First-Mile-Last-Mile Collector-Distributor System Using Shared Autonomous Mobility

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May 30, 2020

Forthcoming in *Transportation Research Record.*

ABSTRACT

High added costs of fully-automated-vehicles (AV) for ownership will fuel the demand for shared mobility, and this will especially be profitable from reduced operating costs. Although sharing ought to be good for the system, congestion is likely to increase without adequate policy measures. Public transit will continue to exist, with or without automation, and carefully-designed policies must be implemented to make full use of this public asset. In this study, a shared fleet of AVs (SAVs) is analyzed as a potential solution to the first-mile-last-mile (FMLM) problem, as an alternative for access/egress trips to public transit. Essentially, SAVs are analyzed as collector-distributor systems for these mass-movers and compared to a door-to-door service. Results from an agent-based simulation of Austin, Texas show that SAVs have the potential to help solving FMLM transit problem when fare benefits are provided to transit users. Restricting SAV use for FMLM trips increases transit coverage, lowers average access/egress walking distance, and shifts demand away from park-and-ride and long walk trips. When SAVs are available for both door-to-door use and FMLM trips, high SAV fares help maintain transit demand, without which the transit demand may reduce significantly, affecting the transit supply and the overall system reliability. Policymakers and planners must be weary of this shift away from transit and must plan to increase transit usage using policies tested in this study.

***Keywords**:* First-mile-last-mile, transit demand, public transportation, shared mobility, autonomous vehicles, Austin, Texas.

BACKGROUND

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Fully-automated or autonomous vehicles (AVs) are in the final stages of testing by technology companies and auto manufacturers. In the early phases of AV use, ownership will be expensive and may not be permitted by suppliers, to better ensure proper AV maintenance and use. Shared services are expected, with transportation network companies (TNCs) like Uber and Lyft already experiencing a large demand market (*1*). Extensive survey research suggests that travelers' interest in shared AVs (SAVs) is likely to grow (*2*, *3*), but will add vehicle-miles traveled (VMT) and congestion (*4*–*6*) from being a low-cost alternative and inducing demand from the elderly and children. Studies suggest that dynamic ride-sharing (DRS) can help moderate such added congestion (*7*, *8*), but, generally, not enough to reduce region-wide VMT across all modes (*9*, *10*). Key opportunities to lower congestion are congestion-pricing policies and DRS via SAVs of all sizes, in support of more traditional (but eventually self-driving) transit services.

Public transit systems offer better road area utilization than other modes (with seating capacities of 35 or more (*11*) while providing moderately accessible alternatives to many travelers. However, public transit comprises only 3 percent of U.S. passenger trips each day, and not more than 10 percent of all local travel in most U.S. cities. Low ridership comes from low population and job densities, easy parking options, low-cost vehicle ownership, and most people's unwillingness to walk more than 1/4 mile or wait more than 10 minutes for bus options (*12*). The cost and difficulty involved in moving people (and goods) to, and from, key nodes in our transport networks (like bus stops and rail stations) is called the first-mile-last-mile (FMLM) problem and is what motivates this research effort.

The FMLM problem is one of the main deterrents to the use of public transport (*13*). Bicycle sharing systems, like that implemented in Beijing, were anticipated to solve access and egress to transit lines, but bike maintenance and safety were concerns (*14*). The use of park-and-ride structures was found to increase transit ridership with the reliability of a personal vehicle for access and egress (*15*). However, this came at the cost of requiring significant infrastructure and was viable only when placed near a reliable transit line. One viable solution was carsharing, which helped increase overall transit use and walking (*16*). Several recent partnerships between TNCs and U.S. transit agencies, aiming to offer subsidized FMLM services, have failed due the lack of ridership and budget constrains (*17*). Reck and Axhausen (*18*) used open-source data sets to study these services and found that transfer penalties of 5-min exceeded travel time savings in up to 40 percent of the urban-area trips. In an AV future, SAVs were posited to be vital in controlling rising VMT by encouraging FMLM trips (*19*). Furthermore, by reducing the cost associated with drivers, SAVs can potentially compete with TNC costs and provide users with additional savings to reduce the impact of transfer delays.

