SHARED AUTONOMOUS VEHICLE OPERATIONS ACROSS DISTINCT DALLAS-FORT WORTH GEOFENCES

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ABSTRACT

Shared autonomous vehicles (SAVs) are predicted to become a common mode and will hasten a transition to a cleaner and sustainable utilization of energy. Using an agent-based model, POLARIS, this study explores the impact of SAV operation on the system in the multicentric Dallas-Fort Worth region. Multiple simultaneous geofences are considered under two scenarios – one consisting of four counties and another with four denser cities (that form a subset of the counties) – to restrict SAV movements within these predefined spatial bounds. Four fixed fleet sizes with and without dynamic ride-sharing (DRS) guided this study. Up to 1% reduction in system VMT was observed in the geofence scenario with respect to the no fence baseline scenario with policy enforced on only 5% of all travel. The proportion of unoccupied miles in SAV VMT increased in larger fleets by 5%. SAV idle time increased by 7 percent points with the geofences, with wait times reducing considerably (to under 5 min) in both scenarios. The balance between fleet operation efficiency (i.e., low percent empty VMT, high average occupancy) and passenger satisfaction (i.e., low wait time, low detour times with DRS) is key, as the latter will most likely take centre stage and can impact the former.

Keywords: *Shared autonomous vehicles, simultaneous geofences, demand management, empty vehicle-miles-traveled*

INTRODUCTION

Legal changes are enabling more use of self-driving or "autonomous" vehicles (AVs) on public roads, with North America accounting for the highest share in planned automated vehicle production of more than 45% in the global market in 2021 (Grand View Research, 2020). Long-term AV technology should boast several advantages over conventional vehicles, including 80%+ fewer crash costs, lower travel costs for SAV users (who may wish to avoid vehicle ownership] and for former drivers, who can make better use of their travel time), and potentially lower emissions and energy demand, at least per vehicle-mile travelled (VMT) (Kockelman et al., 2016; Gurumurthy et al., 2021; Fagnant et al., 2015; Lee and Kockelman 2022).

The advent of AV technologies can enhance the potential benefits of shared mobility systems such as current-day transportation network companies (TNCs) through the consolidation of both car-sharing (e.g., Zipcar, car2go) and ride-sharing (Uber, Lyft) into an integrated commodity of shared autonomous vehicles (SAVs) (Golbabaei et al., 2021). The capability of SAVs to adjust to changing demand in real-time enables them to provide more flexible services than current conventional public transport or shared services (Stocker and Shaheen, 2017). Shared fleet systems have been envisioned as sustainable solutions to urban mobility challenges (such as car vehicle ownership, congestion, and environmental impacts). A number of studies have found that SAVs have the potential to displace conventional vehicles (Fagnant and Kockelman, 2014; Spieser et al., 2014). In addition, AVs are expected to result in 19.6% energy savings, and 13.8% to 44.1% emission reductions if all other factors are equal relative to human-driven vehicles (Liu et al., 2017). The economic benefits of SAVs have also been thoroughly explored in a plethora of studies that focus on travel costs. The high anticipated cost of private, autonomous driving technology necessitates that taxi services, buses, and shared vehicles may first adopt AV technology. They are likely to be operated at substantially lower cost (by foregoing labor costs that constitute up to 50% of total costs), competing closely with private conventional cars (Bösch et al., 2018). Consequently, publicly owned SAVs could offer a more affordable service through subsidies and may aid in replacing a significant proportion of private conventional vehicles (Levin, 2017). Furthermore, SAVs could lower taxi fares by two-thirds and such a system could very much be cost-effective for fleet owners. An estimated19% return is expected based on an investment cost of US$70,000, operating cost of US$0.50 per mile for AVs only, and a fare of US$ 1 per person-trip mile (Fagnant and Kockelman., 2015). Other studies have corroborated these findings with estimated costs falling between US-$ 0.5 to $1 per mile (Becker et al., 2020; Bösch et al., 2018).

Implementing such solutions effectively hinges on enforcing wide-ranging policies on the transportation system (like special pricing strategies) and fleet operation parameters (like fleet sizing, and demand-responsiveness). Without these strategies, the benefits of SAVs could come at a huge cost of increased congestion through uncontrolled unoccupied or empty miles (eVMT). Levin (2017) formulated a linear program for a routing problem and found that larger fleets reduced waiting times since small fleets required more repositioning trips to reach travelers. However, these larger fleets resulted in an increase in average vehicle travel times due to increased congestion. Liu et al., (2017) used Austin's TAZ travel demand predictions to conclude that SAVs may travel more miles than private human-driven vehicles if the SAV fare rate is low enough (though not necessarily lower than the cost of using a human-driven vehicle). They also found that SAV eVMT may compromise the benefits of AV use. Fleet operational strategies involving multi-seat SAVs can allow multiple travelers to share rides or pool (also known as dynamic ridesharing, or DRS). Various studies have shown that DRS proves to be a part of the solution to rising congestion from large SAV demand by bundling travelers, especially if coupled with optimal routing algorithms (Fagnant and Kockelman, 2018; Bischoff and Maciejewski, 2016; Zhu et al., 2016). Consequently, DRS-enabled SAVs could greatly raise public willingness to pay for SAV services although wider uptake remains subject to individual preferences (Gurumurthy and Kockelman, 2020; Lavieri and Bhat, 2019; Zhang et al., 2015). Congestion pricing and other related schemes can also help decision-makers to investigate and resolve the negative impacts of congestion by lowering system VMT (Simoni et al., 2019).

SAVs could charge low fares but the possible added delays from detours and traveler pickup may not be desirable. Passengers sharing confined spaces with strangers may also add some discomfort. The sprawling nature of diffusely developed suburban neighborhoods in the U.S. has fostered longer travel times (on average) to the urban core (from a suburban home to a city's CBD, for example). Because of these limitations, shared vehicles and rides are likely to serve urban trips more efficiently and are unlikely to dominate suburban and rural travel, especially at the current ridesourcing levels. TNCs have been limited by geofences in some cities to curb congestion and reduce conflicts in pick-up and drop-off zones, but the impacts of such policy decisions have not been fully exhausted. There is a need to rigorously evaluate the effects of constraining large-scale fleet operation and to examine the impact of altering the size of the overall service area. This study uses a large-scale agent-based model, POLARIS to compare how SAV fleets perform under different geofencing decisions around the multi-centric Dallas-Fort Worth region, with and without DRS across adjacent downtowns and core neighborhoods, and attempts to formulate fleet size requirements for such regions. Key network metrics like mode shares, vehicle hours traveled (VHT), vehicle miles traveled (VMT), and fleet performance metrics like average vehicle occupancy (AVO), fleet and system VMT, and wait time distribution as a function of underlying land use form the bulk of the results. The remaining sections of the paper are structured as follows: the case study region used for analysis is detailed next, followed by an explanation of the simulation framework, and a description of the scenarios evaluated is presented. The results from these scenarios are discussed and the final section ends with conclusions.

