How Does Network Complexity Impact SAV Fleet Operations? Comparing Complete and Incomplete Networks

Kentaro Mori
Graduate Research Assistant
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
mori@utexas.edu

Fatemeh Fakhrmoosavi, Ph.D.
Assistant Professor
Department of Civil and Environmental Engineering
University of Connecticut
moosavi@uconn.edu

Krishna Murthy Gurumurthy, Ph.D.
Argonne National Laboratory, Energy Transportation and Power Systems Division
9700 S. Cass Avenue
Lemont, IL 60439
kgurumurthy@anl.gov

Kara M. Kockelman, Ph.D., P.E. (corresponding author)
Dewitt Greer Centennial Professor in Engineering
Department of Civil, Architectural, and Environmental Engineering
The University of Texas at Austin
kkockelm@mail.utexas.edu
Tel: 512-471-0210

Pedro Camargo, Ph.D.
Argonne National Laboratory, Transportation and Power Systems Division
9700 S. Cass Avenue, Lemont, IL 60439
pveigadecamargo@anl.gov

Word Count: 5653 words + 2 tables (250 words per table) = 6153 words

Submitted for presentation at the 103rd Transportation Research Board Annual Meeting

Submitted [08/01/23]

ABSTRACT
Agent-based activity-based transportation models have been increasingly used to simulate shared autonomous vehicle (SAV) fleet operations. Through these studies, the transportation research community is beginning to form a collective understanding of the operations, potential impacts, and opportunities of SAVs. However, these studies have been conducted under the premise of a variety of assumptions and simplifications, which, without properly appreciating the implications, can jeopardize our conclusions and weaken our collective understanding. This paper focuses on the issue of network complexity, as a majority of studies are conducted on simplified networks with missing links. Although relevant in all travel demand modeling studies, this issue is especially pertinent for SAVs, a door-to-door service whose success is highly affected by the concentration of travel demand. Using a simplified network locally omits first and last mile travel and aggregates origins and destinations, optimistically biasing SAV simulation results. To this end, we compare SAV fleet operations in Austin using two networks: Austin 6-county region's network from the Capital Area Metropolitan Planning Organization (CAMPO) and a network obtained from OpenStreetMap (OSM). The CAMPO network contains approximately 46% and 42% of lane-miles and road-miles, respectively, of the OSM network. The results indicate that network complexity influences the determination of the minimum SAV fleet size. For a 5000-fleet size across Austin, daily vehicle-miles traveled increased by approximately 23.83%, the percentage of empty vehicle-miles travelled rose by 10.5 percent-points, and the median wait time nearly doubled. Consequently, this study suggests utilizing a complete network for simulating SAVs, whenever feasible.

Keywords: Transportation Network Simplification, Shared Autonomous Vehicle Simulations, Agent-based Modeling, Spatial Aggregation

INTRODUCTION

The shape of transportation to come represents an open frontier, characterized by the emergence of innovative solutions enabled by information technologies and vehicle automation, as well as the growing interest in sustainability and people-centric planning *(1–4)*. In an effort to capture the complex interactions of emerging transportation systems, researchers have turned to agent-based modeling. In particular, the ability to simulate activity-based travel and operations of emerging mobility services has been highly valued. Some current agent-based modeling tools that were developed specifically for transport applications include MATSim *(5)*, POLARIS *(6)*, and SimMobility *(7)*. Advancements in these tools' capabilities and improvements in computer performance have enabled researchers to conduct simulations with unprecedented levels of detail and scale, previously unattainable (e.g., 30M+ trips per 24-hr simulated day across realistic networks with endogenous mode and route choices, mesoscopic traffic assignment features, and congestion feedbacks *(8)*).

One specific application of these tools that has garnered much attention is scenario analyses involving shared and fully automated or "autonomous" vehicles (SAVs). Along with survey-based studies, this is one approach used by transportation researchers to gain major insights into how SAVs will impact the way we travel. The focus of these papers includes travel behavior, operational strategy, and environmental impacts, and they have collectively contributed to improving our understanding of what we can expect and how we can make the most of the highly-anticipated mode. For example. while studies have shown that SAVs can improve transportation equity *(9–11)*, uncontrolled implementation can increase vehicle-miles traveled (VMT) and worsen network congestion *(12–14)*. Dynamic ridesharing (DRS), geofencing, and travel demand management policies like credit-based congestion pricing can mitigate such negative impacts *(15–18)*. Researchers have also studied the ways in which SAVs can support public transit use *(19–25)*.

While significant effort has been put into modeling the complex features of SAVs as an agent, details of more fundamental aspects of transportation simulations that can influence outcomes have been largely neglected. For example, many studies are conducted on simplified networks that only cover a fraction of the actual links in a city and simulate only a small percentage of the total population. Although these simplifications are mainly to save run time, they influence SAV metrics, such as wait times, average vehicle occupancies (AVO), and the share of empty VMT (%eVMT). Without appreciating the implications of such simplifications, the collective understanding of SAV fleet operations and opportunities is weakened and the conclusions (on fleet sizes needed, added VMT, emissions, profitability, etc.) jeopardized. Although these issues are relevant in any transportation simulation involving networks and synthesized demand, the goal of this paper is to contribute to the understanding of the various impacts of these simplifications on SAV operations. Specifically, we examine the effects of network complexity and the common practice of using incomplete networks, which likely optimistically biases SAV and non-SAV simulation results.

To this end, we compare SAV fleet operations in Austin using two networks: Austin 6-county region's network from the Capital Area Metropolitan Planning Organization (CAMPO) and a network obtained from OpenStreetMap (OSM). The CAMPO network contains approximately 46% and 42% of lane-miles and road-miles, respectively, of the OSM network. In

this study, we used POLARIS agent-based traffic simulation tool to run and compare multiple scenarios in terms of SAV fleet size for both networks. POLARIS is an agent-based model, developed by Argonne National Laboratory, which enables simulations of SAV operations within intricate and realistic transportation networks spanning extensive regions *(6)*. Similar to other renowned agent-based models, POLARIS empowers users to meticulously trace the trajectories of individual vehicles and travelers traversing through interconnected roadways, walkways, and bikeway links, all seamlessly tied to their respective destinations. To our knowledge, this study is the first to use two networks from distinct sources for the same city and compare the results. The effects of network complexity on SAV fleet operations is revealed through metrics, such as wait times, VMT, %eVMT, and vehicle occupancy, and the run times are compared.

