A SYSTEM OF SHARED AUTONOMOUS VEHICLES FOR CHICAGO: UNDERSTANDING THE EFFECT OF GEOFENCING THE SERVICE

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ABSTRACT

With autonomous vehicles (AVs) still in the testing phase, researchers and planners must resort to simulation techniques to explore possible futures regarding shared and automated mobility. An agent-based discrete-event transport simulator, POLARIS, is used in this study to simulate travel patterns in the 20-county Chicago region with a shared AV (SAV) mobility option. Using this framework, the SAV-system-performance impacts of different geofences for such services on system performance are studied under four distinct scenarios: service restricted to the city, the suburban core, the exurban core, and no fence, in addition to the choice of dynamic ride-sharing (DRS) versus solo travel in an SAV. Results indicate that service areas need a balanced mix of trip generators and attractors, and an SAV fleet's empty VMT (eVMT) can be curtailed with suitable geofences, and DRS. Geofences also help lower spatial response times, system-wide VMT across all modes, and ensure uniform access to SAVs. DRS is most useful in lowering VMT and %eVMT that arises from sprawling, whereas savings from the use of geofence is higher. Geofences need to target maximum served trip-density, but fleet sizes in these regions need to be designed for equitable access, as opposed to exhaustive use in a 24-hr day.

Keywords: *Shared autonomous vehicles, geofences, agent-based simulation, Chicago, POLARIS, dynamic ride-sharing*

MOTIVATION

The world is evolving rapidly and the era of fully-automated, or autonomous, vehicles (AVs) is around the corner. Public testing was predicted to be carried out starting in 2020, but some companies (e.g., Waymo and Uber) have already achieved this in 2017. Researchers believe that AVs will be publicly available for use as early as 2035, but with more companies entering the "AV-race" (like Ford, Mercedes, GM and other original equipment manufacturers), and several U.S. states (like Arizona, California and Texas) spearheading AV-related policy, it is likely possible to occur sooner rather than later. AVs are expected to boast several advantages over conventional vehicles, over and above eliminating the burden of driving. Crash rates are likely to drop due to the absence of human error (Fagnant and Kockelman, 2015), and these vehicles will operate more smoothly resulting in emission benefits (Ross and Guhathakurta, 2017).

These benefits, however, come at a cost. The state-of-the-art technology will not be affordable in the early stages due to high investment in the development stage and high costs for all the sensors and other equipment required by the system. Acquiring and owning AVs will be expensive and studies reveal a minimum added cost of $7,500 to $10,000 for automation alone (IHS Automotive, 2014; Fagnant and Kockelman, 2015), with no definite picture for insurance and maintenance costs. Studies have shown that AV technology is likely to first be taken up by fleet operators (Bansal and Kockelman, 2017; Quarles et al., 2020), much like current-day Transportation Network Companies (TNCs), who wish to employ shared fleets of AVs and turn a higher profit by avoiding driver-related costs. Cost estimates for shared AV (SAV) fleet are in the range of $0.50 to a $1 per mile (Fagnant and Kockelman, 2015; Bösch et al., 2018; Becker et al., 2020; Loeb and Kockelman, 2019), making them an attractive mode alternative to personally owned vehicles today, which cost about $0.50-$0.80 per mile for a gasoline-powered Sedan depending on use (American Automobile Association, 2019).

If SAVs are preferred in the future, its important that travel demand modelers study the impact SAVs may have on the system to understand and mitigate negative externalities (like congestion, emissions, and inequity) with effective policies. In the recent past, a plethora of studies on single-occupant SAV operation under varying regional settings have warned regions that congestion will worsen through added vehicle-miles traveled (VMT), especially from the non-revenue generating unoccupied miles (empty or eVMT) necessary to pickup travelers (Brownell and Kornhauser, 2014; Spieser et al., 2014; Fagnant et al., 2015; Bischoff and Maciejewski, 2016; Simoni et al., 2019). Fleet operational policy such as allowing multiple travelers to share their rides, called dynamic ride-sharing (DRS), is anticipated to moderate rising congestion from SAV fleets, and, in some cases, even lower congestion by reducing total VMT if large demand for SAVs exist (Alonso-Mora et al., 2017; Martinez and Viegas, 2017; Heilig et al., 2017; Fagnant and Kockelman, 2018). However, traveler willingness to share a ride may not be uniform and will depend on user preference (Gurumurthy and Kockelman, 2020; Lavieri and Bhat, 2019; Stoiber et al., 2019), with some spatial and time-of-day effects. Congestion pricing was shown to help observe system benefits even with single-occupant SAVs, where overall traveler welfare improved with congestion pricing schemes (Simoni et al., 2019; Kaddoura et al., 2020). Pricing trips has also been found to have a moderating effect on rising VMT when combined with DRS when mode shares for SAVs remain low (Gurumurthy et al., 2019). This emphasizes the mixture of policies necessary in order to observe net benefits for all travelers using any mode.

