Simulation-Based Evaluation of Autonomous Vehicle Penetration on Urban Traffic Efficiency and CO_2 Emissions via Integrated PTV VISSIM and Bosch ESTM

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Abstract: Carbon dioxide (CO_2) remains the leading contributor to greenhouse gas (GHG) emissions in the United States, with passenger vehicles playing a significant role. As emerging transportation technologies introduce Autonomous Vehicles (AVs) into the existing fleet, understanding their impact on urban traffic systems becomes increasingly important. This study presents a simulation-based analysis of the effects of AVs on urban mobility, fuel consumption, and CO_2 emissions under mixed traffic conditions. Utilizing the Planung Transport Verkehr(PTV) Verkehr In Städten - SIMulationsmodell (VISSIM) microscopic traffic simulation platform, integrated with the Bosch Environmentally Sensitive Traffic Management (ESTM) module; designed for high-resolution simulation of traffic-related emissions; vehicle behaviors and emissions at a representative U.S. urban signalized intersection is evaluated. The simulation framework models ten AV market penetration scenarios, ranging from 0% to 100% in 10% increments, and captures behavioral distinctions between Autonomous and Human-driven Vehicles through calibrated adjustments to the Wiedemann 99 car-following parameters and vehicle speed distributions. Results indicate that higher AV penetration leads to improved traffic flow and significant reductions in CO_2 emissions. This study highlights the power of high-fidelity, integrated simulation-based methods in assessing future transportation systems and informing sustainable urban mobility planning.

Keywords- Microsimulation; Autonomous Vehicles; Mixed Traffic Flow; Fuel Consumption; CO_2 Emission; VISSIM; Bosch; Driving Behavior

I. INTRODUCTION

Autonomous vehicles (AVs), also known as self-driving cars, are transforming transportation through advanced technologies that enable them to operate with minimal or no human intervention. It is anticipated that privately owned Level 4 AVs, which denote high automation will make up approximately 24.8% of vehicles on roadways in America by 2045 [1]. These vehicles utilize Artificial Intelligence (AI) and machine learning (ML) algorithms to perceive their environment and make informed driving decisions. Equipped with an array of sensors, such as cameras, radar, lidar, and ultrasonic devices, AVs continuously monitor their surroundings to detect objects, interpret traffic signals, and anticipate the actions of other road users. By processing real-time data, they can react faster than human drivers, making them less susceptible to errors caused by distraction, fatigue, or emotion. This technology is expected to enhance road safety, reduce collisions caused by human error, improve traffic flow, and offer greater mobility for individuals who are unable to drive due to age, disability, or other limitation [2].

There has been a growing emphasis on the impact of driving behavior on fuel efficiency and vehicular emissions in the literature investigating models and approaches for assessing the air quality, as well as the carbon footprint of transportation sector across different levels of analysis. These include microscopic levels [3], [4] [5], mesoscopic levels [6], [7], and macroscopic levels [8]- [10]. Aggressive driving is consistently linked to higher fuel consumption and pollutant emissions, while eco-driving improves energy efficiency and reduces CO_2 output [11], [12], [13], [14]. Alessandrini et al. [11] introduced the Eco Index, showing up to 30% CO_2 reduction at low speeds through eco-driving, though benefits diminish above 80–90 km/h. Szumska et al. [15] found urban aggressive driving increases emissions by around 40%. Miotti al.[13] highlighted the emission-reducing potential of manual and automated eco-driving. Suarez et al. [14] reported up to 5% more CO_2 from aggressive acceleration using Worldwide Harmonized Light Vehicles Test Procedure (WLTP), the European standard for measuring vehicle fuel consumption and CO_2 emissions and CO_2MPAS data (results from the European Commission's simulation tool that converts type-approval CO_2 values from the former NEDC test cycle into the WLTP framework).