The structure of the paper is as follows. We first describe the problem of network complexity in transportation modeling and examine simplifications taken in recent studies (<4 years) on agent-based simulations of SAVs. We then delve further into the problem of network complexity in the context of SAV simulations and illustrate what a complete network looks like for several popular cities in literature. Next, we describe the experiment using POLARIS traffic simulation tool and analyze the effects of network complexity on SAV fleet operations. Finally, we discuss the conclusions and future directions.

LITERATURE REVIEW

The origin of transportation modeling can be traced back to the 1950s with Chicago Area Transportation Study's four-step travel model and Beckman's solution to Wardrop's user equilibrium *(26, 27)*.The second breakthrough in transportation modeling occurred in the 1990s with the advent of activity-based models and dynamic traffic assignment (DTA). Since then, various dynamic network modeling software, such as DYNASMART *(28)* and DynaMIT *(29)*, have been introduced to be used in conjunction with demand models. Today, there are various commercial traffic assignment software available, such as Emme, Visum, and TransCAD, offering static traffic assignment, DTA, or both. Recent developments in transportation modeling have been focused on the integration of demand and supply models into one platform. One of the earliest efforts was TRANSIMS, developed by the Los Alamos National Laboratory *(30)*. Some popular comprehensive agent-based activity-based modeling systems currently used for cutting-edge research are MATSim *(5)*, POLARIS *(6)*, and SimMobility *(7)*.

Mainly due to computational constraints, early studies on transportation modeling relied on simple networks for validation before moving on to application in real networks. Some of these toy networks have become deeply engrained in the transportation research community as benchmarking networks. Perhaps the most notable example is the Sioux Falls network introduced by *(31)*. Although there are several versions, the Sioux Falls network is generally comprised of 24 nodes and 76 links. Despite it being well-acknowledged that it is not a realistic network, many recent studies on SAVs have still relied only on the Sioux Falls network, especially research on the operation algorithms of SAVs *(32–37)*. The selection of the Sioux Falls network is often justified due to its well-established status in the transportation field and low computational load, which makes it a proper choice for conducting initial analyses.

However, utilizing realistic networks in the same studies could enhance the comprehensiveness and practicality of their applications.

As agent-based activity-based modeling systems have been introduced, refined, and adopted over the past few years, many studies on SAVs have been conducted on such platforms using networks from various cities around the world. Table 1 shows a sample of recent studies on agent-based simulations of SAVs that contain at least some basic information about the network. Unfortunately, many studies fail to mention basic information about the simulation, such as the number of links and nodes in the network or the ratio of the simulated population. It can be seen that more researchers are starting to obtain more complex networks from OSM in recent years. To the best of our knowledge, only *(45)* has used both a complete network and population. However, their study was conducted in a small local city with a population of 47,000. From the examination of recent literature, it is clear that 1) basic simulation properties in different studies are important in generalizing conclusions and should be stated, 2) there is a gap to conduct simulations on complete networks and compare it with an incomplete one to analyze the level of details missed in different studies, and 3) the effects of using incomplete demand or supply need to be understood.

A few studies have been conducted on the effects of population downscaling in agent-based transportation simulations. Ben-Dor et al. *(50)* investigated this point using a more detailed version of the Sioux Falls network with 334 links and 282 nodes in MATSim. They looked at statistics, such as average travel distance and duration, trip counts, and traffic volume. They found that a simulated population percentage of 25% or higher was required to maintain the full population outcome. Ratios between 10% and 25% led to biases in some statistics, and results from ratios below 10% proved to be unusable. Also using MATSim, Kagho et al. *(51)* studied the effects of population downscaling for a ride-hailing service with DRS in Zurich. They focused on AVO and wait, travel, and detour times. They found that AVO does not asymptotically converge when increasing the simulated population ratio and recommended using the full population or estimating the bias of results when using a partial population. Similarly, Kamijo et al. *(45)* examined the effects of population downscaling on simulations with SAVs in the regional city of Numata, Japan, reporting the minimum required simulated population ratio to keep biases to less than 10%. They examined key statics for describing SAV service, such as wait time, number of trips served, VMT, eVMT%, and profit margin. They found that while SAVs without DRS can be reliably simulated with a population ratio of 10%, the required simulated population ratio is much higher for SAVs with DRS at 60%. The results of *(45)* and *(51)* match the findings of *(15)* and *(52)* in that the performance of a fleet with DRS improves with higher demand density. These studies imply that results of SAV simulations with population downscaling, which is usually around 10%, are likely unreliable.

TABLE 1 Recent studies on agent-based simulations of SAVs

Paper	City	Simulation platform	Network source	Links	Nodes	Population %	Individuals	Trips	Area (sq miles)	Time period
(38)	Austin, USA	POLARIS	MPO*	16,059	10,435	100%	–	–	5,300	24-h
(39)	Austin, USA	POLARIS	MPO	16,100	10,400	100%	–	–	5,300	24-h
(40)	Bloomington, IL, USA	POLARIS	–	4,000	2,500	100% to 2500%	120,000 for 100%	–	74	24-h
(8)	Chicago, USA	POLARIS	MPO	31,000	19,000	100%	11M	30M	11,246	24-h
(41)	Hague, Netherlands	Anylogic	–	836	510	–	–	27,452	–	5:30-10:00 AM
(42)	Lyon, France	–	OSM	27,000	11,310	–	–	480,000	31	6:00-10:00 AM
(43)	Melbourne, Australia	DynaMel	–	55,719	24,502	–	–	–	–	6:00-10:00 AM
(44)	Minneapolis–Saint Paul, USA (7-counties)	MATSim	OSM	42,485	20,746	2%, 5%	180,000 and 457,000	–	6,364	24-h
	Minneapolis–Saint Paul, USA (Twin Cities)					20%	487,000	–	245	
(45)	Numata, Japan	MATSim	OSM	–	–	2% to 100%	–	–	360	24-h
(46)	Singapore	SimMobility	–	15,128	6,375	100%	6.7M	–	283**	24-h
(13)	Singapore	SimMobility	–	15,128	6,375	100%	6.7M	–	283**	24-h
(14)	Singapore	SimMobility	–	15,128	6,375	100%	5.2M and 6.7M	–	283**	24-h
(47)	Tokyo, Japan	MATSim	OSM	338,652	134,112	10%***	200,000	–	208**	AM commute trips
(48)	Vienna, Austria	MATSim	OSM	156,000	71,000	12.5%	200,000	–	1,610	24-h
(49)	Zurich, Switzerland	MATSim	–	150,000	–	10%	220,000	–	–	24-h

