-2. SAV-based transit service design

3.2.3 Simulation Parameters

Stocker and Shaheen (2017) have envisioned four types of potential SAV and service models: micro-vehicles (1 or 2 passengers), small vehicles (3-7 passengers) mid-sized vehicles (7-20 passengers), and large vehicles (20+ passengers). However, one can imagine that the future world may also have a large-capacity SAV – an automated bus to serve a heavy demand transit corridor, but such a corridor probably does not allow micro-vehicles to travel. Therefore, for the

simplicity of vehicle sizes, four types of vehicles are simulated, from a normal sedan size of 5 seats (no driver due to full automation) to an automated bus of 40 seats.

As shown in Table 3-1, background flow uses the SUMO default value for “passenger” vehicle types (Krajewicz et al., 2012). Although there would be differences in the lane-changing model between conventional vehicles, this dissertation focuses on longitudinal effects instead of lateral effects. Therefore, the lane-changing model is assumed to be LC2013, the default from SUMO (Erdmann, 2015).

Automated bus or shuttle tests may proceed with caution at early implementation stages due to unreliable and unstable camera recognition and slow data processing, however, in the future, automated buses will probably have faster speeds than human-driven vehicles (Litman, 2017). In terms of transit operations, comfort is also key to the design of vehicles, based on the study from (Bae et al., 2019), who did a summary of the possible range for acceleration and deceleration rates of a comfort transit vehicle. Since small AVs are nimble and can have faster acceleration and deceleration rates, due to the use of the safety belt, the acceleration was set as the highest value in the range, at 1.47 m/s^2 . The 40-seat SAV bus would have the lowest acceleration in the range, at 0.9 m/s^2 . The other types of vehicles are assumed to have rates in between the small AV and the SAV bus with linear interpolation. Further, the emergency deceleration rate is assumed to align with the normal bus configurations to ensure the comfort of the riders, based on the default SUMO value. Length, width, height, and maximum speed were obtained from the existing sedan, van, and bus size parameters (Ford Motor Company, 2019; GOGO Charters, 2020; Krajewicz et al., 2012). In terms of the minimum gap between vehicles, 2 meters is used for the 40-seat SAV bus and 0.5 meters for the 5-seat SAV, which is adopted from the range that was used in Morando et al.’s (2018) simulation.

Table 3-1. SAV-based transit configurations and other simulation parameters

		Other vehicles in traffic	SAV5	SAV10	SAV20	SAV40	Source
Capacity (# of seats)		4 seats	5	10	20	40	Stocker and Shaheen, 2017
Vehicle dimension	Length (m)	4.3 m	4.3	5.5	7.7	12	Ford Motor Company, 2019; GOGO Charters, 2020; Krajzewicz et al., 2012
	Width (m)	1.8 m	1.8	2.5	2.5	2.5s	
	Height (m)	1.5 m	1.5	2.8	2.8	3.4	
Lane changing model		LC2013					Erdmann, 2015
Car following model	MinGap (m)	2.5 m	0.5	1	1.5	2	Morando et al., 2018
	Acceleration rate (m/s ²)	2.6 m/s ²	1.47	1.28	1.09	0.9	Bae et al., 2019
	Deceleration rate (m/s ²)	4.5 m/s ²	2	1.63	1.27	0.9	
	Emergency deceleration rate (m/s ²)	9 m/s ²	7.5				Krajzewicz et al., 2012
	Other parameters	Krauss					Krauß, 1998
Boarding duration (second per rider)		N/A	3.5 s	4 seconds			Jara-Díaz and Tirachini, 2013

Jara-Díaz and Tirachini's (2013) model showed that the average boarding and alighting time is 3.3 seconds per passenger using a contactless card (or 4 seconds using the magnetic strip) when only the front door is used for boarding and both doors are used for alighting. Currently tested automated shuttles have one door for both boarding and alighting (Francis, 2021), but the door is often wider than that of mid-sized bus. Here 3.5 seconds (considering 0.5-second simulation timestep) is used for the average boarding and alighting time, although there could be variations due to the vehicle design and payment method.

3.2.4 Scenario Design

This chapter tests a base case scenario that has riders' demand varying from 100 riders per hour to 900 riders per hour. Background flow is set to 1260 vphpl, without SAV parking bays at the stop or traffic signals. In terms of the travel demand, the simulated average trip distance is 2.37 miles with a standard deviation of 1.40 miles. Based on the demand and capacity, the headway of SAVs is set for each level of demand such that the total demand can be met considering the total available seats of dispatched SAVs, the average assumed load factor of SAVs, and the average trip length, recognizing riders' potential waiting time at the stops. Table 3-2 gives an example of SAV dispatching headway settings assuming that SAVs are always full (load factor = 1). If one seat can potentially serve 2 person-trips on average along the 6.5-mile corridor, a 2-minute headway of 5-seat SAVs (i.e., 30 SAVs per hour) is required to meet the demand, which equals the number of SAVs $\times$ vehicle size $\times$ load factor $\times$ trips = $30 \times 5 \times 1 \times 2 = 300$ riders per hour. A high load factor indicates a low SAV dispatching frequency. For the base case scenario, a load factor of 0.7 for all types of SAVs is assumed, while a sensitivity analysis of load factor variations is conducted later. Many headway settings here are less than 5 minutes (especially for small size vehicles), which is uncommonly seen, but this simulation mimics a transit corridor that is often shared by more than one bus route and thus a more frequent service.

Table 3-2. Example of SAV headway (min) settings with 100% load factor assumption

SAV Capacity Demand (per hour)	5 seats	10 seats	20 seats	40 seats
100 per hour	6 min	12	24	48
200	3 min	6	12	24
300	2 min	4	8	16

Other than the base case scenario, a few scenarios have been designed for comparison, as shown in Table 3-3. These scenarios include varying the background flow (varying from 0.5 to 0.8 vehicles per second by Poisson distribution), adding station bay and traffic signals, changing the SAV dispatching headways (via various assumed load factors), and different VOTTs. Since VOTT is considered for both background travelers as well as SAV riders, background travelers'

value of driving time is assumed, with SAV riders' value of walking, riding, and waiting time changing accordingly. Using background flow aims to test how the SAV fleet and the system perform under different congestion conditions led by the background vehicles. This could reflect the optimal SAV size when the corridor is under different levels of service. Load factor scenarios are used to investigate operators' decisions in the SAV dispatching frequency to serve various demand levels considering the total system cost. The station bay scenario can present the case when there is a potential to obtain the right of way for SAVs parking at stations without interrupting the background flow. Last, the traffic signal scenario will show the case when the background flow cannot flow freely, which is more likely to happen in a real transit corridor.

Table 3-3. Tested SAV-based transit scenarios

		Background flow (vphpl)	Load factor	Traffic signals?	Station bays?
Base case		1260 vphpl	0.7 person-miles per seat-mile	-	-
Sensitivity analysis	Background flow	900, 1080, 1260, 1440	0.7	-	-
	Station bay	1260	0.7	-	✓
	Traffic signal	1260	0.7	✓	-
	Load factor	1260	0.5, 0.6, 0.7, 0.8	-	-

For the station bay scenario, the simulation sets up an extra lane for SAVs to stop only, to mimic the case when there is a parking bay at the station for SAVs. Capacity at the station bay is unlimited (or large enough to hold many SAVs, because of the extra lane), but the SAVs follow the principle of first-come first-leave. For the traffic signal scenario, a 90-second cycle is assumed, with 3 seconds of yellow time and 10 seconds of red time. The signal locations are set every 1/8 miles, which is about 2 signals per station. Since this transit corridor focuses on the investigations about SAV size and frequency under different travel demands, the locations of traffic lights and the signal timing are arbitrary. Optimization techniques could be involved in a

real-world application. VOTT scenarios are used for the total system travel time analysis, so the simulation results (e.g., vehicle waiting time, riders travel time) are consistent with the base case scenario.

3.2.5 Evaluation Metrics

The average background vehicle travel speed, average rider waiting time, total vehicle travel time, total rider travel time, and total system cost per capita will be evaluated for each scenario. The background vehicle travel speed can evaluate how congested the traffic is, while the average person waiting time shows the efficiency of the transit system. The total travel times of background vehicles and SAVs can show the overall system performance, and the total system cost per capita will evaluate the cost to serve travel demand under different types of vehicles and levels of service. The total system cost per capita considers the travel time cost and operating cost of SAVs and background vehicles. Table 3-4 shows the detailed components of the total system cost calculation. When riding in an SAV, riders are assumed to perceive a VOTT that is half that of driving a human-driven vehicle. However, when they are walking to and from SAV stop locations or waiting for an SAV to arrive, their VOTT is assumed to double that of a driver (Liu et al., 2017). The vehicle cost is calculated using a per-vehicle mile basis. The per-mile cost is adapted from (Bösch et al., 2018), which considered both fixed cost and variable cost for different sizes of SAVs on a per vehicle-mile basis. The total system cost is further transformed to cost per capita, by assuming an average occupancy of 1.2 in background vehicles.

Table 3-4. Total system cost components of SAV-based transit (VOTT = \$15/hr)

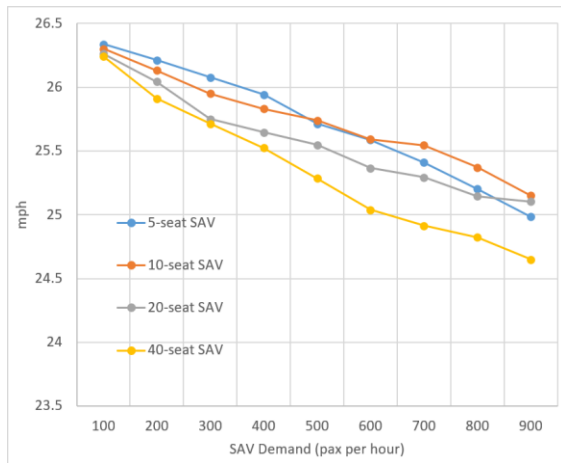
Cost category			Marginal use cost
Human cost	Driver	Background flow	VOTT * driving time
	Rider	Walk	2 * VOTT * travel time
		Ride	$\frac{1}{2}$ * VOTT * travel time
		Wait	2 * VOTT * travel time
Vehicle cost	SAV5		0.25 per mile
	SAV10		0.36 per mile
	SAV20		0.42 per mile
	SAV40		1.24 per mile
	Background flow		0.6 per mile

Note: These cost assumptions are adapted from Bösch et al. (2018).

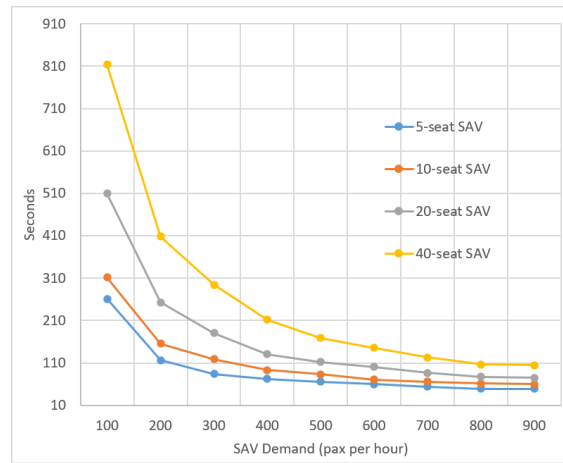
3.3 SAV-BASED TRANSIT APPLICATION AND RESULTS

3.3.1 Base Case, SAV Station Bay, and Traffic Signal Scenarios

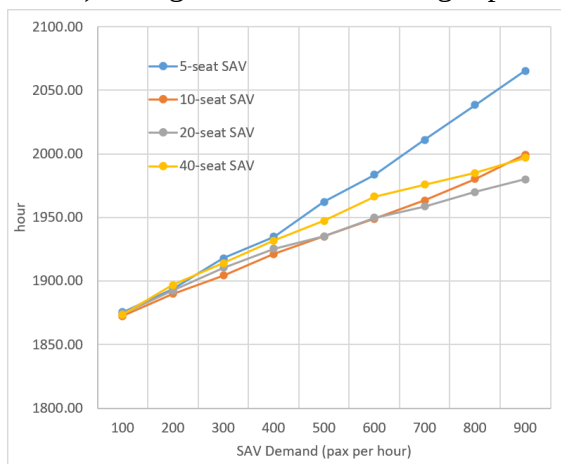
In this section, the analyses of three scenarios are presented: the base case scenario, adding SAV station bays, and adding traffic signals. Each scenario performed five runs and the average value is shown in the results. Figure 3-3 shows the results of the base case scenario. About 7,450 personal vehicles pass through the transit corridor during the 3-hr simulation time, with the number of dispatched SAVs varying from 5 to 386, depending on the demand level and SAV size.



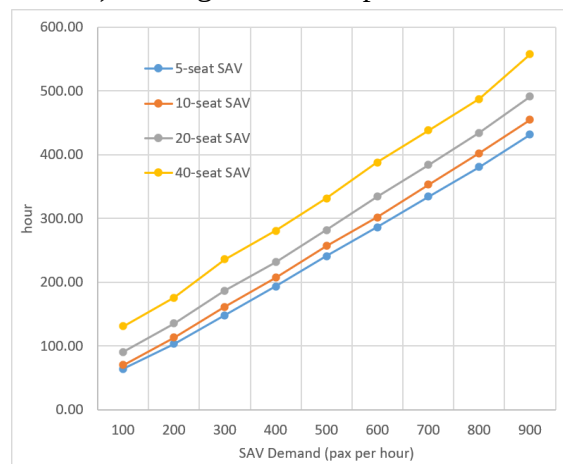
a) Background vehicle average speed



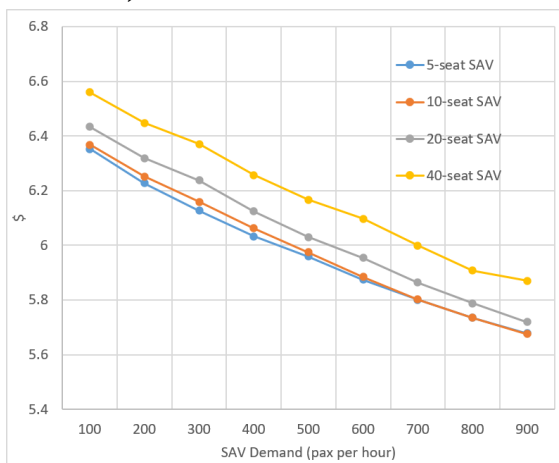
b) Average wait time per SAV rider



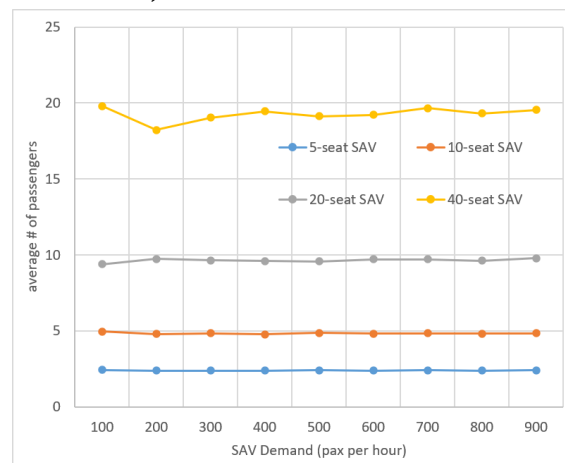
c) Total vehicle travel time



d) Total rider travel time



e) Total system cost per capita



f) Average vehicle occupancy

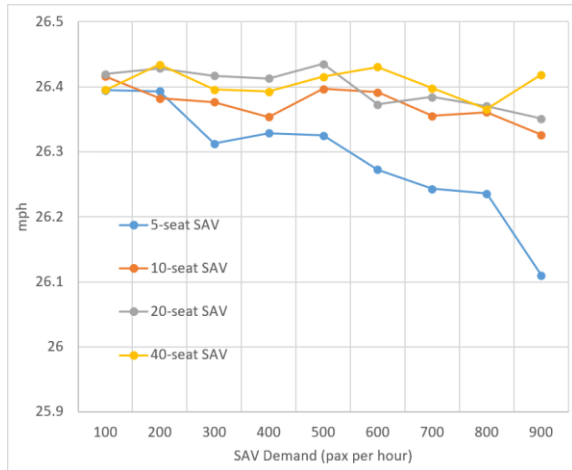
Figure 3-3. Base case scenario of SAV-based transit

Figure 3-3a presents the relationship between different levels of demand and the average background vehicle travel speed for all vehicle sizes. At a very low demand level (i.e., 100 persons/hr), vehicle size hardly affects the average speed of background vehicles, because vehicles stop less frequently. However, the speed of the average background vehicles decreases with increasing passenger demand for all demand levels. More frequent stops are witnessed at higher demand levels, to accommodate greater passenger demand, thus affecting the background traffic. 40-seat SAVs are outperformed by other sizes of SAVs because these large-size vehicles accelerate and decelerate slower and are more likely to dwell frequently at stops to serve riders, while small-size vehicles are more likely to skip stops due to full capacity. Interestingly, the downward trend of decreasing background flow speed in the 5-seat SAV scenario is more prominent than vehicles of other sizes, and the background vehicle speed is lower than 10-seat SAVs when demand is greater than 500 persons/hr and further lower than 20-seat SAVs when demand is greater than 900 persons/hr. This is due to more dispatched SAVs in the corridor which causes congestion from SAVs driving instead of dwelling at the stops.

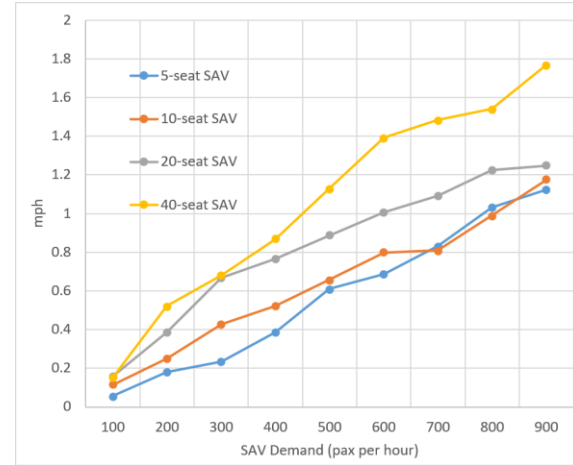
Figure 3-3b shows an expected result: SAVs with more frequent service reduce persons/passenger waiting times at all passenger demand levels. Average waiting time discrepancies between different SAV sizes shrink under a higher demand level due to a higher frequency of all types of vehicles and a large demand base. However, the scale does not change. For example, 40-seat SAVs result in an average passenger wait time 3 times longer than 5-seat SAVs across all demand levels.

Total vehicle travel time and total rider travel time (walk + wait + ride) are shown in Figure 3-3c and Figure 3-3d, respectively. Total vehicle travel time increases with the travel demand (Figure 3-3c), especially for 5-seat SAVs, mainly because there are more vehicles dispatched into the corridor to serve riders that further obstruct more background vehicles for a longer time. High demand levels witness a clear trend, where the increasing trend of 5-seat SAVs and 10-seat SAVs keeps going up but the trend of 20-seat SAVs and 40-seat SAVs tends to flatten out. Of course, more rider demand also leads to more total rider time (Figure 3-3d), but small-size SAVs (with small headways) tend to decrease wait time, and thus their riders experience less journey time across all demand levels.

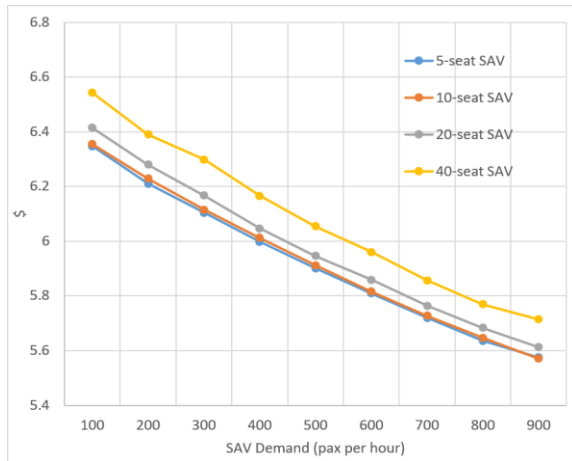
While using smaller SAVs reduces passenger waiting time, it can increase total vehicle travel time and riders' total journey time at high demand levels. Regarding this, the smallest size of SAVs is not necessarily the preferred vehicle size, and thus the total system cost per capita is evaluated. Figure 3-3e illustrates the result of total system cost per capita where all sizes of SAVs enjoy the scale of economy, as seen from the decreasing trend. The 40-seat SAVs and 20-seat SAVs are outperformed by smaller SAVs at all demand levels, respectively. Compared to the 40-seat SAVs, using smaller SAVs would reduce the system cost by up to 4.0%. While the 5-seat SAVs have lower total costs with a demand of 700 persons/hr or less, the 10-seat SAVs have lower total costs with a demand of 700 persons/hr or more. The trend indicates that there is a chance for 20-seat SAVs to be the optimal vehicle size at a higher demand level, but one would not expect it to happen in many middle- or large-size cities. To differentiate the revealed load factor (or simulated load factor) of the SAVs, the ratio of person-miles to seat-miles is expressed as the avo. Figure 3-3f shows such metrics for each vehicle type, which turns out to be stable (about half of vehicle space filled up on average) across vehicle sizes. The reason could be the assumption of SAV dispatching frequency, which is a fixed relationship with vehicle size and passenger demand, as illustrated in Table 3-2. With less dispatch frequency, the AVO is likely to increase, but the riders will wait longer at the stops. This will be further analyzed in sensitivity tests.



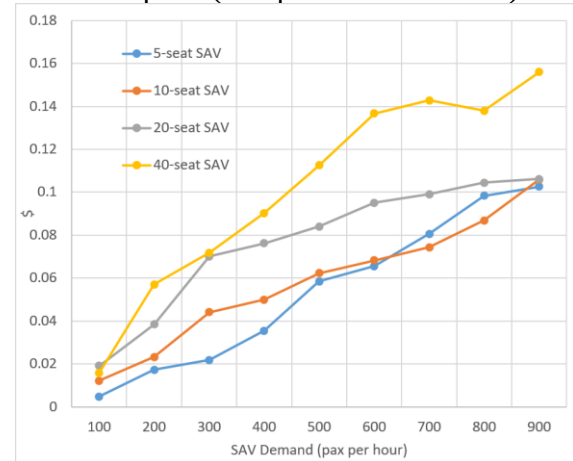
a) Background vehicle average speed



b) Increase of background vehicle average speed (compared to base case)



c) Total system cost per capita



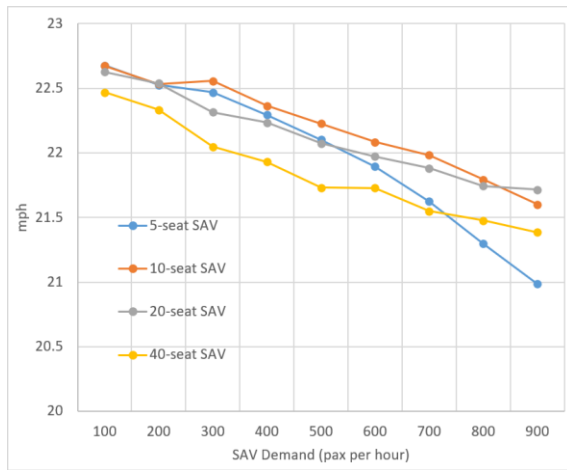
d) Total system cost saving per capita (compared to the base case)

Figure 3-4. SAV station with bay scenario

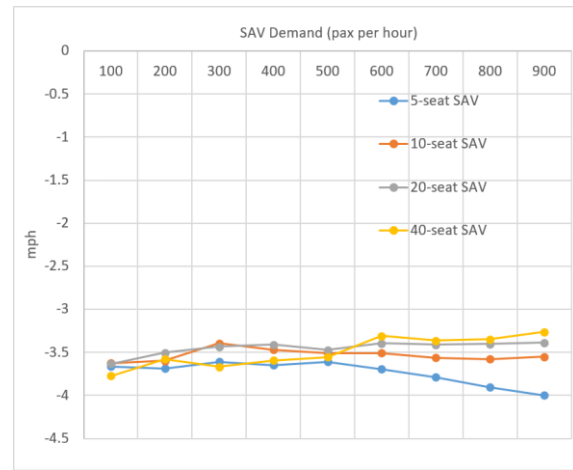
Figure 3-4 summarizes the results of the SAV station bay scenario, showing the new patterns of the average speed of background vehicles and the total cost per capita, as well as their responding changes from the base case scenario. As the stops are now in bays, the impact of SAVs on background traffic becomes negligible, especially for large-size SAVs, as shown in Figure 3-4a. This result aligns with the real-world cases of human-driven vehicles, e.g., Arasan and Koshy (2005), and Zhang et al. (2018). Although there is little difference in average travel speed for various demand levels, 5-seat SAVs still show a decreasing trend for a large demand due to frequent bay entries or exits. Compared with the base case scenario (Figure 3-4b),

provision of bays has more benefits for large-size SAVs across all demand levels, making them competitive to small vehicles in terms of the corridor's average speed. However, 40-seat SAVs are still outperformed by smaller sizes of SAVs, for all demand situations, due to the high cost of large-size SAV operations. Both 5-seat and 10-seat SAVs tend to be more cost-efficient under different levels of travel demand. Using smaller-size SAVs instead of 40-seat SAVs can reduce the system cost by up to 3.2%, which is consistent with the base case scenario, although the benefit shrinks by 0.8% due to the use of bays. This is because the bays mitigate the situation where SAVs previously obstructed the following vehicles and such benefits become more prominent when the riding demand is large (i.e., more stops at the stations). This can also be observed from the total system cost saving per capita (Figure 3-4d), where the small-size SAVs gain slightly more benefits across all demand levels, but more benefits are gained under cases of large demand and large-size SAVs. It is worth noting that the provision of bays also adds construction costs and potentially right-of-way-acquisition costs. For actual applications, site-specific details and a more comprehensive cost-benefit analysis will be needed, before sizing and scheduling SAV transit, recognizing factors like more cross-traffic and/or pedestrians at certain intersections, and higher SAV ridership – with longer boarding times and oncoming traffic.

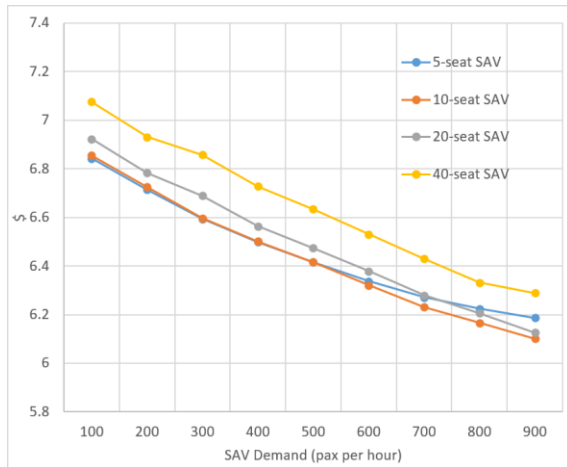
Results of the traffic signal scenario are presented in Figure 3-5. Figure 3-5a and Figure 3-5b show that the average speed of background vehicles is substantially lower compared to the base case scenario due to the delay at traffic signals, dropping by about 3.5 miles/hr on average. The general trend of the average background vehicle speed remains the same across all vehicle sizes, but drops more rapidly in the 5-seat SAV scenario. When passenger demand increases from 100 persons/hr to 900 persons/hr, using 5-seat SAVs decreases the average background vehicle speed by nearly 12%. Due to congestion caused by more 5-seat SAVs dispatched to the corridor and thus more delays caused by the traffic signals, the average background vehicle speed for the 5-seat SAV scenario is lower than the 40-seat SAV scenario when demand is greater than 800 persons/hr.



