Impacts of Shared Autonomous Vehicles on Traffic Operations and Infrastructure Durability in Connecticut

Final Report
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AT THE UNIVERSITY OF MAINE

A report from

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16 Abstract

The growth of ride-hailing services and the introduction of Shared Autonomous Vehicles (SAVs) are set to significantly change how people travel in cities. While these services can improve transportation options and lower costs, they may also create major new challenges for traffic management and road maintenance. A key concern lies in the potential increase in total vehicle-miles traveled (VMT), as automated vehicles may drive empty between passengers and may also increase overall travel demand due to greater travel convenience. These new travel patterns will directly impact our road networks, potentially accelerating pavement wear and altering long-term infrastructure needs.

To better understand and plan for these effects on Connecticut's road networks, this project develops a large-scale, agent-based traffic simulation model for the state. The research involves building a complete digital map of the state's transportation system using data from OpenStreetMap (OSM). Using the POLARIS transportation system simulation tool, the study models dynamic travel needs and how people choose their travel mode. This framework analyzes how various SAV adoption scenarios would change travel patterns, demand, mode share, and empty VMT. The study finds that effective SAV management reduces total VMT through trip consolidation, thereby enhancing infrastructure longevity. The findings from this project provide transportation agencies with vital information to predict future impacts on traffic and road conditions. This will help them develop effective strategies for managing traffic and maintaining the state's infrastructure as self-driving vehicle technology becomes more common.

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List of Key Terms

SAV: Shared Autonomous Vehicle

SAEV: Shared Autonomous Electric Vehicle

VMT: Vehicle-Miles Traveled

eVMT: Empty Vehicle-Miles Traveled

VKT: Vehicle Kilometers Traveled

OSM: Open Street Map

AVs: Autonomous Vehicles

AVO: Average Vehicle Occupancy

SOV: Single Occupancy Vehicle

ABMs: Agent Based Models

DRS: Dynamic Ridesharing

DR-SAV: Dynamic Ridesharing Shared Autonomous Vehicle

CTDOT: Connecticut Department of Transportation

PUDO: Pick-up and Drop-off

AADT: Annual Average Daily Traffic

TAZ: Traffic Analysis Zone

Abstract

The growth of ride-hailing services and the introduction of Shared Autonomous Vehicles (SAVs) are set to significantly change how people travel in cities. While these services can improve transportation options and lower costs, they may also create major new challenges for traffic management and road maintenance. A key concern is the potential increase in total vehicle-miles traveled (VMT), as automated vehicles may drive empty between passengers and may also increase overall travel demand due to greater travel convenience. These new travel patterns will directly impact our road networks, potentially accelerating pavement wear and altering long-term infrastructure needs.

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Chapter 1: Introduction and Background

1.1 Project Motivation

The long-term performance of the U.S. transportation network relies heavily on the health and durability of its physical infrastructure. The arrival of new transportation technologies, particularly Shared Autonomous Vehicles (SAVs), introduces both significant opportunities and new challenges for infrastructure management. While SAVs offer potential improvements in traffic efficiency, lower emissions, and safety, their widespread adoption is expected to cause major changes in travel behavior, traffic patterns, and the overall use of the roadway network as shown in Figure 1.

These changes include potential increases in total Vehicle-Miles Traveled (VMT), partly due to vehicles traveling empty between passenger trips. Such shifts in traffic volume and distribution will place new and different stresses on pavements. Without a clear understanding of these effects, transportation agencies face the risk of accelerated pavement wear, shortened infrastructure service life, and rising maintenance costs. Therefore, there is a clear and urgent need to develop statewide models capable of simulating different scenarios to predict these impacts. Accordingly, this project will focus on this matter for the state of Connecticut, developing a framework to equip transportation agencies with the information needed to effectively plan for a durable infrastructure network.

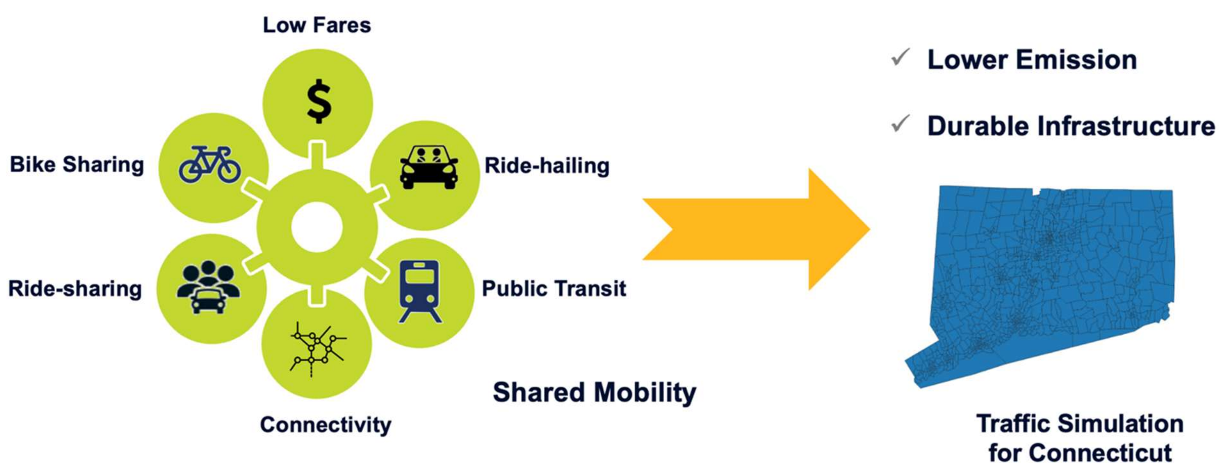


Figure 1: The overarching goal of the shared autonomous vehicle simulation

1.2 Literature Review

The emergence of autonomous vehicles (AVs) represents a transformative milestone for future transportation systems. With rapid advancements in technology, the focus has shifted from technical feasibility to the timing and impact of full commercial deployment, with forecasts ranging from 2040 to 2060 (Litman, 2017). As adoption accelerates, it is crucial to understand the multifaceted impacts of AVs, particularly SAVs, on traffic operations, environmental sustainability, and infrastructure durability.

Initial research into AV adoption revealed a fundamental tension. On one hand, the convenience of AVs may increase overall VMT. Studies projected that by removing traditional barriers to driving, AVs could unlock latent travel demand, especially among non-drivers and seniors, potentially worsening congestion (Harper et al., 2016). On the other hand, the model of SAVs offers a powerful counterbalance. SAVs present an opportunity to reduce private vehicle ownership, decrease parking demand, and improve overall fleet utilization through dynamic repositioning (Fagnant and Kockelman, 2014). Furthermore, by mitigating human error—a primary cause of crashes—SAVs offer significant safety benefits (Islam and Kunnawee, 2008; Nikitas et.al., 2017). This duality frames the central challenge, harnessing the efficiency of SAVs to overcome the potential VMT increase from general AV adoption.

To evaluate these complex interactions, researchers have widely adopted agent-based models (ABMs) as the primary analytical tool. ABMs allow for a disaggregated analysis of individual traveler decisions and their system-wide consequences, making them ideal for studying the deployment of new services like SAVs under various policy scenarios (Kickhöfer et al., 2011).

Early ABM studies focused on foundational questions of operational viability, such as fleet sizing and vehicle placement. Fagnant and Kockelman (2014) established that each SAV could replace approximately eleven private vehicles, a significant efficiency gain, though it came with an 11% increase in travel distance due to empty repositioning trips. Subsequent work by Loeb and Kockelman (2019) in Austin, Texas, further explored the cost dynamics, highlighting that while larger fleets improve service quality by reducing wait times, they are subject to significant operational costs related to vehicle acquisition, battery replacement, and charging infrastructure.

Building on analyses of fleet performance, research has explored the role of SAVs in complementing existing public transportation, particularly in solving the "first- and last-mile" problem. SAVs can act as flexible, on-demand feeders to major transit hubs, reducing walking distances and optimizing resource use. For instance, Shen et al. (2018) demonstrated in Singapore that integrating SAVs with ridesharing enhanced transit efficiency, though they cautioned that a complete replacement of buses with SAVs worsened system performance, suggesting a hybrid approach is optimal. Similarly, a study in Austin, Texas, found that SAVs could expand transit service areas but posed a risk of increasing VMT if low fares incentivized travelers to switch from public transit or active modes like walking. This highlights the need for careful policy design, such as strategic fare controls, to ensure SAVs support rather than cannibalize public transit (Gurumurthy et al., 2020).

A critical strategy for maximizing SAV efficiency is dynamic ridesharing (DRS). Zhang et al. (2015) demonstrated that a DR-SAV system significantly outperforms non-ridesharing systems by reducing delays, lowering trip costs by over 60%, and decreasing VMT by nearly 5%. Their findings also pointed to major co-benefits, with each DR-SAV replacing fourteen private vehicles and reducing parking demand by 90%.

Subsequent research reinforced these benefits across different urban contexts. In New York City, shared autonomous taxis were shown to reduce required fleet sizes by 59%, triple the average vehicle occupancy, and cut travel distances by 55% (Lokhandwala et al., 2018). In Austin, a shared fleet was found to serve 30% of daily trips, with road pricing being an effective tool to mitigate the associated 4.5% VMT increase (Gurumurthy et al., 2019). Further refinement of the DRS model has focused on physical infrastructure, with research by Gurumurthy and Kockelman (2022) using the POLARIS framework (Argonne National Laboratory, 2025) to show that strategically placed pick-up and drop-off (PUDO) zones can improve vehicle occupancy and reduce SAV-induced VMT by up to 39%.

The operational efficiency of SAVs is intrinsically linked to their economic feasibility and pricing strategies. Chen et al. (2016) found that shared autonomous electric vehicles (SAEVs) could replace 3.7 to 6.8 private vehicles at an operational cost of $0.41 to $0.49 per mile, with performance heavily dependent on battery range and charging infrastructure. Fare structures directly influence user adoption and travel patterns. A study by Liu et al. (2017) revealed that lower fares ($0.50/mile) could lead to a 43.3% adoption rate, while higher fares ($1.25/mile) dropped adoption to 7.0%, primarily for shorter urban trips. Critically, while higher fares improved operational efficiency, they also increased the share of empty vehicle miles. To manage the traffic impacts from widespread SAV adoption, policies like congestion pricing have been evaluated. Simoni et al. (2019) showed that such strategies can improve travel efficiency but may impose financial burdens on lower-income travelers, highlighting the need for efficient policy design.

While the previously mentioned factors like ridesharing and pricing influence traffic patterns, the ultimate impact of SAVs on total VMT remains a central and contested topic in the literature (Fakhrmoosavi et al., 2022, 2023, 2024a,b; Kamjoo et al., 2024). Findings vary significantly depending on the study area, operational model, and market penetration. Some studies project a definitive increase in VMT. For example, an early study in Austin found an 8% increase in vehicle kilometers traveled (VKT) at just 1.3% market penetration, driven by empty repositioning trips (Fagnant et al., 2015). In Chicago, an 80% increase in road capacity from connected AVs was predicted to induce a 4% rise in VKT (Auld et al., 2017). Similarly, studies in Melbourne and Singapore projected VKT increases ranging from 17% to as high as 77% in car-sharing scenarios, often accompanied by a decline in public transit use (Javanshour et al., 2019; Oh et al., 2020).

However, other research indicates that under the right conditions, SAVs can reduce VMT. In Stuttgart, a study found that SAVs could lead to a 20% decrease in VKT due to efficient trip pooling (Heilig et al., 2017). Likewise, a simulation in the Minneapolis–Saint Paul region reported a 17% reduction in VMT with dynamic ridesharing (Yan et al., 2020). Other studies focus on the profound impact on fleet size, with analyses in Singapore and Melbourne suggesting that SAV systems could meet travel demand with fleet reductions of 43% to 88%, freeing up vast amounts of urban space previously used for parking, even if these systems still led to a 10-29% VKT increase (Spieser et al., 2014; Dia and Javanshour, 2017). This conflict highlights that the net effect on VMT is not guaranteed and depends heavily on policy and operational strategy.

The effectiveness of an SAV system also depends on which travelers it attracts and which modes of transport it replaces. Simulations in Austin suggest SAEVs could achieve a mode share of 14% to 39%, heavily influenced by pricing (Chen and Kockelman, 2016). In Tokyo, commuters traveling 2–8 km by train or bicycle were identified as likely adopters (Ishibashi and Akiyama, 2022). However, a critical concern is that SAVs may divert users from sustainable modes. A study in Braunschweig, Germany, a city with a compact layout and strong public transit, found that SAVs had minimal impact on the overall modal split, primarily replacing bicycle trips rather than car trips (Cyganski et al., 2018).

Despite the debate over VMT, studies consistently show that well-managed SAV systems offer clear environmental benefits, primarily through ridesharing and fleet electrification. Liu et al. (2018) found that ridesharing strategies could reduce fleet size by up to 27% and lower CO_2

emissions by up to 19%. A similar study modeling New York City taxi found that dynamic ridesharing with SAVs could reduce carbon emissions by 866 metric tons daily, alongside significant reductions in fleet size and travel distances (Lokhandwala and Cai, 2018).

The reviewed literature provides a robust consensus that SAVs will alter traffic operations, though the net effect on VMT remains contested. The existing research has largely focused on the network-level effects, and a clear and critical research gap exists in quantitatively connecting these predicted changes in traffic patterns directly to their long-term consequences for infrastructure durability. This project addresses that specific gap by creating an integrated simulation framework to bridge the analysis of traffic operations with the assessment of infrastructure durability.

1.3 Research, Objectives, and Tasks

The goal of this research project is to develop and implement an agent-based modeling and traffic simulation framework to analyze the impacts of SAVs on traffic operations and infrastructure durability in the state of Connecticut. By simulating various scenarios and conducting a sensitivity analysis between fleet size and pricing of SAVs, this study aims to provide valuable insights into changes in travel patterns and network performance. The primary objectives of this project are:

1. To develop a comprehensive, large-scale transportation network for the state of Connecticut suitable for dynamic traffic simulation.
2. To use local demographic, census, and mobility data to synthesize a realistic population of agents to accurately reflect current travel behaviors.
3. To simulate the deployment of SAVs under various operational scenarios to quantify their effects on traffic operations, including changes in VMT, empty-VMT, and travel times.
4. To evaluate the impacts of altered traffic loads on infrastructure durability.

To achieve these objectives, the project was structured into the following key tasks: (1) A comprehensive literature review to identify existing models and research gaps; (2) The construction and validation of a Connecticut-wide transportation network using OpenStreetMap (OSM) and Connecticut Department of Transportation (CTDOT) data; (3) Mode choice analysis in the presence of SAVs; (4) The execution of SAV simulations under different operational scenarios; and (5) The analysis and documentation of findings.

