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

25 Before Shared Automated Vehicles (SAVs) can be widely adopted, they are anticipated to be 26 implemented commercially in confined regions or fixed routes where the benefits of automation 27 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 28 29 pedestrians. This paper micro-simulates SAVs' operation on a 5 mile-corridor to understand how 30 vehicle size and attributes of SAV-based transit affect traffic, transit passengers, and the system 31 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 32 33 more frequent SAVs leads to reduced passenger waiting times but increased total system travel 34 times. More frequent services of smaller SAVs in general do not significantly affect general 35 traffic due to shorter dwell times. Overall, using smaller SAVs instead of the large 40-seat SAVs 36 can reduce system costs by up to 3.1% while also reducing passenger waiting times, under 37 various demand levels and passenger loading factors. However, the use of 5-seat SAVs does not always have the lowest system costs. 38 39

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

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1 INTRODUCTION

2 Automated vehicles (AVs) and shared mobility will fundamentally change the future traffic

3 pattern, by providing cost, environmental, and safety benefits. Shared AVs (SAVs) offer more

4 potential benefits through a lower-cost on-demand service that can be flexible in both schedule

5 and routes.

6 Currently, SAV tests are being performed all over the world, as people try to envision how SAVs

7 should be operated in both the near and far future (Zhao and Malikopoulos, 2019). Over 40

8 corporations are working on AVs (CBinsight, 2019). Waymo (2017) has tested its AVs in

9 Arizona and Texas, and achieved 4 million self-driven miles by November 2017. Before SAVs

10 can run everywhere, they are anticipated to be implemented commercially in a confined region

11 where full automation benefits can be realized (Hou, 2018; Zhu, 2018). SAVs are more likely to

12 function as paratransit in this case. NAVYA (2019) had over 130 automated shuttles running

13 worldwide in 2019 in 7 types of places (city, airport, campus, hospital, resort, theme park and

14 industry), including Mcity in Michigan and Lake Nona in Orlando.

15 Although extensive ongoing studies are investigating what changes SAVs would bring to the

16 environment, urban congestion and shared economy, the impact of vehicle sizes, considering

17 microscopic interactions with traffic, under different travel demand levels has not been formally

18 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

22 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

24 larger vehicles. Large SAVs usually run fixed-routes and can be more space-efficient (per person-

25 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

27 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

30 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

32 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

34 transit corridor, replacing conventional transit vehicles, and have frequent interaction with other

35 vehicles as well as pedestrians. This work micro-simulates SAVs' operation in a 5 mile-corridor

36 setting to understand how traffic reacts to, and how passengers and system costs are affected by

37 vehicle sizes and performance attributes for SAV-based "transit".

38 LITERATURE REVIEW

39 SAV simulation efforts are made around fleet sizing decisions (Fagnant et al., 2015; Maciejewski

40 and Bischoff, 2016; Spieser et al., 2014) along with other studies on the ride-sharing mechanism

41 (Hyland and Mahmassani, 2018), electric vehicles involving charging decisions (Chen et al.,

42 2016; Chen and Kockelman, 2016) and environmental effects (Fagnant and Kockelman, 2014;

43 Greenblatt and Shaheen, 2015). Spieser et al. (2014) investigated the proper fleet size in

44 Singapore that could serve the travel demand while ensuring a desired level of service. Their

1 results showed that an SAV fleet size of about one-third of the total number of passengers was

2 desired in Singapore. However, a 1 SAV per 9.3 conventional vehicle replacement was shown in

3 Fagnant et al.'s (2015) simulation in the Austin area. Recent fleet sizing decision studies mostly

4 assume that an SAV has a maximum occupancy of 4 passengers, however, the capacity of current

5 SAVs used for the tests is more than 4 passengers (Stocker and Shaheen, 2017) and is expected to

6 be as large as 20 or more passengers.

7 Microsimulation noted in this paper refers to the traffic microsimulation where individual driving

8 behavior is tracked, like detailed car following and lane changing maneuvers. However, many

9 studies are using the term microsimulation to define a simulation where agents' information (e.g.,

10 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'

12 performance attributes (e.g., acceleration, deceleration, and headway) are not usually tracked.