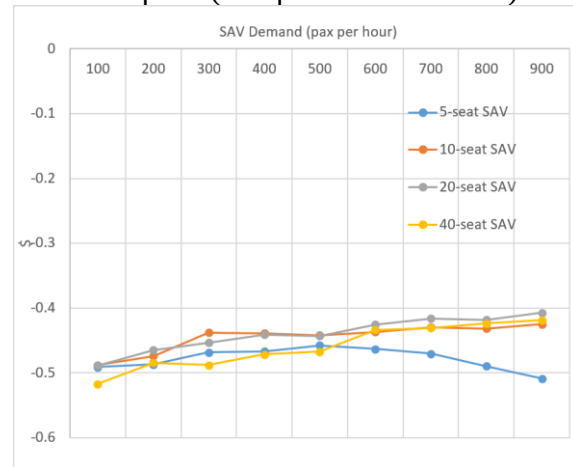
a) Background vehicle average speed



b) Increase of background vehicle average speed (compared to base case)



c) Total system cost per capita



d) Total system cost saving per capita (compared to base case)

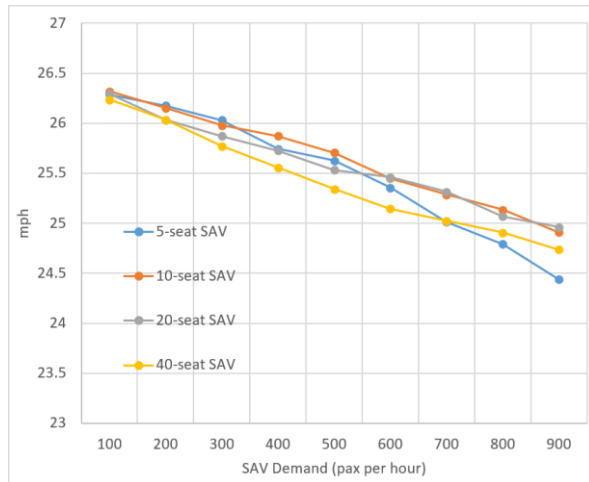
Figure 3-5. Traffic signal scenario

The heavy external cost by traffic signals for 5-seat vehicles can also be observed in Figure 3-3d, where the total system cost per capita is greater than that of 20-seat SAVs and starts to flatten out when the demand is greater than 800 persons/hr. Such impacts can also be observed in Figure 3-5d, as the 5-seat SAVs do not enjoy the scale of economy at high demand, compared to the base case. The general downward trend of total system cost per capita for SAV sizes remains similar, and the 40-seat SAVs still have the highest cost across all demand levels. The best vehicle choice, however, is different from the base case scenario. 5-seat SAVs are only

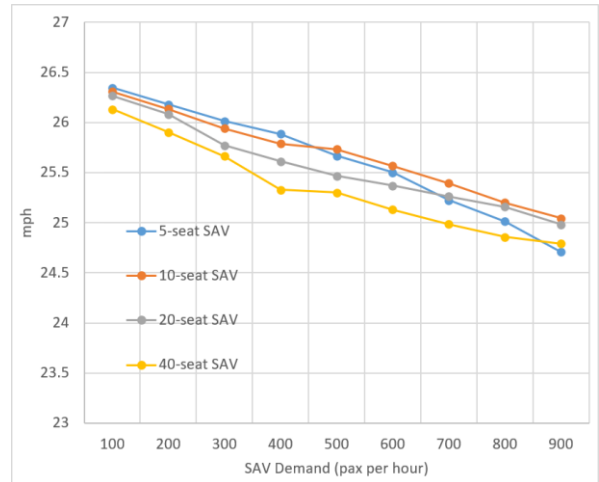
preferred when demand is lower than 300 persons/hr, while the 10-seat SAVs are favored when demand is greater.

3.3.2 Sensitivity Tests on Service Frequency and Background Flow

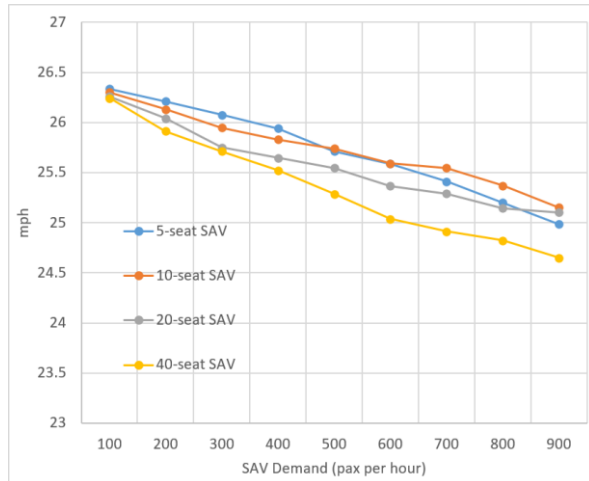
Figure 3-6 to Figure 3-8 demonstrates the effects of SAV headways (via changing assumed load factors) on the base case scenario, by showing changes in background vehicle average speed, total system cost per capita, and average wait time per SAV rider. The average speed of the corridor remains relatively stable across travel demand levels when varying SAV dispatching frequency (Figure 3-6), although the preferred vehicle size changes. Small-size SAVs offer faster speeds when the vehicles are dispatched less frequently, due to less congestion brought by fewer vehicles and fewer obstructions to background vehicles when dwelling at the stops. Although a more frequent service will lead to higher vehicle operating costs, the total system cost per capita decreases slightly for each vehicle size, due to less wait time at the stops for riders (Figure 3-7 and Figure 3-8). 5-seat SAVs are cost-efficient across all demand levels when the SAVs are dispatched infrequently (assuming load factor = 0.8), while 10-seat SAVs are favored at high demand (greater than 400 persons/hr) when service is frequent (assuming load factor = 0.5). However, 40-seat SAVs are still outperformed at all demand levels in terms of the total system cost per capita. The AVO of the SAVs is stable when varying vehicle sizes but increases with less frequent service, from loading 34% (assuming load factor = 0.5) to 55% (assuming load factor = 0.8).



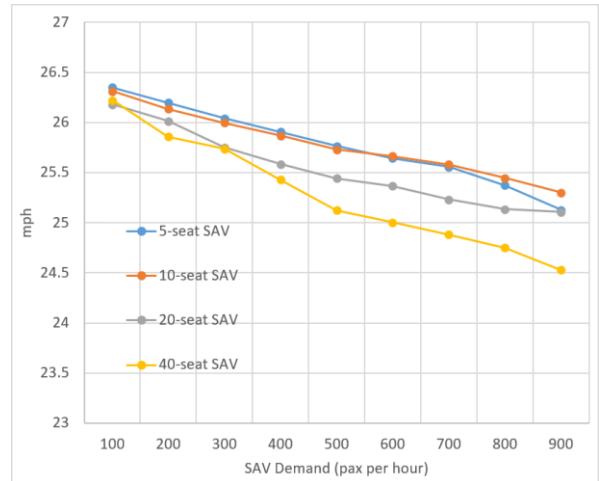
Load factor = 0.5



Load factor = 0.6

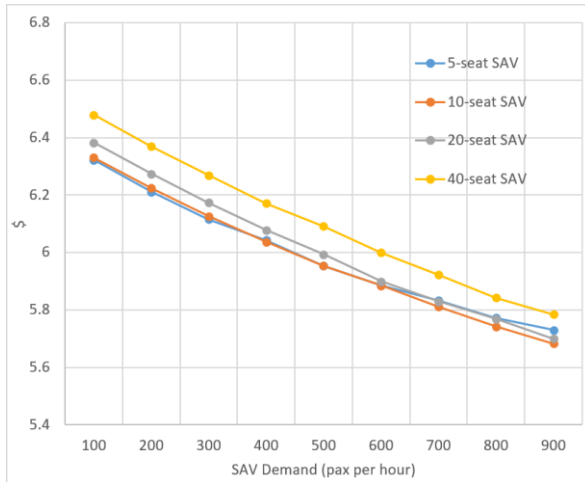


Load factor = 0.7

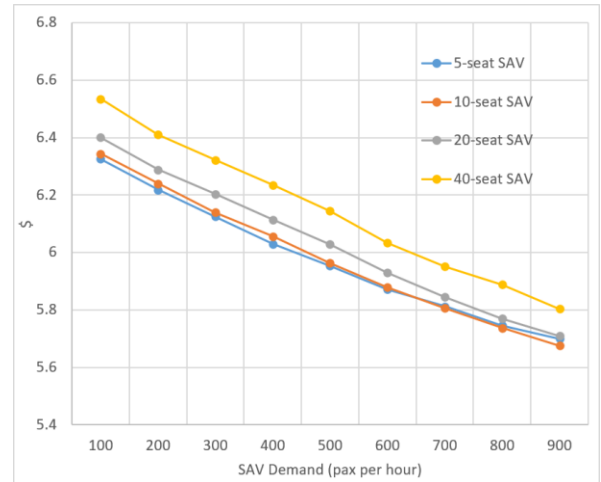


Load factor = 0.8

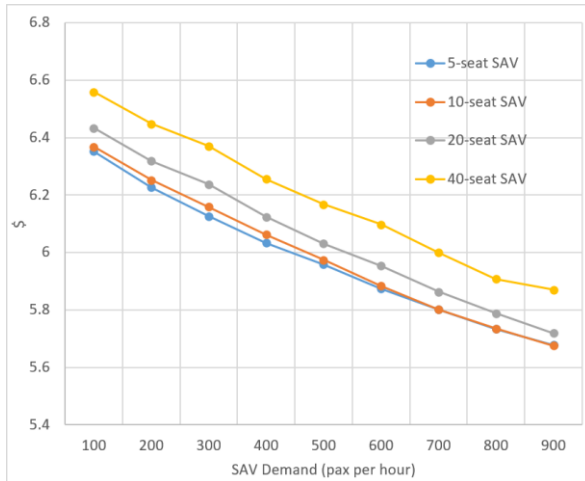
Figure 3-6. Background vehicle average speed (mph) with load factor variations



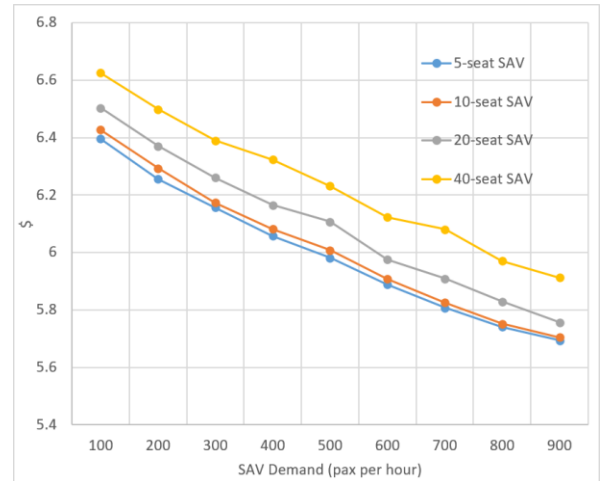
Load factor = 0.5



Load factor = 0.6

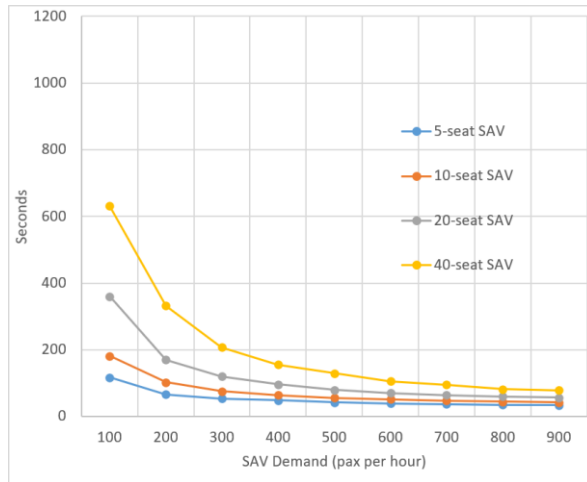


Load factor = 0.7

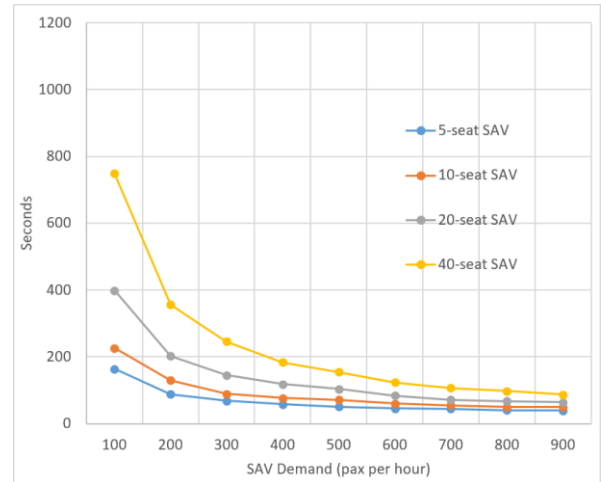


Load factor = 0.8

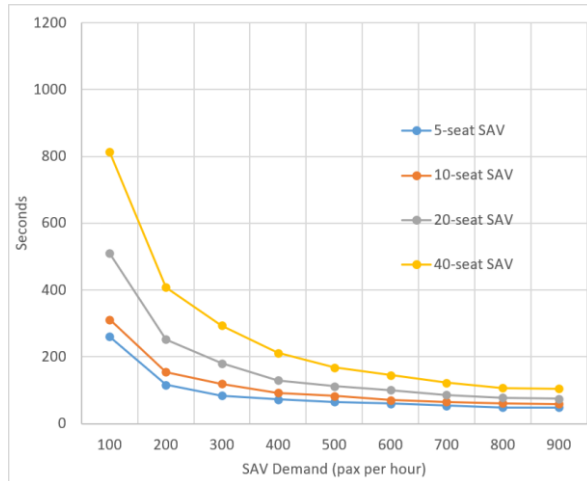
Figure 3-7. Total system cost per capita with load factor variations



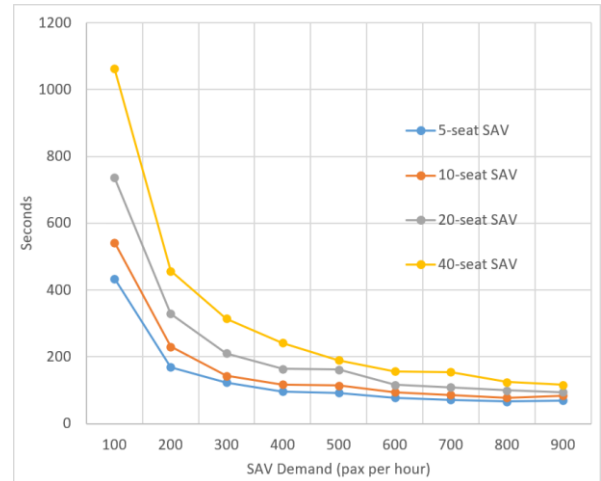
Load factor = 0.5



Load factor = 0.6



Load factor = 0.7

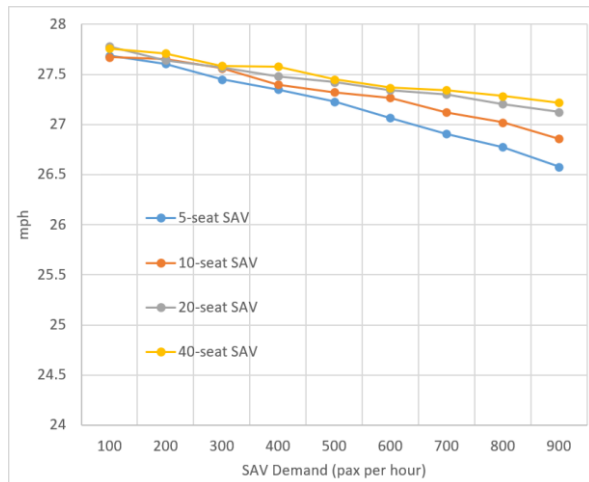


Load factor = 0.8

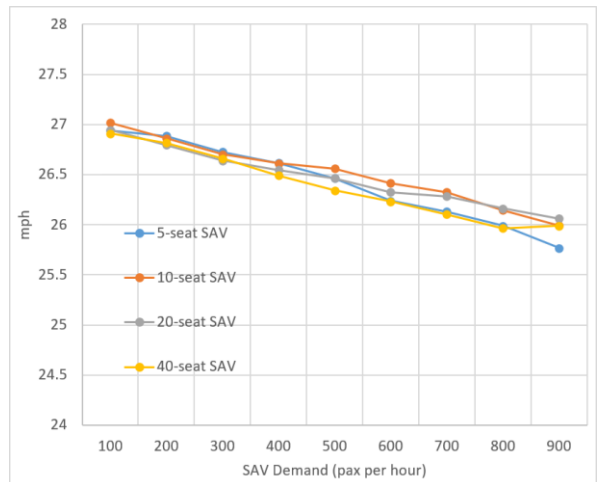
Figure 3-8. Average wait time per SAV rider (second) with load factor variations

Different background flow rates were also tested for the base case scenario. Figure 3-9 and Figure 3-10 show the background vehicle travel speed and total system cost with background flow rates of 900, 1080, 1260 (base case scenario), and 1440 vphpl. Of course, a high rate of background flow would lead to a more congested corridor. When increasing the background flow from 900 vphpl to 1440 vphpl, average background flow speed for the 5-seat SAV scenario drops by up to 8.0% (at high demand level = 900 persons/hr) and average background flow speed for the 40-seat SAV scenario drops by up to 11.4% (at high demand level = 900 persons/hr). When the background flow is low, the corridor enjoys a higher speed provided by large-size

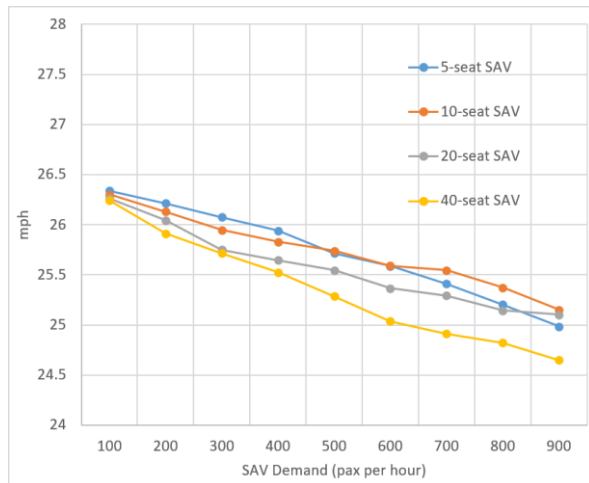
vehicles, because there are few of them to obstruct the background flow. For example, 40-seat SAVs obstruct background flows the least, at 900 vphpl, across all demand levels. However, the nimble small-size SAVs show benefits as the corridor becomes congested. At the background flow rate of 1440 vphpl, 5-seat SAVs provide the least obstruction under passenger demand less than 500 persons/hr and 10-seat SAVs enable faster speeds for higher demand levels, while 40-seat SAVs lead to the lowest speed across all levels of demand. In terms of the total system cost per capita by different levels of demand, the decreasing trend of cost per capita in sensitivity scenarios follows that of the base case scenario with 40-seat SAVs still being the least cost-efficient. Generally, 5-seat and 10-seat SAVs perform relatively well at total system cost per capita, with 5-seat SAVs performing slightly better at lower demand levels and 10-seat SAVs better at high demand levels. Of course, the congestion caused by a higher rate of background flow would lead to an increase in the total system cost per capita. Such an increment for all sizes of SAVs is small at low travel demand levels (about a 3.5% increase) compared to that at high travel demand levels (about a 9.5% increase). These results suggest that large-size SAVs provide slightly better corridor average speed under low background traffic, but small-size SAVs (e.g., 5-seat and 10-seat SAVs) would be more cost-efficient at all congestion and demand levels.



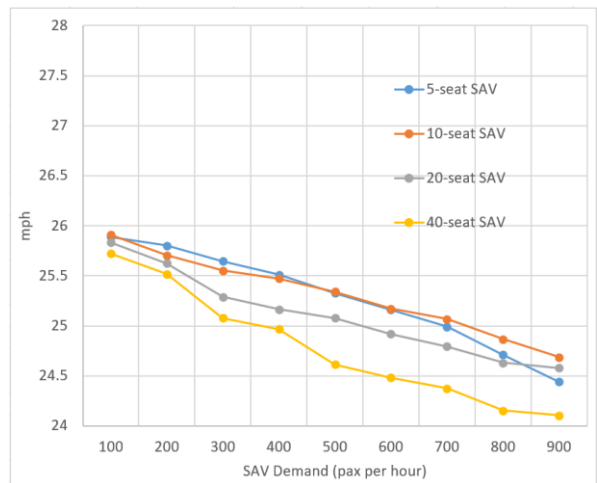
Background flow = 900 vphpl



Background flow = 1080 vphpl

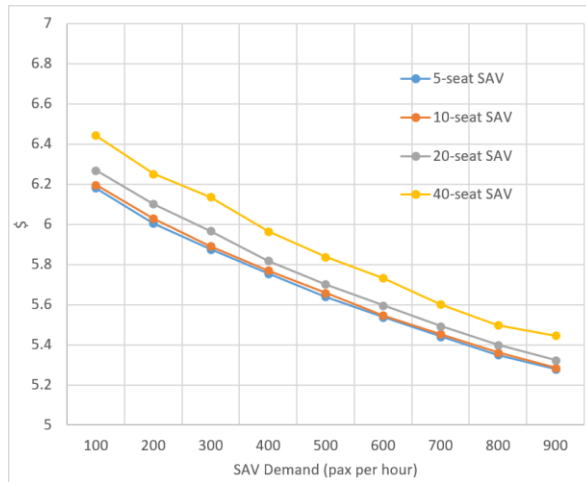


Background flow = 1260 vphpl

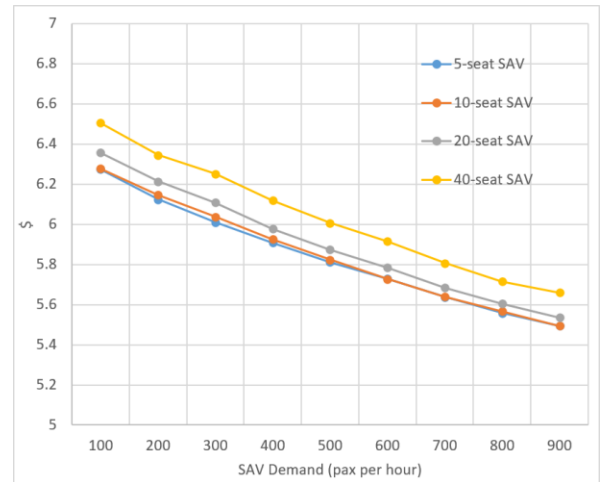


Background flow = 1440 vphpl

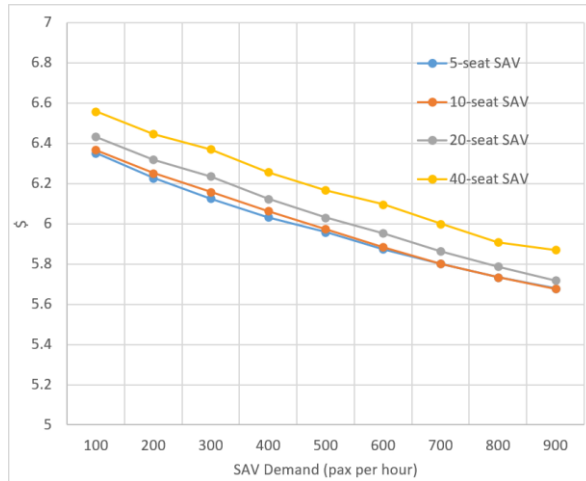
Figure 3-9. Background vehicle average speed (mph) with background vehicle flow rate variations



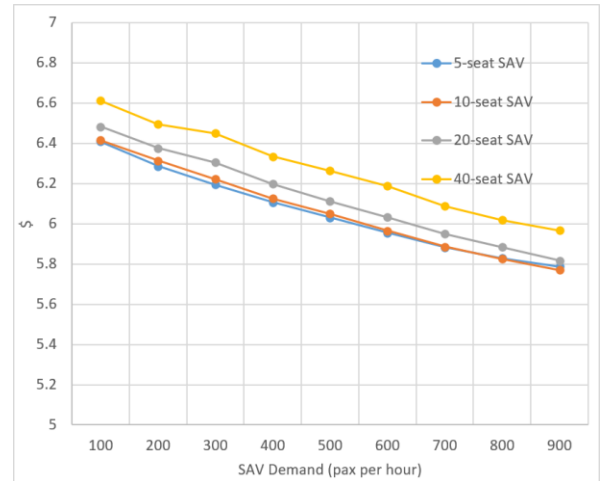
Background flow = 900 vphpl



Background flow = 1080 vphpl



Background flow = 1260 vphpl



Background flow = 1440 vphpl

Figure 3-10. Total system cost per capita with background vehicle flow rate variations

3.4 DISCUSSION

3.4.1 From Human-Driven to Fully Automated

At present, conventional vans have been used to provide mobility in confined regions like college campuses, military bases, airports, or business parks, where the SAVs are more likely to be in the early stages of implementation. Of course, SAVs can provide safety and cost benefits compared to vans, as SAVs have better control while eliminating the need to hire a driver. However, the benefits of SAVs are also expected in the case of serving a busy transit corridor, where 40-seat conventional buses are still dominating currently. This is because 40-seat buses, which require a smaller fleet size compared to using small-size vehicles, allow the fleet operator to efficiently (both in time and cost) manage the drivers (along with their schedule) and the bus fleet, in terms of routing and parking. As an emerging technology, SAVs provide the opportunity of a flexible design of vehicle size as shown in various global tests that are currently being conducted (Stocker and Shaheen, 2017), while the fleet manager does not have to worry about the cost and time burden of driver and vehicle assignment and relocation. One driver is usually assigned to one or two bus lines he/she is familiar with, but SAVs are capable and flexible when switching to other lines. To perform complex interactions with humans and other vehicles, such an SAV service would require a mature automation technology with a high initial cost, but the cost savings would be substantial due to SAVs' efficient routing and repositioning without drivers. Although conventional bus transit scenarios, usually with larger vehicles, are not simulated in this study, their system costs and passenger waiting times would be higher than the 40-seat SAV scenarios, due to SAVs' reduced driver cost, increased safety, and less emission from smooth acceleration and deceleration. Thus, replacing conventional bus transit vehicles with SAVs of smaller sizes would offer greater reductions in costs.

3.4.2 Insights for Real-World Applications

Different scenarios have been tested on the impacts of demand, vehicle size, traffic signals, station bays, load factor, and background vehicle flow rate, but results may still change in practice due to the other assumptions made about the corridor. Changing the speed limit may

not change the pattern of preferred SAV size, but riders' cost per PMT will increase or decrease with the speed limit change, due to the travel time change traversing the whole corridor. However, a higher speed limit means that SAVs may need a longer stopping distance, or brake early, leading to longer queues at the stops and thus causing more delay along the corridor. The spacing between stops may be adjusted in the real world, based on different land-use patterns. Moreover, a stop location can be a far-side stop (after buses proceeding through the intersection), near-side stop (before the intersection), or midblock stop (in between intersections, usually in a well-defined area), and choices should also be adjusted based on the road geometry and the real traffic volume, to minimize conflicts with turning vehicles and reduce intersection clearance time (Delaware Valley Regional Planning Commission, 2012).