1.4 Report Overview

This report details the methodology, results, and conclusions of the project. Chapter 2 describes the research methodology, including the data sources utilized, the process of building the transportation network, and the framework for the simulation. Chapter 3 presents a summary of data processing, network construction, and scenario analyses. Finally, Chapter 4 summarizes the key findings of the study and offers conclusions and recommendations for transportation agencies.

Chapter 2: Methodology

2.1 Data Collection and Preparation

Developing a high-fidelity, large-scale traffic simulation model required the collection, integration, and preparation of multiple datasets. The following primary data sources were utilized to construct the model inputs:

- OpenStreetMap: Publicly available data from OSM served as the foundational layer for the Connecticut transportation network, providing essential information on road links, intersections (nodes), and points of interest (POIs).
- CTDOT: Official statewide datasets were acquired through collaboration with the CTDOT demand modeling team. These authoritative sources included the detailed highway network, Traffic Analysis Zones (TAZ) boundaries, and traffic counts.
- U.S. Census Bureau: Demographic and socioeconomic data were accessed via API to create a detailed and realistic zoning system based on census tracts, which is essential for synthesizing the agent population and modeling travel demand.
- National Renewable Energy Laboratory (NREL): Data on electric vehicle (EV) charging station locations were obtained through an API key to incorporate this critical infrastructure into the network, particularly for modeling electrified SAVs.
- General Transit Feed Specification (GTFS): Where available, transit routes and schedules were acquired from GTFS feeds to model public transportation services within the network.

A significant effort was dedicated to data preparation. This involved extracting relevant features, cleaning and validating datasets for consistency, and converting them from various formats (e.g., shapefiles, CSV, GeoJSON) into a unified SQLite database compatible with the POLARIS simulation framework as shown in a few samples in Figures 2 to 5.

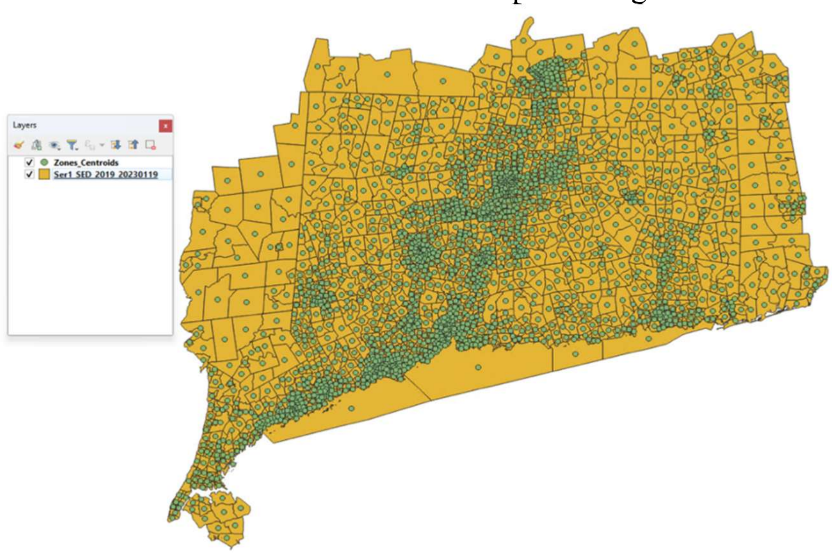


Figure 2: Map of Traffic Analysis Zones (TAZs) and their corresponding centroids (green dots) within the study area. Data sourced from the CTDOT.

	OBJECTID	Z	ID	AREA	NEW_AGG	TAZ_ID	FIPS	ST	TOWN	AREASQ	COUNTY	POP2019	HH2019	EMP2019	RET2019	NRET2019
1	1	1	1	6.94630700000	CT_1	1	9001	CT	Greenwich	6.95567328800	Fairfield	1596.000000	514.000000	1092.000000	0	1092.000000
2	2	10	2	1.26405300000	CT_10	10	9001	CT	Greenwich	1.26575976600	Fairfield	2340.000000	782.000000	652.000000	39.000000	613.000000
3	3	100	3	0.634853	CT_100	100	9001	CT	Norwalk	0.635708915	Fairfield	3336.000000	1206.000000	2620.000000	1292.000000	1327.000000
4	4	1000	4	3.69630900000	CT_1000	1000	9003	CT	Southington	3.70149672400	Hartford	4298.000000	1531.000000	160.000000	7.000000	153.000000
5	5	1001	5	1.32141900000	CT_1001	1001	9003	CT	Southington	1.32327091700	Hartford	1901.000000	735.000000	510.000000	55.000000	455.000000
6	6	1002	6	2.01038500000	CT_1002	1002	9003	CT	Southington	2.01319690300	Hartford	2792.000000	1065.000000	329.000000	47.000000	282.000000
7	7	1003	7	1.81094500000	CT_1003	1003	9003	CT	Southington	1.81348247300	Hartford	3238.000000	1419.000000	2405.000000	230.000000	2175.000000
8	8	1004	8	0.248115	CT_1004	1004	9003	CT	Southington	0.248463518	Hartford	970.000000	403.000000	198.000000	38.000000	159.000000
9	9	1005	9	0.759517	CT_1005	1005	9003	CT	Southington	0.760590342	Hartford	1217.000000	447.000000	402.000000	10.000000	392.000000
10	10	1006	10	1.06186200000	CT_1006	1006	9003	CT	Berlin	1.06336387900	Hartford	1849.000000	741.000000	599.000000	0	599.000000
11	11	1007	11	5.11116900000	CT_1007	1007	9003	CT	Berlin	5.11841487400	Hartford	5238.000000	2129.000000	545.000000	22.000000	523.000000
12	12	1008	12	2.63506700000	CT_1008	1008	9003	CT	Berlin	2.63880608000	Hartford	1291.000000	618.000000	4330.000000	771.000000	3559.000000
13	13	1009	13	2.05398900000	CT_1009	1009	9003	CT	Berlin	2.05690452600	Hartford	1293.000000	658.000000	2516.000000	369.000000	2147.000000
14	14	101	14	0.377562	CT_101	101	9001	CT	Norwalk	0.378070912	Fairfield	1715.000000	683.000000	4877.000000	565.000000	4313.000000
15	15	1010	15	2.91649800000	CT_1010	1010	9003	CT	Berlin	2.92067508900	Hartford	2015.000000	843.000000	1482.000000	55.000000	1427.000000
16	16	1011	16	1.04032600000	CT_1011	1011	9003	CT	Berlin	1.04179575800	Hartford	1461.000000	575.000000	970.000000	15.000000	955.000000
17	17	1012	17	1.06299800000	CT_1012	1012	9003	CT	Berlin	1.06450291600	Hartford	1794.000000	685.000000	358.000000	48.000000	310.000000
18	18	1013	18	0.834664	CT_1013	1013	9003	CT	Berlin	0.835842463	Hartford	1764.000000	658.000000	749.000000	2.000000	747.000000
19	19	1014	19	5.07544300000	CT_1014	1014	9003	CT	Berlin	5.08257621700	Hartford	1104.000000	403.000000	55.000000	1.000000	54.000000
20	20	1015	20	5.15425600000	CT_1015	1015	9003	CT	Berlin	5.16150846900	Hartford	2627.000000	870.000000	205.000000	6.000000	200.000000
21	21	1016	21	0.425952	CT_1016	1016	9003	CT	New Britain	0.426560262	Hartford	1312.000000	664.000000	4025.000000	246.000000	3779.000000
22	22	1017	22	0.685149	CT_1017	1017	9003	CT	New Britain	0.686127667	Hartford	3614.000000	1515.000000	3091.000000	46.000000	3046.000000
23	23	1018	23	0.212228	CT_1018	1018	9003	CT	New Britain	0.212531607	Hartford	2435.000000	973.000000	1080.000000	164.000000	915.000000
24	24	1019	24	0.201662	CT_1019	1019	9003	CT	New Britain	0.201951002	Hartford	2977.000000	1288.000000	119.000000	37.000000	82.000000
25	25	102	25	0.269814	CT_102	102	9001	CT	Norwalk	0.270177408	Fairfield	1610.000000	559.000000	1180.000000	30.000000	1150.000000
26	26	1020	26	0.089375	CT_1020	1020	9003	CT	New Britain	0.089503489	Hartford	1013.000000	448.000000	52.000000	0	52.000000
27	27	1021	27	0.315069	CT_1021	1021	9003	CT	New Britain	0.315519836	Hartford	4741.000000	1818.000000	150.000000	20.000000	129.000000
28	28	1022	28	0.224045	CT_1022	1022	9003	CT	New Britain	0.224365523	Hartford	2794.000000	1054.000000	240.000000	0	240.000000
29	29	1023	29	0.496335	CT_1023	1023	9003	CT	New Britain	0.497046169	Hartford	1562.000000	569.000000	166.000000	1.000000	165.000000

Figure 3: A sample of the attribute data for Traffic Analysis Zones (TAZs), highlighting key information such as TAZ ID, population, and area. Data from CTDOT.

	GEO_ID	STATE	COUNTY	COUSUB	NAME	LSAD	CENSUSAREA	E_GEO	NEWFIELD1	NAICS31	NAICS42	SECONDGEO	COUSUBNUM
1	0600000US4400...	44	003	18640	Coventry	town	59.04500000000...	E600000US4400...	No	524	125	0	18640
2	0600000US4400...	44	003	77720	West Greenwich	town	50.25900000000...	E600000US4400...	No	230	10	0	77720
3	0600000US4400...	44	007	11800	Burrillville	town	55.03499999999...	E600000US4400...	No	637	40	0	11800
4	0600000US4400...	44	007	27460	Foster	town	50.79800000000...	E600000US4400...	No	0	5	0	27460
5	0600000US4400...	44	009	61160	Richmond	town	40.29299999999...	E600000US4400...	No	218	33	0	61160
6	0600000US4400...	44	009	67460	South Kingstown	town	56.44599999999...	E600000US4400...	No	232	122	0	67460
7	0600000US4400...	44	009	77000	Westerly	town	29.52000000000...	E600000US4400...	No	465	253	0	77000
8	0600000US4400...	44	007	30340	Glocester	town	54.18000000000...	E600000US4400...	No	34	0	0	30340
9	0600000US4400...	44	007	64220	Scituate	town	48.16400000000...	E600000US4400...	No	10	60	0	64220
10	0600000US4400...	44	009	14500	Charlestown	town	36.44599999999...	E600000US4400...	No	18	10	0	14500
11	0600000US4400...	44	009	25300	Exeter	town	57.46600000000...	E600000US4400...	No	48	31	0	25300
12	0600000US4400...	44	009	35380	Hopkinton	town	42.95000000000...	E600000US4400...	No	375	40	0	35380
13	0600000US3600...	36	005	08510	Bronx	boro	42.09599999999...	E600000US3600...	No	6197	10510	NULL	8510
14	0600000US3602...	36	027	01693	Amenia	town	43.21999999999...	E600000US3602...	No	75	10	0	1693
15	0600000US3602...	36	027	40299	La Grange	town	39.87899999999...	E600000US3602...	No	167	163	0	40299
16	0600000US3602...	36	027	78388	Washington	town	58.17000000000...	E600000US3602...	No	0	10	0	78388
17	0600000US3607...	36	079	56748	Patterson	town	32.20799999999...	E600000US3607...	No	179	40	0	56748
18	0600000US3608...	36	081	60323	Queens	boro	108.5319999999...	E600000US3608...	No	22240	24171	NULL	60323
19	0600000US3611...	36	119	48895	Mount Kisco	town	3.035000000000...	E600000US3611...	No	188	309	E600000US3611...	48895
20	0600000US3611...	36	119	53517	North Salem	town	21.32600000000...	E600000US3611...	No	0	40	0	53517
21	0600000US3611...	36	119	59685	Pound Ridge	town	22.63800000000...	E600000US3611...	No	0	55	0	59685
22	0600000US3611...	36	119	84077	Yorktown	town	36.64500000000...	E600000US3611...	No	184	240	0	84077
23	0600000US3602...	36	027	05100	Beacon	city	4.739000000000...	E600000US3602...	No	255	40	0	5100
24	0600000US3602...	36	027	05452	Beekman	town	29.83800000000...	E600000US3602...	No	0	10	0	5452
25	0600000US3602...	36	027	20819	Dover	town	55.18999999999...	E600000US3602...	No	275	40	0	20819
26	0600000US3602...	36	027	21996	East Fishkill	town	56.50300000000...	E600000US3602...	No	408	125	0	21996
27	0600000US3602...	36	027	25978	Fishkill	town	27.33599999999...	E600000US3602...	No	48	248	0	25978
28	0600000US3602...	36	027	51891	North East	town	43.16299999999...	E600000US3602...	No	83	0	0	51891
29	0600000US3602...	36	027	56825	Pawling	town	43.83500000000...	E600000US3602...	No	60	10	0	56825
30	0600000US3602...	36	027	58695	Pleasant Valley	town	32.57600000000...	E600000US3602...	No	78	40	0	58695

Figure 4: Data table illustrating the geographic relationship between towns, sub-counties, and counties obtained from CTDOT.

1	centroid_x	centroid_y	speed_ab	speed_ba	lanes_ab	lanes_ba	imp_speed_ab	imp_speed_ba	imp_lanes_ab	imp_lanes_ba
2	-73.29909885	40.8750754	30	30	1	0	1	1	1	1
3	-73.29919695	40.87499955	30	30	1	0	1	1	1	1
4	-73.30060844	40.87432946	30	30	1	0	1	1	1	1
5	-73.3021938	40.87400675	30	30	1	0	1	1	1	1
6	-73.3633748	40.7485119	30	30	1	1	1	1	1	1
7	-73.36315934	40.74842077	30	30	1	1	1	1	1	1
8	-73.36243245	40.74751237	30	30	1	1	1	1	1	1
9	-73.36144525	40.7459888	30	30	1	1	1	1	1	1
10	-73.36100385	40.74530735	30	30	1	1	1	1	1	1
11	-73.36059816	40.74465835	30	30	1	1	1	1	1	1
12	-73.3601251	40.7440237	30	30	1	1	1	1	1	1
13	-73.3600365	40.743934	30	30	1	2	1	1	1	1
14	-73.359693	40.743591	30	30	1	2	1	1	1	1
15	-73.35905883	40.74295076	30	30	1	1	1	1	1	1
16	-73.35825405	40.7421295	30	30	1	1	1	1	1	1
17	-73.23322133	40.72470445	30	30	1	1	1	1	1	1
18	-73.3560821	40.6754913	30	30	1	0	1	1	1	1
19	-73.35482665	40.67612515	30	30	1	0	1	1	1	1
20	-73.35407465	40.6765114	30	30	1	0	1	1	1	1
21	-73.31033558	40.84598255	30	30	1	2	1	1	1	1
22	-73.27408436	40.84769936	30	30	1	1	1	1	1	1
23	-73.27578831	40.84763739	30	30	1	1	1	1	1	1
24	-73.223548	40.89428095	30	30	1	0	1	1	1	1
25	-73.22271855	40.8943874	30	30	1	0	1	1	1	1
26	-73.22186295	40.8944913	30	30	1	0	1	1	1	1
27	-73.2209979	40.89459975	30	30	1	0	1	1	1	1
28	-73.2201376	40.8947057	30	30	1	0	1	1	1	1
29	-73.2192793	40.8948096	30	30	1	0	1	1	1	1
30	-73.2184156	40.8949196	30	30	1	0	1	1	1	1
31	-73.217562	40.8950276	30	30	1	0	1	1	1	1
32	-73.17355115	40.7349007	31	31	2	1	1	1	1	1
33	-73.17315193	40.734267	31	31	2	1	1	1	1	1
34	-73.17223403	40.73334116	31	31	1	1	1	1	1	1

Figure 5: A sample of the road network data extracted from OpenStreetMap (OSM), showing attributes such as number of lanes and speed limits.