As AVs are expected to play a central role in future urban transportation systems, recent research has shifted its focus from conventional traffic networks to mixed traffic flows, where AVs operate alongside human-driven vehicles in both freeway and urban environments. A common method in the literature for assessing the carbon footprint of such mixed

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traffic involves the integration of traffic simulation models with external emission calculation tools [16] [17]. These methods often require extensive data processing, and in cases involving tools like Motor Vehicle Emission Simulator (MOVES), the development of intermediary software is necessary to link mobility and emissions models effectively [5], [18]. Moreover, the process becomes increasingly complex when incorporating multiple simulation scenarios, such as different AV penetration rates or varying road and weather conditions; making it time-consuming, prone to error, and occasionally impractical depending on the software used.

Several studies have explored these integrated modeling approaches. Olia (2016) [19] utilized the PARAMICS microsimulation platform combined with the CMEM (Comprehensive Modal Emissions Model) to continuously estimate fuel consumption and pollutant emissions based on vehicle characteristics, such as type, age, fuel system, and emissions control technology. The study found that increasing the penetration of Connected Autonomous Vehicles (CAVs) leads to emission reductions, with the most substantial benefits occurring at around 50% CAV adoption. Later, Stogios et al. [20] employed the VISSIM microscopic traffic simulation tool integrated with the MOVES model to assess vehicular emissions under different traffic conditions and AV penetration levels. Their work incorporated eight car-following and two lane-changing parameters to simulate AV behavior, revealing that headway time had a significant impact on emissions. In the same year, Conlon et al. [21] used the SUMO traffic microsimulation framework together with the Newton-based Greenhouse Gas Model (NGM) to estimate CO_2 emissions in congested urban road networks. Their findings showed that emissions initially rose at low levels of AV penetration due to interaction inefficiencies between human drivers and AVs, but significant emission reductions emerged at higher penetration levels, eventually plateauing between 40% and 90% AV market share.

These studies collectively highlight the critical role of accurately integrating traffic flow simulation with emission modeling in understanding the environmental implications of AV deployment within mixed traffic ecosystems. They also emphasize the complexity involved in integrating multiple simulation tools, particularly when assessing emissions from modeled traffic flows under various AV penetration scenarios and dynamic traffic conditions, which requires substantial computational resources, data harmonization, and custom interfacing between platforms.

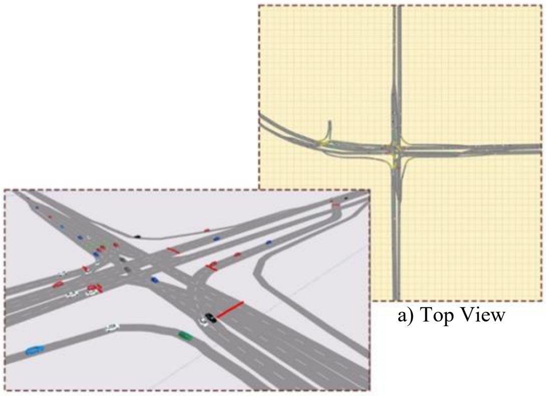
To tackle challenges of complex integration of traffic and external emission models, the extensive and error-prone data processing required, and the limited ability to evaluate CO_2 emissions across different AV penetration scenarios, this paper employs a new emission simulation tool in combination with an established traffic simulation platform. Specifically, this study utilizes the Bosch ESTM Module, which was developed in Germany through a collaboration between Robert Bosch GmbH and PTV Group [22], alongside VISSIM 2022 to investigate CO_2 emissions from light-duty passenger vehicles in mixed traffic flows, ranging from the early stages of AV deployment to a fully automated network. We hypothesize that autonomous vehicles (AVs), when introduced at varying penetration levels, will alter traffic flow efficiency and CO_2 emissions due to differences in car-following behavior, and that the integrated VISSIM–Bosch ESTM framework can provide accurate predictions of emissions and fuel consumption in parallel with mobility results. The model assumes Level 4 AVs operate under the "AV normal" profile calibrated from the CoExist project, balancing efficiency and caution in traffic flow.

