SHARED AUTONOMOUS VEHICLE FLEET OPERATIONS FOR FIRST-MILE LAST-MILE TRANSIT CONNECTIONS WITH DYNAMIC RIDE-SHARING

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Under review for publication in *Computers, Environment, and Urban Systems*
6748 words + 3 tables (750 words) + 4 figures = 7498 words

Submitted July 31, 2020

ABSTRACT
Shared automated vehicles (SAVs) have the potential to promote transit ridership by providing efficient first-mile last-mile (FMLM) connections through reduced operational costs to fleet providers as well as lower out-of-pocket costs to riders. To help plan for a future of integrated mobility, this paper investigates the impacts of SAVs serving FMLM connections, as a mode that provides flexibility in access/egress decisions and is well coordinated with train station schedules. To achieve this objective, a novel dynamic ride-sharing (DRS) algorithm was introduced to match SAVs with riders while coordinating the riders' arrival times at the light-rail station to a known train schedule. Microsimulations of SAVs and travelers throughout two central Austin neighborhoods show how larger service areas, higher levels of SAV demand, and longer arrival times between successive trains require larger SAV fleet sizes and higher SAV utilization rates to deliver shorter traveler wait times. Four-person SAVs appear to perform similar to 6-seat SAVs but will cost less to provide. Using a DRS algorithm tightly coordinated with train arrivals (every 15 minutes) delivers 87% of travelers to the station in time to catch the next train, while uncoordinated SAV assignments result in just 57% of travelers arriving in time to catch the next train.

Keywords: Shared automated vehicles, First-mile last-mile service, Dynamic ridesharing, Transit, Integrated mobility

INTRODUCTION

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

Recent studies on SAVs have focused on aspects such as planning, operation, technology development, and regulation. Implications of SAVs as a door-to-door transport mode (like an autonomous taxi service) include lowered service costs (Chen et al., 2016; Johnson & Walker, 2016), higher vehicle occupancies when dynamic ride-sharing (DRS) is used (Hörl, 2017; Lokhandwala & Cai, 2018), and personal-vehicle replacement thanks to reliable SAV service (Bösch et al., 2016; International Transport Forum, 2015). However, there is no consensus yet on trends in system-wide vehicle-miles traveled (VMT) across various SAV studies (see, e.g., Dia & Javanshour, 2017; Fagnant & Kockelman, 2014; Huang et al., 2019).

With the rapid maturity of automation technology over the past decade, some studies have extended their focus to near-term deployments with an emphasis on geofencing the SAV service area (Fagnant & Kockelman, 2018), SAV seat capacity (Vosooghi et al., 2019), stop aggregation and curb management (Auld et al., 2016). Researchers from the National Renewable Energy Laboratory (NREL) noted that near-term benefits of this emerging technology will be realized by deploying SAVs in geofenced regions, or automated mobility districts (AMDs), where shared mobility is enabled by high trip density (Hou et al., 2018). Further, NREL researchers went on to develop an AMD modeling and simulation toolkit that can be utilized as a decision support tool for planning SAV deployments in geofenced regions (Zhu et al., 2020). Serving first-mile and last-mile (FMLM) trips to access and egress public transit can be a good application for SAVs, in addition to door-to-door service. Using SAVs for FMLM connections has multipronged benefits including but not limited to: i) increased occupancy of ride hail modes (i.e., SAVs), ii) increased transit ridership (and as a result, reduced congestion), as having faster access/egress modes might convert some car trips over to transit, and iii) reduced travel energy consumption due to higher vehicle occupancy (which can be amplified further if the SAVs are electric).

Research exploring the integration of public transit and SAVs (e.g., Shen et al., 2018; Wen et al., 2018) is sparse compared to the body of literature on utilizing SAVs for door-to-door service. Stiglic et al. (2018) showed that integration of manually driven ridesharing vehicles with public transit could increase transit ridership if the drivers are willing to pick up and drop off more than one passenger en route (to and from train stations). Wen et al. (2018) evaluated the performance of a transit-oriented AV system under varying fleet sizes, vehicle capacities, pricing and sharing strategies. Shen et al. (2018) proposed a framework for integrating AVs and the public transit system and simulated an up to 35-vehicle SAV fleet serving first-mile connections for 10% of Singapore's bus riders who reside in a low-demand area, during the 2-hour morning peak period. Their simulations were carried out under an assumed mode split and adopted commonly-used DRS rules for representing the SAV service. A quick scan of the literature identifies two key gaps in investigating the use of SAVs for FMLM connections to transit. First, an implicit assumption is made in most studies that SAVs would be used for first- as well as last-mile connections to transit.

Second, the ridesharing algorithms seek to minimize traveler wait times, or maximize occupancy, but largely function in isolation of the connecting train schedules.

