

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

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22 **ABSTRACT**

23 With autonomous vehicles (AVs) still in the testing phase, researchers and planners must resort to
24 simulation techniques to explore possible futures regarding shared and automated mobility. An
25 agent-based discrete-event transport simulator, POLARIS, is used in this study to simulate travel
26 patterns in the 20-county Chicago region with a shared AV (SAV) mobility option. Using this
27 framework, the SAV-system-performance impacts of different geofences for such services on
28 system performance are studied under six distinct scenarios: service restricted to the central
29 business district (CBD), the urban core, the city, the suburban core, the exurban core, and no
30 geofence, in addition to three inferred rates of SAV adoption. Results indicate that the residents-
31 to-jobs ratio within a geofence influences its efficacy, and an SAV fleet's empty VMT (eVMT)
32 can be curtailed with suitable geofences. They also help lower response times, system-wide VMT
33 across all modes, and ensure uniform access to SAVs. Geofencing SAVs within the CBD or urban
34 core increases eVMT due to the unidirectional nature of trips in and out of the CBD when fenced
35 at the urban core during the morning and evening peaks, respectively, and does not show
36 significant benefits in improving requests met, response times, or lowering system VMT.

37 **Keywords:** *Shared autonomous vehicles, geofences, agent-based simulation, Chicago, POLARIS*

38 **MOTIVATION**

39 The world is evolving rapidly and the era of fully-automated, or autonomous, vehicles (AVs) is
40 just around the corner. Public testing was predicted to be carried out starting 2020, but some
41 companies (e.g., Waymo and Uber) have already achieved this in 2017. Researchers believe that

AVs will be publicly available as early as 2035, but with more companies entering the “AV-race” (like Ford, Mercedes 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 act 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 and Kockelman, 2018), 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.

It is, therefore, important that travel demand modelers study the impact that shared AVs (SAVs) will have on the system to understand and mitigate negative impacts with effective policies. Traditionally, travel demand impacts have been studied using travel surveys and by developing statistical models. In the absence of real-world data for a non-existent scenario, researchers have often used simulation. In the recent past, several studies have analyzed the impact that SAVs (see, Brownell and Kornhauser, 2014; Spieser et al., 2014; Fagnant et al., 2015; Bischoff and Maciejewski, 2016; Bösch et al., 2016; Liu et al., 2017), and electric SAVs, or SAEVs (see, Loeb et al., 2018; Loeb and Kockelman, 2019), can have on different regions around the world while focusing on metrics like vehicle-replacement ratio, vehicle-miles traveled (VMT), and effect of assumed value of travel time (VOTT). Other studies have been conducted for SAVs with dynamic ride-sharing, or DRS (see, Fagnant and Kockelman, 2018; Martinez and Viegas, 2017; Heilig et al., 2017; Hörl, 2017; Loeb et al., 2018; Wang et al., 2018; Gurumurthy et al., 2019), showing SAV viability with metrics like average vehicle occupancy (AVO) in addition to the ones mentioned earlier. While all researchers emphasize the various benefits SAV fleets have to offer, it is important to look closer on the negative impacts that have been discovered and address missing behavior that has not been taken into account.

Brownell and Kornhauser (2014) studied the entire state of New Jersey with significant vehicle-replacement ratios (of 1 SAV for every 3 conventional vehicles) for SAV fleets working to feed transit, but this was based on a coarse approximation of a travel demand model. Spieser et al. (2014) used real-world taxi data for Singapore with results suggesting SAV-viability and a similar replacement ratio, but taxi trips only form a small percentage of all trips. Gurumurthy and Kockelman (2018) use a comprehensive cellphone dataset and a detailed network to show that SAVs may only be viable when trip densities are high and not spread out, and that VMT is likely to increase (up to 4%) for high-use scenarios without the introduction of policies. They do not, however, allow for mode choice and congestion feedback. Congestion feedback, and, consequently mode choice, is important to see how induced demand will be handled by SAVs. Studies using MATSim, an agent-based simulation tool, attempts 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 (Simoni et al., 2019; Gurumurthy et al., 2019). This improves estimates

of replacement rates and induced VMT. However, MATSim does not allow for destination choice. 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. 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, but use 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.

