SHARED AUTONOMOUS VEHICLE FLEETS TO SERVE CHICAGO'S PUBLIC TRANSIT

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ABSTRACT

Shared fully-automated vehicles (SAVs) will provide different services in the future, including door-to-door (D2D) service, first-mile last-mile (FMLM) connections to transit stations, and low-cost public transit service. This paper leverages the agent-based simulator POLARIS to analyze the deployment of the D2D, FMLM, and low cost transit SAV services for a 5% population sample of the Greater Chicago region. When simulating D2D SAV service at $0.50 per vehicle-mile (with dynamic ride-sharing [DRS] enabled), each of the 12,000 SAVs (or 1 per 40 simulated travelers) served an average of 19.4 trips per day and attracted 12% of the region's passenger-travel mode split (with an average person-trip length of 4.6 miles). Addition of the SAV-based FMLM service (at $0.50/mile fare, with DRS) raised the region's transit shared from 5.4% to 6.3% of all person-trips, while adding 12% more trip requests and 4% more vehicle-miles traveled to the SAV fleet. Most FMLM service trips ranged from 1.7 to 1.9 miles in distance, with rail station connections dominating the mix (versus bus stop locations). A willingness-to-pay or "welfare" analysis that suburban

area residents benefited most from the SAV D2D service, followed by those in the urban areas. And residents near suburban transit stations benefited most from addition of SAV services.

Keywords: Shared autonomous vehicles; first-mile last-mile access; large-scale simulation; public transportation; door to door service

INTRODUCTION

The advent of shared, fully-automated or "autonomous" vehicles (SAVs) may dramatically change travel choices in coming years. Studies have demonstrated the added value of SAV fleets serving door-to-door (D2D) travel (Childress et al., 2015; Fagnant & Kockelman, 2018; Narayanan et al., 2020). Trip-cost savings are higher when rides are shared by travelers en route, also called dynamic ride-sharing (DRS), much like UberPool and DiDi Pool. In addition to D2D service, low-cost SAVs may offer 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 fixed-route transit lines in relatively demand-responsive ways, eventually replacing fleets of large, infrequent buses, with their relatively high labor costs (Quarles et al., 2020). While simulations of D2D SAV service are becoming common, evaluations of SAVs for transit-type support are rare (Brownell & Kornhauser, 2014; Martinez & Viegas, 2017). This paper extends the large-scale agent-based POLARIS tool (Auld et al., 2016) to anticipate mode splits, response times, fleet operations, and social welfare across a large U.S. region (of 13 million population) in a fully-integrated manner, to understand the impacts of deploying several SAV-based services.

These are a D2D SAV service with and without DRS, a FMLM service for transit station connections, and SAVs providing fixed-route fixed-stop bus services – all across the 20-county region. Lower-cost operations, smooth vehicle acceleration and deceleration, improved safety, access for all (including those with various disabilities or driving limitations), and centralized dispatch (for rather seamless ride-sharing) are expected to make SAVs a convenient and common choice in coming years. SAVs may increase average vehicle occupancy (AVO) and lower congestion through efficient DRS (Childress et al., 2015; Gurumurthy & Kockelman, 2018). While this D2D service is convenient and low-cost, without sufficient ride-sharing (among strangers) en route, total VMT may rise.

Example SAV deployments around the world (Stocker & Shaheen, 2019) now offer low-speed, geofenced service (Hou et al., 2017). SAVs can provide more convenient and faster services to an from transit stations, as compared to riding a bicycle or walking, while avoiding parking costs or reliance on family and friends for such rides. As AV technologies mature, SAVs may take the lead public transit delivery. A bus- or mid-size SAV may serve traditional fixed-route and fixed- or flexible-stop transit corridors, where heavy transit demand exists, while offering shorter headways and more demand-responsive services - around the clock. SAVs can also proactively relocate (and turn off and on, anywhere at any time), based on instructions from central operators. The future of transit is bright, if public agencies leverage this technology.

To this end, this paper analyzes multiple methods of SAV deployment across the Greater Chicago region. Impacts are revealed through response times, mode splits, network congestion, and consumer welfare under different pricing and service strategies.