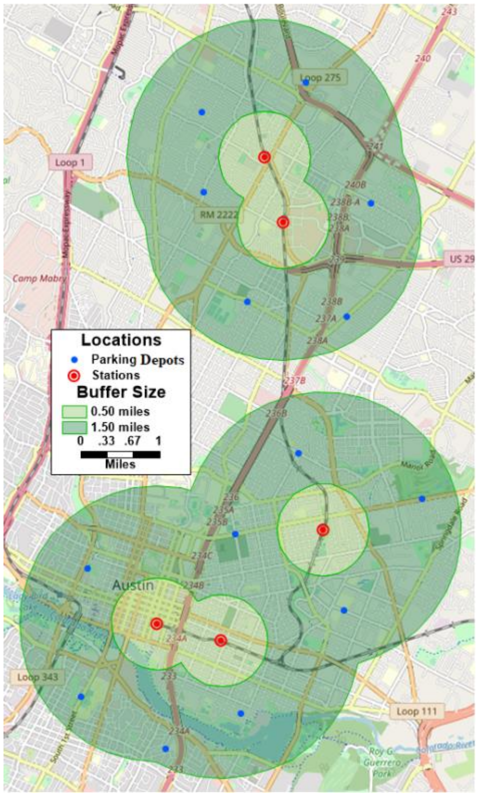
Recognizing the potential benefits of SAVs as an FMLM connection mode, this paper investigates the impacts of an SAV FMLM service integrated with a light-rail transit system, by expanding the capabilities of the AMD modeling and simulation toolkit developed at NREL (Zhu et al., 2020). A full light-rail transit demand set was applied in a 3- by 6-mile area of central Austin, around five stations along Austin's Red Line. Addressing gaps identified in the existing literature, this study allows for flexibility in choosing distinct access and egress modes. For example, an individual might choose to use SAVs as the first mile (FM) connection, and walking as the last mile (LM) connection. This research effort also enhances the traditional dynamic ridesharing (DRS) algorithm to establish coordination between a passenger's expected arrival at the train station and the train schedule.

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

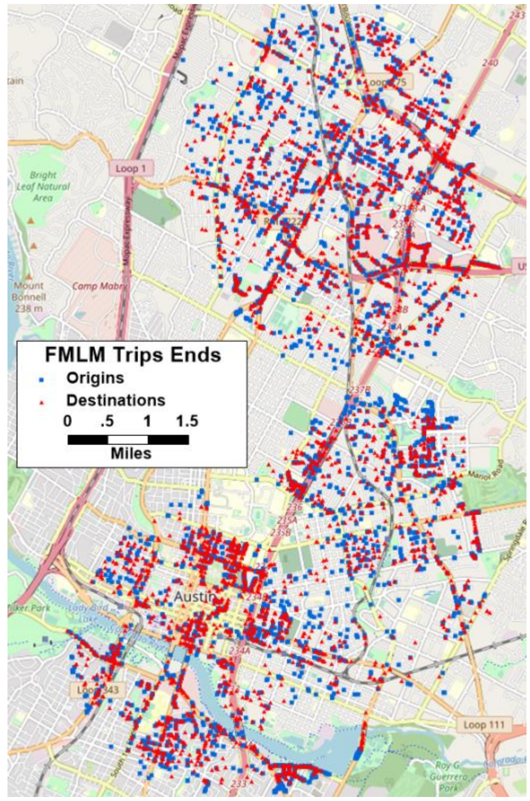
DATA SET

Since SAVs are not expected to foray into the market in the immediate future, travel demand forecasts from Austin's 2030 CAMPO model run were used for this study. Light-rail transit trips were extracted and expanded from the whole travel demand set, using a nested logit mode choice model. The mode choice model builds on Huang et al. (2020a), which considered walk to/from light-rail transit (walk-transit-walk) and SAV to/from transit (SAV-transit-SAV) nested under the transit mode, where the transit mode itself competes with car and walk modes. In this study, two additional transit modes, namely walk-transit-SAV and SAV-transit-walk, were added in the transit nest. This study focuses on the simulation of light-rail transit and SAVs, so transit demand includes three types of travelers: FM travelers who use SAVs as the access mode but walk to their final destinations, LM travelers who walk to train stations but use SAVs as the egress mode, and FMLM travelers who use SAVs as their access and egress mode. Under a 15-minute train headway, the mode choice model estimated 35.2% FMLM travelers, 27.5% FM travelers, and 30.7% LM travelers among the light-rail transit users who utilize SAVs for FM or LM connections (while the remaining 6.6% utilized the walk-transit-walk mode, which is not simulated in the current study). Different levels of FMLM SAV demand to and from the Red Line train stations were used here, with station arrivals (across the 5 central stations) as high as 5,000 person-trips during the 3-hr morning peak period. With a focus on SAV fleet operations, this study only simulates light-rail transit riders who take SAVs as connecting trips (referred to as transit demand or transit riders), namely FM travelers, LM travelers, and FMLM travelers. Other modes are not simulated (e.g., walk-and-ride, car, and bus use).

Figure 1a depicts the light-rail line as well as the geofenced FMLM service area. Walking to the light-rail train station (or walking from train station to final destination) is considered a viable option within a 0.5-mile buffer around the station (based on Nabors et al., 2008), shown with light green shading in Figure 1a. The geofenced SAV mode was made available to those starting or ending their train-based trips within 1.5-miles of the Red Line's stations (shown with dark as well as light green shading in Figure 1a). The geofenced regions will be called automated mobility districts or AMDs for the rest of this paper, with the northern two stations labeled ***AMD1*** and the second geofenced region (with three stations) labeled ***AMD2***. Parking depots for SAVs (shown as dark blue dots) are placed arbitrarily around the train stations. AMD1 has a total of six parking depots while AMD2 has eight. Parking depot locations are used for initializing SAVs at the beginning of the simulation, and for repositioning SAVs that are not actively serving a request and have no service requests in queue. While placement of the depots is chosen arbitrarily for this effort, future efforts may consider optimal placement of these depots . For ease of application (and due to the constraint on SAV availability only within the 1.5-mile buffer), trip origins and destinations are scattered only within the geofenced regions, as shown in Figure 1b.