The research focuses on the behavioral differences between human drivers and AVs and implements an integrated methodology for emissions estimation. To the best of the authors' knowledge, this study is among the few[16] that apply the Bosch ESTM module for project-level CO_2 emissions estimation in mixed traffic flows within an urban setting. This integration with VISSIM enables a detailed comparative analysis of how different AV penetration rates affect emissions and how these outcomes correspond with results from previous studies using alternative emission modelling tools. This study's methodology provides transportation professionals and urban planners with valuable insights into applying the Bosch ESTM module within the widely adopted VISSIM microsimulation platform. The consistency of the results with previous research; despite using different emission modeling tools; demonstrates the reliability of this integrated approach. Furthermore, the findings offer Infrastructure Owners and Operators (IOOs) a clearer understanding of how AV behavior can lower emissions besides contributing to the smooth urban traffic flow. These insights support the need for IOOs to begin preparing existing infrastructure to accommodate high AV penetration rates in the near future, given the significant potential benefits for both mobility and environmental sustainability.

To guide the reader through the remainder of this paper, the structure is organized as follows. Section II presents the methodology. Section III describes the simulation results, covering traffic mobility measures, fuel consumption, and CO_2 emissions. Section IV provides a detailed discussion of the findings, comparing AV and human-driven vehicles performance. Section V outlines potential directions for future work. Finally, Section VI concludes the paper with key insights and contributions of this study.

II. METHODOLOGY

This study employs an integrated simulation approach using PTV VISSIM 2022 and the Bosch Environmentally Sensitive Traffic Management (ESTM) module to assess traffic flow, fuel consumption, and CO_2 emissions at a congested signalized intersection in Saratoga Springs, Utah. The focus is a key intersection where two major five-lane arterials; Redwood Road (north-south) and Pioneer Crossing (east-west); converge. A detailed VISSIM model of the intersection and adjacent road segments was developed using links and connectors in Figure 1 to accurately represent the roadway network [23]. Traffic signals were modeled using a ring-and-barrier structure and in accordance with the Utah Department of Transportation's traffic signal timing guidelines [24].



a) Top View

b) Perspective View

Fig.1. VISSIM Model of the Study Intersection: (a) Top View, (b) Perspective View

Real-world traffic volume data from UDOT's ATSPM system [25] was used to replicate 1.5 hour of weekday evening peak-hour conditions (4.00-5.30 pm). We modeled scenarios with AV penetration rates ranging from 0% to 100%, in 10% increments. Automated vehicles (AVs) and human-driven vehicles were simulated using distinct Wiedemann 99 car-following parameters. The AVs followed the "AV normal" profile, which represents automated vehicles with driving behavior comparable to human drivers. This profile incorporates standard car-following and lane-changing patterns, avoiding both excessive conservatism and aggressiveness. The parameters were adopted from the CoExist project [26], an EU Horizon 2020 initiative that developed simulation frameworks and guidelines to assess mixed traffic environments involving both conventional and automated vehicles. Human-driven vehicles used calibrated values from previous simulator-based research efforts [27]. Speed distributions were assigned based on naturalistic driving data for human-driven vehicles [28] and tightly constrained profiles for AVs [26]. Table 1 presents the categories and definition of each parameter, alongside the adopted values for the Wiedemann 99 car-following model for both AVs and Human-Driven Vehicles in the simulation model.

TABLE I: ADOPTED DRIVING PARAMETER VALUES FOR HUMAN-DRIVEN AND AVS

Parameter Category	**W99 Car following Parameter**	**Definition**	**AVs (normal)**	**Human-Driven Vehicle**
Thresholds for Safety Distance (Δx)	CC0 (m)	Standstill Distance	1.5	4.45
	CC1(s)	Headway Time	0.9	0.87
	CC2 (m)	Following Variation	0	5.28
	CC3 (s)	Threshold for Entering Following	-8	-7.92
Thresholds for Speed (Δv)	CC4 (m/s)	Negative Following Threshold	-0.1	-1.52
	CC5 (m/s)	Positive Following Threshold	0.1	1.52
	CC6 (-)	Speed Dependency of Oscillation	0	0.71
Acceleration Rates	CC7 (m/s^2)	Oscillation Acceleration	0.1	0.31
	CC8 (m/s^2)	Standstill Acceleration	3.5	1.03
	CC9 (m/s^2)	Acceleration at Speed of 80 km/h	1.5	0.33