System-wide and fleet-wide policies are crucial to managing rising congestion, and several fleet-related parameters (such as fleet sizing and response time reliability) are also known to have an effect on realizing the expected policy benefits. Brownell and Kornhauser (2014) analyzed SAVs operating across the entire state of New Jersey, and found significant reduction in region-wide vehicles (one-third the region's personal-vehicle fleet size) needed to serve the same trips when

SAVs work to feed transit. Unlike Brownell and Kornhauser's approximation of a travel demand model, Spieser et al. (2014) used real-world taxi data for Singapore with a similar replacement ratio, but taxi trips only formed a relatively small percentage of all trips. Gurumurthy and Kockelman (2018) used a large cellphone dataset and a detailed network to show that sharing with SAVs may only be viable when trip densities are high, and that VMT is likely to increase (up to 4%) for high-use scenarios without the introduction of other supplementary policies. Congestion feedback, and, consequently mode choice, is important to see how induced demand will be handled by SAVs. Studies using MATSim (Horni et al., 2016), attempted to fill these gaps by using detailed networks (Bösch et al., 2016; Liu et al., 2017; Loeb et al., 2018; Loeb and Kockelman, 2019) while also allowing for mode choice and congestion pricing (Simoni et al., 2019; Gurumurthy et al., 2019). While some previous studies with trips being served only by SAVs showed VMT savings with DRS, Gurumurthy et al.'s (2019) revealed that small mode shares of SAVs may negatively impact system VMT. Congestion pricing, as well as fleet sizing was jointly needed to moderate the rise in system VMT in Gurumurthy et al.'s Austin application.

Higher productivity is expected when traveling in an AV, and this is likely to impact a traveler's destination choice. Short-distance trips that were not frequented in a personal vehicle previously may now be made in an SAV but many MATSim studies do not yet capture this demand shift. Martinez and Viegas, (2017) use mode-choice and destination-choice for Lisbon, Portugal with DRS enabled and predict VMT savings of up to 30%, but they do so using aggregated data. Lisbon is only about one-tenth the size of other cities mentioned here, so valuable insights may have been lost. Similarly, Heilig et al. (2017) predict VMT savings of 20% using SAVs with DRS for Stuttgart, Germany using a macroscopic traffic assignment model, which simplifies link-level congestion. What this means is that, there is a need to use a finer-scale simulation tool that incorporates mode-choice, destination-choice, and congestion feedback along with a comprehensive travel dataset and a detailed network to holistically understand SAV fleet impacts.

In this study, an agent-based discrete event transport simulator, called POLARIS (Auld et al., 2016), is used to understand SAV fleet operation in the Greater Chicago region which contains 20-counties, and is home to nearly 11M people. POLARIS is a detailed agent-based travel simulator with relatively lower computation times than MATsim, and can simulate the region's travel in under 5 hours on a 24-core computer with 128 GB memory. It includes modules for destination choice, timing choice and mode choice, and schedule-based transit simulation, which can be iterated with congestion feedback. This study further contributes by understanding the effect of geofencing the shared service, with and without DRS, for different forecasted SAV demands while focusing on change in system VMT, and empty or unoccupied VMT (eVMT) in an SAV. The remaining sections of the paper are organized as follows: the dataset for the Greater Chicago region is described in detail, followed by a description of POLARIS and its components including the SAV modules used; then, the four scenarios for geofencing the service are described, concluding with the results and discussion.

GREATER CHICAGO DATASET

The dataset for the 20-county Chicago region is based on several statistical models that are fed into a population and travel demand synthesizer to get an accurate representation of trips made in the region. Figure 1 shows the network used here and was obtained from the Chicago Metropolitan Agency for Planning (CMAP), the local metropolitan planning organization. The network consists of about 31,000 links and 19,000 nodes, and around 10 million travelers make about 30 million one-way person-trips in one 24-hr day on this network. All trips that are synthesized are cross-referenced spatially with traffic analysis zones (TAZs). The entire region is comprised of 1,961 TAZs, which are further classified based on land-use and proximity to Chicago's central business district (CBD). Nearly 78% of person-trips are made by private car, 6% by transit, 12% are by walking/biking, and 3% are by taxis & TNCs. Travel patterns from the synthetic population have been validated using the CMAP travel survey for the region (Auld et al., 2016), and has undergone recalibration since.