a) Service Area



b) Trip Ends of Riders

Figure 1 Central Austin Network

METHODOLOGY

SUMO (short for Simulation of Urban MObility) is an open-source traffic simulator, capable of simulating detailed vehicle movements (i.e., car-following, lane-changing, queuing etc.,), traffic operations (signal phasing, turning movements, etc.,) and human behavior (pedestrian movements, accessing the curb etc.,). SUMO can generate second-by-second vehicle and passenger trajectories, which help in computing performance metrics (like wait times and idle times) for vehicle and traveler movements.

The simulation platform used in this study builds on the AMD modeling and simulation toolkit developed by Huang et al. (2020a) and Zhu et al. (2020). Huang et al. (2020a) introduced light-rail transit as a viable modal option in the AMD toolkit, and implemented logic to allow transit access/egress connections walking or using SAVs (with a caveat that the same access and egress mode should be chosen for a transit trip). This study enhances the capabilities of the AMD toolkit proposed in Huang et al. (2020a) by: i) providing flexibility to choose different access and egress modes to train stations (such as walk-transit-

SAV or SAV-transit-walk), ii) conducting simulation experiments with 100% transit demand in the morning peak period, and iii) implementing an enhanced DRS algorithm that is capable of coordinating rider's trip attributes and train schedules. Further, the simulations presented here allow for flexibility in selecting SAV fleet size. SAV fleet size can either be fixed (which could lead to unserved demand, owing to an inadequate supply of SAVs) or variable (where an adequate number of SAVs are initiated in the simulation to serve 100% of the trip requests).

The simulation starts with importing travel demand and network information into SUMO. FMLM service and transit settings (such as SAV fleet size, DRS settings, train headways, and dwell times) are imported next. For the baseline scenario where SAV fleet size is not constrained, an adequate number of SAVs are initialized in the parking depots within the AMD region (i.e., blue dots in Figure 1a). Since the SAV fleet in one AMD is restricted from serving FMLM demand in another AMD, the network is divided into two subnetworks to increase computational efficiency for the shortest path search. Once all the necessary settings are imported and mode choices are assigned, the itinerary for each rider is determined. A rider's itinerary includes access and egress modes, origin, and destination, as well as identification of the 'rail' segment of the trip (i.e., origin and destination stops of the rail segment). After initialization, each rider and each vehicle follow the logical flow shown in Figure 2.

An FMLM rider will go through all the events in a trip which involves taking an access/egress mode as well as transit. Transfers between modes are simulated using walk mode (for example, walking from home to take an SAV, walking to a train platform to board the train, and walking out of a rail station to take an SAV). SAVs are initiated and terminated in SAV parking depots, and are expected to be in operation for the whole duration of the simulation. The dashed line in Figure 2 shows the stages of riders and vehicles when they are considered for rider-vehicle matching. If an SAV is successfully matched to a rider, it is dispatched (or re-routed if already on a trip) to pick up the assigned passenger. A vehicle visiting list is used by each vehicle to track the next pick-up or drop-off location. As long as a vehicle does not reach its capacity, it searches for available passengers at a time resolution of one minute. The visiting list keeps updating every minute and it becomes empty when a vehicle drops off the last passenger on-board. Once the last passenger is dropped off, the vehicle immediately searches for and serves the nearest ride request. Any available SAVs with no active requests are repositioned to the nearest parking depot and wait there until the next ride request is received.