Although the bus station bay and traffic signal scenarios have been tested, the real impacts of background vehicles entering and exiting the corridors are not considered. The background vehicle in the real world may not enter and exit at either end of the corridor, instead entering or exiting at any point along the corridor. This causes more delays in the corridor, the impact of which may even be worse than SAVs dwelling at the stops. Such delay cost from background vehicles as well as their potential parking cost may largely increase the real system cost along the corridor. A different arrival rate of passenger demand may be witnessed in the real world, instead of the passengers being uniformly distributed along the corridor. The arrival rate may change based on different times of day, as the system will serve more travel demand during the morning and afternoon peak hours. Land use patterns will also impact the passengers' arrival distribution at the stops, as a stop near a commercial area or a transfer stop may attract more demand. Change in land use pattern is more outstanding when considering a corridor that is 6.5 miles long, which is likely to go through the urban core and end at suburban areas in some small-size cities. More boardings and alightings will be observed at the urban core, leading to more delays at the SAV stops, especially during peak hours when the corridor may already be congested. On the contrary, the suburban areas will bear less travel demand and the vehicle will be less utilized (i.e., low AVO). Moreover, a real-world transit corridor can be longer than 6.5 miles with different transit lines often sharing the same corridor segments. This brings more variations to the analysis due to more complex interactions among the transit vehicles and

passengers, such as transfers between transit or other multimodal travel methods (e.g., park-and-ride or bike-and-ride).

3.4.3 Planning and Policy Implications

Simulation results illustrate the total-cost benefits of smaller SAVs (i.e., 5-seat or 10-seat SAVs), to serve as public transit vehicles along existing lines or in new locations. Such high-frequency, smaller-vehicle transit-type systems can better serve travel demands in many markets while reducing the heavy footprint of motorized modes (by encouraging more shared rides). Travel demand, from both existing transit users and the new users who enjoy the comfort and the low cost of the new SAV transit service must be considered when planning new SAV transit lines. Signals should be involved in the decision of the service frequency, since the use of signals decreases the corridor's average speed and causes more delays to the whole corridor in addition to the delays caused by SAVs dwelling at stops. Bays can mitigate the negative effect of SAVs blocking one lane when dwelling and can be more effective at minimizing such an effect under the existence of traffic signals. However, since acquiring the right of way is usually expensive, bus bays should be constructed wisely at different locations of the corridor.

Based on a variety of designed SAV sizes, there is a possibility that smaller SAVs can expand transit service areas to places where large-size bus lines could not previously reach (due to low AVO, and thus poor profits). SAVs can run longer transit lines, overlapping existing line segments that large-size buses use where the demand is high. This could function similarly to current subway systems across the globe, where an extra fleet provides more frequent service at the urban core area of a transit line (He et al., 2016). SAVs can help reduce the long access and egress times of many riders, especially those who live near the ends of the lines. Moreover, smaller SAVs may also provide an option for riders who enjoy a more comfortable space (i.e., 4-seat SAV) to rest or work, rather than sharing a bus with 30 or more riders. A higher fare may be priced for riders who want to take small SAVs, but fares can be low when services are first introduced to incentivize riders to use such a public transit service.

With the benefit of eliminating driver costs and SAVs' ability to self-relocate, transit operators may own a larger fleet, due to the use of new transit lines and potential service with mixed-size SAV fleets. A larger parking depot may be desired for such a large fleet, but the

SAVs are also expected to look for proper social parking sites by themselves so that they can utilize vacant overnight parking spaces. As the world is migrating to vehicle electrification, SAEVs are also expected to drive themselves to charging stations throughout the day, by navigating to available stations. It is also worth noting that as the case of fixed-route SAV service is investigated in this chapter, the demand is still expected to be relatively high and dense around the stops. When the demand pattern is sparse, the on-demand service is potentially more efficient (Chow et al., 2020).

3.4.4 Limitations

Some limitations of the microsimulation in this chapter exist. Here, the relationship between headway and demand is assumed to be fixed, based on the assumed load factor of SAVs. Optimization techniques could be utilized to find the best headway as well as vehicle size for the most cost-efficient system, but these techniques would not be easy to integrate. On the other hand, considering the complex behavior of buses waiting for approaching riders and skipping stops when the seats are full is much easier to integrate. Furthermore, it remains uncertain whether future 40-seat SAVs would be able to provide standing areas, in which case the capacity of the vehicle would be more than 40 riders. This study assumes that the capacity of a 40-seat SAV is 40 riders, but 40-seat SAVs have the potential to be favored by operators if standing is allowed on board. Moreover, the results are only averaged over five random runs, due to the computation burden. The trends are generally clear, but increasing the number of runs can help reduce the variations in the data points.

In this microsimulation, background traffic is also simulated with typical driving behaviors. Future research could explore the impacts of SAV-based transit when background traffic is also partly or fully automated by considering different AV penetration rates. For a high-frequency bus corridor, platooning of SAV-based transit vehicles should also be considered, particularly when the flow of small-size SAVs would be high. Future work may also examine the impacts of SAVs' vehicle size on the system's energy consumption.

3.5 SUMMARY

This chapter investigates the performance of an SAV-based bus transit corridor, where different sizes of SAVs replace conventional bus transit vehicles. SUMO is leveraged to simulate microscopic interactions between SAVs and background traffic and between SAVs and transit passengers under various background traffic conditions, SAV sizes and associated characteristics, passenger demand levels, and loading factors. Different configurations of the 6.5-mile bus transit corridor are considered, including a non-signalized corridor, signalized corridor, and corridor with SAV stops in bays. Detailed bus behaviors are also incorporated, including waiting for approaching riders, and skipping stops when the vehicle capacity is reached.

Simulation results show that the use of smaller, but more frequent SAVs leads to reductions in passenger waiting times but increases in total vehicle travel times. More frequent services of smaller SAVs, in general, do not significantly affect background traffic given their shorter dwell times at stops, as seen from the fastest speed provided by 5-seat SAVs for passenger demand under 400 persons/hr, and by 10-seat SAVs for demand higher than 400 persons/hr in the base case scenario.

Results highlight that the systems with 5-seat or 10-seat SAVs have lower total system cost per capita than those with 20-seat or 40-seat SAVs, consistently across most scenarios. While the system with 5-seat SAVs has relatively low total system cost per capita at low passenger demand levels, 10-seat SAVs are favored at higher demand levels. Whether 5-seat or 10-seat SAVs are the most cost-efficient for a certain level of demand is based on the background flow rate and how frequently the SAVs are dispatched to the corridor. Higher background flow and more frequent service would make 10-seat SAVs more appealing, mainly due to efficient vehicle space and fewer vehicles obstructing the traffic compared to 5-seat SAVs. However, 40-seat SAVs are outperformed in total system cost per capita by other vehicle sizes across all scenarios. Compared to the 40-seat SAVs, using smaller SAVs would reduce the system cost per capita by up to 4.0% while improving transit passengers' experience with reduced waiting times.

Provision of bays helps large-size SAVs offer a higher corridor speed, due to fewer SAVs dispatched in the corridor, but the high operating cost allows them to be outperformed by smaller

sizes of SAVs in terms of total system cost per capita. The use of traffic signals substantially lowers the corridor speed, especially for 5-seat SAVs at high passenger demand, making 10-seat SAVs the best choice for most of the demand levels. Results also suggest that the smallest SAVs are not always the optimum solutions; right-sized SAVs and associated frequencies should be considered based on passenger demand, network configuration, and loading factors.

Chapter 4. Quantifying Impacts of Shared Automated Vehicles Serving First-Mile Last-Mile Rail-Transit Connections

4.1 OVERVIEW

SAVs present an attractive solution for FMLM connections to transit. While functioning similar to a ride-sharing mode, SAVs offer advantages in the form of i) Reduced cost to operators (as no drivers are needed), and the cost savings are compounded if the SAVs are electric; ii) Reduced out-of-pocket cost to riders (as a direct consequence of cost savings to operators); iii) Greater control over the fleet as ride-hailing companies can govern the movement of vehicles from a central dispatch system, and iv) Greater availability as SAVs will not need downtime. SAVs can ‘pool’ passengers to share all or a part of their trips in serving as an access and/or egress mode to train stations, which can be big bus depots, ferry stations, airports, or other kinds of stations. Compared with other access and egress modes, SAVs offer faster speeds (compared to walking), greater convenience (than carrying a bike on a transit system), and can be more cost/energy efficient than existing manually driven ride-hail vehicles (Chen et al., 2016).

Several ongoing tests around the world (Stocker and Shaheen, 2019) have indicated an initial low-speed geofenced deployment of SAVs. Researchers at the National Renewable Energy Laboratory (NREL) also coined the term Automated Mobility Districts (AMDs) to define geofenced deployments of SAVs to realize relatively near-term benefits of this emerging technology (Hou et al., 2017). Building on this idea, this chapter investigates the potential of implementing SAV fleets as a FMLM service in a geofenced area to complement public transit. Using SUMO toolkit, a FMLM simulation framework has been established, which incorporates full feedback iterations of a mode choice model and real-time person and vehicle simulation. The mode splits, fleet performance, and other system features are examined by microsimulating two fleets of SAVs providing FMLM ride-sharing service to 10% of central Austin’s trip-makers near five light-rail transit stations.

The following section discusses the data used for the simulation. 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. The application section discusses how the

SAV FMLM service can impact the travel pattern around the central Austin network. The final section provides some concluding marks.

4.2 DATA ASSEMBLY

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

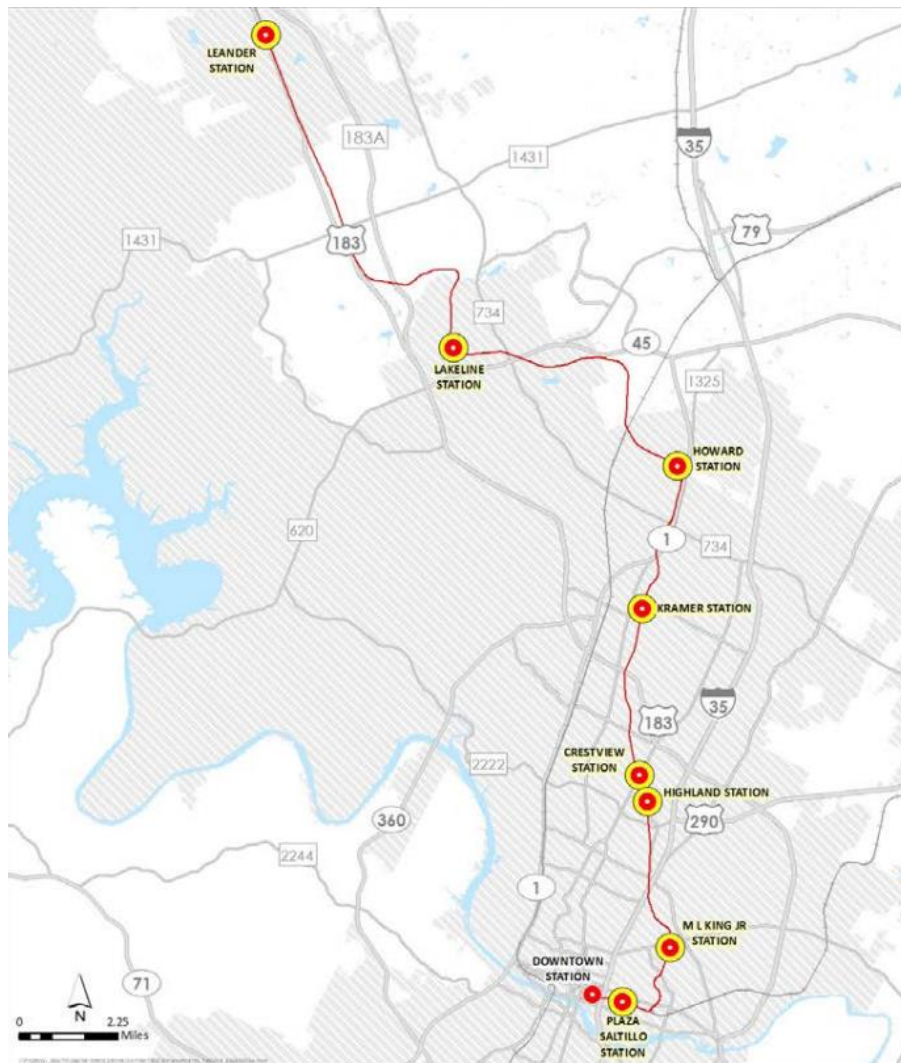


Figure 4-1: Current Red Line transit in Austin

Capital Metro's Metro Rail Red Line Corridor provides a 32-mile commuter rail service that has connected downtown Austin and Leander City in Texas since 2010 (Figure 4-1). 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).

4.2.1 Austin Network

The year 2030 is considered for scenario runs in this analysis, with travel demand across a 3-mile $\times$ 6-mile square region in central Austin, and with a more frequent transit service between Crestview station and downtown Austin. Figure 4-2a shows the network obtained from OSM and Figure 4-2c illustrates the network in SUMO, which contains 11,025 nodes and 25,919 links. The geographical extent of the study area is limited to five stations of the Red Line. Segments of Interstate-35 and Mopac freeway 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 is not capable of simulating bidirectional 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 to access the rail train. Similar modeling is used to represent pick-ups of SAV-and-ride users.

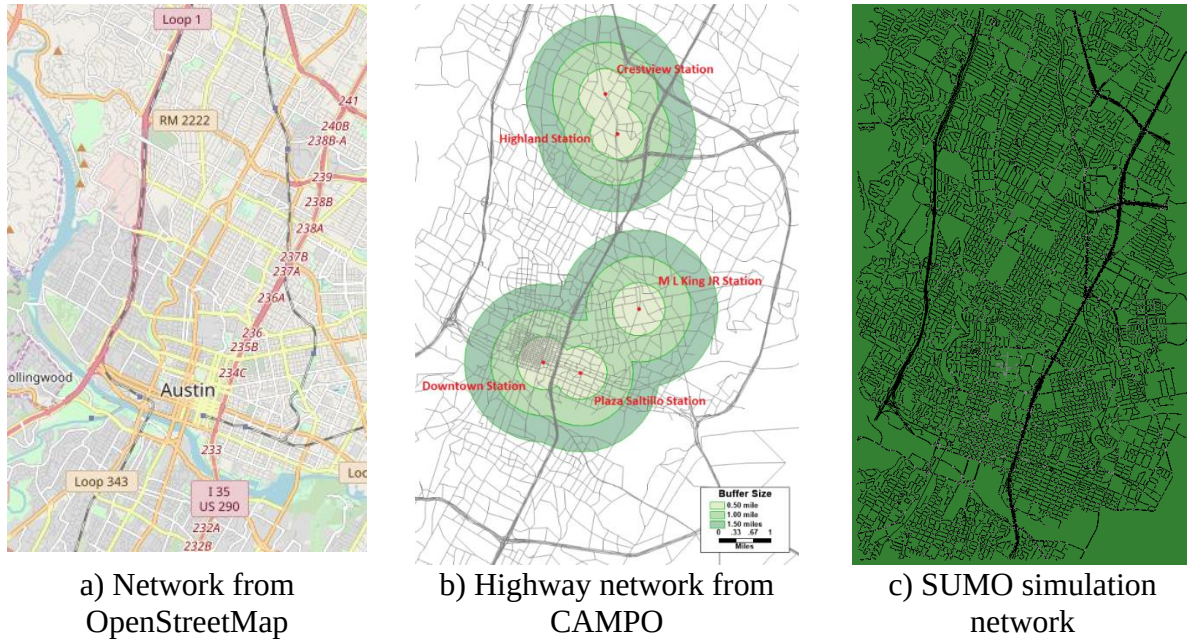


Figure 4-2: Network and automated mobility district boundary

AMDs are usually identified neighborhoods or districts with high trip densities, such as a university campus, central business district, or a military base (Hou et al., 2017). In this study, a buffer from a station is considered as the operational extent of the SAVs. Buffer size is limited to 1.5 miles to avoid excessive overlap between AMDs. In that case, the areas of five rail stations with buffers become two AMDs, as shown in Figure 4-2b. Each AMD has an SAV fleet that provides on-demand FMLM connections to transit trips in the corresponding AMD network. The first AMD contains two stations: Crestview Station and Highland Station, while the second AMD contains three stations: MLK Station, Plaza Saltillo Station, and Downtown Station. Furthermore, 0.25 to 0.5 miles is often seen as the walking distance to transit stations (Nabors et al., 2008), so the maximum buffer for accessing and egressing from stations by walking is set as 0.5 miles (0.5-mile radius, as shown in Figure 4-2b)).

4.2.2 CAMPO Travel Demand

Travel demand used in this study reflects the demand forecasted for the year 2030 by the CAMPO regional travel demand model. The CAMPO model has 2,252 TAZs covering Austin's six-county region. Travel demand between origin-destination (OD) pairs from 246 zones was

extracted from the CAMPO model for this study. Since the network was obtained from OSM, a many-to-one association was established between the OSM links and the CAMPO TAZ boundaries. Based on CAMPO's OD (origin-destination) trip table, every trip was reformatted into an edge-based OD table where the origin edge and destination edge were randomly selected from links associated with the corresponding TAZs. The morning peak period (6-9 am) was used as the simulation horizon. Departure times from each TAZ were randomized using a normal distribution across the simulation time horizon. There were 40,771 trips generated across the 246 TAZ regions during the morning peak period from 6 a.m. to 9 a.m. In this exercise, mode choice was conducted on the whole morning peak demand set, while a 10% sample (4,077 trips) was simulated to reflect a certain level of congestion and avoid excessive microsimulation run times.

4.3 AUTOMATED MOBILITY DISTRICT TOOLKIT

4.3.1 Simulation Framework

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 microsimulations of multimodal vehicles considering the effects of traffic signals, vehicle routes, and driving behavior models such as car-following and lane-changing. 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 a ride-sharing mechanism for on-demand services. SUMO can generate second-by-second vehicle and passenger trajectories, which help in computing performance metrics (like wait times and idle times) for vehicle and traveler movements. Developed by the German Aerospace Center, SUMO has been used in numerous transportation research studies over the past decade. Among examples relevant to this study, Friedrich (2015) used SUMO to analyze the traffic impacts of AVs. Alazzawi et al. (2018) simulated SAVs as an on-demand mode using SUMO for a case study in Milan, Italy, and reported that an SAV penetration of 50% or more can reduce congestion in the study area.

TraCI (Traffic Control Interface) is an application programming interface tool in SUMO that allows to retrieve values of simulated objects and to manipulate their behavior “on-line”

(Krajzewicz et al., 2012). 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 (pickup and drop-off). 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 a fixed route (Zhu et al., 2018). Simulations in this chapter build on previous efforts by Zhu et al. (2018) by incorporating interactions between pedestrians, SAVs, and transit, and by implementing SAVs as a FMLM connection to a larger transit line.

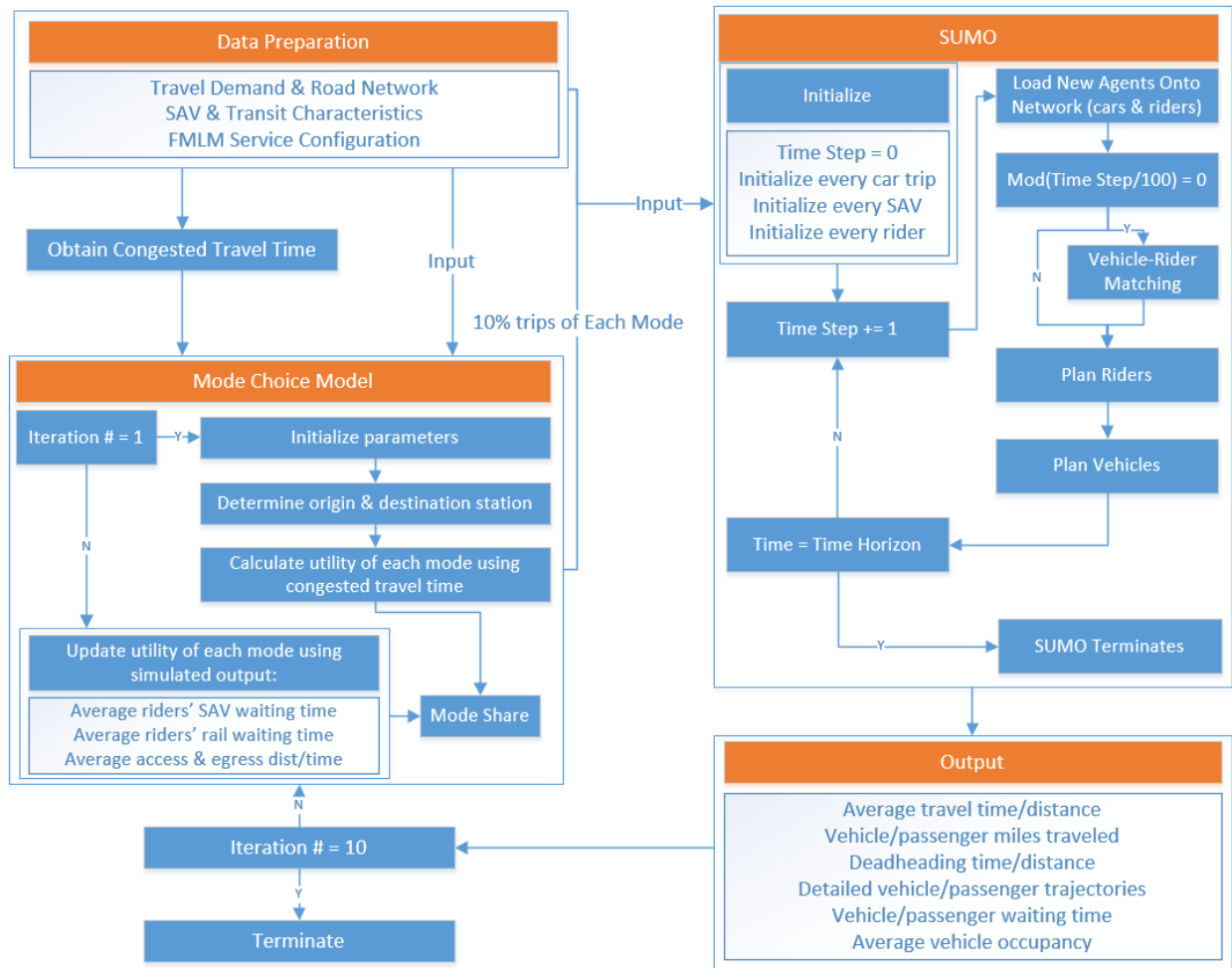


Figure 4-3. New simulation framework design of AMD toolkit

Figure 4-3 shows the details of the whole simulation with feedbacks on waiting time and transit's access and egress travel time. The SUMO simulation routine started with data

preparation and by reading travel demand, road network data, and configurations of FMLM service. Demand data includes trips (derived from the OD trip table as described above) along with departure time. Network data are comprised of all the roadway links, transit lines, curbs, and platforms. Transit was coded as a high-capacity commuter rail running from Crestview Station to downtown, and back to its origin. The commuter rail runs with a headway of 15 minutes and a stop time of 30 seconds at each station. SAVs have a capacity of three riders, an acceleration of 4.82 ft/s^2 , deceleration of 6.56 ft/s^2 , and an emergency deceleration of 24.61 ft/s^2 (Bae et al., 2019; Guo et al., 2020).

For this simulation study, travelers are given a choice spectrum comprising four modes: walking, private automobile (also referred to as car travel), walk-and-ride transit, and SAV-and-ride transit. Mode splits were determined based on mobility characteristics of each mode (like wait time and in-vehicle travel time). Before the first iteration, a complete iterative run assuming all travelers using car mode was conducted to estimate congested travel times. For the first iteration, routes for walk, car, and walk-and-ride modes were determined based on shortest paths measured using those congested travel times in SUMO, and the origin and destination station for transit mode (Walk-and-ride and SAV-and-ride) were calculated for the rest of the simulation. Since there is a feedback mechanism in the mode choice from one iteration to the next, simulated riders' waiting time for SAVs and trains and average access and egress time were then used to update the utility of each mode and thus the mode share for the next iteration. Although mode choice was estimated for all travelers, only 10% of those trips were randomly selected for SUMO simulation.

Vehicles and persons were simulated on a second-by-second basis. SUMO starts by setting the current time step as 0 and reading the trip information from mode choice, so it is aware of when to insert cars, walkers, and riders into the simulation. SAVs are initialized on roads at time 0 and wait for requests. 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 original location or the transit station). Every 100 seconds, SAVs 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 the transit station,

waiting at the origin transit station and taking transit to the destination station, walking out of the station and making another on-demand request, getting on and off an SAV, and walking to the final destination. For the analysis presented in this chapter, the mode of access and egress is assumed to be the same, meaning that walking from the origin location to the transit station, and taking an SAV at the 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 to 0.5 miles around the station, and SAV fleets serve only in the AMDs designated to them (i.e., SAVs designated to serve 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 helps in computing performance metrics for various modes used in the next iteration. Due to the computation complexity of the problem, the whole simulation terminates when the tenth iteration is achieved, to reach a small waiting time difference (less than 5%) between the last two iterations for all tested scenarios (including sensitivity analysis).

4.3.2 Mode Choice Model

Mode choice decisions are modeled at the trip level, using a nested logit model (Uncles et al., 1987). SUMO-generated network travel times and wait time information was used to calculate mode shares. The two-level nested logit model considered walk-and-ride and SAV-and-ride nested under transit mode, which was compared with walk and drive at the same level (shown in Figure 4-4). Parameters and their coefficients in the mode choice model are adapted from relevant literature (Chen and Kockelman, 2016; Liu et al., 2017) with some necessary adjustments and assumptions. The value of in-vehicle travel time (IVTT) for car mode is set as \$17.67 per hour, following Liu et al. (2017). The value of out-of-vehicle travel time (OVTT), comprising of wait and walk times, is assumed to be twice as much as the value of IVTT. The same value of OVTT 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 D2D connectivity. Therefore, it does not have wait nor walk time components. For

SAV-to-ride, the value of OVTT parameter consists of wait time (for an SAV at the origin), walking and waiting time for transit, as well as walking and waiting for an SAV at the transit station. The operating cost of private car (or light-duty vehicle) mode is assumed to be 60 cents per mile, whereas transit has a \$2 flat fee (Liu et al., 2017). The distance coefficient was obtained from Wen et al. (2018) and the alternative-specific constant for car mode utility was calibrated to be -10.3, to align with CAMPO's mode share estimates (Capital Area Metropolitan Planning Organization, 2010).

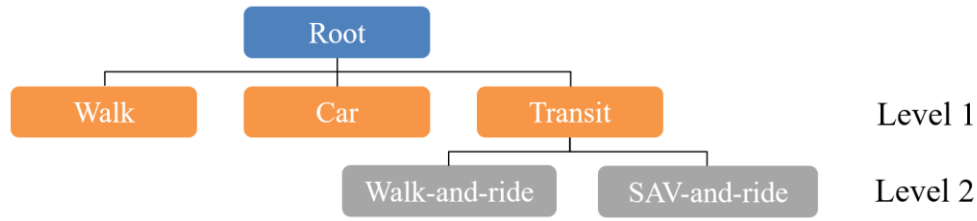


Figure 4-4. Two-level mode choice structure

Walking mode utility does not change after the first iteration, to assume an unchanged behavior and save computation time. Assuming a walking speed of 3.1 mph (Levine and Norenzayan, 1999), the utility of walking mode is:

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

where d_{walk} is the walking distance in miles and t_{walk} is the walking time in hours. Car mode uses driving distance and congested travel from the pre-run and the utility is:

$$V_{car} = -10.3 - 0.6 \times d_{driving} - 17.67 \times t_{driving}$$

The transit utility function calculation is a bit more involved compared to that of other modes. First, the transit stations closest to a trip's origin and destination locations must be identified by examining the shortest Euclidean distance. If the same station is the closest one to both the origin and the destination (i.e., in the case of short trips), transit mode is precluded from the choice set. Since an SAV operates within a designated AMD, the SAV-and-ride mode is not considered a feasible mode if the Euclidean distance from a trip's origin location to a transit station is greater than 1.5 miles (radius of an AMD). For walk-and-ride mode, if the Euclidean distance to the access- or egress-station is greater than 0.5 miles, the walk-and-ride mode is removed from the available mode set, since the distance threshold for walk mode is set at 0.5

miles (Nabors et al., 2008). The transit travel distance is computed as the railway distance between the platform centroid points of the boarding and alighting stations. The average speed of urban rail systems in the U.S. is observed ranging between 19 and 38 mph (Light Rail Progress, 2001). So, the maximum speed of transit mode is set to be 32 mph and is not affected by congestion on the roadway. The maximum vehicle speed of SAVs is set at 30 mph, because the running speed of current demonstrated automated shuttles lies between 15 mph and 30 mph (U.S. Department of Transportation, 2018).