13 Vehicles' lane changing is also ignored as vehicles are traveling on a link (or roadway).

14 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

17 level between SAVs and conventional vehicles, such as at stations. While this is easier for

18 microscopic simulations, SAV micro-simulation studies are not often seen.

19 Alozi and Hamad (2019) used VISSIM to micro-simulate CAVs on a 7-kilometer-freeway

20 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

25 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

ride) are not considered.

28 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 direct bing network.

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

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 a useful toolkit built on the Simulation of Urban Mobility (SUMO) package that can perform

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 \times 8 mi central Austin area with SAVs serving the first-mile

11 ast-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),

37 due to empty SAV driving (between riders).

38 Detailed car following and lane changing models raise the time burden in microscopic

39 simulations, compared with mesoscopic and macroscopic simulations. This leads to a confined

40 simulation area with a low share of realistic travel demand in current microsimulation studies

41 (Zhu et al. 2018). Vehicle data at the trajectory level can only be obtained through micro-

42 simulation, which provides more accurate vehicle movement and energy information.

43 Some other studies also investigate the integration of SAV and transit use (Merlin, 2017; Pinto et

44 al., 2019; Wen et al., 2019; Shen et al., 2018), but they are not at the microscopic level. Shen et

1 al. (2018) simulated an integrated AV and public transportation system based on Singapore's

2 transit structure and demand characteristics. An agent-based supply-side simulation was built to

3 assess the performance of the proposed service with different fleet sizes and ridesharing

- 4 preferences in Singapore's 12 km₂ area during morning peak hours from 7 am to 9 am. Authors
- 5 showed that the integrated system has the potential of enhancing service quality, occupying fewer
- 6 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,
- 9 vehicle capacities (up to 4 passengers), fare schemes and hailing strategies only for the
- 10 connections to the transit station. A nested logit mode choice model was presented, considering 4
- 11 modes (bus, rail, park-and-ride, and AV-and-ride) nested under transit mode. It was reported that
- 12 560 vehicles can accommodate the travel demand in the city if sharing is not available, but the
- 13 fleet size can be reduced to fewer than 200 vehicles if an SAV can be shared by 4 people.
- 14 Pinto et al. (2019) presented a bi-level model illustrating the proper fleet size of SAVs and the
- 15 most efficient transit frequency for 20,920 transit vehicle trips within a 16,819 TAZ Chicago
- 16 region (city of Evanston and a five-mile buffer area). The heuristic solution procedure involves
- 17 solving the upper-level problem using a nonlinear programming solver and solving the lower-
- 18 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

- 20 transit. Results indicate significant traveler benefits, in terms of improved avera
- 21 waiting times compared to the initial transit network design.
- 22 Overall, there has been extensive research, no matter the kind of scope, dedicated to
- 23 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
- 25 model without lane changing. Some consider traffic assignment, which involves the travel
- 26 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
- 29 studied enough in relation to vehicle size decision. Therefore, this work leverages the Simulation
- 30 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.

34 MICRO-SIMULATION DESCRIPTION

- 35 SUMO simulation
- 36 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.
- 39 Such detailed manipulations are achieved through TraCI (Traffic Control Interface), a toolkit in
- 40 SUMO that allows users to retrieve real-time values of simulated objects and to manipulate their
- 41 behavior "on-line" through Python scripts.
- 42 SUMO simulation starts with the input of travel demand and network information. Network
- 43 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

1 (Figure 1). This corridor has a lane width of 3.5 m and a speed limit of 30 mph based on

2 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

4 corridor (Walker, 2012). Each bus stop is ten meters long. SAVs and conventional vehicles

5 (background flow) can travel in both lanes. As the stations are curbside, when SAVs are serving

6 passengers at stations, they will obstruct the vehicles behind. Scenarios that have parking bays for

7 SAVs are also tested.

8 SAVs are inserted into the corridor to serve riders with a fixed schedule (i.e. a fixed frequency)

9 and run a fixed route to the end of the corridor, with stops at the stations. After an SAV completes

10 its journey, it goes back to the starting point of the corridor, assuming that it does not have wait

11 time at the depot. A Poisson distributed background flow of conventional cars with a mean

12 departure rate is assumed. The base case scenario will test an arrival rate of 0.7 vehicles per

13 second (approximately 1260 vphpl), to reflect a common flow rate on a 30-mph corridor (Barr et

14 al., 2010). With a high dispatching rate (frequency) of SAVs, "bus bunching" can be observed, as

15 SAVs can overtake previously dispatched SAVs.

16 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

18 operations of SAVs or conventional vehicles, although there may be taxis, which will stop and

19 pick-up/drop-off passengers, and scooters/bicycles, which potentially slows down the traffic.

