SHARED AUTONOMOUS VEHICLE FLEETS TO SERVE CHICAGO'S PUBLIC TRANSIT

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ABSTRACT

Shared automated vehicles can provide different services in the future, including door-to-door (D2D) service, first-mile last-mile (FMLM) connections to transit stations, and as a low-cost transit vehicle. This paper leverages the agent-based simulator POLARIS to analyze the deployment of different SAV services in an integrated transit system for a 5% population sample of the Greater Chicago region. Accounting for 15% of the mode share, 12,000 SAVs offered D2D service at $0.50 per-mile for trips averaging 4.6 miles. The FMLM service variant can raise the transit use from 5.4% to 6.3%, while the SAV fleet was more utilized by serving 12% more requests per day with only 4% increase in VMT compared to D2D service. Most FMLM service trips ranged from 1.7 to 1.9 miles, and the connections to rail stations dominated the FMLM trips instead of those to bus stations. The welfare analysis shows that residents in the suburban area benefited most from the SAV D2D service, followed by those in the urban area, while residents near transit stations in the suburban areas are also more likely to gain social welfare.

Keywords: Shared autonomous vehicles; first-mile-last-mile; large-scale simulation; public transportation

INTRODUCTION

The advent of shared automated vehicles (SAVs) may dramatically change the future of public transportation system in the coming decade. Studies have demonstrated the benefits and attractiveness of the SAV fleets serving door-to-door (D2D) services (Fagnant & Kockelman, 2018), thanks to safety and environmental benefits brought by the automated driving system, and the cost savings from the lack of drivers on board. These savings are likely to be more when rides are shared by travelers, also called dynamic ride-sharing (DRS), to better utilize available seats. In addition to a D2D service, low-cost SAVs may also be providing other flexible services in the future, such as offering first-mile last-mile (FMLM) connections to transit stations (Farhan et al., 2018; Gurumurthy et al., 2020; Pinto et al., 2020; Shen et al., 2018) and serve on new fixed-route fixed-stop transit lines instead of labor-intensive buses that have a higher operating cost (Quarles et al., 2020). Although different kinds of SAV services have been discussed separately, predictions on integrated public transportation served by SAVs are lacking depth. This paper leverages the large-scale agent-based POLARIS tool (J. Auld et al., 2016) to investigate the mode splits, social welfare, and network performance across a large region in a fully-integrated manner to understand the impacts of deploying various SAV-related services.

Three main SAV services have been envisioned as a likely future for shared mobility – a D2D service with or without DRS, offering FMLM connections to transit, and as low-cost vehicles in a fixed-route fixed-stop service. Low-cost operation from eliminating drivers' wage, smooth vehicle acceleration and deceleration, improved safety through the automated driving system, and a centralized dispatch for seamless DRS has made SAVs a convenient and expected choice for travel in the coming years. Such a service will accommodate induced travel by the elderly and disabled, while having the potential to reduce total vehicle-miles traveled (VMT) and increase average vehicle occupancy (AVO) through efficient DRS (Childress et al., 2015; Gurumurthy & Kockelman, 2018). While this D2D service is convenient and low-cost, without sufficient demand for sharing rides the total VMT change may be positive. Several ongoing tests around the world (Stocker & Shaheen, 2019) also indicate an initial low-speed geofenced deployment of SAVs (Hou et al., 2017). In such situations, SAVs can be leveraged to serve the FMLM connections to transit stations, as they provide a more convenient and faster service compared to riding a bicycle and walking to transit stations, while releasing the burden and cost of parking a personal vehicle near the transit stations. As the technology further matures, SAVs may eventually take the lead in the public transportation system, in addition to offering the D2D alternative, through a fleet of heterogeneous vehicle sizes. The bus- or mid-size SAVs may serve traditional fixed-route fixed- or flexible-stop transit corridors where heavy transit demand exists. More importantly, SAVs' self-relocation centralized via an operator may result in a much cheaper and more convenient fleet deployment and management. The fleet operator can manage a large fleet and thus lead to an expanded transit service area.

With the multi-faceted nature of an SAV service, it is essential to investigate each component thoroughly and using a common tool to best understand the nuances involved in such a deployment. Shaheen & Cohen (2018) noted that infill development brought by SAVs may increase public transportation ridership and even transform bus transit to rail transit in urban cores. Lenz & Fraedrich (2016) mentioned that SAVs may be better in providing public transport services than conventional buses, since they may be cost-effective even in the suburban and rural areas. Although a D2D service may gain mode share from both personal vehicles and public transit (Liu et al., 2017), SAVs serving FMLM connections can help increase the catchment area for public transit and reduce connection times to transit stations, making public transit more preferred (Huang et al., 2021). Moreover, the traditional transit lines themselves can also benefit economically from using SAVs, by replacing existing transit lines or establishing new transit lines using these low-cost vehicles. The services that SAVs can provide will compete with existing public transit service for travelers with high value of time, support transit by increasing choice riders, while also functioning as vehicles in transit lines eventually. Therefore, the mixed role of SAVs within a transportation system demand a thorough examination, especially for large-scale networks (e.g., Chicago and New York) where the transit use is high.

This paper analyzes the deployment of SAVs in an integrated transit system in the Greater Chicago region. The impacts of the SAV fleets are revealed through mode splits, social warfare, and network performance . The recommendations are provided on the prioritization of the SAV services, and how the service should be mixed. The rest of the paper is organized as follows. The literature on SAV services is reviewed first, followed by the description of the Chicago network data. The POLARIS model is then introduced, including how the three SAV services are modeled. Model results and various sensitivity analyses are described, before providing the paper's conclusions and recommendations.

LITERATURE REVIEW

Numerous studies on SAVs focus on predicting its impacts under various scenarios, including travel behavior, land-use change, increased travel safety, environmental and economic benefits, and traffic impacts (Narayanan et al., 2020). Gurumurthy et al. (2019), and Zhao & Malikopoulos (2019) provide a detailed summary of recent research on SAVs. Most current SAV studies focus on the D2D service, and only a handful have ventured into a discussion on SAVs in a multi-modal network.

Narayanan et al. (2020) reviewed several articles and concluded that incorporating public transit was essential when discussing the use of SAVs. More recently, studies have begun investigating SAVs' impacts on a multi-modal network to reflect a more reasonable real-world application. For example, Snelder et al. (2019) explored the mobility impacts of SAVs in a mixed traffic environment, with a novel mode that captures demand elasticities and a combination of destination and mode choice models. In an SAV scenario, a large modal shift from all modes to SAVs was predicted, given low costs and low passengers' value of travel time (VOTT). Merlin (2017) simulated SAVs and transit in the relatively small Ann Arbor network, with a focus on how SAVs will reshape transit. It was anticipated that SAVs are preferred in comparison to the current bus transit system due to comparable wait times, shorter travel times, significantly lower costs per day and passenger mile traveled, and lower carbon emissions.

