SAV OPERATIONS ON A BUS LINE CORRIDOR: TRAVEL DEMAND, SERVICE FREQUENCY AND VEHICLE SIZE

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ABSTRACT

Before Shared Automated Vehicles (SAVs) can be widely adopted, they are anticipated to be implemented commercially in confined regions or fixed routes where the benefits of automation can be realized. SAVs would be likely to operate in a traditional transit corridor, replacing conventional transit vehicles, and have frequent interactions with other vehicles as well as pedestrians. This paper micro-simulates SAVs' operation on a 5 mile-corridor to understand how vehicle size and attributes of SAV-based transit affect traffic, transit passengers, and the system cost. The SUMO (Simulation of Urban MObility) package is employed to model microscopic interactions among SAVs, transit passengers, and traffic. Results show that the use of smaller, but more frequent SAVs leads to reduced passenger waiting times but increased total system travel times. More frequent services of smaller SAVs in general do not significantly affect general traffic due to shorter dwell times. Overall, using smaller SAVs instead of the large 40-seat SAVs can reduce system costs by up to 3.1% while also reducing passenger waiting times, under various demand levels and passenger loading factors. However, the use of 5-seat SAVs does not always have the lowest system costs.

Keywords: Shared Automated Vehicles, Bus Line corridor, Micro-simulation, Vehicle Size and Service frequency

INTRODUCTION

Automated vehicles (AVs) and shared mobility will fundamentally change the future traffic pattern, by providing cost, environmental, and safety benefits. Shared AVs (SAVs) offer more potential benefits through a lower-cost on-demand service that can be flexible in both schedule and routes.

Currently, SAV tests are being performed all over the world, as people try to envision how SAVs should be operated in both the near and far future (Zhao and Malikopoulos, 2019). Over 40 corporations are working on AVs (CBinsight, 2019). Waymo (2017) has tested its AVs in Arizona and Texas, and achieved 4 million self-driven miles by November 2017. Before SAVs can run everywhere, they are anticipated to be implemented commercially in a confined region where full automation benefits can be realized (Hou, 2018; Zhu, 2018). SAVs are more likely to function as paratransit in this case. NAVYA (2019) had over 130 automated shuttles running worldwide in 2019 in 7 types of places (city, airport, campus, hospital, resort, theme park and industry), including Mcity in Michigan and Lake Nona in Orlando.

Although extensive ongoing studies are investigating what changes SAVs would bring to the environment, urban congestion and shared economy, the impact of vehicle sizes, considering microscopic interactions with traffic, under different travel demand levels has not been formally examined. SAVs can have a passenger capacity that varies from 5 passengers (like the common size of a personal owned AV) to 20 (e.g. fixed-route automated shuttle), or even 40 (e.g. automated bus). Smaller SAVs (like 5-seat sedans) are nimbler and easier to park, can accelerate faster, and may cause less congestion and sightline issues. 5-seat sedans can more easily run flexible routes for point-to-point on-demand services without frequent stops. Riders may experience rerouting in 5-seat sedans, but will experience fewer pick-ups and drop-offs than in larger vehicles. Large SAVs usually run fixed-routes and can be more space-efficient (per person-mile traveled) but will have to stop more often at stations. The SAV size that is best for transit corridor operations is not only related to the preferences of riders but is also important to the stakeholders. 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.

Currently, automated shuttles are operating at a low speed (usually less than 30 miles/h) with limited interactions with traffic modes. It is often seen that these SAVs have their dedicated right of way, or share the right of way with pedestrians . In this way, SAVs have more frequent interactions with pedestrians than with other vehicles. However, with the development of automated technology and the sharing economy, SAVs would be likely to operate in a traditional transit corridor, replacing conventional transit vehicles, and have frequent interaction with other vehicles as well as pedestrians. This work micro-simulates SAVs' operation in a 5 mile-corridor setting to understand how traffic reacts to, and how passengers and system costs are affected by vehicle sizes and performance attributes for SAV-based "transit".

LITERATURE REVIEW

SAV simulation efforts are made around fleet sizing decisions (Fagnant et al., 2015; Maciejewski and Bischoff, 2016; Spieser et al., 2014) along with other studies on the ride-sharing mechanism (Hyland and Mahmassani, 2018), electric vehicles involving charging decisions (Chen et al., 2016; Chen and Kockelman, 2016) and environmental effects (Fagnant and Kockelman, 2014; Greenblatt and Shaheen, 2015). Spieser et al. (2014) investigated the proper fleet size in Singapore that could serve the travel demand while ensuring a desired level of service. Their results showed that an SAV fleet size of about one-third of the total number of passengers was desired in Singapore. However, a 1 SAV per 9.3 conventional vehicle replacement was shown in Fagnant et al.'s (2015) simulation in the Austin area. Recent fleet sizing decision studies mostly assume that an SAV has a maximum occupancy of 4 passengers, however, the capacity of current SAVs used for the tests is more than 4 passengers (Stocker and Shaheen, 2017) and is expected to be as large as 20 or more passengers.

Microsimulation noted in this paper refers to the traffic microsimulation where individual driving behavior is tracked, like detailed car following and lane changing maneuvers. However, many studies are using the term microsimulation to define a simulation where agents' information (e.g., route, speed and mode) are tracked. More often, such kinds of simulations are described by researchers as "mesoscopic", given the underlying traffic models are mesoscopic. Vehicles' performance attributes (e.g., acceleration, deceleration, and headway) are not usually tracked. Vehicles' lane changing is also ignored as vehicles are traveling on a link (or roadway). Mesoscopic simulations provide valuable results in regional fleet sizing decisions, mechanisms of ridesharing or even dynamic ridesharing, and traffic patterns under dynamic traffic assignment, but they are not able to capture vehicle trajectories and especially interactions at the microscopic level between SAVs and conventional vehicles, such as at stations. While this is easier for microscopic simulations, SAV micro-simulation studies are not often seen.

Alozi and Hamad (2019) used VISSIM to micro-simulate CAVs on a 7-kilometer-freeway segment in Dubai. Results from various CAV market penetrations were compared, in terms of vehicle delay, speed and travel time. Since VISSIM provides adjusted car following and lane changing models (Alozi and Hamad, 2019) to accommodate CAV features, these models were applied directly. Authors observed an 86% decrease in delay under a 100% CAV penetration scenario and results showed that the greatest benefits of CAVs are obtained when market penetration of CAVs is ranging from 0% to 20%, and from 70% to 80%. However, this is a simulation study that investigates the impacts of personal owned CAVs only, as SAVs (shared ride) are not considered.

