FIRST-MILE-LAST-MILE COLLECTOR-DISTRIBUTOR SYSTEM USING SHARED AUTONOMOUS MOBILITY

Krishna Murthy Gurumurthy
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
gkmurthy10@utexas.edu

Kara M. Kockelman, Ph.D., P.E.
(Corresponding Author)
Professor and Dewitt Greer Centennial Professor of Transportation Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin – 6.9 E. Cockrell Jr. Hall
Austin, TX 78712-1076
kkockelm@mail.utexas.edu

Natalia Zuniga-Garcia
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
nzuniga@utexas.edu

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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, shared mobility, autonomous vehicles, dynamic ride-sharing, Austin, Texas.

BACKGROUND

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 ride-hailing companies already experiencing a large demand market (Shaheen et al., 2016). Extensive survey research suggests that travelers' interest in shared AVs (SAVs) is likely to grow (Krueger et al., 2016; Kockelman et al., 2018), but will add vehicle-miles traveled (VMT) and congestion (Fagnant et al., 2015; Levin et al., 2017; Simoni et al., 2019) 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 (Agatz et al., 2011; Fagnant and Kockelman, 2018), but, generally, not enough to reduce region-wide VMT across all modes (Gurumurthy and Kockelman, 2018; Gurumurthy et al., 2019). 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 (National Academies of Sciences, Engineering, and Medicine, 2013), while offering 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 (El-Geneidy et al., 2014). 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 (Wang and Odoni, 2016). 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 (Liu et al., 2012). The use of park-and-ride structures were found to increase transit ridership with the reliability of a personal vehicle for access and egress (Kim et al., 2007). 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 (Martin and Shaheen, 2011). In an AV future, SAVs were posited to be vital in controlling rising VMT by encouraging FMLM trips (Shaheen and Chan, 2016).

The operational viability of SAVs serving FMLM trips to transit lines were studied by only a few (Liang et al., 2016; Scheltes and Correia, 2017; Alemi and Rodier, 2018; Rodier et al., 2018). Liang et al. (2016) 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 (2017) 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 reduction in waiting time and travel time) were required to make it competitive with other modes. Shen et al. (2018) 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. (2018) 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., 2017 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.

Alemi and Rodier (2018) 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 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. (2018) included SAVs in their analysis to identify the potential market for first mile transit access service for the same location 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 may 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., 2018 micro-modeled transit interaction (i.e., transit users rejecting a boarding if the transit vehicle was full) and analyzed SAV as a FMLM provider, and as a separate service. Fares were found to play a key role in deciding the mode choice and the authors recommend further study by using better mode-choice models.

In this study, an SAV fleet serving as transit access and egress modes, as well as a door-to-door service, is analyzed. This study is largely built around contributions by Leich and Bischoff (2018) for FMLM trips which used the multi-agent transport simulator, or MATSim (Horni et al., 2016), 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 were provided, which is followed by the simulation methodology, results and conclusion, and a discussion on future work.

METHODOLOGY

The multi-agent transport simulation, MATSim (Horni et al., 2016), is used in this study to simulate travel patterns. 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. Re-planning is then done to check alternative modes, routes, and activity start times and duration for each agent using a co-evolutionary algorithm. This constitutes one iteration of the MATSim simulation. Re-planning 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.

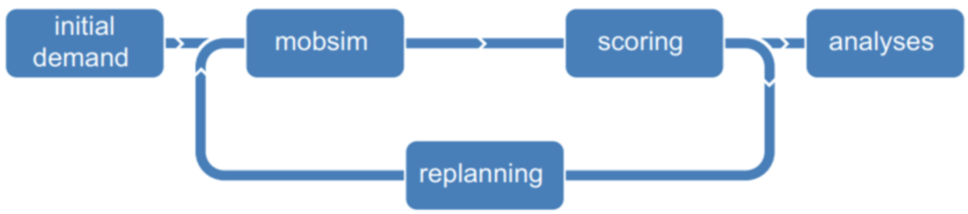


Figure 1 The MATSim loop (source: Horni et al., 2016)

The focus of this study is on the City of Austin, Texas. Activity and trip data for a 5 percent population sample was extracted from a travel dataset that was used by Liu et al. (2017) for the 6-county Austin region. The sample contains plans for approximately 45,000 agents, and the base case scenario has been validated in other studies (Simoni et al., 2019; Gurumurthy et al., 2019). For the base case, the mode shares are split 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 the AV contribution by Hörl (2017) which helps simulate the dynamic nature of SAVs responding to real-time requests within one iteration of the simulation. 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 estimated on the network.