Compared to the case when SAVs only provide D2D service, an integrated SAV fleet and transit system is more complicated to model, as it involves multimodality in finding shortest paths across several combinations, in addition to seamlessly integrating it to an on-demand service for the first and last mile. Moreover, from a demand perspective, public transportation is often not the first choice for travel in most U.S. cities, and using SAVs for FMLM connections to existing public transit systems do not appear to be as attractive as a direct D2D service. Despite the modeling difficulties and the relatively low interest in FMLM use, there are still many studies that quantify SAV impacts when used for FMLM. Yap et al. (2016) surveyed detailed traveler preferences for AVs in an integrated public transportation system and predicted that AVs had the most potential for first-class train travelers as a last-mile transport between the train station and the final destination. Abe (2021) investigated 2,300 Tokyo residents' preference of using AVs for FMLM connections to urban rail transit. Analyses of the survey data showed that FMLM service by AVs tend to be favored by those who currently have restrictions in accessing transit, and such a service is more likely to substitute for access and egress modes like feeder bus and personal cars, but not for active modes like cycling and walking.

Simulations are typically the preferred tool and can reflect vehicle operations and road congestion well. Zachariah et al. (2014) synthesized the New Jersey trip data and simulated a ride-sharing system of SAVs providing FMLM service to train stations. Authors noted that train stations will have a substantial potential for rideshare, especially during peak hours, and taking advantage of these spatial and temporal peaks in ridesharing demand are likely key to an optimized ride-sharing system. Vakayil et al., (2017) simulated a multi-modal transit system that integrates a FMLM service with mass-transit services, considering transit frequency, transfer costs, and vehicle relocation. Results indicated up to 50% reduction in congestion and vehicular emissions thanks to FMLM service. Gurumurthy et al. (2020) compared an SAV fleet's FMLM service to a D2D service across the Austin region through a 5% sample simulated in MATsim. Pricing scheme turned up to be the key factor impacting demand elasticity. Shen et al. (2018) simulated an integrated AV and public transportation system based on Singapore's mass-transit across a 12 km^2 service area during morning peak hours. They showed that the integrated system has the potential of enhancing service quality, occupying fewer road resources, being financially sustainable, and utilizing bus services more efficiently.

Electrified fleets work even better overall. Farhan et al. (2018) showed how shared autonomous electric vehicles (SAEVs) can complement existing public transit services. Results showed great potential for leveraging SAEVs to increase transit catchment area, but reduced demand for park and ride infrastructure. The simulated SAEV fleet could reduce system-wide VMT by 37% through ridesharing and fast charging, which also effectively decreases fleet size and wait time. Scheltes and de Almeida Correia (2017) studied the use of SAEVs serving last-mile ride-hailing service of a train line segment in Delft. Even with the high preference for non-motorized modes in the Netherlands, they concluded that the SAEV system can compete with walking but not with cycling. Their simulated SAEV system was able to reduce average passenger travel time and waiting time, especially when pre-booking was allowed.

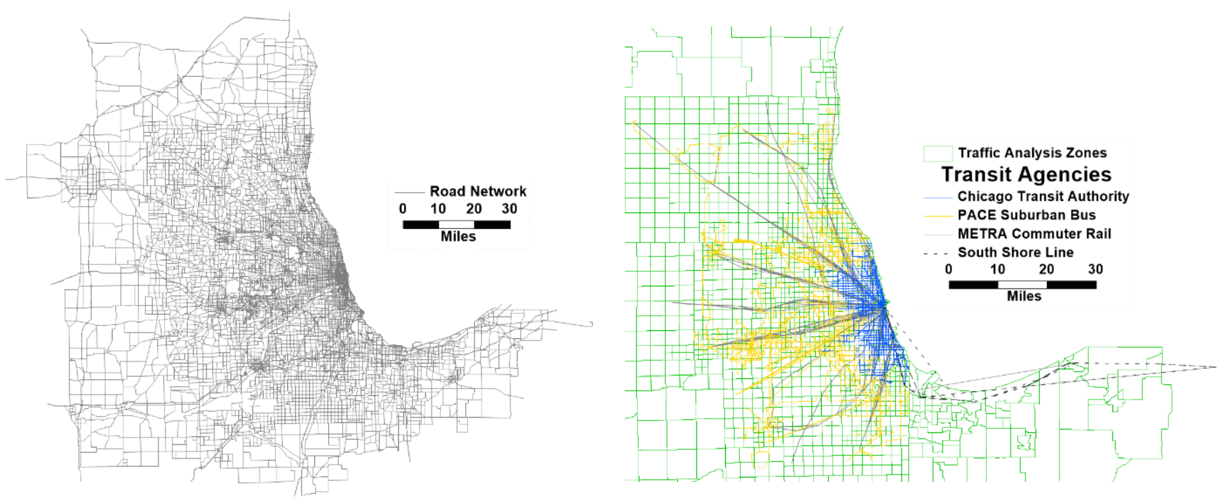
While FMLM connections by themselves have shown promise in improving traveler wait times and travel times, new transit lines leveraging a SAVs can also be useful to an ailing public transit system. Current studies on SAV-based transit lines focus mainly on acceptance (Bernhard et al., 2020; Nordhoff et al., 2019), but planning and operational insights are still lacking. For example, Mirnig et al. (2020) surveyed and concluded that the functionalities of booking and reserving spots in an automated bus have more impact on the vulnerable population. Bernhard et al. (2020) explored 942 participants' willingness to use SAV-based transit (autonomous minibus called EMMA) offered by a transport company in the City of Mainz, Germany. The participants turned out to consider the safety and environmental friendliness of the minibus as most important, and the performance expectancy impacted the acceptance of automated public transport the most. Moorthy et al. (2017) conducted a cost analysis comparing conventional public transit and a hypothetical SAV system for transit between Ann Arbor and Detroit Wayne County Airport, with simplified network and vehicle operations. Results showed that the SAV system could provide up to 37% energy savings, which is sensitive to vehicle powertrain and ridership parameters. However, this study still focused on the FMLM service to the airport, compared to a feeder bus line that already exists, and ignored vehicle stopping and routing.