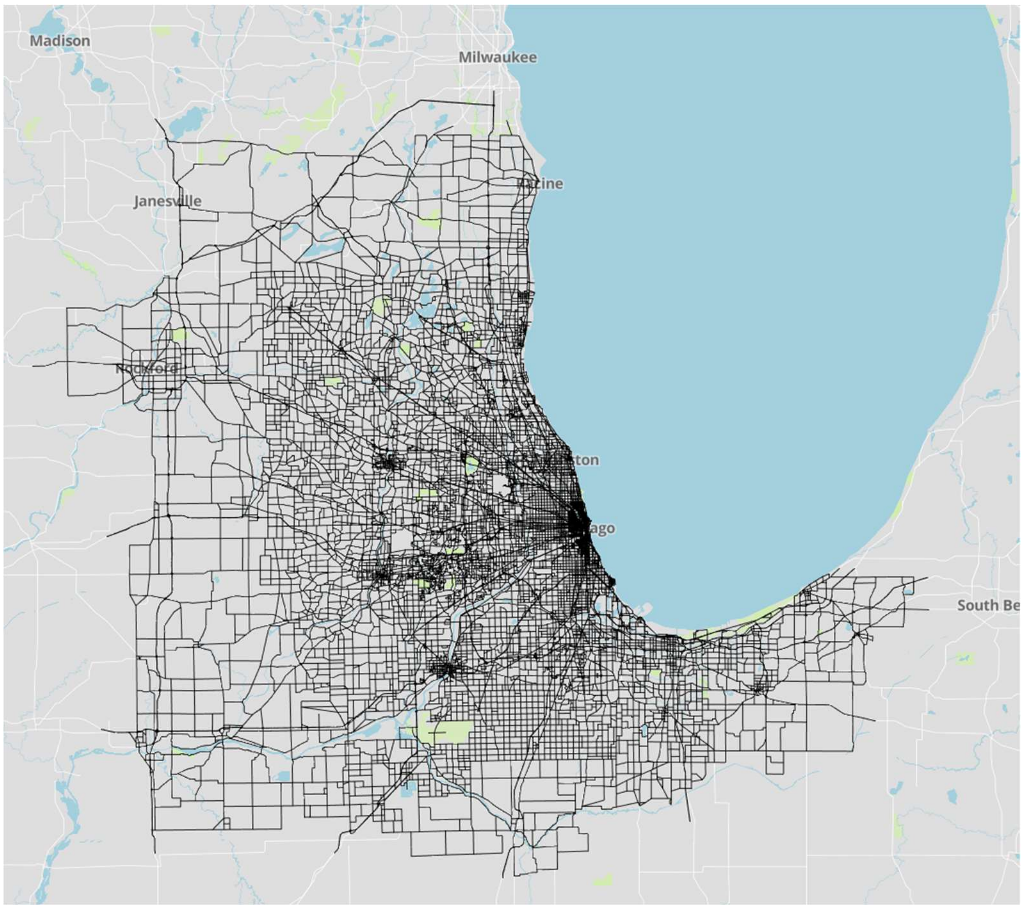

Figure 1 Detailed network of the 20-county Chicago region

MODELING IN POLARIS

POLARIS is an agent-based transport simulation tool that uses a discrete-event engine to simulate activities for all travelers. It comprises of different modules that handle person, vehicle, activity, transit, and logging tasks. A population synthesizer creates a representative set of travelers for the region, and a series of behavioral econometric models create the activities and travel itinerary for each individual. During the simulation, an activity conflict monitor tracks delays in travel. Personal vehicle ownership, vehicle technology, departure time, and mode choice are controlled at the household and person levels. The planning and scheduling of travelers' activities has been adapted from the ADAPTS model (Auld and Mohammadian, 2009 & 2012). Detailed workflow diagrams for POLARIS are presented in Auld et al. (2016). A hybrid dynamic traffic assignment method is used where travelers are able to switch routes based on delays. Routing in POLARIS uses a time-dependent A-star router (Verbas et al., 2018), where resulting route travel times is looped back to activity and trip choices. At the link level, a mesoscopic traffic-flow model provides speed and accuracy in modeling vehicle flow every 6 seconds (de Souza et al., 2019).

Shared Autonomous Vehicles

SAV operations are adapted from Gurumurthy et al. (2020) and extended to limit the spatial scope of service within a geofence. SAV demand was modeled to closely resemble TNC use, and is impacted by average response times and fare, in addition to user preference for SAV use. SAVs operate on the same network as other simulated modes and was able to capture congestion effects. SAVs were matched to trip requests through a central fleet operator such that the location and status of every SAV was available at all times. A zone-based matching structure was used for computational efficiency, as detailed in Gurumurthy et al. (2020). This structure allowed for a pre-defined input to limit maximum response times, which is assumed to be 30 min in this study. Requests originating in the periphery of the region may be skipped with a smaller threshold, but by using a 30-min maximum, the response times observed for such trip requests can be visualized and critiqued. All analysis assumes that SAVs operate on the roadway like traditional ridesourced vehicles. SAV vehicles stores information about assigned requests, current occupants, and real-time location, which is communicated with the central operator for future request assignment. Detailed trip level information is logged such that SAV tours, consisting of a pickup and dropoff component, or a chain of the same, can be analyzed.

The on-demand service offered by SAVs can be priced by the mile and by the minute along with a base fare, as is widely practiced by TNCs. A base case simulation run here used present-day averages of TNC and taxi fares: a base fare of $3.30, $1.25 per mi and $0.25 per min. Fares impact the outcome of the mode choice for each person, and SAV demand is likely to be influenced from low-cost fares in the future. Studies have shown that the likely costs for operation are about 50¢/mi to $1/mi ((Fagnant et al., 2015; Loeb and Kockelman, 2019; Bösch et al., 2018; Becker et al., 2020). To simplify the analyses, only a per-mile fare is used such that the average cost of operation is exactly 50¢/mi.

Travelers requesting rides in the future may also be willing to share rides. DRS is modeled in POLARIS, but with the assumption that all travelers were willing to share rides if using the SAV fleet. Research on traveler willingness to share rides have found that the predominant factor not to share a ride is the extent of delays observed (Lavieri and Bhat, 2019; Bilali et al., 2019; Gurumurthy and Kockelman, 2020). A heuristic is implemented to manage traveler delays, but the extent of experienced delay is not known at the start of a trip to influence choice. The heuristic tracks the delay experienced at several stages of the trip, and stops an SAV from accepting new rides if any occupant experiences an approximate delay greater than a pre-defined input (5 min or 5% of delay). Trip matching is also restricted to travelers traveling in the approximately the same direction (a 10-degree cone such that destinations far away can have a larger leeway in detour), so that experienced delays are not much higher than the threshold used. For a detailed overview of the DRS heuristic used in POLARIS, refer to Gurumurthy and Kockelman (2020).