The parameters are grouped into three main categories: thresholds for safety distance (Δx), thresholds for speed (Δv), and acceleration rates. Each scenario was simulated 10 times at 10 Hz resolution. Emissions were calculated through the Bosch ESTM cloud-based tool, which has a separate license to processes second-by-second vehicle trajectory data directly from VISSIM; eliminating the need for external data conversion [29][30]. Bosch provides VISSIM with a JSON file containing emission data for multiple vehicle classes. These classes are defined by six elements: Emission vehicle category, Emission vehicle class, Emission stage, Fuel type, Size class, and Use class, which differentiate vehicles based on their emission characteristics. During simulation, VISSIM generates a trajectory for each vehicle, which is then transferred to ESTM for emission calculation. The driving behavior element that most impacts emissions in Bosch ESTM is the dynamic profile of vehicle movement; particularly accelerations, decelerations, and stop-and-go patterns [29]. Bosch also offers lane-level visualization and real-time emission mapping across the network. For emission class distribution, the predefined MOVES-based 2022 profile for light-duty gas and diesel passenger vehicles was applied, representing U.S. fleet composition from 1992–2020. This approach ensures that emission outcomes isolate the effects of AV behavior and driving patterns, independent of variations in fuel or engine types.

III. SIMULATION RESULTS

For each scenario, 10 simulation repetitions were conducted following the recommendation in the VISSIM manual by MDOT [23]. This approach ensured that our results met established best practices and provided stable, representative averages. The results showed negligible variation across runs; therefore, the average values presented in Figures 2-5 are considered representative, with minimal variability observed across repetitions."

A. *Mobility Results*

As AV penetration increases, traffic performance improves across all metrics. According to Figure 2, the average number of stops shows an overall decline, with a slight increase at 10% AV, a significant reduction from 10% to 90%, and a minor uptick at 100% penetration. Average delay drops sharply from 440 seconds at 0% AV to a minimum of below 380 seconds at 50% penetration rate, then fluctuates slightly, stabilizing near 382 seconds at full penetration (Figure 3). Similarly, average speed increases from 62.38 km/h at 0% AV to 71.81 km/h at 50%, reaching a maximum of 73.92 km/h at 100% AV (Figure 4).

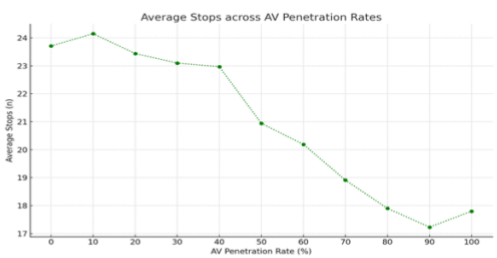


Fig.2. AV Penetration vs. Average Number of Stops (-)

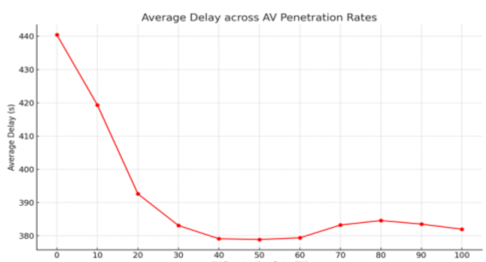


Fig.3. AV Penetration vs. Average Delay (s)

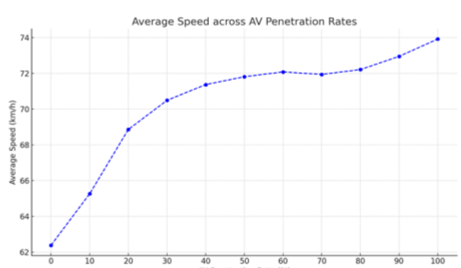


Fig.4. AV Penetration vs. Average Speed (km/h)

The mobility results of the baseline scenario (0% AVs) simulation were validated using Utah ATSPM peak-hour traffic data (4:00–5:30 PM). The recorded approach speed (38 mph/61 km/h), shown in Figure 5, closely matched the simulated average (38.7 mph/62.38 km/h), yielding 97.78% accuracy. Similarly, the average vehicle delays from simulation (38 s) aligned with ATSPM data (39 s), confirming the reliability of the results. This validated baseline therefore serves as the benchmark for evaluating the subsequent scenarios.