The operational viability of SAVs serving FMLM trips to transit lines was studied by only a few. Liang et al. (*20*) developed an optimization framework for the FMLM problem, with SAVs providing a last-mile option for train trips in Delft, Netherlands. The study focused on fleet size to meet trip demand from existing data, with recommendations to switch to electric SAVs, but congestion effects could not be inferred. Scheltes and Correia (*21*) used an agent-based simulation model to explore the use of SAVs as last-mile connection mode for train trips in Delft. They concluded little to no VMT benefits and found that SAVs were only able to compete with the walking mode. Additional measures (such as a reduction in waiting time and travel time) were required to make it competitive with other modes. Shen et al. (*22*) modeled FMLM trips to and from a heavy rail station in Singapore and identified fleet sizes required with DRS to serve a static toy dataset. Their results suggested that SAVs were best used in replacing transit lines that were scarcely used. Farhan et al. (*23*) combined FMLM analysis along with real data and an optimization model and was able to quantify congestion benefits with DRS use. Their study showed that DRS reduced the fleet's VMT by 48 percent, with no comments on system-wide VMT with respect to the base case, making it hard to infer how the FMLM service upheld to its expectations. From an energy perspective, Moorthy et al. (*24*) quantified the benefits of using SAVs for first-mile service to the airport in Ann Arbor as up to 37 percent energy savings and sustainable transit operation. When considering only the potential of DRS and transit use, Stiglic et al. (*25*) was able to show that the transit use can significantly improve, especially when travelers have flexibility in matching with others, and when transit is more frequent.

Alemi and Rodier (*26*) shifted focus to larger regions and studied FMLM using travel demand data in the San Francisco Bay Area, California. They observed that nearly 31 percent of the existing single-occupant work trips could be shifted to public transit by using a TNC vehicle as an access mode. However, egress modes were not modeled and may have provided more benefits. TNCs were priced at about $2/mile for single-occupant trips (excluding the driver) and $1/mi for shared rides. SAVs will eliminate driver costs, and lower fares will become feasible, so larger benefits are likely. Only a handful of studies have explored FMLM with a microscopic approach. Rodier et al. (*27*) included SAVs in their analysis to identify the potential market for first-mile transit access service for the same location in California using an activity-based model and a dynamic assignment model, and compared them to TNCs. Study results indicated that TNC use for first-mile access might benefit as many as one-third of travelers, however, the use of SAVs tripled the share of travelers benefiting from the same service. Pinto et al. (*28*) micro-modeled transit interaction (i.e., transit users rejecting a boarding if the transit vehicle was full) and analyzed SAV as a first-mile provider, and as a separate service. Pinto et al. (*29*) used their own problem solver (*28*), created a bi-level optimization model to identify demand for transit versus an SAV fleet, and found considerable changes in traveler behavior in choosing the two modes. The study suggested that incorporating price elasticity and congestion into such modeling can also significantly impact travel patterns. Although most studies show SAV FMLM services in a positive light, there is no conclusive evidence that this is true across all regions and transit lines. Huang et al. (*30*) used a microscopic simulator to observe FMLM trips to and from Austin's Red (light-rail) Line. Their results suggested reduced mode shares for personal cars but significant additions to VMT and stressed the importance of frequent transit routes and SAV routing strategies to minimize FMLM plus on-board travel times. One study supports this idea of sufficient transit demand and high frequency by showing that rural transit lines, even if served by SAVs for FMLM, can be cost-effectively replaced by SAV fleet vehicles (*31*).

In this paper, an SAV fleet serving transit access and egress trips, as well as a door-to-door trips, is analyzed. This work is largely built around contributions by Leich and Bischoff (*32*) for FMLM trips, They use the multi-agent transport simulator "MATSim" (*33*) to model access and egress mode choice to public transit. In their Berlin study, they studied how SAVs compare to underutilized transit lines and concluded that there were little savings involved in replacing conventional transit lines. The focus here, however, is to see how the introduction SAVs will impact public transit use from a mode choice perspective, and whether the use of SAVs will complement or supplement transit lines. Hypothetical future scenarios are simulated here with assumptions on SAV use, transit use, and preferential fare structures to see how these systems interact.