The introduction of inexpensive SAV fleets may cause VMT to rise due to induced demand, especially when DRS is not available/offered, and studies show that willingness to DRS is improving (Gurumurthy and Kockelman, 2019). Policies must be studied to curb this threat even if DRS is not widely chosen. In this study, an agent-based discrete event transport simulator, called POLARIS (Auld et al., 2016), is used to understand the operation of a fleet of SAVs in the Greater Chicago region which contains 20 counties. POLARIS is a detailed agent-based travel simulator with low computation times and can simulate the region's travel patterns 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 for different levels of SAV use while focusing on change in system VMT, and VMT with no travelers in the SAV (empty VMT, or eVMT). 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 developed, then, the six 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 synthesizer to get accurate travel demand for the population. Figure 1 shows the network used for the study which was obtained from the Chicago Metropolitan Agency for Planning (CMAP), the local MPO. It consists of 31,000 links and 19,000 nodes, and around 10 million travelers that make 27 million one-way person-trips in one day on this network. All trips that are synthesized are cross-referenced with traffic analysis zones (TAZs) of origin and destination. The entire region is comprised of 1961 TAZs and these are further classified based on land-use type and location in the region. The central business district (CBD), or downtown, of the City of Chicago is represented by 47 TAZs, which is surrounded by an additional 251 TAZs to cover the entire city. The suburban core around, and including, the city is comprised of 501 TAZs and the remaining represent the exurban and rural areas. Nearly 74% of person-trips are by private car, 7% by transit, 15% are by walking/biking, and 4% 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).

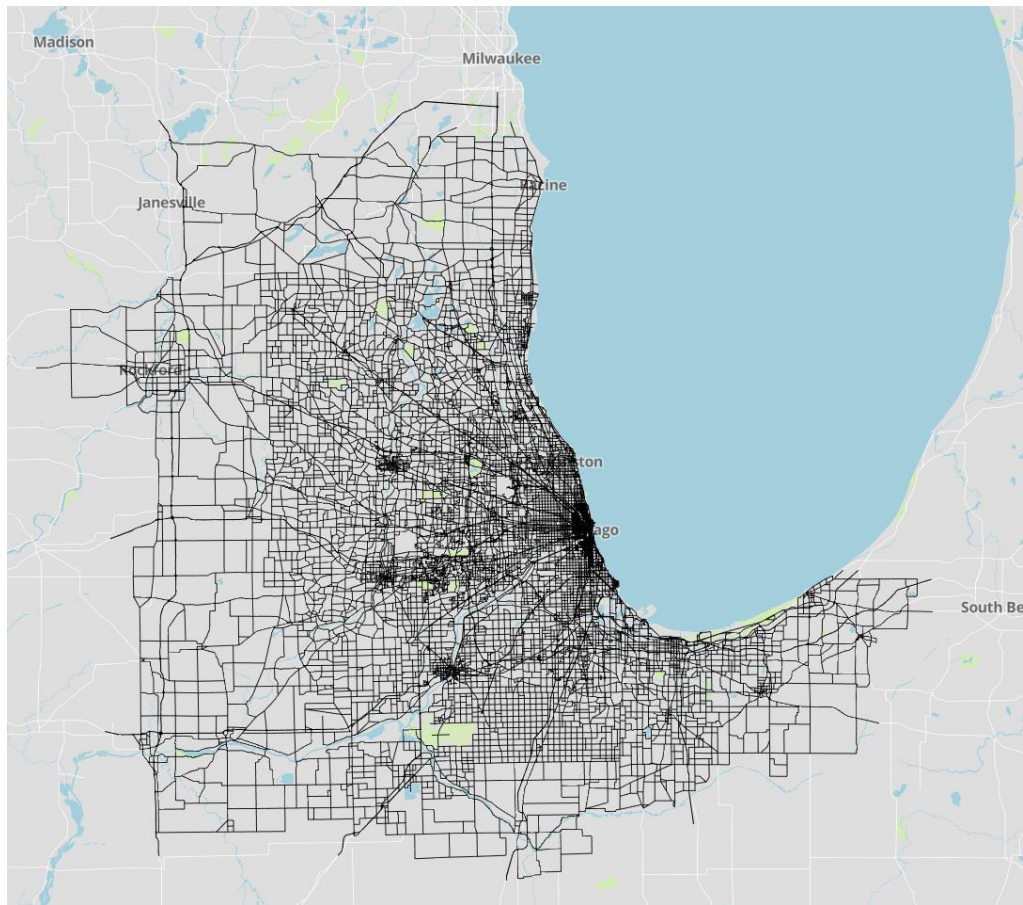


Figure 1 Detailed network of the 20-county Chicago region

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 the set of travelers, then a series of behavioral models create the activities that a person is likely to carry out for a given simulation period based on calibrated activity models. This is kept in check during the simulation by the activity module in terms of conflict monitoring and delays in execution. These activities are used by the person module to plan, schedule and move travelers throughout the network. Vehicle ownership is controlled at the household level and routing decisions are handled by either the vehicle module or the person behavior module depending on who is operating the vehicle. Finally, every activity and trip made by the person, including the vehicle trajectory, is logged for post-processing. 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).