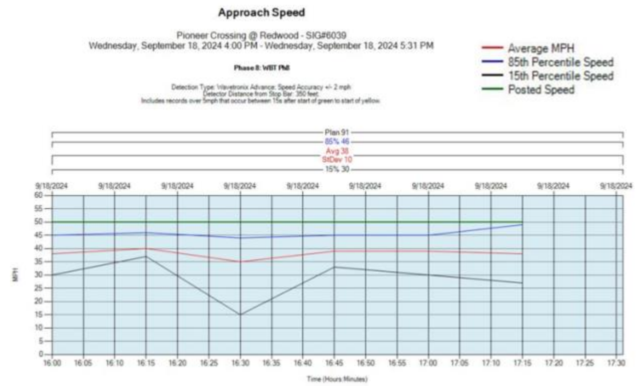


Fig.5. Chart of the Average Approach Speed of Vehicles During Peak Hour; Example of Westbound Through (WBT)- Utah ATSPM[25]

B. *Fuel Consumption and CO_2 Emission Results*

The emission results are not computed by VISSIM itself. VISSIM was used to simulate vehicle trajectories, and these outputs were then processed in the Bosch Environmentally Sensitive Traffic Management (ESTM). The Bosch ESTM applies vehicle-specific fuel consumption and emission models to the VISSIM trajectory data. The reported results represent aggregated outputs from Bosch ESTM, averaged over ten independent simulation runs of 1.5-hours (5400s) each per scenario and vehicle class. A warm-up period of 900s was applied at the beginning and the end of each simulation run, in accordance with the PTV VISSIM Manual, to ensure that the results capture stabilized traffic conditions [31].

Bosch results show a direct relationship between increasing AV penetration and decreasing fuel consumption and CO_2 emissions. As AV penetration rises from 0% to 100%, CO_2 emissions decrease by approximately 54.51%. However, the rate of reduction varies across different penetration levels. From 0% to 20% AV penetration, emissions drop by about 8%. Between 20% and 50%, emissions decline by around 12.5%. The most pronounced reduction occurs from 50% to 100%, with a drop of roughly 34%. A sharper decline is observed particularly between 70% and 100%, highlighting the potential for greater environmental gains as AV usage nears full saturation. The line chart in Figure 6 clearly illustrates CO_2 emission levels across different stages of AV penetration, from 0% to a fully autonomous network.

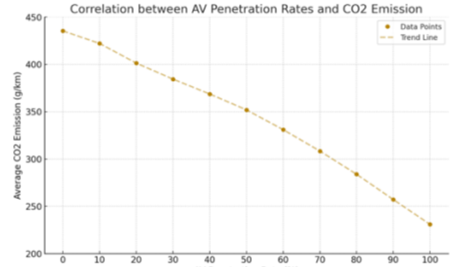
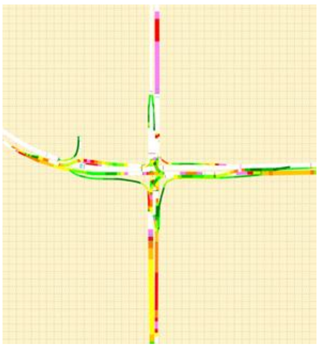
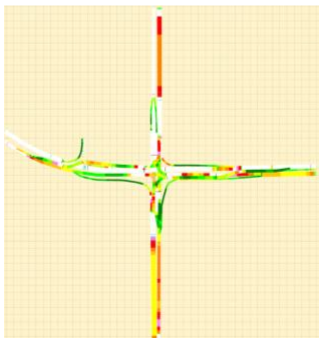