CASE STUDY OF THE DALLAS-FORT WORTH NETWORK

Texas' Dallas-Fort Worth metroplex (DFW) provides a unique opportunity owing to its multi-centric spatial disposition. The region consists of 11 counties and houses nearly 8 million people. Dallas and Fort Worth, formerly separate cities, have merged due to urban sprawl, to encompass 30 miles of more than 150 cities and suburbs. DFW's road and transit network input data files were obtained from the North Central Texas Council of Governments (NCTCOG), including traffic analysis zones to create the supply, and available survey data for calibration. These disparate data sources were aggregated into the SQLite databases using QGIS and a POLARIS plugin for QGIS that helped edit and refine the data resulting in consistent and functional network parameters across 5352 traffic analysis zones. Roadway network data from 2018 consisted of 42,527 road links and 28,421 nodes. Overall, the region spans 9,286 sq. mi, with about 25 million person-trips made across the 600,000 households present in the 11 counties. Calibration for mode shares, destination choice, activity start time and duration choice were all done using an automated script that sourced data from the National Household Travel Survey (NHTS) data for the region. Figure 1 below shows the road network along with the five most populated city limits highlighted.

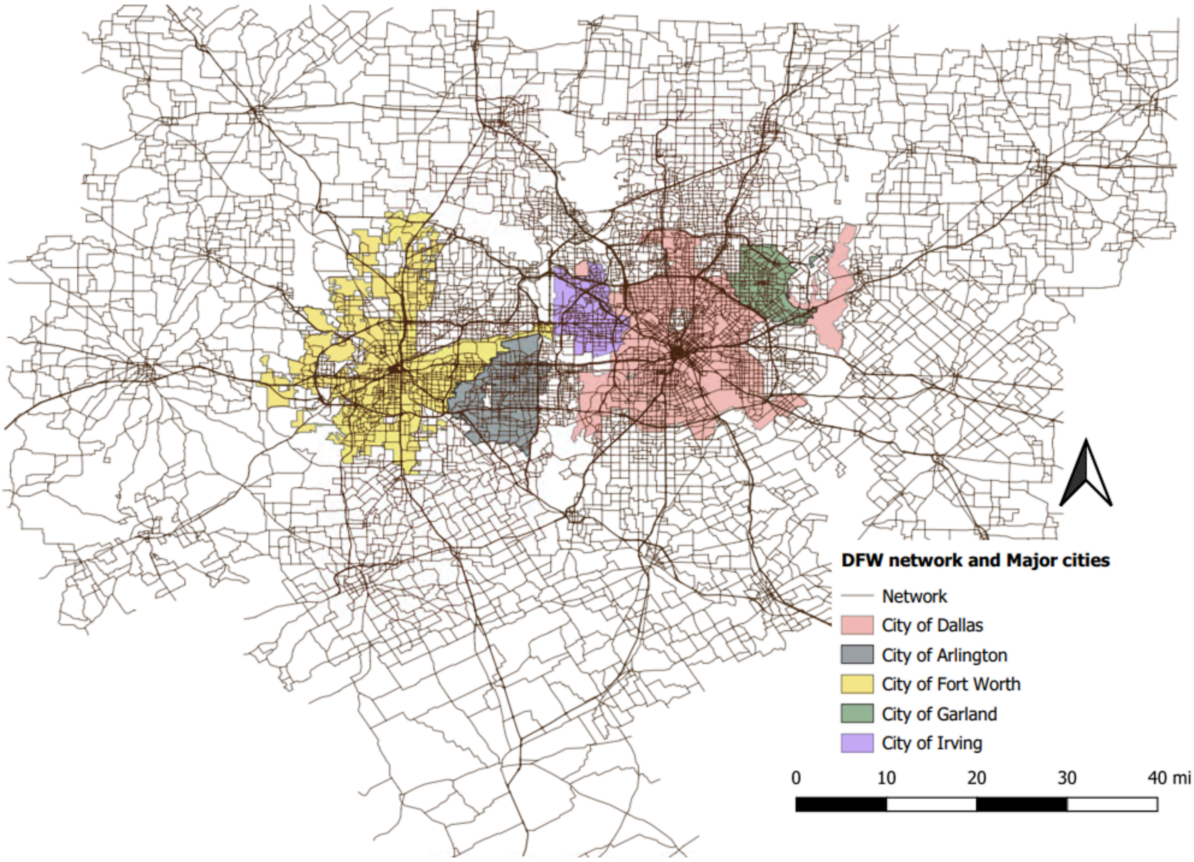

Figure 1: Detailed network of the 12-county multicentric DFW region and major cities.

SIMULATION FRAMEWORK

The agent-based activity-based travel demand simulator called POLARIS (Auld et al., 2016) is used to simulate SAV fleet operations (Gurumurthy et al., 2020) in the Dallas-Forth Worth region. Agent-based models provide the advantage of modeling each individual passenger and vehicle with tailored behavior, and allows complex interactions, which provides an approximation of travel behavior in the transportation systems (Zhao and Malikopoulos, 2022). The framework utilizes travel demand models to simulate agents' daily weekday activities. This requires the generation of synthetic populations during a model initialization stage, followed by calibration and network validation. The appendix contains further details on the three processes mentioned in building this framework. The population synthesizer module is based on an iterative fitting approach using household-level attributes and person control variables to correct the assumption of independent individual probabilities (Beckman et al., 1996). The module creates a representative set of travelers for the region, and a series of core behavioral models, which are calibrated using NHTS data, are used to create the daily activities and travel itineraries for each agent. These itineraries are run according to a non-compete hazard formulation while traveler trip purposes are produced by a competing hazard formulation (Auld et al., 2011). Consequently, the activity and travel history for each agent is updated to inform the core models of each individual's flexible travel choices in order to create a schedule of traveler activities as well as the necessary attributes of each activity, leveraging the ADAPTS model (Auld and Mohammadian, 2012). The core models informed by traveler choices include a nested logit mode choice model, multinomial logit destination choice model, and a hybrid random-utility random-regret minimization model for departure-time. A time-dependent dynamic traffic assignment method is then used to route individual vehicles according to traffic conditions while skim travel times and link-level congestion are reflected through a mesoscopic traffic flow model based on the link transmission model. (Auld et al., 2019; Verbas et al., 2018). Scheduled activity start times and durations of activities are subjected to a conflict analyzer to avoid conflicts and competition of activities that could lead to travel delays.