LITERATURE REVIEW

Numerous studies predict AV impacts on travel choice and traffic, safety, cost, and the environment (Narayanan et al., 2020, Gurumurthy et al. 2019, and Zhao & Malikopoulos 2019). Most SAV studies focus on D2D service, and few enable inter-modal and multi-modal operations for SAV users .

Narayanan et al.'s (2020) review concluded that incorporating public transit is essential when studying SAV use. Snelder et al. (2019) explored SAVs' mobility impacts in mixed traffic environments, via a special model specification to ensure elastic demands, across destination and mode choices. Merlin (2017) simulated SAVs and transit use for the relatively small Ann Arbor, Michigan network, with a focus on transit impacts. He estimated that SAVs will be preferred to buses, thanks to lower travel times and travel costs per day, alongside lower carbon emissions.

Compared simulating SAVs offering only D2D service, integration with transit stations for intermodal tirp-making is more complicated. Such systems must find shortest paths across many mode and stop combinations, while still ensuring on-demand service for the first and last miles. Yap et al. (2016) carefully surveyed traveler preferences for AVs in an integrated public system and predicted that AVs had the most potential for first-class train travelers using SAVs in their "last mile" (to a final destination). Abe (2021) investigated 2,300 Tokyo residents' willingness to use SAVs for FMLM connections to urban rail transit. Those with station-access issues were most inclined to use SAVs in this way, as a substitute for feeder bus and personal cars, but not for cycling and walking (to and from urban train stations).

Zachariah et al. (2014) synthesized New Jersey person-trip data to simulates SAVs providing FMLM service to that US state's train stations, with substantial potential for rideshare, especially during peak train (arrival and departure) hours. Vakayil et al. (2017) simulated SAV services across different transit frequencies, transfer costs, and SAV relocation strategies. They estimated up to 50% reduction in network congestion and vehicule emissions thanks to FMLM services. Gurumurthy et al. (2020) compared an SAV fleet's FMLM service to a D2D service across the Austin, Texas region through a 5% sample simulated in MATsim. Pricing decisions were key to mode splits and traffic impacts. Shen et al. (2018) simulated Singapore's mass-transit system (just 4.6 square miles) during morning peak hours, and estimate that such services will enhance system efficiency, using fewer road resources and being financially sustainable.

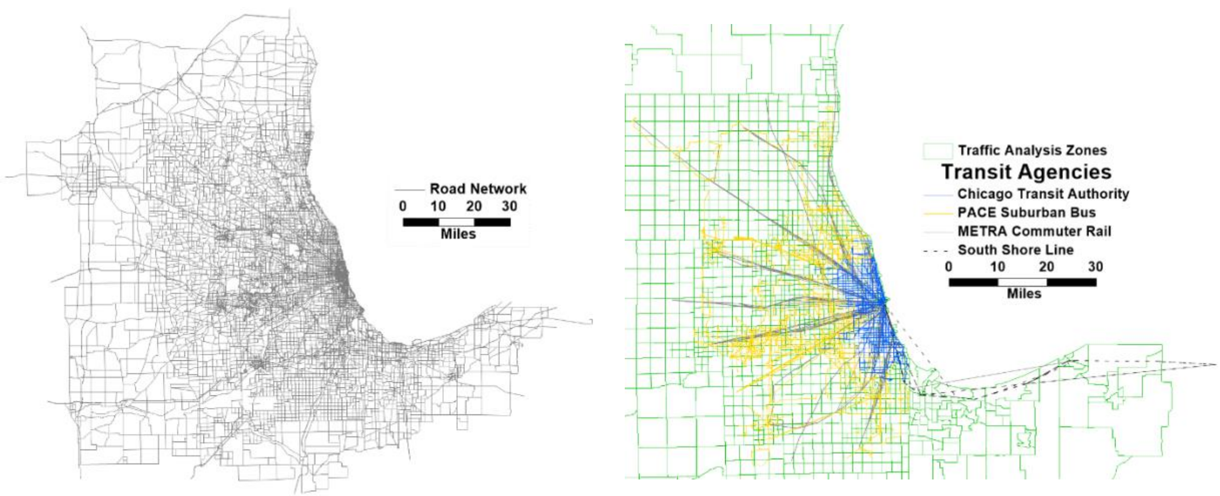
While FMLM connections by themselves may improve the attractiveness of rail sytems and some bus lines, transit lines based on high-frequency, self-driving minibuses or SAVs can also increase transit ridership. Current studies of SAV-based transit focus mainly on acceptance (Bernhard et al., 2020; Nordhoff et al., 2019), so 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 will have more impacts on vulnerable populations (like the disabled and aged). Bernhard et al. (2020) explored 942 participants' willingness to use self-driving minibuses in Mainz, Germany, and found respondents to be most concerned about system safety and environmental benefits. Moorthy et al. (2017) compared costs of conventional public transit to a hypothetical SAV system for transit between Ann Arbor and Detroit's Wayne County Airport, with simplified network and operating assumptions. They estimated at that SAVs could provide up to 37% energy savings, depending on vehicle powertrain and ridership parameters. They neglected vehicle stopping and routing, for thousands or millions of origin-destination pairs, which is what real systems will seek to address.