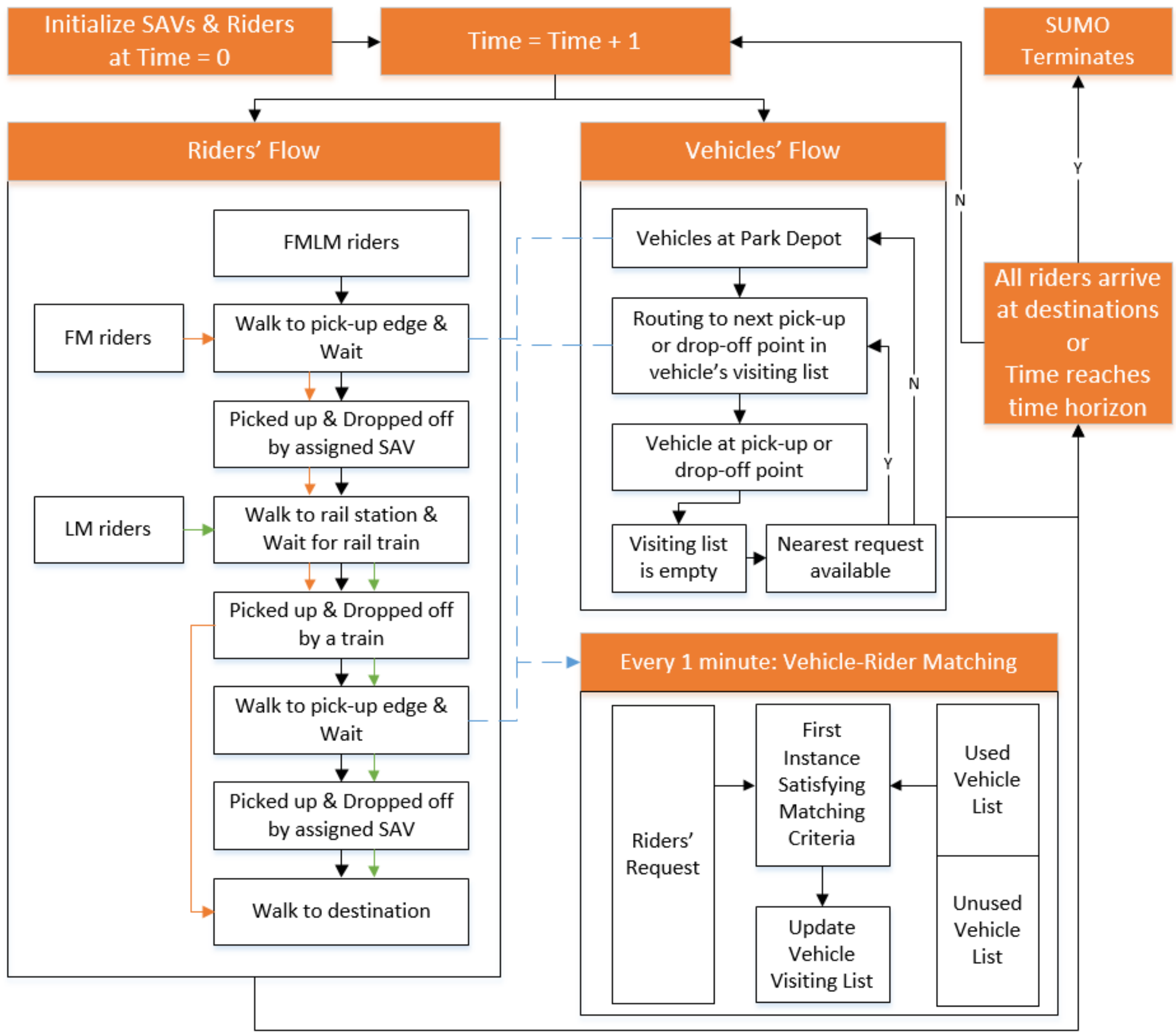


Figure 2. Simulation Framework

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

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

Dynamic Ridesharing

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

The vehicle-rider matching procedure is controlled by constantly evaluating the visiting list of a vehicle. For example, Figure 3 shows the visiting list of an SAV with the next stop denoted as (B, 1), which indicates a pick-up stop for person B. Similarly, (C, -1) denotes a drop-off stop for person C. The visiting list shown in Figure 3 includes three pick-ups and drop-offs, respectively, for three persons. Figure 3 also shows the case where another rider D is picked up after picking up B and dropped off after picking up C.

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

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

(1) The pickup time of the new rider should not exceed t_1 when matching is performed:

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

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

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

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

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

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

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

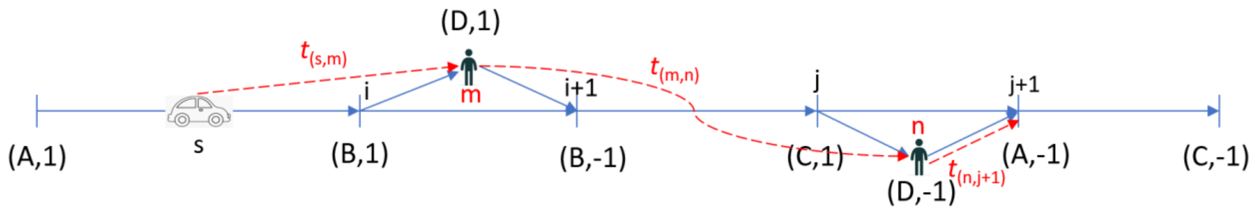


Figure 3. SAV Visiting List Example

A solution pair (m, n) satisfying the constraints for accepting the potential rider will have the rider's pick-up after i_{th} stop and drop-off after j_{th} stop. When a person has been dropped off, the person's pick-up and drop-off stops are removed from the list. For example, if B has been dropped off after person D is picked up as shown in Figure 3, the vehicle visiting list becomes: (A, 1), (D, 1), (C, 1), (D, -1), (A, -1), (C, -1). For computational efficiency, an SAV always picks up the potential rider before the next stop (either a pick-up or a drop-off) in the visiting list (i.e., i and s are assumed to be zero), but drop-off can take place after any stop depending on the matching result. This ignores the case when pick-up of this potential rider happens after the SAV's next stop, by reducing the computational complexity from O(n_2) to O(n).

SIMULATION RESULTS

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

AMD Performance

Two fleets of SAVs are used to serve FMLM demand in the AMD region. Each AMD has its own dedicated SAV fleet, so if a trip originates in AMD1 and terminates in AMD2, the SAV fleets in AMD1 and AMD2 cater to the FM and LM connections, respectively, of the same trip. The fleet boundary restriction was implemented to see how SAVs would perform in geofenced travel bubbles, and also to ensure reasonable travel times for riders within each AMD. This constraint can be relaxed in a straightforward manner in future simulations. The baseline scenario considers a train headway of 15 minutes, with adequate 4-seat SAVs serving each AMD, under a total travel demand of 4,000 riders during the 3-hr morning peak (across both AMDs). Mode shares of the 4,000 light-rail transit riders followed mode splits mentioned in the data description section, resulting in 1,507 FMLM trips, 1,189 FM trips and 1,304 LM trips. Figure 4 shows the boarding and alighting passenger totals at each station for southbound and northbound trains. From the figure it can be observed that highest number of boardings and alightings occurred at the end of the line in the simulation (i.e., Downtown station in the south, and Crestview station in the north). The majority of the travel happened between AMDs, but there are also a minor portion of transit trips that originated and terminated within the same AMD (for example, a good number of trips took place between Plaza Saltillo and the Downtown station which are both in AMD1).