Zhu et al. (2018) quantified the mobility and energy benefits of SAVs running a fixed route in a toy network. SAVs can take ridesharing requests, and pick up and drop off passengers through a dispatching pattern. However, the simulation does not provide a service in a realistic network considering the impact of SAV sizes on the realistic traffic flow. This microsimulation presented a useful toolkit built on the Simulation of Urban Mobility (SUMO) package that can perform real-time micro-simulation control of passengers and vehicles. Based on Zhu et al.'s (2018) work, Huang et al. (2020) simulated a 5 mi × 8 mi central Austin area with SAVs serving the first-mile last-mile (FMLM) to Austin's Red Line commuter rail. VMT was predicted to rise 3.7% in central Austin with average vehicle occupancy falling 30% (from 1 to 0.74 persons per vehicle), due to empty SAV driving (between riders).

Detailed car following and lane changing models raise the time burden in microscopic simulations, compared with mesoscopic and macroscopic simulations. This leads to a confined simulation area with a low share of realistic travel demand in current microsimulation studies (Zhu et al. 2018). Vehicle data at the trajectory level can only be obtained through micro-simulation, which provides more accurate vehicle movement and energy information.

Some other studies also investigate the integration of SAV and transit use (Merlin, 2017; Pinto et al., 2019; Wen et al., 2019; Shen et al., 2018), but they are not at the microscopic level. Shen et al. (2018) simulated an integrated AV and public transportation system based on Singapore's transit structure and demand characteristics. An agent-based supply-side simulation was built to assess the performance of the proposed service with different fleet sizes and ridesharing preferences in Singapore's 12 km^2 area during morning peak hours from 7 am to 9 am. Authors showed that the integrated system has the potential of enhancing service quality, occupying fewer road resources, being financially sustainable, and utilizing bus services more efficiently. Wen et al. (2019) investigated the opportunities of 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 passengers), fare schemes and hailing strategies only for the connections to the transit station. A nested logit mode choice model was presented, considering 4 modes (bus, rail, park-and-ride, and AV-and-ride) nested under transit mode. It was reported that 560 vehicles can accommodate the travel demand in the city if sharing is not available, but the fleet size can be reduced to fewer than 200 vehicles if an SAV can be shared by 4 people.

Pinto et al. (2019) presented a bi-level model illustrating the proper fleet size of SAVs and the most efficient transit frequency for 20,920 transit vehicle trips within a 16,819 TAZ 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 were simulated, and four modes are involved: walk, transit, SAVs, and SAVs + transit. Results indicate significant traveler benefits, in terms of improved average traveler waiting times compared to the initial transit network design.

Overall, there has been extensive research, no matter the kind of scope, dedicated to understanding the future travel pattern with automation technology. The focus is on the desired vehicle fleet size to meet travel demand, considering the simple link model and car-following model without lane changing. Some consider traffic assignment, which involves the travel behavior of user equilibrium and the integrated system of SAV and transit, but traffic modelling is still simplified. Microsimulation has also been investigated, but vehicles' performance attributes and interactions between SAVs and traffic at the microscopic level have not been studied enough in relation to vehicle size decision. Therefore, this work leverages the Simulation of Urban MObility (SUMO) software (Krajzewicz et al., 2012) to simulate the relationships among vehicles sizes, service frequencies, and travel demand, by considering SAVs serving a transit corridor, to provide insight on how vehicle sizes would impact transit passenger, traffic, and system costs.

MICRO-SIMULATION DESCRIPTION

SUMO simulation

SUMO software is a powerful tool used to simulate multimodal transportation, as it has advantages in micro-simulating interactions among different modes. For example, it can simulate the accurate process of transit access and egress, as well as riders getting on and off the transit. Such detailed manipulations are achieved through TraCI (Traffic Control Interface), a toolkit in SUMO that allows users to retrieve real-time values of simulated objects and to manipulate their behavior "on-line" through Python scripts.

SUMO simulation starts with the input of travel demand and network information. Network information includes all the roadways, links, junctions with signals, and transit platforms. The simulation network setup in this study is a 5-mile, 2-lane, straight corridor with traffic signals

(Figure 1). This corridor has a lane width of 3.5 m and a speed limit of 30 mph based on recommended designing practice from the American Public Transportation Association (Barr et al., 2010). SAV stations (or bus stops) are evenly placed (about every quarter mile) along the corridor (Walker, 2012). Each bus stop is ten meters long. SAVs and conventional vehicles (background flow) can travel in both lanes. As the stations are curbside, when SAVs are serving passengers at stations, they will obstruct the vehicles behind. Scenarios that have parking bays for SAVs are also tested.

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. After an SAV completes its journey, it goes back to the starting point of the corridor, assuming that it does not have wait time at the depot. A Poisson distributed background flow of conventional cars with a mean departure rate is assumed. The base case scenario will test an arrival rate of 0.7 vehicles per second (approximately 1260 vphpl), to reflect a common flow rate on a 30-mph corridor (Barr et al., 2010).With a high dispatching rate (frequency) of SAVs, “bus bunching” can be observed, as SAVs can overtake previously dispatched SAVs.

Travel demand is determined by SAV riders/passengers, who walk on the road, 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 slows down the traffic. Passengers are uniformly generated at random along the corridor, arriving with a uniform distribution in a 3-hr peak time period. 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 randomly generated along the corridor. Riders (bus line users) walk to the nearest station, get on the next available SAV and get off at the station closest to his/her destination. An SAV that has not reached its capacity will stop at a station where new riders are waiting or where current riders want to alight. Further, SAVs wait for passengers running towards the bus, if the bus is stopped at a station and the running passenger can catch the SAV in 10 seconds. After a rider gets off the SAV, he or she will walk to their destination location and then disappear from the simulator.