Travel Demand

The region's population was sampled at 25% and used to calibrate the travel demand for the region. Mode choice, destination choice, and activity timing choices constrained when and where travelers may choose the SAV mode. Additionally, parameters in the mode choice model also imposed constraints on expected SAV fare and wait time for a given origin-destination pair. The choice constants in each model are adjusted iteratively after each calibration run, based on the difference between the observed and simulated distributions of the respective choices. If less of a given choice (e.g., TNC mode) is obtained from the simulation than in the observed distribution, the alternative constant for that choice is increased in the next run. Like TNCs, the SAV fare comprises a fixed cost per trip (base fare), a distance-varying component (priced by mile), and a time-varying component (priced by minute). The simulation used averages of $1.00 base fare and $0.50 per mile to simplify the analyses based on previous studies (Bösch et al., 2018; Fagnant and Kockelman, 2018; Richter et al., 2021). On calibration, only trips that satisfied all above constraints were available in the final travel demand and included all modes. These trips were then processed to simulate all non-SAV trips as fixed background traffic (i.e., having fixed origin and destination, but still responding to congestion when finding a route and traversing the network). On the other hand, SAV trips were subject to constraints imposed by the SAV module, such as vehicle availability in the vicinity of a trip request, geofence applied that limits SAV operation, and maximum allowable wait time to be served.

SAV Operations

SAV functionality in POLARIS was extended from Gurumurthy et al., (2021) and used in this study. SAV operations were limited within the extent of a spatial geofence and all analyses had SAVs operating in a realistic traffic environment with time-dependent background traffic from synthesized travel demand mentioned in the previous subsection. Travel demand was retrieved after calibration and processed to form fixed demand for simulation runs in this study. A centralized operator managed trip assignment for the SAV system, where the ridesharing option is evaluated to provide an appropriate match. Vehicle assignment followed zone-based architectures which matched ride requests to SAVs in the same or nearby zones (Gurumurthy et al., 2020). Willingness to travel is partly affected by TNC fares in the mode choice but does not contribute to choosing to use an SAV in the scenarios studied. Travelers who choose to share rides are catered for in the model through the DRS algorithm that employs a heuristic to manage travel delays experienced at several stages of the trip as elaborated upon in Gurumurthy and Kockelman (2022). Several fleet sizes of 1 SAV for every 10, 50, 100 and 200 residents in each spatial boundary served are considered, with and without DRS. Fleet sizing is essential to identify a practical size with the fewest vehicles able to serve the most person-trips possible while adhering to TNC-specific level of service variables.

Geofences

The DFW region is vast and consists of several city centres, and land use and trip densities vary drastically from downtown areas to suburban regions. Fagnant and Kockelman, (2018) argued that scaling a fleet to serve increased trip demands over a geofence may generate economies of density in trip matching, reducing overall VMT and the share of empty VMT. Only trips originating and ending geographically within the enforced geofence will be served by SAVs. Trips outside the geofences are assumed to rely on alternative modes. The geofenced region restricts initial SAV operations to areas with high trip density, high population density, or high job density and extends out to suburban neighborhoods – which would be most suitable for SAV operation, in terms of both lower traveler wait times and less unoccupied SAV travel (as SAVs navigate between one traveler drop-off to the next traveler pick-up). The geofences are simultaneously allowed and are restricted to the four counties including their major suburbs in the metropolitan region with the highest population and consequently trip densities to reflect the initial expectation. The four chosen geofence boundaries are that of: Dallas County comprising of the Cities of Dallas, Garland, and Irving; Tarrant County comprises of the Cities of Fort Worth and Arlington; Denton County has City of Denton, and, finally, Collin County contains City of Plano. **Table 1** shows areas of different geofences while **Figure 2** shows the extent of the geofence service areas.

Table 1: Areas of geofences

Geofence boundary	Area (sq miles)
Total Area	10487
City of Dallas	347
City of Fort Worth	282
City of Denton	172
City of Plano	250
Dallas County	909
Tarrant County	898
Collin County	858
Denton County	899

SCENARIO VARIATIONS

Two geofence scenarios were compared to a baseline no-fence situation, and each of these scenarios were tested with varying fleet sizes of 1 SAV for every 10, 50, 100, and 200 residents, with and without DRS. In each scenario, the operator distributes the vehicles depending on the population density of the spatial boundary simultaneously within four specified geofence service areas at the county and suburban levels. Movement outside the spatial boundaries does not have the option to choose an SAV and occurs with alternative modes. Owing to the scarcity of real data on travel patterns, it becomes difficult to estimate a mode choice model for SAVs while taxis and ride-sourcing vehicles (which essentially operate like SAVs) are underrepresented in the NHTS data. Mode choice alternative specific constants were, therefore, scaled up to depict a 7% mode share compared to the initial 0.3% obtained from travel survey data. This assumption is based on previous studies that have shown that large proportions of the population could switch from car to AV, leading to a decrease in the availability of privately owned vehicles up to 60% (Simoni et al., 2019).