20 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

22 miles, passengers who have origins and destinations between two consecutive stations probably

23 give up taking transit. Therefore, only those passengers who have a trip distance longer than 1/3

24 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

27 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.

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1 Framework



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Figure 2. Flow of Simulation

4 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 5 6 then processed to determine the start point of the journey, departure station, arrival station and 7 destination point of the itinerary. After that, simulation in SUMO starts and the itinerary of riders 8 is processed by the simulator at time 0. Beginning at the first step of simulation, background flow 9 comes out on the corridor and every few minutes an SAV departs from the start point of the 10 corridor. During every step of the simulation, which is every 0.5 seconds, the status of riders and 11 SAVs are simulated and tracked. Riders' status is tracked so that SAVs can react based on riders' 12 information (e.g. whether riders are still walking to the bus station, waiting at the bus station, or 13 already on board). The status and locations of SAVs are tracked, to determine whether the SAVs 14 need to stop at the next station. Basically, the simulation checks whether riders need to get off at 15 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 16 17 checking whether a rider can catch the SAV in 10 seconds and will then let those people get on 18 the SAV. After the SAV leaves the station, it sets stops for all new riders' destination stations. 19 SAVs and riders' status and locations are checked every timestep until the simulation reaches the 20 time horizon. The output includes vehicles' and riders' travel time and waiting time, and riders' 21 walking distance and riding distance.

22 Simulation parameters

1 Stocker and Shaheen (2017) have envisioned four types of potential SAV and service models:

2 micro-vehicles (1 or 2 passengers), small vehicles (3-7 passengers) mid-sized vehicles (7-20

3 passengers) and large vehicles (20+ passengers). However, one can imagine that the future world

4 may also have a large capacity SAV – an automated bus to serve a heavy demand transit corridor,

5 but such a corridor probably does not allow micro-vehicles to travel. Therefore, for the simplicity

6 of vehicle sizes, four types of vehicles are simulated, from a normal sedan size of 5 seats (no

7 driver due to full automation) to an automated bus of 40 seats.

8

Table 1	Vehicle	configurations	and other	simulation	narameters
	Venicie	configurations	and other	sinulation	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)	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		
Width (m)	1.8	1.8	2.5	2.5	2.5	Krajzewicz et al., 2012;	
Height (m)	1.5	1.5	2.8	2.8	3.4	Morando et al., 2018; Ford Motor Company, 2018:	
MinGap (m)	2.5	0.5	1	1.5	2	GOGO Charters, 2020.	
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	5 4			Jara-Díaz, S. and Tirachini, A., 2013	

9

10 As shown in Table 1, background flow uses the SUMO default value for "passenger" vehicle

11 types (Krajzewicz et al., 2012). Although there would be differences in the lane-changing model

12 between conventional vehicles, this study focuses on longitudinal effects instead of lateral effects.

13 Therefore, the lane-changing model is assumed to be LC2013, the default from SUMO (Erdmann,

14 2015). The LC 2013 model also provides flexibility in setting strategic, cooperative, tactical and

15 regulatory lane changes (Erdmann, 2015).

16 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, 17 automated buses will probably have faster speeds than human-driven vehicles (Litman, 2017). In 18 19 terms of transit operations, comfort is also key to the design of vehicles, based on the study from 20 Bae et al. (2012), who did a summary of the possible range for acceleration and deceleration rates 21 of a comfort transit vehicle. Since small AVs are nimble and can have faster acceleration and 22 deceleration rates, due to the use of the safety belt, the acceleration was set as the highest value in 23 the range, as 1.47 m/s₂. The 40-seat SAV bus would have the lowest acceleration in the range, at 0.9 m/s₂. The other types of vehicles are assumed to have rates in between the small AV and the 24 25 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 26 27 SUMO value. Length, width, height, and maximum speed were obtained from the existing sedan, 28 van and bus size parameters (Krajzewicz et al., 2012; Ford Motor Company, 2018; GOGO