The model allows to charge fares as a base fare, time-varying fare, and distance-varying fare across all SAVs. A real-time analyzer was developed 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, that is a fleet size of 4500 SAVs. This is larger than suggested by Gurumurthy et al. (2019), 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., 2017) 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, 2018, 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 (Capital Metropolitan Transportation Authority, 2019), 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.

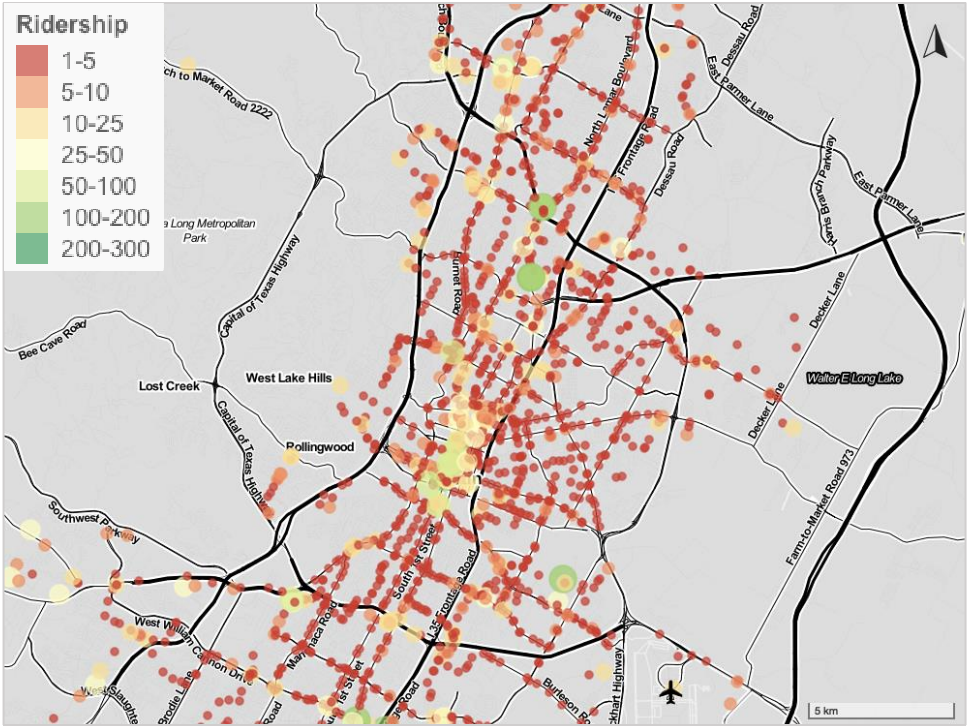


Figure 2 Transit ridership by stop location for current Austin conditions

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 current 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 total vehicle-miles traveled (ΔVMT), empty VMT (eVMT) percentage, 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	**Revenue (in USD)**	**Avg. Response Time (in min)**	**eVMT (% of total 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, and 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, and use of SAVs for access and egress is high (15 percent), as expected. This is likely arising from the fact that D2D trips are likely longer than the FMLM trips, so large usage of SAVs for FMLM still does not add a lot of VMT. Figure 3 indicates that the average SAV access/egress distance for FMLM trips is approximately six miles for the sample used. However, when SAVs are only serving D2D trips, the distance to complete the entire trip is likely higher. Thus, it is expected that the change in VMT is lower when SAVs are serving FMLM only.

Higher fares translated to higher revenue for SAVs, even when the fares reduced the SAV mode share. This result suggest that high-fares can potentially help reduce system-wide VMT while generating considerable revenue for SAV providers. The average response time for trip requests when charging high fares is higher, likely from sparse nature of trip requests, than when more travelers are using SAVs which helps distribute them across the network.