Shared Autonomous Vehicles

The shared fleet is implemented using two additional modules, which includes definitions for an SAV operator and an SAV vehicle. Figure 2 shows the functionality of and interaction between these modules. In addition to this, they are able to interact with existing modules within POLARIS

to preserve the simulation flow and exhibit realistic congestion. The SAV operator includes functionality required to listen to incoming travel requests from travelers and assigns it to a nearby SAV, when available. Two heuristic strategies for request assignment have been implemented. A zone-based matching heuristic assigns a request to a vehicle based on the request's zone and a randomly available SAV in that zone. If an SAV is not available, all zones satisfying the queen's contiguity is checked for an available SAV. The alternative to the zone-based heuristic is simply matching the nearest SAV based on Euclidian distance to the request. In both the cases, a threshold wait time is respected in vehicle-to-request matching. The zone-based matching heuristic proved to be considerably faster in terms of computation, and is used in this study. Multiple operators are allowed to be included in the simulation to represent the real-world market competition, but was not explored for this study.

The SAV vehicle module inherits functionality from a conventional vehicle in the simulation, but is allowed to travel empty (i.e., without a driver). These vehicles are also able to travel faster, and with smaller headways, as is expected of an AV. However, this also depends on other vehicles in the roadway. To keep things simple, all analysis assumes that SAVs behave like traditional TNC vehicles in their movement. SAV vehicles stores information about assigned requests, current occupants, and real-time location to communicate with the SAV operator for the assignment of future requests. Key characteristics pertaining to an SAV fleet at the system level are VMT and eVMT. At the fleet level, it is important to know the wait time, which comprises of the assignment and response time, to ascertain service performance. Vehicle assignment time is defined as the amount of time that a traveler is waiting before being assigned to an available SAV. Response time, therefore, is the time taken by the SAV to arrive at the traveler's location for pickup, once assigned.

The on-demand service that SAVs offer is modeled to be priced by the mile and by the minute along with a base fare in this simulation, as is widely practiced by TNCs. The choice of pricing the fleet impacts the outcome of the mode choice for each person. Forecasting the operational cost of a futuristic fleet with no data is difficult. Studies have shown that the likely costs for operation are about 50¢/mi to \$1/mi (Fagnant et al., 2015; Simoni et al., 2019; Loeb and Kockelman, 2019). To simplify the analyses, only a per-mile fare is used so that the average cost of operation turns out to always be around 50¢/mi in this study.