- 1 Charters, 2020.). In terms of the minimum gap between vehicles, 2 meters is used for the 40-seat
- 2 SAV bus and 0.5 meters for the 5-seat SAV, which lies within the range that was used in
- 3 Morando et al.'s (2018) simulation.
- 4 A model from Jara-Díaz and Tirachini (2013) showed that average boarding and alighting time is
- 5 3.3 seconds/passenger using a contactless card or 4 seconds/passenger using the magnetic strip
- 6 when the only front door is used for boarding and both doors are used for alighting. The current
- 7 tested automated shuttles have one door for both boarding and alighting, but the door is wider
- 8 than the mid-sized bus. Here 3.5 seconds (considering 0.5-second simulation timestep) is used for
- 9 the average boarding and alighting time, although there could be variations due to the vehicle
- 10 design and payment method.

11 Scenario design

12 This paper tests a base case scenario that has riders' demand varying from 100 riders per hour to

- 13 600 riders per hour. Background flow is set to 1260 vehicles per hour per lane, with no parking
- 14 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
- 16 available seats of dispatched SAVs and an average loading factor of SAVs, recognizing that there
- 17 is waiting time for riders at the station. Table 3 shows the headway of SAVs when assuming that
- 18 SAVs are always full (load factor = 1), while the base case assumes a load factor of 0.7 for all
- 19 types of SAVs. For example, when assuming SAVs are always full, 0.5 min headway of SAV
- 20 (120 SAVs/hr) is required to meet the demand of $120 \times$ vehicle size \times load factor = $120 \times 5 \times 1$ = 21 600 persons/hr. In this case, a high load factor indicates a low frequency.
- 22

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

23 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
- 26 SAV headways (via various assumed load factor), and different value of travel times (VOTTs).
- 27 Since VOTT is considered for both background travelers as well as SAV riders, background
- 28 travelers' VOTT is tested, with SAV riders' value of walking, riding, and waiting time changing
- 29 accordingly. Background flow scenarios aim to test how the SAV fleet and the system perform
- 30 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
- 32 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
- 34 the case when there is a potential to obtain the right of way for SAVs parking at stations without

1 interrupting the background flow. Last, the traffic signal scenario will show the case when the

2 background flow cannot flow freely, which is more likely to happen in a real transit corridor.

3 For the station bay scenario, the simulation sets up another lane for SAVs to stop only, to mimic

4 the case when there is a parking bay at the station for SAVs. For the traffic signal scenario, a 90-

5 second cycle is assumed, with 3 seconds of yellow time and 10 seconds of red time. The signals

6 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

8 traffic lights and the signal timing are arbitrary. Optimization techniques could be involved in a
9 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

10 simulation res

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Table 4.	Tested	Scenarios

		Background flow (vphpl)	Loading Factor	Traffic Signal	Station Bay	Value of Driving Time (\$/hr)
BaseLine		1260	0.7	×	×	15
	Background flow	720, 900, 1080, 1260, 1440	0.7	*	×	15
	Station Bay	1260	0.7	×	✓	15
Sensitivity	Traffic Signal	1260	0.7	✓	×	15
Analysis	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

13 Evaluation metrics

14 The average vehicle travel time, average person/passenger waiting time, total system travel time 15 and total system cost will be evaluated for each scenario. The average vehicle travel time 16 (background vehicles) can evaluate how congested the traffic is, while the average person waiting 17 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 18 19 system cost will evaluate the total cost to serve travel demand under different types of vehicles 20 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. 21 22 When riding in an SAV, riders are assumed to perceive a VOTT that is half that of those driving 23 vehicles. However, when they are walking to and from SAV stop locations or waiting for an SAV 24 to arrive, their VOTT is assumed to be double that of a driver (Liu et al., 2017). The vehicle cost 25 is calculated using a per-vehicle mile basis. The per-mile cost is adapted from Bösch et al. (2019), 26 which considered both fixed cost and variable cost for different sizes of SAVs by a per vehicle-27 mile basis.