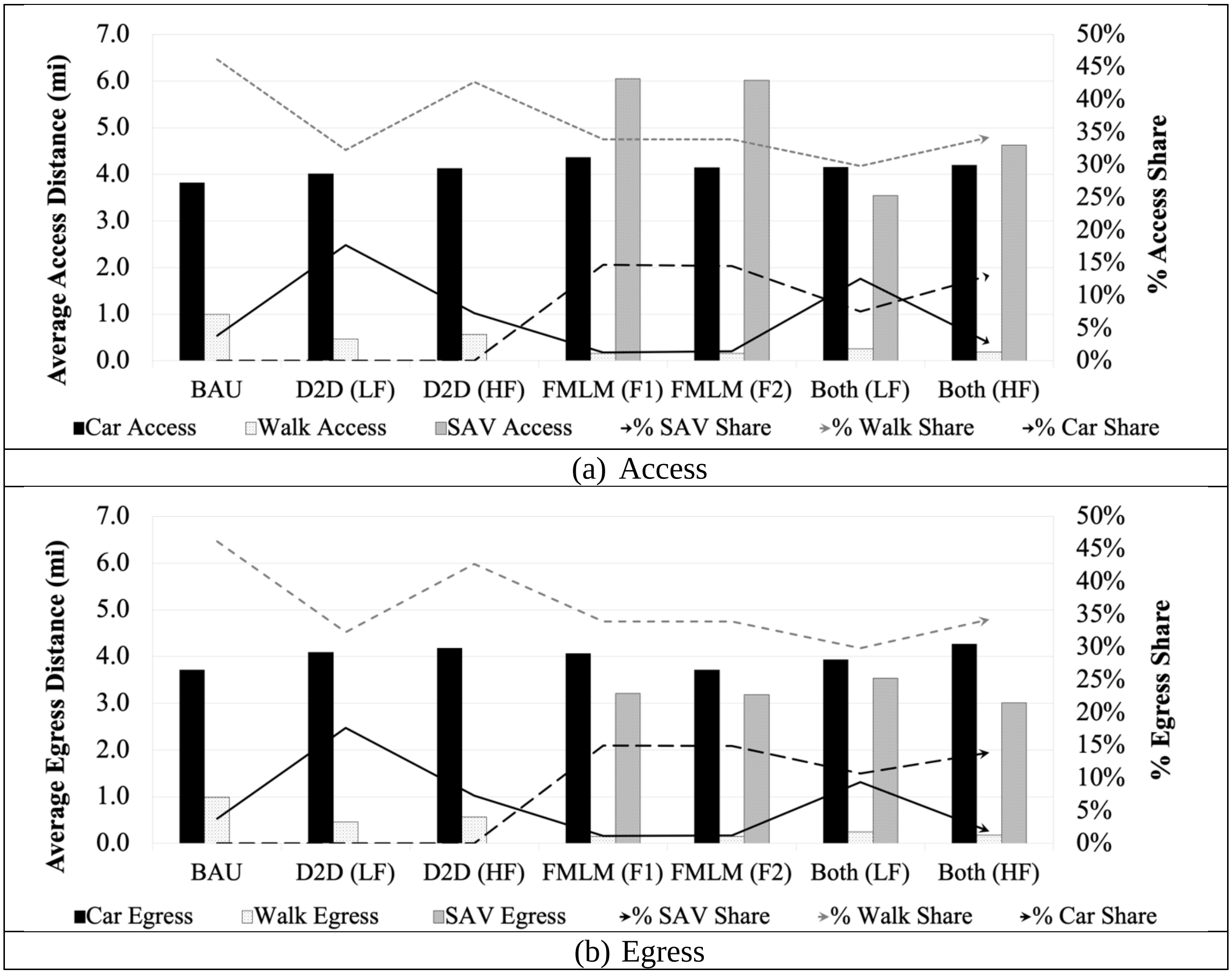


Figure 3 Access and egress statistics by scenario

Figure 3 also shows a decrease in walk access/egress distance in the presence of SAVs. The lowest average walking access/egress distance corresponds to the case where SAVs are serving only FMLM. 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 the coverage radius of the transit service increases significantly compared to the average walking distance access of 0.25 miles observed today.