Only a handful of papers have discussed an integrated transit system with SAV-based transit (Gurumurthy et al., 2019; Harb et al., 2021; Narayanan et al., 2020; Zhao & Malikopoulos, 2020). A thorough investigation on the operations of an integrated system involving various SAV services is warranted and is the prime motivation for this study.

DATASET

This study simulates vehicle and person movements across the 11,116 sq. mi Chicago region. The large-scale network has 1,961 traffic analysis zones with about 32,000 road links (Figure 1a) and 33,000 transit links (Figure 1b). The daily travel patterns from 2.6 billion travelers from 1 billion households across the region are synthesized and validated by Auld et al. (2016), leveraging the CMAP travel survey data.

The transit network was obtained as a General Transit Feed Specification (GTFS), and was organized, tested and calibrated by Verbas et al. (2018) for the POLARIS model. Four transit agencies are considered in the model: Chicago Transit Authority, PACE suburban bus, METRA commuter rail, and South Shore Line. The Chicago Transit Authority (CTA) provides service in City of Chicago and 10 surrounding suburbs, while the PACE suburban bus serves a larger area, connecting six counties, including Cook, Lake, Will, Kane, McHenry, and DuPage (American Public Transportation Association, 2021; Chicago Transit Authority, 2016). Since the bus service is the main service from CTA and PACE, the SAVs are assumed to replace regular bus service only (excluding bus rapid transit), with adjustments for vehicle size and fleet schedules. METRA and South Shore are both commuter rail services, which are assumed to maintain the status quo, although there may be expansions in the future under the impacts of SAV use. A total of 349 unique transit lines are coded into the model, among which 134 lines are from CTA and 202 lines are from PACE (Verbas et al., 2018). Buses used for CTA and PACE's regular bus services are set to have 30 seats and a standing capacity for 30 travelers. Considering different departures for each transit line, about 2,100 routes are assembled to offer 28,000 total transit trips throughout a workday. The bus stops in this chapters are considered as "stations", so the two terms are used interchangeably, recognizing that stations may be larger in size and include more bus layover accommodations.



a. Road network b. Transit network

Figure 1. Chicago Network

POLARIS MODEL

POLARIS is a large-scale multi-agent activity-based travel demand model which simulates both person and freight trips for a 24-hour day. The model is initialized with a population synthesis module (see Auld & Mohammadian, 2010), which includes home, school, and work location choices for synthesized households and individuals based on data from U.S. Census tracts, Public Use Microdata Areas (PUMAs), and the American Community Survey (ACS). With person and household level details known from the synthesis step, all activities expected to be made by each agent in the 24-hr period are generated. A hazard-based formulation is used to produce start times and durations for each of these activities (Auld et al., 2011). The activity plan for each individual agent is then updated to include an activity location (through a multinomial logit destination choice model) (Auld & Mohammadian, 2012) and mode (through a nested logit mode choice model for different trip types). The travel scheduling process incorporates four different travel choices, which are the destination choice, mode choice, departure time choice, and travel party choice (Auld & Mohammadian, 2011; Gurumurthy et al., 2020). Conflicts among activity plans and travel schedules are managed via a conflict monitor in a rescheduling model (Auld et al., 2009). With all trips defined for each traveler, dynamic traffic assignment is used for vehicle routing and the link-level congestion is reflected through a link transmission model.

Shared Automated Vehicles' Door-To-Door Service and Dynamic Ride-Sharing

POLARIS currently allows for D2D solo traveler simulation (Gurumurthy et al., 2020) as well as dynamic ride-sharing (Gurumurthy & Kockelman, 2020) and this is fully integrated with all traveler choices and congestion feedback. Travelers choose to ride in a TNC through mode choice and request a ride from the TNC operator. The operator is aware of all vehicles in the region and their specific locations. This allows for centralized dispatch control and helps assign trips to nearby vehicles efficiently. A zone-based approach is taken to store vehicles in underlying TAZs for computational efficiency. Although the nearest vehicle is not matched, the first available vehicle falling within a pre-defined maximum wait time threshold is assigned to maintain acceptable service.

The dynamic ride-sharing module matches new trip requests to vehicles idling or en route to its pickup or dropoff. The match is made such that the request's destination is along the direction of ongoing travel with slight modifications based on the exact operation that is ongoing. If a pickup trip is ongoing, the current and ongoing trip is in the same set of TAZs within the pre-defined maximum wait threshold time from the use of zone-based storage of vehicles, and is easily matched. If a dropoff is ongoing, and is in the same set of TAZs as the new request's origin, then these trips are bundled. If a dropoff is ongoing and the destination is further away, the angle between Euclidian lines of ongoing trip and the request is calculated. The request is matched if this angle is within a pre-defined threshold of 10 degrees. This helps manage detour time added to the traveler when sharing their ride. Once matched, all requests assigned to a vehicle is ordered for minimal Euclidian distances while taking into account pickup-dropoff constraints (i.e., a traveler cannot be dropped off before being picked up). The activity-based model in POLARIS currently allows only single-party trip requests, so all requests matched to vehicles take up one seat space. In reality, travelers are expected to travel in party sizes greater than 1, with their friends and family, so the DRS results can be conservative estimates of what is possible when the fleet is deployed. No traveler-side model is used to determine sharing choice, so all travelers are subject to share their trips when DRS is allowed. Therefore, single-party trips and full sharing adoption is likely to balance out the extremes expected from their individual effects.

First-Mile-Last-Mile Modes

This study focuses on the simulation of first-mile-last-mile modes across several service types. The full integration of this new mode involves both supply and demand side changes in POLARIS. On the demand side, travelers willing to choose FMLM as a mode need to be identified appropriately based on destination and time of day. These trips then need to be routed appropriately by utilizing multimodal shortest paths that take into account time-varying travel times and congestion.

Mode Choice and Feedback Iteration

The SAV D2D service is assumed to replace the traditional taxi service with adjustments to its cost assumptions. The FMLM service is added to the mode choice model as two new modes. One uses SAV

FMLM service to access and egress bus transit stations, and the other connects rail transit stations. Rail transit in the model includes both commuter rail and light rail. Since SAVs have not been widely deployed for FMLM service, there is no revealed preference data to calibrate the utility functions of the two new modes. Here, the parameters and variables of the FMLM utility functions are adopted from both the existing taxi, bus, and rail modes by considering travel time and cost of both SAV and transit trips, penalties for the number of transfers, and also demographic attributes of the traveler. Both SAVs' travel time for D2D service and SAVs' access and egress travel time for FMLM service are recorded and fed back to the mode choice model in following iterations, until the simulation arrives at the equilibrium of mode shares.