The paper is organized as follows: the background and literature review are provided above, followed now by the simulation methodology (which discusses tools and algorithms used). Results from all simulation scenarios are then explained, and corresponding conclusions derived. This paper ends with a discussion of future work opportunities in this important topic area, to help make the most of existing transit investments and high-capacity travel modes.

METHODOLOGY

The multi-agent transport simulation, MATSim (*33*), is used in this study to simulate travel patterns in Austin, Texas. The existing demand observed in a region is converted to represent all agents' travel and activity plans. This serves as the initial input along with the corresponding region's network and the scenario configuration that is to be simulated. One simulation iteration in MATSim involves the traffic assignment, itinerary scoring, and re-planning for mode choice. A queue-based dynamic traffic assignment model is used for the mobility simulation, which captures congestion throughout the simulation period. Agents are expected to be performing an activity when not traveling. At the end of the simulation period, all agents are scored for overall utility – gains from performing activities and losses from traveling. Replanning is then done to improve an agent's utility by checking for alternative modes, routes, and activity start times and duration using a co-evolutionary algorithm. This constitutes one iteration of the MATSim simulation. Replanning is allowed to continue for a pre-specified number of iterations to create choices between itineraries, after which all agents seek to choose the best available option, and, accordingly, choose the best route depending on congestion. The final set of traveler itineraries, when converged, represent dynamic user equilibrium and is used to determine travel behavior for a representative day. Post-processing can be done on this convergent set to analyze how trip patterns and mode choices have changed for each scenario tested. Figure 1 shows the MATSim loop that captures the moving parts of MATSim succinctly.

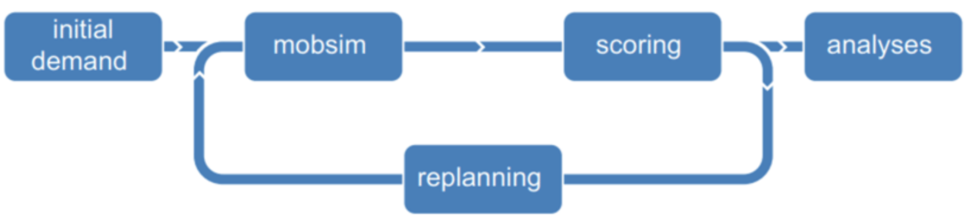


Figure 1 The MATSim loop [source: (*33*)]

This study focused on the City of Austin, Texas. Activity and trip data for a 5 percent population sample were extracted from a travel dataset used by Liu et al. (*34*) for the 6-county Austin region. Trips extracted from this broader region help deliver realistic congestion levels for the simulated areas of interest, which is the region's core City. The sample contains daily itineraries or travel plans for approximately 45,000 persons or "agents", and the base case scenario has been validated in other studies (*6*, *10*), with base-case mode shares of 88.7, 4.1, and 7.2 percent for car, public transit, and walk/bike modes, respectively.

Shared Autonomous Vehicle Fleet

SAVs in MATSim are adapted from Horl's (*35*) AV contribution, which helped simulate the dynamic nature of SAVs responding to real-time requests within one iteration. When travelers request rides in SAVs, the request is processed by a central operator depending on the availability of SAVs versus the number of requests pending to be served. The objective of request matching is to match the request to the closest vehicle or match the vehicle to the closest request, to increase computational efficiency.SAVs are assigned to requests only if they are within a 30 min time radius of the traveler, as estimated on the network.

The model assumes that SAV costs include a base fare (F_0), time-varying fare (F_t), and distance-varying fare (F_d). A 5-mile SAV trip made in 15 min would thus cost the sum of $F_{0,}$ F_t times 15, and F_d times 5. Different scenarios come with different F_0, F_t and F_d value assumptions. A real-time analyzer was also coded to obtain important fleet-level metrics - such as total VMT, empty VMT, revenue, and average response times.

A 1-in-10 SAV availability is assumed for this study, meaning that 1 SAV is available for every 10 travelers (or approximately every 35 person-trips), resulting in a fleet size of 4500 SAVs. This is larger than suggested by Gurumurthy et al. (*10*), but was chosen to maintain good availability of SAVs throughout the region and dissociate fleet effects in finding and using the service. The maximum search radius for finding trips to serve is set at 30 min to observe the average response time that is found to be acceptable by travelers in the convergent solution based on assumed utility.