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Table 5. Components of Total System Cost

	Cost Category	Cost
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	Driver Backround Flow		VOTT * driving time
Human Cost		Walk	2 * VOTT * travel time
Huilian Cost	Rider	Ride	¹ / ₂ * VOTT * travel time
		Wait	2 * VOTT * travel time
	AV1		0.25 per mile
	AV2		0.36 per mile
Vehicle Cost	AV3		0.42 per mile
	AV4		1.24 per mile
	Background Flow		0.6 per mile

1

2 **RESULTS**

3 Base case, SAV station bay, and traffic signal scenarios

4 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 5 6 is shown in the results. Figure 3 shows the results of the base case scenario. For each SAV size, 7 the average background vehicle travel time increases with increasing passenger demand (see 8 Figure 3a). This is because SAVs stop more frequently, affecting background traffic, to 9 accommodate greater passenger demand. In this base case scenario, smaller SAVs in general do 10 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 11 12 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 13 result: SAVs with more frequent services reduce persons/passenger waiting times at all passenger 14 demand levels. Waiting time discrepancies between different SAV sizes shinks under a higher 15 16 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 17 passenger demand (in Figure 3c). This is consistent with the increase in the background vehicle 18 19 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, 20 21 particularly with high passenger demand. It is noted that the flow of SAVs is quite substantial 22 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 23 24 size. Figure 3d illustrates the results of total system costs where the 40-seat SAVs are 25 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 26 27 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. 28



1

2 Figure 4 summarizes the results of the SAV station bay scenario. As the stations are now in bays, 3 the impact of SAVs on background traffic is negligible, as shown in Figure 4a. With 5-seat 4 SAVs, the average vehicle travel time lightly increases with greater passenger demand, which is 5 less than 15 seconds. This slight increase would be attributed to the noticeable flow of 5-seat 6 SAVs (i.e. headway of 0.35 minutes when passenger demand is 600 persons per hr). Like the base 7 case scenario, smaller SAVs reduce passenger waiting time, but increase total system travel time. 8 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 9 demonstrates the benefits of providing station bays. Figure 4d suggests using smaller-size SAVs 10 11 instead of 40-seat SAVs can reduce the system cost by up to 1.4%, which is consistent with the 12 base case scenario. 10-seat SAVs tend to be more cost-efficient under different levels of travel 13 demand. Regarding the improvement in total system travel time compared to the base case 14 scenario, little reduction in cost due to station bay is observed when travel demand is low, and the 15 total system cost falls up to 1.8% in the 600-transit-users-per-hour scenario during the 3-hour 16 morning peak. It is worth noticing that such cost savings are under the situation when a bay is 17 built for each of the stations in this 5-mile corridor, which will add construction costs and 18 potentially right-of-way costs. In a real network, there is a need for cost-benefit analysis across a 19 long evaluation time horizon and for a more specific area (e.g., with congested intersections, or 20 higher SAV ridership, leading to longer stopping times at stations).



2

Figure 4. SAV Station with Bay Scenario

3 Results of the traffic signal scenario are presented in Figure 5. The average vehicle travel time for

4 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 5

same, but the increasing trend for 5-seat SAVs is more obvious. When passenger demand 6 increases from 100 persons/hr to 600 persons/hr, using 5-seat SAVs increases the average vehicle 7

8

travel time by nearly 10%. This contributes to the higher system costs of 5-seat SAVs when 9 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 10

11 300 persons or less, the 5-seat SAVs still perform well in terms of system costs, and 10-seat

12 SAVs are the most cost-efficient for a demand less than 500 persons/hr.



1

2 Sensitivity tests on background flow and loading factor

3 Different background flow rates, ranging from 720 vphpl to 1440 vphpl, were tested for the base 4 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 5 1260 vphpl in Figure 3d. That is, total system costs increase almost linearly with increasing 6 7 passenger demand and the system with 40-seat SAVs has higher costs. While the system with 5-8 seat SAVs performs well when passenger demand is low, its performance decreases compared to 9 the mid-size SAVs (10 and 20 seats) when passenger demand is larger than 300 persons/hr, owing 10 to the higher frequency of 5-seat SAVs. These results suggest the adoption of smaller-size SAVs, 11 rather than large 40-seat SAVs, would reduce the system costs, by up to 2.7%, in both low and 12 high passenger and background traffic demand levels. Of course, a higher background flow will 13 lead to higher system costs, due to a higher flow of traffic and thus more vehicle-mile costs.