Multimodal Routing

The FMLM service in the model is considered to use SAVs to connect trips from/to transit stations. These routes are calculated based on the multimodal shortest path, which is built based on the shortest link prevailing travel times from origin to destination, leveraging network links of all possible types (e.g., driving, walking, or transit links). Adjustments and penalties are also incorporated to ensure a reasonable multimodal path, including the number of transfers, walking time, and driving distance. As long as a multimodal shortest path contains at least one SAV path segment, the trip is identified as a FMLM trip. Transfers are allowed between different transit lines, and such transfers can involve either walking trips or otherwise, to mimic the case when a person can transfer at the same station or walk to another nearby station for transfer. For normal bus and rail trips, in which riders simply walk from/to stations, the station can be accessed within about 3 miles of walking distance. However, there is no distance constraint for accessing and egressing transit stations using the FMLM service. Although the multimodal shortest path algorithm identifies the shortest driving path for SAVs, the actual FMLM service with dynamic ride-sharing will not exactly follow the shortest driving path, due to some detours of pickups and drop-offs for shared rides. This multimodal routing scheme is an extension to the multimodal A* that was already implemented in POLARIS (Verbas et al., 2018).

APPLICATION AND RESULTS

Different FMLM and transit services were simulated for the Greater Chicago region. The baseline scenario is the year 2018 Chicago run using 5% of the total synthesized population, which ended up with 201k households and 520k persons. The business as usual (BAU) case in Figure 1 shows the mode share for the calibrated baseline, in which there are no SAV services but only taxi service is provided. The single-occupancy vehicle (SOV) dominated the travel mode, followed by the high-occupancy vehicle (HOV). Transit travel share were about 5% across the whole area, but significantly higher in the City of Chicago (at 30%), while taxi travel accounted for about 4%. There is a \$3.3 fare for taxi service, which further charges \$1.5 per mile. Based on the BAU case, scenarios involving SAVs were designed to have one additional SAV service each time, so one can see the incremental changes of the new SAV service brought to the whole network. The first change was to use SAV D2D service to replace traditional taxi service across the whole region, the second one added SAV's FMLM service, and the last one further added SAV-based transit to replaces the regular bus service (CTA and PACE bus lines). All the scenario runs simulated a 24-hour weekday, starting from midnight.

SAV Door-to-door Service

The first scenario tested SAVs' D2D service as a replacement for traditional taxi service across the whole network. SAVs have the same vehicle behavior as cars or taxis, but charges a lower fare compared to taxis. Assuming a future that uses mature automation technology, the SAV D2D service is priced at \$0.50 per mile, based on the predictions and assumptions in previous studies (Becker et al., 2020; Bösch et al., 2018; Fagnant & Kockelman, 2018). Each SAV was deployed for 40 persons on average across the network, so approximately 12 thousand SAVs are in use in the simulated day. The large fleet of SAVs may also lead to many households relinquishing their old vehicles and reduce household vehicle ownership. Therefore, Menon et al.'s (2019) vehicle ownership reduction model was leveraged to update the new vehicle ownership distribution under the impacts of SAV on-demand services. Under the impact of SAVs' reduced cost and the households which lower their vehicle ownership, the SAV D2D services gained more than 10% of the mode share (see SAV-D2D in Figure 2), mostly borrowing from the SOV mode. The HOV mode share also increased to about 20%, compared to 12% in the baseline scenario, because of the reduced vehicle ownership and increased necessity to share rides.

Table 1 shows the fleet performance of the 12k SAVs serving 5% of the synthesized Chicago population. One SAV operated more than 4 hours a day, generating 131 VMT on average by serving nearly 20 requests, but 25% of them were just empty travel (i.e., traveling without passengers onboard). The SAV fleet offered an average 15-minute service (riding time + wait time) for D2D riders, who rode 4.6 miles on average. The average distance corresponds with the trip-length distribution in Figure 3a, which peaks at trips longer than 0.5 mile but shorter than 1.5 miles. Figure 3a also tells that most riders prefer using the SAV D2D service for short-distance trips, but also some prefer sharing long rides that are more than 50 miles in the large Chicago region.

Table 1 SAV Fleet Performance of On-demand Service (SAV-D2D & SAV-FMLM)

Scenarios	**SAV-D2D**	**SAV-D2D + SAV-FMLM**	**SAV-D2D + SAV-FMLM + SAV-based Transit**
Avg. Travel Time per Person (min per person-trip)	10.0 min	12.6	12.3
Avg. Wait Time per Person (min)	4.9 min	4.6	4.3
# SAV Requests/day	232,247	260,355	259,685
% Requests Met (with 15-min max wait time)	99.4	98.8	99.0
AVO by Revenue-trips	1.10 persons	1.13	1.11
AVO by Revenue-miles	1.05 persons	1.05	1.05
Avg. Person-Trips/SAV/day	19.4 trips/day	23.6	23.5
% eVMT	25%	26%	25%
SAV VMT/person/day	3.03 mi	3.16	3.11
VMT/SAV/day	131.4 mi	136.9	134.9
Hours in Operation/SAV/day	4.2 hr	4.4	4.3