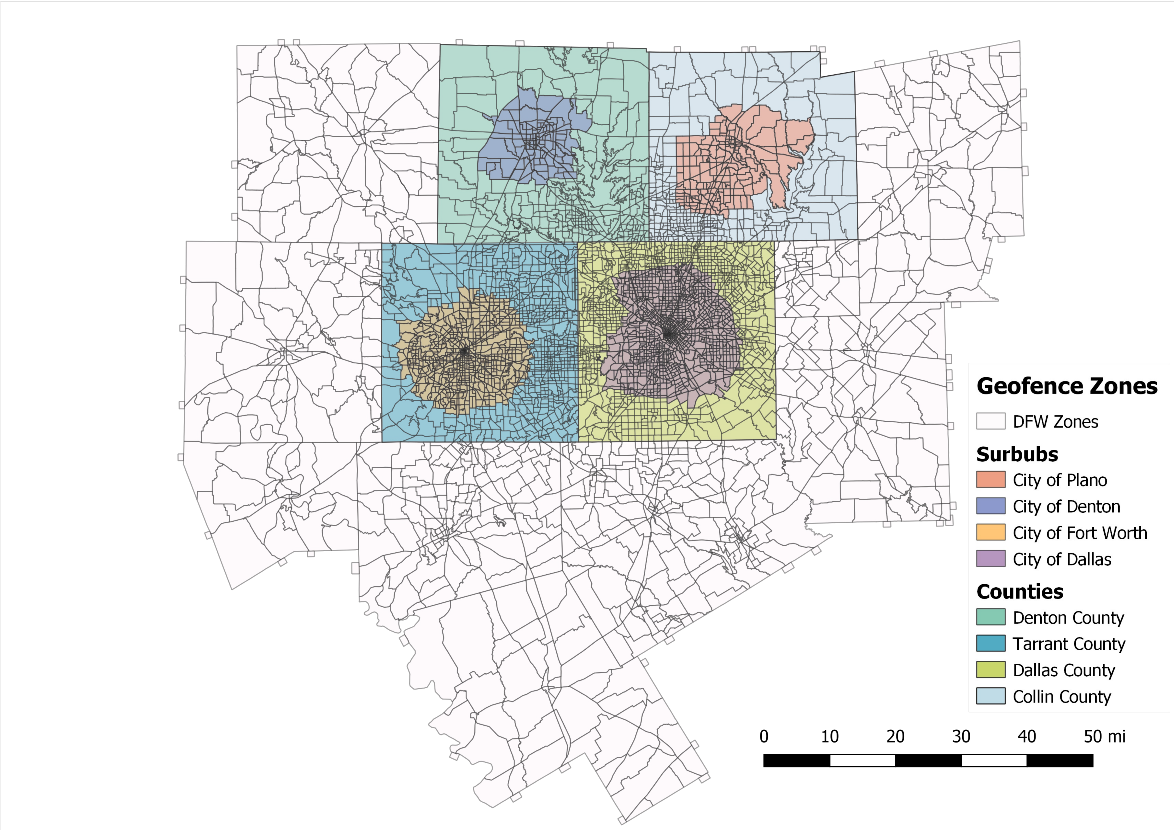

Figure 2: Extent of geofences

Table 2: Baseline Fleet performance indicators under different fleet sizes

DRS	Fleet size	Avg peak hour Wait Time (minutes)	%eVMT	Avg daily trip length (miles/trip/day)	Avg daily VMT per SAV (miles/SAV/day)	Avg daily person trips per SAV	Avg % daily idle time per SAV	Revenue Trip weighted AVO	Revenue Distance weighted AVO	Served trip density (persons per sq mile)	Share of trips made by SAVs (%)
YES	1 SAV every 10 persons	3.0	10.9	6.6	33.7	1.5	95.5	1.08	1.06	105.8	5.1
	1 SAV every 50 persons	4.6	15.6	6.1	89.8	7.2	88.6	1.20	1.14	103.3	5.0
	1 SAV every 100 persons	5.7	17.7	5.8	129.2	14.1	83.7	1.28	1.19	98.7	4.9
	1 SAV every 200 persons	6.5	19.4	5.5	213.7	27.3	73.6	1.32	1.22	93.8	4.7
NO	1 SAV every 10 persons	2.7	11.9	7.1	34.3	1.5	95.5	1.0	1.0	105.7	5.1
	1 SAV every 50 persons	5.1	20.8	6.9	96.6	7.1	87.2			100.3	4.9
	1 SAV every 100 persons	6.5	23.2	6.8	135.8	13.6	82.3			93.8	4.7
	1 SAV every 200 persons	8.7	26.1	6.7	236.8	26.4	69.0			88.9	4.6

Table 3: Geofence fleet performance metrics for the Four **suburbs** scenario, DRS

Geofence Service Area	Fleet size,	Avg peak hour Wait Time (minutes)	%eVMT	Avg Daily trip length (miles/trip /day)	Avg daily VMT per SAV (miles/SAV /day)	Avg daily person trips per SAV	Avg % daily idle time per SAV	Revenue trip weighted AVO	Revenue Distance weighted AVO	Served trip density (persons per sq mile)
City of Dallas	1 SAV every 10 persons	2.2	13.1	3.9	22.6	1.8	96.9	1.09	1.07	155.6
	1 SAV every 50 persons	3.5	25.6	3.6	56.5	8.7	92.1	1.21	1.17	153.1
	1 SAV every 100 persons	4.6	21.9	3.6	92.8	17.6	87	1.24	1.19	154.6
	1 SAV every 200 persons	4.9	23.8	3.4	163.8	32.2	77.6	1.27	1.21	140.9
City of Fort Worth	1 SAV every 10 persons	2.5	16.9	3.9	29	1.5	96.1	1.14	1.11	115.8
	1 SAV every 50 persons	3.7	27.9	3.6	60.9	7.5	91.9	1.24	1.19	114.7
	1 SAV every 100 persons	4.6	22.8	3.6	86.1	15.1	88.4	1.26	1.21	114.6

Geofence Service Area	Fleet size,	Avg peak hour Wait Time (minutes)	%eVMT	Avg Daily trip length (miles/trip /day)	Avg daily VMT per SAV (miles/SAV /day)	Avg daily person trips per SAV	Avg % daily idle time per SAV	Revenue trip weighted AVO	Revenue Distance weighted AVO	Served trip density (persons per sq mile)
	1 SAV every 200 persons	4.8	24.5	3.5	143	27	81	1.29	1.22	102.0
City of Denton	1 SAV every 10 persons	2.3	21.6	3.2	13.4	1.5	98.3	1.05	1.04	37.1
	1 SAV every 50 persons	2.8	25.9	2.5	36.7	7.6	95.3	1.03	1.06	37.6
	1 SAV every 100 persons	2.9	27.1	3.1	64.5	15	91.2	1.11	1.08	37.1
	1 SAV every 200 persons	3.6	29.9	3.9	124.3	26	84.2	1.17	1.12	32.2
City of Plano	1 SAV every 10 persons	2.7	21.3	3.8	12.2	0.4	98.3	1.03	1.02	17.6
	1 SAV every 50 persons	2.8	22.5	3.1	19.6	1.9	97.2	1.08	1.03	17.8
	1 SAV every 100 persons	2.8	24.5	3.7	27.7	3.9	96.3	1.03	1.03	17.6

Geofence Service Area	Fleet size,	Avg peak hour Wait Time (minutes)	%eVMT	Avg Daily trip length (miles/trip /day)	Avg daily VMT per SAV (miles/SAV /day)	Avg daily person trips per SAV	Avg % daily idle time per SAV	Revenue trip weighted AVO	Revenue Distance weighted AVO	Served trip density (persons per sq mile)
	1 SAV every 200 persons	3.8	25.2	3.1	32.6	5.2	95.3	1.03	1.02	12.0

Table 4: Geofence fleet performance metrics for the Four suburbs scenario, NO-DRS

Geofence Service Area	Fleet size,	Avg peak hour Wait Time (minutes)	%eVMT	Avg Daily trip length (miles/trip /day)	Avg daily VMT per SAV (miles/SAV /day)	Avg daily person trips per SAV	Avg % daily idle time per SAV	Revenue trip weighted AVO	Revenue Distance weighted AVO	Served trip density (persons per sq mile)
City of Dallas	1 SAV every 10 persons	2.0	15.9	4.2	23.7	1.8	96.7	1	1	153.8
	1 SAV every 50 persons	4.1	26.8	4.2	63.3	8.7	91.1			153.1
	1 SAV every 100 persons	4.7	28.3	4.2	106.4	17.3	85.3			151.9
	1 SAV every 200 persons	5.3	30.2	4.1	192	32.5	72.7			142.4

Geofence Service Area	Fleet size,	Avg peak hour Wait Time (minutes)	%eVMT	Avg Daily trip length (miles/trip /day)	Avg daily VMT per SAV (miles/SAV /day)	Avg daily person trips per SAV	Avg % daily idle time per SAV	Revenue trip weighted AVO	Revenue Distance weighted AVO	Served trip density (persons per sq mile)
City of Fort Worth	1 SAV every 10 persons	2.7	21.5	4.3	32.2	1.5	95.6	1	1	115.6
	1 SAV every 50 persons	4	29	4.3	68	7.7	91			116.4
	1 SAV every 100 persons	4.7	29.8	4.3	101.4	15.3	86.6			115.4
	1 SAV every 200 persons	4.9	31.2	4.2	163.9	27.1	78.3			102.6
City of Denton	1 SAV every 10 persons	2.4	21.8	3.4	13.5	1.5	98.3	1	1	37.1
	1 SAV every 50 persons	2.7	26.6	3.3	37.2	2	95.3			36.7
	1 SAV every 100 persons	3	29	3.3	70.4	14.9	91.1			36.8
	1 SAV every 200 persons	3.5	32.9	3.3	133.6	26.9	82.7			33.3