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

2 Figure 7 demonstrates the effects of SAV headways (via changing assumed loading factors) on 3 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 4 5 travel demand. The total system cost of the 5-seat SAV system is greater than that of the 40-seat 6 SAV system when the demand is 600 persons/hr. When varying the headway of service, the 7 systems with 10-seat and 20-seat SAVs consistently have lower costs compared to those with the 8 40-seat SAVs, favoring 10-seat SAVs at low demand and 20-seat SAVs at high demand. The 9 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). 10 11 For example, cost reductions are between 0.7% and 2.3% when the loading factor is 0.6, and 12 between 1.7% and 3.1% when the loading factor is 0.8.





3 Figure 8 shows the change in average vehicle occupancy (AVO) for different SAV sizes when

4 varying the frequency of SAVs. The figure only shows the case when the demand of riders is 100

5 persons/hr, because the AVO is robust to the travel demand, probably due to the fixed

6 relationship between SAV dispatching headway and the travel demand. With a higher frequency

7 (low loading factor), AVO trends to increase, but large-size vehicles witness a large increment

8 compared with small-size vehicles. When load factor increases from 0.5 to 0.9, AVO of 5-seat

9 SAVs slightly goes up from 0.9 to 1.6, but AVO of large size SAVs raises from 6.9 to 12.7.

10 However, the percentages in AVO are stable for all sizes of vehicles, from 17% to 31%, when the

11 load factor climbs up from 0.5 to 0.9. The AVO percentages also align with statistics from current

12 studies (FTA, 2016).





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



4



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

1 riders. Heterogeneity in road users' VOTT could also exist. However, this is beyond the

2 discussion of this study, but could lead to more practical results.

3

4 CONCLUSION

5 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 6 7 interactions between SAVs and background traffic and between SAVs and transit passengers, under various background traffic conditions, SAV sizes and associated characteristics, passenger 8 9 demand levels, and loading factors. Different configurations of the 5-mile bus transit corridor 10 were considered, including non-signalized corridor, signalized corridor, and corridor with SAV stations in bays. Detailed bus behaviors were incorporated, including waiting for approaching 11 12 riders, and skipping stops when the vehicle capacity is reached.

13 Simulation results show that the use of smaller, but more frequent SAVs leads to reductions in 14 passenger waiting times but increases in total system travel times. It is found that more frequent 15 services of smaller SAVs in general do not significantly affect background traffic given their 16 shorter dwell times at stations. There are few exceptions, such as in traffic signal scenarios with 17 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 18 19 SAVs have lower costs than those with 40-seat SAVs, consistently across various scenarios. 20 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 21 22 substantially. Indeed, the cost of the 5-seat SAV system can exceed that of the 40-seat SAV 23 system in high passenger demand scenarios when there are traffic signals, or the loading factor is 24 low. Overall, using smaller SAVs instead of the large 40-seat SAVs can reduce system costs by 25 up to 3.1% while improving transit passenger experience with reduced waiting times. Although 26 conventional bus transit scenarios, usually with larger vehicles are not simulated in this study, 27 their system costs and passenger waiting times would be higher than the 40-seat SAV scenarios. 28 Thus, replacing conventional bus transit vehicles with SAVs of smaller sizes would offer greater 29 reductions in system costs and passenger waiting times. Results also suggest that the smallest 30 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. 31

However, limitations of the micro-simulation in this study still exist. The relationship betweenheadway and demand is assumed to be fixed, based on the assumed load factor of SAVs.

34 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

37 stops when the seats are full is much easier to integrate. It is also not clear whether future 40-seat

38 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-

40 seat SAVs have the potential to be favored by the operators if standing is allowed on board.

41 It should be acknowledged that in the micro-simulation, background traffic is simulated with

42 typical driving behaviors. Future research could explore the impacts of SAV-based transit when

43 background traffic is also partly or fully automated by considering different AV penetration rates.