Conventional Vehicle Ownership

Lower fares for SAVs are expected to attract a large share of users in the future, especially when they do not have access to personal cars, or are, otherwise, unable to drive one. The mode choice model used by POLARIS takes into account mode-specific generalized costs, as well as expected mode travel times, which are good predictors of mode choice, in addition to other estimated household- and person-level parameters. In the case of modeling SAVs, however, it is difficult to estimate a mode choice model with real data, since there exists none. Using lower fares alone, as stated earlier, does not produce the expected change in shares, since the data used to estimate them were based on present-day TNCs that charge higher fares, and extrapolating a model to a region with no data is not advisable. Some research points to the gradual decline of conventional vehicle ownership, and, consequent adoption of SAVs when personal AVs are still expensive (Lavieri et al., 2017; Quarles et al., 2019; Menon et al., 2019). In this future, households are expected to own fewer conventional vehicles and prefer to make trips by low-cost SAVs. Households located closer to economic hubs, like downtown Chicago, may especially exhibit this behavior. More households in the suburbs may also be willing to let go of one or more vehicles, than those in exurban areas, thereby increasing the demand for shared modes. Menon et al.'s (2019) ordered-probit model was implemented in POLARIS as explained in Gurumurthy et al. (2020). The use of individual, household, land-use and trip data provides a plausible forecast of reduced household vehicle ownership. The resulting increase in SAV reliance in these neighborhoods may necessitate a reliable SAV service. In addition to the model estimated by Menon et al. (2019), and other land-use and accessibility variables, SAV reliability may also influence households to let go of more vehicles. Reverse dependence of SAV fleet size and fare was also included in the model, to observe a differential travel demand when large low-cost fleets are available on-demand. However, this behavior could not be calibrated, but provides for household vehicle disposal in the direction suggested by Menon et al.'s (2019) model. The SAV mode share is not expected to dominate with the models observed here, as they are based on a possible future of AV use, whereas public opinion is still evolving. Fleet size for both single-occupant and DRS operation was estimated for this future vehicle scenario such that one SAV is available for every 100 residents served in the region.

Past work has shown that increased trip-making density also has a marginal positive impact on fleet operations through better trip matching if travelers are able to pool their rides (Yan et al., 2020; Gurumurthy and Kockelman, 2020). Yan et al. (2020) used a small sample for Minneapolis-St Pauls, whereas Gurumurthy and Kockelman (2020) focused on the small region of Bloomington, Illinois, so there is little known on how trip-making density in sprawling region affects SAV operation. To this end, an alternative scenario with high SAV preference is explored, where, in addition to using the future vehicle ownership model by Menon et al. (2019), the mode choice is artificially directed away from personal vehicle use. Fleet size was assumed such that one SAV is available for every 50 residents in the region served in anticipation of the spike in SAV demand. This increased fleet size also feeds back into the vehicle ownership model, encouraging more households to dispose one or more vehicles. Results from this SAV preference scenario will help explore whether geofences are effective when a larger proportion of trips are made using SAVs.

The Geofence

Past studies point toward the rise in VMT and eVMT with the use of SAVs as noted earlier. Research has shown that DRS can mitigate a part of this issue, but the percentage of travelers willing to share their rides in the near future is key, but remains low (Krueger et al., 2016; Stoiber et al., 2019; Lavieri and Bhat, 2019; Gurumurthy and Kockelman, 2020). With the sprawling nature of urban regions in the U.S., trips being made, for example, from a city's CBD to a suburban or exurban home is, on average, longer than the average trip length for city dwellers. SAVs are expected to be beneficial with cost-savings and emission-benefits, but, at the same time, an in-depth analysis of policies that can curb rising VMT needs to be studied. Fagnant et al. (2015)

suggest that areas with higher trip densities are better suited for an SAV operation since SAVs in these settings add lower VMT to the system. Constraining SAV fleet service within a carefully chosen geofence may provide some congestion mitigation, but the impact of such a policy has not been tested. Many cities and regions in the US have some regulation presently if ridesourcing companies operate within their jurisdiction, but these fleets are mostly unregulated otherwise, and its hard to know if these services are operating in the periphery. With current ridesourcing levels expected to be low in rural settings, there has been no locus for constraining fleet operation within fixed boundaries. Even if demand rose, regulating a geofence may be a logistical nightmare for networks of all sizes.

With SAVs anticipated to have state-of-the-art GPS technology, tracking and enforcement is likely to require no added effort, making spatial regulation feasible. Travelers will also be able to identify whether an SAV service is available based on their location. This study incorporates a virtual geofence closely resembling the spatial extents of TAZs, an intrinsic component of the POLARIS framework. With a geofence, only trips originating and ending geographically within the enforced fence will be served by SAVs. The Chicago region is vast and consists of several suburban cities, and land-use and trip-densities vary drastically from the City of Chicago's CBD to the exurban region. Four scenarios are proposed here with three distinct geofences, and one without a fence for baseline comparison. The geofences are chosen based on either municipal jurisdiction – like the City of Chicago – or the varying land-use based on home density and job density - suburbs and exurban region. Figure 2 shows the spatial expanse of the geofences stacked, such that an exurban geofence, for example, covers suburban and City limits.