Public Transit and Access/Egress Modes

Schedule-based public transit was also incorporated into the model with congestion feedback using a transit router. The input schedule was obtained from Austin's public transit agency, Capital Metro, in the general transit feed specification (GTFS) format for the year 2018. This was processed similar to Poletti et al. (*35*) to obtain a MATSim-readable transit schedule, along with transit line specifications that can replicate Austin's transit service on the network. In traditional modeling, transit users are assumed to access and egress transit stops by walking or biking. In order to provide a FMLM service using SAVs, itinerary modifications had to be made to introduce FMLM behavior in MATSim using SAVs as access and egress legs, in addition to walking. This was adapted from a contribution by Leich and Bischoff (*32*), and essentially allows variable access by adding access and egress legs to public transit trips, with the mode chosen depending on the distance to the transit stop or destination. By executing this in the re-planning stage, the travelers in the simulation are given an alternative option for travel which they can accept or reject based on the itinerary's score. A quarter-mile suggested maximum access/egress distance is assumed for walk trips since buses are a dominant part of Austin's transit service (*36*), but is relaxed depending on available alternative modes. The upper-bound for SAV access/egress is left unspecified to observe acceptable averages based on utility derived. Longer access/egress trips are not expected owing to the inherent travel disutility as compared to a direct auto trip. This also ensures that travelers will be unwilling to use SAVs to access public transit that is not in the direction of intended travel. Car access/egress is also allowed here, but specific park-and-ride locations are not specified. Parking lot availability is an important consideration to accurately model car access and egress, but it is assumed that the low share of travelers chaining trips with public transit will do so only depending on their tour. Figure 2 shows the transit boarding pattern observed from a 24-hr base case simulation in MATSim. Although boarding trends are not validated, the hotspots are indicative of stops in Austin where large ridership is observed.

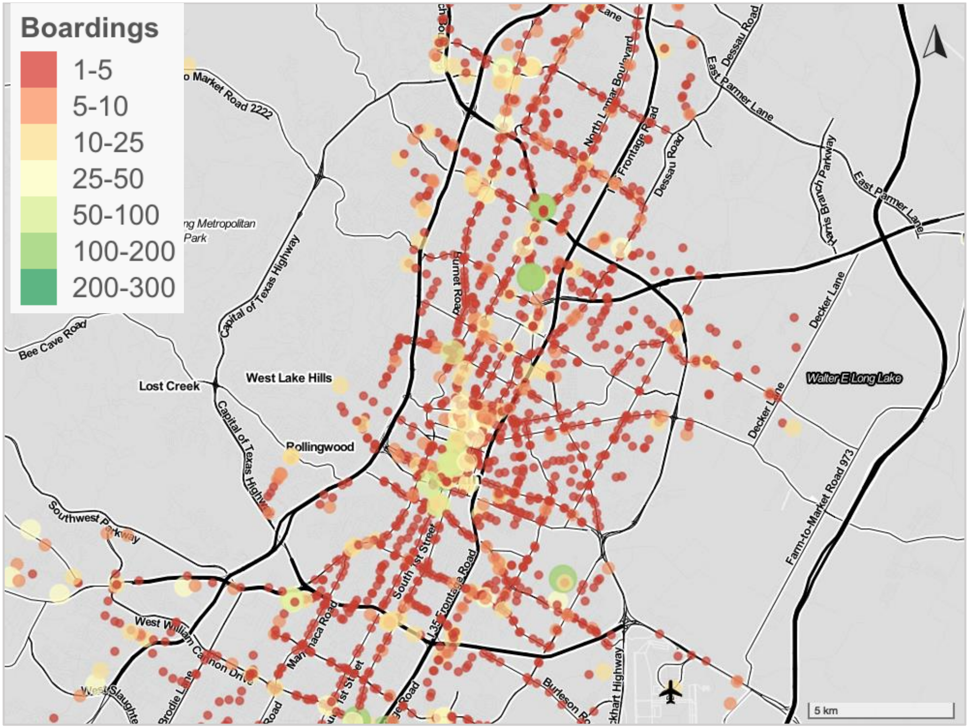


Figure 2 Transit boardings by stop location for current Austin conditions over a 24-hr period