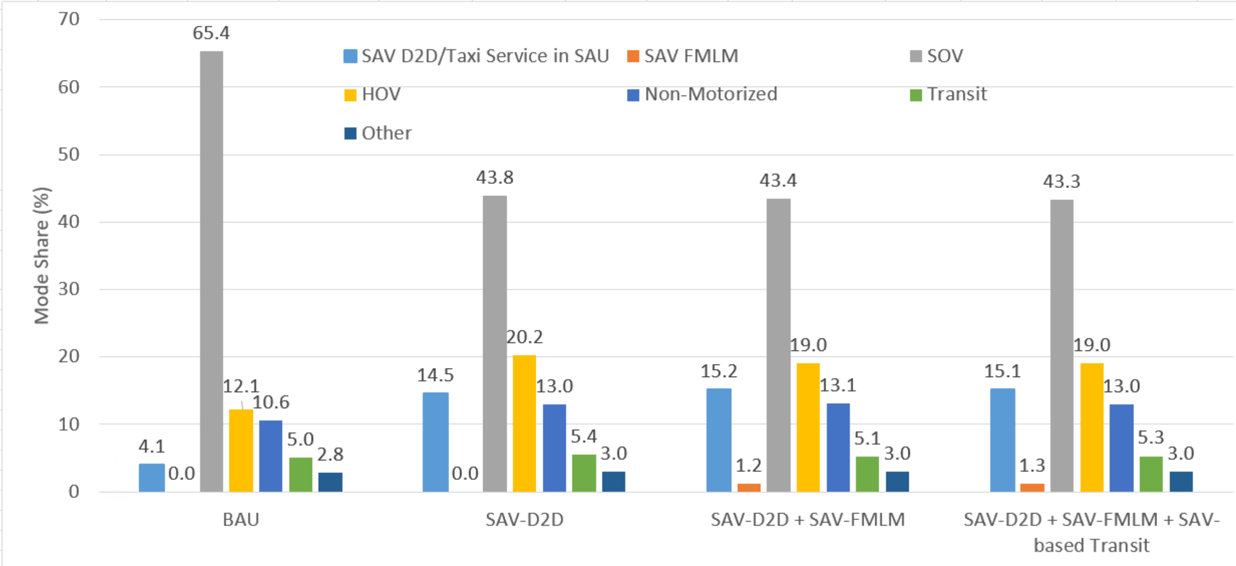


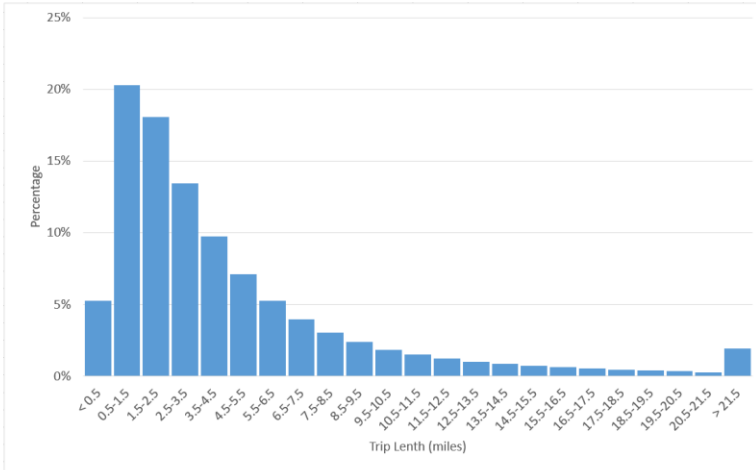
Figure 2. Mode Splits for Different SAV Scenarios

SAV FMLM Service

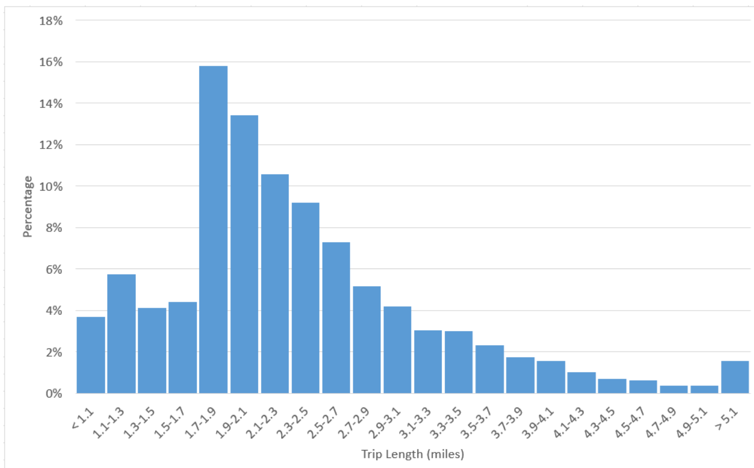
The SAV FMLM service is incorporated into the simulation when the SAV D2D service is already available. Adding an SAV FMLM service on top of a D2D service would not only make up for the gap in previous studies that do not incorporate SAV demand to/from transit stations, but also explores the situation when the SAV fleet provider and the transit service provider cooperate to form an integrated and more efficient transit system.

The new SAV FMLM service raised the total transit mode share from 5.4% to 6.3% (sum of FMLM mode and transit mode in Figure 2, “SAV-D2D + SAV-FMLM” scenario), while the other modes remained quite stable. The mode share increment in transit was relatively small, but this is still a good sign for promoting transit use and increasing the transit catchment area, especially since this scenario is discussed under the availability of the SAV D2D service, which can already be popular for shared mobility. Without SAV D2D service, or when the automation technology is not mature enough and SAVs are only capable of providing low-speed FMLM service in geofenced regions, more transit demand may be attracted (Huang et al., 2020).

Since D2D and FMLM requests were both needed to be served by SAVs, the fleet was better utilized, as seen from the increased SAV VMT per day and operating hours, as well as more trips served per SAV (Figure 1). However, the gain in fleet utilization is small due to the low FMLM share. For the 5% sample simulated, there are about 22k FMLM service requests (to/from transit stations), which are 10% of the D2D service requests. Interestingly, the travel time is about 2.6 minutes longer per travelers compared to D2D service only, due to more trip requests (thus more rerouting), but the wait time is slightly lower because of the request aggregation at the transit stations.