Geofence Service Area	**Fleet size,**	**Avg peak hour Wait Time (minutes)**	**%eVMT**	**Avg Daily trip length (miles/trip /day)**	**Avg daily VMT per SAV (miles/SAV /day)**	**Avg daily person trips per SAV**	**Avg % daily idle time per SAV**	**Revenue trip weighted AVO**	**Revenue Distance weighted AVO**	**Served trip density (persons per sq mile)**
City of Plano	1 SAV every 10 persons	2.7	21.9	3.9	12.1	0.4	98.3	1	1	17.8
	1 SAV every 50 persons	2.9	23.7	3.8	19.9	7.4	97.3			18.2
	1 SAV every 100 persons	3	25.7	3.8	28.6	3.9	96.2			18.1
	1 SAV every 200 persons	3.2	27.1	3.9	33.7	5.1	95.1			11.6

Table 5: Geofence fleet performance metrics for the Four **county** scenario, DRS

Geofence Service Area	Fleet size,	Avg peak hour Wait Time (minutes)	%eVMT	Avg Daily trip length (miles/trip /day)	Avg daily VMT per SAV (miles/SAV /day)	Avg daily person trips per SAV	Avg % daily idle time per SAV	Revenue trip weighted AVO	Revenue Distance weighted AVO	Served trip density (persons per sq mile)
Dallas County	1 SAV every 10 persons	2.1	11	4.7	22.5	1.4	97	1.05	1.04	99.3
	1 SAV every 50 persons	3.17	18.3	4.4	60.5	6.9	92	1.18	1.13	98.8
	1 SAV every 100 persons	4.14	21.1	4.2	96.4	13.8	87.4	1.22	1.17	98.0
	1 SAV every 200 persons	5.05	23.4	4.1	150.4	24.6	80.2	1.26	1.19	87.3
Tarrant County	1 SAV every 10 persons	2.31	13.8	4.6	23.3	0.96	97	1.07	1.06	54.5
	1 SAV every 50 persons	3.2	20	4.3	59.4	4.8	92.4	1.18	1.14	54.5
	1 SAV every 100 persons	4.24	23.5	4.2	86	9.6	89	1.24	1.19	54.7
	1 SAV every 200 persons	4.83	25.3	4.1	110	15.7	86	1.26	1.2	44.7
Denton County	1 SAV every 10 persons	3.74	18.9	5	17.4	0.71	97.7	1.05	1.04	17.3
	1 SAV every 50 persons	4.15	20.4	4.9	31.6	3.5	95.9	1.07	1.06	17.3
	1 SAV every 100 persons	4.48	21.7	4.9	52.4	7.1	93.2	1.09	1.07	17.3
	1 SAV every 200 persons	4.38	23.5	4.9	84.5	11.9	89	1.12	1.09	14.5

Geofence Service Area	Fleet size,	Avg peak hour Wait Time (minutes)	%eVMT	Avg Daily trip length (miles/trip /day)	Avg daily VMT per SAV (miles/SAV /day)	Avg daily person trips per SAV	Avg % daily idle time per SAV	Revenue trip weighted AVO	Revenue Distance weighted AVO	Served trip density (persons per sq mile)
Collin County	1 SAV every 10 persons	2.8	18.4	4.2	13.2	0.54	98	1.02	1.02	16.0
	1 SAV every 50 persons	3.25	20.1	4.2	22.7	2.6	96.7	1.03	1.02	15.6
	1 SAV every 100 persons	3.52	22.1	4.2	35.9	5.2	94.8	1.04	1.03	15.7
	1 SAV every 200 persons	5.01	22.9	4.3	49.3	7.8	92.6	1.04	1.03	11.6

Table 6: Geofence fleet performance metrics for the Four **county** scenario, NO DRS

<table>
<tr><th>Geofence Service Area</th><th>Fleet size,</th><th>Avg peak hour Wait Time (minutes)</th><th>%eVMT</th><th>Avg Daily trip length (miles/trip /day)</th><th>Avg daily VMT per SAV (miles/SAV /day)</th><th>Avg daily person trips per SAV</th><th>Avg % daily idle time per SAV</th><th>Revenue trip weighted AVO</th><th>Revenue Distance weighted AVO</th><th>Served trip density (persons per sq mile)</th></tr>
<tr><td rowspan="2">Dallas County</td><td>1 SAV every 10 persons</td><td>1.9</td><td>11.7</td><td>4.9</td><td>22.7</td><td>1.4</td><td>96.9</td><td rowspan="2">1</td><td rowspan="2">1</td><td>99.0</td></tr>
<tr><td>1 SAV every 50 persons</td><td>3.7</td><td>23.9</td><td>4.9</td><td>67.2</td><td>6.9</td><td>90.9</td><td>98.1</td></tr>
</table>

Geofence Service Area	**Fleet size,**	**Avg peak hour Wait Time (minutes)**	**%eVMT**	**Avg Daily trip length (miles/trip /day)**	**Avg daily VMT per SAV (miles/SAV /day)**	**Avg daily person trips per SAV**	**Avg % daily idle time per SAV**	**Revenue trip weighted AVO**	**Revenue Distance weighted AVO**	**Served trip density (persons per sq mile)**
	1 SAV every 100 persons	4.8	27.6	4.9	107	13.8	85.7			97.7
	1 SAV every 200 persons	5.5	29.3	4.9	167.7	24.2	77.9			85.4
Tarrant County	1 SAV every 10 persons	2.3	15.4	4.9	24.2	0.96	96.7	1	1	54.8
	1 SAV every 50 persons	3.5	27.1	4.9	68.8	4.8	91.2			54.8
	1 SAV every 100 persons	4.8	31.4	4.9	99.5	9.5	87.3			53.8
	1 SAV every 200 persons	5.4	32.3	4.9	126.6	15.6	83.9			43.9
Denton County	1 SAV every 10 persons	4.8	20	5.2	17.1	0.71	97.5	1	1	17.6
	1 SAV every 50 persons	4.4	21.2	5.3	32.3	3.6	95.7			17.3