The value of IVTT for both modes nested under transit is assumed to be half that of the personal cars (Liu et al., 2017). Walking time for accessing and egressing transit (i.e. $t_{access_{walk}}, t_{egress_{walk}}$) is calculated based on the network's shortest distance path for each person. For the first iteration, waiting time for rail ($t_{waiting}$) is assumed to be half of the transit headway, both for walk-and-ride and SAV-and-ride modes. For the iterations afterward, the wait time for rail is extracted from previous iterations and updated using the method of successive average (MSA). Using the superscript n for the index of iteration n , the average waiting time for rail can be expressed as:

$$t_{waiting}^{n+1} = \frac{n-1}{n} t_{waiting}^{n-1} + \frac{1}{n} t_{waiting}^n$$

After obtaining the locations of the origin and destination stations, the utility of walk-and-ride mode can be computed using:

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

Waiting time for SAVs for both first-mile and last-mile (i.e. $t_{FM-waiting_{SAV}}, t_{LM-waiting_{SAV}}$) is assumed to be 2.5 minutes in the first iteration but will be updated using MSA in the following iteration based on the simulated average waiting time.

First-mile SAV travel distance ($d_{FM_{SAV}}$) used in SAV-and-ride utility for each traveler is assumed to be the congested network travel distance from origin to station; however, it is computationally expensive to track and update the travel distance of each passenger for every iteration. This metric is calculated using congested network travel distance from origin to station for the first iteration ($d_{FM_{SAV}}^1$), but is approximated via expanding (or shrinking) the first-iteration distance by a factor K for the iteration afterward ($d_{FM_{SAV}}^n, n \geq 2$). The factor K is the

ratio of the modified simulated average first-mile distance ($D_{FM_{avg}}^n$) across all SAV-and-rider users to the average first-mile distance in the first iteration ($d_{FM_{avg}}$) across all SAV-and-ride users:

$$d_{FM_{SAV}}^{n+1} = d_{FM_{SAV}}^1 * \left(\frac{D_{FM_{avg}}^n}{d_{FM_{avg}}} \right)$$

where the modified simulated average first-mile distance index is calculated based on the simulated average first-mile travel distance ($d_{FM_{avg}}^n$) of the two most recent iterations, using MSA:

$$D_{FM_{avg}}^n = \frac{n-1}{n} d_{FM_{avg}}^{n-1} + \frac{1}{n} d_{FM_{avg}}^n \quad (n \geq 2)$$

Similar calculations are conducted to deal with last-mile SAV travel distance ($d_{LM_{SAV}}$), as well as first-mile and last-mile SAV travel time ($t_{FM_{SAV}}$ and $t_{LM_{SAV}}$). Assuming the operating cost of an SAV is \$1/mile (Liu et al., 2017), the utility of SAV-and-ride comes out to be:

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

The nesting coefficient for transit is set as 0.7 based on the mode choice component of the CAMPO travel demand model (Brinckerhoff, 2012); 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. Mode share changes when entering a new iteration based on the information from the previous iteration.

4.3.3 Real-time Simulation Control

The real-time simulation control primarily focuses on passenger and SAV movements for the transit riders choosing the 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 simulation controller can obtain and react to a riders' current status and location. SAV ride requests from passengers are evaluated every 100 seconds. Armed with information on 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 was implemented in the preliminary analysis.

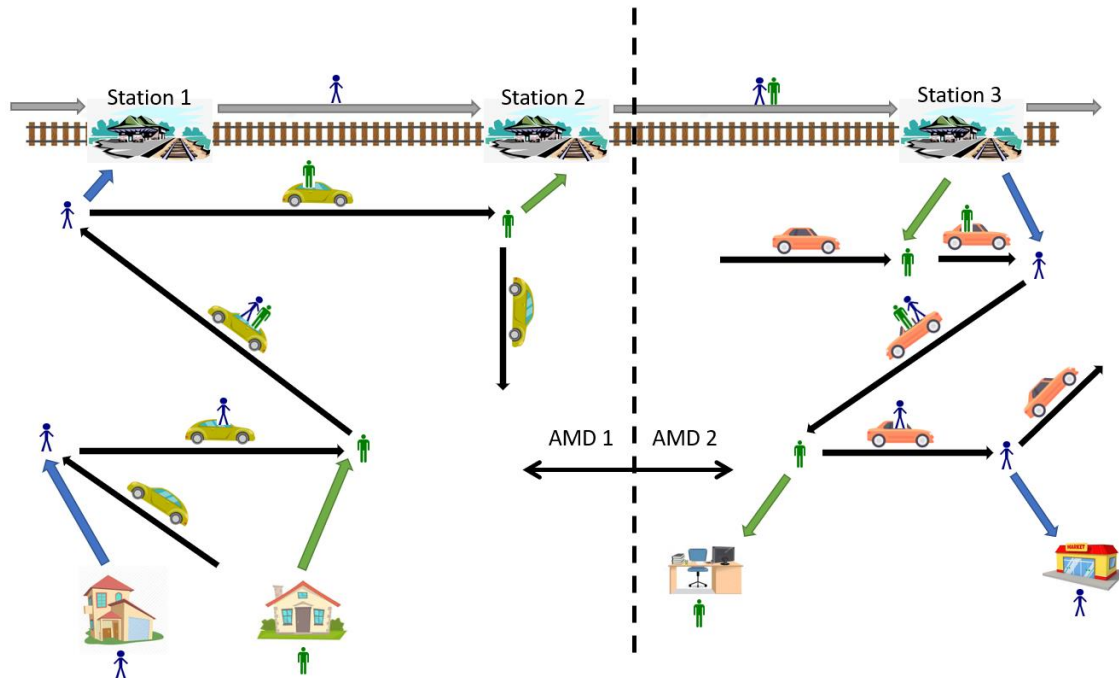


Figure 4-5. Example flow of two SAV-and-ride users and their SAV movement

From the rider perspective, Figure 4-5 gives an example of two SAV-and-ride users. Ben (marked in blue) chose to travel from home to work by taking transit from station 1 to station 3, and Jerry (marked in green) chose to travel from home to a shopping location, by taking transit from station 2 to station 3. First, Ben and Jerry both walked to the street where they can be picked up by an SAV. Since station 1 and station 2 are in AMD 1, a yellow SAV serving AMD 1 was assigned to pick up and drop off Ben and Jerry at their respective transit stops. The yellow SAV made an empty-vehicle trip to pick up Ben, and then proceeded along to pick up Jerry. The SAV then traveled to station 1 to drop off Ben (as he was picked up first and this was his selected origin station), and then dropped off Jerry at his selected origin station (#2). After dropping all the passengers off, the yellow SAV was relocated to a nearby location on the network where it can park itself and wait for the next trip request. Ben and Jerry walked to the station and waited for the train. Once the train arrived, Ben and Jerry boarded the train at their

respective stations and got off the train at station 3. Both Ben and Jerry walked out of the station to be picked up by an SAV. Since station 3 is in AMD 2, an orange SAV serving AMD 2 was then assigned to pick Ben and Jerry up. Following the same ride-sharing logic, Ben and Jerry walked to their destination locations after being dropped off by the SAV. The orange SAV was relocated in a similar fashion as described for the yellow SAV.

The various stages in SAV-and-ride operation are described in Table 4-1. The terms transit rider, user, and SAV-and-ride user are used interchangeably in the description.

Table 4-1. Person flow for naïve ride-sharing

Stage	Rider real-time control
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 the user will be picked up.
1	SAV-and-ride user arrives at the 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 100 second time bin).
2	SAV-and-ride user boards the vehicle and the SAV proceeds to pick up the next user assigned to it. If 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.
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.

Table 4-1. Person flow for naïve ride-sharing (cont.)

Stage	Rider real-time control
4	An SAV-and-ride user has been 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.
5	An SAV-and-ride user arrives at the origin station and waits (at a random point within the platform) 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.
6	Once the train arrives at the station, the rider will board the train.
7	The SAV-and-ride user is dropped off at the destination station and walks to the location where he/she will be picked up by an SAV.
8 - 10	These stages represent the SAV routing logic for the last mile, as described in Stages 1-3.
11	SAV-and-ride user is dropped off at the final destination edge.

The SAVs are controlled using the TraCI module in SUMO, constantly reacting to the status of the SAV-and-ride transit users. The maximum vehicle speed of SAVs is set at 45 mph, considering most automated shuttles currently being demonstrated see top speeds around 40 mph or so. Various stages in SAVs operations are described in Table 4-2:

Table 4-2. Vehicle control for naïve ride-sharing

Stage	SAV real-time control
0	Initialization. SAVs are placed at random locations in their designated AMDs.
1	Idling. Before receiving a request (evaluated every 100 seconds), SAVs are parked and wait for a trip request.
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. If the vehicles are all occupied by passengers, the remaining riders will not be served during this re-plan step. They will have the priority to be assigned an SAV at the next re-plan step (after 100 seconds). During the waiting process, riders are not able to shift travel mode, which has been defined before SUMO starts.
3	Redistribute. 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).

4.4 AUSTIN APPLICATION

4.4.1 Baseline Scenario Versus FMLM Scenario

For the Austin case study, the baseline scenario only considers walk, drive, and walk-and-ride modes as the modal alternatives. Transit is assumed to be running between Crestview Station and downtown Austin with a headway of 15 minutes in the baseline (as well as FMLM) scenario. FMLM scenarios are tested with each AMD served by a fleet of 15 SAVs, which has been tested to deliver a reasonable average waiting time (under 5 minutes) for SAVs. Table 4-3

shows the mode share results for the baseline scenario as well as FMLM scenarios. All scenarios run with 4,077 trips, which is 10% of the total morning peak travel demand for the defined region.

Table 4-3. Comparison results of the base case and FMLM service using SAVs

Scenarios	Mode share				AVO	Vehicle-miles traveled in thousands (10% of AM peak travel demand)			
	Car	SAV& Ride	Walk& Ride	Walk		Car	SAV	Empty	Total
Base	91.1%	0%	0.35%	8.52%	1.00	14.0	0	0	14.0
	37,153 trips	0	143	3,475					
FMLM	87.4%	3.71%	0.35%	8.53%	0.74	13.1	1.0	0.5	14.7
	35,639 trips	1,514	141	3,477					
	On-board time (min per person)		Wait time (min per person)		Walking time (min per person)		Travel distance (miles per person)		Total time (min per person)
	SAV*	Transit	SAV	Transit	SAV	Transit	SAV	Transit	
	7.0	14.4	6.8	7.6	3.8	3.8	2.04	1.93	

**Note: SAV column shows the sum of first-mile and last-mile distances/time traveled on one-way trips to final destinations.*

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 study simulated 10% of total demand, the analysis would capture 176 trips spread across all the 9 stations. Further assuming that these boarding trips are distributed uniformly across all stations, 78 daily transit trips would be captured in the five stations investigated in this chapter (among 9 stations that have been built currently), across the whole day. Therefore, 14 trips during the AM peak for walk-and-ride mode align reasonably well with the 2011 field observation. Further, the CAMPO model shows a walking mode share of 4% across Austin's 6-county region, while the baseline scenario

estimated a walking mode share of 8.5%, which is reasonable for central Austin, where walking is more likely to happen. The baseline scenario also provides a car mode share of 91.1%, which aligns well with CAMPO's 92.0% prediction.

The share of walk-and-ride, as well as walking, remains almost unchanged between the baseline scenario and the FMLM scenarios. The 0.5-mile constraint on walking to transit might be playing a part in keeping the mode share for walk-and-ride constant. For the FMLM scenario using 15 vehicles serving each AMD under a rail headway of 15 min, SAV-and-ride mode gains mode share from car, about 1,514 trips, which accounts for 3.71% of the total demand. The reasons for this could be cost- and time-effectiveness of SAV mode, compared with car mode. The use of transit increased from 0.35% to 4.06% when SAVs are introduced, which is an increase of more than 10 times. This is such a substantial increase so the Red Line station sizes or line capacity may not be able to handle such increases without significant investment and design changes. Since the access and egress mode is assumed to be the same, 30 SAVs (with 15 in each AMD) in this 10% morning peak travel demand scenario can serve 302 person-trips in total, about 10 person-trips served by each SAV during the 3-hour morning peak.

Although SAV modes gain mode share, the average occupancy of all vehicles dropped to 0.74 persons in the FMLM simulation, 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 48% of SAV VMT (and 3.4% of total VMT), which is in close alignment with deadhead miles quantified using real-world TNC data (Henao and Marshall, 2019). The naïve ride-matching and routing logic used for preliminary analysis may also be a reason for the SAV empty VMT observed here. Based on this logic, SAVs always pick up passengers in the order of their requests and drop them 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 6.4% (from 14,028 to 13,149), although using SAVs increases the total VMT by 5%. This could reduce congestion on the highway and increase travel speeds but could lead to increased congestion at local places around transit stations.

When rail trains come every 15 min and 15 SAVs serve in each AMD, the average total travel time per passenger for SAV-and-ride mode is 41.4 min, which consists of riders' travel

time on both SAVs and rail, wait time for SAVs and rail as well as the walking time from the edge outside the station to the railway platform and from the railway platform to the edge outside the station. The average waiting time for an SAV trip (either FM or LM) is 3.4 minutes, with 3.5 minutes of average onboard time. Although the maximum speed of the railway is 32 mph, the results show an average speed of 8.0 mph when riders are on board, because of the train frequently stopping and waiting at each station. A person's wait time for transit is close to half of the transit headway, which could be a uniform-distributed arrival at the train station.

4.4.2 Sensitivity Analysis

After exploring the impacts of implementing SAVs as a modal alternative to car and walk-and-ride modes, sensitivity analysis exercises (see Table 4-4) were carried out to understand the impact of fleet size and transit frequency on the performance of the SAV mode. The FMLM scenario presented above has a transit headway of 15 minutes and a 15-vehicle fleet in each of the two AMDs (30 vehicles total). Building on this, scenarios were developed to test the performance of the SAV-and-ride mode, based on transit frequencies of 5 min, 10 min, 15 min, and 20 min, and increasing the SAV fleet size in each AMD from 5 to 20 vehicles (in increments of 5 vehicles).

With a more frequent transit service, the SAV-and-ride mode took a larger mode share, up to 5.78%, about 225 trips (450 person-trips by SAVs) among 10% of the morning peak travel demand. This means the SAVs were utilized more when the transit service was frequent, as also shown in the increased AVO as well as more VMT by SAVs and fewer VMT by cars. Further, SAV onboard time, wait time, and average trip length per person also increased as the headway decreased, due to more shared rides, since SAVs would pick up and drop off more passengers in one routing plan, which led to longer wait times for the second and third passengers. Waiting time for transit saw a significant reduction when transit service frequency increased, as expected. However, the total time remained similar (about 45 minutes) among the four scenarios varying the railway headway, showing that people are more concerned with the total travel time when deciding the mode to use: if the transit service is frequent, they are more willing to wait longer for an SAV. Since only central Austin was simulated, the average transit distance per person showed a slightly increasing trend, possibly due to the people who are likely to take the SAV-

and-ride mode when the transit service is frequent despite the short transit distance. However, one may see a clear pattern when the simulation can be extended to Austin's six-county region. Walking time is also quite stable among the scenarios (within 4 minutes for summed walking time for FM and LM, and within 4 minutes from the SAV's drop-off edge to platform), with some fluctuations in transit wait time, owing to different lengths of the railway platforms.

A larger fleet size led to a higher mode share of SAV-and-ride, mostly because of the increased SAV service accessibility. The SAVs were utilized more under a large fleet size since a small fleet size was not enough to provide the desired level of service and people moved away from the SAV-and-ride mode. As expected, a larger fleet size would lead to more VMT by SAVs, while the empty VMT remained approximately 48% of all vehicle-miles driven by SAVs. A larger fleet size led to shorter wait times, but total travel times among fleet size scenarios were quite stable, meaning that fleet size would not affect the riders' D2D travel time too much. Smaller SAV fleet sizes are not enough to accommodate riders' requests and lead to a smaller mode share for SAVs serving the rail stations, along with shorter-distance rides, and longer wait times, on average.

Table 4-4. Sensitivity analysis of rail transit frequency and fleet size

Scenarios		Mode share				Average vehicle occupancy	1,000 VMT per day (10% of AM peak travel demand)			
		Car	SAV & Ride	Walk & Ride	Walk		Car	SAV	Empty	Total
Base		91.1%	0.00%	0.35%	8.52%	1.00	14.0	-	-	14.0
Headway (minutes between trains)	5	85.3%	5.78%	0.36%	8.51%	0.92	12.8	1.6	0.7	15.1
	10	86.6%	4.48%	0.36%	8.52%	0.83	13.1	1.2	0.5	14.9
	15	87.4%	3.71%	0.35%	8.53%	0.74	13.1	1.0	0.5	14.7
	20	88.9%	2.25%	0.33%	8.55%	0.69	13.3	0.6	0.3	14.2
Fleet size (#SAVs in each AMD)	5	90.2%	0.89%	0.35%	8.53%	0.43	13.1	0.3	0.2	13.6
	10	88.7%	2.42%	0.35%	8.53%	0.64	13.0	0.7	0.3	14.0
	15	87.4%	3.71%	0.35%	8.53%	0.74	13.1	1.0	0.5	14.7
	20	85.3%	5.86%	0.35%	8.53%	0.82	12.3	1.6	0.8	14.7
Scenarios		On-board time (minutes per person)		Wait time (minutes per person)		Walking time (minutes per person)		Travel distance (miles per person)		Total time (min per person)
		SAV*	Transit	SAV	Transit	SAV	Transit	SAV	Transit	
Headway (minutes between trains)	5	10.3	13.8	10.5	2.5	3.8	4.7	3.17	1.78	45.6
	10	8.9	13.7	9.2	5.1	3.8	5.3	2.80	1.95	46.0
	15	7.0	14.4	6.8	7.6	3.8	3.8	2.04	1.93	43.3
	20	6.5	14.2	6.5	10.0	3.7	3.8	1.99	2.02	44.7
Fleet size (#SAVs in each AMD)	5	5.5	15.1	7.3	7.0	4.0	4.3	1.46	2.39	43.3
	10	7.0	16.1	7.2	7.4	3.7	4.4	2.04	2.18	45.7
	15	7.0	14.4	6.8	7.6	3.8	3.8	2.04	1.93	43.3
	20	7.1	16.9	6.4	7.5	3.6	5.5	2.13	2.44	47.0

Note: Rail headway = 15 min for scenarios varying fleet size, fleet size = 15 SAVs per AMD for scenarios varying rail headway. SAV column shows the sum of first-mile and last-mile distances/time traveled on one-way trips to final destinations.

4.4.3 Discussion

Due to the computation burden of the microscopic simulation, this chapter only simulates 10% of central Austin's travel demand. If the simulation is expanded include to all morning peak demand, more SAVs are needed to serve Austin's rail-transit connections. Results can also be affected using larger-size SAVs (e.g., vans and minibuses), less demand-responsive routing of SAVs, and longer SAV-to-rider matching periods (e.g., 100 seconds used here rather than 1 second). Such shifts can create greater efficiencies but depend on the density of demand in time and space, and the willingness of travelers to call ahead or walk to pick-up points.

This chapter's use of SUMO for SAV and FMLM microsimulations can realistically reflect such behaviors, though computing times and scale of demonstration remain an issue. While some mesoscopic simulators are capable of simulating millions of distinct agents over a typical travel day (Gurumurthy et al., 2020), high-performance computers are required, and computation times are not short. For example, Chapter 6 integrates the SAV services in a large-scale network using meso-simulator POLARIS, which gains more insights into the whole picture but loses some of the passenger and vehicle details. For a look at FMLM behaviors around transit stations, including walk access details, transit facility geometries, and traffic impacts of idling SAVs (during curbside pickup and drop-offs, for example), the SUMO microsimulation used here is a good choice.

4.5 SUMMARY

Extending the concept of deploying SAVs in geofenced regions with a high trip density (labeled as an automated mobility district, or an AMD), this chapter explores the idea of using SAVs to provide 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 work is one of the first attempts to understand the scope of the impacts of adopting SAVs for FMLM connections using the microscopic simulation tool SUMO. This chapter not only models detailed transit operations (such as stopping duration, schedule, shared intersections by railway and roadway, and railway platforms 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 consumption, and performance metrics for the SAV mode (e.g., ride-sharing time, walking time, and waiting time). With rising interest in SAV technology as an urban mobility solution, AMD deployments may become common (with SAVs providing FMLM services to transit stations, on-demand).

This chapter uses SAV fleets around Austin's light-rail Red Line stations. 10% percent of the region's travel demand was evaluated and then microsimulated using the open-source SUMO tool, augmented with a nested-logit model for mode (and access-mode) choices. With SAVs serving FM or LM requests in their designated AMDs, an estimated 3.71% of current person-trip-making would shift from private-car modes to the SAV-and-ride mode, leading to a 10-times increase in the use of transit with stable walk-and-ride mode share. SAV use raises systemwide VMT slightly, while lowering AVO slightly, owing primarily to SAVs' empty-vehicle travel (between customers). Since FMLM trips to rail stations are very directed in the AM peak period, 48% of the SAVs' VMT was empty (no occupants), comprising 3.4% of total VMT in the 3 mi x 6 mi system. This calls for the development of deadhead minimization routines, to reduce empty VMT from SAVs and AVs. Using sensitivity testing across scenario settings, SAVs were utilized more when train service was more frequent. Lower train headways also lowered SAV onboard time, wait time, and average trip length. Mode choice in using SAVs for FMLM connections increased with more frequent transit service and larger fleet size, but total travel time served as the biggest determinant in trip-makers' mode choices. Average walking times were quite stable across scenarios, at most 4 min for both SAVs and transit. Total (door-to-door) travel times were also quite stable, across SAV fleet size scenarios.

While this chapter makes an initial attempt at simulating SAVs as an FMLM connection to transit, a few shortcomings remain. It was observed that the implemented naïve ride-matching and routing logic led to increased empty-vehicle travel in the system. Immediate efforts will focus on enhancing operational logic with features such as DRS and deadhead minimization. This is improved and discussed in more detail in Chapter 5. The mode choice model would be more realistic if the parameters were calibrated by collecting the data via a stated preference survey. Access- and egress-legs to transit were enforced to be the same in the simulation for

simplicity. This is also tackled in Chapter 5, as transit riders in all likelihood could take an SAV to access a transit station but walk to the final destination for the egress leg of the trip (or vice-versa). The results presented in this chapter consider 10% of the demand for the region of interest, owing to the computational complexity of the microsimulation. Solutions will be explored to simulate 100% of the AMD's travel demand using advanced computing resources.

Chapter 5. First-Mile Last-Mile Shared Automated Vehicle Service with Dynamic Ride-Sharing and Train Schedule Coordination

5.1 OVERVIEW

As discussed in Chapter 4, serving FMLM trips to access and egress public transit can be a good application for SAVs, in addition to providing D2D service. Using SAVs for FMLM connections has multipronged benefits including but not limited to: i) increased occupancy of shared modes, ii) increased transit ridership (and as a result, reduced congestion), as having faster access/egress modes might convert some car trips over to transit, and iii) reduced travel energy consumption due to higher vehicle occupancy (which can be amplified further if the SAVs are electric).

Recognizing the potential benefits of SAVs as an FMLM connection mode, Chapter 4 has investigated the impacts of an SAV FMLM service integrated with a light-rail transit system, by expanding the capabilities of the AMD modeling and simulation toolkit developed at NREL (Zhu et al., 2020). This chapter further enhances the SAV FMLM toolkit built in the last chapter, by 1) allowing for flexibility in choosing distinct access and egress modes. For example, an individual might choose to use SAVs as the first mile (FM) connection, and walking as the last mile (LM) connection. 2) enhancing the traditional DRS algorithm to allow en route rerouting for new pick-ups; 3) establishing coordination between a passenger's expected arrival at the train station and the train schedule; 4) expanding and simulating full SAV FMLM travel demand in a future year scenario; 5) adding SAVs' self-relocating behavior to parking depots. More detailed examinations are conducted at the person and vehicle level for the same network, in the 3- by 6-mile area of central Austin, around five stations along Austin's Red Line.

The rest of the chapter is organized as follows. The next section introduces the dataset used for simulating SAV FMLM connections to train stations. The methodology section details the simulation setup and explains the DRS mechanism. The results section presents a thorough analysis of the performance metrics of interest under scenarios with varying train headways, SAV fleet sizes, and seat capacities. The final section presents discussions and some concluding thoughts.

5.2 FIRST-MILE LAST-MILE TRAVEL DATASET

Since SAVs are not expected to foray into the market in the immediate future, travel demand forecasts from Austin’s 2030 CAMPO model run were used for this study. Light-rail transit trips were extracted and expanded from the whole travel demand set, using a nested logit mode choice model.

5.2.1 Mode Choice and Travel Demand

The mode choice model builds on Chapter 4, which considers walk to/from light-rail transit (walk-transit-walk) and SAV to/from transit (SAV-transit-SAV) nested under the transit mode, where the transit mode itself competes with car and walk modes. In this chapter, two additional transit modes, namely walk-transit-SAV and SAV-transit-walk, were added in the transit nest (Figure 5-1) to finalize the mode choice model. This chapter focuses on the simulation of light-rail transit and SAVs, so transit demand includes three types of travelers: FM travelers who use SAVs as their access mode but walk to their final destinations, LM travelers who walk to train stations but use SAVs as their egress mode, and FMLM travelers who use SAVs as their access and egress mode.

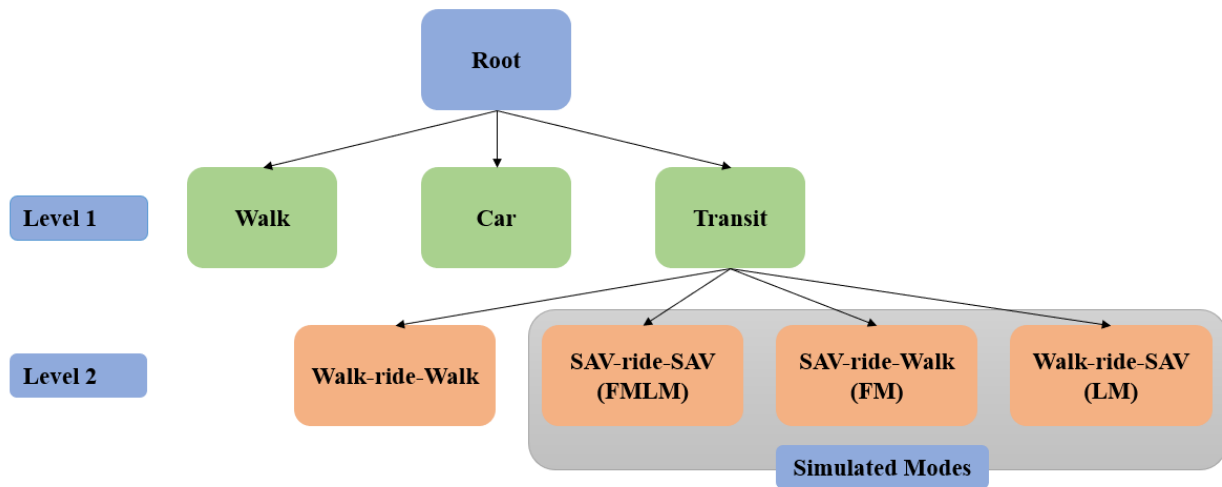


Figure 5-1. Two-level mode choice structure with flexible FMLM connecting modes

Parameters and their coefficients in the mode choice model are adapted from Chapter 4. Value of IVTT for car mode ($VOTT_{driving}$) is set as \$17.67 per hour, following Liu et al (2017).