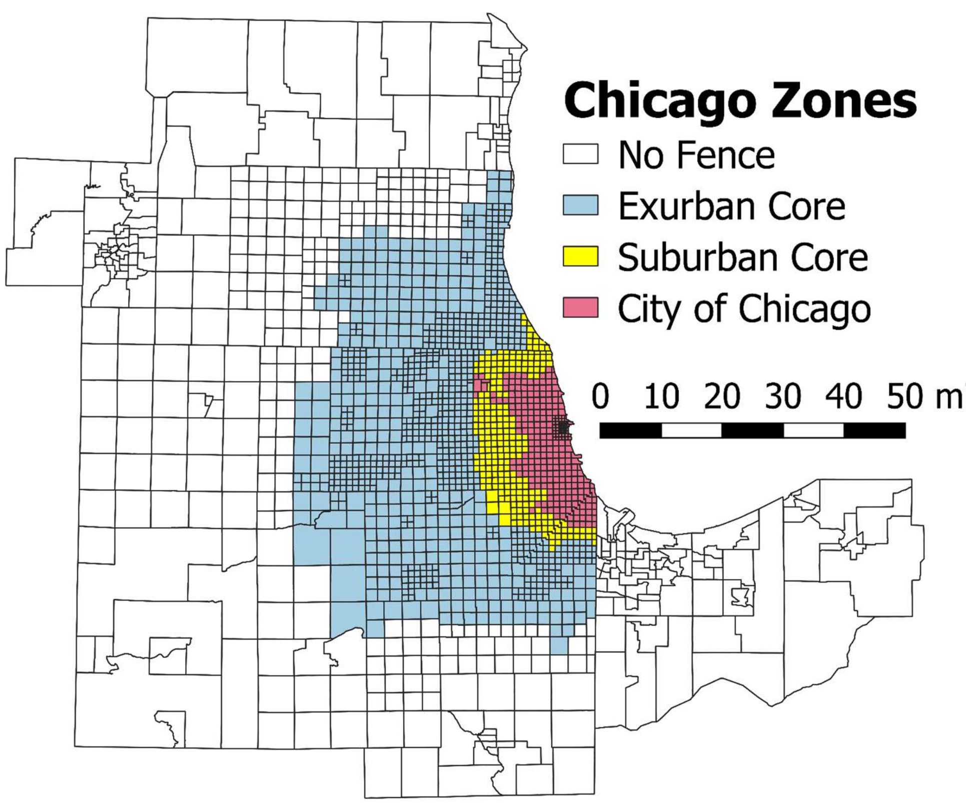

Figure 2 Spatial extent of geofences (stacked) in the Chicago region's TAZs

RESULTS

POLARIS was used to simulate travel for three geofence scenarios mentioned above to restrict SAV eVMT. The simulation results partially confirmed the initial hypothesis that geofencing trips served by SAVs can decrease eVMT and lower SAV wait times. Although average response times does not decrease by much, the spatial variation of response times becomes more uniform and equitable. However, it was also apparent that the spatial choice of the geofence played a significant role, at least when SAVs formed only a part of the mode share. To understand the characteristic of a geofence that helped lower eVMT, the ratio of residents to jobs within the geofenced region was compared with observed eVMT. The ratio of residents to jobs is a simplified ratio of generators to attractors, and is a good indicator here for trips made within the region. A ratio less than one means that the region may experience an influx of people for most part of the workday, whereas high values imply an outflux of people potentially for work. Other ratios comparing persons to non-work activities can also be explored similarly.

Figure 3 shows bar plots of eVMT along with the ratio of residents-to-jobs for each scenario discussed. A base case eVMT is also plotted alongside the single-occupant and DRS operation. The base case values stem from a present-day scenario without geofences or low-cost SAVs. Instead eVMT in this case refers to deadheading trips in a TNC, but it is important to note that time-varying fleet and decentralized dispatch was not modeled for a true ridesourcing application. For a fair comparison, trips originating and ending within the geofenced region were used to compute the share of deadheading trips. There is some bias here since the comparison uses deadheading trips as the only reference, which means that the consequent dropoff trip may have left the geofence. Regardless, the clear rise in residents-to-jobs ratio observed when transitioning from a suburban geofence to an exurban or lack of a geofence, corresponds well to a similar rise in %eVMT for all SAV scenarios illustrated. This change in land-use is seen to significantly influence the viability of the geofence. For a desirable SAV operation, most trips need to start and end within a dense region. New York is a good example where most trips start and end within the dense island, if trips are made on road. The eVMT with a geofence around the city was about 14%, but total trips average idle times shown in Table 1 imply the use of an oversized fleet. Empty VMT for the City of Chicago is comparable to that of Austin, Texas (Gurumurthy et al., 2019), as is their spatial extent. DRS helps lower %eVMT further, and this decrease is higher when larger areas are served. Sprawling regions may see pickup trips in several distinct directions if serving only one traveler at a time, so the use of DRS has more scope in sprawling regions than in dense regions. However, DRS can moderate rising eVMT only to some extent, beyond which trip-density plays a larger role. SAVs serving trips within the exurban geofence show similar %eVMT as the use of no fence. Demand outside of the exurban area may decrease radially outward, partly from the vehicle ownership model pushing suburban households to dispose vehicles more than exurban households. Compared to the base case with a smaller demand for the ridesourcing fleet, %eVMT increased when not using a fence. Percent eVMT in the SAV preferred scenario also remained low thanks to increased trip density and DRS that may have helped chain trips even in the periphery of the service area (Table 2).