Geofence Service Area	**Fleet size,**	**Avg peak hour Wait Time (minutes)**	**%eVMT**	**Avg Daily trip length (miles/trip /day)**	**Avg daily VMT per SAV (miles/SAV /day)**	**Avg daily person trips per SAV**	**Avg % daily idle time per SAV**	**Revenue trip weighted AVO**	**Revenue Distance weighted AVO**	**Served trip density (persons per sq mile)**
	1 SAV every 100 persons	4.2	23.1	5.2	54.4	7.2	93			17.3
	1 SAV every 200 persons	5.2	25.1	5.3	85.7	11.8	88.8			14.2
Collin County	1 SAV every 10 persons	2.7	19.1	4.3	13.2	0.53	98	1	1	15.8
	1 SAV every 50 persons	3.1	20.7	4.2	23.2	2.6	96.5			15.7
	1 SAV every 100 persons	3.3	23.4	4.2	36.3	5.2	94.7			15.5
	1 SAV every 200 persons	4	24.8	4.3	48	7.7	92.7			11.6

RESULTS

This study simulated 25% of the DFW region's 25 million daily person-trips and 7% SAV mode shares in the 11-county DFW region under fixed fleet-based DRS and non-DRS scenarios to better understand system performance. Varying fleet sizes using artificial SAV mode shares helped understand regional impacts on traveler wait time, response time, total VMT, empty VMT, and the fleet's average vehicle occupancy (AVO), while also varying geofences as shown in Table 2 to Table 6.

Figure 3 shows that the use of DRS lowers eVMT by about 5% compared to the absence of pooling, and %eVMT was moderately higher for the 1:200 fleet than the 1:10 fleet, largely due to intensity of operation for the former and high vehicle idling for the latter. Contrary to Gurumurthy et al.'s geofence study, %eVMT also rose with multiple simultaneous geofences, from 16% without a fence to between 20.5% and 23.0% in the DRS-enabled scenarios for the county and city core scenarios, respectively. The difference may be arising from the trip distribution differences in single- and multi-centric regions. The 1:10 fleet shows a 3% higher eVMT with a county-level geofence, while its lower (only 2%) between the county-level and city-level geofences. Similarly, smaller fleets show a 5% increase in eVMT comparing county-level fences to the absence of a fence, and a 3% increase between the county and city fences. This could be due to the lower SAV demand served when considering only four county or city-level fences, with previous studies only showing a reduction in eVMT as trip densities increased (Gurumurthy et al., 2021). DRS by itself did not have a substantial effect on reducing eVMT in both geofence scenarios owing to the markedly low demand within a geofence.

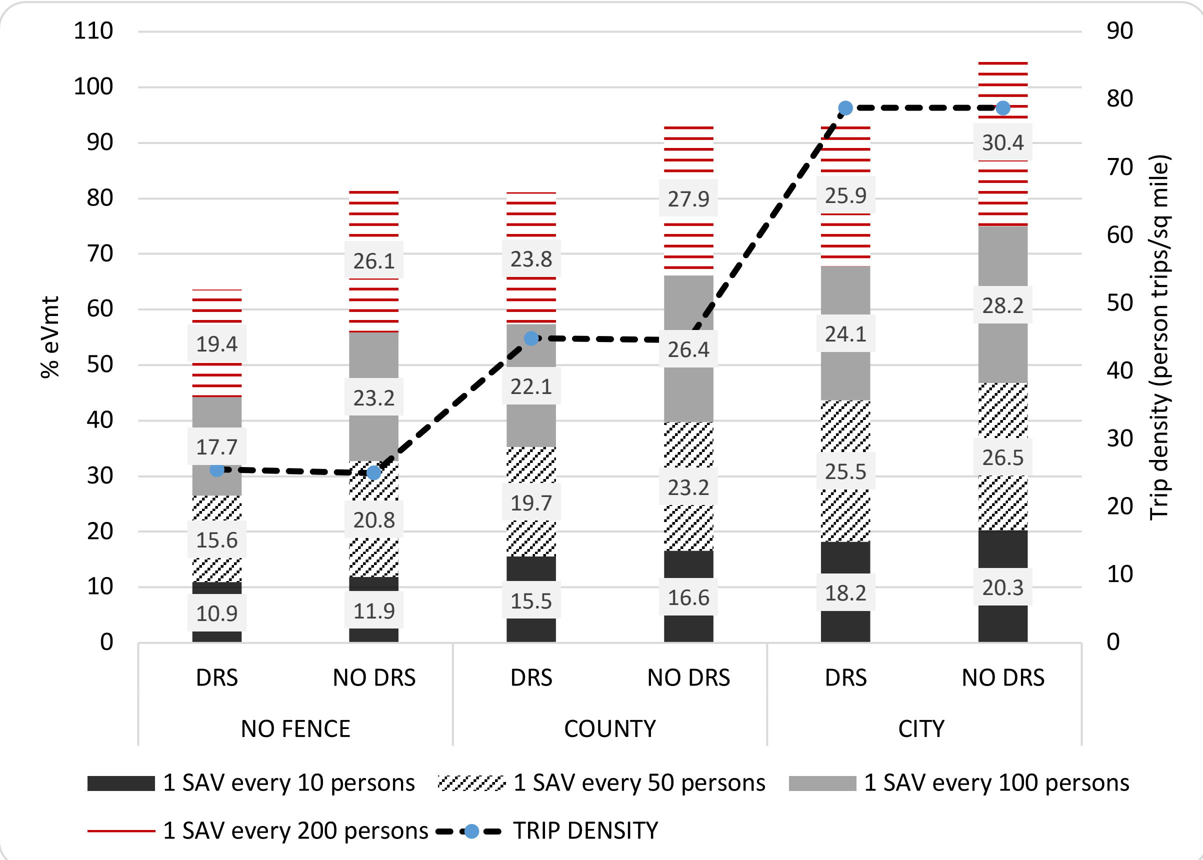

Figure 3: Effect of geofencing on percent eVMT and trip density

A 1% decline in SAV VMT for the1:10 fleets and a 10% increase in SAV VMT for 1:200 fleets is observed as the area of operation reduces from county to the denser city limits. Figure 4 illustrates that the average daily SAV VMT is reduced by 53% for 1:200 fleets and by 45% for 1:10 fleets with the introduction of geofences at the county and city regions with respect to the base case. DRS saves more VMT when there's no fence used, owing likely to the availability of sufficient trip request demand. The no-DRS case follows a similar trend with a VMT reduction 50%. Idle time increased by 6% when geofencing was applied from 85-92% but remained relatively constant within the county and denser city service areas, indicating higher fleet utilization without a fence. Assuming fixed fleet ratios for different geofences create an imbalance in trip requests to vehicles available, creating deficits and surpluses in vehicles needed depending on the extent of demand in the geofence. Idle times are high even with 1:200 fleets, prompting the question of whether larger capacity SAVs (but fewer in operation) would make sense for such geofenced regions. A combination of strategies may be required to increase fleet utilization while fulfilling desired levels of service.