Figure 1. Bus Line Simulation

Framework

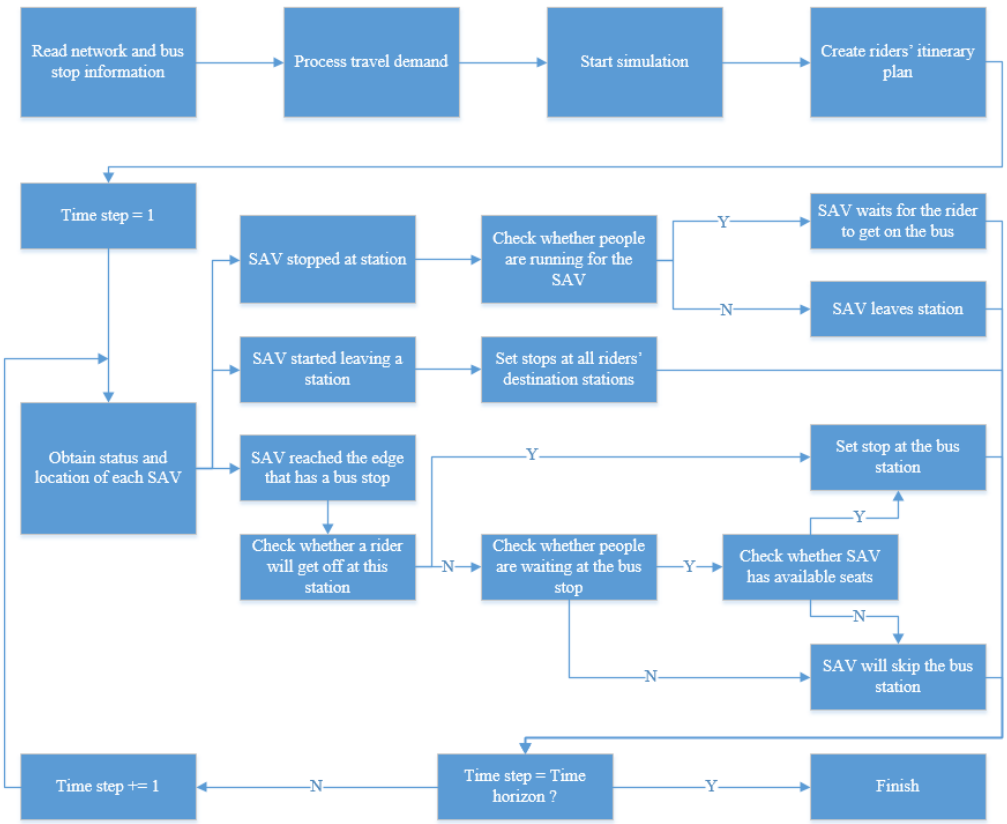


Figure 2. Flow of Simulation

Figure 2 shows the flow of the simulation. Road network and bus stop information are first read, including the edge length, as well as the length and position of the bus stop. Travel demand is then processed to determine the start point of the journey, departure station, arrival station and destination point of the itinerary. After that, simulation in SUMO starts and the itinerary of riders is processed by the simulator at time 0. Beginning at the first step of simulation, background flow comes out on the corridor and every few minutes an SAV departs from the start point of the corridor. During every step of the simulation, which is every 0.5 seconds, the status of riders and SAVs are simulated and tracked. Riders' status is tracked so that SAVs can react based on riders' information (e.g. whether riders are still walking to the bus station, waiting at the bus station, or already on board). The status and locations of SAVs are tracked, to determine whether the SAVs need to stop at the next station. Basically, the simulation 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 parking at the bus 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 stops for all new riders' destination stations. SAVs and riders' status and locations are checked every timestep until the simulation reaches the time horizon. The output includes vehicles' and riders' travel time and waiting time, and riders' walking distance and riding distance.

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.

Table 1. Vehicle configurations and other simulation parameters

	Background Flow	AV1	AV2	AV3	AV4	Source
Capacity	4	5	10	20	40	Stocker and Shaheen, 2017
Acceleration rate (m/s^2)	2.6	1.47	1.28	1.09	0.9	Bae et al., 2012
Deceleration rate (m/s^2)	4.5	2	1.63	1.27	0.9	Bae et al., 2012
Emergency deceleration rate (m/s^2)	9	7.5				Krajzewicz et al., 2012
Length (m)	4.3	4.3	5.5	7.7	12	Krajzewicz et al., 2012; Morando et al., 2018; Ford Motor Company, 2018; GOGO Charters, 2020.
Width (m)	1.8	1.8	2.5	2.5	2.5	
Height (m)	1.5	1.5	2.8	2.8	3.4	
MinGap (m)	2.5	0.5	1	1.5	2	
MaxSpeed (km/h)	180	180	120	100	85	
Lane changing model	LC2013					Krajzewicz et al., 2012
Car following model	Krauss					Krajzewicz et al., 2012
Boarding duration (second per pax)	N/A	3.5	4			Jara-Díaz, S. and Tirachini, A., 2013

As shown in Table 1, background flow uses the SUMO default value for “passenger” vehicle types (Krajzewicz et al., 2012). Although there would be differences in the lane-changing model between conventional vehicles, this study focuses on longitudinal effects instead of lateral effects. Therefore, the lane-changing model is assumed to be LC2013, the default from SUMO (Erdmann, 2015). The LC 2013 model also provides flexibility in setting strategic, cooperative, tactical and regulatory lane changes (Erdmann, 2015).

Automated bus or shuttle tests may proceed with caution at early implementation stages due to the 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. (2012), 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, as 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 (Krajzewicz et al., 2012; Ford Motor Company, 2018; GOGO

Charters, 2020.). 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 lies within the range that was used in Morando et al.'s (2018) simulation.

A model from Jara-Díaz and Tirachini (2013) showed that average boarding and alighting time is 3.3 seconds/passenger using a contactless card or 4 seconds/passenger using the magnetic strip when the only front door is used for boarding and both doors are used for alighting. The current tested automated shuttles have one door for both boarding and alighting, but the door is wider than the 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.

Scenario design

This paper tests a base case scenario that has riders' demand varying from 100 riders per hour to 600 riders per hour. Background flow is set to 1260 vehicles per hour per lane, with no parking bay at the station and no traffic signals. 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 and an average loading factor of SAVs, recognizing that there is waiting time for riders at the station. Table 3 shows the headway of SAVs when assuming that SAVs are always full (load factor = 1), while the base case assumes a load factor of 0.7 for all types of SAVs. For example, when assuming SAVs are always full, 0.5 min headway of SAV (120 SAVs/hr) is required to meet the demand of 120 × vehicle size × load factor = 120 × 5 × 1 = 600 persons/hr. In this case, a high load factor indicates a low frequency.