The car and walk share declined in the presence of SAV, which indicates the potential change in users' mode shift without promoting FMLM. The number of users that access/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 mode share varies from 43 percent (D2D–HF case) to 30 percent (Both–LF case). This trend seems to denote that the majority of mode shifts come from previous car users and walk users with significantly high access/egress distance. These results also help to explain the low change in VMT found for FMLM case.

Spatio-temporal transit patterns are analyzed for each scenario using Austin's transit system information. Figure 4 illustrates the hourly transit ridership which was evaluated using Austin's 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.

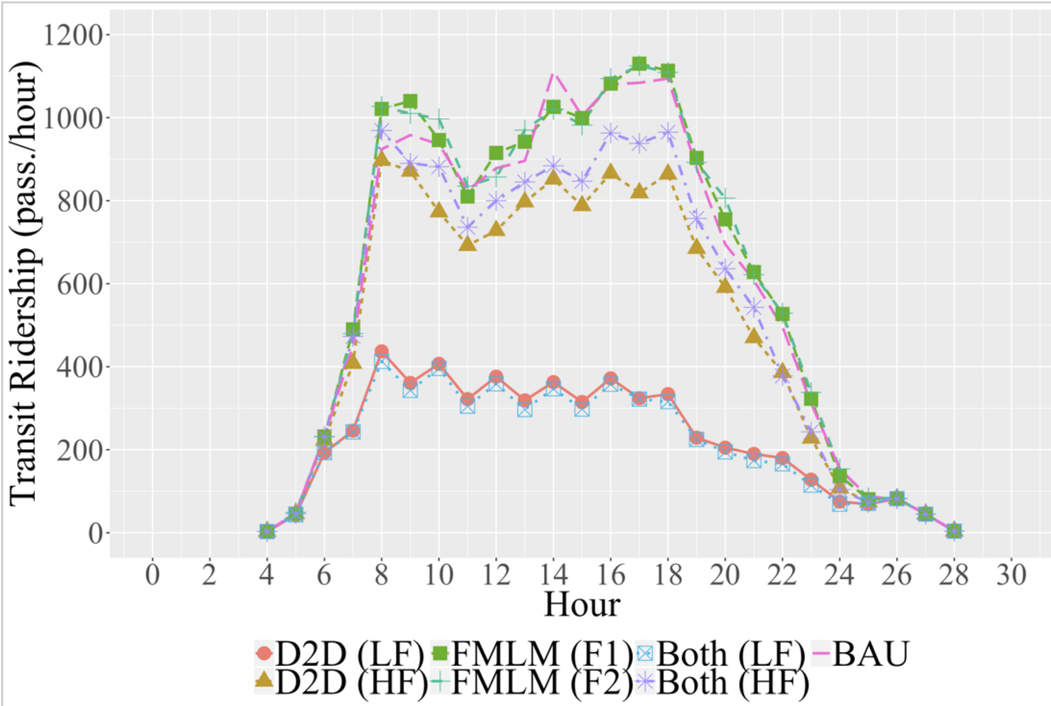
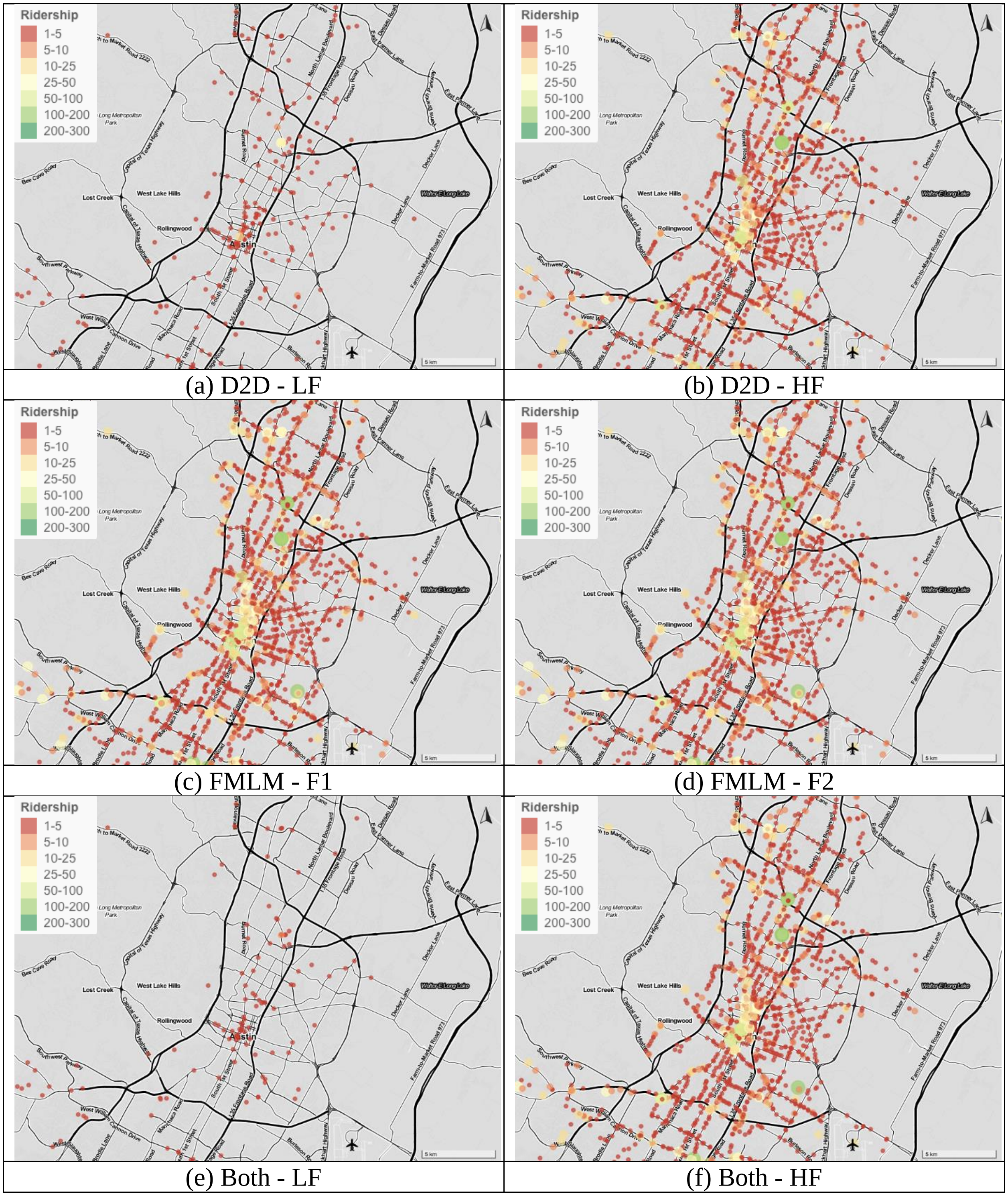