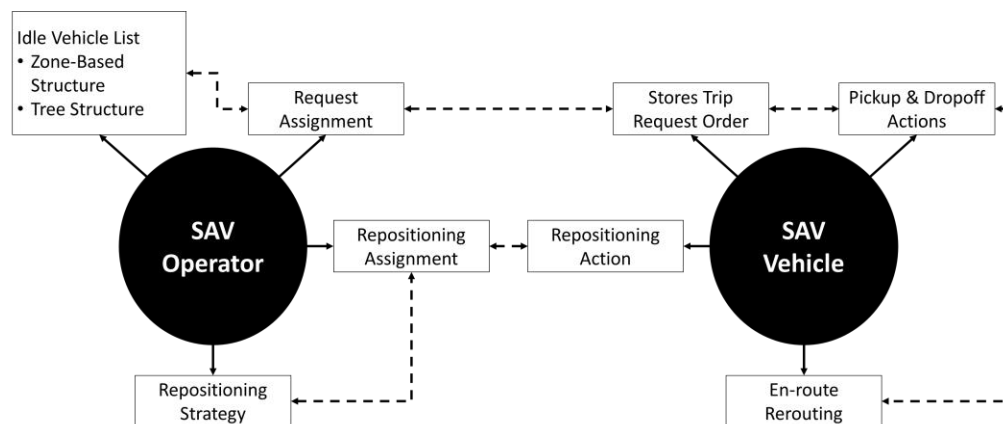


Figure 2 Interactions between the SAV operator and vehicle modules

1 Conventional Vehicle Ownership

2 Lower fares for SAVs are expected to attract a large share of users in the future, especially when
 3 they do not have access to cars, or are, otherwise, unable to drive one. The mode choice model
 4 used as a part of the synthesizer in POLARIS takes into account mode-specific generalized costs,
 5 as well as expected mode travel times, which are good predictors of mode choice in addition to
 6 other estimated household-level and person-level parameters. In the case of modeling SAVs,
 7 however, it is difficult to estimate a mode choice model with real data, since there exists none.
 8 Using lower fares in these models alone does not produce the expected change in shares, since the
 9 data used to estimate them were based on higher fares (such as from using present-day TNCs).
 10 Some research points to the gradual decline of conventional vehicle ownership and adoption of
 11 SAVs, when personal AVs are still expensive (Lavieri et al., 2017; (Quarles, Kockelman, et al.,
 12 2019). This expected behavior is incorporated into POLARIS using a randomized vehicle
 13 ownership reduction factor for each household. With a given probability, a household may lose
 14 one or more vehicles. Without no grounded expectation for the future in this regard, a sensitivity
 15 analysis is also included to interpret the behavior in three stages: a 10 percent, 50 percent and 100
 16 percent reduction in conventional vehicle ownership. SAV availability per capita was kept fairly
 17 constant in the 10 percent and 50 percent cases but still depended on the outcome of the mode
 18 choice model. On average, about 1 SAV was made available for every 100 travelers. Under 100
 19 percent reduction in vehicle ownership (i.e., when all trips are served by SAVs), a larger fleet of
 20 SAVs was required to serve most trips. On average, 1 SAV was available for every 18 travelers
 21 for the 100% case, and was maintained between the geofence scenarios.

22 The Geofence

23 Past studies point toward the rise in VMT and eVMT with the use of SAVs as noted earlier.
 24 Research has shown that DRS can mitigate this issue, but the percentage of travelers willing to
 25 share their rides in the near future remains low (Krueger et al., 2016; Gurumurthy and Kockelman,
 26 2019). With the sprawling nature of urban regions in the U.S., it is common knowledge that trips
 27 being made, for example, from a city's CBD to a suburban or exurban home is, on average, longer
 28 than the average trip length. SAVs are expected to be beneficial with cost-savings and emission-
 29 benefits, but at the same time, an in-depth analysis of policies that can curb rising VMT needs to
 30 be studied. Fagnant et al. (2015) suggest that areas with higher trip densities have better fleet
 31 performance metrics and adds lesser VMT. Constraining an SAV fleet's service within such a
 32 carefully chosen geofence may be key to mitigating congestion, but such a policy has not been
 33 tested.

34 This study incorporates a virtual geofence based on the distinction of a subset of traffic analysis
 35 zones, an intrinsic component of the POLARIS framework. With SAVs having state-of-the-art
 36 technology and GPS information, no added effort is expected from an operator's perspective to
 37 operate the fleet within the geofence or for a traveler to know on their smartphone whether the
 38 service is not available in a given location. This would simply serve as an additional rule in the
 39 already complex set of instructions that drives the AV technology. The Chicago region is vast and
 40 consists of several zones as previously mentioned, but also with varying densities from the CBD
 41 to the exurban region. Six scenarios are proposed here with five distinct geofences and one without
 42 a fence to compare. Table 1 shows these scenarios with a description of the extent of each of them
 43 and Figure 3 shows the spatial expanse of the same.

Table 1 Boundaries covered by the geofences

Geofence Scenario	Boundary of Virtual Geofence	Population
1	Downtown Chicago: SAVs only serve trips originating and ending in the central business district of the City of Chicago	51.3 K
2	Urban Core: SAVs serve the central part of the City of Chicago within the <i>Cook</i> county	179.9 K
3	City of Chicago: SAVs serve the entire City of Chicago	2.9 M
4	Suburban Core: SAVs serve the city as well as the closest suburbs around it, which include parts of <i>DuPage</i> county	4.0 M
5	Exurban Core: SAVs service all areas mentioned in scenario 4, as well as parts of <i>Lake</i> and <i>Will</i> counties in Illinois	8.0 M
No Fence	Unrestricted: SAVs are allowed to service trips starting and ending anywhere in the network which includes, <i>Cook</i> , <i>DuPage</i> , <i>Kane</i> , <i>Kendall</i> , <i>Lake</i> , <i>McHenry</i> and <i>Will</i> counties in Illinois, <i>Kenosha</i> and <i>Racine</i> counties in Wisconsin, and <i>Lake</i> , <i>LaPorte</i> , and <i>Porter</i> counties in Indiana	10.7 M