Few papers have examined realistic systems of SAV-based *transit* lines (Gurumurthy et al., 2019; Harb et al., 2021; Narayanan et al., 2020; Zhao & Malikopoulos, 2020). SAVs (of various seating capacities) may be the future of bus-type transit. So a thorough investigation on the operations of an integrated system recognizing 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. This large-scale network has 1,961 traffic analysis zones and about 32,000 road links (Figure 1a) and 33,000 transit links (Figure 1b). The daily travel patterns from 2.6 million travelers from 1 billion households across the region were synthesized by Auld et al. (2016), leveraging the region's CMAP travel survey data.

Chicago's transit network was obtained as a General Transit Feed Specification (GTFS), and then organized, tested and calibrated by Verbas et al. (2018) for the POLARIS model. The Chicago Transit Authority (CTA) provides service in the 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 (APTA, 2021; CTA, 2016). This paper's transit-line SAVs are assumed to replace regular bus service (excluding bus rapid transit), but at half the seating capacity (per automated bus) in order to double each line's frequency. Chicago's METRA and South Shore are both commuter rail services, and assumed to maintain their status quo. A total of 349 unique transit lines were coded into the model, with 134 from CTA and 202 from PACE (Verbas et al., 2018). Buses used for CTA and PACE's regular bus services are set to have 30 seats plus standing capacity for 30 travelers. Considering different departures for each transit line, about 2,100 routes were assembled to offer 28,000 total transit trips throughout a workday. The bus stops are also considered "stations", though train stations are typically larger, with more amenities.



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 DRS 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.

Multi-modal Passenger Routing

The FMLM service in the model is considered to use SAVs to connect trips to and from 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 Non-transit SAV Fleet Performance with DRS(SAV-D2D & SAV-FMLM)

Scenarios	**SAV-D2D**	**SAV-D2D + SAV-FMLM**	**SAV-D2D + SAV-FMLM + aBuses**
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 SAV rides/day	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/vehicle	1.13	1.11
AVO by Revenue-miles	1.05 person	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/SAV	136.9	134.9
Hours in Operation/SAV/day	4.2 hr	4.4	4.3