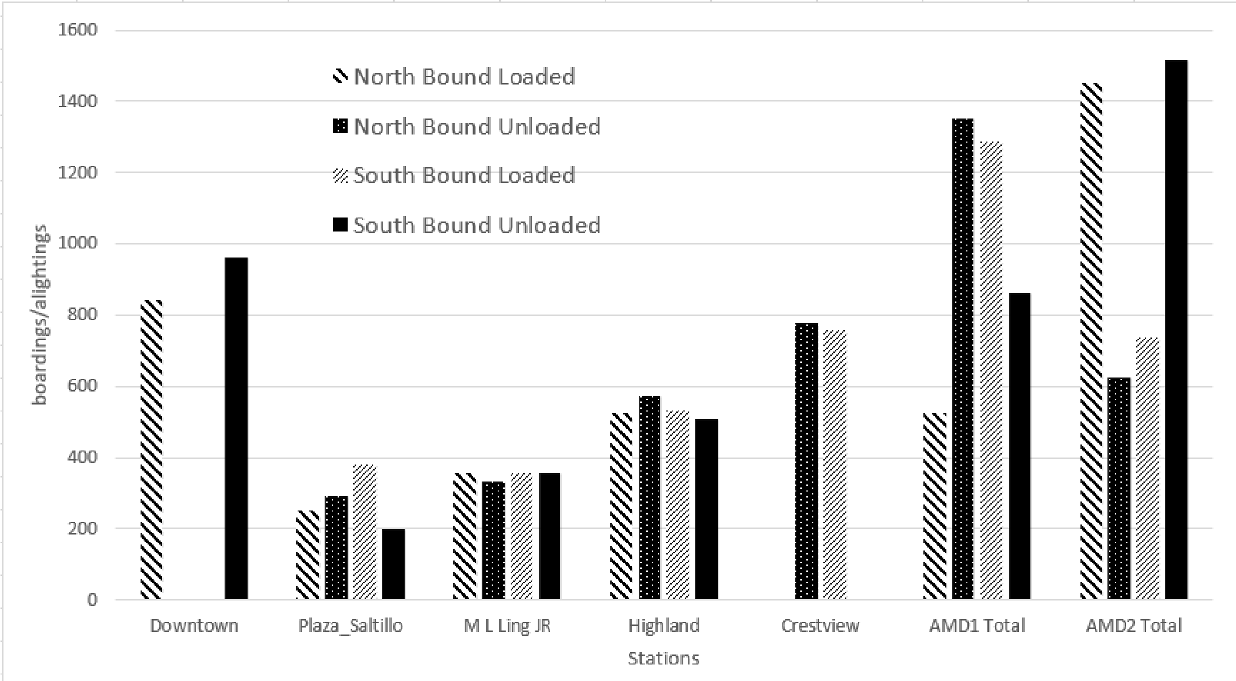


Figure 4. Number of Loaded and Unloaded Riders at Each Station

Table 1 presents the details on performance of SAV fleets in both the AMDs. As no constraints are placed on SAV fleet size, it was found that a total of 240 SAVs are required to keep the average wait time around 4.5 minutes in AMD1. Of the total transit demand in the 3-hour peak period, 1,208 and 1,316 originated and terminated, respectively, in AMD1. An interesting observation in Table 1 is that the proportion of shared trips in AMD 1 is ~90% but the proportion of shared vehicle miles is only 31%. This is because a trip is tagged as a shared trip even if a portion of the trip occurred with more than one passenger on the vehicle. As observed from the shared distance per trip metric, on average, only 23.1% of a trip is served as a shared trip. SAV operations in AMD1 resulted in over 5,800 VMT, of which 31% were shared VMT, and 25.8% were eVMT.

Fleet size requirement in AMD2 scaled proportionally with the size of the demand compared to AMD1 (19% increase in fleet size for a 20% increase in demand). Compared to AMD1, AMD2 sees an 8% increase in VMT, but a higher share of shared VMT (and trips), coupled with an increase in AVO. A greater proportion of shared trips and shared VMT in AMD2 show an impact on average wait time and service duration, both of which are slightly higher in AMD2 than AMD1. From a vehicle utilization standpoint, there are complementary effects at play between AMD1 and AMD2. AMD1 observes a higher magnitude of shared distance per trip, but also a higher amount of deadheading per trip. While AMD2 sees a lower magnitude of shared distance per trip compared to AMD1, the deadheading factor is reduced in AMD2 in comparison with AMD1.

Results across the whole area are shown in the last column of Table 1.With almost 90% of total trips served as shared rides (albeit with a 30% shared distance per trip), shared VMT came out to be a third of total VMT. While vehicle occupancy of the SAVs is reasonable, a greater demand density can drive vehicle utilization higher (as seen in comparisons between AMD 1 and AMD2). The application of SAVs to serve FMLM connections to train stations shows a strong utilization of SAV fleets, compared to door-to-door service, which often shows a low proportion of shared VMT (Fagnant & Kockelman, 2018).