Figure 4 Transit ridership by simulation-hour

Spatial transit ridership is estimated using stop-level counts from simulations results. Figure 5 illustrates the spatial distribution of transit trips 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) D2D - LF | (b) D2D - HF

(c) FMLM - F1 | (d) FMLM - F2

(e) Both - LF | (f) Both - HF

Figure 5 Transit ridership by stop location for the different scenarios

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. 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 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, results suggest that the 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 and can guide toward the most assertive ways to implement policies that incentivize transit usage. Second, from a transit agency perspective, spatio-temporal level information of ridership change can be used in predicting usage changes, detecting hot-spots and peak hour demand to adjust operation conditions and increase user level of service. Third, this study reveals the need for more research in the area of SAVs interacting with transit.

Although robust, this study faced computational limitations which restricted the sample of agents to five percent of the population. Induced demand was not captured since MATSim operates on a fixed set of itineraries. Future work in this area can explore how larger samples affect SAV and transit usage, and whether DRS diminishes transit demand further.

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.

REFERENCES

Agatz, N., Erera, A.L., Savelsbergh, M.W.P., Wang, X., 2011. Dynamic Ride-Sharing: a Simulation Study in Metro Atlanta. Procedia - Soc. Behav. Sci., Papers selected for the 19th International Symposium on Transportation and Traffic Theory 17, 532–550. https://doi.org/10.1016/j.sbspro.2011.04.530

Alemi, F., Rodier, C., 2018. Simulation of Ridesourcing Using Agent-Based Demand and Supply Models Regional: Potential Market Demand for First Mile Transit Travel and Reduction in Vehicle Miles Traveled in the San Francisco Bay Area. Presented at the 97th Annual Meeting of the Transportation Research Board.

Capital Metropolitan Transportation Authority, n.d. Metro Performance Dashboard: Ridership [WWW Document]. URL https://capmetro.org/ridership-stats/ (accessed 7.21.19).

El-Geneidy, A., Grimsrud, M., Wasfi, R., Tétreault, P., Surprenant-Legault, J., 2014. New evidence on walking distances to transit stops: identifying redundancies and gaps using variable service areas. Transportation 41, 193–210. https://doi.org/10.1007/s11116-013-9508-z

Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 45, 143–158. https://doi.org/10.1007/s11116-016-9729-z

Fagnant, D.J., Kockelman, K.M., Bansal, P., 2015. Operations of Shared Autonomous Vehicle Fleet for Austin, Texas, Market. Transp. Res. Rec. J. Transp. Res. Board 2536, 98–106. https://doi.org/10.3141/2536-12

Farhan, J., Chen, T.D., Zhang, Z., 2018. Leveraging Shared Autonomous Electric Vehicles for First/Last Mile Mobility. Presented at the 97th Annual Meeting of the Transportation Research Board, Washington, D.C.

Gurumurthy, K.M., Kockelman, K.M., 2018. Analyzing the dynamic ride-sharing potential for shared autonomous vehicle fleets using cellphone data from Orlando, Florida. Comput. Environ. Urban Syst. 71, 177–185. https://doi.org/10.1016/j.compenvurbsys.2018.05.008

Gurumurthy, K.M., Kockelman, K.M., Simoni, M.D., 2019a. Benefits & Costs of Ride-Sharing in Shared Automated Vehicles across Austin, Texas: Opportunities for Congestion Pricing. Presented at the 98th Annual Meeting of the Transportation Research Board, Washington, D.C.

Gurumurthy, K.M., Kockelman, K.M., Simoni, M.D., 2019b. Benefits and Costs of Ride-Sharing in Shared Automated Vehicles across Austin, Texas: Opportunities for Congestion Pricing. Transp. Res. Rec. 0361198119850785. https://doi.org/10.1177/0361198119850785

Hörl, S., 2017. Agent-based simulation of autonomous taxi services with dynamic demand responses. Procedia Comput. Sci. 109, 899–904. https://doi.org/10.1016/j.procs.2017.05.418

Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity Press. https://doi.org/10.5334/baw

Kim, S., Ulfarsson, G.F., Todd Hennessy, J., 2007. Analysis of light rail rider travel behavior: Impacts of individual, built environment, and crime characteristics on transit access. Transp. Res. Part Policy Pract. 41, 511–522. https://doi.org/10.1016/j.tra.2006.11.001

Kockelman, K., Boyles, S., Claudel, C., Stone, P., Loftus-Otway, L., Sturgeon, P., Sharon, G., Gurumurthy, K.M., Huang, Y., Simoni, M., Lei, T., Patel, R., He, D., Mohamed, A., Liu, J., Yarmohammadi, S., Thorn, E., Wagner, W., Stewart, D., Albert, M., Hanna, J., 2018. Phase 2 - Bringing Smart Transport to Texans: Ensuring the Benefits of a Connected and Autonomous Transport System in Texas (No. FHWA/TX-18/0-6838-3). TxDOT.

Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transp. Res. Part C Emerg. Technol. 69, 343–355. https://doi.org/10.1016/j.trc.2016.06.015

Leich, G., Bischoff, J., 2018. Should autonomous shared taxis replace buses? A simulation study. VSP Working Paper 18-05, TU Berlin, Transport Systems Planning and Transport ….