* Metropolitan planning organization
** estimated by us based on information given in the cited paper
*** of corresponding entries in OD table from the Tokyo Person Trip Survey

NETWORK COMPLETENESS IN SAV SIMULATIONS

The use of incomplete networks is a key concern in generalizing the output of SAV simulations because most studies assume that SAVs will provide door-to-door (address point to address point) service, which means first-mile and last-mile travel on missing (or uncoded) minor roads/links. Additionally, simplified networks have the effect of aggregating pickup and dropoff (PUDO) positions of travelers, as it restricts PUDOs to the coded links, resulting in easier ridesharing. Both these features are likely to optimistically bias SAV and non-SAV simulation results. Figures 1 through 4 show the difference between simulated/coded and actual networks, for a range of examples used in the published literature.

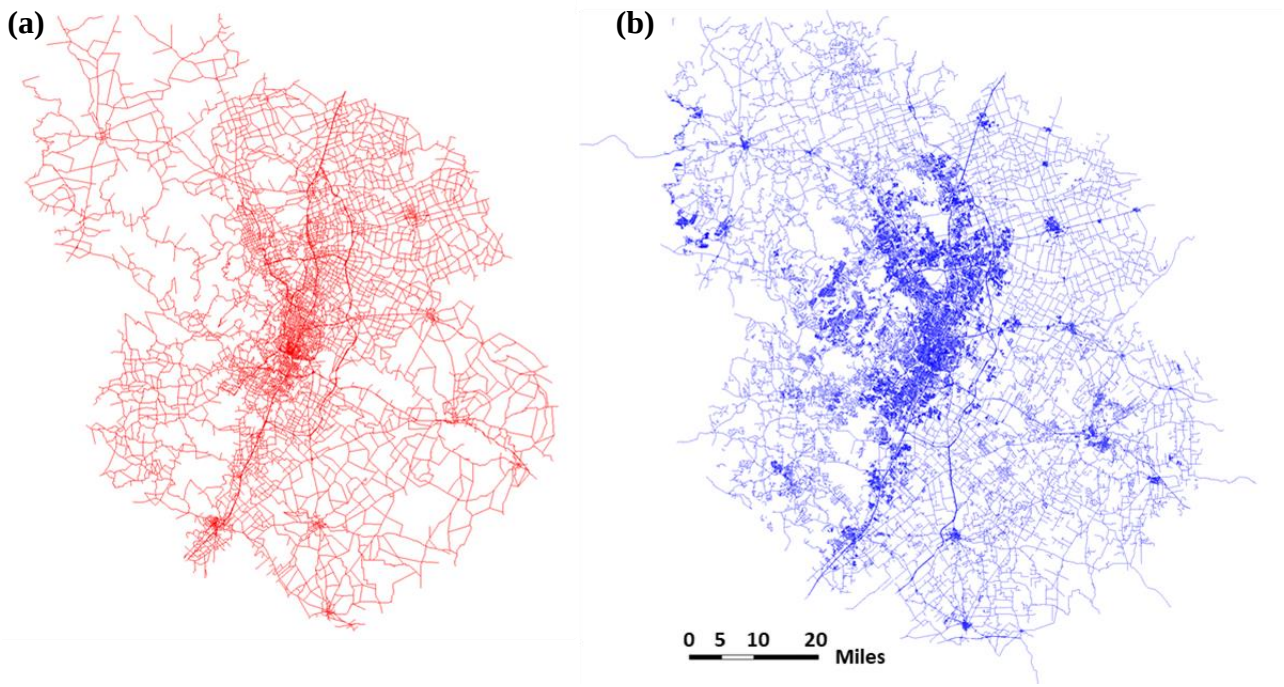

Figure 1 (a) Austin's 6-county network used in several published works and (b) the OSM network of the Austin 6-county area

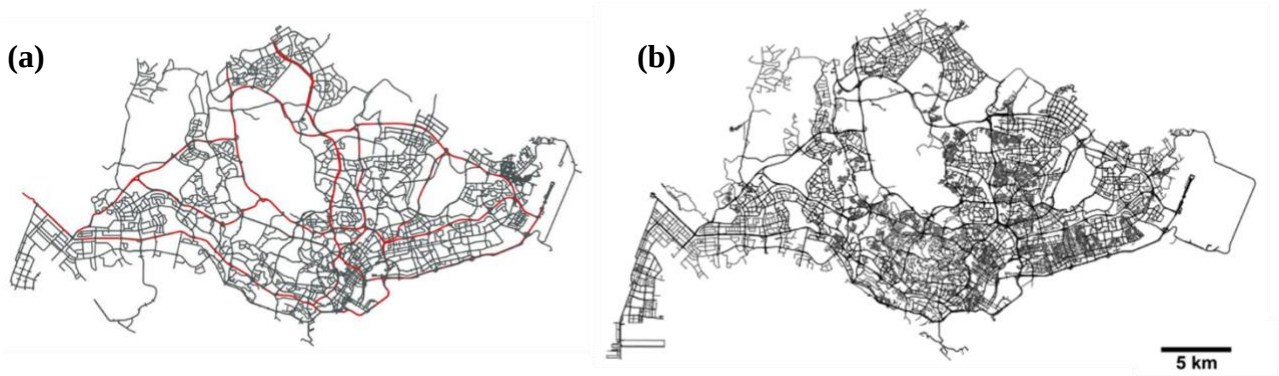

Figure 2 (a) Singapore network *(53)* used in several published works and (b) the OpenStreetMap network of Singapore