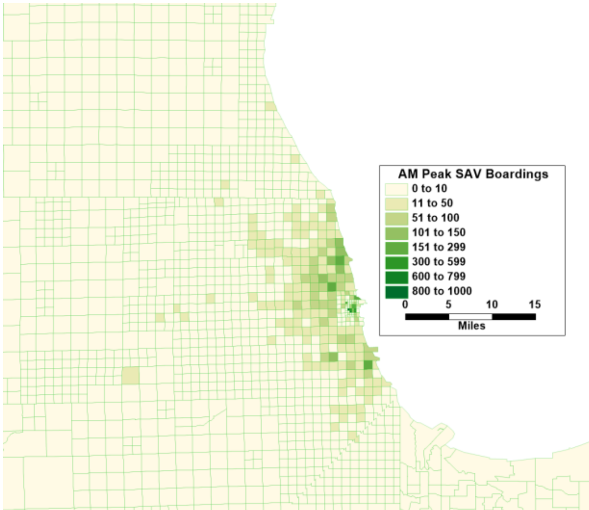
a. SAV door-to-door service



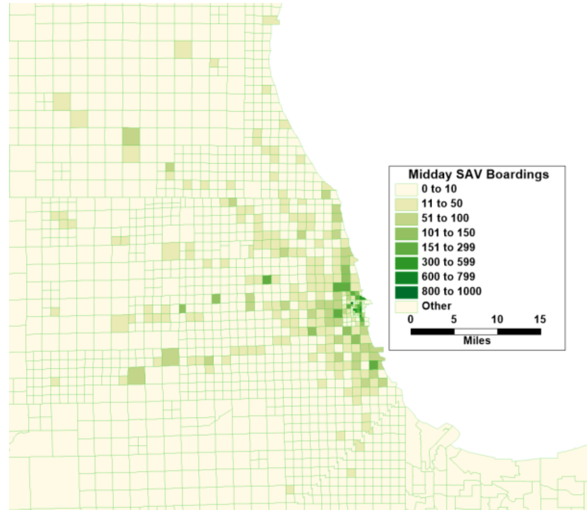
b. SAV first-mile last-mile service

Figure 3. SAV Trip Length Distribution

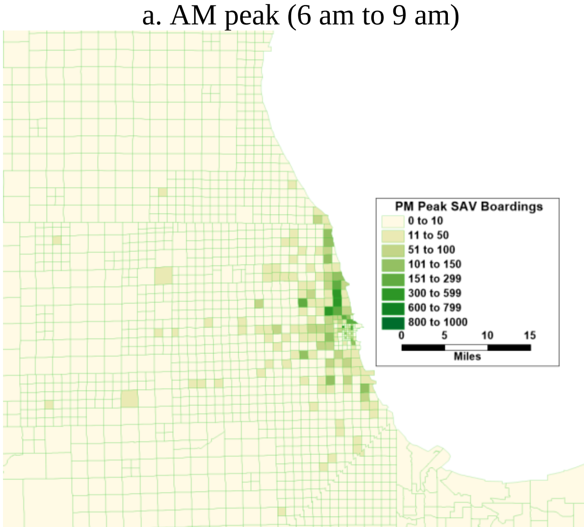
In contrast to the long average trip length of SAV D2D service, the trip distance of FMLM service was shorter, on average, because FMLM service only offered connections to/from transit stations (Figure 3b). Most FMLM trips were about 1.7 to 1.9 miles, but there were some FMLM trips longer than 5 miles. Since walking to transit stations is usually 0.25 miles on average (Nabors et al., 2008), implementing the FMLM service largely increased the transit catchment area. As seen from the low share of FMLM trip distances shorter than 1.1 miles, most riders who walk to transit stations will probably retain their previous behavior, but a few will shift to the new FMLM SAV service (indicated by the drop in the mode share). Therefore, FMLM service will mostly attract those who live from 1.7 to 3.5 miles away from transit stations, which is usually beyond the walking distance for accessing and egressing these transit stations. This can also be reflected through Figure 4, especially Figure 4b and 4c, that most boardings of FMLM trips happened not far from the transit lines. For example, the radial pattern follows the PACE suburban bus and the METRA commuter rail, while downtown Chicago is where most of the CTA bus stations are located.



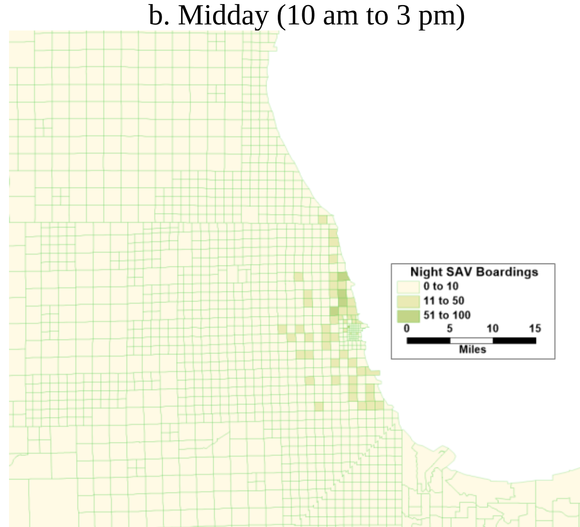
a. AM peak (6 am to 9 am)



b. Midday (10 am to 3 pm)



c. PM peak (4 pm to 7 pm)



d. Night (8 pm to 5 am)

Figure 4. Boardings of FMLM SAV Service by Four Times of Day

Figure 4 presents the spatial and temporal distribution of the boardings onto the SAVs which offer FMLM service. People are shown to prefer FMLM SAV service in the day rather than the nighttime when few buses and rail lines are operating. Midday is the time when boardings happened the most and are more spatially spread out. Downtown Chicago is the busy zone for FMLM trips, which can be either first-mile or last-mile trips. This also tells that one end of the whole trip (considering both FMLM and transit trip segments) mostly occur downtown but the other end is often near the transit lines, especially at those in suburban areas.

Figure 5 further shows the distribution of FMLM trip counts by the hour, while differentiating trips accessing and egressing bus stations from rail stations. The trip counts over time follow the pattern in Figure 4. Few buses and rail lines were operating before 6 am so the SAV use for connecting transit stations was rare. The highest peak across the day happened at 9 am, and the second peak happened in the afternoon at 5 pm. Interestingly, the third small peak happened during the midday at 1 pm, although during midday there was a drop after the morning peak hours. The lunch trips are often short so the midday trips are expected to be minimal. However, there may still exist several commuting trips or other business trips by travelers who work with flexible schedules. Figure 5 also shows that trips to/from rail lines are dominating the

FMLM trips, with a ratio of 6 to 1. This is expected because rail trip is often longer, not impacted by the road congestion, and has longer access and egress distance compared to bus trips. Therefore, accessing and egressing rail stations using the FMLM SAV service may reduce the total trip cost, considering the transfer penalties and walk/ride times. However, many bus riders already have one or two transfers between bus trips and often have shorter access and egress walking distance, so adding another SAV trip to the whole journey would largely raise the transfer burden and, thus, the overall trip cost. In addition, commuter or light rail stations often have pick-up or drop-off areas nearby, but this is not the case for every bus station. If too many SAVs access and egress bus stops, curbside congestion may be serious, and, thus, more road congestion could increase the overall trip cost.