Table 1. Performance of SAV Fleet

Metric	AMD1	AMD2	Whole Area
Fleet Size	240	286	526
VMT	5836	6355	12191
eVMT	25.8%	25.0%	25.4%
Shared Vehicle-Miles	31.0%	31.9%	31.4%
AVO	1.48	1.52	1.50
Shared Trips	89.8%	90.7%	90.3%
FM trips	1208	1488	2696
LM trips	1316	1495	2811
Average Wait Time	4.48	4.77	4.61
Average Ride Distance	2.58	2.46	2.52
Average Service Duration	14.0	15.9	15.0
Deadheading distance per trip (mile)	0.60	0.53	0.56
Shared distance per trip (mile)	0.72	0.68	0.70
Deadheading distance per trip (%)	27.8%	27.6%	22.3%
Shared distance per trip (%)	23.1%	21.6%	27.7%

Scenario Exercises

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

Vehicle Size: This set of scenarios explores the impact of seat capacity on SAV fleet performance. Vehicles with seat capacities of 2, 4, and 6 passengers were simulated along with a 1-seat AV case for comparison. Table 2 shows seat capacity is inversely proportional to SAV fleet size. VMT consumption (as well as eVMT) is highest in the 1-seat SAV scenario, as trips cannot be pooled in one-person SAVs. However, SAVs with two or more seats provided a service duration that was about twice as long as 1-seat service albeit with reduced fleet size and VMT consumption. It was also interesting to see that with no sharing (i.e, one-person SAVs) small-sized SAVs were supposed to pick passengers up faster, but riders under a small-sized SAV FMLM service experienced a longer waiting time. As the DRS settings (for maximum pick-up time and maximum delayed drop-off time) are held constant across all vehicle scenarios, one possible explanation for longer wait times is that larger fleet size in the 1-seat SAV scenario might lead to excessive curb congestion around the station area. All of these findings are important factors to consider when right sizing SAVs, as size reduction can have intended (i.e., lesser service duration) as well as unintended consequences, such as increased VMT, and increased wait times. It can also be observed that reduction in fleet size and corresponding increase in vehicle utilization (depicted by AVO) flattens out with the four-seater SAV scenario. The incremental benefits of having six-seater SAVs are minimal, if any, in the context of this simulation.

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

Table 2. System Performance Under Various Settings

Scenarios		Fleet size			VMT			AVO	Average Wait Time (min)	Average Ride Distance (mile)	Average Service Duration (min)
		Total	**AMD 1**	**AMD 2**	**Total**	**empty**	**Shared**				
Vehicle Size (seats per SAV)	1	992	437	555	16,996	51.3%	0.0%	1.00	5.1	1.52	7.4
	2	532	230	302	13,365	25.0%	23.4%	1.31	4.8	2.40	14.0
	4*	526	240	286	12,191	25.4%	31.4%	1.50	4.6	2.52	15.0
	6	498	217	281	12,187	25.2%	31.7%	1.50	4.5	2.52	15.3
Demand (riders in 3-hour AM peak)	3000	421	170	251	9,347	25.6%	30.9%	1.49	4.5	2.56	14.3
	4000*	526	240	286	12,191	25.4%	31.4%	1.50	4.6	2.52	15.0
	5000	598	271	327	15,067	24.4%	32.4%	1.52	4.6	2.54	14.8
Train Headway (min)	5	459	190	269	11,944	24.4%	32.2%	1.51	4.4	2.50	14.2
	10	496	214	282	12,128	24.1%	32.2%	1.50	4.5	2.55	14.4
	15*	526	240	286	12,191	25.4%	31.4%	1.50	4.6	2.52	15.0
	20	565	240	325	12,315	26.5%	31.3%	1.51	4.7	2.51	14.6
	25	594	260	334	12,566	28.1%	31.1%	1.53	5.0	2.53	15.1
Fleet Size Scale to Baseline Scenario	100%*				12,191	25.4%	31.4%	1.50	4.6	2.52	15.0
	90%				12,206	25.1%	32.0%	1.52	4.6	2.54	14.5
	80%				12,211	24.9%	31.7%	1.50	4.5	2.53	14.4
	70%				12,185	25.1%	31.8%	1.51	4.5	2.54	14.5
	60%				12,194	24.3%	32.9%	1.53	4.6	2.57	14.7
	50%				11,592	21.7%	36.8%	1.59	5.5	2.63	15.9

Note: Scenario marked with asterisk is the baseline scenario.

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

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

Improved DRS for Train schedules

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

Results shown in Table 3 indicate that the tighter the constraint on FMLM service parameters, the greater the fleet size requirement. As expected, the most stringent pick-up constraint (of 1-minute) resulted in extremely low shared vehicle-miles (of 4.4%), and an AVO of 1.08. In this case, the riders' distance was nearly the direct travel distance, which was 1.6 miles and the whole journey could be completed in under 8 minutes. Conversely, the scenario with most relaxed constraints on FMLM service parameters (10-minute pick up time threshold, and 20-minute delayed pick-up or drop-off threshold) sees a high AVO, and a greater proportion (47.1%) of shared vehicle miles. Trip level metrics (average wait time, ride distance, and service duration) increase with a higher percentage of shared VMT across scenarios. This is understandable, as with higher levels of sharing, SAVs may reroute to other stops, leading to greater distances and durations across the board. Generally, scenarios with larger fleet sizes see higher VMT and lower eVMT, compared to scenarios with smaller fleet sizes (i.e., more relaxed service parameters). However, the total VMT increased a little in scenario 4 compared to the baseline scenario, which is possible because a tighter constraint will have more deadheading VMT, but a more relaxed constraint will lead to more shared VMT, which consists of more added detours.