2.2 Transportation Network Development

As explained in section 2.1, construction of a robust digital transportation network for the state of Connecticut was a multi-stage process designed to ensure accuracy, completeness, and simulation readiness. In order to build the network, the following steps were taken:

1. Baseline Network Construction: The initial network was created from OpenStreetMap road data to provide a comprehensive baseline of links and nodes. This baseline was then enriched with additional data layers, including a zoning system derived from U.S. Census data, parking facilities, and EV charging station locations.
2. Integration of Authoritative Data: The baseline network was augmented and cross-validated with the official highway network and Traffic Analysis Zone (TAZ) data from CTDOT. This step ensured the accuracy of local road classifications, speed limits, and administrative boundaries.
3. Network Refinement and Validation: Topological integrity was ensured by checking the combined network for connectivity issues using QGIS. This validation process involved identifying and correcting isolated road segments "islands" to guarantee full network connectivity and prevent routing failures during simulation. Furthermore, external locations were established to model trips entering and exiting the state, ensuring proper handling of the model boundary.
4. **4.** Finalization for Simulation: Once validated, the multi-layer network was imported into the POLARIS framework. This final step involved network simplification based on block-groups and the integration of transit data from GTFS feeds to produce the final, comprehensive model of Connecticut's transportation supply.

2.3 Simulation Framework

The core of this research utilizes an agent-based traffic simulation tool, POLARIS (Planning and Operations Language for Agent-based Regional Integrated Simulation). POLARIS is an advanced modeling suite developed by Argonne National Laboratory (Auld et al., 2014). It is specifically designed to simulate complex transportation systems by modeling the behavior of individual "agents" (e.g., travelers, vehicles) and their interactions with each other and the transportation network. This agent-based approach provides a powerful tool for analyzing the disaggregate impacts of new technologies like SAVs.

In general, an agent-based traffic simulation, as shown in Figure 6, begins by generating a synthetic population that is reflective of the demographics in the study region, using data from sources such as the U.S. Census Bureau and the American Community Survey (Auld and Mohammadian, 2010). Once this population is initialized, the framework's activity-based demand model generates daily activity patterns for each agent. This is a continuous process that informs the core models of each person's travel plan (Auld et al., 2011).

The simulation then proceeds through a sequence of integrated models. A zone-based destination choice model is followed by nested logit models for mode choice, which include SAVs as a potential travel option (Gurumurthy et al., 2020). After scheduling the start time and duration of activities, the model performs pre-trip route planning for all vehicle movements on the network. For SAV operations, heuristics are used to match incoming service requests to available vehicles. Once an SAV is assigned, it follows the optimal route to pick up the traveler and proceeds to the destination. After drop-off, the SAV becomes idle and awaits the next request. This detailed step-by-step modeling of individual decisions and vehicle movements allows for a highly realistic simulation of the entire transportation system over a 24-hour period.

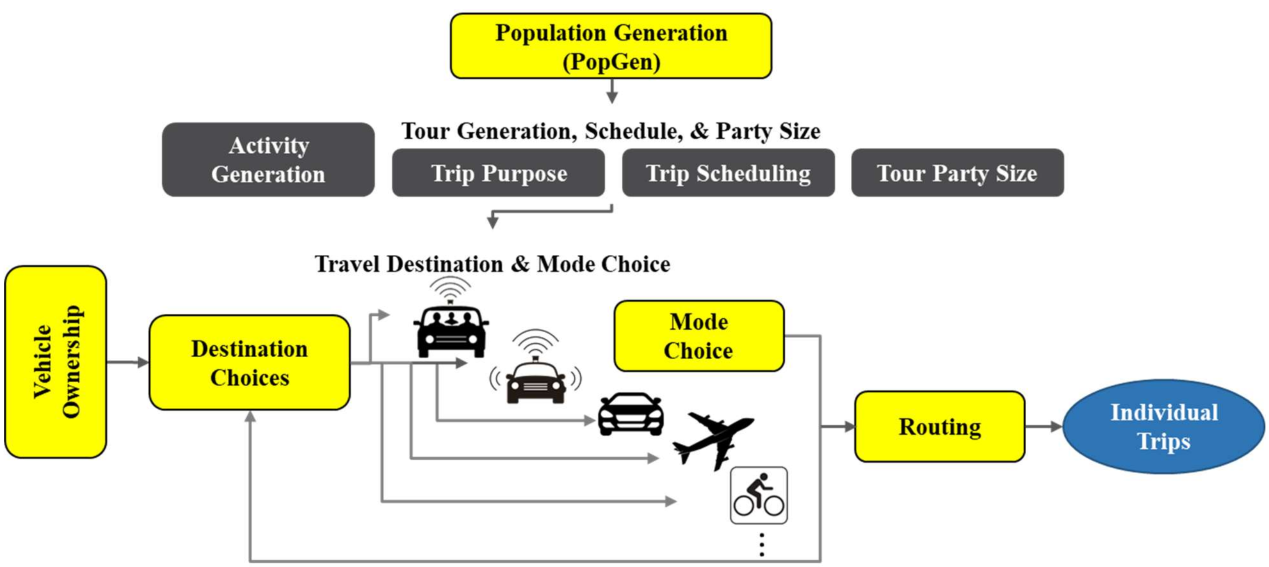
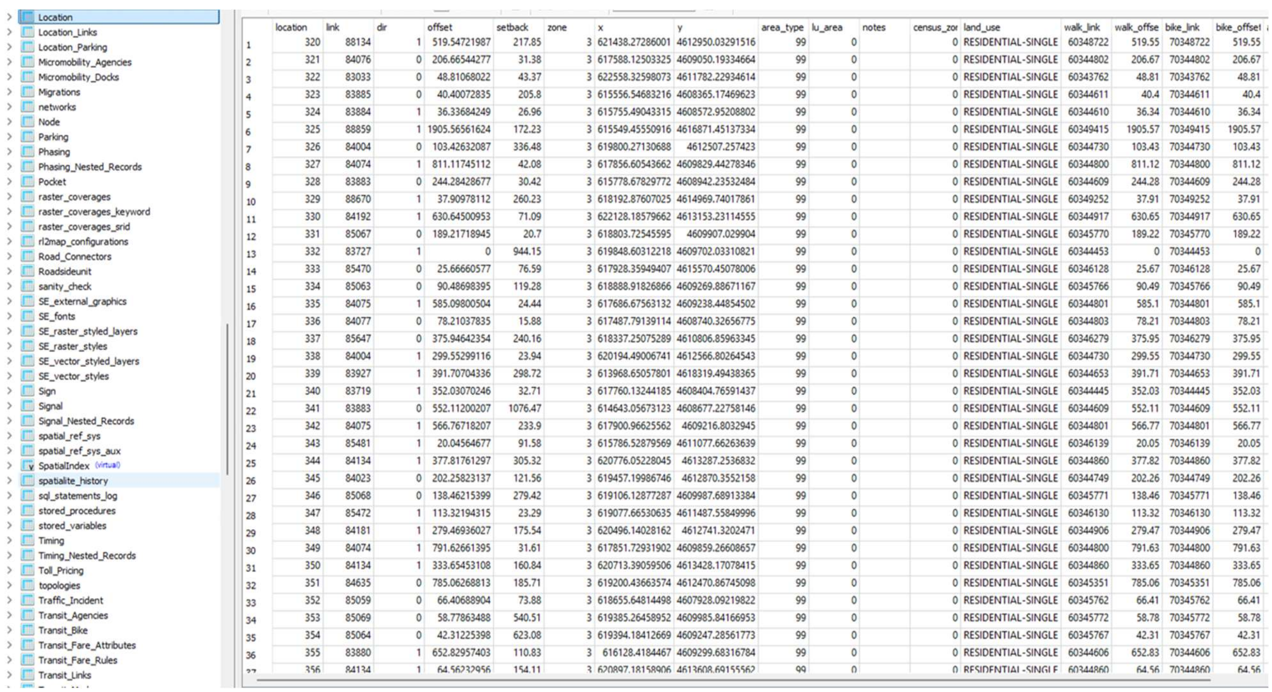


Figure 6: Transportation Systems Simulator Design Overviews (Kockelman et al., 2022).

Chapter 3: Results and Discussion

3.1 Final Transportation Supply Database

The primary outcome of the data preparation process is a single, unified SQLite database. This file functions as the complete transportation supply input, formatted for direct compatibility with the POLARIS simulation framework. The database contains the finalized, multi-layered transportation network, which integrates road data from OpenStreetMap with authoritative highway and Traffic Analysis Zone (TAZ) data from CTDOT. The network is topologically validated to ensure full connectivity, providing a robust infrastructural basis for all simulations. In addition to the network geometry, the database consolidates all supporting datasets required for the model, including link attributes (e.g., speed, capacity), demographic information, and public transit routes, into a single, structured source (Figures 7-14).



	location	link	dir	offset	setback	zone	x	y	area_type	lu_area	notes	census_zor	land_use	walk_link	walk_offse	bike_link	bike_offset
1	320	88134	1	519.54721987	217.85	3	621438.27286001	4612950.03291516	99	0		0	RESIDENTIAL-SINGLE	60348722	519.55	70348722	519.55
2	321	84076	0	206.66544277	31.38	3	617588.12503325	4609050.19334664	99	0		0	RESIDENTIAL-SINGLE	60344802	206.67	70344802	206.67
3	322	83033	0	48.81068022	43.37	3	622558.32598073	4611782.22934614	99	0		0	RESIDENTIAL-SINGLE	60343762	48.81	70343762	48.81
4	323	83885	0	40.40072835	205.8	3	615556.54683216	4608365.17469623	99	0		0	RESIDENTIAL-SINGLE	60344611	40.4	70344611	40.4
5	324	83884	1	36.33684249	26.96	3	615755.49043315	4608572.95208802	99	0		0	RESIDENTIAL-SINGLE	60344610	36.34	70344610	36.34
6	325	88859	1	1905.56561624	172.23	3	615549.45550916	4616871.45137334	99	0		0	RESIDENTIAL-SINGLE	60349415	1905.57	70349415	1905.57
7	326	84004	0	103.42632087	336.48	3	619800.27130688	4612507.257423	99	0		0	RESIDENTIAL-SINGLE	60344730	103.43	70344730	103.43
8	327	84074	1	811.11745112	42.08	3	617856.60543662	4609829.44278346	99	0		0	RESIDENTIAL-SINGLE	60344800	811.12	70344800	811.12
9	328	83883	0	244.28428677	30.42	3	615778.67829772	4608942.23532484	99	0		0	RESIDENTIAL-SINGLE	60344609	244.28	70344609	244.28
10	329	88670	1	37.90978112	260.23	3	618192.87607025	4614969.74017861	99	0		0	RESIDENTIAL-SINGLE	60349252	37.91	70349252	37.91
11	330	84192	1	630.64500953	71.09	3	622128.18579662	4613153.23114555	99	0		0	RESIDENTIAL-SINGLE	60344917	630.65	70344917	630.65
12	331	85067	0	189.21718945	20.7	3	618803.72545595	4609907.029904	99	0		0	RESIDENTIAL-SINGLE	60345770	189.22	70345770	189.22
13	332	83727	1	0	944.15	3	619848.60312218	4609702.03310821	99	0		0	RESIDENTIAL-SINGLE	60344453	0	70344453	0
14	333	85470	0	25.66660577	76.59	3	617928.35949407	4615570.45078006	99	0		0	RESIDENTIAL-SINGLE	60346128	25.67	70346128	25.67
15	334	85063	0	90.48698395	119.28	3	618888.91826866	4609269.88671167	99	0		0	RESIDENTIAL-SINGLE	60345766	90.49	70345766	90.49
16	335	84075	1	585.09800504	24.44	3	617686.67563132	4609238.44854502	99	0		0	RESIDENTIAL-SINGLE	60344801	585.1	70344801	585.1
17	336	84077	0	78.21037835	15.88	3	617487.79139114	4608740.32656775	99	0		0	RESIDENTIAL-SINGLE	60344803	78.21	70344803	78.21
18	337	85647	0	375.94642354	240.16	3	618337.25075289	4610806.85963345	99	0		0	RESIDENTIAL-SINGLE	60346279	375.95	70346279	375.95
19	338	84004	1	299.55299116	23.94	3	620194.49006741	4612566.80264543	99	0		0	RESIDENTIAL-SINGLE	60344730	299.55	70344730	299.55
20	339	83927	1	391.70704336	298.72	3	613968.65057801	4618319.49438365	99	0		0	RESIDENTIAL-SINGLE	60344653	391.71	70344653	391.71
21	340	83719	1	352.03070246	32.71	3	617760.13244185	4608404.76591437	99	0		0	RESIDENTIAL-SINGLE	60344445	352.03	70344445	352.03
22	341	83883	0	552.11200207	1076.47	3	614643.05673123	4608677.22758146	99	0		0	RESIDENTIAL-SINGLE	60344609	552.11	70344609	552.11
23	342	84075	1	566.76718207	233.9	3	617900.96625562	4609216.8032945	99	0		0	RESIDENTIAL-SINGLE	60344801	566.77	70344801	566.77
24	343	85481	1	20.04564677	91.58	3	615786.52879569	4611077.66263639	99	0		0	RESIDENTIAL-SINGLE	60346139	20.05	70346139	20.05
25	344	84134	1	377.81761297	305.32	3	620776.05228045	4613287.2536832	99	0		0	RESIDENTIAL-SINGLE	60344860	377.82	70344860	377.82
26	345	84023	0	202.25823137	121.56	3	619457.19986746	4612870.3552158	99	0		0	RESIDENTIAL-SINGLE	60344749	202.26	70344749	202.26
27	346	85068	0	138.46215399	279.42	3	619106.12877287	4609987.68913384	99	0		0	RESIDENTIAL-SINGLE	60345771	138.46	70345771	138.46
28	347	85472	1	113.32194315	23.29	3	619077.66530635	4611487.55849996	99	0		0	RESIDENTIAL-SINGLE	60346130	113.32	70346130	113.32
29	348	84181	1	279.46936027	175.54	3	620496.14028162	4612741.3202471	99	0		0	RESIDENTIAL-SINGLE	60344906	279.47	70344906	279.47
30	349	84074	1	791.62661395	31.61	3	617851.72931902	4609859.26608657	99	0		0	RESIDENTIAL-SINGLE	60344800	791.63	70344800	791.63
31	350	84134	1	333.65453108	160.84	3	620713.39059506	4613428.17078415	99	0		0	RESIDENTIAL-SINGLE	60344860	333.65	70344860	333.65
32	351	84635	0	785.06268813	185.71	3	619200.43663574	4612470.86745098	99	0		0	RESIDENTIAL-SINGLE	60345351	785.06	70345351	785.06
33	352	85059	0	66.40688904	73.88	3	618655.64814498	4607928.09219822	99	0		0	RESIDENTIAL-SINGLE	60345762	66.41	70345762	66.41
34	353	85069	0	58.77863488	540.51	3	619385.26458952	4609985.84166953	99	0		0	RESIDENTIAL-SINGLE	60345772	58.78	70345772	58.78
35	354	85064	0	42.31225398	623.08	3	619394.18412669	4609247.28561773	99	0		0	RESIDENTIAL-SINGLE	60345767	42.31	70345767	42.31
36	355	83880	1	652.82957403	110.83	3	616128.4184467	4609299.68316784	99	0		0	RESIDENTIAL-SINGLE	60344606	652.83	70344606	652.83
37	356	84134	1	64.56232956	154.11	3	620897.18158906	4613608.69155562	99	0		0	RESIDENTIAL-SINGLE	60344860	64.56	70344860	64.56