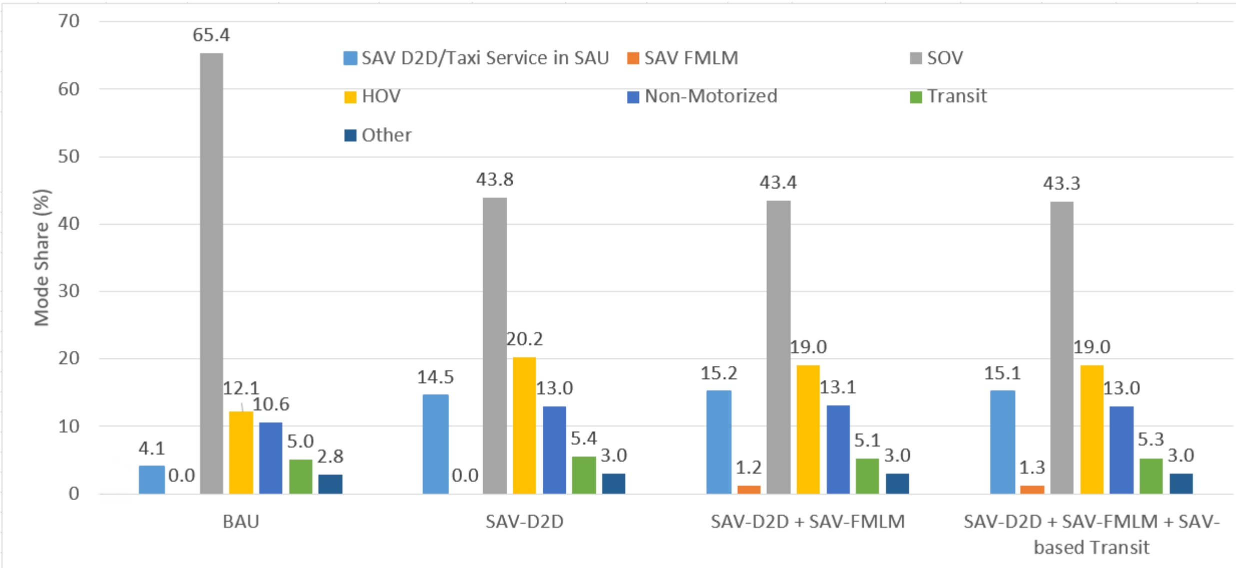


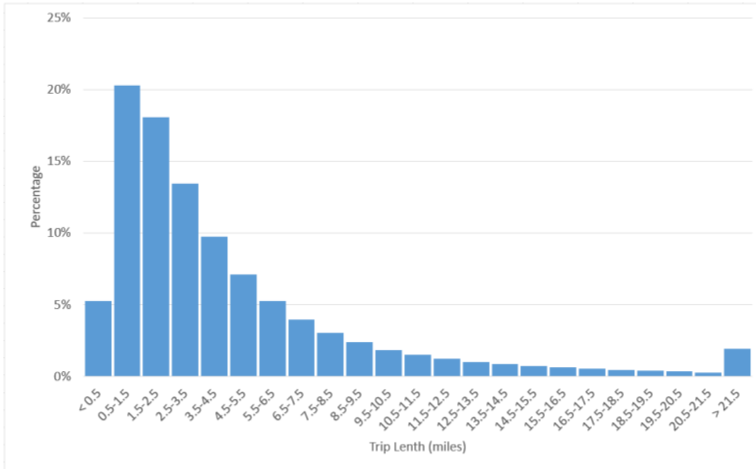
Figure 2. Mode Splits across Different SAV Scenarios

SAV FMLM Service

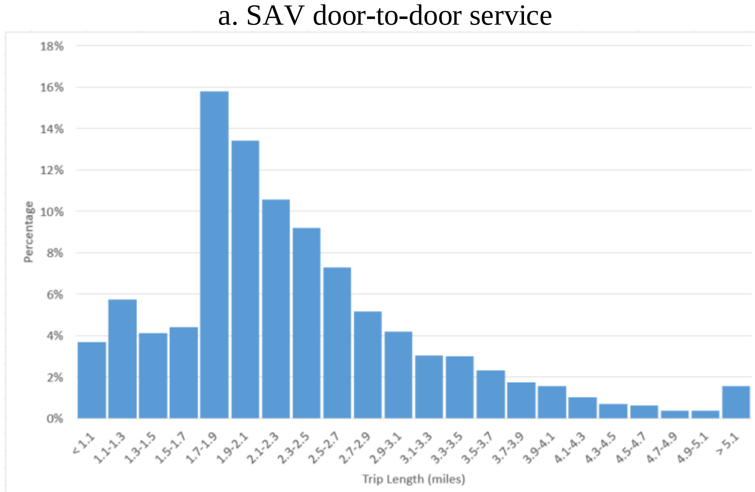
The SAV FMLM service is incorporated into the simulation when the SAV D2D service is already available. Adding an SAV FMLM service on top of a D2D service would not only make up for the gap in previous studies that do not incorporate SAV demand to/from transit stations, but also explores the situation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