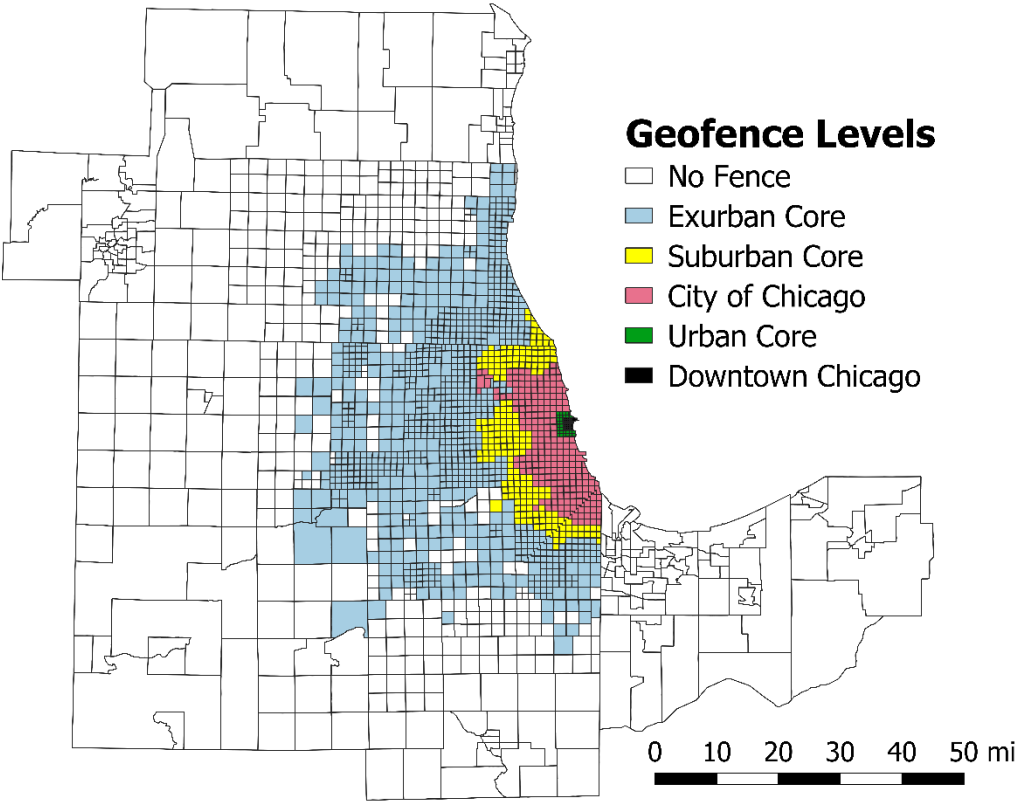


Figure 3 Spatial extent of geofencing (overlapped) in the Chicago region’s TAZs

1 RESULTS

2 POLARIS was used to simulate travel for each of the geofence scenarios mentioned above with
3 the SAV mode available. The simulation results partially confirmed the initial hypothesis that
4 geofencing the trips served by SAVs can decrease eVMT and lower SAV wait times. However, it
5 was also apparent that the spatial choice of the geofence played a significant role, at least when
6 SAVs formed only a part of the mode share. To understand the characteristic of a geofence that
7 helped lower eVMT, the ratio of persons living in the geofenced area to the number of jobs
8 available was compared with observed eVMT. Figure 4 shows bar plots of eVMT along with the
9 ratio of residents-to-jobs for each scenario discussed. A clear rise in residents-to-jobs ratio is
10 observed within the City of Chicago, with more jobs available in the CBD and urban core than
11 people living in that area. This change in land-use is seen to significantly influence the viability of
12 the geofence. This is also intuitive since the number of trips beginning and ending within the
13 geofence need to be significant in order for the service to work, and the geofence to be beneficial.
14 The eVMT with a geofence around the city was about 24%, which is still fairly high in comparison
15 to other studies (Gurumurthy et al., 2019), but the significant difference in size between the
16 Chicago region and Austin, Texas needs to be factored into the comparison. The eVMT with smaller
17 geofences was in the range of 40-50%, and can be largely attributed to the access and egress nature
18 of all trips in the CBD in the morning and evening peaks, respectively, when fencing around the
19 urban core. In general, the large percent eVMT within the CBD and urban core may have stemmed
20 from pickup and dropoff trips having similar lengths inside the small area. However, the share of
21 SAV requests is very low in these scenarios compared to that without a fence. The SAV fleet's
22 eVMT is also high in the 50% vehicle ownership reduction scenario as opposed to 10% or 100%
23 across the board. The constant fleet assumption in the 10% and 50% cases can explain the higher
24 percentage of eVMT when the same SAV fleet is performing more trips. The increase in fleet size,
25 and, consequently, better spatial availability, when all personal vehicle trips are made by SAVs in
26 the 100% case is likely why percent eVMT is lower.