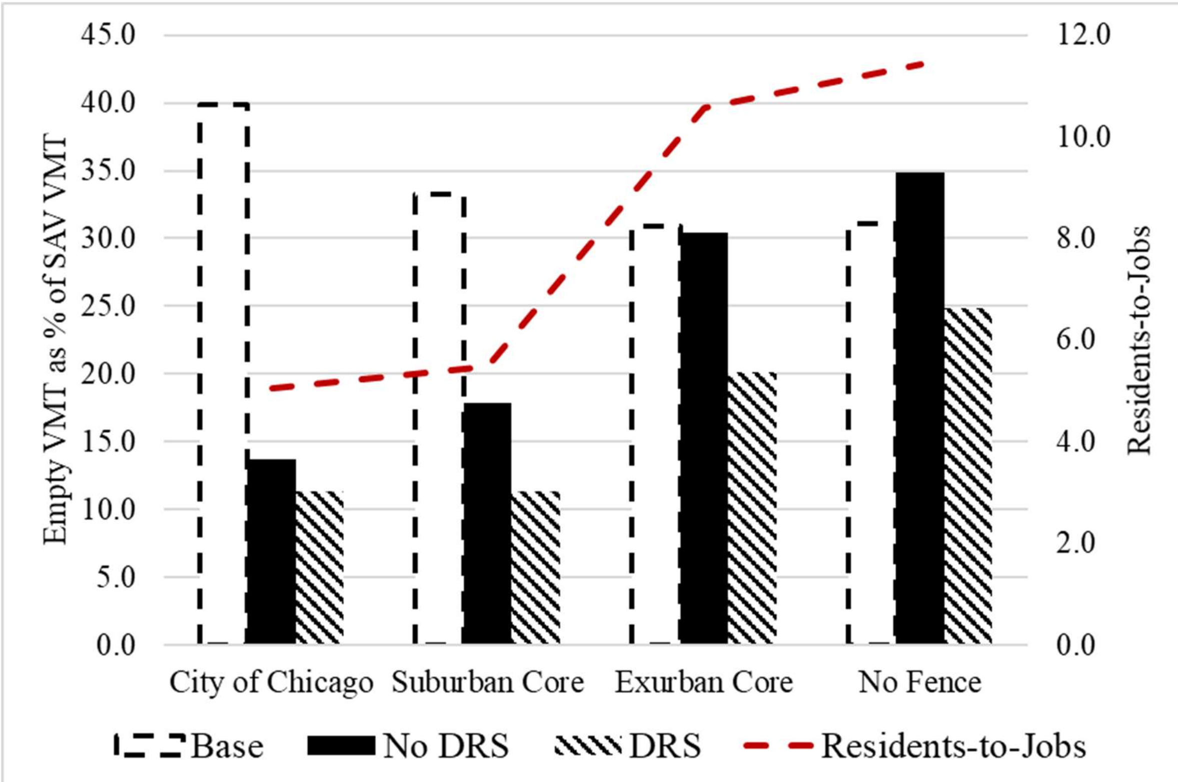

Figure 3 Residents-to-jobs ratio in geofence influencing empty VMT

Figure 4 shows the change in system VMT for each of the geofence, with and without DRS, and when SAV demand rises considerably. Large fleets of SAVs serving large demands are expected to add considerably VMT, even though %eVMT remains lower than low SAV demand scenarios. The use of DRS is not seen to have a considerable effect on lowering VMT by itself (comparing solid black and hashed black bars) when demand remains comparable. DRS saves VMT when there's no fence used, but those savings are lower than when more travelers switch to SAVs and adopt DRS more widely.

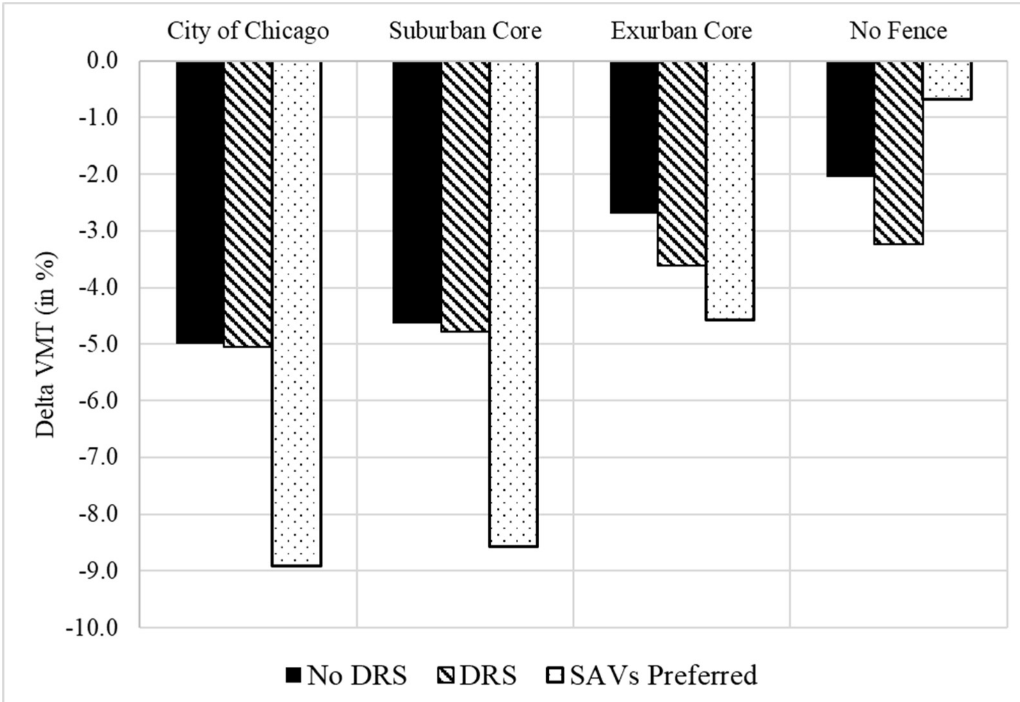

Figure 4 Change in system VMT observed with geofences and DRS

Table 1 shows the average response time, average person-trips served per SAV per day, % idle time in a 24-hr day, and the average VMT traveled per SAV in the simulation day. The observed average household vehicle ownership within these geofences from using Menon et al.'s (2019) vehicle disposal model is also reported, and can be compared to the base case average vehicle ownership of 1.63 vehicles per household.