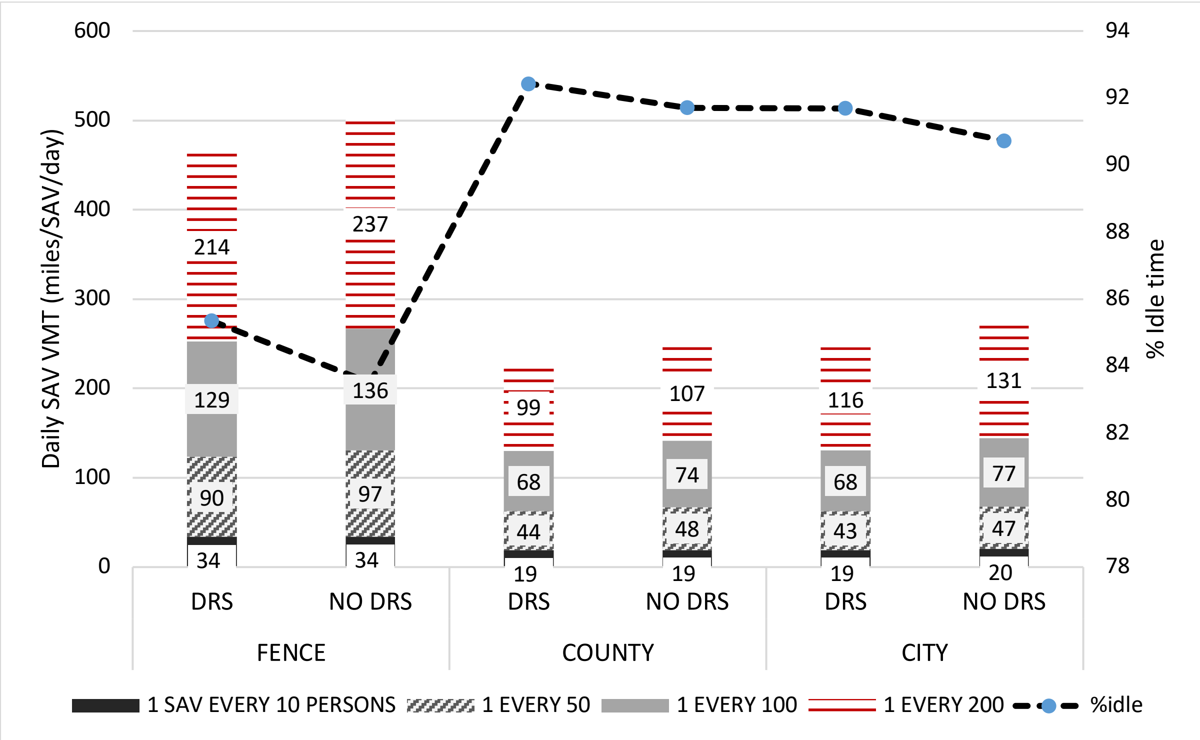

Figure 4: Effect of geofencing on SAV VMT and idle time

Figure 5 reveals a maximum of only 1% reduction in system VMT across all scenarios arising primarily with DRS and when geofences are bounding core cities in the mutli-centric region. The low magnitude difference can be attributed to the low mode share when dissecting artificial SAV demand by geofence. Higher percentages of SAV demand dissected by geofence may provide better benefits. This also follows from a pattern of diminishing VMT across geofence scenarios, with increased trip shareability as demand of shared trips lowers. Travelers could face delays when sharing rides if the system and or fleet VMT lessen unless demand remains above a specific threshold. While an average SAV is expected to serve about 30 person-trips per day (Fagnant et al., 2015), a maximum of 25.0 and 32.2 person-trips per SAV per day were observed in the county and city geofence scenarios, respectively, when employing the 1:200

sized fleet. Moreover, SAVs inevitably contribute to eVMT due to traveling between drop-off of one trip and the pick-up for the next trip, or when operating with little to no demand (Gurumurthy and Kockelman, 2022; Simoni et al., 2019).