Figure 7: The data structure of the 'Locations' table within the project's SQLite database, detailing key point-of-interest attributes.

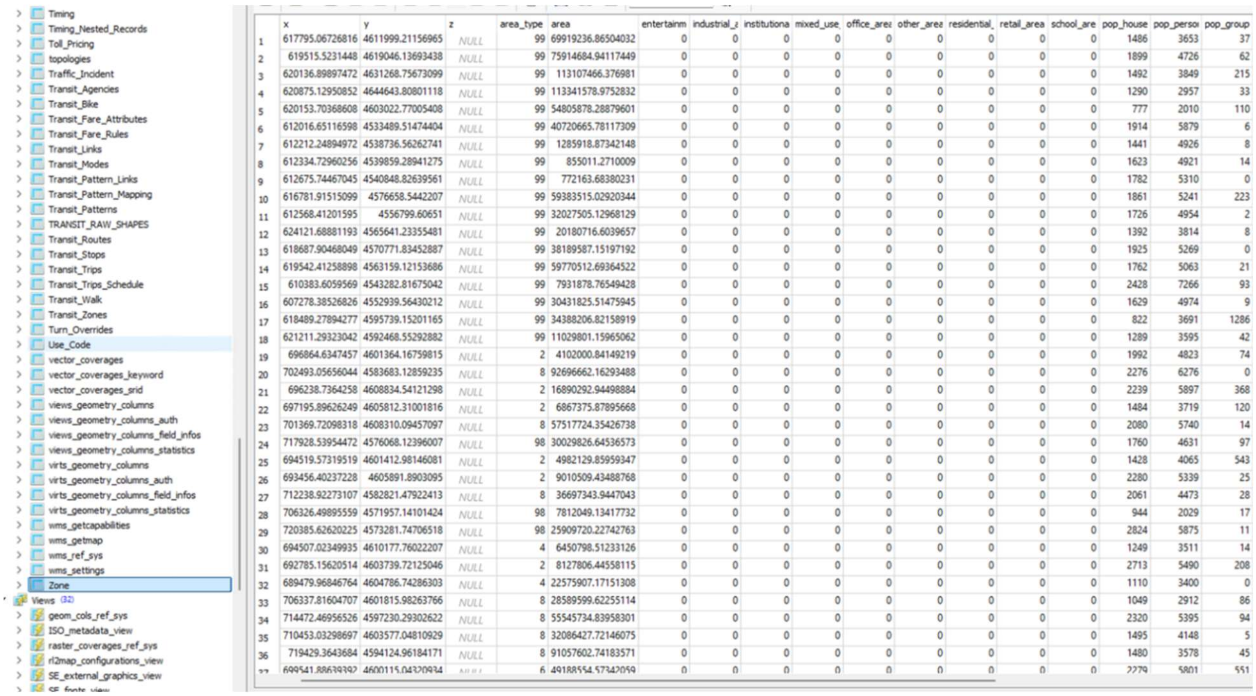


Figure 8: A view of the consolidated 'Zone' data table, integrating TAZ attributes for network analysis within the SQLite database.

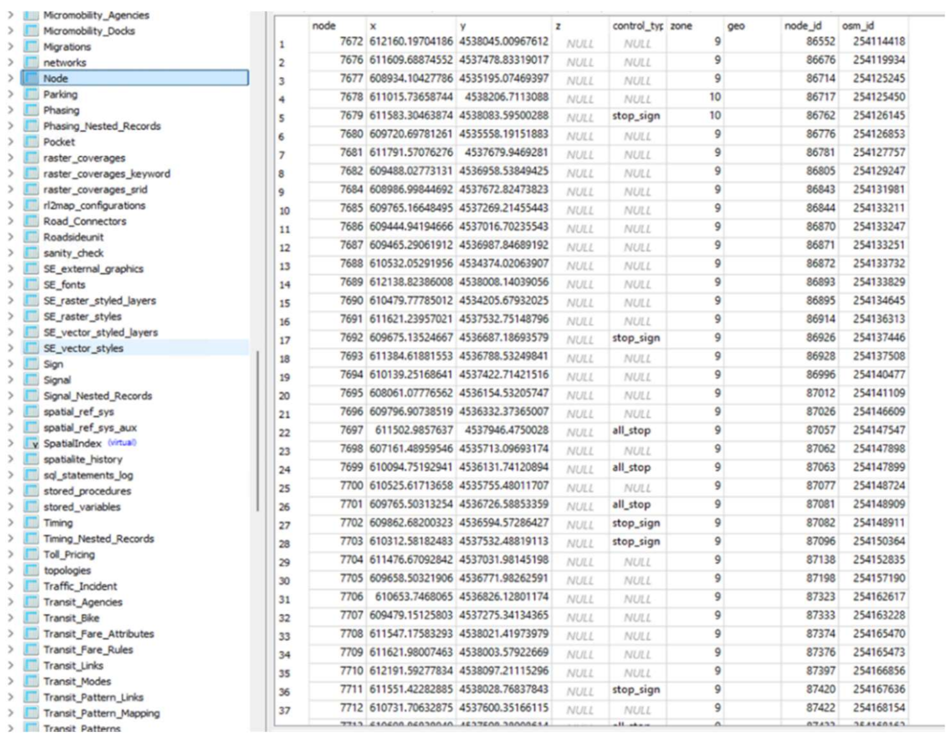
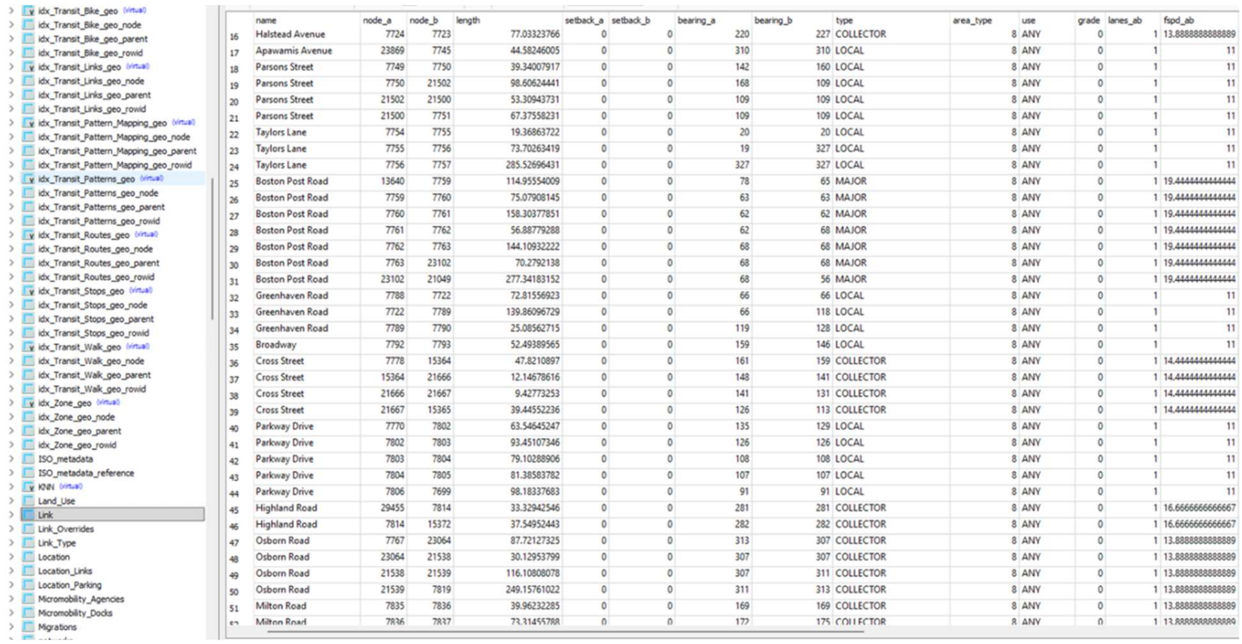


Figure 9: The 'Nodes' table from the SQLite database, representing the intersections and endpoints with their control type.



	name	node_a	node_b	length	setback_a	setback_b	bearing_a	bearing_b	type	area_type	use	grade	lanes_ab	fspd_ab
16	Halstead Avenue	7724	7723	77.03323766	0	0	220	227	COLLECTOR	8	ANY	0	1	13.8888888888889
17	Apawamis Avenue	23869	7745	44.58246005	0	0	310	310	LOCAL	8	ANY	0	1	11
18	Parsons Street	7749	7750	39.34007917	0	0	142	160	LOCAL	8	ANY	0	1	11
19	Parsons Street	7750	21502	98.60624441	0	0	168	109	LOCAL	8	ANY	0	1	11
20	Parsons Street	21502	21500	53.30943731	0	0	109	109	LOCAL	8	ANY	0	1	11
21	Parsons Street	21500	7751	67.37558231	0	0	109	109	LOCAL	8	ANY	0	1	11
22	Taylors Lane	7754	7755	19.36863722	0	0	20	20	LOCAL	8	ANY	0	1	11
23	Taylors Lane	7755	7756	73.70263419	0	0	19	327	LOCAL	8	ANY	0	1	11
24	Taylors Lane	7756	7757	285.52696431	0	0	327	327	LOCAL	8	ANY	0	1	11
25	Boston Post Road	13640	7759	114.95554009	0	0	78	65	MAJOR	8	ANY	0	1	19.4444444444444
26	Boston Post Road	7759	7760	75.07908145	0	0	63	63	MAJOR	8	ANY	0	1	19.4444444444444
27	Boston Post Road	7760	7761	158.30377851	0	0	62	62	MAJOR	8	ANY	0	1	19.4444444444444
28	Boston Post Road	7761	7762	56.88779288	0	0	62	68	MAJOR	8	ANY	0	1	19.4444444444444
29	Boston Post Road	7762	7763	144.10932222	0	0	68	68	MAJOR	8	ANY	0	1	19.4444444444444
30	Boston Post Road	7763	23102	70.2792138	0	0	68	68	MAJOR	8	ANY	0	1	19.4444444444444
31	Boston Post Road	23102	21049	277.34183152	0	0	68	56	MAJOR	8	ANY	0	1	19.4444444444444
32	Greenhaven Road	7788	7722	72.81556923	0	0	66	66	LOCAL	8	ANY	0	1	11
33	Greenhaven Road	7722	7789	139.86096729	0	0	66	118	LOCAL	8	ANY	0	1	11
34	Greenhaven Road	7789	7790	25.08562715	0	0	119	128	LOCAL	8	ANY	0	1	11
35	Broadway	7792	7793	52.49389565	0	0	159	146	LOCAL	8	ANY	0	1	11
36	Cross Street	7778	15364	47.8210897	0	0	161	159	COLLECTOR	8	ANY	0	1	14.4444444444444
37	Cross Street	15364	21666	12.14678616	0	0	148	141	COLLECTOR	8	ANY	0	1	14.4444444444444
38	Cross Street	21666	21667	9.42773253	0	0	141	131	COLLECTOR	8	ANY	0	1	14.4444444444444
39	Cross Street	21667	15365	39.44552236	0	0	126	113	COLLECTOR	8	ANY	0	1	14.4444444444444
40	Parkway Drive	7770	7802	63.54645247	0	0	135	129	LOCAL	8	ANY	0	1	11
41	Parkway Drive	7802	7803	93.45107346	0	0	126	126	LOCAL	8	ANY	0	1	11
42	Parkway Drive	7803	7804	79.10288906	0	0	108	108	LOCAL	8	ANY	0	1	11
43	Parkway Drive	7804	7805	81.38583782	0	0	107	107	LOCAL	8	ANY	0	1	11
44	Parkway Drive	7806	7699	98.18337683	0	0	91	91	LOCAL	8	ANY	0	1	11
45	Highland Road	29455	7814	33.32942546	0	0	281	281	COLLECTOR	8	ANY	0	1	16.6666666666667
46	Highland Road	7814	15372	37.54952443	0	0	282	282	COLLECTOR	8	ANY	0	1	16.6666666666667
47	Osborn Road	7767	23064	87.72127325	0	0	313	307	COLLECTOR	8	ANY	0	1	13.8888888888889
48	Osborn Road	23064	21538	30.12953799	0	0	307	307	COLLECTOR	8	ANY	0	1	13.8888888888889
49	Osborn Road	21538	21539	116.10808078	0	0	307	311	COLLECTOR	8	ANY	0	1	13.8888888888889
50	Osborn Road	21539	7819	249.15761022	0	0	311	313	COLLECTOR	8	ANY	0	1	13.8888888888889
51	Milton Road	7835	7836	39.96232285	0	0	169	169	COLLECTOR	8	ANY	0	1	13.8888888888889
52	Milton Road	7836	7837	73.31455788	0	0	172	175	COLLECTOR	8	ANY	0	1	13.8888888888889

Figure 10: Attribute structure of the 'Links' table, representing the transportation network's road segments. Key fields include length, area type, number of lanes, and free-flow speed, with the latter formatted in meters per second (m/s).