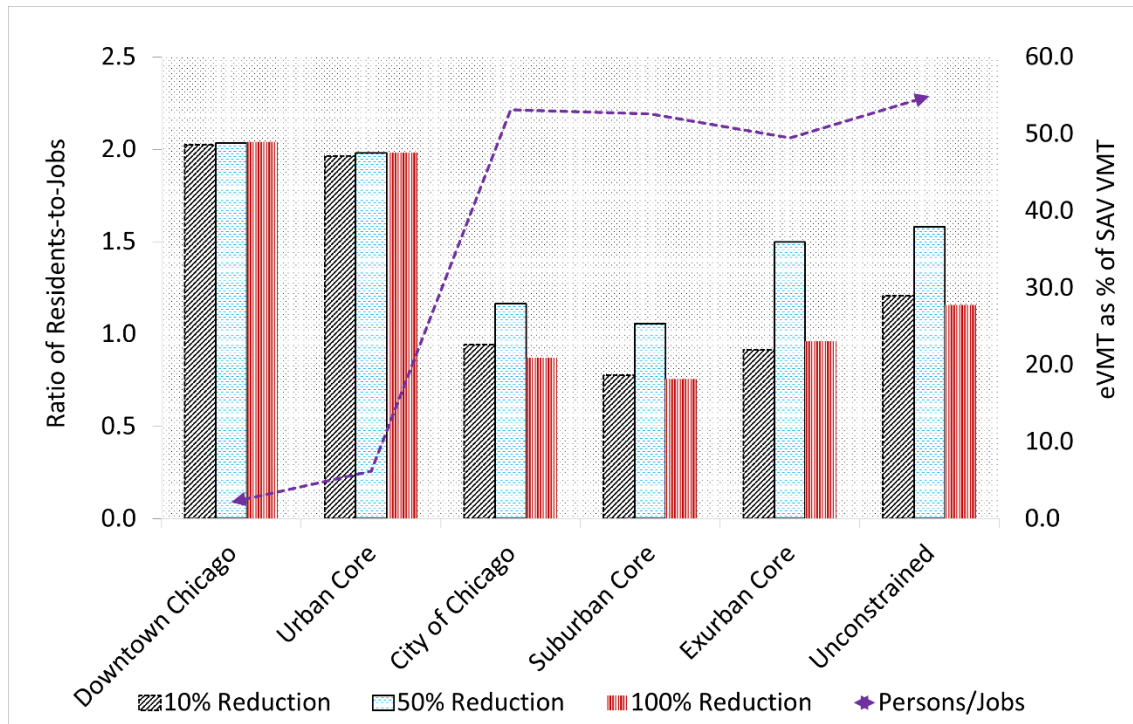


Figure 4 Residents-to-jobs ratio in geofence influencing empty VMT

Note: % reduction denoted in figure represents assumed random-change in vehicle ownership.

The fleet of SAVs performed better within these geofences in terms of wait times and percentage of requests that was met within the maximum allowed wait time of 30 min. Table 2 shows the average response time, average wait time, percentage of requests met, average person trips made per SAV, average idle time as a percent of 24 hours, and the resulting percentage change in VMT across the region for each geofence and vehicle-ownership-reduction scenarios. The observed average household vehicle ownership is also reported, with the base case ownership at 1.57 vehicles per household.

Without a fence, the average wait times were consistently higher across all ownership scenarios compared to fences encompassing the city or more. System VMT reduced the least without a fence largely owing to higher eVMT of the SAV fleet. Lower rate of SAV request in the 10% reduction case translated to more of them being served, as compared to the 50% case with the same fleet. The percentage of requests met rose significantly in these two cases with the use of geofences because of higher trip densities. When all trips were served by SAVs, the increase in percentage of requests met was not significant. This may be due to the larger fleet required to serve the region without the fence to begin with.

Geofences chosen around the CBD or urban core did not prove to be useful, and lowered vehicle ownership was not seen to be influential since the number of households in the CBD is likely low compared to the suburbs. Nearly half the fleet's VMT was without a passenger and average wait times were 5 min (in 10% and 50% cases) to 15 min (in 100% case) more depending on percentage reduction in ownership. System VMT was still lower than the base case because the share of SAV VMT was very low in the 10% and 50% ownership reduction cases. The large VMT reductions observed under these geofences in the 100% case was counterintuitive, and may have been a result

of undercounting the VMT of a trip unserved by an SAV outside of the geofence. In the initial stages of SAV adoption, a large number of short trips within a well-developed CBD is most likely to be captured by transit or other non-motorized modes.