A constant SAV availability assumption based on residents in the region is only a substitute for ratio of person-trips to SAVs. However, mode choice that is affected by fleet size makes it difficult to maintain a constant ratio across geofences. Without a fence, the average response times were higher compared to any fence. It is interesting to note that response times remain unaffected by DRS when SAVs serve larger spatial extents, with almost 1 min of response time added to the average for the City and suburban geofences. This effect may be seen as DRS being more useful in sprawling regions than densely packed regions. More trips were served, on average, with DRS when including the sprawling regions. This may also be attributed to more travelers willing to use SAVs than was allowed by the same fleet size without DRS. Low % idle times for service within the exurban region and without a fence show that the fleet was likely used exhaustively. This can also explain the steep increase in %eVMT observed. Since average SAV VMT per day is higher than most studies, it is likely that the demand within the exurban region is considerably more per SAV provided in suburban or City limits. Large AVO when serving a larger region is counter-intuitive from a trip density perspective, since trip density peaked within the suburban geofence, but average trips served is lower than that in the exurban region. Turning back to average idle time, number of SAVs serving the suburban region is likely high for the number of trips made there. Right sizing the fleet for trips within the suburban region seems to hold key potential based on trips served in the relatively small region.

Table 1 Fleet Metrics for 1 SAV for every 100 Residents with and without DRS

DRS?	Avg. HH Vehicles	Geofence Scenarios	Avg. Response Time (in min)	Avg. Person-Trips per SAV per day	Avg. % Idle Time per SAV per Day	AVO	Avg. SAV VMT per Day	Served Trip Density (in person-trips per sq. mi)
N	0.51	City of Chicago	3.2 min	10.5	86.2%	1.00	105.4 mi/SAV/day	562.9
	0.66	Suburban Core	4.6	21.5	66.0		254.2	816.7
	1.00	Exurban Core	9.1	28.9	41.9		495.8	402.7
	1.15	No Fence	11.1	22.8	49.9		441.8	92.1
Y	0.51	City of Chicago	4.0	10.5	87.2	1.22	98.2	560.7
	0.66	Suburban Core	5.2	21.8	70.9	1.35	229.6	818.8
	1.00	Exurban Core	9.1	33.0	42.4	1.53	503.4	460.5
	1.15	No Fence	11.5	25.8	48.6	1.70	445.2	103.6

Table 2 shows similar SAV fleet operation metrics, but for the SAV preferred scenario where fleet size was doubled. The trip density for SAVs in these scenarios is about 50-80% higher than the previous scenario, but the metrics are largely similar. Increasing trip density did not have a considerable impact on trip shareability but a larger fleet was used. If demand was compromised slightly, more trips may have been clubbed. This is an extreme scenario since travelers may experience extraordinary detours if SAVs were not widely available. SAV fleet serving the exurban geofence was able to serve, on average, 40 person-trips per SAV per day. Comparable values may be realized for suburban trips as well, since the trip-demand density is slightly higher. The disproportional jump in trip density in exurban region is likely due to the artificial push to use SAVs. As demand for SAVs increase in the future, it may be prudent for the Chicago region to expand the geofence to the exurban region, assuming that a suburban geofence was used initially, and that demand increased.

Table 2 Fleet Metrics for an SAV Preferred Scenario Operating 1 SAV for every 50 Residents

Avg. HH Vehicles	Geofence Scenarios	Avg. Response Time (in min)	Avg. Trips per SAV per day	Avg. % Idle Time per SAV per Day	% eVMT	Revenue-Trip AVO	Avg. SAV VMT per Day	Served Trip Density (in person-trips per sq. mi)
0.33	City of Chicago	2.2 min	9.2	91.4%	11.3%	1.26	82.6 mi/SAV/day	967.4
0.44	Suburban Core	4.3	19.6	77.9	10.9	1.38	200.5	1477.9
0.72	Exurban Core	7.4	40.0	42.3	18.4	1.57	584.7	1115.6
0.90	No Fence	9.3	33.6	44.1	22.7	1.74	580.1	281.6

Geofences were also found to be useful in providing equitable access to SAVs to large regions. Figure 5 shows response times by TAZs, comparing the service without a fence and that applied at the city and exurban limits. Although average response times reported in Table 1 and Table 2 were low, the average TAZ response times show the inequity in access without a fence. TAZs in the periphery of the region experience greater than 20 min response times. This is starkly different than the uniform response times observed by Yan et al. (2020) in Minneapolis-St. Pauls. In a practical application, TAZs with average response times greater than 15 min, for example, may not even see equal access to SAVs. A geofence around the exurban core considerably improves response times throughout, by lowering it by 5 min across TAZs. The response times across the City TAZs are almost all less than 5 min. This equitable spread in response times is useful but seems to be achieved with a fleet oversupply. If SAVs are meant to help relieve driving burdens it may be prudent to require oversizing the fleet for equity concerns, even if it means higher % idle times, and lower person-trips served by an average SAV per day.