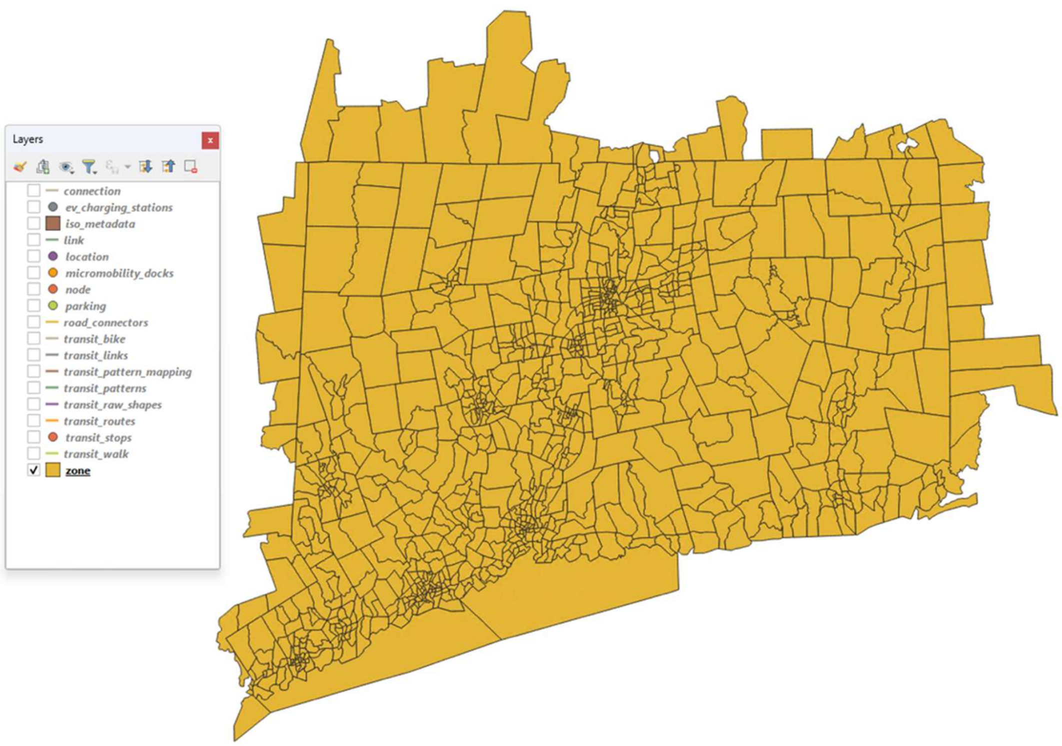


Figure 11: The refined delineation of Traffic Analysis Zones (TAZs) within the study area following data processing and simplification.

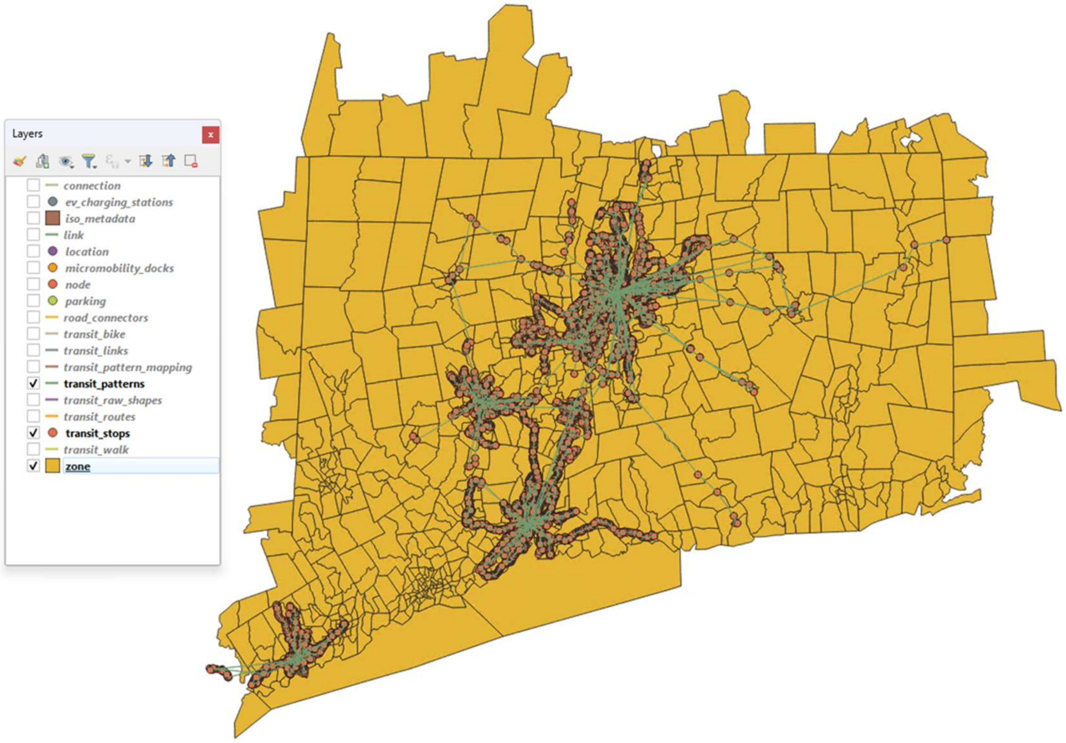


Figure 12: Spatial distribution of public transit routes and stop locations overlaid on the finalized TAZ geography.

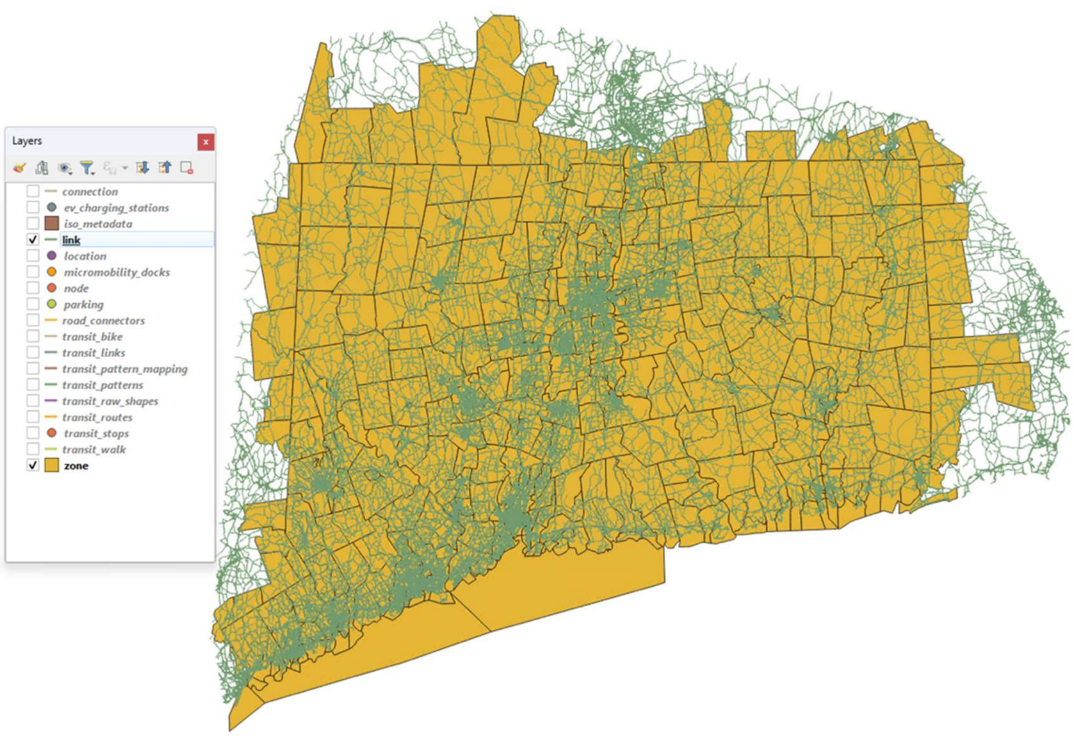


Figure 13: Distribution of links overlaid on Zone layer.

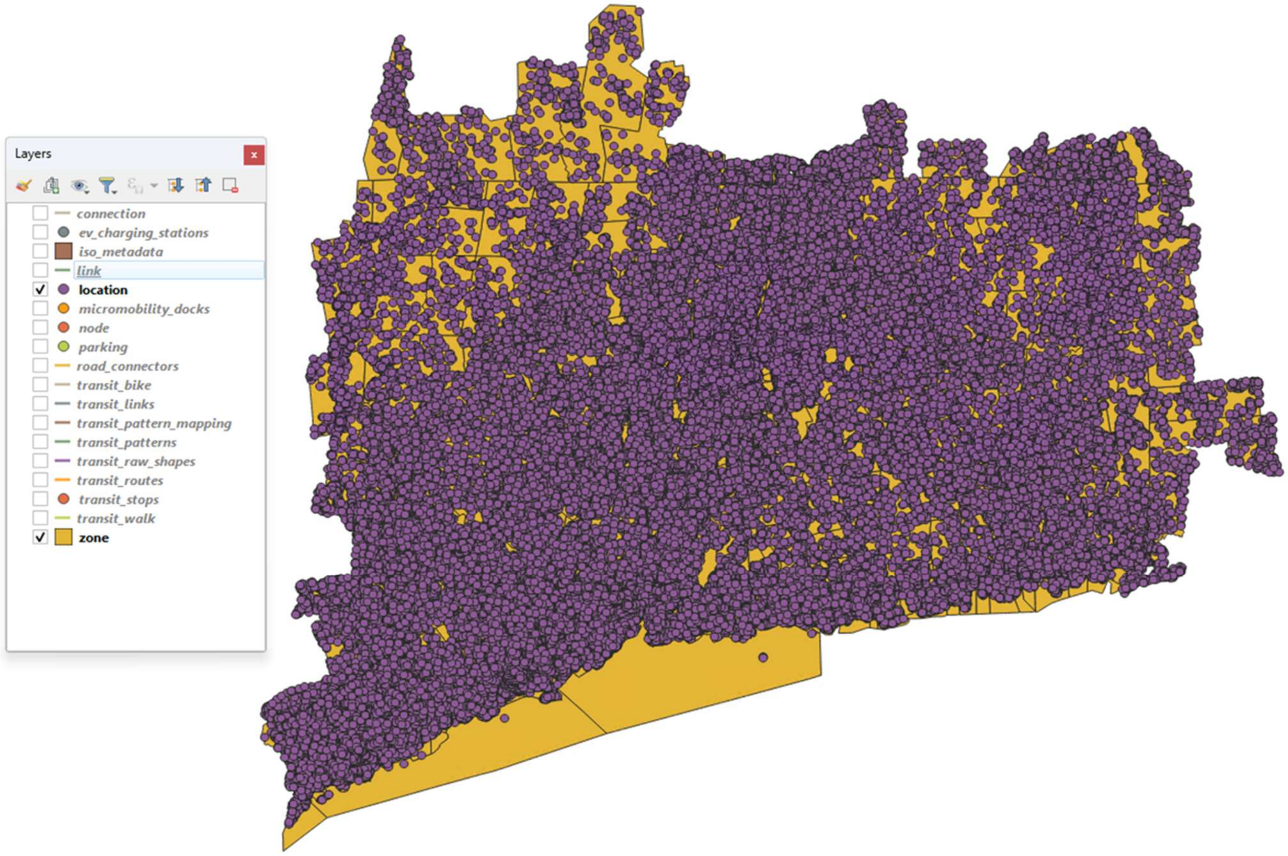


Figure 14: Geographic distribution of Points of Interest (POIs) across the study area's Zones.

3.2 SAV Simulation and Scenario Analysis

To establish a benchmark for comparison, a scenario was simulated without any SAV service. This allows for a clear analysis of how engaging SAVs affects total VMT, a key indicator of impact on the transportation infrastructure. Against this benchmark, three distinct SAV operational scenarios were then simulated across five different fleet sizes: 500, 1,000, 2,000, 5,000, and 10,000 vehicles. These scenarios, detailed in Section 3.2.1, were designed to explore how different strategies for service quality and pricing impact a wide range of system performance metrics. The three SAV scenarios are the Base scenario, a time-based scenario with stricter service timing, and a price-based scenario with higher fares. The results of this analysis are presented in Section 3.2.2.

To ensure manageable simulation times across the many scenarios and fleet sizes tested, all simulations were conducted within the geofence area shown in Figure 15. This area spans 72 zones where DRS was enabled. This setup, which includes a population of approximately 350,000 people, was designed to reflect realistic conditions. The selected zones cover a diverse mix of urban, suburban, and rural land uses. This variety provides a comprehensive and practical environment to analyze how SAVs would operate under real-world conditions.

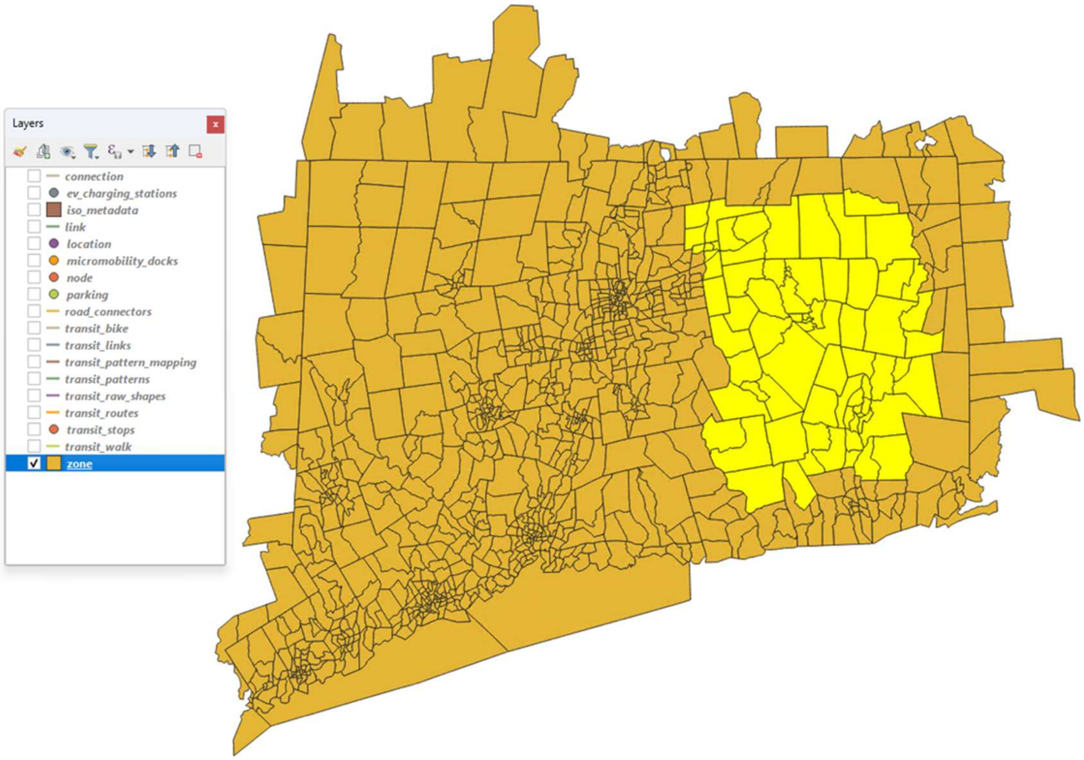


Figure 15: Geofenced area covering 72 zones for the Dynamic Ride Sharing (DRS).