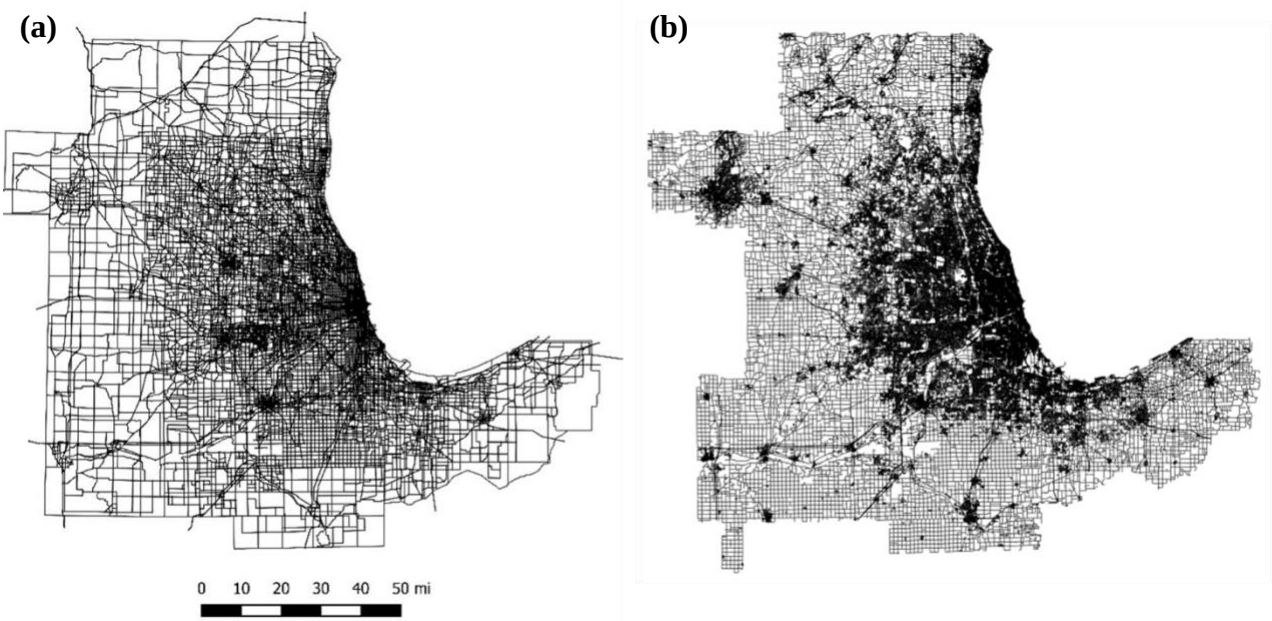

Figure 3 (a) Chicago's 20-county network *(17)* used in several published works and (b) the OSM network of the 20-county Chicago region

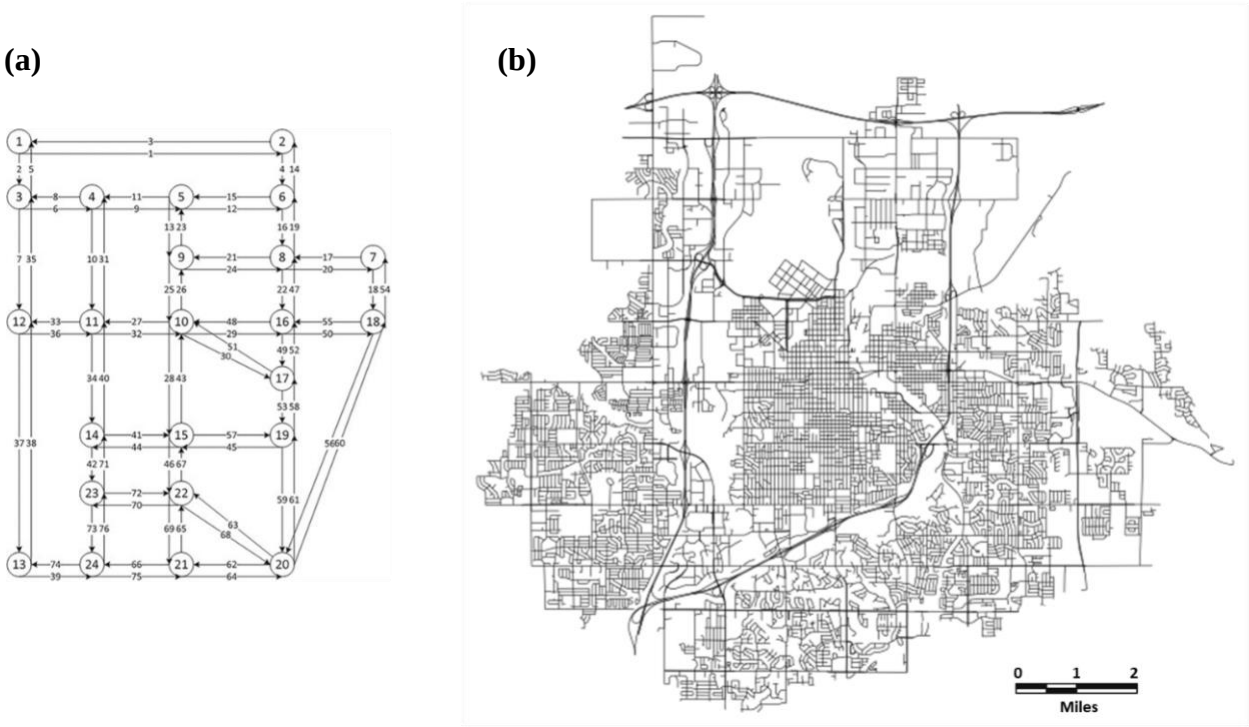

Figure 4 (a) The classic Sioux Falls network *(36)* and (b) the OSM network of Sioux Falls

On the demand side, using a smaller synthesized population is a common simplification. Since SAV performance is influenced by population density, simulated population ratio is also a

concern. Many studies simulate approximately 10% of the total population in order to save computational cost. To this end, *(45)* and *(51)* simulated on-demand vehicle services with DRS using various population ratios and recommends using population ratios that are much higher than what has typically been used in literature. Thanks to their work, the effects of simulated population rates on SAV simulation outcomes has been illuminated. However, a similar comparative study looking at the effects of the level of network completeness has not been conducted. Arguably, this issue is more serious than that of simulated population ratio, since networks require additional data and effort to alter and are often used repeatedly in consecutive studies, whereas simulated population ratios are simply a matter of computational cost.

Therefore, in this study, we compare the results of simulations involving SAVs in POLARIS using Austin 6-county region's network from the Capital Area Metropolitan Planning Organization (CAMPO) and a network obtained from OpenStreetMap (OSM) (Figure 1). The CAMPO network is a well-established network that has been used in numerous previous studies of various topics *(15, 38, 39, 54–555657)*. It contains approximately 18,268 lane-miles and 8,034 road-miles, which are approximately 46% and 42% of lane-miles and road-miles, respectively, of the OSM network. The OSM network of Austin has previously been used by *(16)*, *(21)*, and *(58*), but *(16)* simulated only 5% of the population and the analysis in *(58*) was limited to a 18 sq. mile central region. To our knowledge, this study is the first to use two networks from distinct sources for the same city.