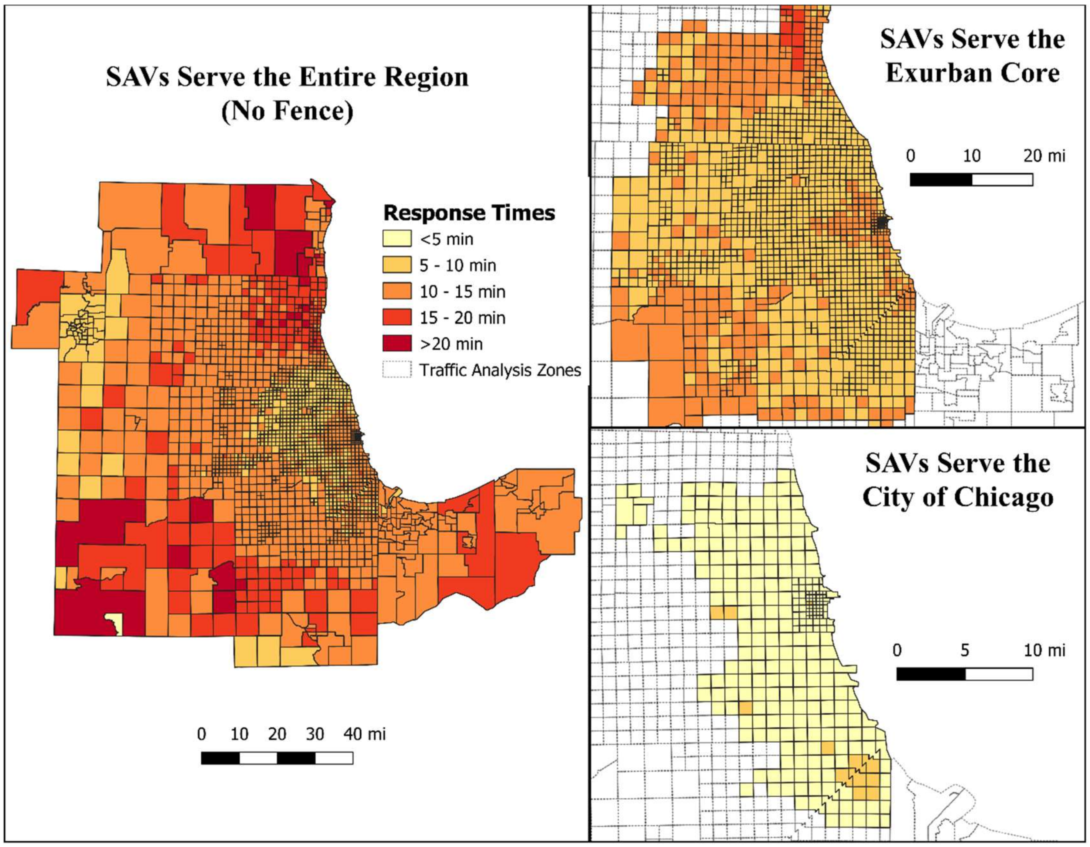

Figure 5 Comparing response times by TAZ between no-fence service and two geofence levels without DRS at the City and exurban limits

CONCLUSIONS

Shared mobility is on the horizon and policy must be developed to tackle initial and future large-scale adoption of SAVs. Regions like Chicago with urban sprawl are expected to have high percentages of eVMT arising from longer-than-average trip distances when servicing the exurban areas. In this study, the use of geofences in curbing high anticipated eVMT and VMT is explored. Percent eVMT followed the ratio of residents to jobs in the region served, meaning that balanced generators and attractors in dense regions is ideal if the sole goal is %eVMT. Fleet size is important to take advantage of high trip densities within a geofence, but fleet size decisions directly impact equity concerns. Fleets must be large enough to provide equitable access spatially, and small enough such that SAVs are used exhaustively in a day (low % idle time) to warrant the high capital costs of an SAV fleet.

The use of DRS in addition to geofences revealed that DRS alone may not provide large VMT savings. The use of geofences provides provides larger savings in VMT and this is compounded with higher SAV demand. If regions, like Chicago, are able to shift demands within the suburban extent to SAVs and transit and non-motorized modes, then region-wide VMT savings are realized.

Allowing car reliance in rural areas maybe acceptable, especially knowing that those roadways are typically not congested. DRS benefits are more pronounced when serving regions with sprawl, as there is more scope for trip bundling. DRS within City-wide geofences showed relatively small changes in total VMT and %eVMT.

Equity of SAV access is also addressed by using geofences since it lowers average trip lengths served. The model did use a high threshold for response time to critique the realized response times. Critical demand across the extremities are likely to not use SAVs from poor access. The geofences enforced in this study were centered around the City of Chicago. With large regions like this having many smaller CBDs, other geofences can be envisioned around smaller towns. This will not only curb %eVMT and added VMT, but will also ensure equitable access to most activities less than say 10 min or 10 mi away. Transit lines or 8-seat automated buses (aBuses) may be able to provide economical access to longer trips without adding considerable congestion on the highway infrastructure.

This study provides an important policy tool in testing travel patterns in large regions with recommendations for use of geofences and a behavioral model informing future SAV demand, but it is also important to keep in mind the limitations that arise from some assumptions made here. Constant SAV availability based on residents limits scope of comparison. Other metrics can be used as proxy to see how better the SAV service may have been, but it is hard to pre-determine the right fleet size for each geofence scenario. The eVMT resulting from the lack of central operation is likely to be higher and needs to be studied to compare how better regions can do compared to TNC-related congestion added to streets in several regions. Finally, studies need to evaluate how SAV repositioning in conjunction with the use of geofences can benefit the system.

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AUTHOR CONTRIBUTION STATEMENT

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

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