3.2.1 Scenario Definitions

The specific parameters for each scenario are defined to isolate the effects of time constraints and cost on system performance and user adoption. The Base scenario represents a standard operational model. The time-based scenario halves the allowable wait and delay times, and the price-based scenario doubles all cost components, testing demand elasticity. The parameters for each are detailed in Table 1.

Table 1: Scenario parameters for geofenced area

Parameter	Without - SAV	Base Scenario	Time-Based Scenario	Price-Based Scenario
SAV Max Wait Time (minutes)	-	20	10	20
DRS Max Allowable Delay (minutes)	-	20	10	20
DRS Max Percentage Delay (minutes)	-	20	10	20
Rideshare Cost Per Mile ($)	-	0.75	0.75	1.5
Rideshare Cost Per Minute ($)	-	0.15	0.15	0.3
Rideshare Base Fare ($)	-	2	2	4

3.2.2 Simulation Results and Analysis

The simulation results highlight key trade-offs among fleet size, service quality, pricing, and operational efficiency. As more cars are added to the fleet, certain aspects of service quality improve, such as dramatically shorter wait times (Figure 16). However, this expansion comes at a steep cost to efficiency. With more vehicles competing for riders, each car completes far fewer trips per day as shown in Figure 17, leading to longer idle times. These findings demonstrate a clear pattern of diminishing returns, suggesting that simply expanding the fleet is not an effective strategy beyond an optimal point.

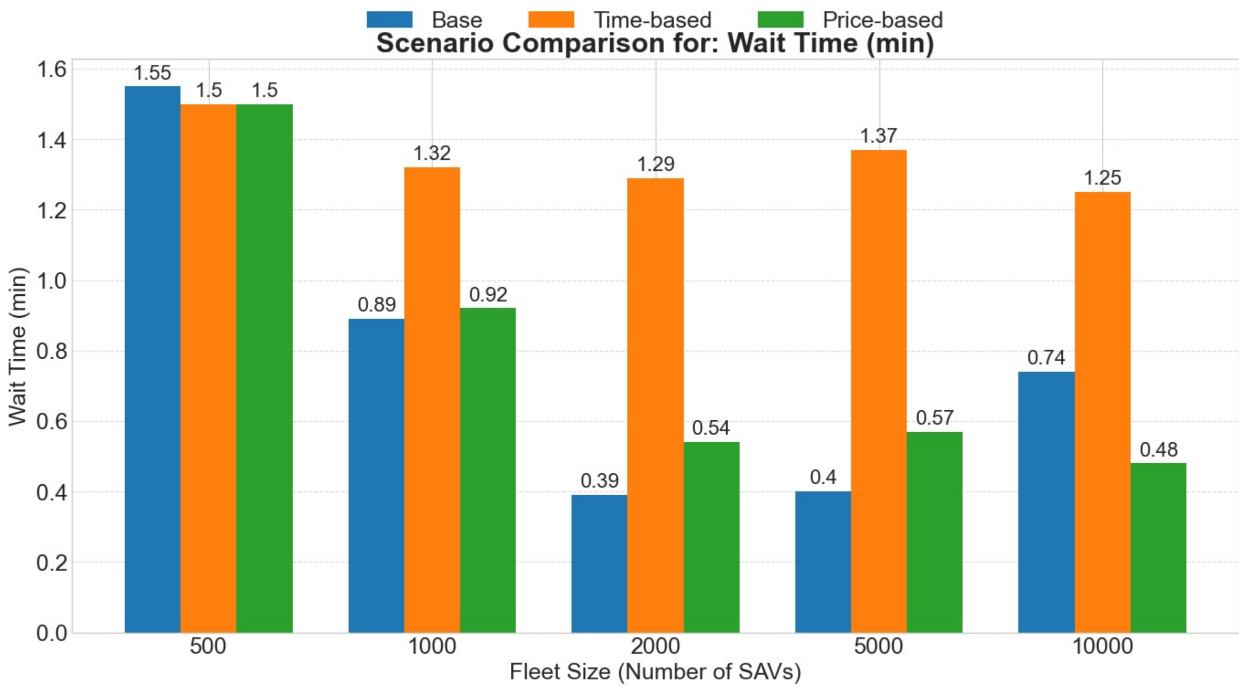


Figure 16: The effect of fleet size on average wait time.

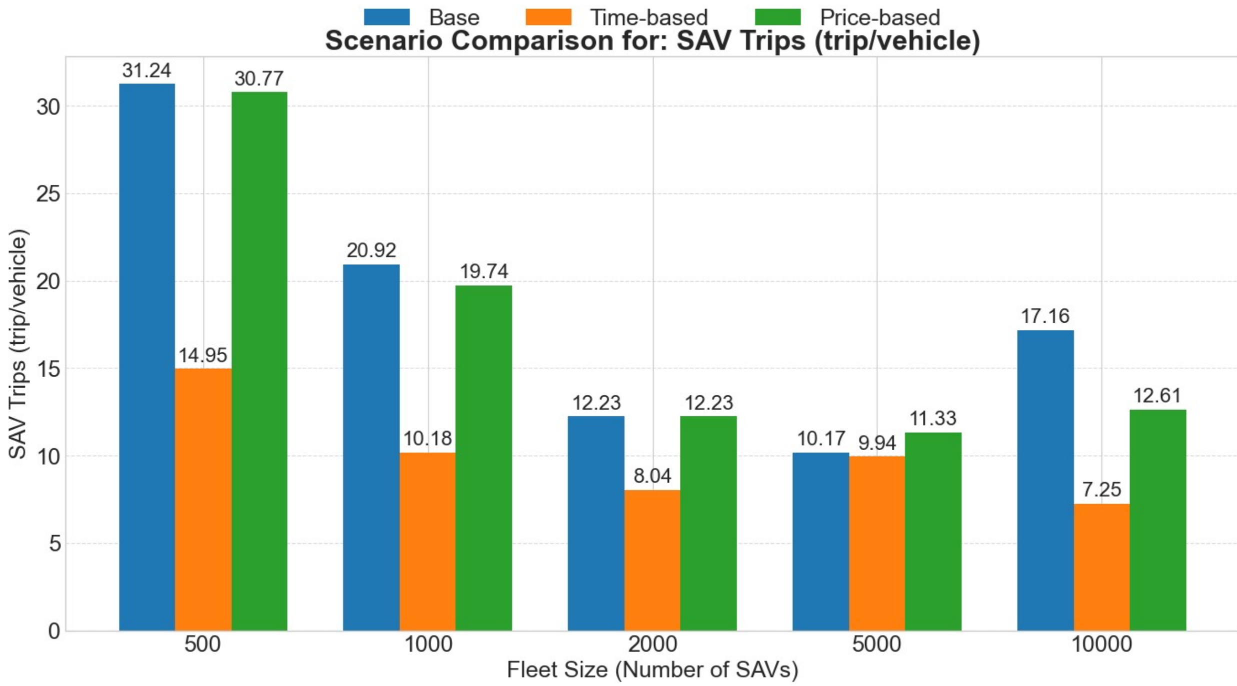


Figure 17: Vehicle productivity (trips per vehicle) across different fleet sizes.

The three scenarios tested reveal a classic conflict between profitability and keeping customers happy. The higher fares in the price-based scenario were likely intended to boost income. However, this improvement came at the cost of customer loss. For instance, with a fleet of 5,000 vehicles, the SAV market share declined from 7.32% in the Base scenario to 6.65%, accompanied by a reduction in demand of almost 600 rides. While this drop seems small, it shows that higher prices made the service less attractive as shown in Figures 18 and 19.

On the other hand, the time-based scenario—designed to speed up service—successfully reduced pickup delay (the time for a dispatched vehicle to arrive) to the lowest levels of any scenario in Figure 20. However, it also produced the lowest overall demand. A key factor behind this is Connecticut's land use pattern. Unlike dense urban centers, points of interest across the state are widely dispersed. As shown in the QGIS data in section 3.1 for POIs, SAVs often cannot efficiently reach these scattered locations. This, combined with the lowest acceptance rate among all scenarios, as shown in Figure 21, indicates that the geographic context is a critical factor in SAV viability. Consequently, the mode share for SAVs in this scenario peaked at only 3%, highlighting their limited appeal in this specific operational model.

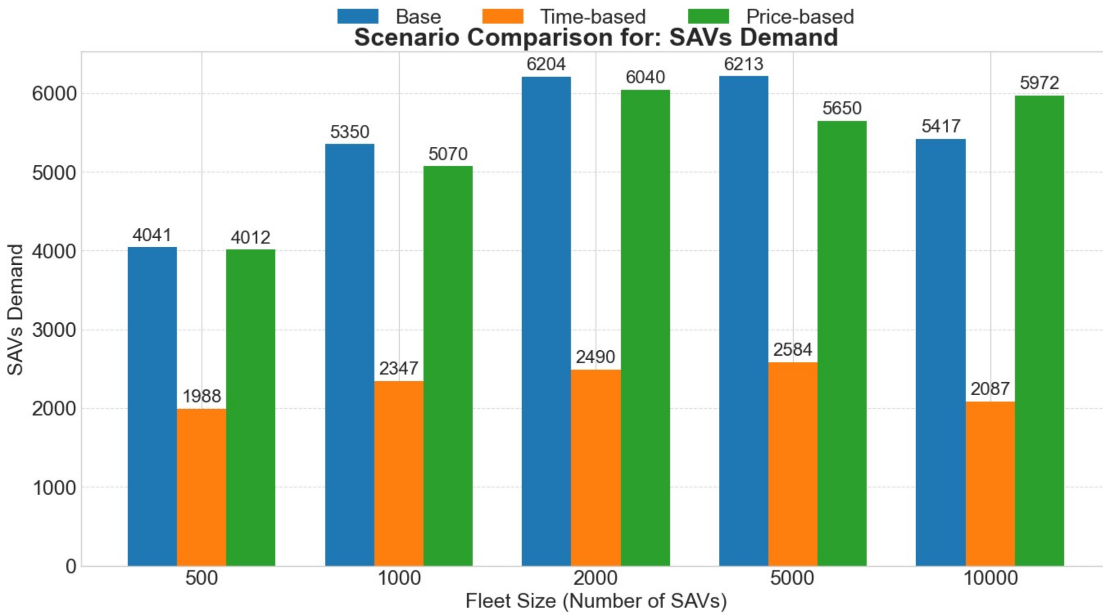


Figure 18:Comparison of total demand met by fleet size and scenario.

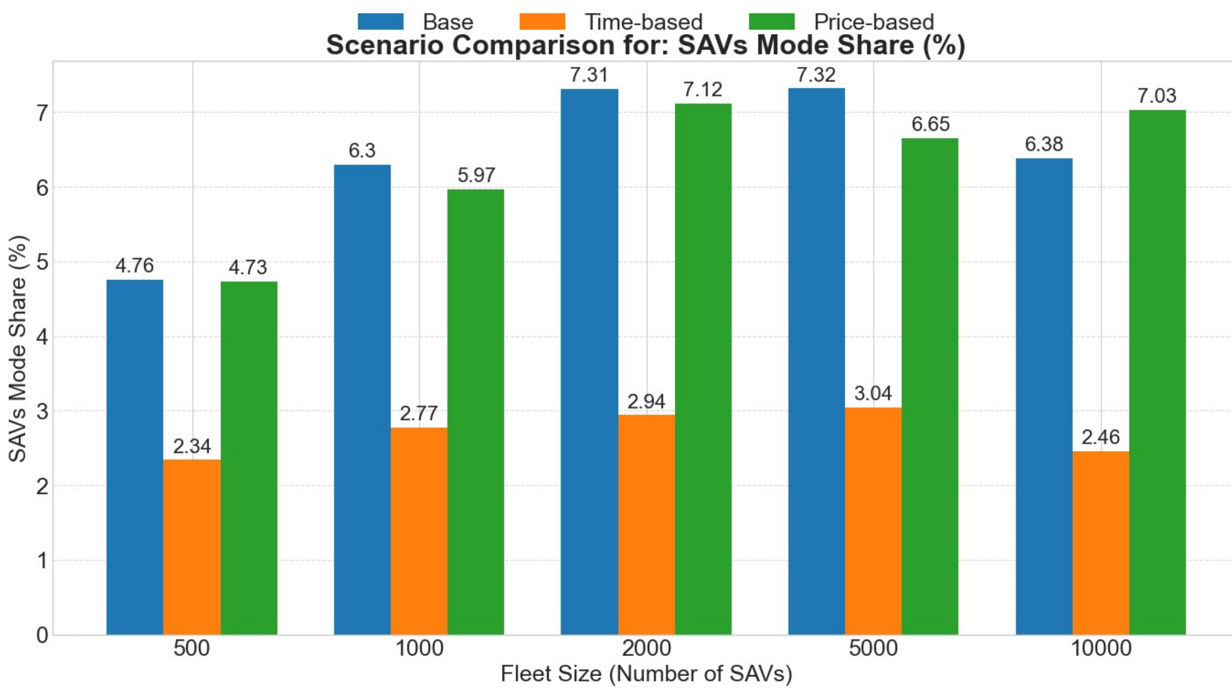


Figure 19:The impact of fleet size on SAV mode share.