Table 3. SAV Headway (min) Settings when Load Factor = 1

Capacity / Demand (per hour)	5	10	20	40
600	0.5 min	1.2	2	4
500	0.6	1.2	2.4	4.8
400	0.75	1.5	3	6
300	1	2	4	8
200	1.5	3	6	12
100	3	6	12	24

Other than the base case scenarios, a few scenarios have been generated for comparison, as shown in Table 4. These scenarios include varying the background flow (varying from 0.4 to 0.8 vehicles per second by Poisson distribution), adding station bay and traffic signals, varying the SAV headways (via various assumed load factor), and different value of travel times (VOTTs). Since VOTT is considered for both background travelers as well as SAV riders, background travelers' VOTT is tested, with SAV riders' value of walking, riding, and waiting time changing accordingly. Background flow scenarios aim 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 services. Load factor scenarios are used to investigate operators' decisions in the frequency of dispatching SAVs to serve various demand levels considering the total system cost. The station bay scenario will be able to 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.

For the station bay scenario, the simulation sets up another lane for SAVs to stop only, to mimic the case when there is a parking bay at the station for SAVs. For the traffic signal scenario, a 90-second cycle is assumed, with 3 seconds of yellow time and 10 seconds of red time. The signals 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.

Table 4. Tested Scenarios

		Background flow (vphpl)	Loading Factor	Traffic Signal	Station Bay	Value of Driving Time ($/hr)
BaseLine		1260	0.7	✗	✗	15
Sensitivity Analysis	Background flow	720, 900, 1080, 1260, 1440	0.7	✗	✗	15
	Station Bay	1260	0.7	✗	✓	15
	Traffic Signal	1260	0.7	✓	✗	15
	Loading Factor	720	0.5, 0.6, 0.7, 0.8, 0.9	✗	✗	15
	Value of Driving Time	1260	0.7	✗	✗	5, 10, 15, 20, 25

Evaluation metrics

The average vehicle travel time, average person/passenger waiting time, total system travel time and total system cost will be evaluated for each scenario. The average vehicle travel time (background vehicles) can evaluate how congested the traffic is, while the average person waiting time shows the efficiency of the transit system. The total system travel time, considering travel times of background vehicles and SAVs, can show the overall system performance and the total system cost will evaluate the total cost to serve travel demand under different types of vehicles and levels of service. The total system cost considers the travel time cost and operating cost of SAVs and background vehicles. Table 5 shows the details components of the total system cost. When riding in an SAV, riders are assumed to perceive a VOTT that is half that of those driving vehicles. However, when they are walking to and from SAV stop locations or waiting for an SAV to arrive, their VOTT is assumed to be 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. (2019), which considered both fixed cost and variable cost for different sizes of SAVs by a per vehicle-mile basis.

Table 5. Components of Total System Cost

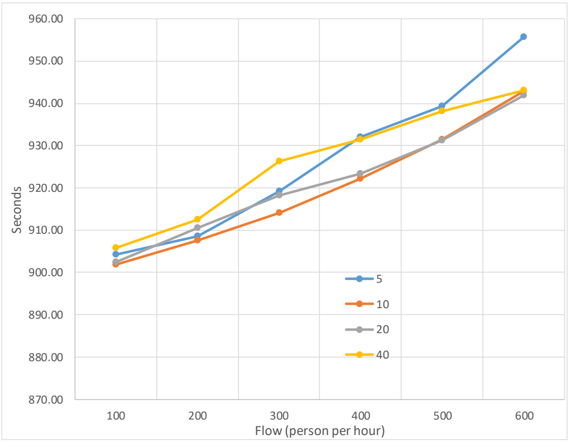
Cost Category	Cost

Human Cost	Driver	Backround Flow	VOTT * driving time
	Rider	Walk	2 * VOTT * travel time
		Ride	½ * VOTT * travel time
		Wait	2 * VOTT * travel time
Vehicle Cost	AV1		0.25 per mile
	AV2		0.36 per mile
	AV3		0.42 per mile
	AV4		1.24 per mile
	Background Flow		0.6 per mile

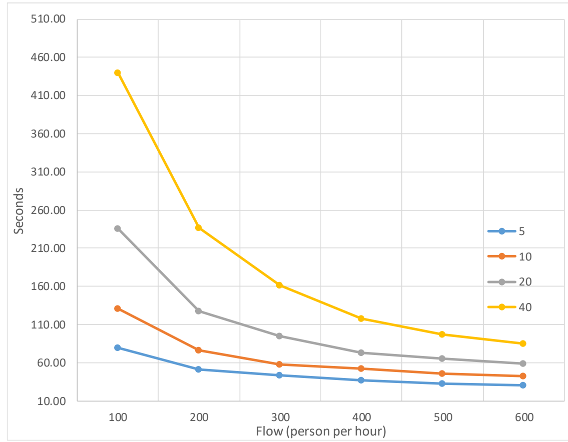
RESULTS

Base case, SAV station bay, and traffic signal scenarios

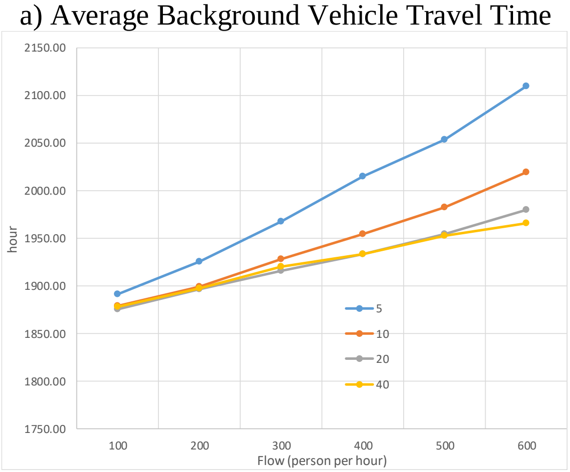
In this section, the analysis of three scenarios are presented: the base case scenario, adding SAV station bays, and adding traffic signals. Each scenario performed five runs and the average value is shown in the results. Figure 3 shows the results of the base case scenario. For each SAV size, the average background vehicle travel time increases with increasing passenger demand (see Figure 3a). This is because SAVs stop more frequently, affecting background traffic, to accommodate greater passenger demand. In this base case scenario, smaller SAVs in general do not significantly affect background traffic, except for the combination of the 5-seat SAVs and highest passenger demand of 600 persons/hr when the SAV flow is substantial. While smaller SAVs mean more frequent services to serve the same number of passengers, dwell times at each stop and thus the durations of affecting traffic would be shorter. Figure 3b shows an expected result: SAVs with more frequent services reduce persons/passenger waiting times at all passenger demand levels. Waiting time discrepancies between different SAV sizes shinks under a higher demand level, due to a higher frequency of all types of vehicles. For each SAV size, the total system travel time, considering both background vehicles and SAVs, increases with greater passenger demand (in Figure 3c). This is consistent with the increase in the background vehicle travel time when passenger demand is greater. However, the effect of SAV sizes on total system travel time is evident as smaller SAVs are associated with higher total system travel times, particularly with high passenger demand. It is noted that the flow of SAVs is quite substantial with high passenger demand. While using smaller SAVs reduces passenger waiting time, it can increase total system travel time. Thus, the smallest size of SAVs is not necessarily the optimum size. Figure 3d illustrates the results of total system costs where the 40-seat SAVs are outperformed by smaller SAVs at all passenger demand levels. Compared to the 40-seat SAVs, using smaller SAVs would reduce the system cost by up to 1.9%. While the 5-seat and 10-seat SAVs have lower total costs with the demand of 300 persons/hr or less, the 10-seat and 20-seat SAVs have lower total costs with the demand of 400 persons/hr or more.