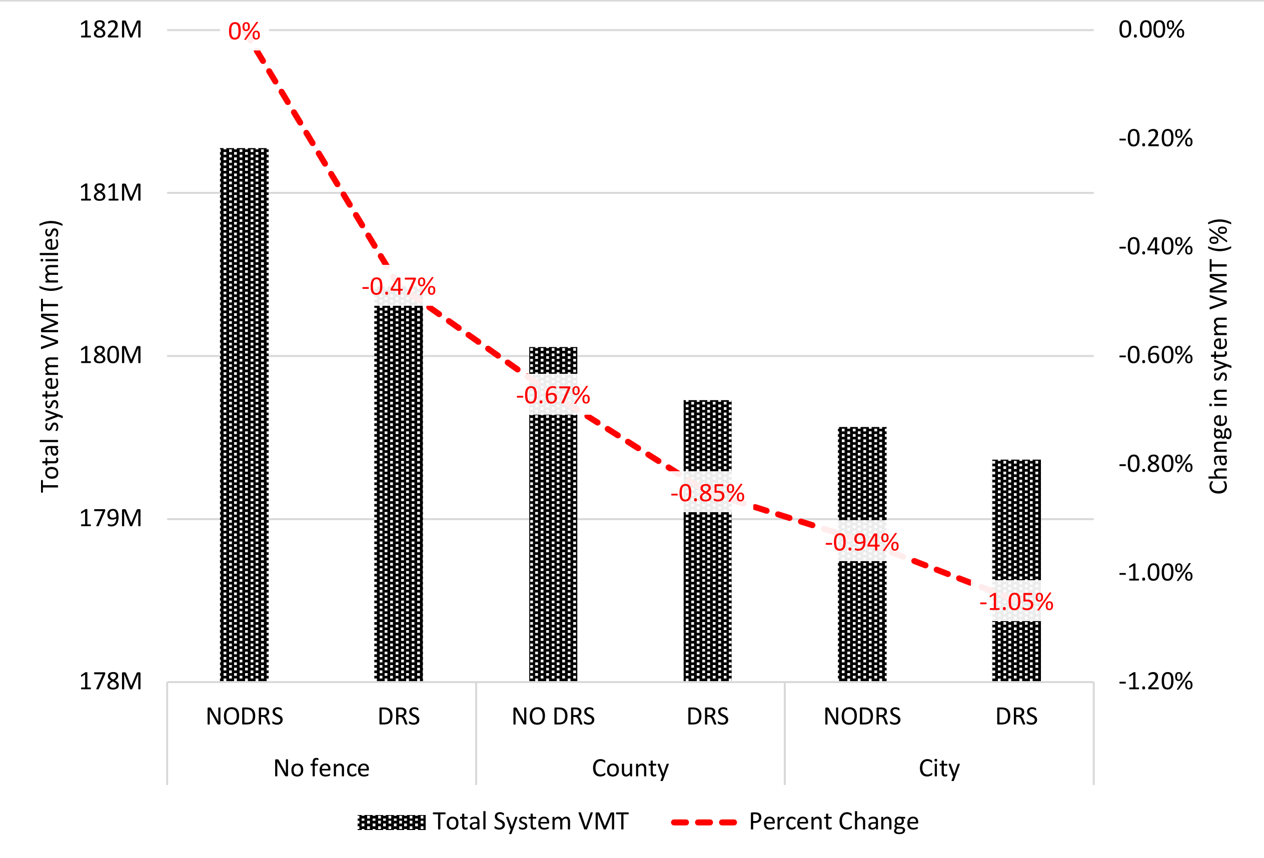

Figure 5: Effect of DRS and geofencing on system VMT

Small fleet sizes increase wait time considerably, as expected, and limit the number of people that are served within an acceptable wait time. Figure 6 illustrates the distribution of peak hour average wait times and AVO across the two scenarios. High wait times can also drive the demand for SAVs down which affects AVO. AVO values are higher in the base case compared to the two geofence scenarios due to higher demand, although this does not concur with the expected corollary of the impact of low trip density in large areas. AVO is generally higher in smaller fleet sizes and reduces more slightly with the addition of geofences while larger fleets seem to have a marginal change in AVO. Average passenger wait times increase by 3.5 minutes across the largest to the smallest fleet in the base case with DRS while the increase is considerably higher at 6 minutes without DRS. Geofencing lowers these differences in wait time across fleet sizes to under 2 minutes regardless of DRS.

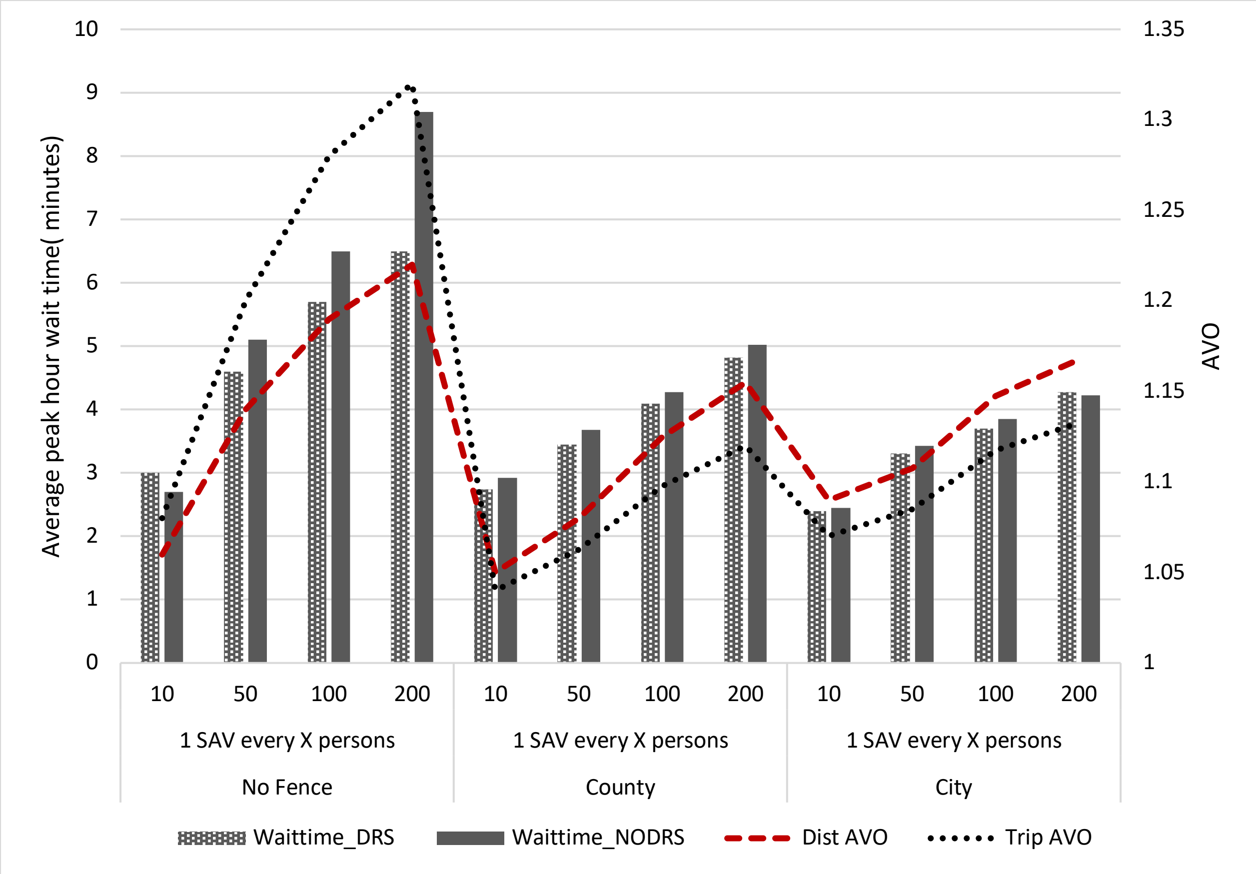

Figure 6: Effect of geofencing on wait time and AVO

CONCLUDING REMARKS.

This study simulated travel in the multi-centric DFW region and provides results on the effect of multiple simultaneous geofences used to constrain fleet operation under potentially high demand-density areas. Results suggest that geofencing in the manner described reduced system VMT by up to 1%, mainly due to the curtailment of longer-than-average trip lengths between geofence regions. Shared rides also decreased as the area of operation diminished owing to lower absolute demand. Such a region is certain to generate high VMT due to various sprawling neighborhoods that are accessible and close to multiple cities. Moreover, these relatively sizable multiple cities with high trip densitites present a unique opportunity to study SAV behavior across a large region analogous to TNCs like Uber and Lyft, under different policies. Varying fleet sizes under multiple geofence scenarios also revealed that peak hour average wait times were reduced to under 5 minutes from over 7 minutes within each geofence scenario, which could facilitate accommodating more person-trips if there were such demand. The functional transit and rail system of the area serving the major cities of Dallas and Fort Worth has fostered quicker access to the outskirts of congested cities, making it ideal for future SAV minibus operations. While shorter trips lower travel times, it also means that relocation and unoccupied travel could comprise a greater share of the total VMT. Idle time was also shown to increase by 7% from 85 to 92% when geofencing was enforced even with larger fleet sizes. The efficacy of fleet sizing can reveal itself if other factors are taken into consideration, like different pricing strategies for trips to encourage more ride sharing.

Limitations and Future Work

Some limitations were encountered in this study setup, such as the assumption on mode share, which can be improved. The assumption of only 7% SAV mode share can be modified through a series of sensitivity tests, to understand if benefits are higher demands. Similarly, geofences covering the entire region may be useful, such that all demand has access to an SAV (either a single or dual-compartment seater for intra-zonal travel, or a higher-capacity minibus for inter-zonal travel). Identifying more ways to accommodate all travel, while limiting %eVMT is key to realizing greater system benefits. The unlikely increase in eVMT with the geofencing scenarios could be because we did not cover all demand in the region while assuming the same fleet size for all the geofence service areas. Detour times by zones with lower trip density could be adjusted to reflect demand in the region to account for eVMT.

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APPENDIX

POLARIS Model Calibration