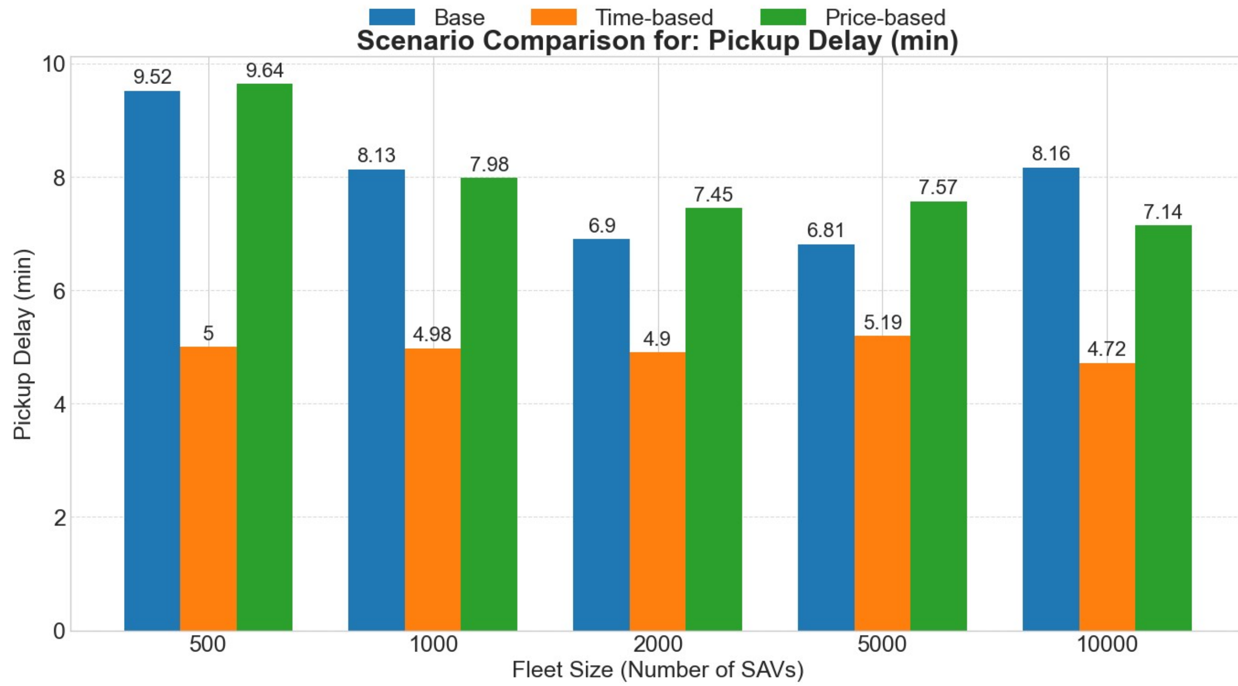


Figure 20:The effect of fleet size on average pickup time.

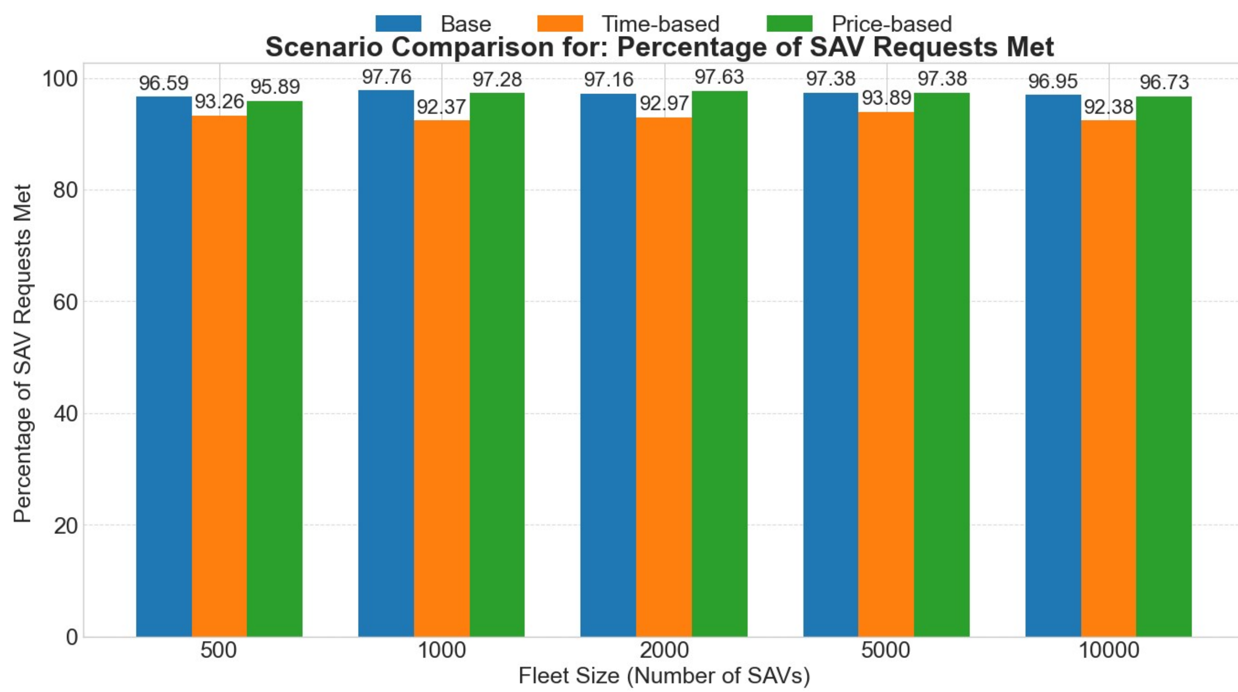


Figure 21:The percentage of demand met across all scenarios.

The simulation results carry important implications for city infrastructure. A critical component of VMT is empty VMT (eVMT), which represents miles driven without passengers. It is important to distinguish between the absolute number of empty miles in Figure 22 and the share of empty miles as a percentage of total travel shown in Figure 23, which is a better measure of inefficiency. The time-based scenario yielded the lowest absolute eVMT. However, given its very low demand, largely resulting from difficulties in reaching certain locations, this case is not considered desirable. Consequently, when comparing the Base condition with the price-based scenario, the latter demonstrates lower efficiency, as a larger share of its vehicle miles are traveled without passengers.

The simulation results reveal that SAVs offer a significant and direct benefit to infrastructure durability through the proven mechanism of trip consolidation. As shown in Figure 24, the average vehicle occupancy (AVO) consistently exceeds one, confirming that the system successfully replaces single-occupancy vehicles (SOVs) with shared rides. This consolidation is the primary way SAVs reduce the total number of vehicles on the road, which in turn eases road wear, mitigates congestion, and ultimately lowers long-term maintenance needs. This benefit to infrastructure is further amplified by a direct reduction in total VMT. As shown in Figure 25, deploying an SAV fleet significantly lowers the network's total VMT compared to the base condition where no SAVs are active. This finding provides a powerful second mechanism, alongside trip consolidation, for enhancing infrastructure durability. The simulation shows that this reduction can be substantial, with a fleet of 5,000 vehicles achieving a 2.23% decrease in total VMT. Ultimately, this demonstrates that a well-deployed SAV system not only reduces the number of cars on the road but also lessens their total travel distance, directly translating to less wear and tear and improved longevity for road infrastructure.

Finally, the data strongly points to an optimal configuration for maximizing system effectiveness. The base scenario with a fleet of 5,000 vehicles emerges as the most balanced approach. At this level, demand and mode share reach their peak (Figures 18 and 19) before the system suffers from significant diminishing returns in operational efficiency. While larger fleets offer marginal improvements in wait times, the sharp drop in vehicle productivity suggests that expanding the fleet beyond this point becomes counterproductive. Therefore, this configuration represents the sweet spot between serving the maximum number of travelers and maintaining a sustainable and efficient operation. Additional details on system performance, such as average trip time (Figure 26) and average trip distance (Figure 27), provide further context for these findings.

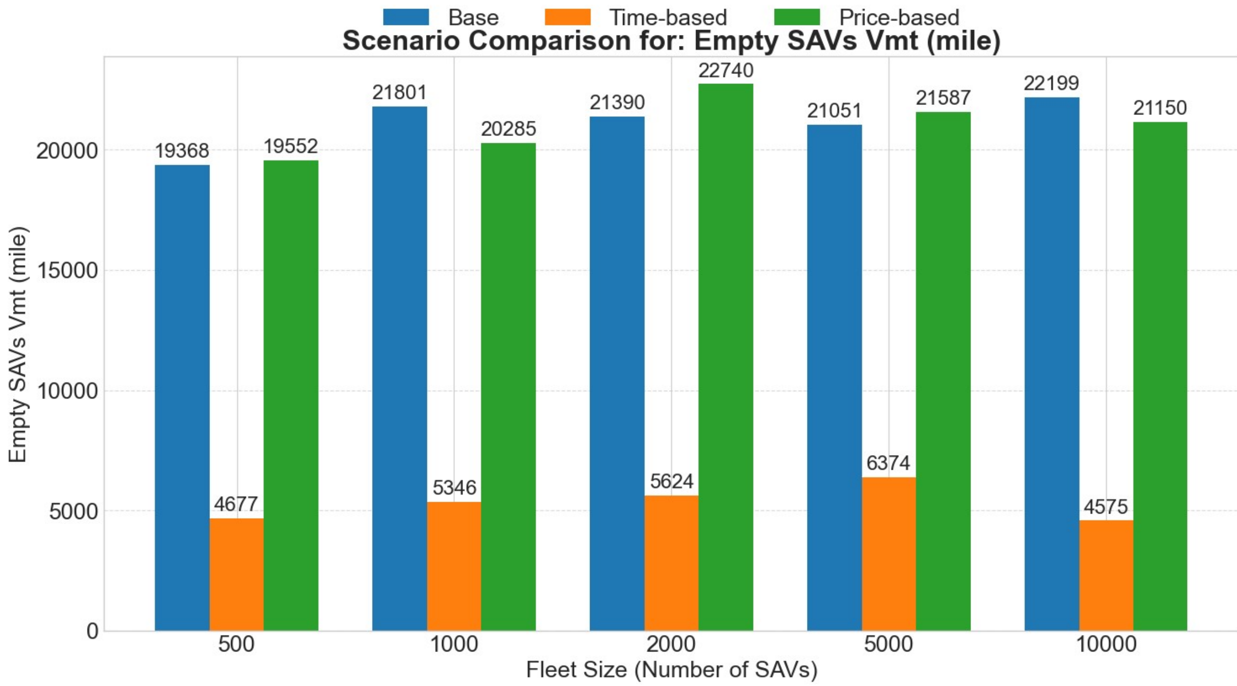


Figure 22:Share of empty vehicle miles traveled as a function of fleet size.

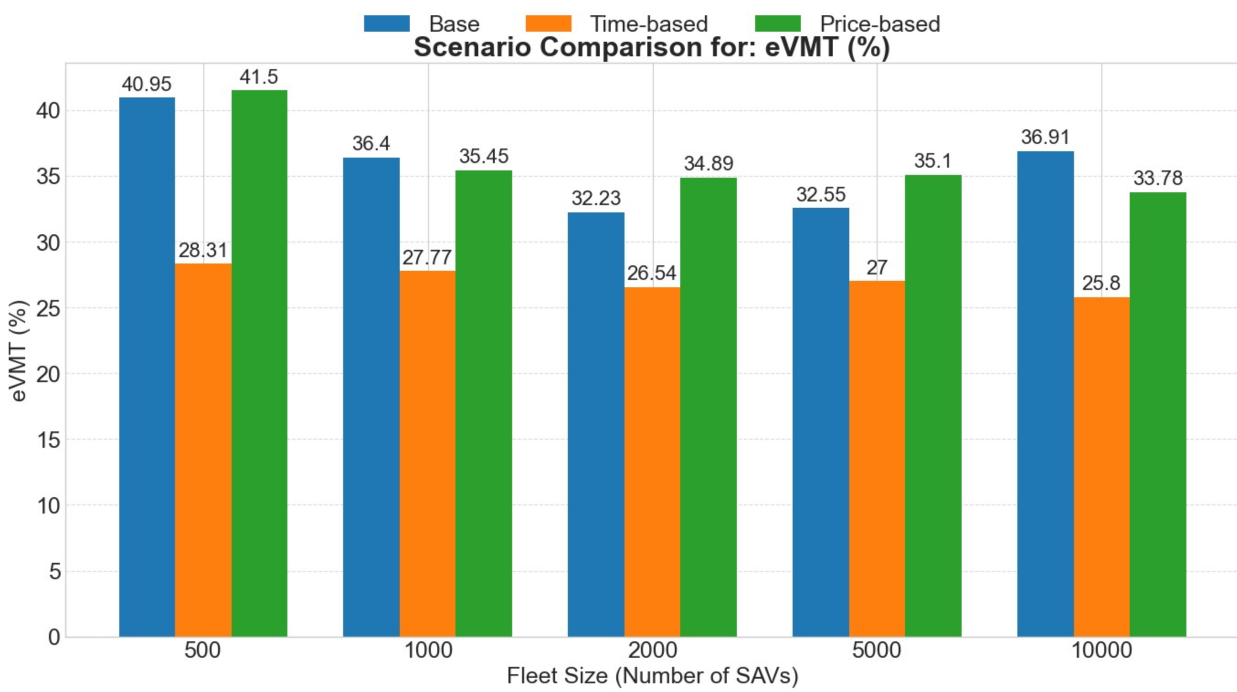


Figure 23: The share of empty vehicle miles traveled.

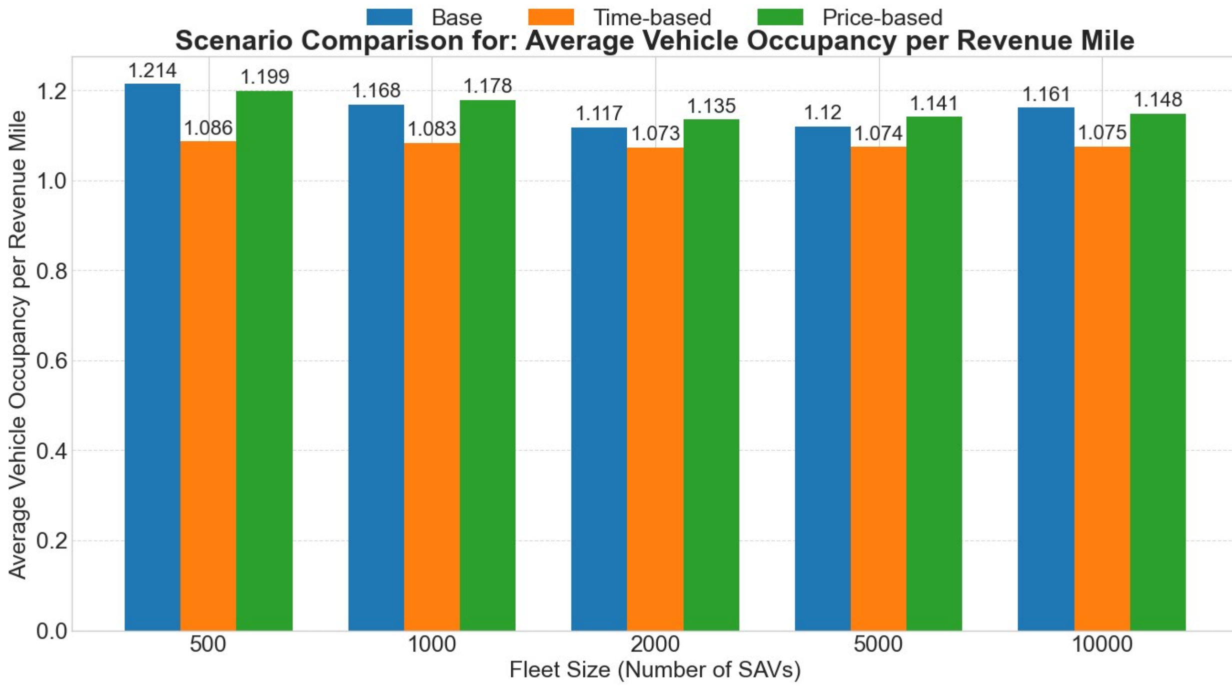


Figure 24:Scenario analysis of average vehicle occupancy per revenue mile.