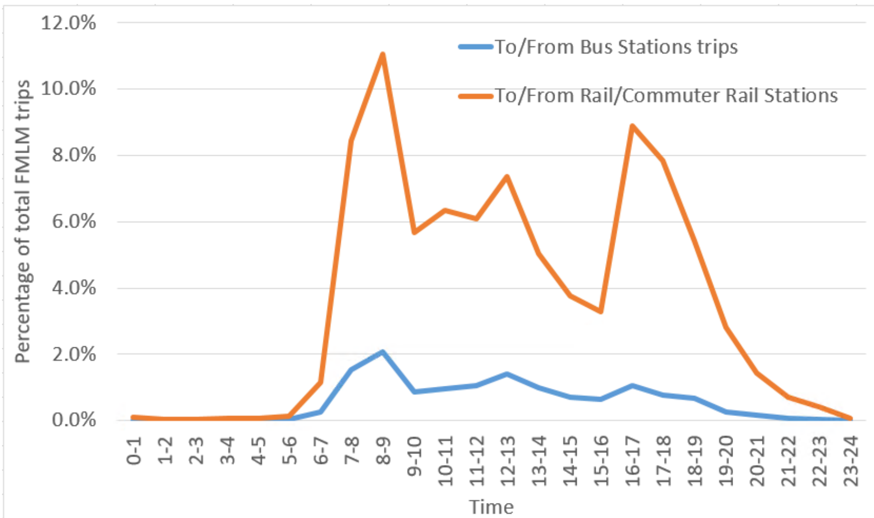


Figure 5. First-mile Last-mile Trip Count Distribution by the hour

SAV-based Transit Service

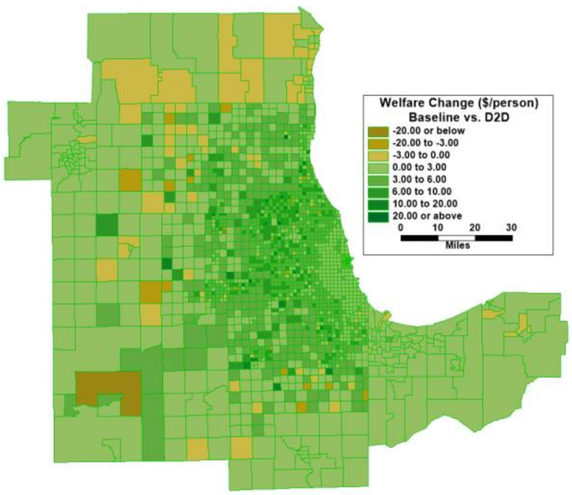
Next, in addition to SAV's D2D and FMLM service, the scenario discussed in this section further uses SAV-based transit service to substitute the regular CTA and PACE bus service with new 15-seat SAVs following a doubled dispatching frequency. The 15-seat SAVs also have 15 standing spaces, mimicking the current SAV shuttles that are tested around the globe (Stocker & Shaheen, 2019). Since this scenario assumes that the SAV's D2D and FMLM services exist, the SAV-based transit or automated bus (Abus) is also assumed to have mature automation technology. The SAV-based transit fare is assumed to be 60% of the traditional transit service (Quarles et al., 2020), since Abuses can reduce the operating cost by eliminating the need for drivers.

With a 40% reduced fare for the SAV-based transit service, the mode share of transit slightly increased. Similarly, a 5% increase in FMLM mode share was noted (Table 1). Since most of the FMLM trips were connected to rail stations, the fleet performance of SAV's D2D and FMLM service remained quite stable (Figure 2). This means that the SAVs' on-demand service and the transit-based bus service may not have frequent interactions in this case.

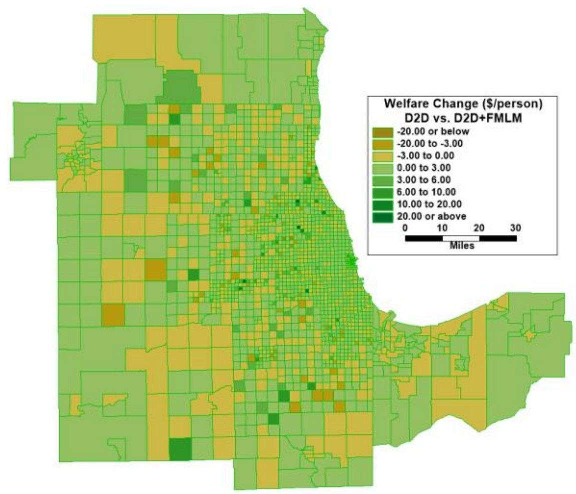
However, there is potential to integrate the Abus service and the FMLM service. For example, the pricing of the service can combine the fare for the FMLM and Abus services. The transit use could be promoted if the FMLM price is halved when connecting to bus stations, or the transit fare can be eliminated if people are willing to take shared rides to access or egress bus transit. More importantly, the utilization of the SAV fleet could be improved through self-relocation and shared-use between these two different services. In this paper, the SAV on-demand service (D2D service and FMLM service) uses 4-seater vehicles, while the Abuses are 15-seaters with 15 standing spaces. These 4 seat vehicles can sometimes help serve part of the existing transit lines or some lines that do not have high demand, while the 15seater SAVs can also help cater to demand for on-demand services.

Welfare Analysis

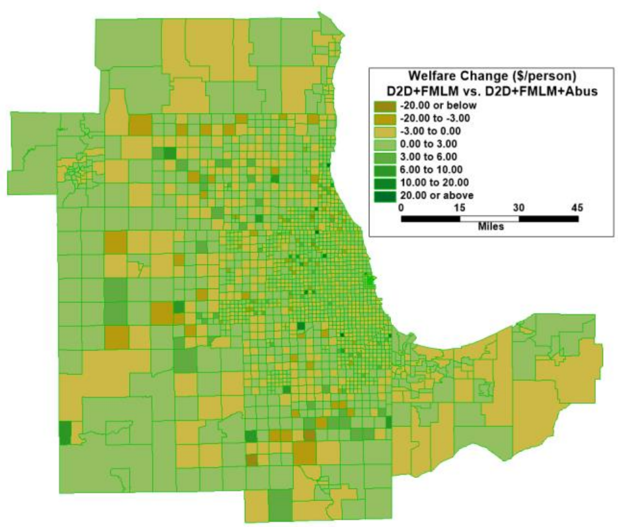
Welfare analysis has been widely used to compare the social benefit change across scenarios in terms of different policies, like new highway insertion (Kockelman & Lemp, 2011) and congestion pricing (Li et al., 2020). In this paper, the incremental change in social welfare of introducing different SAV services are presented as the changes in consumer surplus. In this study, the changes in consumer welfare or surplus (ΔCS) from one scenario to another for each traveler was computed as the logsum differences between those two scenarios (de Jong et al., 2007).



a. Baseline vs. D2D



b. D2D vs. D2D + FMLM



c. D2D + FMLM vs. D2D + FMLM + SAV-based Transit

Figure 6. Welfare Change ($/person)

A person's consumer plus (CS) is the utility measured as money for a certain choice. If the unobserved error term of the utility function is independent and identically distributed (IID) and the utility is linear in income, the expected utility is the logsum of the logit choice utilities divided by the marginal utility of cost

α_p (de Jong et al., 2007). Therefore, the change in consumer surplus for a certain traveler *i* given a new scenario (identified with a superscript 1) with respect to the status quo (identified with a superscript 0), can be shown as the following equation:

$$\Delta CS_i = \frac{1}{\alpha_p}\{logsum_i^1 - logsum_i^0\}$$

where the logsum incorporate the mode choice utilities.