Table 3. System Performance under DRS Variations

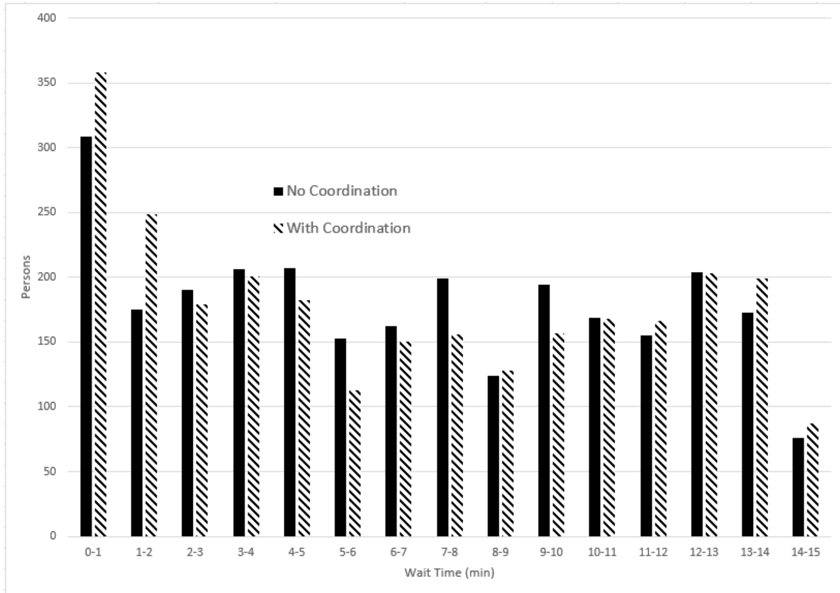
Scenarios	1	2	3*	4	With Coordination
Max Pick-up Time t_1 (min)	1	2	5	10	5
Max Delayed Drop-off Time t_2 (min)	2	4	10	20	by train schedule
Fleet Size	822	661	526	408	514
AMD1 Fleet Size	357	309	240	184	236
AMD2 Fleet Size	465	352	286	224	278
Total VMT	15,243	13,235	12,191	12,873	15,107
eVMT	47.8%	40.9%	25.4%	17.2%	16.1%
Shared Vehicle-miles	4.4%	12.9%	31.4%	47.1%	60.4%
AVO	1.08	1.23	1.50	1.79	2.29
Shared Trips	30.7%	62.4%	90.3%	93.7%	83.0%
Average Wait Time (min)	3.9	4.5	4.6	5.6	6.8
Average Ride Distance (mile)	1.6	1.8	2.5	3.5	5.5
Average Service Duration (min)	7.9	8.8	15.0	19.0	27.9

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

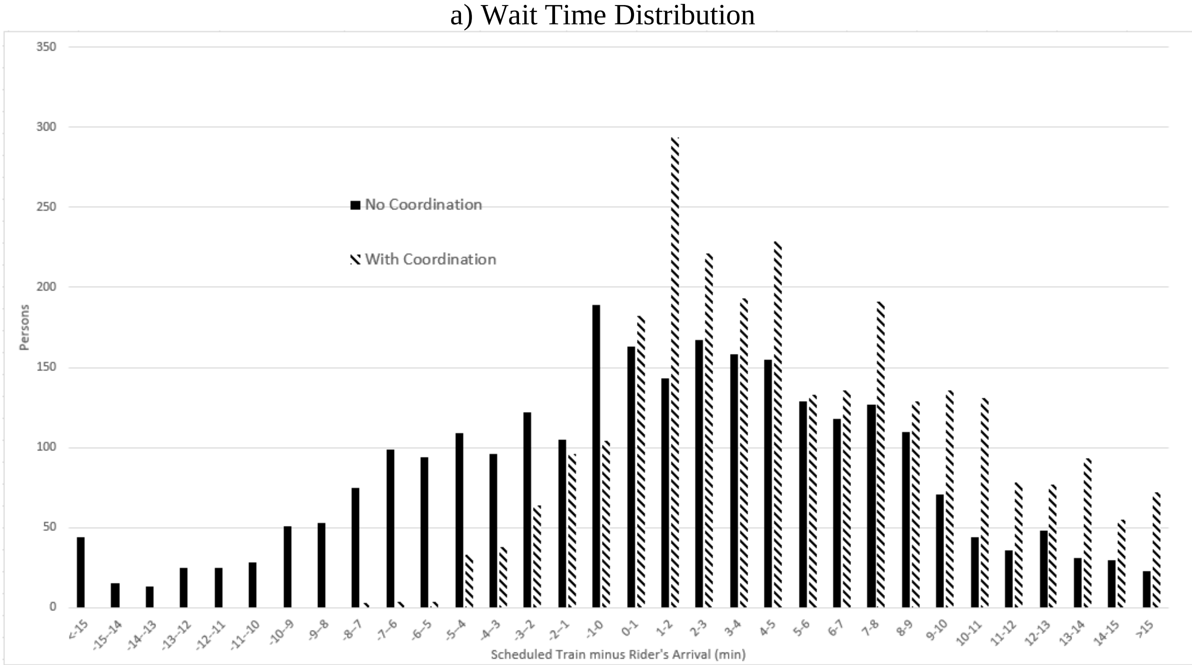
As the SAVs exclusively serve Red Line travel demand in this study, having a close coordination between DRS and train schedules can help improve SAV utilization, as well as rider experience. To accomplish this, the DRS algorithm has been modified to account for riders' arrival time constraints at the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