SIMULATION FRAMEWORK

This study uses the POLARIS transportation system simulation tool *(6)* to simulate SAV fleet operations in the Austin 6-county region. POLARIS is an agent-based activity-based modeling framework. It is able to create a synthetic population through iterative proportional fitting, simulate a full day of activities for that entire population, and track the movements of individual agents routed through a time-dependent dynamic traffic assignment model. POLARIS contains many features for simulating traffic network company (TNC) vehicles, including SAVs, and is able to output key metrics for understanding the performance of fleet operations, such as wait times, VMT, %eVMT, and vehicle occupancy. In POLARIS, TNC vehicles are centrally controlled by a TNC operator, which gives assignment, operation, and repositioning instructions while considering network congestion *(17)*. POLARIS is the able to simulate DRS, a process by which a single vehicle can be arranged (in real time) to concurrently satisfy the travel demands of multiple travelers *(15)*.

TNC fleet model in POLARIS considers demand and supply sides correlated. The demand side generates TNC requests based on vehicle-ownership and mode-choice models while the supply side involves the fleet operator that centrally assigns requests to vehicles and the TNC vehicle that carries out the tasks. The operator assigns trips to the closest available vehicle to reduce empty travel distance and waiting time. The TNC vehicle maintains a task list, calculates optimal paths from the current location to the next operation location for the certain task, and records trip details *(17)*. In this model structure, incomplete networks might lead to missing some of the links taken by vehicles, which needs to be investigated.

In this study, we evaluate the effects of network complexity on the performance of SAV fleets of three different fleet sizes (5,000, 7,500, and 10,000 vehicles) using two different networks. For the base scenarios, we used the CAMPO network (Figure 1a) of the Austin 6-county region. For the more complex or complete network, we used the network of the same

region obtained from OSM (Figure 1b). The raw OSM network data was converted to the general modeling network specification (GMNS) format using an open-source Python package *osm2gmns (59)*, demonstrating the ease of obtaining a more complete network for any city. The GMNS network was then converted to the native POLARIS format and combined with other existing supply inputs for Austin (e.g., zones, locations, transit network) using a Python package developed in this study. The CAMPO network contains approximately 18,268 lane-miles and 8,034 road-miles, which are approximately 46% and 42% of lane-miles and road-miles, respectively, of the OSM network. In POLARIS, each location is connected to up to four links to avoid network loadings that would create artificially high levels of congestion when using a simplified network. For the CAMPO network, the threshold for connecting to multiple links was set to 2 kilometers. For the OSM network, because it is a more complex network, this threshold was lowered to 500 meters. Other than these differences, all scenarios were identical in terms of synthesized population, activity-based model parameters, locations, and other features.

RESULTS

The results of the simulations are summarized in Table 2, showcasing key insights into the performance of SAVs in the two networks. We conducted these simulations on the Texas Advanced Computing Center's Lonestar6 high-performance computing system, utilizing 2 nodes equipped with 2x AMD EPYC 7763 64-Core Processors and 256 GB (3200 MT/s) DDR4 RAM. The run times for the CAMPO network were approximately 1 hour 40 minutes, while the OSM scenarios took around 5 hours 20 minutes.

As expected, increasing network complexity led to higher average on-network trip distances extracted from trip trajectories and VMT for all fleet sizes. The 5000-vehicle fleet, in particular, was significantly impacted by the network changes. In the OSM network, the percentage of requests satisfied by the fleets was 11.2 percent-points lower than in the CAMPO network. Additionally, daily VMT increased by approximately 23.83% (from 831K mi to 1.029M mi), and the percentage of eVMT rose by 10.5 percent-points. The median wait time also nearly doubled, further highlighting the network's influence on fleet performance. These metrics clearly demonstrate that the 5,000-vehicle fleet performed notably worse in the OSM network than in the CAMPO network. Such findings underscore the bias in minimum fleet size conclusions based on simplified networks, making it essential to consider comprehensive networks.

The impact of network complexity on SAV operations is further illustrated by the number of vehicles utilized for each scenario. In the CAMPO network, approximately 3,800 vehicles were utilized regardless of the fleet size. However, in the OSM network, the entire fleet was utilized for fleet sizes of 5,000 and 7,500, while 8,887 vehicles were used for the scenario with 10,000 SAVs. This disparity highlights the significantly different fleet size requirements between the two networks.

Interestingly, the fleets comprising 7,500 and 10,000 vehicles showed slight improvements in the OSM network, characterized by lower %eVMTs and reduced median wait times. Furthermore, AVO was consistently higher in the OSM network across all scenarios. The observed differences in the two networks may be attributed to the trip choice models (e.g., departure time, mode choice, destination choice) producing higher SAV demand in the OSM network, as marked by the higher trips per SAV metric. This higher number of trips, in turn, leads to a higher demand density, enabling more efficient assignment and DRS practices. However, to gain a more understanding of these changes, further investigation is required.

TABLE 2 Summary of SAV simulation results

Network	Fleet size	Trips/SAV	% requests met	Vehicles utilized	VMT (mi)	VMT/SAV	% eVMT	Avg trip distance (miles)	Revenue trip AVO	Revenue distance AVO	Median wait time (min)
CAMPO	5,000	31.7	98.6	3,838	831K	166.2	31.5	3.08	1.36	1.30	3.60
	7,500	21.1	98.5	3,866	826K	110.2	31.3	3.08	1.36	1.30	3.57
	10,000	15.9	98.6	3,833	828K	82.8	31.4	3.09	1.36	1.30	3.55
OSM	5,000	32.9	87.4	5,000	1,029K	205.9	42.0	3.18	1.48	1.37	7.02
	7,500	25.9	98.0	7,500	965K	128.6	27.4	3.23	1.41	1.32	3.35
	10,000	19.5	98.2	8,887	957K	95.7	26.0	3.25	1.41	1.31	3.23