Scenarios Tested

This study particularly looks at three different policy scenarios to evaluate SAV usage and its potential effect on the FMLM transit problem. They are described as follows:

Door-to-door (D2D): The first scenario simulates the introduction of SAVs in the City of Austin serving door-to-door trips only. Travelers are intentionally not allowed to use SAVs to access or egress from the transit lines. The objective of this scenario is to reveal changes in transit demand due to introduction of SAVs, assuming that the transit system functions similar to present-day schedule and reliability.

***FMLM*:** The second scenario uses SAVs as a collector-distributor system to serve only FMLM trips. The objective is to capture the effect of SAV availability on transit demand and to evaluate the potential benefits of SAVs to solve the FMLM problem.

***Both D2D and FMLM*:** The final scenario includes the two previous cases. It uses SAVs to serve both door-to-door service and FMLM trips. This case intends to capture the combined effect and to measure if SAVs are supplementing or complementing transit.

In addition to the three cases of study, two levels of SAV fares are tested – which shall be termed high (HF) and low (LF) fares for convenient nomenclature. High fares are those that are comparable to present day TNCs charged at $2 per mile. Low fares of 20¢ per trip, 10¢/mi and 4¢/min are charged for every trip based on the lack of driver-related costs that will continue to keep SAVs viable. In addition to SAV fare structures for D2D use, FMLM trips tested in the second scenario are tested with two fare policies – where FMLM trips are free (F1), and both FMLM trips and transit trips are free (F2), ideally subsidized by federal funds.

RESULTS

Distinct scenarios were tested in this study to understand the impact of an SAV service on transit use. The first scenario assumes that SAVs serve D2D services only, while the second uses SAVs as a collector-distributor for transit trips, serving FMLM only. A third scenario uses SAV to serve both door-to-door and FMLM trips. The base case, or business as usual (BAU), corresponds to the simulation using present-day travel patterns for a sample of 5 percent population in the City of Austin, along with the existing transit conditions. Table 1 shows the system-wide VMT change and fleet statistics including the change in system vehicle-miles traveled (ΔVMT), percentage empty VMT (eVMT), average response time, and the daily net revenue of the SAV fleet, which are used to compare these distinct scenarios.

Table 1 System effects and fleet statistics by scenario

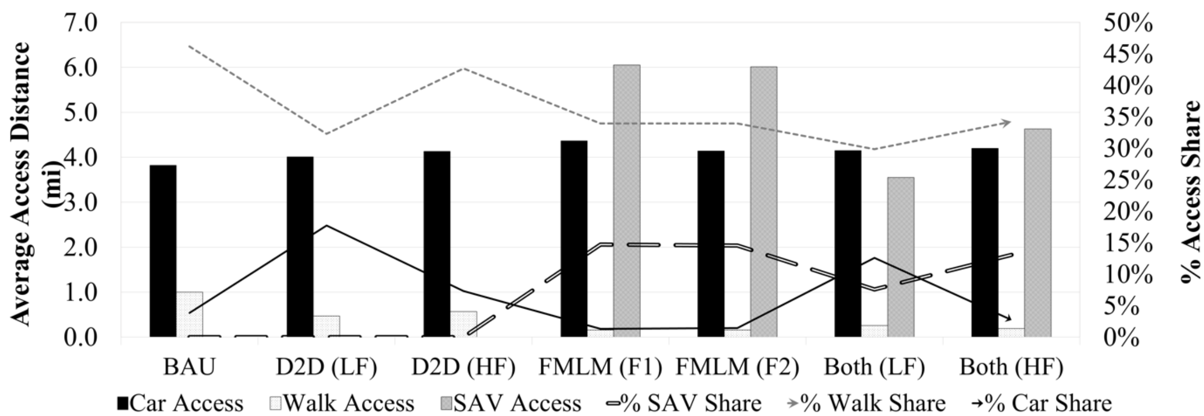
Case	Fleet Statistics			
	Δ System VMT (w.r.t BAU)	**Revenue** (in USD)	**Avg. Response Time** (in min)	**eVMT** (% of system VMT)
D2D (LF)	6.8%	70,253	5.9	0.43%
D2D (HF)	1.0%	125,743	12.9	0.02%
FMLM (F1)	1.7%	-	12.1	0.45%
FMLM (F2)	1.6%	-	12.2	0.43%
Both (LF)	6.7%	67,875	6.6	0.40%
Both (HF)	1.0%	121,330	9.3	0.05%