Fig.6. AV Penetration vs. Average CO_2 Emission (g/km)

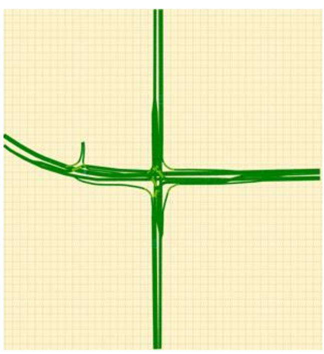
As illustrated in the emission distribution maps generated within the VISSIM interface (Figure 7a–c), which use distinct color gradients to represent CO_2 emission levels across road segments, a 50% AV penetration leads to an approximate 25% reduction in emissions compared to the baseline scenario with 0% AVs. At 100% AV penetration (Figure 7c), emissions are reduced by approximately 55% relative to the mixed traffic scenario with equal shares of AVs and human-driven vehicles (HDVs) shown in Figure 7b.



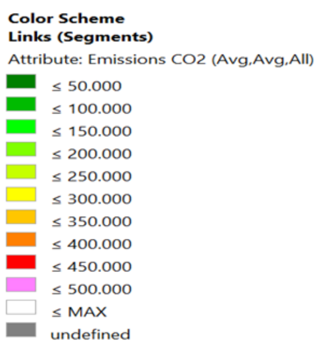
(a) 100% HDV, 0% AV



(b) 50% AVs, 50% HDVs



(c) 100% AVs, 0% HDV



(d) Legend of CO_2 Distribution Map(g/km)

Fig. 7. CO_2 emission comparison at the intersection for three AV penetration rates: (a)100% Human-driven Vehicles (HDVs) ,0% AVs; (b)50% AVs,50%HDVs; (c)100% AVs,0%HDV

The findings of our study on CO_2 emissions and fuel consumption at signalized intersections align with previous literature. According to the U.S. Environmental Protection Agency [32], the average CO_2 emission from vehicles is 248.5 g per kilometer (approximately 400 g per mile). Our simulation results under the baseline scenario, showing a 43% increase compared to this benchmark, are validated by Szumska and Jurecki [12], who concluded that driving behavior near intersections can increase CO_2 emissions by 39–46% relative to calm driving. Furthermore, our results on emission patterns in the presence of Automated Vehicles are consistent with Tomas et al. [33], who found that automation at penetration rates of 30% or below yields only modest reductions. Similarly, the studies by Conlon et al. [21] and Rezaei et al. [34] demonstrated that the greatest fuel savings and CO_2 reductions occur within a fully autonomous network.

IV. DISCUSSIONS

By examining the W99 car-following parameters and their influence on network performance in mixed traffic flow, this study reveals a dual impact of AV behavior at signalized intersections. AV behavior not only improves overall traffic flow but also significantly reduce CO_2 emission levels. Table 2 provides a comparison of driving behaviors for AVs and human-driven vehicles in car-following scenarios. It also presents comparative mobility and emission outcomes across two network types as an example: one composed solely of human-driven vehicles and another with mixed traffic. For each parameter, the greater absolute value; whether associated with AVs or human-driven vehicles; is highlighted in color, making performance contrasts visually clear. The table demonstrates that AVs consistently outperform human drivers across key behavioral metrics, resulting in smoother traffic dynamics which resulted in reduced CO_2 Emission.

TABLE II. COMPARISON OF DRIVING BEHAVIOR, MOBILITY, AND EMISSIONS IN AV AND HUMAN-DRIVEN TRAFFIC SCENARIOS

Parameters	**AVs**	**Human-Driven Vehicles**
Level of Caution (CC0, CC1, CC2)		
Level of Perception-Reaction (CC3)		
Level of Sensitivity to the Dec/Acc (CC4, CC5)		
Level of Acceleration Oscillation (CC7)		
Level of Standstill acceleration (CC8)		
Speed Distribution		
Mobility Measures	**Mixed Traffic Flow**	**Traditional Network**
Average Speed (km/h)		
Average Stops (-)		
Average Delay(s)		
Bosch Emission Measures		
CO_2 Emission		
Fuel Consumption		