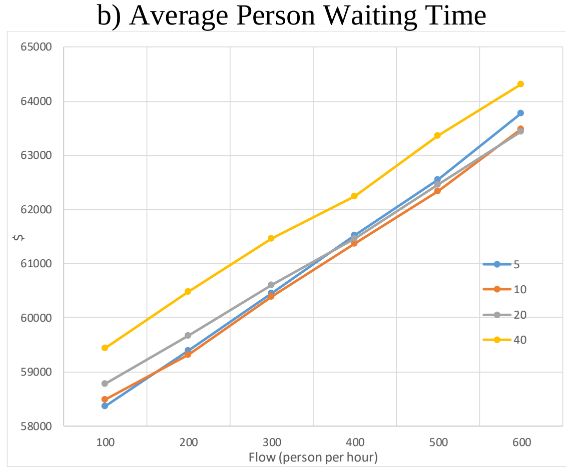
a) Average Background Vehicle Travel Time



b) Average Person Waiting Time



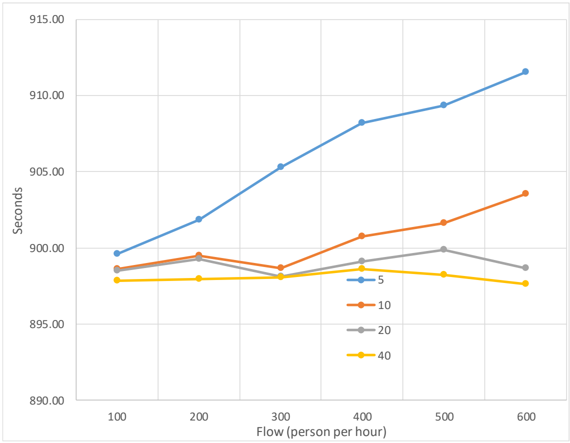
c) Total System Travel Time



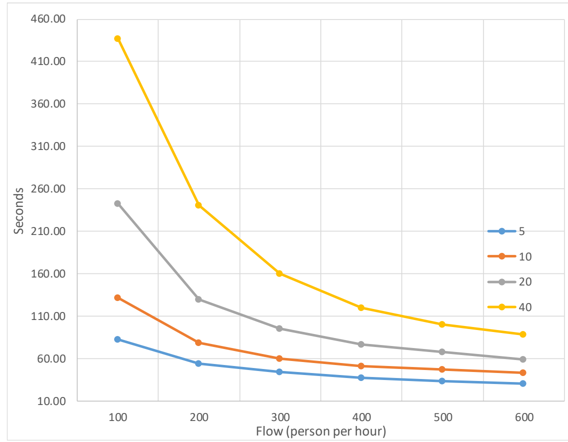
d) Total System Cost

Figure 3. Base Case Scenario

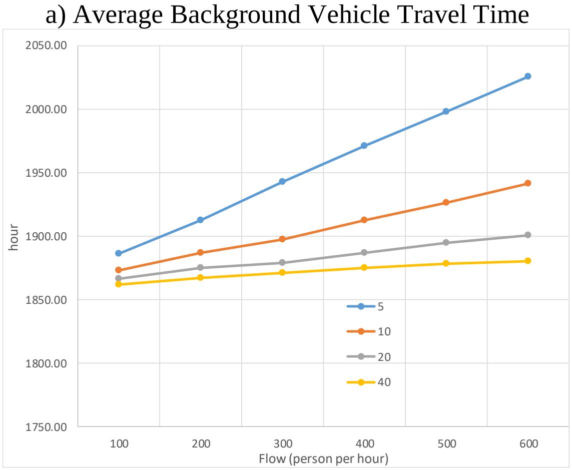
Figure 4 summarizes the results of the SAV station bay scenario. As the stations are now in bays, the impact of SAVs on background traffic is negligible, as shown in Figure 4a. With 5-seat SAVs, the average vehicle travel time lightly increases with greater passenger demand, which is less than 15 seconds. This slight increase would be attributed to the noticeable flow of 5-seat SAVs (i.e. headway of 0.35 minutes when passenger demand is 600 persons per hr). Like the base case scenario, smaller SAVs reduce passenger waiting time, but increase total system travel time. Compared to the base case scenario, the total system travel time in the SAV station bay scenario is lower (up to approximately 4% lower when the passenger demand is 600 persons/hr). This demonstrates the benefits of providing station bays. Figure 4d suggests using smaller-size SAVs instead of 40-seat SAVs can reduce the system cost by up to 1.4%, which is consistent with the base case scenario. 10-seat SAVs tend to be more cost-efficient under different levels of travel demand. Regarding the improvement in total system travel time compared to the base case scenario, little reduction in cost due to station bay is observed when travel demand is low, and the total system cost falls up to 1.8% in the 600-transit-users-per-hour scenario during the 3-hour morning peak. It is worth noticing that such cost savings are under the situation when a bay is built for each of the stations in this 5-mile corridor, which will add construction costs and potentially right-of-way costs. In a real network, there is a need for cost-benefit analysis across a long evaluation time horizon and for a more specific area (e.g., with congested intersections, or higher SAV ridership, leading to longer stopping times at stations).