All the cases analyzed showed an increase in system-wide VMT, likely arising from mode shift from walk and transit to SAVs (similar to Pinto et al. (*28*)), and, particularly, eVMT from SAV pickup trips. Results denote that the presence of low-fare SAVs increases VMT by at least six percent, while high-fares show the lowest changes in VMT (one percent or lower). Low SAV fares are likely to shift users away from walk, transit and car modes. When SAVs are used for serving FMLM trips, the change in VMT is only 1.6 percent, even when their use for access and egress is high (15 percent), as expected. This is likely arising from the fact that FMLM trips are relatively short, and shorter than a D2D trip for the same origin and destination. So increased use of SAVs for FMLM still does not add a lot of system VMT. However, when SAVs serve only D2D trips, resulting in higher VMT.

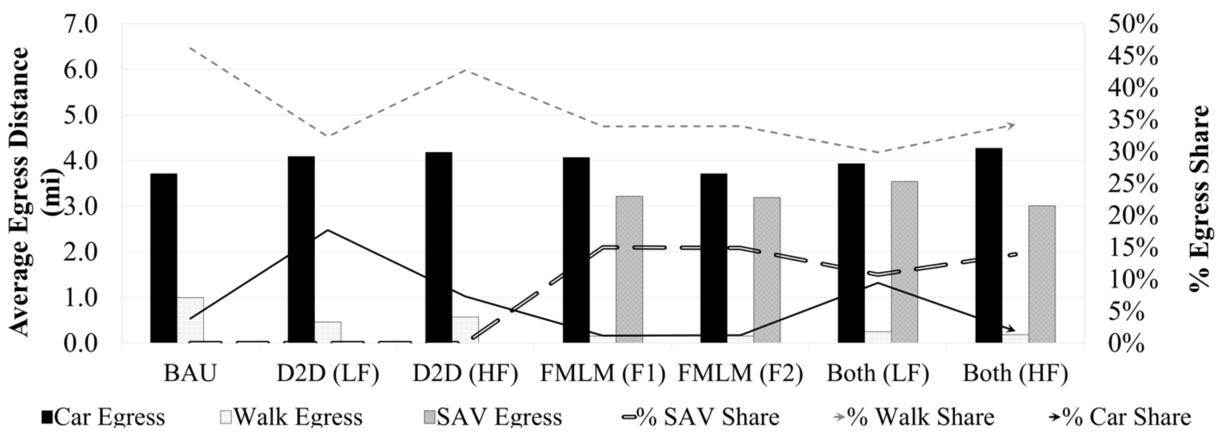
The fares assumed also have an impact on SAV response time, or the time taken by an SAV to reach a new pickup request. High fares deter SAV use, and new requests are spatially sparse – thus increasing average response times. On the other hand, low fares attract more SAV users and lower average response times. The number of travelers using SAVs for FMLM service only is low - irrespective of the fare structure (F1 or F2) - so this trip-request sparsity also contributes to high average response times. Higher fares translate to higher SAV revenues in these scenarios, even though SAV mode shares fall. This result suggest that high-fares may help moderate added system-wide VMT while generating considerable revenue for SAV fleet owners. The average response time for trip requests when charging high fares is higher, likely from lowered demand, than when more travelers are using SAVs which helps distribute them across the network.

Figure 3 indicates that the average SAV access/egress distance for FMLM trips is approximately six miles for the Austin sample used here. There is a notable decrease in walk access/egress distance in the presence of SAVs. The lowest average walking access/egress distance corresponds to the case where SAVs serve only FMLM trips. While the SAVs' average access/egress distance is six miles, the walking mode access/egress distance is about 0.15 miles. This result implies that coverage radius of the transit service rises significantly as compared to the average walking distance access of 0.25 miles observed today (*12*).