CONCLUSIONS

In this study, we evaluated the influence of network complexity on SAV fleet operations using the POLARIS agent-based modeling platform. We simulated SAV fleet operations in Austin using two networks: Austin 6-county region's network from the Capital Area Metropolitan Planning Organization and a network extracted from OpenStreetMap. The CAMPO network represented approximately 46% and 42% of lane-miles and road-miles, respectively, compared to the OSM network. The results highlight the significant implications of network complexity on determining the minimum fleet size. Specifically, the performance of the fleet with 5,000 vehicles (the smallest of the evaluated fleet sizes) was significantly worse in the OSM network compared to the CAMPO network considering key metrics like the percentage of satisfied trip requests, VMT, %eVMT, and median wait time. These changes can be attributed to the addition of the new links, higher demand in the OSM network, or different travel choice model calibration requirements. Additionally, fleet utilization patterns were drastically different in the two networks. In the CAMPO network, the number of vehicles deployed remained relatively constant around 3,800 vehicles regardless of the fleet size, owing to discretization errors across zone boundaries, and skim travel time values being updated with a lower precision. However, in the OSM network, full utilization was observed for fleet sizes of 5,000 and 7,500, with an 88.9% utilization for the 10,000-vehicle fleet. Overall, average trip distance and VMT were consistently higher in the OSM network for all fleet sizes, because of adding the first- and last-mile links that were not modeled in the CAMPO network.

Although this study provides insights into the impact of network simplifications on SAV operations, there are certain limitations that warrant consideration. In this study, we did not perform calibration for the OSM network and directly applied the demand model estimates from the CAMPO network. Consequently, the demand for SAVs in the OSM network was approximately 20% higher than that in the CAMPO network. Despite this limitation, our conclusions still hold, as the observed effects cannot be solely attributed to the 20% increase in the number of requests. Additional simulation iterations to get feedback might be necessary to reach convergence, which could affect the reported values.

Another aspect of network complexity, not covered in this study, is the impact of using actual addresses. While traditional travel demand models have long relied on traffic analysis zones (TAZs) as the smallest spatial unit of analysis and used zone centroids as the possible origins and destinations *(60)*, agent-based simulation tools like POLARIS offer a more granular approach by tracking travel at the level of individual "locations" or "addresses" serving as origins and destinations *(38)*. While this approach is an improvement over relying on TAZ centroids, the level of detail provided by the simulated addresses can still pose an issue and have a similar effect on SAV simulations as missing links, because simulated addresses essentially act as aggregated PUDO points. Future research can investigate the effects of aggregating addresses on SAV fleet operations.

ACKNOWLEDGEMENTS

The work done in this paper was sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The U.S. Government retains for itself, and others acting on its behalf, a paid-up nonexclusive, irrevocable worldwide license in said

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: F. Fakhrmoosavi, K.M. Kockelman; data collection and processing: K. Mori, F. Fakhrmoosavi, K.M. Gurumurthy, P. Camargo; analysis and interpretation of results: K. Mori, F. Fakhrmoosavi, K.M. Gurumurthy; draft manuscript preparation: K. Mori, F. Fakhrmoosavi, K.M. Kockelman. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Dominković, D. F., I. Bačeković, A. S. Pedersen, and G. Krajačić. The Future of Transportation in Sustainable Energy Systems: Opportunities and Barriers in a Clean Energy Transition. *Renewable and Sustainable Energy Reviews*, Vol. 82, 2018, pp. 1823-1838.
2. Hancock, P. A., I. Nourbakhsh, and J. Stewartd. On the Future of Transportation in an Era of Automated and Autonomous Vehicles. *Proceedings of the National Academy of Sciences - PNAS*, Vol. 116, No. 16, 2019, pp. 7684-7691.
3. Sumalee, A., and H. W. Ho. Smarter and More Connected: Future Intelligent Transportation System. *IATSS Research*, Vol. 42, No. 2, 2018, pp. 67-71.
4. von Schönfeld, K. C., and L. Bertolini. Urban Streets: Epitomes of Planning Challenges and Opportunities at the Interface of Public Space and Mobility. *Cities*, Vol. 68, 2017, pp. 48-55.
5. Axhausen, K. W., A. Horni, and K. Nagel. *The Multi-Agent Transport Simulation MATSim.* Ubiquity Press, 2016.
6. Auld, J., M. Hope, H. Ley, V. Sokolov, B. Xu, and K. Zhang. POLARIS: Agent-Based Modeling Framework Development and Implementation for Integrated Travel Demand and Network and Operations Simulations. *Transportation Research Part C: Emerging Technologies*, Vol. 64, 2016, pp. 101-116.
7. Lu, Y., M. Adnan, K. Basak, F. C. Pereira, C. Carrion, V. H. Saber, H. Loganathan, and M. E. Ben-Akiva. SimMobility Mid-Term Simulator: A State of the Art Integrated Agent Based Demand and Supply Model. In *94th Annual Meeting of the Transportation Research Board*, Washington, DC, 2015.
8. Gurumurthy, K. M., K. M. Kockelman, and J. Auld. A System of Shared Autonomous Vehicles for Chicago; Understanding the Effects of Geofencing the Service. *Journal of Transport and Land Use*, Vol. 14, No. 1, 2021, pp. 933-948.
9. Lee, J., and K. M. Kockelman. Access Benefits of Shared Autonomous Vehicle Fleets: Focus on Vulnerable Populations. *Transportation Research Record*, Vol. 2676, No. 11, 2022, pp. 568-582.
10. Nahmias-Biran, B., J. B. Oke, N. Kumar, C. Lima Azevedo, and M. Ben-Akiva. Evaluating the Impacts of Shared Automated Mobility on-Demand Services: An Activity-Based Accessibility Approach. *Transportation*, Vol. 48, No. 4, 2021, pp. 1613-1638.
11. Nahmias-Biran, B., J. B. Oke, and N. Kumar. Who Benefits from AVs? Equity Implications of Automated Vehicles Policies in Full-Scale Prototype Cities. *Transportation Research Part A: Policy and Practice*, Vol. 154, 2021, pp. 92-107.
12. Bischoff, J., and M. Maciejewski. Simulation of City-Wide Replacement of Private Cars with Autonomous Taxis in Berlin. *Procedia Computer Science*, Vol. 83, 2016, pp. 237-244.