a) Average Background Vehicle Travel Time



b) Average Person Waiting Time

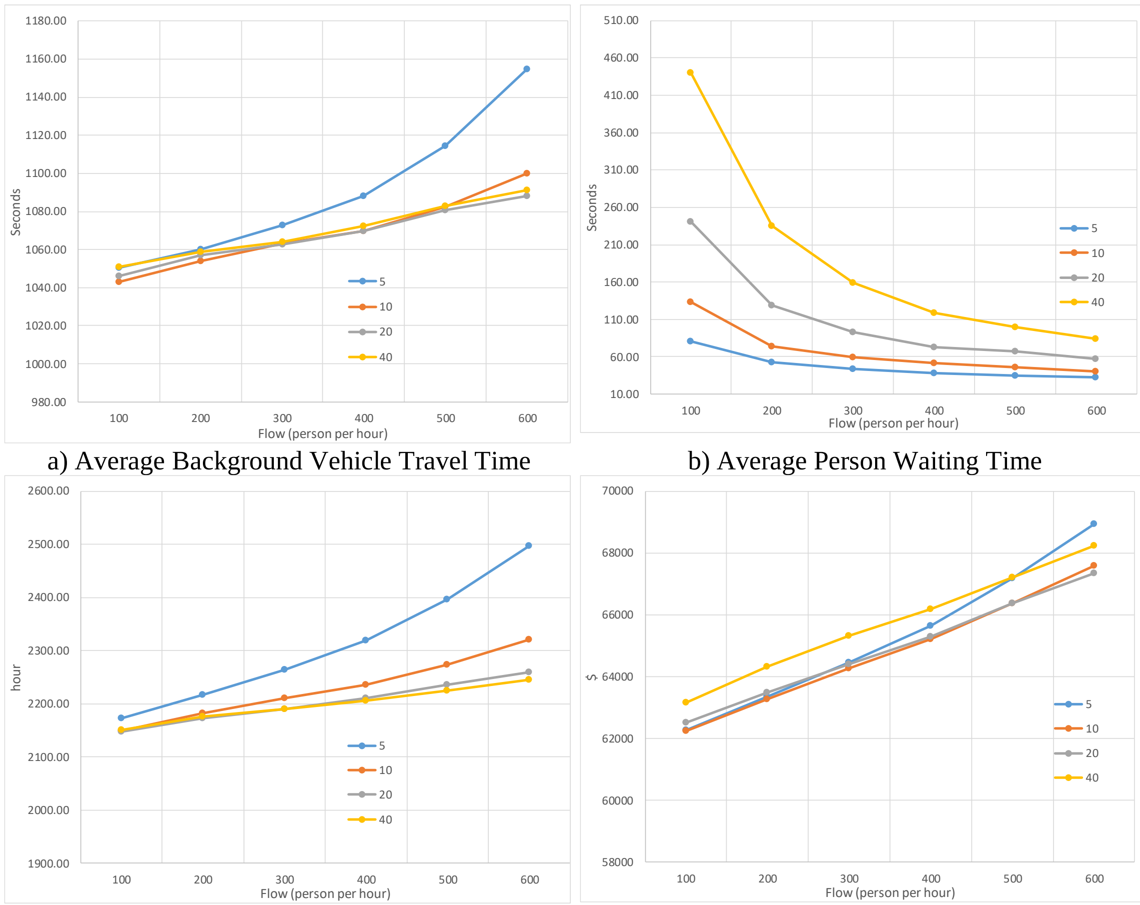


c) Total System Travel Time

d) Total System Cost

Figure 4. SAV Station with Bay Scenario

Results of the traffic signal scenario are presented in Figure 5. The average vehicle travel time for all SAV sizes under various travel demands is substantially higher compared to the previous scenarios due to delays at traffic signals. The trend of the average vehicle travel time remains the same, but the increasing trend for 5-seat SAVs is more obvious. When passenger demand increases from 100 persons/hr to 600 persons/hr, using 5-seat SAVs increases the average vehicle travel time by nearly 10%. This contributes to the higher system costs of 5-seat SAVs when compared to 40-seat SAVs with the demand of 600 persons/hr. Other than that, 40-seat SAVs tend to have higher system costs compared to smaller SAVs. It is noted that when the demand is 300 persons or less, the 5-seat SAVs still perform well in terms of system costs, and 10-seat SAVs are the most cost-efficient for a demand less than 500 persons/hr.



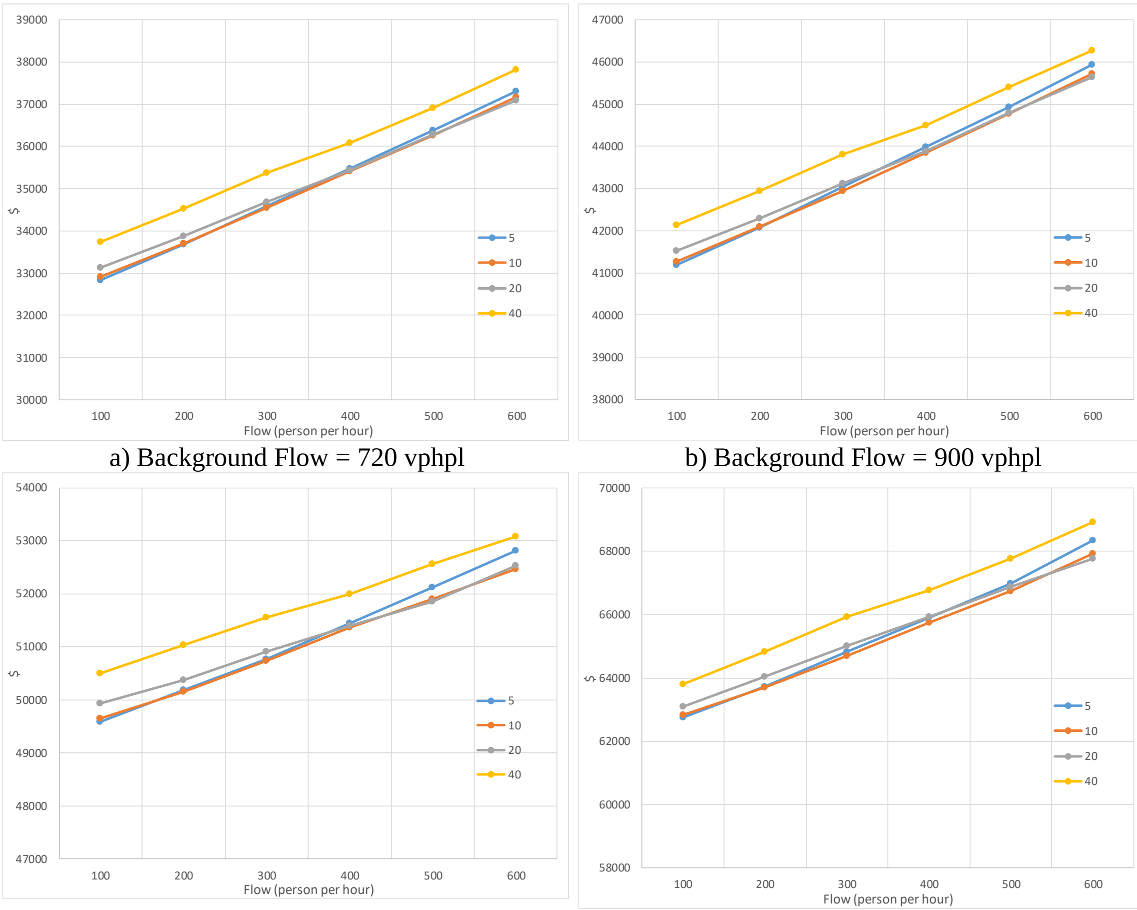
a) Average Background Vehicle Travel Time b) Average Person Waiting Time