In this paper, three different comparisons are conducted: 1) adding SAV D2D service compared to the base case, 2) adding SAV FMLM service to SAV D2D scenario with SAV D2D scenario to be the baseline, 3) adding SAV-based transit to SAV D2D+FMLM scenario with SAV D2D+FMLM scenario as the baseline. Furthermore, ΔCS was aggregated at the TAZ level and averaged across the synthesized population in the corresponding TAZs.

Implementing SAV D2D service increased the social welfare of most people in urban and suburban Chicago (Figure 6a). Although the urban area experienced a small increase, many TAZs in the suburban area experienced an increase of more than $6 per person per day. This is because the fleet of SAVs improved the mobility of the whole area, especially in the suburban area where people used to travel by car and or transit. Downtown Chicago has a well-connected transit system, so the welfare increase is limited. Since the suburban area and the urban area were the places where most of the shared rides happened, some rural areas experienced a welfare loss.

When further adding the FMLM service, the social welfare in downtown Chicago remained stable (Figure 6b). This is also due to the well-connected bus and rail transit system, where people sometimes can easily replace the FMLM trip with walk and bus trips. However, a more mixed pattern was observed for the suburban area. TAZs which experienced welfare increase are more likely to be the TAZs near transit stations (e.g., within 3.5 miles). Since the SAV fleet size is fixed, the riders outside the 3.5-mile buffer of the transit stations may have longer wait times for SAVs and longer detour times in shared rides, compared to the case when only D2D service was provided. Therefore, these people are likely to suffer welfare loss.

The pattern of the welfare change when adding the SAV-base transit is similar to the case when adding the FMLM service. The SAV-based service, which has lower fares and more frequent service but smaller vehicle capacity, has attracted more riders, but travelers are also more likely to skip D2D SAVs and wait longer at the station due to the small SAV-transitcapacity. The road congestion of the transit corridor may also increase due to more SAVs being dispatched. Therefore, a mixed pattern of social welfare change is shown in Figure 6c.

CONCLUSIONS

This study integrates SAVs' D2D service, FMLM service, and the SAV-based transit service, and reveals the possible mode shares, fleet performance, and social welfare change for the 5% population sample across the Chicago network. POLARIS was leveraged to simulate the detailed behavior of agents, with novel functions added that focuses on the integrated modeling of multimodal routing and the transfer behavior between SAVs and transit. Since most of the previous transit-related simulations do not optimize the multimodal routing for a mixed-use of SAVs and transit lines, the multimodal routing in this study ensures the best routes are considered by taking the travel time,cost, and number of transfers between different modes into account.

SAV D2D service accounts for 15% of the mode share under the assumption of $0.50 per mile fare and households' willingness to relinquish their vehicle for future years. A fleet of 12k SAVs serving 5% of the Chicago population, or 1 SAV every 40 residents , could offer 15-minute service for trips averaging 4.6 miles. Operating for more than 4 hours, on average, each SAV served nearly 20 requests per day. Most SAV riders preferred to use the SAV D2D service for relatively short-distance trips, but the trip could be longer than 50 miles given the large nature of the region. Based on the distribution of the social welfare change, residents in the suburban area benefited most from the SAV D2D service, followed by those in the urban area. When the same SAV fleet offered both D2D service and FMLM service at the same time, the SAV fleet was more utilized, by serving 12% more requests per day per SAV with only a 4% increase in VMT. The transit use was also brought up from 5.4% to 6.3%, with a stable mode split among other modes compared to only using D2D service. The average trip distance of FMLM service was also shorter, most of which were between 1.7 to 1.9 miles. This indicated a prominent expansion of the transit catchment area, from a typical 0.25-mile average walking distance. The spatial patterns of SAV FMLM service also indicated such improvement, as many more boardings were observed in the TAZs along the transit lines (e.g., PACE suburban bus and the METRA commuter rail). Downtown Chicago is also the busy zone for FMLM trips, due to the CTA bus service. FMLM service boarding happened mostly across the day, especially during morning peak and midday. Trips to/from rail lines dominated the FMLM trips, compared to the bus stations, with a ratio of 6:1. When adding the FMLM service, the social welfare does not change much in the downtown area, because of the multiple travel choices. TAZs near transit stations in the suburban areas are more likely to have welfare gain. Lastly, when the SAV-based transit service was added to the scenario, the performance of the on-demand SAV fleet did not change much since the FMLM service mainly focused on connecting to rail. The social welfare change also showed a mixed pattern in both the urban and suburban areas. The reason for this is likely to be riders skipping SAVs due to small-size Abuses and the road congestion in the transit corridor caused by more frequently dispatched SAVs, although some riders enjoyed lower fares and more frequent service.

Although simulating FMLM in POLARIS yielded interesting and detailed observations, some limitations continue to exist and require future work. The FMLM service in this paper only offers access to and egress from bus and rail stations, but one would expect longer trips to connect airports. SAVs also have the potential to offer more variations of the SAV-based transit, like semi-fixed route service to replace or extend existing bus lines with more flexible vehicle sizes and fleet sizes. Therefore, there is a potential to simulate a larger integrated system with more realistic considerations for future planning. Different dynamic ride-sharing strategies can be tested to explore the best one that fits different SAV services in the large-scale network, like coordination with transit schedules (Vinet & Zhedanov, 2011) and large travel party size for sharing rides. The added mode of FMLM in the mode choice model assumes one alternative-specific constant value, which is the average of taxi and the conventional car mode. Sensitivity analysis can be conducted to explore the change in the fleet and network performance as well as the social welfare under different penetrations of FMLM service.

Based on the various service options tested here, SAVs can provide promising integration with future public transportation systems. The low fare D2D service will be key to reducing vehicle ownership, encouraging more shared rides, and gaining social welfare in the suburban area, while the FMLM service can increase transit ridership and catchment area. The SAV-based transit will also offer a cost-efficient service, and the network and fleet performance may be improved through integrations with on-demand service fleet and new pricing strategies.

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