13. Oh, S., A. F. Lentzakis, R. Seshadri, and M. Ben-Akiva. Impacts of Automated Mobility-on-Demand on Traffic Dynamics, Energy and Emissions: A Case Study of Singapore. *Simulation Modelling Practice and Theory*, Vol. 110, 2021, pp. 102327.
14. Oh, S., R. Seshadri, C. L. Azevedo, N. Kumar, K. Basak, and M. Ben-Akiva. Assessing the Impacts of Automated Mobility-on-Demand through Agent-Based Simulation: A Study of Singapore. *Transportation Research Part A: Policy and Practice*, Vol. 138, 2020, pp. 367-388.
15. Fagnant, D. J., and K. M. Kockelman. Dynamic Ride-Sharing and Fleet Sizing for a System of Shared Autonomous Vehicles in Austin, Texas. *Transportation*, Vol. 45, No. 1, 2018, pp. 143-158.
16. Gurumurthy, K. M., K. M. Kockelman, and M. D. Simoni. Benefits and Costs of Ride-Sharing in Shared Automated Vehicles Across Austin, Texas: Opportunities for Congestion Pricing. Transportation Research Record, Vol. 2673, No. 6, 2019, pp. 548-556.
17. Gurumurthy, K. M., F. de Souza, A. Enam, and J. Auld. Integrating Supply and Demand Perspectives for a Large-Scale Simulation of Shared Autonomous Vehicles. Transportation Research Record, Vol. 2674, No. 7, 2020, pp. 181-192.
18. Simoni, M. D., K. M. Kockelman, K. M. Gurumurthy, and J. Bischoff. Congestion Pricing in a World of Self-Driving Vehicles: An Analysis of Different Strategies in Alternative Future Scenarios. *Transportation Research Part C: Emerging Technologies*, Vol. 98, 2019, pp. 167-185.
19. Basu, R., A. Araldo, P. A. Arun, N. B. Bat Hen, K. Basak, R. Seshadri, N. Deshmukh, N. Kumar, L. A. Carlos, and Moshe Ben-Akiva. Automated Mobility-on-Demand Vs. Mass Transit: A Multi-Modal Activity-Driven Agent-Based Simulation Approach. *Transportation Research Record*, Vol. 2672, No. 8, 2018, pp. 608-618.
20. Gurumurthy, K. M., K. M. Kockelman, and N. Zuniga-Garcia. First-Mile-Last-Mile Collector-Distributor System using Shared Autonomous Mobility. Transportation Research Record, Vol. 2674, No. 10, 2020, pp. 638-647.
21. Huang, Y., K. M. Kockelman, V. Garikapati, L. Zhu, and S. Young. Use of Shared Automated Vehicles for First-Mile Last-Mile Service: Micro-Simulation of Rail-Transit Connections in Austin, Texas. Transportation Research Record, Vol. 2675, No. 2, 2021, pp. 135-149.
22. Huang, Y., K. M. Kockelman, and V. Garikapati. Shared Automated Vehicle Fleet Operations for First-Mile Last-Mile Transit Connections with Dynamic Pooling. *Computers, Environment and Urban Systems*, Vol. 92, 2022, pp. 101730.
23. Oke, J. B., A. P. Akkinepally, S. Chen, Y. Xie, Y. M. Aboutaleb, C. L. Azevedo, P. C. Zegras, J. Ferreira, and M. Ben-Akiva. Evaluating the Systemic Effects of Automated Mobility-on-Demand Services Via Large-Scale Agent-Based Simulation of Auto-Dependent Prototype Cities. *Transportation Research Part A: Policy and Practice*, Vol. 140, 2020, pp. 98-126.
24. Shen, Y., H. Zhang, and J. Zhao. Integrating Shared Autonomous Vehicle in Public Transportation System: A Supply-Side Simulation of the First-Mile Service in Singapore. *Transportation Research Part A: Policy and Practice*, Vol. 113, 2018, pp. 125-136.
25. Wen, J., Y. X. Chen, N. Nassir, and J. Zhao. Transit-Oriented Autonomous Vehicle Operation with Integrated Demand-Supply Interaction. *Transportation Research Part C: Emerging Technologies*, Vol. 97, 2018, pp. 216-234.

26. Weiner, E. Urban Transportation Planning in the United States: An Historical Overview., 1997.

27. Beckmann, M. J., C. B. McGuire, and C. B. Winston. *Studies in the Economics of Transportation* . Yale University Press, New Haven, CT, 1956.
28. Jayakrishnan, R., H. S. Mahmassani, and T. Hu. An Evaluation Tool for Advanced Traffic Information and Management Systems in Urban Networks. *Transportation Research Part C: Emerging Technologies*, Vol. 2, No. 3, 1994, pp. 129-147.
29. Ben-Akiva, M., M. Bierlaire, H. Koutsopoulos, and R. Mishalani. DynaMIT: A Simulation-Based System for Traffic Prediction. In *DACCORD Short Term Forecasting Workshop*, Delft, The Netherlands, February, 1998.
30. Smith, L., R. Beckman, K. Baggerly, D. Anson, and M. Williams. *TRANSIMS: Transportation Analysis and Simulation System.* , Los Alamos, NM, 1995.
31. LeBlanc, L. J., E. K. Morlok, and W. P. Pierskalla. An Efficient Approach to Solving the Road Network Equilibrium Traffic Assignment Problem. *Transportation Research*, Vol. 9, No. 5, 1975, pp. 309-318.
32. Hasanpour Jesri, S. O., and M. Akbarpour Shirazi. Bi Objective Peer-to-Peer Ridesharing Model for Balancing Passengers Time and Costs. *Sustainability*, Vol. 14, No. 12, 2022.
33. Noruzoliaee, M., and B. Zou. One-to-Many Matching and Section-Based Formulation of Autonomous Ridesharing Equilibrium. *Transportation Research Part B: Methodological*, Vol. 155, 2022, pp. 72-100.
34. S. Rong, C. Tang, and M. Chen. Dynamic Shared Autonomous Vehicles Dispatching Algorithm. In - *ISCTT 2022; 7th International Conference on Information Science, Computer Technology and Transportation*, 2022, pp. 1-5.
35. Tian, J., H. Jia, G. Wang, Y. Lin, R. Wu, and A. Lv. A Long-Term Shared Autonomous Vehicle System Design Problem Considering Relocation and Pricing. *Journal of Advanced Transportation*, Vol. 2022, 2022, pp. 1905526.
36. Xu, T., M. Cieniawski, and M. W. Levin. FMS-Dispatch: A Fast Maximum Stability Dispatch Policy for Shared Autonomous Vehicles Including Exiting Passengers Under Stochastic Travel Demand. *Transportmetrica A: Transport Science*, 2023, pp. 1-39.
37. Zhou, Z., and C. Roncoli. A Scalable Vehicle Assignment and Routing Strategy for Real-Time on-Demand Ridesharing Considering Endogenous Congestion. *Transportation Research Part C: Emerging Technologies*, Vol. 139, 2022, pp. 103658.
38. Hunter, C. B., K. M. Kockelman, and S. Djavadian. Curb Allocation and Pick-Up Drop-Off Aggregation for a Shared Autonomous Vehicle Fleet. *International Regional Science Review*, pp. 01600176231160498.
39. Dean, M. D., K. M. Gurumurthy, F. de Souza, J. Auld, and K. M. Kockelman. Synergies between Repositioning and Charging Strategies for Shared Autonomous Electric Vehicle Fleets. *Transportation Research Part D: Transport and Environment*, Vol. 108, 2022, pp. 103314.
40. Gurumurthy, K. M., and K. M. Kockelman. Dynamic Ride-Sharing Impacts of Greater Trip Demand and Aggregation at Stops in Shared Autonomous Vehicle Systems. *Transportation Research Part A: Policy and Practice*, Vol. 160, 2022, pp. 114-125.
41. Wang, S., G. H. d. Almeida Correia, and H. X. Lin. Effects of Coordinated Formation of Vehicle Platooning in a Fleet of Shared Automated Vehicles: An Agent-Based Model. *Transportation Research Procedia*, Vol. 47, 2020, pp. 377-384.