Value of OVTT, comprised of wait ($VOTT_{wait}$) and walk ($VOTT_{walk}$) times, is assumed to be twice as much as IVTT. The same value of OVTT is used for all modes, knowing that different modes will have different configurations of wait and walk times. For example, the SAV-ride-walk mode does not have a wait time component for its last-mile leg. For the SAV-ride-SAV mode, the value of OVTT parameter is set up the same for SAV wait times at the origin and at the final train station, as well as wait time for the train.

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

$$V_{walk} = \beta_{walk} \times d_{walk} - VOTT_{walk} \times t_{walk}$$

where d_{walk} is the walking distance in miles, t_{walk} is the walking time in hours, and the distance coefficient $\beta_{walk} = -1.2$ was obtained from Wen et al. (2018).

The car mode utility uses driving distance and free-flow travel time and is as follows:

$$V_{car} = ASC_{car} - \beta_{driving} \times d_{driving} - VOTT_{driving} \times t_{driving}$$

where $d_{driving}$ is the shortest path driving distance in miles, $t_{driving}$ is the free-flow travel time in hours, and ASC_{car} was calibrated to be -10.3, to align with CAMPO's (2010) mode share estimates for the Austin region. The operating cost $\beta_{driving}$ of private car (or light-duty vehicle) mode is assumed to be 60 cents per mile.

Value of IVTT for all modes (i.e., transit and SAVs) nested under transit (i.e., $VOTT_{transit}$) is assumed to be half that of those in a car, since riders do not need to drive (Liu et al., 2017). Walking time for accessing and egressing transit (i.e., $t_{access_{walk}}$, $t_{egress_{walk}}$) was calculated based on the network's shortest walk path. After obtaining the locations of a traveler's origin and destination stations (see Chapter 4), the utility of walk-ride-walk mode can be computed using:

$$V_{walk-ride-walk} = -Fare - VOTT_{transit} \times t_{rail} - VOTT_{walk} \times (t_{access_{walk}} + t_{egress_{walk}}) - VOTT_{wait} \times t_{wait}$$

where transit has a \$2 ($Fare$) flat fee, t_{rail} is calculated using 32 mph average speed without being affected by congestion on the roadway, and t_{wait} is the wait time at light-rail station, which is assumed to be half of train headway.

Utility of modes using SAVs to connect transit consider fares, travel time cost of riders on transit and SAVs, distance cost, and wait time cost. First-mile and last-mile SAV travel

distances (i.e., $d_{FM_{SAV}}$, $d_{LM_{SAV}}$) were computed using shortest-path distances. First-mile and last-mile SAV travel times (i.e., $t_{FM_{SAV}}$, $t_{LM_{SAV}}$) were further calculated, assuming a maximum SAV speed of 30 mph. Assuming SAV operating cost (β_{SAV}) to be \$1/mile (Liu et al., 2017), the utility of SAV-ride-SAV is as follows:

$$V_{SAV-ride-SAV} = -Fare - VOTT_{transit} \times t_{rail} - \beta_{SAV} \times (d_{FM_{SAV}} + d_{LM_{SAV}}) - VOTT_{transit} \times (t_{FM_{SAV}} + t_{LM_{SAV}}) - VOTT_{wait} \times (2 \times t_{wait_{SAV}} + t_{wait})$$

where $t_{waiting_{SAV}} = 3.4$ minutes, which is the average waiting time for an SAV obtained in Chapter 4, considering feedbacks in the mode choice model. Similar equations can be obtained when using SAVs only for access or egress:

$$\begin{aligned} V_{SAV-ride-walk} &= -Fare - VOTT_{transit} \times t_{rail} - \beta_{SAV} \times d_{FM_{SAV}} - VOTT_{transit} \times t_{FM_{SAV}} - \\ &\quad VOTT_{wait} \times (t_{wait_{SAV}} + t_{wait}) - VOTT_{walk} \times t_{access_{walk}} \\ V_{walk-ride-SAV} &= -Fare - VOTT_{transit} \times t_{rail} - \beta_{SAV} \times d_{LM_{SAV}} - VOTT_{transit} \times t_{LM_{SAV}} - \\ &\quad VOTT_{wait} \times (t_{wait_{SAV}} + t_{wait}) - VOTT_{walk} \times t_{egress_{walk}} \end{aligned}$$

The nesting coefficient for transit is set as 0.7, based on the mode choice component of the CAMPO travel demand model (Brinckerhoff, 2012). Thus, transit's utility is as follows:

$$V_{transit} = 0.7 \times \log \left(\frac{\exp\left(\frac{V_{walk-ride-walk}}{0.7}\right) + \exp\left(\frac{V_{SAV-ride-SAV}}{0.7}\right)}{\exp\left(\frac{V_{SAV-ride-walk}}{0.7}\right) + \exp\left(\frac{V_{walk-ride-SAV}}{0.7}\right)} \right)$$

Under a 15-minute train headway, the mode choice model estimated 35.2% FMLM travelers, 27.5% FM travelers, and 30.7% LM travelers among the light-rail transit users who utilize SAVs for FM or LM connections (while the remaining 6.6% utilized the walk-transit-walk mode, which is not simulated in this study). Austin has a low Red Line light-rail-line ridership, averaging just 3,823 riders per weekday in March 2019 (Capital Metro, 2020). This study is set in 2030, so counts were raised to reflect continued growth in downtown congestion and development around the train stations as well as greater train ridership due to SAVs serving train stations with an FMLM connection. Different levels of FMLM SAV demand to and from the Red Line train stations were used here, with station arrivals (across the 5 central stations) as high as 5,000 person-trips during the 3-hr morning peak period. With a focus on SAV fleet operations, this study only simulates light-rail transit riders who take SAVs for connecting trips

(referred to as transit demand or transit riders), namely FM travelers, LM travelers, and FMLM travelers. Other modes are not simulated (e.g., walk-and-ride, car, and bus use).

5.2.2 Central Austin Network

Figure 5-2a depicts the light-rail line as well as the geofenced FMLM service area. Walking to the light-rail train station (or walking from the train station to a final destination) is considered a viable option within a 0.5-mile buffer around the station (based on Nabors et al., 2008), shown with light green shading in Figure 5-2a. The geofenced SAV mode was made available to those starting or ending their train-based trips within 1.5-miles of the Red Line's stations (shown with dark as well as light green shading in Figure 5-2a). The geofenced regions are called automated mobility districts or AMDs, with the northern two stations labeled **AMD1** and the second geofenced region (with three stations) labeled **AMD2**. Parking depots for SAVs (shown as dark blue dots) are placed arbitrarily around the train stations. AMD1 has a total of six parking depots while AMD2 has eight. Parking depot locations are used for initializing SAVs at the beginning of the simulation, and for repositioning SAVs that are not actively serving a request and have no service requests in queue. While the placement of the depots is chosen arbitrarily for this effort, future efforts may consider the optimal placement of these depots. For ease of application (and due to the constraint on SAV availability only within 1.5-mile buffer), trip origins and destinations are scattered only within the geofenced regions, as shown in Figure 5-2b. Trip origins are represented with blue squares while the trip destinations are shown with red triangles. Departure times of riders were randomized using a normal distribution across the three-hour morning peak. Future research efforts will extend this analysis by having either the trip origin or the trip destination outside the AMD region. Another important caveat to note here is that SAVs in AMD1 do not serve FMLM connections in AMD2 and vice versa. This constraint will be relaxed in future iterations of the study.

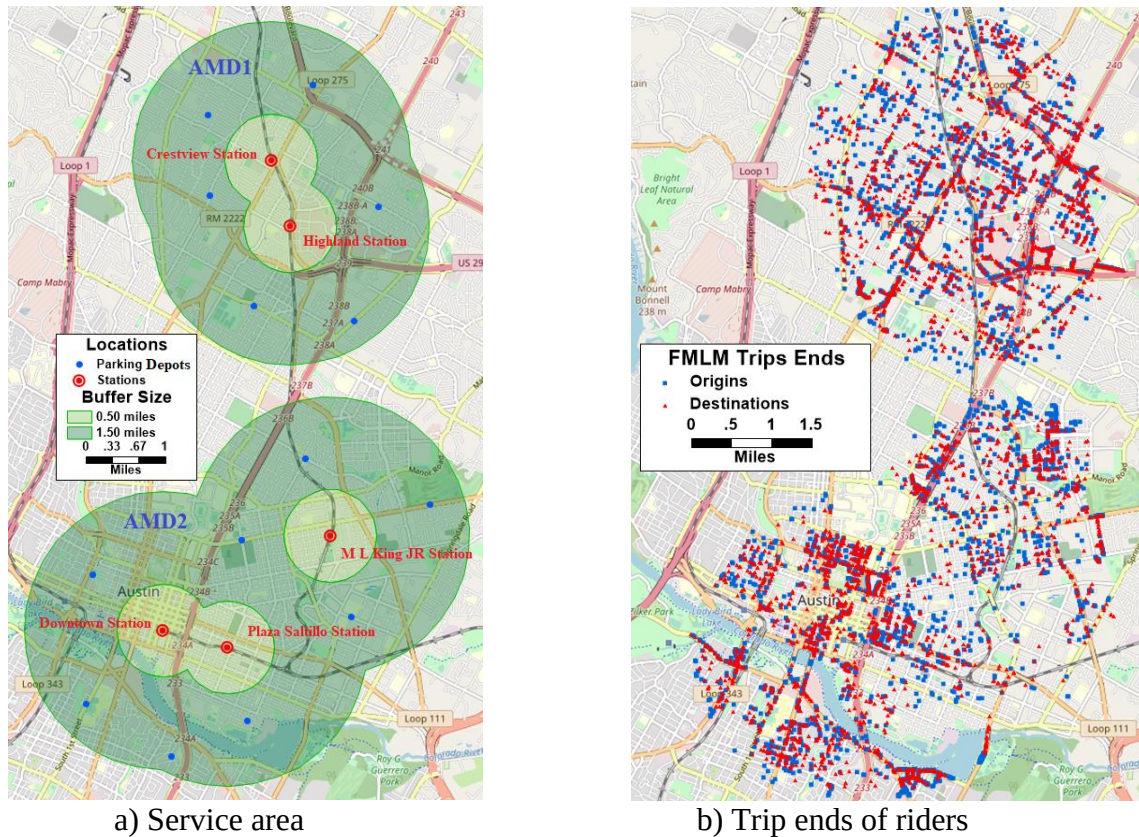


Figure 5-2. Central Austin network

5.3 ENHANCED AUTOMATED MOBILITY DISTRICT TOOLKIT

Chapter 4 implemented light-rail transit as a viable modal option in the AMD toolkit, and added logic to allow transit access/egress connections by walking or using SAVs (with a caveat that the same access and egress mode must be chosen for a transit trip). This chapter enhances the capabilities of the AMD toolkit proposed in Chapter 4 by: i) providing the flexibility to choose different access and egress modes to train stations (such as walk-transit-SAV or SAV-transit-walk), ii) conducting simulation experiments with 100% transit demand in the morning peak period, and iii) implementing an enhanced DRS algorithm that is capable of coordinating riders' trip attributes and train schedules. Further, the simulations presented here allow for flexibility in selecting SAV fleet size. SAV fleet size can either be fixed (which could lead to unserved demand, owing to an inadequate supply of SAVs) or variable (where an adequate number of SAVs are initiated in the simulation to serve 100% of the trip requests). However, in

order to focus on SAV operations, this chapter implements a simple mode choice procedure (without feedback, as introduced in the Data Set section) to determine SAV-transit mode shares (for FM, LM and FM+LM). Other modes' congestion impacts are not well reflected in the simulation, due to the microsimulation's computing power demands, and can be useful to include in non-microscopic simulations.

SUMO's application programming interface TraCI (short for Traffic Control Interface) was leveraged to extract information regarding the positions and actions of riders and vehicles in every simulation time step. Information gathered in the simulation time step (t) is used to manipulate passenger and vehicle movements in the time step ($t + 1$). The A* algorithm available in SUMO was used to calculate the shortest routes for SAVs based on experienced travel time from the last 300-second time interval.

The simulation starts with importing travel demand and network information into SUMO. FMLM service and transit settings (such as SAV fleet size, DRS settings, train headways, and dwell times) are imported next. For the baseline scenario where SAV fleet size is not constrained, an adequate number of SAVs are initialized in the parking depots within the AMD region (i.e., blue dots in Figure 5-2a). Since the SAV fleet in one AMD is restricted from serving FMLM demand in another AMD, the network is divided into two subnetworks to increase computational efficiency for the shortest path search. Once all the necessary settings are imported and mode choices are assigned, the itinerary for each rider is determined. A rider's itinerary includes access and egress modes, origin, destination, and identification of the 'rail' segment of the trip (i.e., origin and destination stops of the rail segment). After initialization, each rider and each vehicle follow the logical flow shown in Figure 5-3.

An FMLM rider will go through all the events in a trip, which involves taking an access/egress mode as well as transit. Transfers between modes are simulated using walk mode (for example, walking from home to take an SAV, walking from an SAV to a train platform to board the train, and walking out of a rail station to take an SAV). SAVs are initiated and terminated in SAV parking depots, and are expected to be in operation for the whole duration of the simulation. The dashed line in Figure 5-3 shows the stages of riders and vehicles when they are considered for rider-vehicle matching. If an SAV is successfully matched to a rider, it is dispatched (or re-routed if already on a trip) to pick up the assigned passenger. A vehicle visiting

list is used by each vehicle to track the next pick-up or drop-off location. As long as a vehicle does not reach its capacity, it searches for available passengers at a time resolution of one minute. The visiting list keeps updating every minute and it becomes empty when a vehicle drops off the last passenger on-board. Once the last passenger is dropped off, the vehicle immediately searches for and serves the nearest ride request. Any available SAVs with no active requests are repositioned to the nearest parking depot and wait there until the next ride request is received.

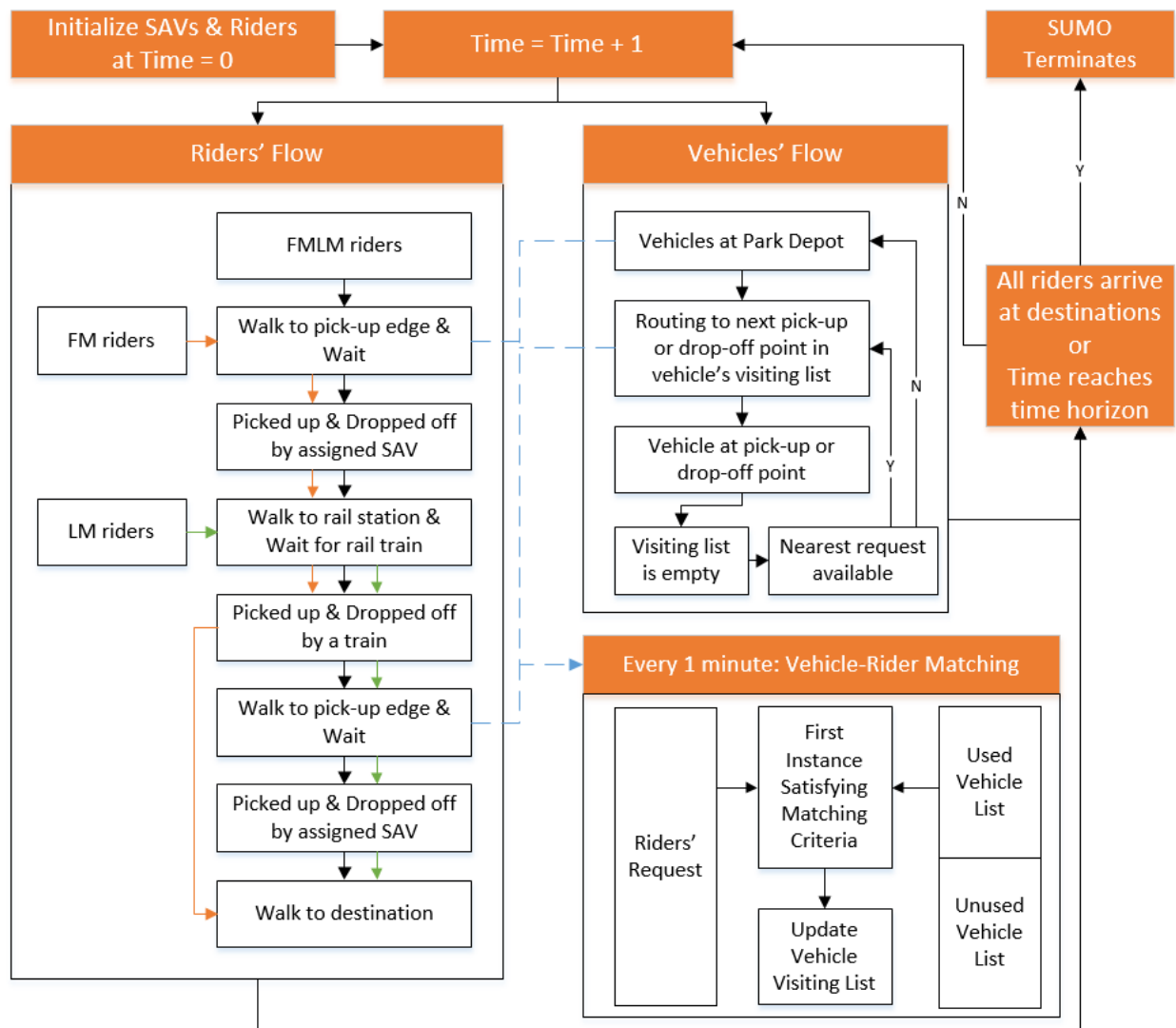


Figure 5-3. Simulated flow of riders and vehicles with dynamic ride-sharing

The riders are ‘sorted’ by the time at which they requested a ride, and the vehicles are ‘sorted’ by the magnitude of their estimated travel time from a specific rider. The vehicle list is split into two sub-lists, one with all “active” SAVs (i.e., the vehicles that have provided service), and another with all “inactive” SAVs (i.e., SAVs that have been parked in the depot since the start of the simulation). Both these vehicle lists are sorted by the magnitude of each vehicle’s travel time from a rider. For a new ride request, the “active” SAVs are first checked for a feasible match. To keep the fleet size to a minimum, a new SAV is initiated for picking up a passenger only when an active SAV cannot be matched to a new ride request. For scenarios where fleet size is not restricted, the matching rate is always 100% (as an unmatched request will be served by introducing a new SAV into the system). If the fleet size is restricted, a portion of the demand may be left unserved. Since this study assumes that a failed match or a late arrival does not alter a rider’s mode choice, any unserved demand must be served in the next round(s) of vehicle-rider matching. The simulation terminates when all riders arrive at their destinations or when the time horizon (3-hour simulation and 30 minutes cooldown) is reached.

By analyzing the second-by-second trajectories (of vehicles as well as passengers) extracted from the microsimulation, vehicle- and trip-level performance measures such as VMT, empty VMT (eVMT), AVO, and average wait time can be generated.

5.3.1 Dynamic Ride-sharing (DRS)

DRS is known as the multiple vehicle pickup and delivery problem, which is NP-hard to solve. Most research efforts apply heuristics or metaheuristic methods (e.g., simulated annealing and Tabu search) to solve DRS problems. To solve the ride-matching problem, Alonso-Mora et al. (2017) proposed an integer LP branch and bound solution hot started with a greedy heuristic that is fast enough to dispatch vehicles in real-time. Liu et al. (2019) described a quadratic variant of the pickup and delivery problem that can solve small subsets of the problem and may be viable for real-time adjacent traffic simulation.

Most agent-based simulations pursue simple heuristics for matching vehicles with riders, owing primarily to the difficulty of obtaining an optimal solution to the NP-hard DRS problem. Such rules can be as naïve as matching the traveler with the closest available vehicle, or can accommodate complex constraints pertaining to vehicles and riders. For example, Gurumurthy

and Kockelman (2018) compared the performance of en-route DRS with Origin-Destination (O–D) DRS. Fagnant and Kockelman (2018) devised a set of rules (based on the increase in passengers’ trip duration, total IVTT, waiting time for subsequent travelers, etc.) that can quickly assess DRS opportunities. Shen et al. (2018) considered a total detour factor and incremental detour factor for each passenger as constraints in DRS.

This study uses a rule-based vehicle-rider matching algorithm, governed by a maximum pick-up time threshold t_1 for a potential rider and an added drop-off time threshold t_2 for all matched riders. Having the coupled criteria on pick-up and drop-off thresholds ensures a reasonable travel time for all passengers. If either the pick-up or drop-off threshold is compromised, a new passenger is simply not picked up by an SAV that is already serving other passengers. Furthermore, en-route rerouting is allowed, which means that a vehicle can reroute to pick up a passenger in the middle of a trip (if such a pick-up meets the criteria described above).

The vehicle-rider matching procedure is controlled by constantly evaluating the visiting list of a vehicle. For example, Figure 5-4 shows the visiting list of an SAV with the next stop denoted as (B, 1), which indicates a pick-up stop for person B. Similarly, (C, -1) denotes a drop-off stop for person C. The visiting list shown in Figure 5-4 includes three pick-ups and drop-offs, respectively, for three persons. Figure 5-4 also shows the case of new inserted matching where another rider D is picked up after picking up B and dropped off after picking up C.

The procedure to determine the pick-up and drop-off stops is demonstrated as follows. Let k be the index of the stop in the list, s be the index of the stop that the SAV is serving, m be the pseudo index of the potential riders’ pick-up stop, which is after the i^{th} stop (e.g., $m = i + 1/2$), n be the pseudo index of the potential riders’ drop-off stop, which is after the j^{th} stop (e.g., $n = j + 1/2$), $I_{(k)}$ be the binary indicator showing whether a stop k is a drop-off point, and let L be the total list length.

In order to check the matching criteria, $t_{(i,j)}$ indicates the estimated shortest path travel time from stop i to stop j . The direct arrival time and the rerouting arrival time at stop k are denoted as $D_{(k)}$ and $R_{(k)}$, respectively. Whenever a vehicle-rider matching is conducted, the existing values of D and R are known based on the previous matching. A successful matching (m,n) should satisfy the following two conditions:

(1) The direct pickup time of the new rider should not exceed t_1 when matching is performed (Passenger-SAV search radius):

$$t_{(s,m)} \leq t_1 \quad (1)$$

(2) The added drop-off time threshold for all matched riders is always less than t_2 (Max ride-sharing delay):

$$R_{(j)} + t_{(i,m)} + C(t_{(j,n)} + t_{(m,i+1)}) - (R_{(s)} + t_{(s,m)} + t_{(m,n)}) \leq t_2 \quad (2)$$

$$I_{(k)}(R_{(k)} - D_{(k)} + t_{(i,m)} + t_{(m,i+1)}) \leq t_2 \quad \forall k \in (m, n), k \in \text{int} \quad (3)$$

$$I_{(k)}(R_{(k)} - D_{(k)} + t_{(i,m)} + t_{(m,i+1)} + t_{(j,n)} + t_{(n,j+1)}) \leq t_2 \quad \forall k \in (n, L], k \in \text{int} \quad (4)$$

$$C = \begin{cases} 1 & m < n \\ 0 & m = n \end{cases}, m \leq n \quad (5)$$

The potential riders' drop-off time due to rerouting is constrained by Equation (2) and (5). Equation (3) ensures that drop-offs happen after potential riders' pick-up but before potential riders' drop-offs. Similarly, Equation (4) checks the drop-offs that will happen after the potential rider's drop-off, by adding potential riders' rerouting time to both pick-ups and drop-offs of subsequent passengers.

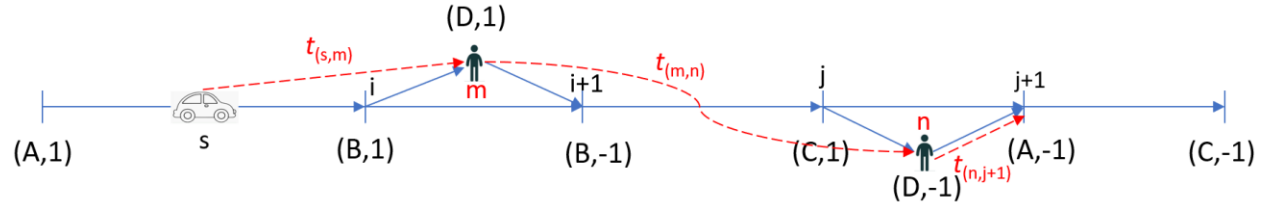


Figure 5-4. SAV passenger-visit-list example

A solution pair (m, n) satisfying the constraints for accepting the potential rider will have the rider's pick-up after i^{th} stop and drop-off after j^{th} stop. When a person has been dropped off, the person's pick-up and drop-off stops are removed from the list. For example, if B has been dropped off after person D is picked up as shown in Figure 5-4, the vehicle visiting list becomes: (A, 1), (D, 1), (C, 1), (D, -1), (A, -1), (C, -1).

For computational efficiency, an SAV always picks up the potential rider before the next stop (either a pick-up or a drop-off) in the visiting list (i.e., i and s are assumed to be zero), but drop-off can take place after any stop depending on the matching result. This ignores the case

when the pick-up of this potential rider happens after the SAV's next stop, by reducing the computational complexity from $O(n^2)$ to $O(n)$.

For computational efficiency, travel times used by the DRS algorithm (to compute shortest paths) are updated once every five minutes. This can lead to some unexpected delays in the microsimulation owing to factors such as vehicles stopping at the traffic signals; yielding at junctions, gridlock, and making U-turns if a vehicle goes past the pick-up point due to network topology. To account for unexpected network delays, the routing travel time is updated before vehicle-rider matching (or after a SAV arrives at a stop), by adding or subtracting a '*time gap*' for all the following stops. The time gap is simply the difference between the estimated arrival time (i.e., when a SAV is expected to arrive at a stop) and the actual arrival time (i.e., when a SAV actually arrives at a stop). The issue of repeated visits can happen in the simulation when a potential rider's pick-up or drop-off node already exists in a vehicle's visiting list. The DRS algorithm has been enhanced to avoid repeated visits by implementing the logic that a potential stop is added to a vehicle's visiting list only if that stop does not already exist in its list. This ensures that the current action (pick up or drop off of existing passengers), and the planned action (potential riders pick-up or drop-off) for the vehicle happen together but not disjointly (when the stops overlap). Since the vehicle visiting list is easy to track (through SUMO's TraCI API), and there is no length limit for the visit list, the DRS algorithm is not endogenously constrained by vehicle capacity. As long as the vehicle-rider pairs meet the matching criteria, the algorithm allows unlimited matches, making it easy to test SAVs of any size in the simulation environment.

5.3.2 Dynamic Ride-sharing with Transit Schedule Coordination

As the SAVs exclusively serve Red Line travel demand in this study, having close coordination between DRS and train schedules can help improve SAV utilization, as well as rider experience. To accomplish this, the DRS algorithm has been modified to account for riders' arrival time constraints at the train station. The modified DRS algorithm assumes that riders would rather spend additional time in an SAV than arrive early at the train station and wait for the train. As a result, the matching procedure allows vehicles to make extra stops, as long as all the riders on board will arrive at their respective train stations on time.

Based on these settings, the second set of constraints on an FM rider in the DRS algorithm (Equations 2 through 5) was replaced with a new set to determine whether or not this rider's pick-up and drop-off points can be added to a vehicle's visiting list. This is achieved by first defining a "scheduled train" for each rider. This is the train a rider who takes the nearest empty SAV (including those stationed in the 14 parking lots) can catch, by arriving at the station directly without sharing. Since the train schedule is fixed (based on the headway setting), SAVs may make extra stops if there is spare time to pick up another rider, or directly drop the rider off if there is no spare time before the arrival of the next train. In this case, the constraint for t_2 is dropped, because a rider only needs to arrive at stations on time, while allowing vehicles to reroute to accommodate other shared trips. Secondly, it is also necessary to ensure that a vehicle's drop-off time for an FM connection is earlier than the next scheduled train. There are two reasons for this: i) A rider would prefer to arrive a few minutes earlier at the train station, and ii) Increase the time reliability in the microsimulation system, as estimated travel time may not always guarantee the rider's arrival before the scheduled train. To accommodate this, a time buffer (of 10% of the train headway) is provided, so FM riders will have adequate time to walk to their trains.