44 For a high frequency bus corridor, platooning of SAV-based transit vehicles should also be

- 1 considered, particularly when the flow of small-size SAVs would be high. Future work should
- 2 also examine the impacts of SAVs' vehicle size on the system's enery consumption.
- 3

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- 10

11 **REFERENCES**

- 12 Alozi, A.R. and Hamad, K., 2019. Quantifying Impacts of Connected and Autonomous Vehicles
- 13 on Traffic Operation using Micro-simulation in Dubai, UAE. In Proceedings of the 5th
- 14 International Conference on Vehicle Technology and Intelligent Transport, pp. 528-535. URL:
- 15 https://pdfs.semanticscholar.org/22dd/a5098e45c63b2644dacf2e1d74973362fc31.pdf
- Bae, I., Moon, J. and Seo, J., 2019. Toward a Comfortable Driving Experience for a Self-Driving
 Shuttle Bus. *Electronics*, 8(9), p.943.
- 18 Barr, J., Beveridge, J., Clayton, C., Danaher., A., Gonsalves, J., Koziol, B. and Rathwell, S.,
- 19 2020. Designing Bus Rapid Transit Running Ways. American Public Transportation Association.
- 20 URL: https://nacto.org/wp-content/uploads/2016/05/2-7_APTA-Designing-Bus-Rapid-Transit-
- 21 Running-Ways_2010.pdf
- Bösch, P.M., Becker, F., Becker, H. and Axhausen, K.W., 2018. Cost-based analysis of
 autonomous mobility services. *Transport Policy*, 64, pp.76-91.
- CBinsight, 2019. 40+ Corporations Working on Autonomous Vehicles. Retrieved from:
 https://www.cbinsights.com/research/autonomous-driverless-vehicles-corporations-list/
- 26 Chen, T.D., Kockelman, K.M. and Hanna, J.P., 2016. Operations of a shared, autonomous,
- electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. *Transportation Research Part A: Policy and Practice*, 94: 243-254.
- Chen, T.D. and Kockelman, K.M., 2016. Management of a shared autonomous electric vehicle
 fleet: Implications of pricing schemes. *Transportation Research Record*, 2572(1), pp.37-46.
- 31 Cregger, J., Dawes, M., Fischer, S., Lowenthal, C., Machek, E. and Perlman, D., 2018. Low-
- 32 *Speed Automated Shuttles: State of the Practice* (No. FHWA-JPO-18-692).
- Erdmann, J., 2015. SUMO's lane-changing model. In *Modeling Mobility with Open Data* (pp. 105-123). Springer, Cham.
- 35 Fagnant, D.J. and Kockelman, K.M., 2014. The travel and environmental implications of shared
- 36 autonomous vehicles, using agent-based model scenarios. Transportation Research Part C:
- 37 *Emerging Technologies*, 40: 1-13.