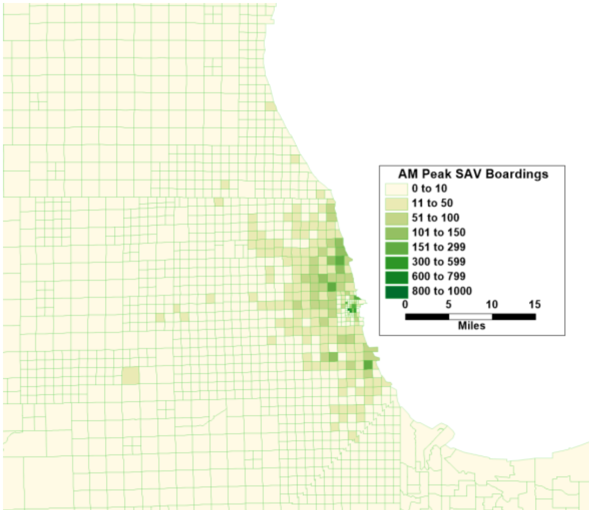
a. SAV door-to-door service



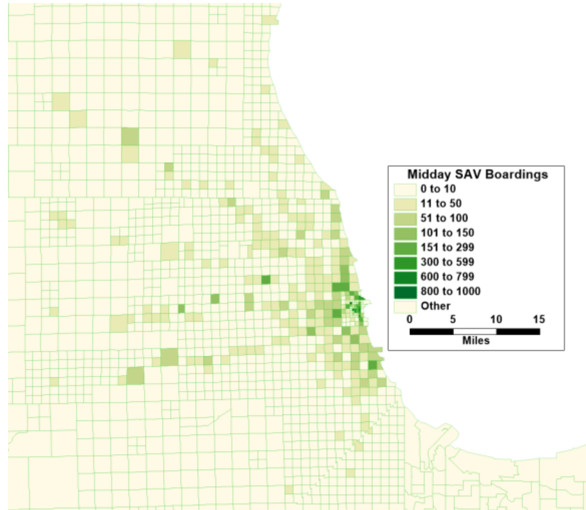
b. SAV first-mile last-mile service

Figure 3. SAV Trip Length Distribution

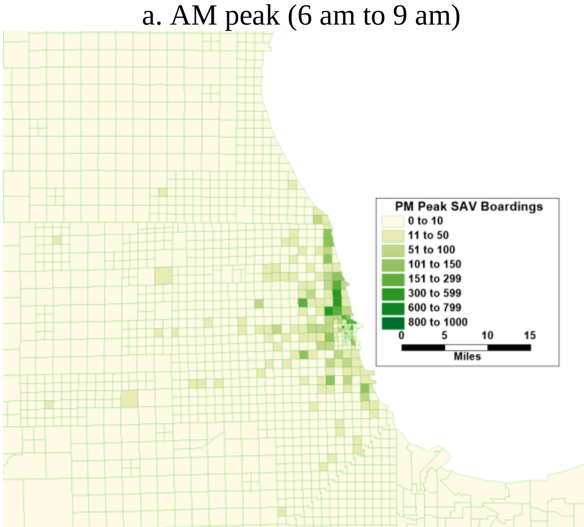
In contrast to the long average trip length for SAV D2D services, FMLM SAV trips were shorter, as expected (Figure 3b). Most FMLM trips were about 1.7 to 1.9 miles, but there were some FMLM trips longer than 5 miles. Since walking to transit stations is usually 0.25 miles on average (Nabors et al., 2008), 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.