The car and walk share for access and egress declined in the presence of SAVs, which indicates the potential change in users' mode without promoting FMLM use. The number of users that access or egress transit by car (park-and-ride) decreased from 18 percent (D2D–LF case) to less than one percent (FMLM–F1 case), while the walk share varies from 43 percent (D2D–HF case) to 30 percent (Both–LF case). This trend seems to denote that the majority of shifts for access or egress come from previous car users and walk users who had a significantly high access or egress distance. These results also help to explain the low change in VMT found for FMLM case. Interestingly, when SAVs serve both D2D and FMLM trips with low fares (Both-LF case), there is an increase in the share of access and egress trips made by car. This can be attributed to D2D dominating FMLM owing to low fares that drive down the supply for FMLM SAV trips. Depending on the origin and destination, the walk mode may still be infeasible and travelers opt to access and egress transit via a park-and-ride.



(a) Access



(b) Egress

Figure 3 Access and egress statistics by scenario

Spatio-temporal transit patterns were also analyzed for each scenario using Austin's transit system information. Figure 4 illustrates the hourly transit ridership which was evaluated using Austin's General Transit Feed Specification (GTFS) schedule. For the cases where SAVs are used for D2D and both (D2D and FMLM), low-fare SAV scenarios decrease transit usage, mainly during peak hours. High SAV fares cause a significant increase in transit usage. In this case, AM and PM peak match BAU scenario. However, when SAVs are used to serve trips for FMLM only, there is an increment in AM and PM peak ridership compared to BAU case. This result suggests that, under the preferential SAV fares for FMLM trips, SAVs can potentially be used to supplement transit trips.

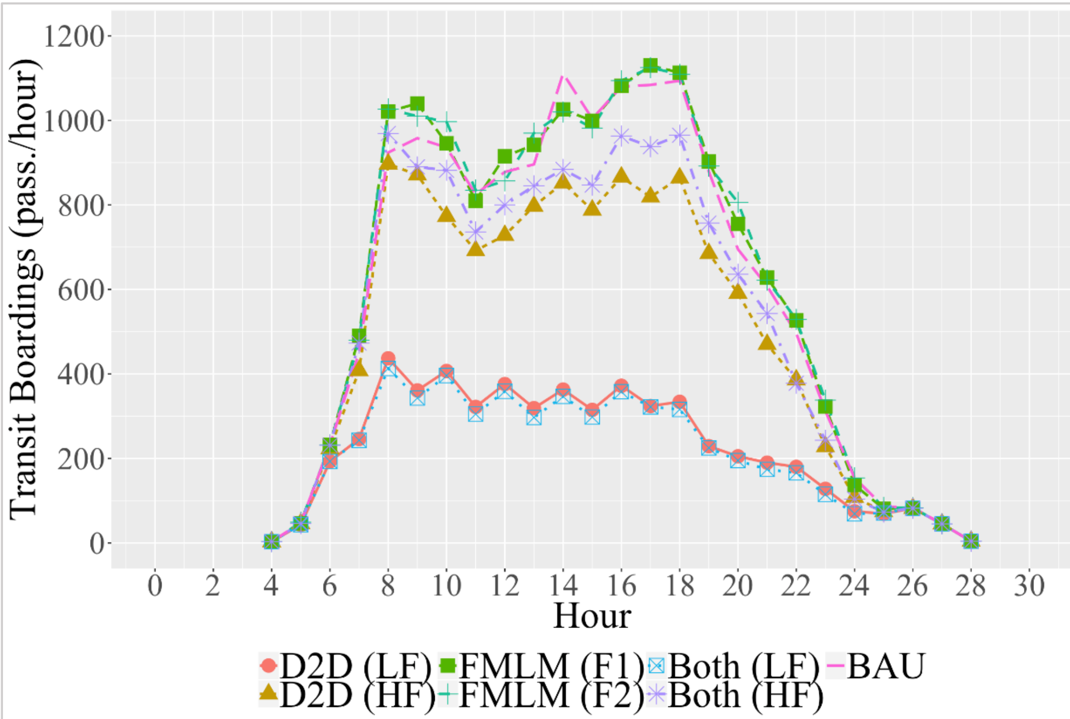


Figure 4 Transit boardings by simulation-hour

Spatial transit boardings was calculated using stop-level counts from simulations results. Figure 5 illustrates the spatial distribution of transit boardings over the 24-hr simulation period for the different cases analyzed. Results suggest that low-fare SAVs reduce transit demand across the city, and demand patterns do not seem to concentrate in high density areas and are rather sparse, which would potentially cause a reduction of service in different suburban areas. The implementation of high-fare SAVs cause an increase in transit trips in high population-density areas, and demand seems to match BAU conditions which was shown in Figure 2.