42. Alisoltani, N., M. Zargayouna, and L. Leclercq. Real-Time Autonomous Taxi Service: An Agent-Based Simulation. In *Agents and Multi-Agent Systems: Technologies and Applications 20*, Springer Singapore, Singapore, 2020, pp. 199-207.
43. Shafiei, S., Z. Gu, H. Grzybowska, and C. Cai. Impact of Self-Parking Autonomous Vehicles on Urban Traffic Congestion. *Transportation*, Vol. 50, No. 1, 2023, pp. 183-203.
44. Yan, H., K. M. Kockelman, and K. M. Gurumurthy. Shared Autonomous Vehicle Fleet Performance: Impacts of Trip Densities and Parking Limitations. *Transportation Research Part D: Transport and Environment*, Vol. 89, 2020, pp. 102577.
45. Kamijo, Y., G. Parady, and K. Takami. Required Simulated Population Ratios for Valid Assessment of Shared Autonomous Vehicles' Impact using Agent-Based Models. *SSRN Electronic Journal*, 2022.
46. Nguyen-Phuoc, D. Q., M. Zhou, M. Hong Chua, A. Romano Alho, S. Oh, R. Seshadri, and D. Le. Examining the Effects of Automated Mobility-on-Demand Services on Public Transport Systems using an Agent-Based Simulation Approach. *Transportation Research Part A: Policy and Practice*, Vol. 169, 2023, pp. 103583.
47. Ishibashi, Y., and E. Akiyama. Predicting the Impact of Shared Autonomous Vehicles on Tokyo Transportation using MATSim. In - 2022 IEEE International Conference on Big Data (Big Data), 2022, pp. 3258-3265.
48. Müller, J., M. Straub, A. Naqvi, G. Richter, S. Peer, and C. Rudloff. MATSim Model Vienna: Analyzing the Socioeconomic Impacts for Different Fleet Sizes and Pricing Schemes of Shared Autonomous Electric Vehicles. In *Transportation Research Board 100th Annual Meeting*, Washington, D.C., 2021.
49. Hörl, S., F. Becker, and K. W. Axhausen. Simulation of Price, Customer Behaviour and System Impact for a Cost-Covering Automated Taxi System in Zurich. *Transportation Research Part C: Emerging Technologies*, Vol. 123, 2021, pp. 102974.
50. Ben-Dor, G., E. Ben-Elia, and I. Benenson. Population Downscaling in Multi-Agent Transportation Simulations: A Review and Case Study. *Simulation Modelling Practice and Theory*, Vol. 108, 2021, pp. 102233.
51. Kagho, G. O., J. Meli, D. Walser, and M. Balac. Effects of Population Sampling on Agent-Based Transport Simulation of on-Demand Services. *Procedia Computer Science*, Vol. 201, 2022, pp. 305-312.
52. Zwick, F., N. Kuehnel, R. Moeckel, and K. W. Axhausen. Ride-Pooling Efficiency in Large, Medium-Sized and Small Towns -Simulation Assessment in the Munich Metropolitan Region. *Procedia Computer Science*, Vol. 184, 2021, pp. 662-667.
53. Alho, A. R., T. Sakai, S. Oh, C. Cheng, R. Seshadri, W. H. Chong, Y. Hara, J. Caravias, L. Cheah, and M. Ben-Akiva. A Simulation-Based Evaluation of a Cargo-Hitching Service for E-Commerce using Mobility-on-Demand Vehicles. *Future Transportation*, Vol. 1, No. 3, 2021, pp. 656.
54. Duthie, J., and A. Unnikrishnan. Optimization Framework for Bicycle Network Design. *Journal of Transportation Engineering*, Vol. 140, No. 7, 2014, pp. 04014028.
55. Hu, X., Y. Chiu, and J. Shelton. Development of a Behaviorally Induced System Optimal Travel Demand Management System. *Journal of Intelligent Transportation Systems*, Vol. 21, No. 1, 2017, pp. 12-25.
56. Perrine, K., A. Khani, and Natalia Ruiz-Juri. Map-Matching Algorithm for Applications in Multimodal Transportation Network Modeling. *Transportation Research Record*, Vol. 2537, No. 1, 2015, pp. 62-70.

57. Zhao, Y., and K. M. Kockelman. Anticipating the Regional Impacts of Connected and Automated Vehicle Travel in Austin, Texas. Journal of Urban Planning and Development, Vol. 144, No. 4, 2018.
58. Liu, J., K. M. Kockelman, P. M. Boesch, and F. Ciari. Tracking a System of Shared Autonomous Vehicles Across the Austin, Texas Network using Agent-Based Simulation. *Transportation*, Vol. 44, No. 6, 2017, pp. 1261-1278.
59. Lu, J., and X. S. Zhou. Modeling Partially Schedulable Connected and Automated Mobility Systems on Layered Virtual-Track Networks: Modeling Framework and Open-Source Tools., 2022.
60. Miller, E. J. *Traffic Analysis Zone Definition: Issues & Guidance.*, 2021.