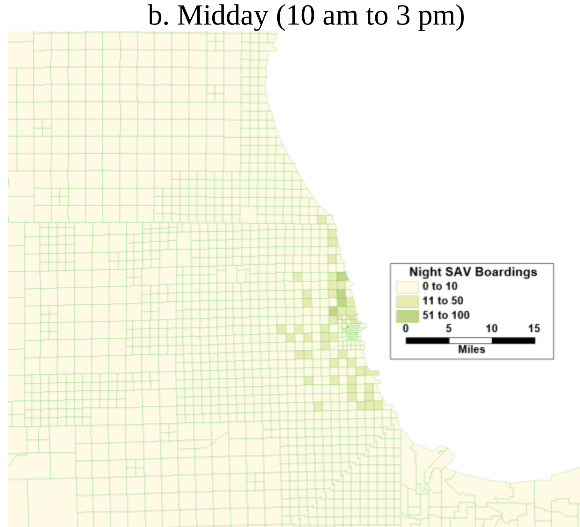
a. AM peak (6 am to 9 am)



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.

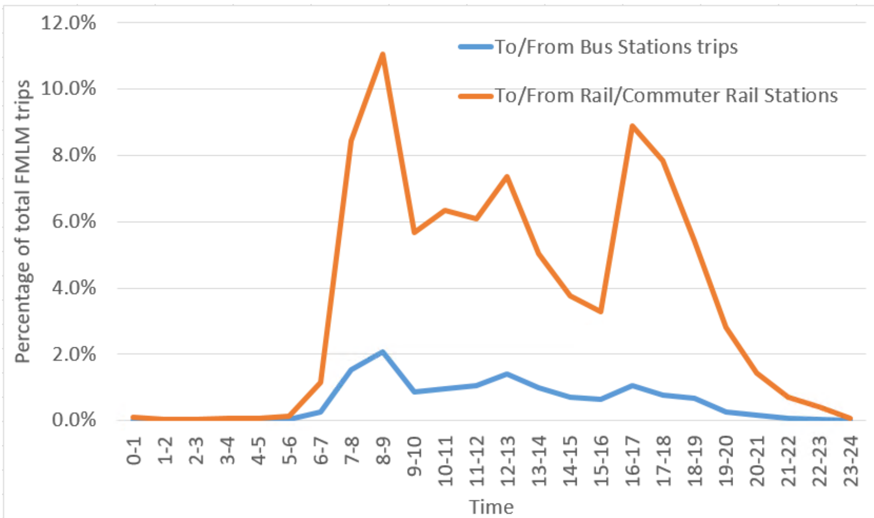


Figure 5. First-mile Last-mile Trip Count Distribution by the hour

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 person's consumer plus (CS) is added benefits or willingness to pay beyond what one actually pays for a good or service. If the unobserved error term of the logit model's utility function is independent and identically distributed (IID) Gumbel and the utility is linear in income, the expected maximum utility achieved (across alternatives) is the logsum of the logit choice utilities (de Jong et al., 2007). Therefore, the change in consumer surplus (expressed in monetary units) 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) is follows:

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

where the logsum incorporate the mode choice utilities. The logsum term is the natural log of the sum of all exponential functions of the utilities in the choice set:

$$\begin{aligned} logsum = \log\Big(&\exp(U_{bicycle}) + \exp\big(IV_{auto} \times \log(\exp(U_{SOV}) + \exp(U_{TAXI}))\big) + \exp(U_{HOV}) \\ &+ \exp\Big(IV_{rail} \times \log\big(\exp(U_{PARK\_AND\_RAIL}) + \exp(U_{RAIL})\big)\Big) + \exp(U_{WALK}) \\ &+ \exp\Big(IV_{bus} \times \log\big(\exp(U_{PARK\_AND\_RIDE}) + \exp(U_{BUS})\big)\Big) + \exp(U_{TNC\_AND\_RIDE}) \\ &+ \exp(U_{TNC\_AND\_RAIL})\Big) \end{aligned}$$