The performance of SAV fleets under the enhanced DRS algorithm is shown in the last column in Table 3. Keeping the pick-up time constraint same as the baseline, but having a tighter coordination between the DRS algorithm and the train schedule resulted in the highest proportion of shared miles (60.4%) coupled with the highest AVO (2.29), and lowest proportion of eVMT (16.1%) across all scenarios. This is understandable, as under this scenario, the algorithm will keep a rider on board for a longer duration if his/her train arrival is still minutes away. The increased vehicle utilization comes at the cost of longer wait time (48% increase from the baseline) and trip duration (86% increase from the baseline). This analysis provides an interesting insight on the possible gains in vehicle efficiency if SAV routing is coordinated with train schedules (at the cost of increased wait and ride times).

Although riders' wait time (for the SAV) increased in the coordinated train schedule scenario, they did not necessarily arrive late for their train. Figure 5a shows the distribution of wait times at the train station and Figure 5b shows the time difference between riders' arrival at the train stop and the scheduled train arrival. From Figure 5a, it can be observed that the modified algorithm helped increase the number of riders who arrived within 2 minutes before train departure, but the general distribution remained the same. In Figure 5b, positive values indicate earlier arrivals at the station, while negative values indicate a late arrival (i.e., after the train has departed). With a DRS mechanism that only considers pick-up time and drop-off time (i.e., the baseline scenario), the arrival time presents in the shape of a normal distribution with the train's arrival time as the mean. However, with the modified DRS algorithm which coordinates with the train schedule, the number of riders arriving ahead of the train's arrival increased and the number of riders arriving after the train has departed decreased greatly. With the enhanced DRS algorithm, the proportion of riders that can catch their scheduled train increased to 87.2% (from 57.5% in the baseline).



a) Wait Time Distribution



b) Distribution of Time Gaps between Scheduled Train Arrival and Riders' Arrival

Figure 5. Performance of Coordinated DRS Algorithm

CONCLUSION

Utilizing SAVs for FMLM connections to transit presents multifold benefits, including reduced costs to the operator and the passenger as well as reduced congestion on the roadways (owing to shift from car modes to SAV-to-transit modes). This paper investigates the impacts of SAVs serving as FMLM connections to/from five train stations (partitioned into two geofenced regions labeled as automated mobility districts or AMDs) along Austin's Red line. The contributions of this paper are three-fold. First, instead of forcing FM and LM to be the same mode to access light-rail transit, the simulations conducted in this paper allow for flexible FM and LM access (e.g., SAV-transit-walk). Second, unlike many SAV studies which simulated only a portion of the observed demand, this study simulates the full extent of central Austin's morning peak light-rail transit demand in 2030. Finally, this paper proposes an enhanced DRS algorithm that closely couples SAV operations with train schedules. Such an integrated algorithm is shown to increase vehicle utilization, and on-time arrivals at the train station. Detailed simulations were carried out in two AMDs, and the performance of the SAV fleet was analyzed in light of varying levels of travel demand, train frequency, SAV vehicle size, fleet size, and DRS settings.

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

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

While this study successfully demonstrates the efficacy of SAVs serving as FMLM connections to transit, it has some limitations. Although congestion has been observed around rail stations, realistic levels of congestion could not be reflected in the simulation due to lack of representation of other road modes such as private cars and buses. Also, this study focuses exclusively on SAVs being utilized as an FMLM mode but does not consider other forms of SAV services (fixed route-flexible schedule, and direct door-to-door services). Future research efforts may focus on addressing these gaps as well as optimizing parking depot locations for SAV initialization and relocation. Further research is also needed in regard to optimizing the size of geofenced regions (AMDs) for efficient FMLM services. The coordination between train schedules and SAVs can be extended to account for passengers' pick-ups, in addition to drop-offs at the train station. Finally, while this study looked solely on the mobility related impacts of SAV FMLM operations, future research should extend the focus to energy impacts of SAVs and electrified SAVs for FMLM connections to transit.

ACKNOWLEDGMENTS

This work was authored (in part) by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding was provided by the DOE Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The authors acknowledge Stan Young of NREL for leading the Urban Science Pillar of the SMART Mobility Laboratory Consortium. The following DOE Office of Energy Efficiency and Renewable Energy (EERE) managers played important roles in establishing the project concept, advancing implementation, and providing ongoing guidance: Prasad Gupte, Erin Boyd, Heather Croteau, and David Anderson. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes. The authors also thank TACC for high-performance computing support and Jade (Maizy) Jeong for her excellent editing and submission support.

AUTHOR CONTRIBUTIONS

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

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