A rider's "scheduled train" is the next train at the nearby station that will arrive after the closest SAV picks up and then drops off that rider. The process assumes that a rider's mode choice is fixed, and the SAV fleet management algorithm will assign as best it can. In reality, some riders will shift modes when realizing that they may miss the first train. Another implicit assumption here for the "scheduled train" excludes situations when a rider would like more time at the station (e.g., to buy food or wait for a friend to travel with).

5.4 AUSTIN SIMULATION RESULTS

This section presents the results from two sets of simulation experiments conducted to evaluate the performance of SAVs as an FMLM connection to train stations. The first set of scenarios are run under varying levels of travel demand, train headways, SAV fleet size and seat capacity. The second set of scenario runs focuses on the impacts of DRS settings on SAV performance. All the simulations are carried out in the five-station, two-AMD region of Austin's Red line for the three-hour morning peak travel period. Results for the baseline simulation for

each AMD are presented first, followed by aggregated results for the whole simulation for the two sets of scenarios defined above.

5.4.1 AMD Performance

Two fleets of SAVs are used to serve FMLM demand in the AMD region. Each AMD has its own dedicated SAV fleet, so if a trip originates in AMD1 and terminates in AMD2, the SAV fleets in AMD1 and AMD2 cater to the FM and LM connections, respectively, of the same trip. The fleet boundary restriction was implemented to see how SAVs would perform in geofenced travel bubbles, and also to ensure reasonable travel times for riders within each AMD. This constraint can be relaxed in a straightforward manner in future simulations. The baseline scenario considers a train headway of 15 minutes, with adequate 4-seat SAVs serving each AMD, under a total travel demand of 4,000 riders during the 3-hr morning peak (across both AMDs). Mode shares of the 4,000 light-rail transit riders followed mode splits mentioned in the data description section, resulting in 1,507 FMLM trips, 1,189 FM trips and 1,304 LM trips.

Table 5-1. Number of riders' boardings and alightings at each station

		AMD1			AMD2		Total boardings
		MLK	Highland	Crestview	Downtown	Plaza Saltillo	
AMD1	MLK	0	237	120	268	89	714
	Highland	255	0	524	194	84	1,057
	Crestview	100	508	0	123	25	756
AMD2	Downtown	237	217	96	0	293	843
	Plaza Saltillo	94	118	39	379	0	630
Total alightings		686	1,080	779	964	491	4,000

Table 5-1 shows the boarding and alighting passenger totals at each station. As shown, the highest numbers of boardings and alightings occur at Austin's Downtown Station, at the

south end, and Highland Station in the north. 40% of trips occur between AMDs, but most trips (60%) originate and terminate within the same AMD (for example, a good number of trips occur between Highland and Crestview stations, which are both inside AMD1).

Table 5-2 presents the details on the performance of SAV fleets in both the AMDs. As no constraints are placed on SAV fleet size, it was found that a total of 240 SAVs are required to keep the average wait time around 4.5 minutes in AMD1. Of the total transit demand in the 3-hour peak period, 1,208 and 1,316 trips originated and terminated, respectively, in AMD1. An interesting observation in Table 5-2 is that the proportion of shared trips in AMD 1 is about 90% but the proportion of shared vehicle miles is only 31%. This is because a trip is tagged as a shared trip even if only a portion of the trip occurred with more than one passenger on the vehicle. As observed from the shared distance per trip metric, on average, only 23.1% of a trip is served as a shared trip. SAV operations in AMD1 resulted in over 5,800 VMT, of which 31% were shared VMT, and 25.8% were eVMT. Since the SAVs are serving short-distance connecting trips to/from rail stations with shared rides, the eVMT share is smaller than Austin's TNC ride-hailing services. For example, Wenzel et al. (2019) estimated 45% to be deadheading VMT based on 1.5 million individual rides provided by RideAustin.

Fleet size requirements in AMD2 were scaled proportionally with the size of the demand compared to AMD1 (19% increase in fleet size for a 20% increase in demand). Compared to AMD1, AMD2 sees an 8% increase in VMT, but a higher share of shared VMT (and trips), coupled with an increase in AVO. A greater proportion of shared trips and shared VMT in AMD2 show an impact on average wait time and service duration, both of which are slightly higher in AMD2 than AMD1. From a vehicle utilization standpoint, there are complementary effects at play between AMD1 and AMD2. AMD1 observes a higher magnitude of shared distance per trip, but also a higher amount of deadheading per trip. The modeled area produces 12,191 VMT over the 3-hour AM PK time window via 526 SAVs (to and from stations or directly between origins and destinations). Replacing these with shortest-path car-trips would require 12,652 VMT/day across 4000 cars. Although the studied area requires a 7.35-mile light rail line running, the total automobile-miles traveled has decreased by 3.6%, and the system reduced 4000 on-road cars to 526 SAVs.

Results across the whole area are shown in the last column of Table 5-2. With almost 90% of total trips served as shared rides (albeit with a 30% shared distance per trip), shared VMT came out to be a third of total VMT. While AVO of the SAVs is reasonable, higher demand densities can push vehicle utilization higher (as seen in comparisons between AMD 1 and AMD 2). The average distance to station for these travelers is 1.52 miles, and sharing rides led to a one-mile detour per person-trip, on average. Results also suggest an average 4.93 min wait time for SAVs called from non-station origins and 4.47 min wait time at stations, because the trips at the stations are nicely aggregated in space and time, enabling more ride-sharing and thus faster response times.

Table 5-2. SAV fleet performance for FMLM service

Metric	AMD1	AMD2	AMD1+AMD2 areas
Fleet size	240	286	526
Vehicle miles-traveled (in 3-hr AM PK)	5,836	6,355	12,191
% eVMT	25.8%	25.0%	25.4%
Shared vehicle-miles	31.0%	31.9%	31.4%
AVO (persons per vehicle)	1.48	1.52	1.50
Shared person-trips	89.8%	90.7%	90.3%
FM trips in 3-hr AM PK	1,208	1,488	2,696
LM trips in 3-hr AM PK	1,316	1,495	2,811
Average wait time (min)	4.48	4.77	4.61
Average ride distance (mi)	2.58	2.46	2.52
Average service duration per trip (min)	14.0 min	15.9	15.0
Deadheading distance per trip (miles)	0.60 mi	0.53	0.56
Shared distance per trip (miles)	0.72 mi	0.68	0.70
Shared distance per trip (%)	27.8%	27.6%	27.7%

5.4.2 Scenario Exercises

This section presents the results of scenario exercises carried out with varying levels of travel demand, train frequency, SAV fleet size and vehicle capacity. In each of the scenarios, all factors except the one being investigated were held at the baseline levels.

Vehicle Size: This set of scenarios explores the impact of seat capacity on SAV fleet performance. Vehicles with seat capacities of 2, 4, and 6 passengers were simulated along with a 1-seat AV case for comparison. Table 5-3 shows that seat capacity is inversely proportional to the SAV fleet size. VMT (as well as eVMT) is highest in the 1-seat SAV scenario, as trips cannot be pooled in one-person SAVs. If SAVs are not permitted to carry more than 1 person at a time, the total VMT to and from these 5 train stations is simulated to be 16,996 miles in the 3-hour morning peak period (with 4,000 FMLM travel demand). This entails 51.3% eVMT, suggesting that the other 8,720 VMT exists when these train station users rely on their own vehicles to simply drive, park, and ride (and then the reverse, when they return home each day). This might suggest a 40% increase in train station-related VMT when using SAVs with DRS for FMLM connections (i.e., the baseline scenario), leading to increased congestion around the transit stations, especially at the curbside. However, park-and-ride is generally only at the home end of one's train trip, with walking at the other end (or vice versa). So the added VMT may be closer to 20 percent, for those using SAVs instead of their own vehicles to access train stations. Second, even though total VMT for FMLM connections rises in these applications, vehicle ownership is likely to fall, helping avoid private vehicle use in other trips. In this setting, 4,000 personal vehicles could be replaced by just 526 SAVs (plus some trains), or just 315 SAVs (when we allow 5% unmatched SAV requests). Moreover, park-and-ride users typically must pay for parking at/near train stations, so that cost is avoided here, along with excessive parking as land use in high-rent locations. SAVs with two or more seats provided a service duration that was about twice as long as 1-seat service albeit with reduced fleet size and VMT consumption. It was also interesting to see that with no sharing (i.e., one-person SAVs), small-sized SAVs were supposed to pick passengers up faster, but riders under a small-sized SAV FMLM service experienced a longer waiting time. As the DRS settings (for maximum pick-up time and maximum delayed drop-off time) are held constant across all vehicle scenarios, one possible

explanation for longer wait times is that a larger fleet size in the 1-seat SAV scenario might lead to excessive curb congestion around the station area. All of these findings are important factors to consider when right-sizing SAVs, as size reduction can have intended (i.e., lesser service duration) as well as unintended consequences, such as increased VMT, and increased wait times. It can also be observed that a reduction in fleet size and a corresponding increase in vehicle utilization (depicted by AVO) flattens out with the four-seater SAV scenario. The incremental benefits of having six-seater SAVs are minimal, if any, in the context of this simulation.

Travel Demand: Scenarios were run with light-rail transit travel demand of 3,000, 4,000, and 5,000 person-trips over the three-hour morning peak period. As expected, a larger transit demand leads to greater SAV fleet size requirements. Increased transit demand (or more generally, greater trip density) improves utilization of the SAVs, indicated by increases in shared VMT and AVO. However, sharing rides slightly increases riders' wait time and service duration, with trip distance staying more or less stable across all scenarios.

Train Headway: FMLM service differs from traditional D2D pick-up and drop-off service, as FMLM demand comes in spurts (governed by train schedules) whereas D2D trip demand is more dispersed. Therefore, a larger train headway resulted in a larger fleet size requirement. It is interesting to see a higher eVMT share in scenarios with larger train headways. Although a larger train headway led to more shared rides at the station, it also reduced the chance for FM trips to be shared. Such a combined effect was imposed on both FM and LM trips, leading to a slight increase in AVO, but also more eVMT.

Fleet Size Reduction: The scenarios presented so far did not place any restrictions on fleet size. However, fleet size restrictions are inevitable at times due to budget constraints, among other factors. Therefore, consecutive scenarios with a 10% cumulative decrease in fleet size from the baseline are run all the way up to a reduction of 50% in fleet size. Surprisingly, the system performance was more or less stable until a 60% reduction in fleet size; in fact, AVO increased with a reduction in fleet size. When the fleet is reduced to half of the original size, the average wait time increases by a minute.

Table 5-3. System performance of SAV fleet under various demand and supply settings

Scenarios		Fleet size	Vehicle miles-traveled			AVO	Average wait time (min)	Average ride distance (mile)	Average service duration (min)
		Total	Total (miles)	Empty %	Shared %				
Vehicle size (seats per SAV)	1	992	16,996	51.3%	0.0%	1.00	5.1	1.52	7.4
	2	532	13,365	25.0%	23.4%	1.31	4.8	2.40	14.0
	4*	526	12,191	25.4%	31.4%	1.50	4.6	2.52	15.0
	6	498	12,187	25.2%	31.7%	1.50	4.5	2.52	15.3
Demand (riders in 3-hour AM peak)	3000	421	9,347	25.6%	30.9%	1.49	4.5	2.56	14.3
	4000*	526	12,191	25.4%	31.4%	1.50	4.6	2.52	15.0
	5000	598	15,067	24.4%	32.4%	1.52	4.6	2.54	14.8
Train headway (min)	5	459	11,944	24.4%	32.2%	1.51	4.4	2.50	14.2
	10	496	12,128	24.1%	32.2%	1.50	4.5	2.55	14.4
	15*	526	12,191	25.4%	31.4%	1.50	4.6	2.52	15.0
	20	565	12,315	26.5%	31.3%	1.51	4.7	2.51	14.6
	25	594	12,566	28.1%	31.1%	1.53	5.0	2.53	15.1
Fleet size scale to baseline scenario	100%*		12,191	25.4%	31.4%	1.50	4.6	2.52	15.0
	90%		12,206	25.1%	32.0%	1.52	4.6	2.54	14.5
	80%		12,211	24.9%	31.7%	1.50	4.5	2.53	14.4
	70%		12,185	25.1%	31.8%	1.51	4.5	2.54	14.5
	60%		12,194	24.3%	32.9%	1.53	4.6	2.57	14.7
	50%		11,592	21.7%	36.8%	1.59	5.5	2.63	15.9

Note: Scenario marked with an asterisk is the baseline scenario.

5.4.3 Improved DRS for Train schedules

This section presents the impacts of DRS settings on the performance of the SAV fleets. Four scenarios (including the baseline) were tested with various combinations of the parameters in vehicle-rider matching criteria. An additional scenario was run where the DRS worked in conjunction with the train schedule. The baseline scenario (scenario 3) considers a maximum pick-up threshold of 5 minutes (when multiple riders are matched on a trip), and a maximum delayed drop-off time of no more than 10 minutes for each passenger. Three other scenarios were tested, with pick-up time thresholds ranging from 1 minute to 10 minutes, and the maximum delayed drop-off time being twice the pick-up time. It should be noted here that these scenarios do not constrain the SAV fleet size.

Results shown in Table 5-4 indicate that the tighter the constraint on FMLM service parameters, the greater the fleet size requirement. As expected, the most stringent pick-up constraint (1-minute) resulted in extremely low shared vehicle miles (of 4.4%), and an AVO of 1.08. In this case, the riders' average distance was nearly the direct travel distance, which was 1.6 miles and the whole journey could be completed in under 8 minutes. Conversely, the scenario with the most relaxed constraints on FMLM service parameters (10-minute pick-up time threshold, and 20-minute delayed pick-up or drop-off threshold) sees a high AVO, and a greater proportion (47.1%) of shared vehicle miles. Trip level metrics (average wait time, ride distance, and service duration) increase with a higher percentage of shared VMT across scenarios. This is understandable, as with higher levels of sharing, SAVs may reroute to other stops, leading to greater distances and durations across the board. Generally, scenarios with larger fleet sizes see higher VMT and lower eVMT, compared to scenarios with smaller fleet sizes (i.e., more relaxed service parameters). However, the total VMT increased a little in scenario 4 compared to the baseline scenario, which is possible because a tighter constraint will have more deadheading VMT, but a more relaxed constraint will lead to more shared VMT, which consists of more added detours.

The performance of SAV fleets under the enhanced DRS algorithm is shown in Table 5-4's final column. Keeping the pick-up time constraint the same as the baseline, but having tighter coordination between the DRS algorithm and the train schedule resulted in the highest

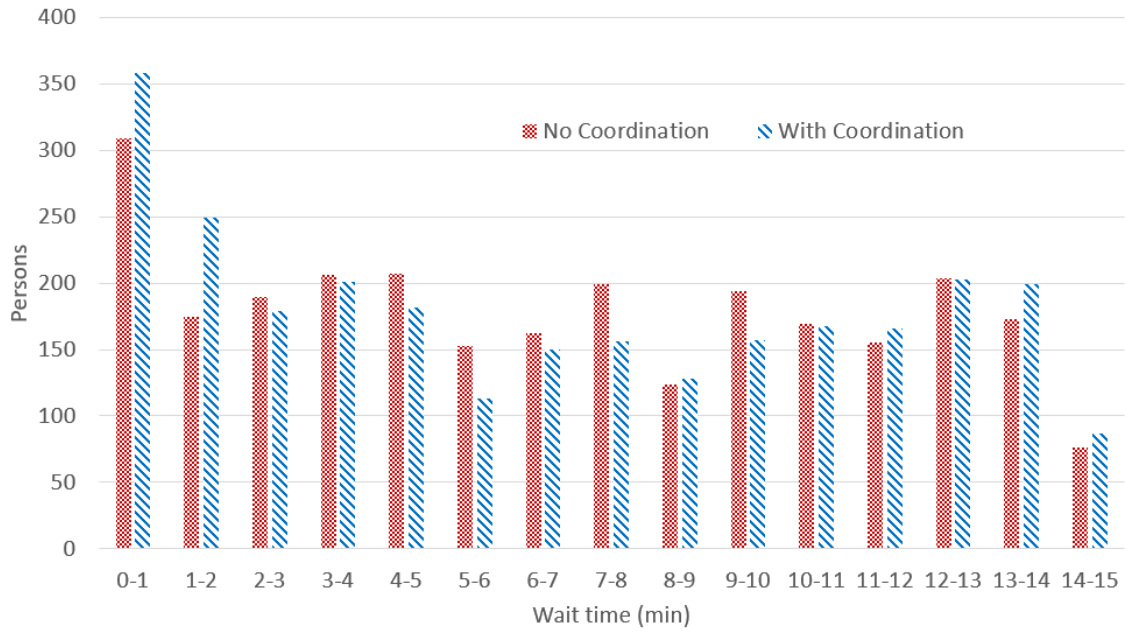
proportion of shared miles (60.4%) coupled with the highest AVO (2.29 persons), and the lowest proportion of eVMT (16.1%), across all scenarios. This is as expected because under this scenario, the algorithm will keep a rider on board for a longer duration if his/her train arrival is still minutes away. The increased vehicle utilization comes at the cost of a longer wait time (48% increase from the baseline) and trip duration (86% increase from the baseline). This analysis provides an interesting insight into the possible gains in vehicle efficiency if SAV routing is coordinated with train schedules (at the cost of increased wait and ride times).

Table 5-4. System performance of SAV fleet under DRS variations

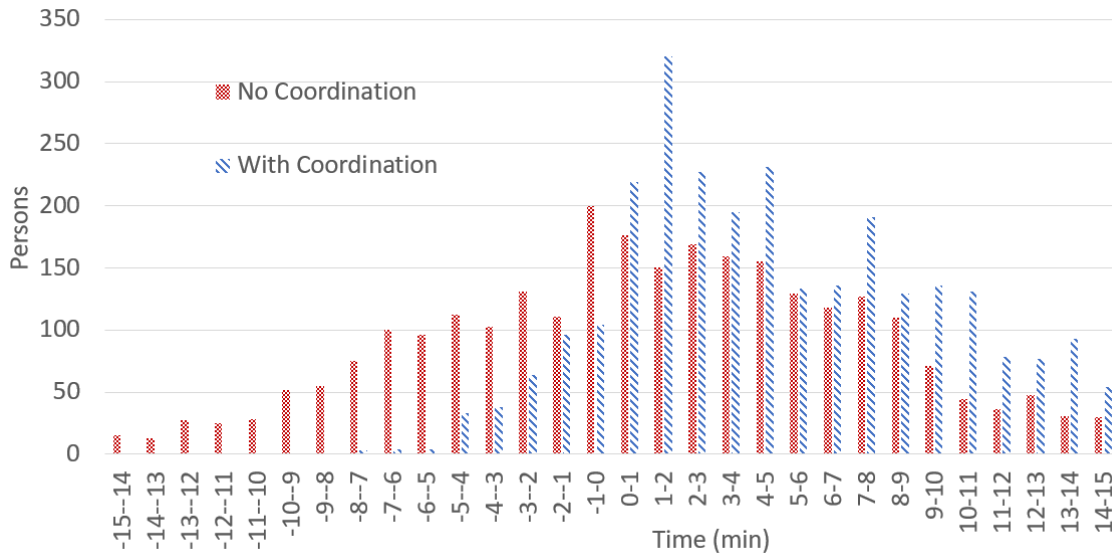
Scenarios	1	2	3*	4	With coordination
Pax-SAV search radius t_1 (min)	1 min	2	5	10	5
Max ride-sharing delay t_2 (min)	2 min	4	10	20	by train schedule
Total #SAVs (fleet size)	822 SAVs	661	526	408	514
AMD1 fleet size	357	309	240	184	236
AMD2 fleet size	465	352	286	224	278
Total VMT (miles over 3-hr AM PK)	15,243	13,235	12,191	12,873	15,107
% eVMT	47.8%	40.9%	25.4%	17.2%	16.1%
Shared vehicle-miles	4.4%	12.9%	31.4%	47.1%	60.4%
AVO (person-miles per occupied-SAV-mile)	1.08	1.23	1.50	1.79	2.29
% Ride-shared trips	30.7%	62.4%	90.3%	93.7%	83.0%
Average wait time (min)	3.9	4.5	4.6	5.6	6.8
Average ride distance (mile)	1.6	1.8	2.5	3.5	5.5
Average service duration (min)	7.9	8.8	15.0	19.0	27.9

*Note: Scenario marked with an asterisk is the baseline scenario.

Although riders' wait time (for the SAV) increased in the coordinated train schedule scenario, they did not necessarily arrive late for their train. Figure 5-5a shows the distribution of wait times at the train station and Figure 5-5b shows the time difference between riders' arrival at the train stop and the scheduled train arrival. From Figure 5-5a, it can be observed that the modified algorithm helped increase the number of riders who arrived within 2 minutes before train departure, but the general distribution remained the same. In Figure 5-5b, positive values indicate earlier arrivals at the station, while negative values indicate a late arrival (i.e., after the train has departed). With a DRS mechanism that only considers pick-up time and drop-off time (i.e., the baseline scenario), the arrival time presents in the shape of a normal distribution with the train's arrival time as the mean. However, with the modified DRS algorithm which coordinates with the train schedule, the number of riders arriving ahead of the train's arrival increased and the number of riders arriving after the train's departure decreased greatly. With the enhanced DRS algorithm under a 10% train headway early arrival, the proportion of riders that can catch their scheduled train increased to 87.2% (from 57.5% in the baseline). With larger early-arrival buffers (of 20% and 30% of train headways) in the DRS algorithm, the rate increased to 92% and 97%, respectively, but SAV riders' wait times also rose. When considering the buffer to reserve, the SAV fleet operator may seek a balance between shorter wait times and better coordination (i.e., a higher share of riders able to catch the next train). Here, the buffers are set as a percentage of train headways, but this decision may benefit from some information on riders' preferences, for how early they want to arrive at train stations.



a) Distribution of wait time for the next available train



b) Distribution of time gaps between scheduled train arrival and riders' arrival

Figure 5-5. Performance of coordinated DRS algorithm

5.5 SUMMARY

Utilizing SAVs for FMLM connections to transit presents multifold benefits, including reduced costs to the operator and the passenger as well as reduced congestion on the roadways (owing to a shift from car modes to SAV-to-transit modes). This chapter investigates the impacts of SAVs serving as FMLM connections to/from five train stations along Austin's Red Line, by extending the simulation tool from the last chapter. This chapter proposes an enhanced DRS algorithm that closely couples SAV operations with train schedules. Such an integrated algorithm is shown to increase vehicle utilization and improve on-time arrival rates at the train stations. In addition, instead of forcing FM and LM to be the same mode to access light-rail transit, the simulations conducted in this chapter also allow for flexible FM and LM access (e.g., SAV-transit-walk). Unlike many SAV studies that simulated only a portion of the observed demand, this chapter further simulates and expands the full extent of central Austin's morning peak light-rail transit demand in 2030. Detailed simulations are carried out in two AMDs, and the performance of the SAV fleet is analyzed in light of varying levels of travel demand, train frequency, SAV vehicle size, fleet size, and DRS settings.

Results indicated that about 90% of the trips in both Austin's AMDs were served as shared trips. However, with only 30% of each trip (on average) served as a shared trip, shared VMT constituted only a third of the total SAV VMT across the study region. Results specific to SAV deployments in AMD 1 and AMD2 demonstrated that a greater demand density can lead to a higher vehicle utilization rate (as evidenced by a higher vehicle occupancy, and lower eVMT percentage in the AMD with higher demand). From the scenario runs of 1-, 2-, 4-, and 6-seat SAVs, it was observed that larger SAV seat capacity led to a smaller SAV fleet size requirements, and that vehicle utilization increases with seat capacity. However, for the application context presented in this chapter, results showed that increases in vehicle utilization rates flattened out with the 4-seater SAV scenario. An interesting insight from the scenarios on vehicle seat capacity is that reduction in seat capacity (particularly with 1-seater SAVs) can lead to unintended consequences, such as increased curb congestion.

A higher level of transit demand resulted in a larger SAV fleet size and more VMT, with greater utilization of the SAV fleet. However, better SAV utilization comes at the expense of

increased wait time and service duration for riders. A less frequent train service (i.e., larger headway) resulted in a larger fleet size with a greater vehicle utilization rate. Furthermore, the scenario exercises with fixed fleet size restrictions revealed that baseline system performance can be achieved even when the fleet size is reduced to 60%. This finding shows that the proposed vehicle-rider matching algorithm guarantees a stable system performance even under a reduced fleet size. DRS settings are also closely related to system performance. Stringent matching criteria led to larger fleet size, and underutilization of the SAV fleet. Relaxing the matching criteria resulted in greater vehicle utilization, but at the expense of increased wait times and service durations for the riders. With a DRS algorithm that is tightly coupled with train schedules, it was observed that over 87.2% of the riders could catch their desired train, compared to 57.5% under the baseline DRS algorithm (i.e., no transit coordination). This signifies the importance of integrated transit planning for efficient FMLM connectivity.

While this part successfully demonstrates the efficacy of SAVs serving as FMLM connections to transit, it has some limitations. Although congestion has been observed around rail stations, realistic levels of congestion could not be reflected in the simulation due to the lack of other road modes such as private cars and buses. Future research efforts may focus on addressing these gaps as well as optimizing parking depot locations for SAV initialization and relocation. Further research is also needed concerning optimizing the size of geofenced regions (AMDs) for efficient FMLM services. The coordination between train schedules and SAVs can be extended to account for passengers' pick-ups, in addition to drop-offs at the train station. The simulation toolkit has been demonstrated to be successful in simulating FMLM scenarios with various SAV settings, but the results are mostly prepared for the central Austin area, and the operation strategies may vary for other city networks, depending on the AMD size and the spacing between rail stations.

Chapter 6. SAV Fleets for a More Integrated Mobility System

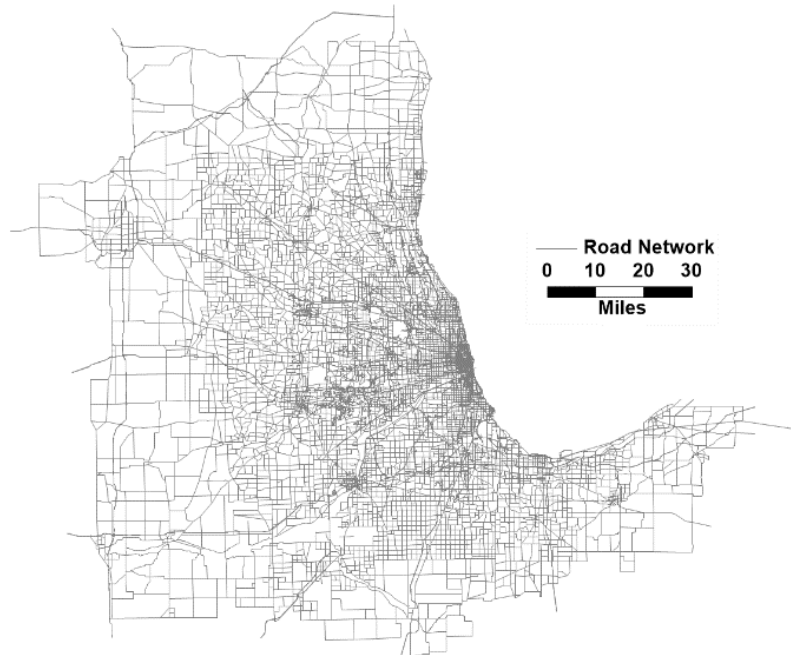
6.1 OVERVIEW

Regarding the multi-faceted service that SAVs can provide, it is essential to investigate SAVs as a part of the transit system. SAV D2D service is expected to be a popular and favored choice for future shared mobility, due to reduced cost, smooth vehicle acceleration and deceleration, improved safety through the automated driving system, and centralized-controlled ride-sharing service. Serving FMLM connections can help increase the catchment area of public transit and reduce connection times to transit stations, making public transit more preferred. Moreover, the traditional transit lines themselves can also benefit from the deployment of SAVs, as the SAVs may replace existing transit lines or establish new transit lines. The services that SAVs can provide will both complement and compete with existing public transit services, while they will also function as transit eventually. Therefore, the mixed roles of SAVs within a public transportation system request a thorough examination, especially for large-scale networks where the transit use is high (e.g., Chicago and New York).