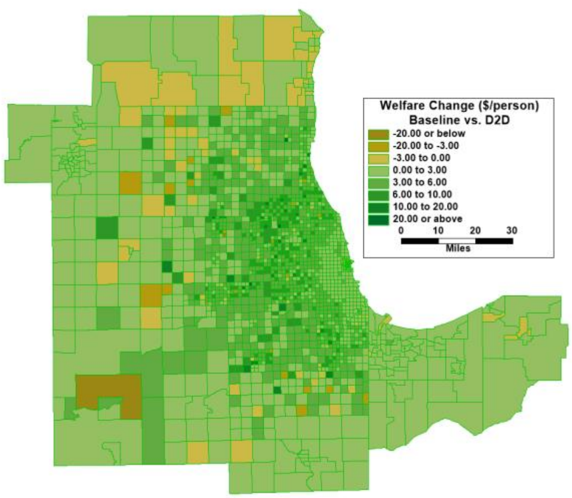
Personal owned vehicle and taxi travel are nested under the automobile nest. Rail nest consists of rail modes that have walking as both access and egress mode, and personal car as the access mode and walking as the egress mode. Similarly, bus nest consists of bus modes that have walking as both access and egress mode, and personal car as the access mode and walking as the egress mode. High occupancy vehicle, walk, bicycle, and FMLM last modes are assumed not nested with any other modes. When a choice is considered not available, the utility is set as a large negative value, so the $\exp(U)$ value is nearly zero.

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.

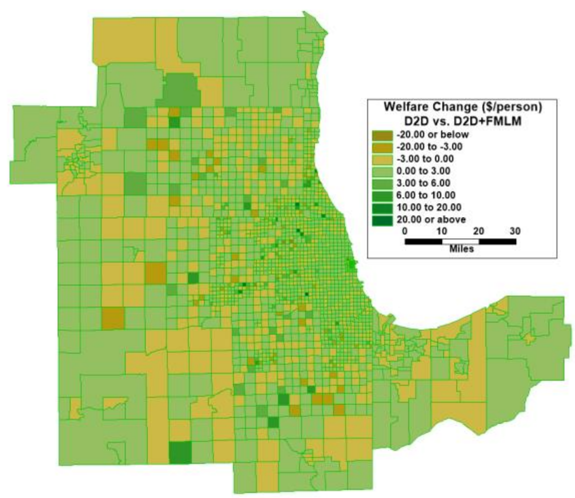
Implementing SAV D2D service increased the social welfare of most people in urban and suburban Chicago (Figure 6a). Although the urban area experienced a small increase, many TAZs in the suburban area experienced an increase of more than $6 per person per day. This is because the fleet of SAVs improved 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.

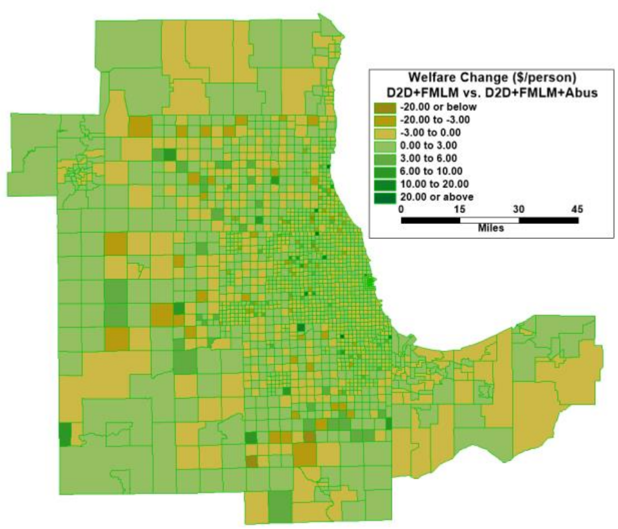
The pattern of the welfare change when adding the SAV-base transit is similar to the case when adding the FMLM service. The SAV-based service, which has lower fares and more frequent service but smaller vehicle capacity, has attracted more riders, but travelers are also more likely to skip D2D SAVs and 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.



a. Baseline vs. D2D



b. D2D vs. D2D + FMLM



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

Figure 6. Welfare Change ($/person)

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.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Y. Huang, K.M. Gurumurthy and K. Kockelman; Establishment of simulation models: Y. Huang and K.M. Gurumurthy; analysis and interpretation of results: Y. Huang and K.M. Gurumurthy; draft manuscript preparation: Y. Huang, K.M. Gurumurthy and K. Kockelman. All authors reviewed the results and approved the final version of the manuscript.

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