Levin, M.W., Kockelman, K.M., Boyles, S.D., Li, T., 2017. A general framework for modeling shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing application. Comput. Environ. Urban Syst. 64, 373–383. https://doi.org/10.1016/j.compenvurbsys.2017.04.006

Liang, X., Correia, G.H. de A., van Arem, B., 2016. Optimizing the service area and trip selection of an electric automated taxi system used for the last mile of train trips. Transp. Res. Part E Logist. Transp. Rev. 93, 115–129. https://doi.org/10.1016/j.tre.2016.05.006

Liu, J., Kockelman, K.M., Bösch, P.M., Ciari, F., 2017. Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. Transportation 44, 1261–1278. https://doi.org/10.1007/s11116-017-9811-1

Liu, Z., Jia, X., Cheng, W., 2012. Solving the Last Mile Problem: Ensure the Success of Public Bicycle System in Beijing. Procedia - Soc. Behav. Sci., 8th International Conference on Traffic and Transportation Studies (ICTTS 2012) 43, 73–78. https://doi.org/10.1016/j.sbspro.2012.04.079

Martin, E., Shaheen, S., 2011. The Impact of Carsharing on Public Transit and Non-Motorized Travel: An Exploration of North American Carsharing Survey Data. Energies 4, 2094–2114. https://doi.org/10.3390/en4112094

Moorthy, A., De Kleine, R., Keoleian, G., Good, J., Lewis, G., 2017. Shared Autonomous Vehicles as a Sustainable Solution to the Last Mile Problem: A Case Study of Ann Arbor-Detroit Area. SAE Int. J. Passeng. Cars - Electron. Electr. Syst. 10. https://doi.org/10.4271/2017-01-1276

National Academies of Sciences, Engineering, and Medicine, 2013. Transit Capacity and Quality of Service Manual, Third Edition. The National Academies Press, Washington, DC. https://doi.org/10.17226/24766

Pinto, H.K.R. de F., Hyland, M.F., Verbas, İ.Ö., Mahmassani, H.S., 2018. Integrated Mode Choice and Dynamic Traveler Assignment-Simulation Framework to Assess the Impact of a Suburban First-Mile Shared Autonomous Vehicle Fleet Service on Transit Demand. Presented at the 97th Annual Meeting of the Transportation Research Board, Washington, D.C.

Poletti, F., Bösch, P.M., Ciari, F., Axhausen, K.W., 2017. Public Transit Route Mapping for Large-Scale Multimodal Networks. ISPRS Int. J. Geo-Inf. 6, 268. https://doi.org/10.3390/ijgi6090268

Rodier, C., Jaller, M., Pourrahmani, E., Bischoff, J., Freedman, J., Pahwa, A., 2018. Automated Vehicle Scenarios: Simulation of System-Level Travel Effects Using Agent-Based Demand and Supply Models in the San Francisco Bay Area. California Department of Transportation.

Scheltes, A., de Almeida Correia, G.H., 2017. Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to Delft, Netherlands. Int. J. Transp. Sci. Technol., Connected and Automated Vehicles: Effects on Traffic, Mobility and Urban Design 6, 28–41. https://doi.org/10.1016/j.ijtst.2017.05.004

Shaheen, S., Chan, N., 2016. Mobility and the Sharing Economy: Potential to Facilitate the First- and Last-Mile Public Transit Connections [WWW Document]. https://doi.org/info:doi/10.2148/benv.42.4.573

Shaheen, S.A., Coehn, A., Zohdy, I., 2016. Shared Mobility: Current Practices and Guiding Principles (No. FHWA-HOP-16-022). FHWA.

Shen, Y., Zhang, H., Zhao, J., 2018. Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. Transp. Res. Part Policy Pract. 113, 125–136. https://doi.org/10.1016/j.tra.2018.04.004

Simoni, M.D., Kockelman, K.M., Gurumurthy, K.M., Bischoff, J., 2019. Congestion pricing in a world of self-driving vehicles: An analysis of different strategies in alternative future scenarios. Transp. Res. Part C Emerg. Technol. 98, 167–185. https://doi.org/10.1016/j.trc.2018.11.002

Wang, H., Odoni, A., 2016. Approximating the Performance of a “Last Mile” Transportation System. Transp. Sci. 50, 659–675. https://doi.org/10.1287/trsc.2014.0553