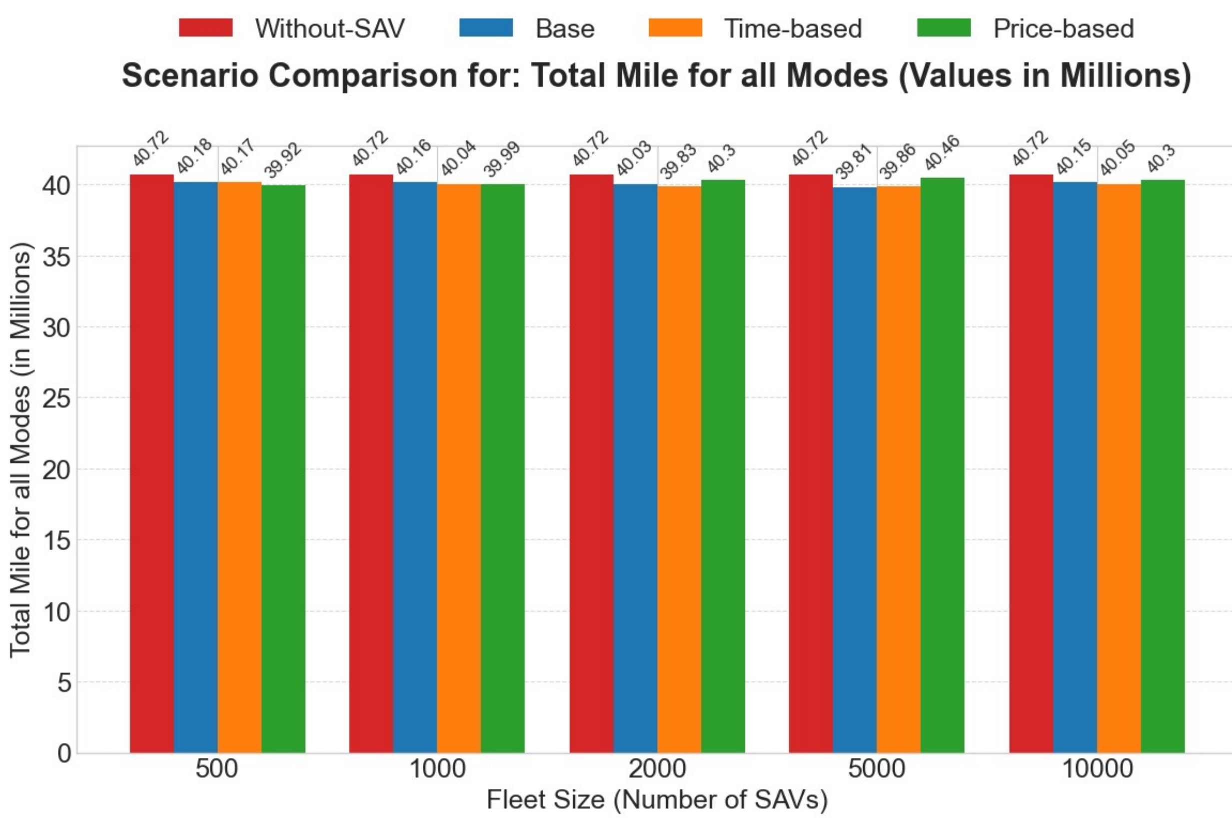


Figure 25:Total miles traveled in all modes during simulation.

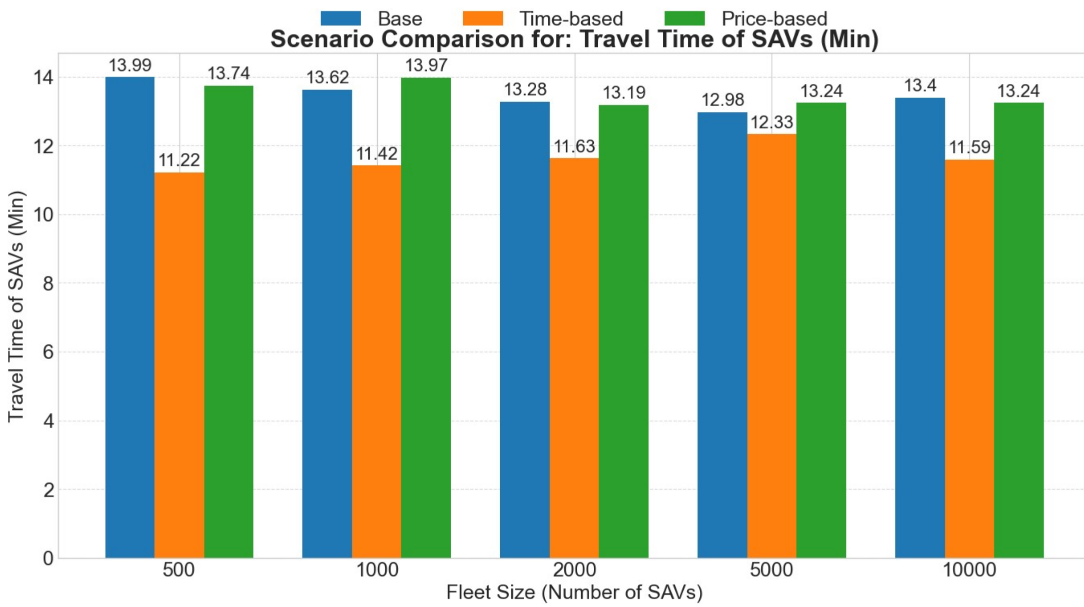


Figure 26:The effect of fleet size and scenario on average trip time.

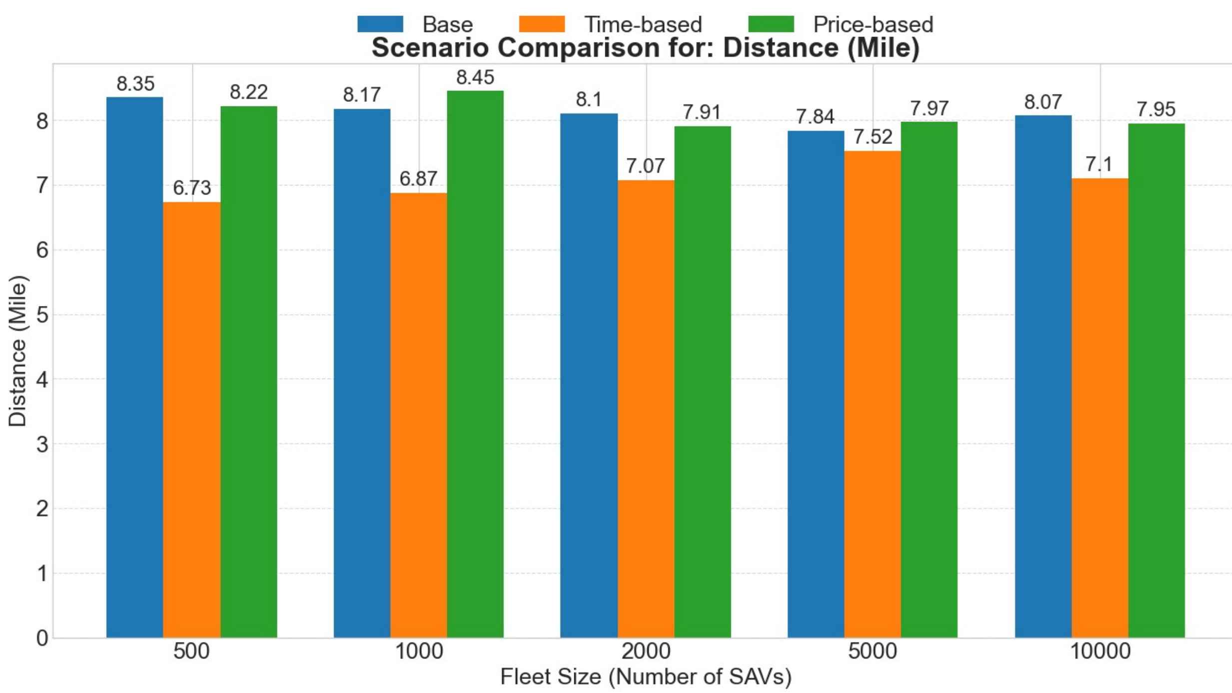


Figure 27:Analysis of average trip distance as a function of fleet size.

To quantify the impact of this 2.23% VMT reduction, established infrastructure performance models offer a direct method for translating lower traffic volumes into extended asset life. The effect is particularly pronounced for surface assets like pavement markings, where traffic exposure is a primary driver of degradation. We applied the 2.23% VMT reduction to the service life models developed by Lertworawanich & Karoonsoontawong (2012), which are based on the following equations:

- White Shoulder Line:

$$\text{Average Service Life (months)} = \frac{5.152 \times e^{(6.1534-0.000238\times AADT\ per\ Lane)}}{30} \quad (1)$$

- White Lane-Separating Line:

$$\text{Average Service Life (months)} = \frac{6.169 \times e^{(5.842-0.00022951\times AADT\ per\ Lane)}}{30} \quad (2)$$

Given that VMT is a direct function of AADT and the simulation utilizes a static road network, we assume that the 2.23% VMT reduction corresponds to a comparable average reduction in AADT. On a road segment with an AADT of approximately 5,100 vehicles per lane—a value noted by Lertworawanich & Karoonsoontawong (2012) as the threshold below which markings tend to meet their 24-month service life specification —this reduction in traffic would extend the average functional life of white shoulder markings by an estimated 2.7%. Similarly, on a segment with 4,715 vehicles per lane (the corresponding threshold for lane-separating lines), the VMT reduction extends the life of white lane-separating markings by an estimated 2.6%. This principle is supported by other models, such as the one by Sitzabee et al. (2009), which found that every 1,000-vehicle increase in AADT reduces a thermoplastic marking's retroreflectivity by an additional 1.1 mcd/m²/lx.

The benefits of lower traffic extend beyond markings to the pavement structure itself. Studies such as Rahman et al. (2017) confirm that AADT is a statistically significant ($p < 0.001$) factor in increasing the International Roughness Index (IRI), a key measure of road deterioration. Their regression model for asphalt concrete pavements quantifies this by assigning a coefficient of +14.686 to the $\log_{10}$ AADT variable. This number provides a mathematical link showing that as traffic volume increases, road roughness gets quantifiably worse, leading to a decline in ride quality. These models show that the VMT reduction achieved in the simulation directly corresponds to slower infrastructure wear, leading to reduced maintenance frequency and long-term cost savings.

Chapter 4: Conclusions and Future Directions

This study evaluated the impacts of SAVs on traffic operations and infrastructure durability in Connecticut. The simulation results of a geofence area around Hartford, CT confirm that SAVs have the potential to be beneficial for infrastructure, but their effectiveness is also dependent on strategic implementation. The key conclusions are as follows:

1. Trip Consolidation and VMT Reduction Directly Link to Improved Infrastructure Durability: This study demonstrates that SAVs can improve infrastructure through two

primary mechanisms: trip consolidation and net VMT reduction. The simulation's finding of a consistent AVO greater than one confirms that SAVs replace multiple single-occupancy vehicles, thereby reducing the total number of vehicles passing on the network. This reduction is critical, as foundational pavement engineering principles identify traffic repetitions as a primary driver of structural deterioration (Huang, 2004). This principle is corroborated by empirical models showing that Annual Average Daily Traffic (AADT) is a statistically significant factor in declining road ride quality (Rahman et al., 2017). Since total VMT is a function of AADT across the network, this finding links overall vehicle usage to infrastructure wear. Furthermore, multiple studies confirm that AADT is the most significant cause of degradation for surface assets like pavement markings, directly shortening their service life (Lertworawanich & Karoonsoontawong, 2012; Sitzabee et al., 2009).

2. Strategic Deployment is Key to Maximizing VMT Reduction: The simulation revealed that deploying SAVs leads to a net reduction in total VMT, with a fleet of 5,000 vehicles achieving a 2.23% decrease. This positive outcome demonstrates that SAVs can lessen the overall burden on roadways. However, the magnitude of this benefit is highly sensitive to operational strategy. To maximize this VMT reduction, policy focused on targeted service areas and competitive pricing will be critical to ensuring SAVs primarily replace less-efficient SOV trips, rather than competing with zero-VMT modes like walking.
3. An Optimal Fleet Configuration Exists: The principle that "more is better" does not apply to SAV deployment. The analysis identified an optimal balance between service quality and operational efficiency, with the Base scenario using a fleet of 5,000 vehicles emerging as the most effective configuration. This setup maximized demand and mode share before the system was hampered by the significant diminishing returns on efficiency seen with larger fleets. Within the selected geofence area, this configuration equates to a fleet density of 1 SAV per 70 people.

A key limitation of this study is its reliance on a nested-logit mode choice model developed by Gurumurthy et al. (2020) for the Chicago network. While this model provided a robust foundation, a crucial next step is to calibrate it using local Connecticut datasets. A locally calibrated model would better reflect the unique travel behaviors of Connecticut residents, refining the optimal fleet size and the precise impact of policies. Building on this, the study's findings suggest that for SAVs to be beneficial, they must be implemented strategically. State policy should encourage SAVs to function as first-mile/last-mile connectors to transit hubs, complementing public transit rather than competing with it. A phased, data-driven deployment, starting with a smaller fleet, would allow for continuous monitoring and adjustment, ensuring operational models are sophisticated enough to handle Connecticut’s dispersed land use effectively.

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Appendices

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