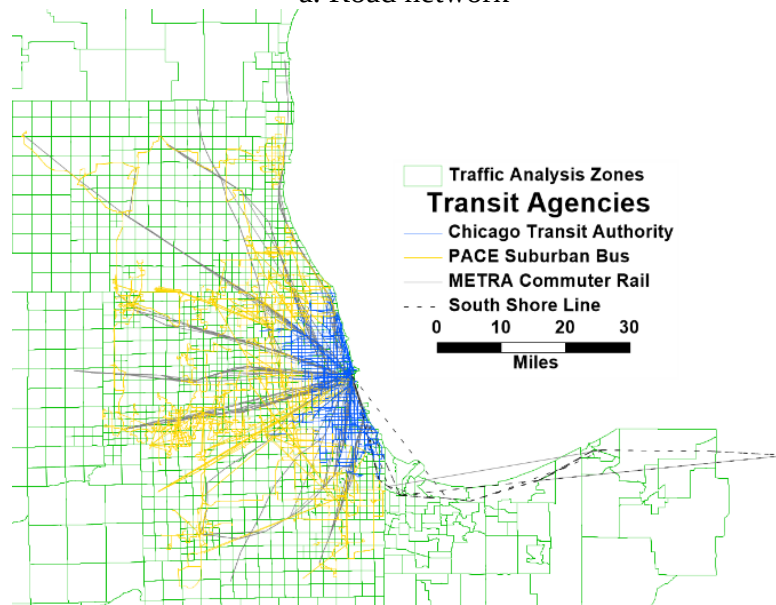
Since the microscopic simulations limit the network size in application from Chapters 4 and 5, this chapter leverages the mesoscopic agent-based simulator POLARIS to analyze the deployment of different SAV services in an integrated transit system for 5% of the population in the Greater Chicago region. The impacts of the SAV fleets are revealed through mode splits, social warfare, and network performance. The chapter is organized as follows. The Chicago network data are introduced first, followed by the POLARIS model, including how the three SAV services are modeled. Model results and analysis are then presented, before providing the conclusions and recommendations.

6.2 CHICAGO DATASET

This study simulates vehicle and person movements across the 11,116 sq. mi Chicago region. This large-scale network has 1,961 TAZs and about 32,000 road links (Figure 6-1a) and 33,000 transit links (Figure 6-1b). The daily travel patterns from 13 million travelers across the region are synthesized and validated by Auld et al. (2016), leveraging the CMAP travel survey data.



a. Road network



b. Transit network

Figure 6-1. Chicago passenger-transport networks

Chicago's transit network was obtained as a General Transit Feed Specification (GTFS), and then organized, tested and calibrated by Verbas et al. (2018) for the POLARIS model. Four transit agencies are considered in the model: Chicago Transit Authority, PACE suburban bus,

METRA commuter rail, and South Shore Line. The Chicago Transit Authority (CTA) provides service in the City of Chicago and 10 surrounding suburbs, while the PACE suburban bus serves a larger area, connecting six counties, including Cook, Lake, Will, Kane, McHenry, and DuPage (APTA (American Public Transportation Association), 2021; CTA, 2016). Transit-line SAVs, or automated bus (aBus), are assumed to replace regular bus service (excluding bus rapid transit), but at half the seating capacity (per automated bus) in order to double each line's frequency. Chicago's METRA and South Shore are both commuter rail services, and assumed to maintain their status quo. A total of 349 unique transit lines were coded into the model, with 134 lines from CTA and 202 lines from PACE (Verbas et al., 2018). Buses used for CTA and PACE's regular bus services are set to have 30 seats plus standing capacity for 30 travelers. Considering different departures for each transit line, about 2,100 routes were assembled to offer 28,000 total transit-vehicle trips (from origin station to final station) throughout a workday. The bus stops are also considered "stations", although train stations are typically larger, with more amenities.

6.3 POLARIS SIMULATION

POLARIS is a large-scale multi-agent activity-based travel demand model to simulate both person and freight trips over a 24-hour day. POLARIS' population and activity module (Auld and Mohammadian, 2010) includes home, school, and work location choices for synthetic households and individuals, based on U.S. Census tract data, Public Use Microdata Areas (PUMAs), the American Community Survey (ACS), and regional household travel surveys. A hazard-based specification is used to produce start times and durations for each person's daily activities (Auld et al., 2011), with a multinomial logit model of destination choices (Auld and Mohammadian, 2012) and nested logit models of mode choice (by trip type). The travel scheduling process incorporates four choices: destination, mode, departure time, and travel party choice (Auld and Mohammadian, 2011; Gurumurthy et al., 2020). Conflicts among activity plans, household-vehicle choices, and travel schedules are managed via a conflict monitor in a rescheduling model (Auld et al., 2009). With all trips defined for each traveler, dynamic traffic

assignment to route vehicles, and link-level congestion is reflected through a link transmission model.

6.3.1 Shared Automated Vehicles' D2D Service and Dynamic Ride-Sharing

POLARIS allows for D2D travel and DRS in SAVs for individuals (Gurumurthy et al., 2020, Gurumurthy and Kockelman, 2020), with SAV response time and travel time/congestion feedbacks to mode (and destination and departure time) choices. Travelers request a ride from a single SAV fleet operator, who is aware of all vehicles in the region and their specific locations. This centralized dispatch of SAVs helps assign trips to nearby vehicles efficiently. A zone-based approach is taken to store vehicles in underlying TAZs for computational efficiency. While the nearest vehicle is not always assigned to each call, the first available vehicle falling within a pre-defined maximum wait time threshold is assigned to maintain acceptable response times (Gurumurthy et al., 2020).

The DRS module matches new trip requests to vehicles idling or en route to a pickup or dropoff location. The match is made such that the request's destination is along the direction of ongoing travel with slight modifications based on the exact operation that is ongoing. If a pickup trip is ongoing, and within the pre-defined maximum wait threshold time (using a zone-based storage of vehicles), the two are easily matched. If a dropoff is ongoing, and is in the same set of TAZs as the new request's origin, then those two trips are bundled. If a dropoff is ongoing and its destination is further away, the angle between Euclidean lines (of the ongoing trip and the requested trip) is calculated. The request is matched to the ongoing trip if this angle is less than 10 degrees (to avoid long detour times for those already en route). Once matched, all requests assigned to a vehicle are ordered for minimal Euclidean distances while reflecting standard pickup-and-dropoff constraints (e.g., a traveler cannot be dropped off before being picked up). POLARIS' activity-based travel-demand model currently allows only single-party trip requests, so all requests matched to vehicles take up one seat space. In reality, travelers will often travel in party sizes greater than 1, with friends and family, so the DRS results produced here are conservative estimates of vehicle occupancies when the fleet is deployed. No traveler-side model is used to determine sharing choice, so all travelers are expected to be willing to share their trips

with strangers when DRS is allowed. Therefore, single-party trips and DRS-mode adoption are likely to balance out the extremes expected from their individual effects.

6.3.2 First-Mile Last-Mile (FMLM) Modes

The full integration of new FMLM modes required both supply and demand-side changes to POLARIS' code. On the demand side, travelers willing to choose FMLM as a mode needed to be identified appropriately, based on destination and time of day. These trips then needed to be routed appropriately via multimodal shortest paths that reflect variable travel times and congestion.

6.3.2.1 Mode Choice and Feedback Iteration

The SAV D2D service is assumed to replace the traditional taxi service with new cost assumptions. The FMLM service was added to POLARIS' mode choice model as two new modes: One uses SAV FMLM service to access and egress Chicago's bus stops and stations, and the other connects to rail transit stations, including both commuter rail and light rail. Since SAVs have not been deployed for FMLM service, there is no revealed preference data to calibrate the utility functions of these new modes. So parameters were adopted based on existing taxi, bus, and rail mode parameters, as a function of travel time and cost for SAV FMLM services and the transit trips, penalties for the number of transfers, and travelers' demographics. SAVs' travel times for D2D service and access and egress times for FMLM service are recorded and fed back to POLARIS' mode choice model, for an iterative process until the mode choices and travel times appear to equilibrate.

6.3.2.2 Multimodal Passenger Routing

POLARIS' new FMLM (with transit) service routes are based on multimodal shortest paths, leveraging network links of all types (e.g., driving, walking, and/or transit links). Adjustments and penalties ensure reasonable multimodal paths, by counting transfers, walk times, and driving distances. As long as a multimodal shortest path contains at least one SAV path segment, the trip is identified as a FMLM trip. Transfers are allowed between different

transit lines, and can involve walking, to mimic real options in Chicago's extensive networks. For normal bus and rail trips, 3 miles is assumed to be a maximum walking distance, but there is no distance constraint for accessing and egressing transit stations using the SAV FMLM service. Although the multimodal shortest-path algorithm identifies the shortest driving path for SAVs, the actual FMLM service with DRS can involve some detours, for shared-ride (DRS) pickups and drop-offs. This multimodal routing scheme is an extension to the multimodal A* program that already existed in POLARIS (Verbas et al., 2018).

6.4 CHICAGO APPLICATION AND RESULTS

Different FMLM and transit services were simulated for the Greater Chicago region. The baseline scenario is the year 2018 Chicago run using 5% of the total synthesized population, which is a total of 201,000 households and 520,000 persons. Figure 6-1's business as usual (BAU) case shows mode splits for the calibrated baseline, so there is taxi but no SAV services under BAU conditions. The single-occupancy (private, motorized) vehicle (SOV) dominates mode choice, followed by high-occupancy vehicles (HOVs). Transit's travel share was about 5% across the 20-county region, but 30% in the City of Chicago, and TNC + taxi travel accounted for about 4%. There is a flat/fixed/pickup fee of \$3.30 assumed for TNC and taxi services, plus another \$1.50 per taxi-mile. Starting from the BAU case, scenarios involving new SAV services were added, so one can see the incremental effects of each new SAV service, when added to the region. The first service added was SAV D2D, to replace traditional TNC and taxi services across the region. The second added SAV-based FMLM service, and the final scenario added SAV-based transit to replace regular bus service (CTA and PACE bus lines). All scenarios simulate the same 24-hour workday/weekday, starting from midnight.

6.4.1 SAV Door-to-Door (D2D) Service

The first scenario tested SAV D2D service as a replacement for existing TNC and taxi services across the region. SAVs have the same vehicle behavior as cars and taxis but charge a lower fare: just \$0.50 per mile, based on predictions and assumptions in prior studies (Becker et al., 2020; Bösch et al., 2018; Fagnant and Kockelman, 2018). One SAV was deployed for every

40 persons in the region, so 12,741 SAVs are available for rides on the simulated day. Such a large SAV fleet can lead to many households relinquishing (retiring or selling) their old vehicles and reducing vehicle ownership. Menon et al.'s (2019) vehicle ownership reduction model was leveraged to update POLARIS' code. Thanks to lowered ride-hailing costs, the SAV D2D mode split was more than 10% of the BAU's TNC/taxi mode share (as shown in Figure 6-2), with HOV mode split rising by 8% (presumably due to lower vehicle ownership levels) and SOV mode split falling by more than 20%.

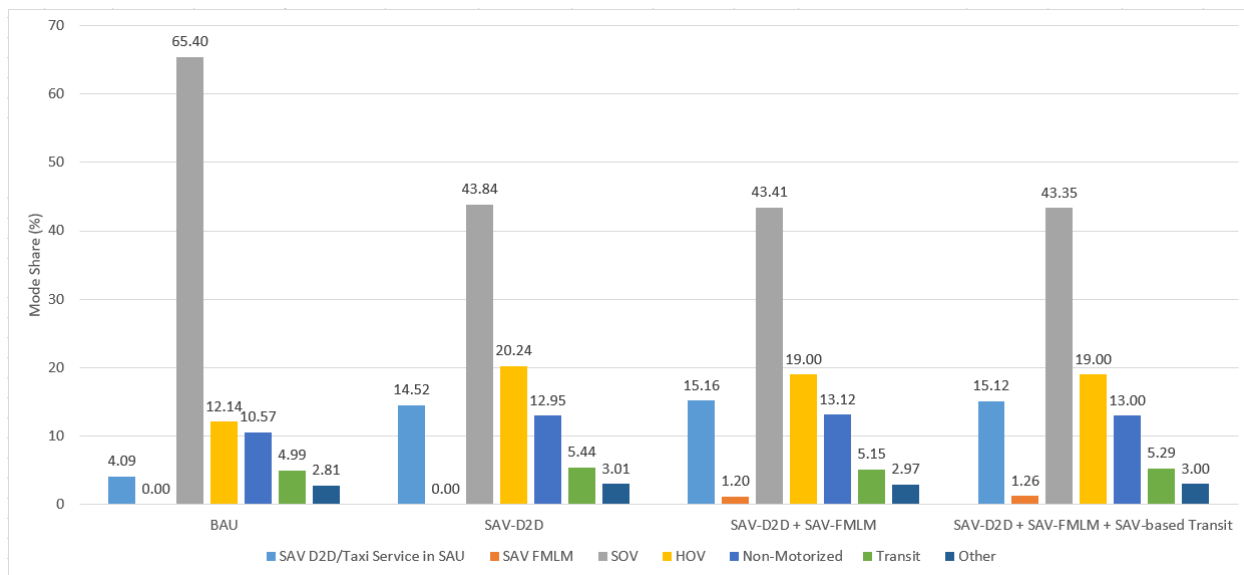


Figure 6-2. Mode splits for BAU vs. SAV scenarios

Table 6-1 shows the fleet performance of the 12,741 SAVs serving 5% of the synthesized Chicago population. Each SAV worked less than 5 hours a day, on average, which is low utilization (over a 24-hour day). Each SAV drove about 131 vehicle-miles per day, to serve, on average, nearly 20 trips requests, and 25% of the fleet's VMT was empty travel (without passengers onboard). The SAV fleet offered an average 15-minute service time (riding time plus wait time) for D2D riders, who rode 4.6 miles on average. Figure 6-3a shows SAV users' trip-length distribution, which peaks between just 0.5 miles and 1.5 miles, suggesting that most SAV riders use such SAV D2D service for short-distance trips, though many end up sharing long rides (over 50 miles in one-way distance), across the extensive Chicago region. Of course, many SAV

fleet operators will also charge a flat pickup fee, so that kind of pricing would shift trips away from the very short distances seen in Figure 6-3a.

Table 6-1. Non-transit SAV fleet performance with DRS (SAV-D2D and SAV-FMLM services)

Scenarios	SAV-D2D	SAV-D2D + SAV-FMLM	SAV-D2D + SAV-FMLM + aBuses
Avg. travel time per person (minutes per person-trip)	10.0 min	12.6	12.3
Avg. wait time (minutes per person-trip)	4.9 min	4.6	4.3
# SAV requests/day	232,247 SAV rides/day	260,355	259,685
% Requests met (with 15- minnute max wait time)	99.4%	98.8%	99.0%
AVO by revenue-trips	1.10 persons/vehicle	1.13	1.11
AVO by revenue-miles	1.05	1.05	1.05
Avg. person-Trips/SAV/day	19.4 trips/day	23.6	23.5
% eVMT	25%	26%	25%
SAV VMT/person/day	3.03 mi	3.16	3.11
VMT/SAV/day	131.4 mi/SAV	136.9	134.9
Hours in operation/SAV/day	4.2 hr	4.4	4.3

6.4.2 SAV FMLM Service

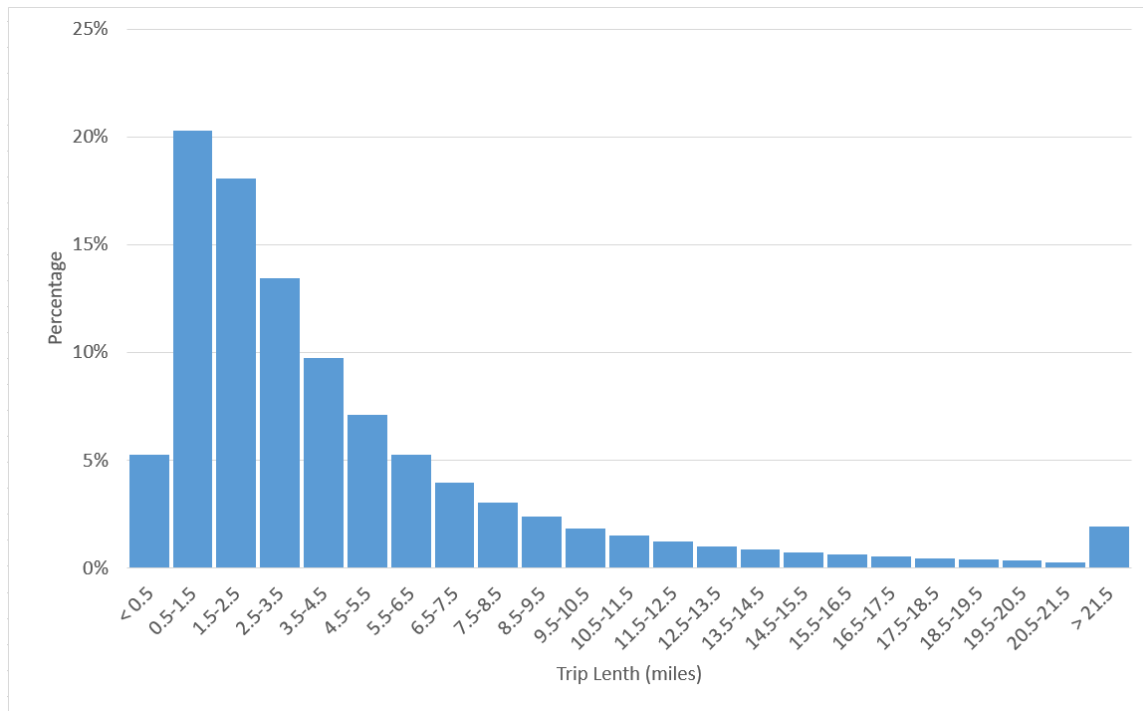
The SAV FMLM service is added to the simulation when the D2D service is already available. Adding an SAV FMLM service addresses a clear gap in prior SAV studies while allowing SAV fleet managers to coordinate with transit agencies to provide more integrated and efficient transit systems.

The addition of SAV FMLM service raised the region's transit mode share from 5.4% to 6.3% (summing the FMLM mode and transit mode splits in Figure 6-2's "SAV-D2D + SAV-

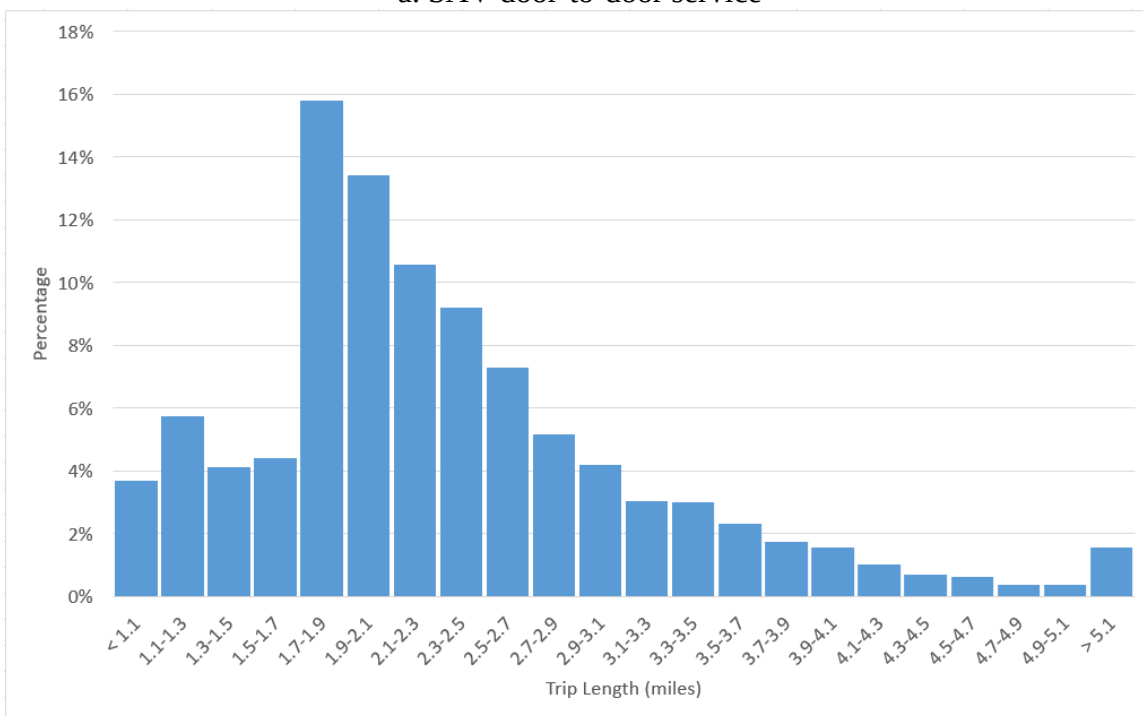
FMLM” scenario), while the other modes remained quite stable. The mode share increment in transit was relatively small, but this is still a good sign for promoting transit use and increasing the transit catchment area. One should note that the FMLM service is discussed under the availability of the SAV D2D service, which is already an attractive travel choice. Without SAV D2D service, or when the automation technology is not mature enough and SAVs are only capable of providing low-speed FMLM service in geofenced regions, more transit demand may be attracted, as seen from Chapter 4.

Since both D2D and FMLM requests were served by SAVs, the fleet was better utilized, as seen from the increased SAV VMT per day and operating hours, as well as more trips served per SAV (Figure 6-1). However, the increase in fleet utilization is small due to the low FMLM share. For the 5% sample simulated, there are about 22k FMLM service requests (to/from transit stations), which are 10% of the D2D service requests. Interestingly, the travel time is about 2.6 minutes longer per traveler compared to when only D2D service is offered, due to more trip requests (thus more rerouting), but the wait time is slightly lower because of the request aggregation at transit stations.

In contrast to the long average trip length for SAV D2D services, FMLM SAV trips were shorter, as expected (Figure 6-3b). Most FMLM trips were about 1.7 to 1.9 miles, but there were some FMLM trips longer than 5 miles. Since walking to transit stations is usually 0.25 miles on average (Nabors et al., 2008), implementing the FMLM service largely increased the transit catchment area. As seen from the low share of FMLM trip distances shorter than 1.1 miles, most riders who walk to transit stations will probably retain their previous behavior, but a few will shift to the new FMLM SAV service (indicated by the drop in the mode share). Therefore, FMLM service will mostly attract those who live from 1.7 to 3.5 miles away from transit stations, which is usually beyond the walking distance for accessing and egressing these transit stations. This can also be reflected through Figure 6-4, especially Figure 6-4b and Figure 6-4c, that most boardings of FMLM trips happened not far from the transit lines. For example, the radial pattern follows the PACE suburban bus and the METRA commuter rail, while downtown Chicago is where most of the CTA bus stations are located.



a. SAV door-to-door service



b. SAV first-mile last-mile service

Figure 6-3. SAV trip length distribution

Figure 6-4 presents the spatial and temporal distribution of the boardings onto the SAVs which offer FMLM service. People are shown to prefer FMLM SAV service during the day rather than at nighttime when few buses and rail lines are operating. Most boardings occur midday, and are more spatially spread out. Downtown Chicago is the busy zone for FMLM trips, which can be either first-mile or last-mile trips. This also indicates that one end of the whole trip (considering both FMLM and transit trip segments) mostly occurs downtown but the other end is often near the transit lines, especially those trips in suburban areas.