As the geofence was progressively expanded to cover larger regions, like the City of Chicago or the suburban core, average response times reduced significantly, up to half that without a fence. The use of the same fleet size in the 10% and 50% ownership reduction scenarios, showed an inability to meet all trip requests even with a geofence due to larger rate of requests in the latter, reaffirming that fleet choice decision is a vital planning component. The average trips served by an SAV increased within a geofence when there was sufficient demand as seen in the 50% case between the fence on the exurban core and the unfenced result. However, the availability of SAVs for each trip request is also a factor, since this behavior was not observed when all trips within the geofence was served by a larger fleet. Fencing trips within the suburban core translated to the best operational metrics for SAVs, likely from a good residents-to-jobs ratio.

TABLE 2 SAV Fleet Metrics by Geofence Scenario and Vehicle Ownership Reduction

Vehicle Ownership Reduction and Avg. HH Vehicles		Geofence Scenarios	Avg. Response Time (in min)	Avg. Assignment Time (in min)	% Requests Met	Avg. Trips per SAV per day	Avg. Idle Time per Day (in % of 24 hr)	% Change in VMT
10% reduction	0.59	1	15.9 min	0.6 min	64.8%	11.3	74.8%	-4.6%
	0.68	2	14.1	0.6	49.2	7.8	83.7	-4.8
	0.95	3	6.5	0.5	63.3	13.0	73.7	-4.3
	1.08	4	5.5	0.5	99.8	12.9	73.9	-4.4
	1.35	5	7.0	0.6	99.1	14.7	67.5	-3.9
	1.41	No Fence	10.1	0.8	89.1	16.3	57.9	-3.0
50% reduction	0.33	1	17.3 min	1.3 min	60.5%	15.4	62.3%	-19.1%
	0.38	2	15.5	0.6	71.7	11.1	75.0	-18.9
	0.55	3	8.0	0.7	90.6	19.3	62.2	-18.6
	0.63	4	7.4	0.6	91.4	20.3	60.2	-18.4
	0.81	5	11.8	1.2	79.6	25.2	42.6	-16.5
	0.85	No Fence	13.0	1.4	69.4	22.3	45.5	-15.2
100% reduction	1	24.1 min	0.7 min	47.8%	5.6	81.1%	-27.3%	
	2	20.5	0.7	58.9	4.1	87.8	-26.7	
	3	5.3	0.5	92.4	7.6	87.0	-25.1	
	4	4.6	0.5	94.9	9.1	84.7	-24.5	
	5	7.0	0.6	92.8	16.8	66.5	-20.0	
	No Fence	9.4	0.7	92.3	18.1	56.8	-13.1	

Geofences were also found to be useful in providing equitable access to SAVs to large regions. Figure 5 shows response times by zone, comparing the service without a fence and that applied at the city and suburban core levels. Without a fence, zones that are away from the CBD were seen to have average response times much higher than the region-wide average response times. This

may be skewed by the number of requests arising in these zones, but with a geofence around the city, a more equitable spread of response times was observed. This was not true with a geofence at the exurban core, where all zones in the extremities witness higher than average response times.