c) Total System Travel Time d) Total System Cost

Figure 5. Traffic Signal Scenario

Sensitivity tests on background flow and loading factor

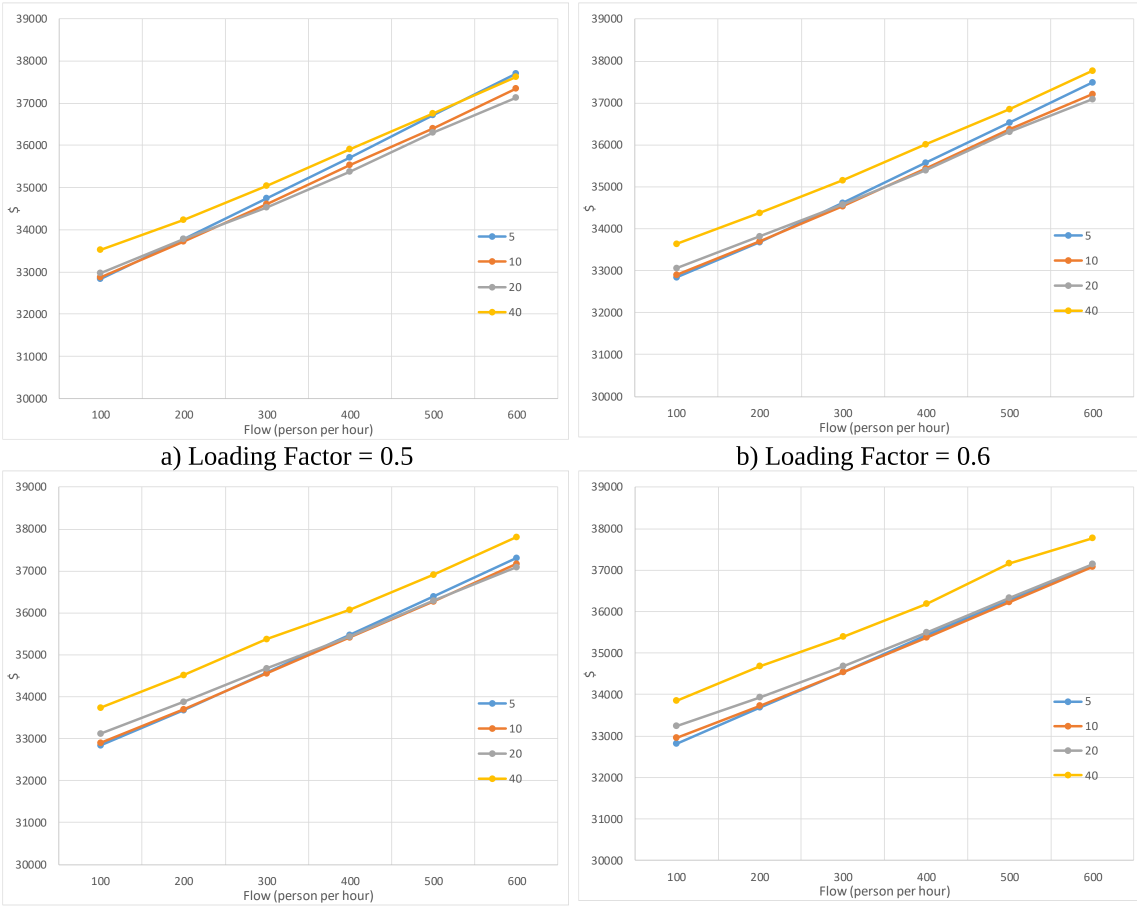
Different background flow rates, ranging from 720 vphpl to 1440 vphpl, were tested for the base case scenario. Figure 6 shows total system costs with background flow rates of 720, 900, 1080, and 1440 vphpl, which have a similar pattern compared to the results of a background flow rate of 1260 vphpl in Figure 3d. That is, total system costs increase almost linearly with increasing passenger demand and the system with 40-seat SAVs has higher costs. While the system with 5-seat SAVs performs well when passenger demand is low, its performance decreases compared to the mid-size SAVs (10 and 20 seats) when passenger demand is larger than 300 persons/hr, owing to the higher frequency of 5-seat SAVs. These results suggest the adoption of smaller-size SAVs, rather than large 40-seat SAVs, would reduce the system costs, by up to 2.7%, in both low and high passenger and background traffic demand levels. Of course, a higher background flow will lead to higher system costs, due to a higher flow of traffic and thus more vehicle-mile costs.



a) Background Flow = 720 vphpl
b) Background Flow = 900 vphpl
c) Background Flow = 1080 vphpl
d) Background Flow =1440 vphpl

Figure 6. Total System Cost in Base Case Scenario with Varying Background Vehicle Flow Rates

Figure 7 demonstrates the effects of SAV headways (via changing assumed loading factors) on total system costs when the background flow is 720 vphpl. Figure 7a shows the total system cost when the headway is half of the value shown in Table 3, under each SAV size and each level of travel demand. The total system cost of the 5-seat SAV system is greater than that of the 40-seat SAV system when the demand is 600 persons/hr. When varying the headway of service, the systems with 10-seat and 20-seat SAVs consistently have lower costs compared to those with the 40-seat SAVs, favoring 10-seat SAVs at low demand and 20-seat SAVs at high demand. The total cost is generally stable across these scenarios, but the benefits of using smaller-size SAVs instead of 40-seat SAVs tend to be greater with increasing loading factor (decreasing frequency). For example, cost reductions are between 0.7% and 2.3% when the loading factor is 0.6, and between 1.7% and 3.1% when the loading factor is 0.8.



a) Loading Factor = 0.5

b) Loading Factor = 0.6

c) Loading Factor = 0.7

d) Loading Factor = 0.9

Figure 7. Total System Cost with 720 vphpl Background Flow and Varying Loading Factors

Figure 8 shows the change in average vehicle occupancy (AVO) for different SAV sizes when varying the frequency of SAVs. The figure only shows the case when the demand of riders is 100 persons/hr, because the AVO is robust to the travel demand, probably due to the fixed relationship between SAV dispatching headway and the travel demand. With a higher frequency (low loading factor), AVO trends to increase, but large-size vehicles witness a large increment compared with small-size vehicles. When load factor increases from 0.5 to 0.9, AVO of 5-seat SAVs slightly goes up from 0.9 to 1.6, but AVO of large size SAVs raises from 6.9 to 12.7. However, the percentages in AVO are stable for all sizes of vehicles, from 17% to 31%, when the load factor climbs up from 0.5 to 0.9. The AVO percentages also align with statistics from current studies (FTA, 2016).