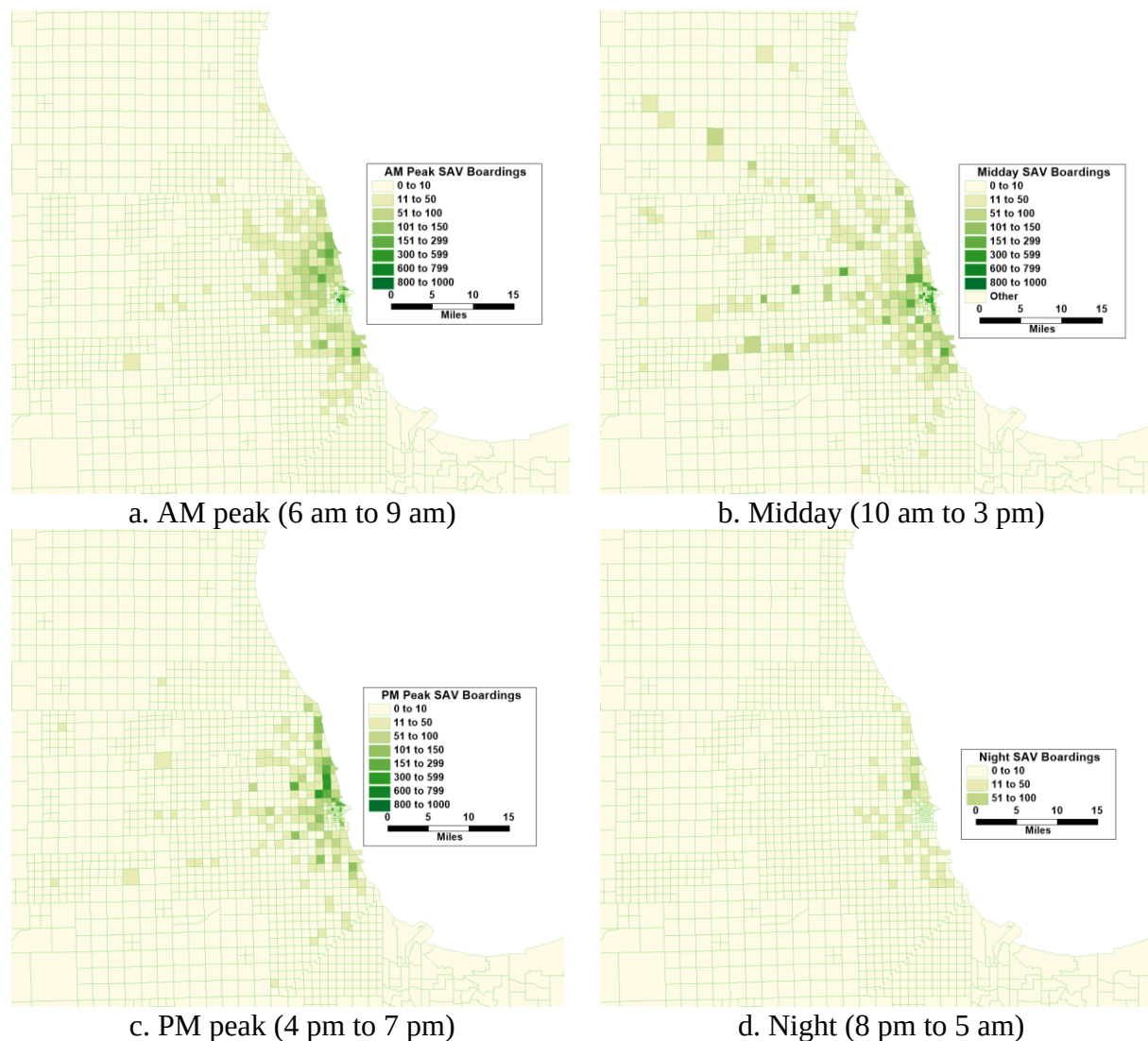


Figure 6-4. Boardings of FMLM SAV service by four times of day

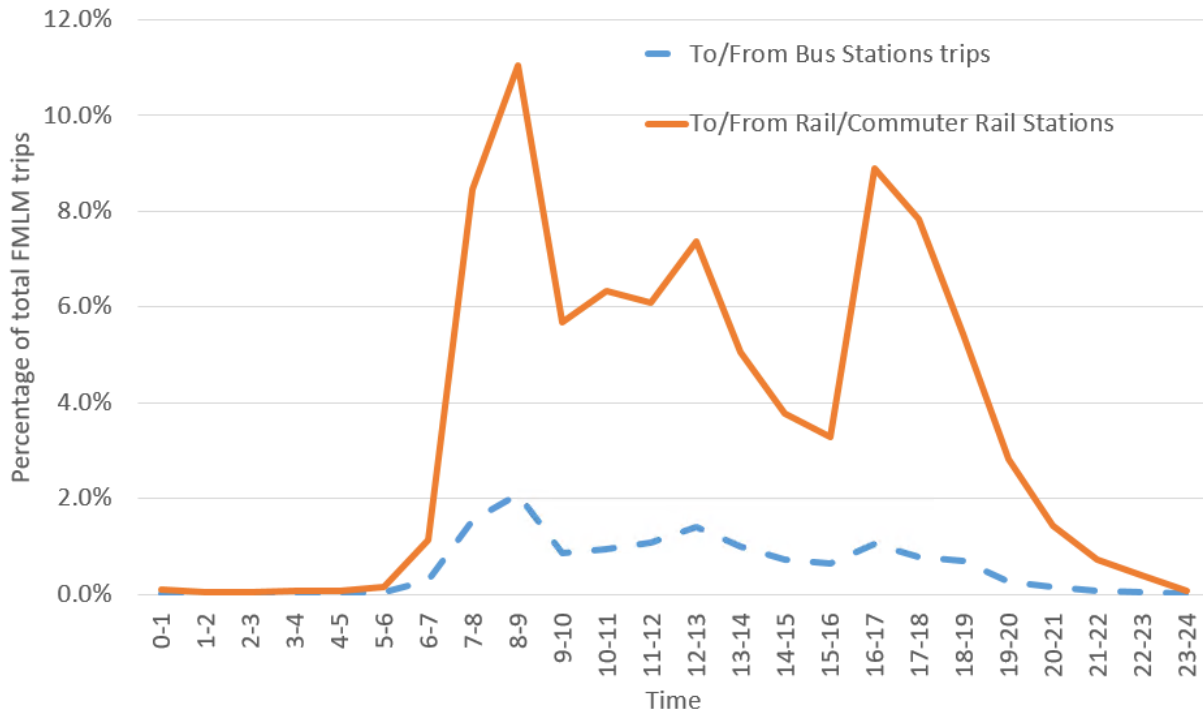


Figure 6-5. First-mile last-mile trip count distribution by the hour

Figure 6-5 further shows the distribution of FMLM trip counts by the hour, while differentiating trips accessing and egressing bus stations from rail stations. The trip counts over time follow the pattern in Figure 6-4. Few buses and rail lines were operating before 6 am so the use of SAVs to connect to transit stations was rare. The highest peak across the day happened at 9 am, and the second peak happened in the afternoon at 5 pm. Interestingly, a third small peak occurred midday at 1 pm, although there was a drop after the morning peak hours. Lunch trips are often short so the number of midday trips is expected to be minimal. However, there may still exist several commuting trips or other business trips by travelers who work with flexible schedules. Figure 6-5 also shows that trips to/from rail lines dominates FMLM trips, with a ratio of 6 to 1. This is expected because rail trips are often longer, not impacted by road congestion, and have longer access and egress distance compared to bus trips. Therefore, accessing and egressing rail stations using the FMLM SAV service may reduce the total trip cost, considering the transfer penalties and walk/ride times. However, many bus riders already have one or two transfers between bus trips and often have shorter access and egress walking distance, so adding

another SAV trip to the whole journey would largely raise the transfer burden and, thus, the overall trip cost. In addition, commuter or light rail stations often have pick-up or drop-off areas nearby, but this is not the case for every bus station. If too many SAVs access and egress bus stops, curbside congestion may be serious, and, thus, more road congestion could increase the overall trip cost.

6.4.3 SAV-Based Transit Service

Next, in addition to SAV's D2D and FMLM service, the scenario discussed in this section further uses an SAV-based transit service to substitute the regular CTA and PACE bus service with new 15-seat SAVs following a doubled dispatching frequency. The 15-seat SAVs also have 15 standing spaces, mimicking the current SAV shuttles that are tested around the globe (Stocker and Shaheen, 2019). Since this scenario assumes that SAV D2D and FMLM services exist, the SAV-based transit is also assumed to have mature automation technology. The SAV-based transit fare is assumed to be 60% of the traditional transit service (Quarles et al., 2020), since aBuses can reduce the operating cost by eliminating the need for drivers.

With a 40% reduced fare for the SAV-based transit service, the mode share of transit slightly increased. Similarly, a 5% increase in FMLM mode share was noted (Figure 6-2). Since most of the FMLM trips were connected to rail stations, the fleet performance of SAV D2D and FMLM service remained quite stable (Figure 6-2). This means that the SAVs' on-demand service and the transit-based bus service may not have frequent interactions in this case.

However, there is potential to integrate the aBus service and the FMLM service. For example, the pricing of the service can combine the fare for the FMLM and aBus services. The transit use could be promoted if the FMLM price is halved when connecting to bus stations, or the transit fare can be eliminated if people are willing to take shared rides to access or egress bus transit. More importantly, the utilization of the SAV fleet could be improved through self-relocation and shared-use between these two different services. In this chapter, the SAV on-demand service (D2D service and FMLM service) uses 4-seater vehicles, while the aBuses are 15-seaters with 15 standing spaces. These 4-seater vehicles can sometimes help serve part of the existing transit lines or some lines that do not have high demand, while the 15-seater SAVs can also help cater to travel demand requesting on-demand services.

6.4.4 Welfare Analysis

Welfare analysis has been widely used to compare the impacts of different investments and policies, like added highways (Kockelman and Lemp, 2011) and congestion pricing (Li et al., 2020). Here, the social welfare impacts of introducing different SAV services are presented as changes in consumer surplus or Chicagoans' willingness to pay for the new service scenarios. These changes in consumer surplus (ΔCS) are computed as normalized logsum differences between pairs of scenarios (de Jong et al., 2007).

A person's consumer plus (CS) is added benefits or willingness to pay beyond what one actually pays for a good or service. If the unobserved error term of the logit model's utility function is an independent and identically distributed (IID) Gumbel variable and utility is linear in cost, the expected maximum utility achieved (across alternatives) is the logsum of the logit choice utilities (de Jong et al., 2007). Therefore, the change in consumer surplus (expressed in monetary units) for a certain traveler i given a new scenario (identified with a superscript 1) compared to a base scenario (identified with a superscript 0) is as follows:

$$\Delta CS_i = \frac{1}{\alpha_p} \{ \logsum_i^1 - \logsum_i^0 \}$$

where the logsum incorporates the mode choice utilities. The logsum term is the natural log of the sum of all exponential functions of the utilities in the choice set:

$$\begin{aligned} \logsum = & \log \left(\exp(U_{bicycle}) + \exp(IV_{auto} \times \log(\exp(U_{SOV}) + \exp(U_{TAXI}))) + \exp(U_{HOV}) \right. \\ & + \exp \left(IV_{rail} \times \log(\exp(U_{PARK_AND_RAIL}) + \exp(U_{RAIL})) \right) + \exp(U_{WALK}) \\ & + \exp \left(IV_{bus} \times \log(\exp(U_{PARK_AND_RIDE}) + \exp(U_{BUS})) \right) \\ & \left. + \exp(U_{TNC_AND_RIDE}) + \exp(U_{TNC_AND_RAIL}) \right) \end{aligned}$$

Personally owned vehicle travel and TNC/taxi travel are nested under the automobile nest. Rail nest consists of rail modes that have walking as both access and egress mode, and personal car as the access mode and walking as the egress mode. Similarly, bus nest consists of bus modes that have walking as both access and egress mode, and personal car as the access mode and walking as the egress mode. High occupancy vehicle, walk, bicycle, and FMLM last

modes are assumed not nested with any other modes. When a choice is considered not available, the utility is set as a large negative value, so the $\exp(U)$ value is nearly zero.

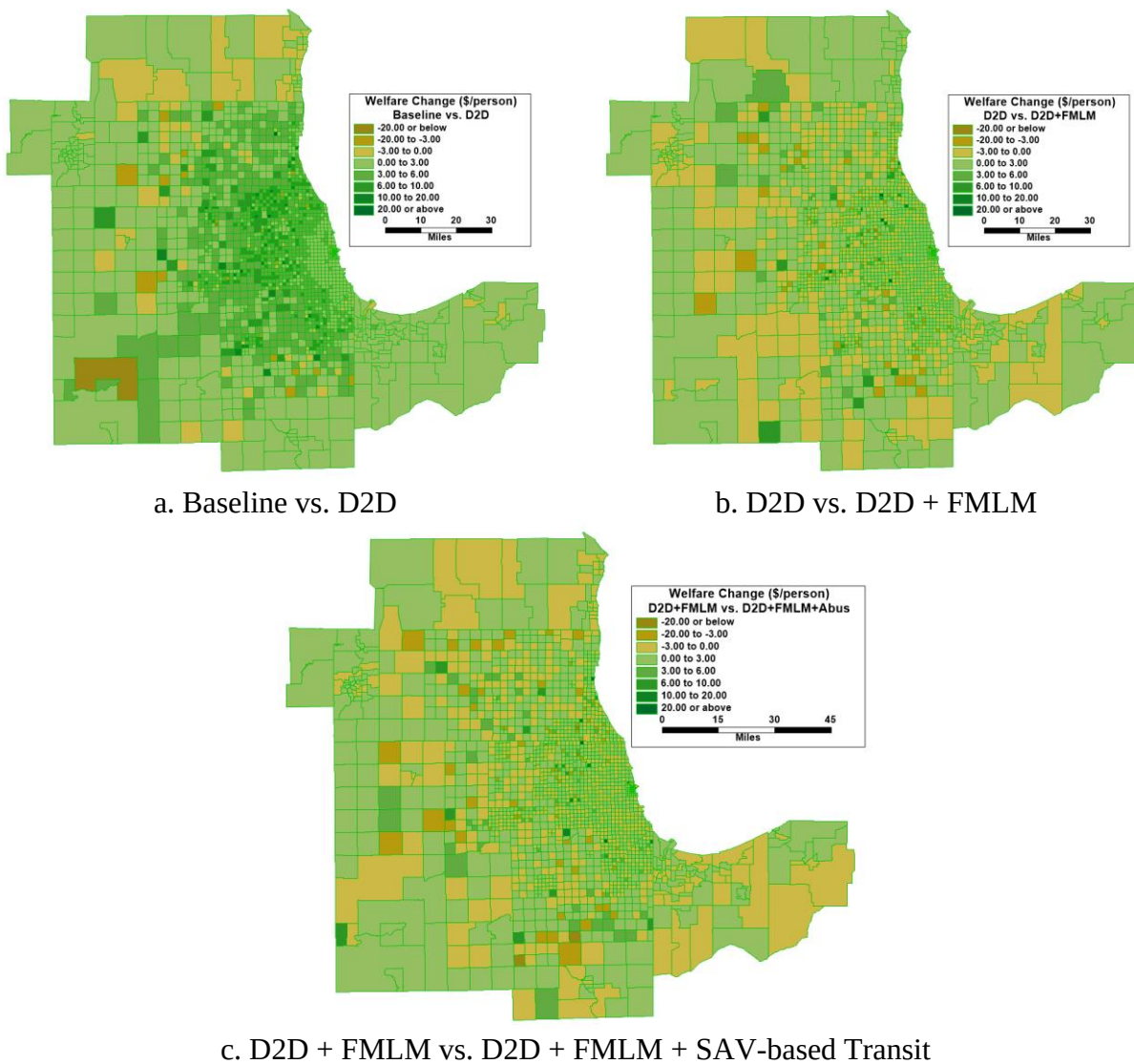


Figure 6-6. Welfare change across SAV service types (\$/person)

In this chapter, three different comparisons are conducted: 1) adding SAV D2D service compared to the base case, 2) adding SAV FMLM service to SAV D2D scenario with SAV D2D scenario to be the baseline, 3) adding SAV-based transit to SAV D2D+FMLM scenario with SAV D2D+FMLM scenario as the baseline. Furthermore, ΔCS was aggregated at the TAZ level and averaged across the synthesized population in the corresponding TAZs.

Implementing SAV D2D service increased the social welfare of most people in urban and suburban Chicago (Figure 6-6a). Although the urban area experienced a small increase, many TAZs in the suburban area experienced an increase of more than \$6 per person per day. This is because the fleet of SAVs improved the mobility of the whole area, especially in the suburban area where people used to travel by car and or transit. Downtown Chicago has a well-connected transit system, so the welfare increase is limited. Since the suburban area and the urban area were the places where most of the shared rides happened, some rural areas experienced a welfare loss.

When further adding the FMLM service, the social welfare in downtown Chicago remained stable (Figure 6-6b). This is also due to the well-connected bus and rail transit system, where people sometimes can easily replace FMLM trips with walk and bus trips. However, a more mixed pattern was observed for the suburban area. TAZs that experienced a welfare increase are more likely to be the TAZs near transit stations (e.g., within 3.5 miles). Since the SAV fleet size is fixed, the riders outside the 3.5-mile buffer of the transit stations may have longer wait times for SAVs and longer detour times in shared rides, compared to the case when only D2D service was provided. Therefore, these people are likely to suffer welfare loss.

The pattern of the welfare change when adding the SAV-base transit is similar to the case when adding the FMLM service. The SAV-based service, which has lower fares and more frequent service but smaller vehicle capacity, attracted more riders, but travelers are also more likely to skip D2D SAVs and wait longer at the station due to the small SAV-transit capacity. The road congestion of the transit corridor may also increase due to more SAVs being dispatched. Therefore, Figure 6-6c shows a mixed pattern of social welfare change.

6.5 SUMMARY

This chapter integrates SAVs' D2D service, FMLM service, and the SAV-based transit service, and reveals the possible mode shares, fleet performance, and social welfare change for the 5% population sample across the Chicago network. POLARIS was leveraged to simulate the detailed behavior of agents, with novel functions added that focuses on the integrated modeling of multimodal routing and the transfer behavior between SAVs and transit. Since most of the previous transit-related simulations do not optimize the multimodal routing for a mixed-use of SAVs and transit lines, the multimodal routing in this study ensures the best routes are

considered by taking the travel time, cost, and the number of transfers between different modes into account.

SAV D2D service accounts for 15% of the mode share under the assumption of a \$0.50 per-mile fare and households' willingness to relinquish their vehicle for future years. A fleet of 12,741 SAVs serving 5% of the Chicago population, or 1 SAV for every 40 residents, could offer 15-minute service for trips averaging 4.6 miles. Operating for more than 4 hours, on average, each SAV served nearly 20 requests per day. Most SAV riders preferred to use the SAV D2D service for relatively short-distance trips, but the trip could be longer than 50 miles given the large nature of the region. Based on the distribution of the social welfare change, residents in the suburban area benefited most from the SAV D2D service, followed by those in the urban area. When the same SAV fleet offered both D2D service and FMLM service at the same time, the SAV fleet was more utilized, by serving 12% more requests per day per SAV with only a 4% increase in VMT. The transit use was also brought up from 5.4% to 6.3%, with a stable mode split among other modes compared to only using D2D service. The average trip distance of FMLM service was also shorter, with most trips ranging from 1.7 to 1.9 miles. This indicated a prominent expansion of the transit catchment area, from a typical 0.25-mile average walking distance. The spatial patterns of SAV FMLM service also indicated such improvement, as many more boardings were observed in the TAZs along the transit lines (e.g., PACE suburban bus and the METRA commuter rail). Downtown Chicago is also the busy zone for FMLM trips, due to the presence of the CTA bus service. FMLM service boarding occurred mostly during the day, especially during morning peak and midday. Trips to/from rail lines dominated the FMLM trips, compared to the bus stations, with a ratio of 6:1. When adding the FMLM service, social welfare does not change much in the downtown area, because there are multiple travel choices. TAZs near transit stations in the suburban areas are more likely to have welfare gain. Lastly, when the SAV-based transit service was added to the scenario, the performance of the on-demand SAV fleet did not change much since the FMLM service mainly focused on connecting to rail. The social welfare change also showed a mixed pattern in both the urban and suburban areas. The reason for this is likely to be riders skipping SAVs due to small-size aBuses and the road congestion in the transit corridor caused by more frequently dispatched SAVs, although some riders enjoyed lower fares and more frequent service.

Further tests can be conducted to enhance the discussion. For example, the coordination with transit schedules used in Chapter 5 can be added and a large travel party size for sharing rides can be incorporated. The utility functions of SAV FMLM in the mode choice model assume one alternative-specific constant value, which is the average of taxi and the conventional car mode. Sensitivity analysis can be conducted to explore the change in the fleet and network performance as well as the social welfare under different penetrations of FMLM service.

Based on the various service options tested here, SAVs can provide promising integration with future public transportation systems. The low fare D2D service will be key to reducing vehicle ownership, encouraging more shared rides, and gaining social welfare in the suburban area, while the FMLM service can increase transit ridership and catchment area. The SAV-based transit will also offer a cost-efficient service, and the network and fleet performance may be improved through integrations with the on-demand service fleet and new pricing strategies.

Chapter 7. Conclusion

7.1 SUMMARY AND CONTRIBUTIONS

Three main SAV services can support communities' future mobility. Elimination of drivers' wages, smooth vehicle acceleration and deceleration, improved safety through cameras and automated driving systems, and centralized-controlled for more efficient ride-sharing make SAV door-to-door (D2D) service a popular choice in the future. Such services can support the elderly and disabled, while potentially reducing total vehicle-miles traveled (VMT) and increasing average vehicle occupancy (AVO) via dynamic ride-sharing (DRS) (Childress et al., 2015; Gurumurthy and Kockelman, 2018). Thanks to lower-speed, geofenced deployments around the world (Stocker and Shaheen, 2019; Hou et al., 2017), SAVs may initially serve first-mile last-mile (FMLM) connections and from transit stations. But D2D service (with and without DRS) will also be important, for longer and longer trips, as a fleet's speed limits and geofences expand. SAVs may eventually take the lead in public transit systems, via a variety of vehicle sizes: a bus-sized or mid-size SAV may serve traditional routes, where heavy transit demand already exists.

This dissertation investigates the multi-faceted service that SAVs can provide, as a part of existing and future transit systems. Chapter 2 identifies the gaps in SAV studies, especially on planning methods and modeling techniques for different SAV services. Most studies focus on D2D services, so FMLM service and SAV-based transit studies are lacking. Simulation methods have been leading research on SAVs, with mostly heuristic methods pursuing optimized objectives. In addition, road congestion and integration of different SAV service types are not reflected properly in most studies.

To address such research gaps, Chapter 3 micro-simulates SAV-based transit in a 6.5 mile-corridor setting in mixed traffic with human-driven cars, to understand how traffic reacts to, and how riders and system costs are affected by SAV sizes and performance attributes. Microscopic models capture the detailed person and vehicle behavior, and cost analysis is conducted to investigate the preferred vehicle size choice under different demand levels, road congestion, and settings of traffic signals and parking bays. Simulation results show that the system with 5-seat SAVs has relatively low total system cost per capita at low passenger demand

levels, but 10-seat SAVs are favored at higher demand levels. More frequent services of smaller SAVs, in general, do not significantly affect background traffic given their shorter dwell times at stops. Provision of bays helps large-size vehicles offer a higher corridor speed, due to fewer vehicles dispatched in the corridor, but the high operating cost allows them to be outperformed by smaller sizes of SAVs in terms of total system cost per capita. The use of traffic signals substantially lowers the corridor speed, especially for 5-seat vehicles at high passenger demand, making 10-seat SAVs the best choice for most of the demand levels.

Chapter 4 explores the idea of using SAVs to provide FMLM connectivity to transit in automated mobility districts (AMDs). The FMLM service module is established in the simulation toolkit developed at NREL (Zhu et al., 2020), considering the feedback of SAV users' wait time in the mode choice model. The SAV microsimulation not only models detailed transit operations (such as stopping duration, schedule, shared intersections by railway and roadway, and railway platforms for getting on and off) but also makes a foray into incorporating operational logic associated with deploying SAVs for FMLM connections to transit. Mode splits, wait times and other system features are examined by implementing two SAV fleets offering FMLM ride-sharing service to 10% of central Austin's trip-makers near five light-rail transit stations. With 15-minute rail service headway, and 15 SAVs serving FMLM connections to and from each geofenced area around rail-transit stations, simulations predict that 3.7% of the person-trip-making will shift from driving alone to transit use in a 3-mile by 6-mile central Austin area. Sensitivity analysis of transit headways (from 5 to 20 minutes) and fleet sizes (from 5 to 20 vehicles in each AMD) shows an increase in FMLM mode share with more frequent transit service and larger fleet size, but total travel time served as the biggest determinant in trip-makers' mode share. In this application, FMLM service is demonstrated to be an efficient tool to offer connections to rail stations, although the total VMT increases due to empty travel.

Chapter 5 examines more details of person and vehicle for the same 3-mile by 6-mile area of central Austin, around five stations along Austin's Red Line, by enhancing the SAV FMLM toolkit, including allowing for flexibility in choosing distinct access and egress modes, allowing en route rerouting for SAVs' new pickups, coordinating SAV operations with train schedules, simulating full SAV FMLM travel demand, and adding SAVs' self-relocating to parking depots. Results indicate that about 90% of the SAV trips are shared trips, but shared

VMT constituted only a third of the total SAV VMT across the study region. A higher level of transit demand results in a larger SAV fleet size and more VMT, with greater utilization of the SAV fleet. However, better SAV utilization comes at the expense of increased wait time and service duration for riders. Furthermore, the scenario exercises with fixed fleet size restrictions revealed that baseline system performance can be achieved even when the fleet size is reduced to 60%. This finding shows that the proposed vehicle-rider matching algorithm guarantees a stable system performance even under a reduced fleet size. DRS settings are also closely related to system performance. Stringent matching criteria led to a larger fleet size requirement and underutilization of the SAV fleet. Relaxing the matching criteria resulted in greater vehicle utilization but at the expense of increased wait times and service durations for the riders. With a DRS algorithm tightly coupled to train schedules, over 87.2% of the riders catch their desired train, compared to 57.5% under the baseline DRS algorithm (i.e., with no transit coordination), underscoring the importance of integrated transit planning for efficient FMLM connectivity.

Due to the limitation of network size in microscopic simulations, Chapters 4 and 5 explore the FMLM service in a relatively small region. Chapter 6 utilizes the mesoscopic POLARIS model to anticipate the impact of an integrated SAV system in the Greater Chicago region, which has a much larger transit network. Starting from 5% travel demand of the 2018 Chicago network as the base case, scenarios involving SAVs were designed to have one additional SAV service each time (i.e., SAV D2D service, SAV FMLM service, and SAV-based transit), to explore the incremental changes of the new SAV service brought to the whole network. Accounting for 15% of the mode share, 12,741 SAVs offer 15-minute \$0.50 per-mile D2D service for trips averaging 4.6 miles. Offering FMLM service raised transit's mode share from 5.4% to 6.3%, while enabling the large SAV fleet to serve 12% more requests per day, with only 4% added VMT (as compared to the D2D-service-only scenario). Most SAV FMLM trips are 1.7 to 1.9 miles long, and rail station connections dominate those FMLM trips (instead of to and from bus stops and stations). This work's welfare analysis suggests that residents in Chicago's more suburban areas benefit most from the addition of SAV D2D services (especially those near transit stations), followed by those in the urban area. Such methods and findings should prove helpful to fleet owners, transit agencies, and transport planners and policymakers,

in anticipating behaviors while designing and managing systems that better meet each communities' goals.

7.2 FUTURE RESEARCH DIRECTIONS

Based on these investigations, useful future directions for SAV studies, in connection with public transportation systems, include code and scenario expansions. For example, this dissertation examined the case of a single transit-service type (fixed-route and fixed-stop) using existing bus routes around the Chicago region, and a homogenous fleet of automated buses. More variations in SAV-based transit, like semi-fixed route service to replace or extending existing bus lines with more flexible vehicle sizes and fleet sizes, will be helpful.

SAV FMLM service can also do more than connect travelers to bus and rail stations. Airport and long-distance ground connections may be very popular, and possibly reserved ahead of time. Similar to the coordination with transit schedules, SAVs can coordinate with flight schedules and long-distance trip departure times, to better serve these connecting trips.

POLARIS simulation can be made more realistic by incorporating additional person and vehicle details, such as considering travel time reliability of the picking up and dropping off (Alonso-González et al., 2020), and using stop-aggregations to improve SAV fleet efficiency (Gurumurthy and Kockelman, 2020). On the other hand, a more realistic simulation consumes more resources for computing, as seen from this dissertation's micro- and mesoscopic simulations. This demands faster ride-sharing and shortest-path algorithms with better multi-thread computing techniques. Moreover, the ride-sharing algorithms are often rule-based myopic heuristics, but better formulations can potentially offer system-optimized or user-equilibrated solutions to better control the SAV fleets across multiple services. The travel party size for SAV services can be modeled to have more than one person, to realistically reflect the case when people travel with family and friends. This may make SAVs more popular than discussed in this dissertation.

This dissertation focuses on the spatial integration of the SAV services. Temporal integration can also be incorporated to better use SAVs in off-peak periods, since the travel demand varies across SAV service types. SAV use can shift by time of day, and day of year, based on different service time windows, as discussed in Atasoy et al. (2015). Related to this,

last-mile freight transportation may be a popular use of SAVs. For example, ride-sharing can add pick-ups and drop-offs of smaller goods, in concert with SAV's D2D service.

Finally, SAVs are very likely to be electric vehicles (EVs) when deployed. Fleet evaluations should consider the battery-charging needs and environmental benefits of shared automated all-electric vehicles (SAEVs) (Chen et al., 2016; Loeb et al., 2018; Loeb & Kockelman, 2019). This will involve more strategies in deploying and specifying the fleet, including charging station deployment (Huang and Kockelman, 2020). Due to the constraint on the SAEV driving distance as well as the charging duration based on different types of charger available, schedule optimization will become more important in the POLARIS code. Policies like credit-based congestion pricing and EV or electric-power subsidies, to lower congestion and/or emissions, are also important to consider, to help enable most sustainable and efficient cities and nations.

AVs make travel easier, and SAVs make such travel more affordable for the masses. But such technologies can gridlock our communities, so smart transit planning is now needed.

Glossary

aBus	Automated Bus
AMD	Automated Mobility District
AV	(Fully-) Automated Vehicle
AVO	Average Vehicle Occupancy
BAU	Business as Usual
CTA	Chicago Transit Authority
D2D	Door-to-Door
DRS	Dynamic Ride-Sharing
EV	Electric Vehicle
eVMT	Empty Vehicle-Miles Traveled
FMLM	First-Mile Last-Mile
HOV	High Occupancy Vehicle
IVTT	In-Vehicle Travel Time
MATSim	Multi-Agent Transport Simulation
CAMPO	Capital Area Metropolitan Planning Organization
MSA	Method of Successive Averages
mph	Miles per Hour
OD	Origin-Destination
OVTT	Out-of-Vehicle Travel Time
POLARIS	Planning and Operations Language for Agent-Based Regional Integrated Simulation
SAEV	Shared Autonomous Electric Vehicle
SAV	Shared Autonomous Vehicle
SOV	Single Occupancy Vehicle
SUMO	Simulation of Urban MObility
TAZ	Traffic Analysis Zone
TNC	Transportation Network Company

VMT	Vehicle-Miles Traveled
VOTT	Value of Travel Time
vphpl	Vehicles per Hour per Lane

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