- 1 Fagnant, D.J., Kockelman, K.M. and Bansal, P., 2015. Operations of shared autonomous vehicle
- 2 fleet for Austin, Texas, market. *Transportation Research Record*, 2563(1): 98-106.
- **3** Federal Transit Administration (FTA), 2016. National Transit Summary and Trends: Appendix.
- 4 Retrieved from
- 5 https://www.transit.dot.gov/sites/fta.dot.gov/files/docs/2015%20NTST%20Appendix.pdf
- 6 Ford Motor Company, 2018. 2019 Transit: passenger van and cargo van. Retrieved from:
- 7 https://www.ford.com/services/assets/Brochure?make=Ford&model=Transit&year=2019
- 8 GOGO Charters, 2020. Minibus Comparison Chart. Retrieved from:
- 9 https://gogocharters.com/mini-bus-comparison-chart
- 10 Greenblatt, J.B. and Shaheen, S., 2015. Automated vehicles, on-demand mobility, and
- 11 environmental impacts. *Current sustainable/renewable energy reports*, 2(3), pp.74-81.
- Hou, Y., Young, S.E., Garikapati, V., Chen, Y. and Zhu, L., 2018. *Initial Assessment and*
- 13 Modeling Framework Development for Automated Mobility Districts (No. NREL/CP-5400-
- 14 68290). National Renewable Energy Lab. (NREL), Golden, CO (United States).
- 15 Huang, Y., Kockelman, K., Garikapati, V., Zhu, L. and Young, S., 2020. Use of Shared
- 16 Automated Vehicles for First-Mile Last-Mile Service: Micro-Simulation of Rail-Transit
- 17 Connections in Austin, Texas. Presented at the 99th Annual Meeting of the Transportation18 Research Board.
- 19 Hyland, M. and Mahmassani, H.S., 2018. Dynamic autonomous vehicle fleet operations:
- 20 Optimization-based strategies to assign AVs to immediate traveler demand
- 21 requests. *Transportation Research Part C: Emerging Technologies*, 92: 278-297.
- Jara-Díaz, S. and Tirachini, A., 2013. Urban bus transport: open all doors for boarding. *Journal of Transport Economics and Policy (JTEP)*, 47(1), pp.91-106.
- 24 Krajzewicz, D., Erdmann, J., Behrisch, M. and Bieker, L., 2012. Recent development and
- applications of SUMO-Simulation of Urban MObility. *International Journal On Advances in Systems and Measurements*, 5(3&4).
- 27 Litman, T., 2017. Autonomous vehicle implementation predictions (p. 28). Victoria, Canada:
- 28 Victoria Transport Policy Institute.
- 29 Liu, J., Kockelman, K.M., Boesch, P.M. and Ciari, F., 2017. Tracking a system of shared
- 30 autonomous vehicles across the Austin, Texas network using agent-based
- **31** simulation. *Transportation*, *44*(6), pp.1261-1278.
- 32 Maciejewski, M. and Bischoff, J., 2016. Congestion effects of autonomous taxi fleets. Vilnius
- 33 Gediminas Technical University. URL: https://depositonce.tu-berlin.de//handle/11303/8559
- Merlin, L. A., 2017. Comparing Automated Shared Taxis and Conventional Bus Transit for a
 Small City. *Journal of Public Transportation*, 20 (2): 19-39.
- 36 Morando, M.M., Tian, Q., Truong, L.T. and Vu, H.L., 2018. Studying the safety impact of
- autonomous vehicles using simulation-based surrogate safety measures. *Journal of advanced transportation*, 2018.

- 1 NAVYA, 2019. Providing Fluid Mobility with Autonomous Shuttles. Retrieved from:
- 2 https://navya.tech/wp-content/uploads/documents/Brochure_Shuttle_EN.pdf
- 3 Pinto, H.K., Hyland, M.F., Mahmassani, H.S. and Verbas, I.Ö., 2019. Joint design of multimodal
- 4 transit networks and shared autonomous mobility fleets. Transportation Research Part C:
- 5 *Emerging Technologies*.
- 6 Shen, Y., Zhang, H. and Zhao, J., 2018. Integrating shared autonomous vehicle in public
 7 transportation system: A supply-side simulation of the first-mile service in
 8 Singapore. *Transportation Research Part A: Policy and Practice*, 113: 125-136.
- 9 Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D. and Pavone, M., 2014. Toward a
- 10 systematic approach to the design and evaluation of automated mobility-on-demand systems: A
- 11 case study in Singapore. *Road vehicle automation*: 229-245.
- 12 Stocker, A. and Shaheen, S., 2017. Shared automated vehicles: Review of business models.
- 13 International Transport Forum Discussion Paper.

Walker, J., 2012. *Human transit: How clearer thinking about public transit can enrich our communities and our lives*. Island Press.

- 16 Waymo, 2017. Say hello to Waymo. Retrieved from:
- 17 https://orfe.princeton.edu/~alaink/SmartDrivingCars/PDFs/AHB30_Waymo_Papandreou.pdf
- 18 Wen, J., Chen, Y.X., Nassir, N. and Zhao, J., 2018. Transit-oriented autonomous vehicle operation
- 19 with integrated demand-supply interaction. Transportation Research Part C: Emerging
- **20** *Technologies*, *97*: 216-234.
- 21 Zhao, L. and Malikopoulos, A.A., 2019. Enhanced Mobility with Connectivity and Automation:
- 22 A Review of Shared Autonomous Vehicle Systems. *arXiv preprint arXiv:1905.12602*.
- 23 Zhu, L., Garikapati, V., Chen, Y., Hou, Y., Aziz, H.A. and Young, S., 2018, July. Quantifying the
- 24 Mobility and Energy Benefits of Automated Mobility Districts Using Microscopic Traffic
- 25 Simulation. In International Conference on Transportation and Development 2018: Connected
- 26 and Autonomous Vehicles and Transportation Safety (pp. 98-108). Reston, VA: American
- 27 Society of Civil Engineers.