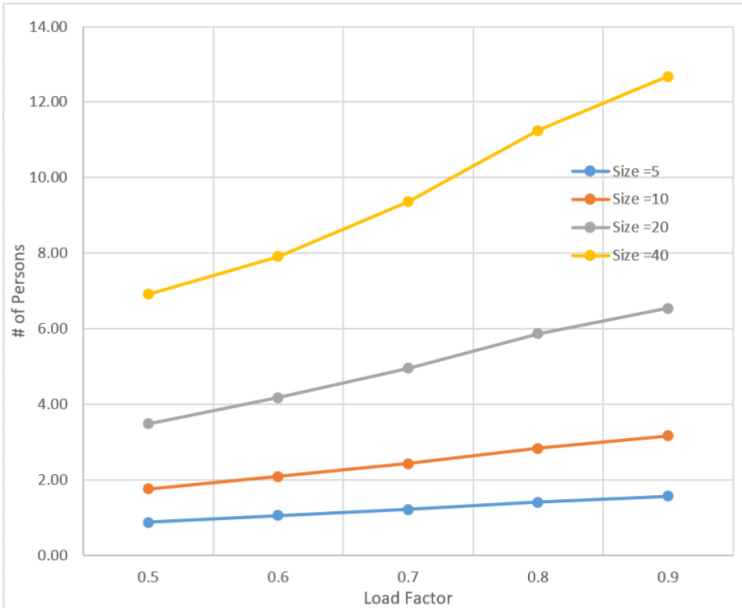


Figure 8. Average Vehicle Occupancy with 100 persons/hr demand and Varying Load Factors and Vehicle Size

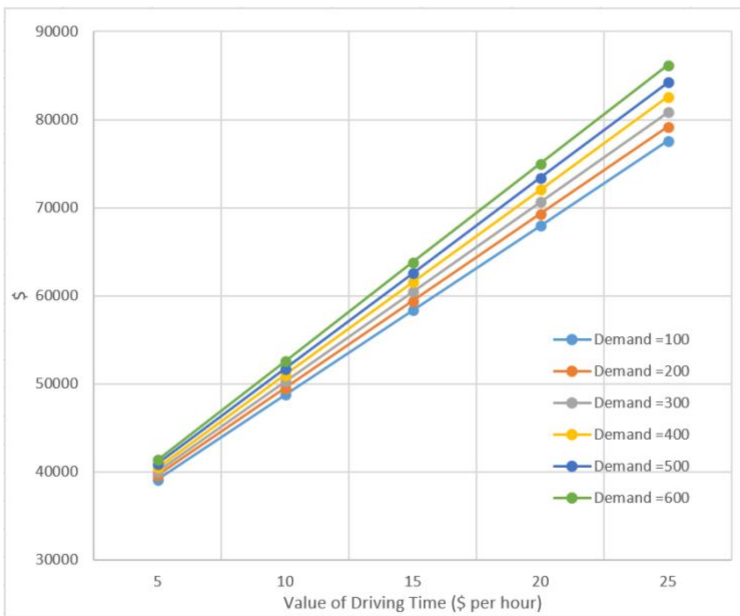


Figure 9. Total System Cost with 5-seat SAV and Varying Value of Driving Time and Travel Demand

Figure 9 shows the total system cost comparison when the VOTT varies. The value of walking, riding and waiting time also changed based on the assumption in Table 5. The total system cost increases linearly with the increase of VOTT, due to the linear function in calculating the cost of background drivers and SAV riders. With a higher VOTT, the discrepancies in total system cost between each level of demand also increase. This can be explained by the added cost when more riders perceive higher VOTT. Although the results are straightforward, it should be noted that VOTT also impacts the other mode choice of road users, not only personal drivers and SAV riders. Heterogeneity in road users' VOTT could also exist. However, this is beyond the discussion of this study, but could lead to more practical results.

CONCLUSION

This study investigated the performance of an SAV-based bus transit corridor, where different sizes of SAVs replace conventional bus transit vehicles. SUMO was used 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 5-mile bus transit corridor were considered, including non-signalized corridor, signalized corridor, and corridor with SAV stations in bays. Detailed bus behaviors were 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 system travel times. It is found that more frequent services of smaller SAVs in general do not significantly affect background traffic given their shorter dwell times at stations. There are few exceptions, such as in traffic signal scenarios with 5-seat SAVs and high passenger demand, where the substantial flow of 5-seat SAVs negatively affects background vehicle travel times. Results highlight that the systems with 10-seat or 20-seat SAVs have lower costs than those with 40-seat SAVs, consistently across various scenarios. While the system with 5-seat SAVs has relatively low costs at low passenger demand, its requirement of high SAV frequencies at high passenger demand can increase system costs substantially. Indeed, the cost of the 5-seat SAV system can exceed that of the 40-seat SAV system in high passenger demand scenarios when there are traffic signals, or the loading factor is low. Overall, using smaller SAVs instead of the large 40-seat SAVs can reduce system costs by up to 3.1% while improving transit passenger experience with reduced waiting times. 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. Thus, replacing conventional bus transit vehicles with SAVs of smaller sizes would offer greater reductions in system costs and passenger waiting times. 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.

However, limitations of the micro-simulation in this study still exist. 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. It is also not clear whether future 40-seat SAVs would be able to provide standing area, in which case the capacity of the vehicle would be more than 40 seats. 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 the operators if standing is allowed on board.

It should be acknowledged that in the micro-simulation, background traffic is 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 should also examine the impacts of SAVs' vehicle size on the system's enery consumption.

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