(a) Both FMLM & D2D trips – Low-fare (LF) SAVs

(b) Both FMLM & D2D trips – High-fare (HF) SAVs

Figure 5 Fare effect on transit boardings by stop location over a 24-hr period

CONCLUSIONS

An agent-based simulation was carried out to identify the impact of SAVs serving as both an access/egress mode, as well as a door-to-door service, with a focus on the City of Austin, Texas. The analysis included activity and trip information from a five percent sample of Austin's population and used public transportation information obtained from Austin's transit agency to simulate different conditions. Three different scenarios were tested to evaluate the potential effects of the introduction of SAVs. The first one uses SAVs to serve door-to-door trips only, and it aims to assess the impact of SAVs and demand changes on the transit system under current conditions. The second scenario uses SAVs to as collector-distributions for Austin's transit system and provides reduced fares to incentivize usage. The last scenario combines both door-to-door and FMLM trips.

Results from this study indicate that SAVs have potential to help solving FMLM transit problem when proper fare benefits are provided to users. When SAVs are used to serve as collector-distributor for the transit system, the transit coverage increases, average walking access/egress distance reduces, and there is a mode shift away from the park-and-ride and long-distance walk trips. When SAVs are available for both door-door and FMLM trips, high SAV fares help maintain transit demand indicating the need for policies to regulate SAV fares. If SAVs are widely available for door-to-door trips with a reduced fare, transit service demand may reduce significantly. This scenario would eventually affect the transit supply and the overall system reliability. Planners and transit agencies must prepare for an SAV future by implementing policies that boost transit-users' benefits that can ensure that the transit service is attractive to the population.

The results and methods presented in this research effort can serve multiple purposes. First, the cases analyzed in this paper can help policymakers and planners to visualize possible SAV effects on the transit system for regions similar to Austin, Texas – as with a comparable transit presence. They suggest strategic policies for incentivizing transit usage. More generally, the methods developed here can be extended to any region of the world. Moreover, from a transit agency's perspective, ridership data over time and space can be used to predict SAV and transit use changes, while detecting hot-spots (also in time and space) to adjust operational decisions and increase levels of service for transit and SAV-FMLM users. This work also reveals the need for more research in the area of SAVs interacting with transit systems and fixed investments.

Although paper results are robust, some computational limitations restricted microsimulation to just 5 percent of Austin's population. Larger regions with above-average transit use are likely to benefit even more from FMLM scenarios with subsidies, as suggested in this study. Induced demand was not captured here, since MATSim operates on a fixed set of travel itineraries. Future work in this area can explore how larger samples and higher densities of demand affect SAV and transit use, and whether offering DRS in SAVs diminishes transit demand further. Policies assumed here, like fully subsidizing transit use (F1 and F2), need to be further evaluated for practical barriers in implementation. A 1989-1990 implementation of free bus rides all day in Austin, Texas proved unsuccessful, and attracted many problematic riders, thereby deterring choice riders from finding the service attractive (*37*). The provision of these services at high fares also deters mobility equity. The distribution of services in the region as a result of the proposed policies can be studied. Finally, the impact of reducing walk trips on public health is an important and related topic of interest.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Gurumurthy. K.M., Zuniga-Garcia, N., and Kockelman, K.; methodology: Gurumurthy. K.M.; analysis and interpretation of results: Gurumurthy. K.M., Zuniga-Garcia, N., and Kockelman, K.; manuscript preparation: Gurumurthy, K.M., Zuniga-Garcia, N., and Kockelman, K. All authors reviewed the results and approved the final version of this manuscript.

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