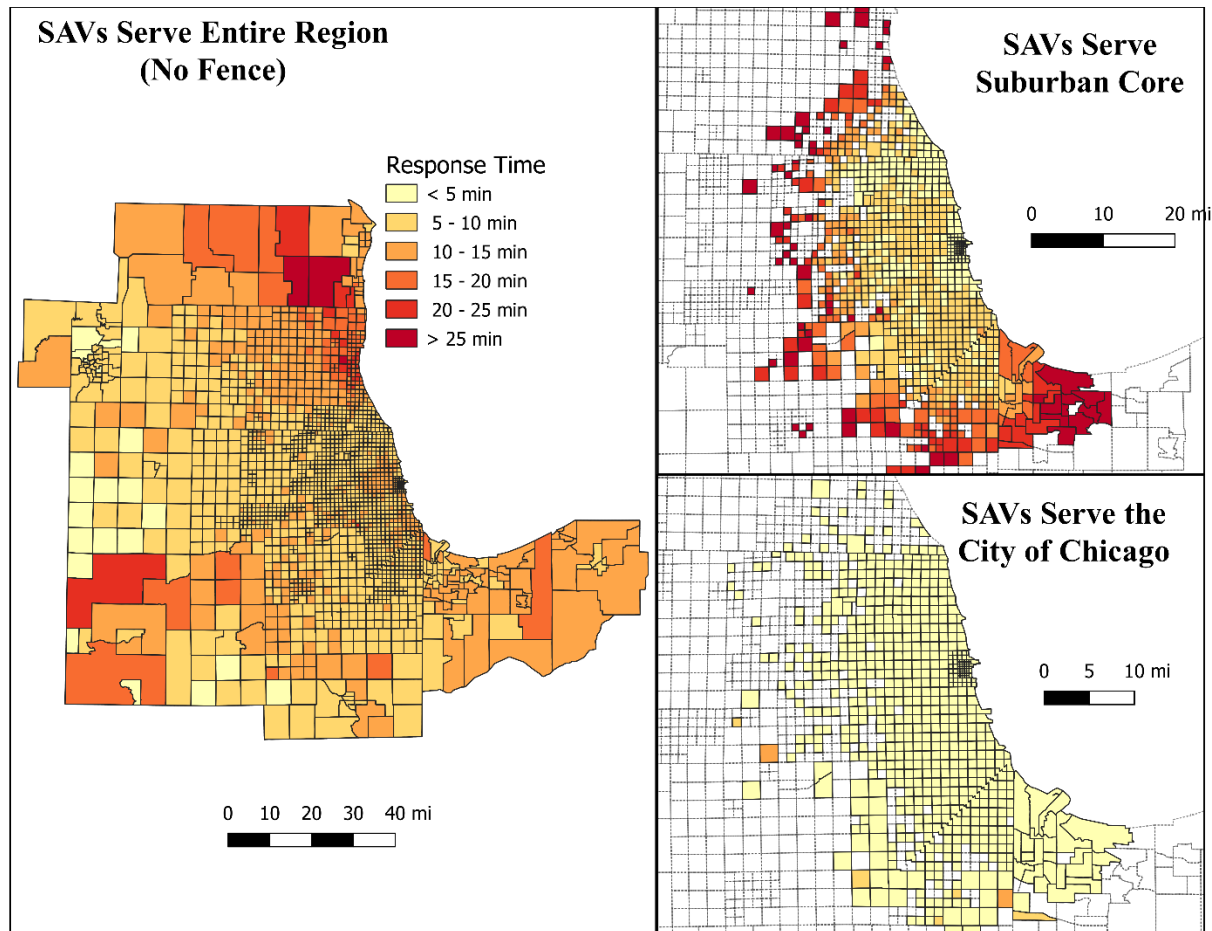


Figure 5 Comparing response times by zone between unconstrained service and two geofence levels in the 10 percent vehicle ownership reduction case

CONCLUSION

Shared mobility is on the horizon and policy must be developed to tackle initial and future large-scale adoption of SAVs. Regions with urban sprawl are expected to have high percentages of eVMT arising from longer-than-average trip distances when servicing the suburban and exurban areas. In this study, the use of geofences in curbing high anticipated eVMT is explored. The spatial extent and ratio of residents-to-jobs within a geofence is seen to influence the eVMT observed within the region. Limiting the SAV service to the suburban core, was found desirable for the Chicago region in terms of curbing eVMT. However, a smaller geofence at the city level was also seen to enforce uniform SAV access. These geofences also helped lower response times for using an SAV from higher trip densities within the geofences. Smaller geofences, like that around the CBD and urban core, showed high percentage of eVMT, largely due to the unidirectional nature of trips found in the well-developed CBD at any time of day.

Larger levels of eVMT without the use of geofences is suggestive of the fact that smarter algorithms governing the ride-matching, vehicle-to-traveler assignment and vehicle repositioning, will be required to achieve lower congestion if shared mobility is to be deployed everywhere. Until such algorithms are developed to curb added VMT, services should likely be restricted to the city or suburban core to minimize negative impacts on the overall transportation system through added eVMT from the shared fleet. The sensitivity on the extent to which SAVs are adopted showed that large-scale adoption may not necessarily benefit from geofences. However, the smart use of geofences and SAVs was found to lower system VMT at all levels, with geofences lowering VMT to a greater extent than the lack thereof.

The use of geofences does bring up the issue of equity of access to travelers in regions outside a geofence. However, these geofences were designed with respect to the CBD of Chicago. Other geofences around the smaller towns in the region can also help curb eVMT. Commuter lines running radially throughout the region is likely to be able to cater to longer trips without causing 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, but it also important to keep in mind the limitations that arise from some assumptions made here. In order to focus the attention on the effectiveness of geofences, the availability of SAVs per capita was kept constant across the scenarios where travelers continued to own conventional vehicles (the 10% and 50% cases), but a larger fleet was required to serve all trips. Results between these scenarios must be interpreted after factoring in the availability of SAVs per trip, which depends on the mode choice model and was not constant. The number of trips within geofences also dramatically varied because of the spatial extent of each of them. In the 100% case, on the other hand, since all auto trips are served by SAVs, the fleet characteristics is bound to be different than when there were auto mode alternatives. Finally, studies need to evaluate how SAV repositioning in conjunction with the use of geofences can benefit the system, and how these compare to the benefits of DRS.

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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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