The analysis of car-following behavior differences between human drivers and AVs across (CC0–CC9) parameters in Table 2, also provides a clearer understanding of the observed results. Human drivers tend to exhibit more cautious behavior, maintaining higher standstill distances (CC0) and longer headway times (CC1), which results in larger safe following distances. They also require more extra distance (CC2) before moving closer to a lead vehicle, whereas AVs typically operate with a CC2 value close to zero. In terms of perception and reaction, AVs demonstrate quicker responsiveness, indicated by lower CC3 values, while human drivers generally respond more slowly, contributing to frequent stops and delays. Human drivers also display greater sensitivity to the acceleration and deceleration of leading vehicles, reflected in higher absolute values of CC4 and CC5. This heightened sensitivity causes frequent fluctuations in speed, reducing traffic flow efficiency. In contrast, AVs respond more smoothly, which helps maintain steady traffic movement. During stop-and-go scenarios, human drivers tend to accelerate more aggressively (higher CC7), leading to erratic driving patterns, whereas AVs show much lower acceleration oscillations, resulting in smoother motion. Additionally, AVs exhibit stronger acceleration capabilities both from a standstill (CC8) and at higher speeds, 80 km/h (CC9), further contributing to consistent and efficient driving behavior.

These behavioral differences have direct implications for traffic flow and environmental impact. Human-driven traffic is characterized by frequent stop-and-go movements, abrupt accelerations, and longer delays, all of which lead to higher fuel consumption and CO_2 emissions. Simulation results from Bosch confirm that such inconsistent driving behavior significantly increases emissions and energy use in networks dominated by human drivers. In contrast, traffic scenarios incorporating AVs demonstrate improved mobility, greater energy efficiency, and lower environmental impact. The higher the proportion of AVs in the urban network, the more pronounced the reductions in fuel consumption and emissions. In fully autonomous networks, the most substantial benefits are observed, with CO_2 emissions and fuel usage reduced by over 50%. These improvements are largely due to the smoother, more homogenous, and consistent traffic flow facilitated by AVs. However, these results reflect the assumption that AVs operate with "normal" driving behavior, balancing efficiency and caution. What if the AV fleet exhibited heterogeneous driving styles, with some vehicles programmed conservatively and others more aggressively? This indicates that fleetwide behavioral programming should be studied as a critical determinant of outcomes. Furthermore, the present analysis assumed AVs were not connected to infrastructure. If AVs were integrated with adaptive signal control in a fully automated network, vehicle-to-infrastructure (V2I) connectivity could enable smoother progression through intersections, further reducing unnecessary stops and acceleration spikes, and potentially amplifying emission reductions beyond the levels observed here Another consideration is the infrastructure readiness at lower penetration levels. What if modest AV adoption (e.g., 30-40%) were paired with adaptive infrastructure? Could such a scenario achieve mobility and emission outcomes comparable to, or even surpassing those of a fully automated network operating without infrastructure modifications? This possibility indicates that investing in infrastructure to support AVs during transitional phases may be as important as advancing the vehicle technology itself in realizing sustainable benefits.

V. CONCLUSION AND FURURE WORK

This study applied an integrated VISSIM–Bosch ESTM framework to evaluate the impacts of Level 4 automated vehicles (AVs) on traffic performance, CO_2 emissions, and fuel consumption at a congested urban intersection. The results confirmed substantial environmental benefits, with emissions reduced by more than 50% at full AV adoption. Improvements were modest at low penetration rates, while the steepest benefits occurred between 70% and 100% adoption. At 100% AV penetration, a slight increase in vehicle stops was observed, suggesting potential operational challenges in fully autonomous environments. This indicates that the full benefits of AV technology depend not only on high adoption rates but also on supportive infrastructure, realistic driving profiles, and well-designed policy frameworks. Low levels of AV integration may yield only incremental improvements, while complete automation could introduce new challenges, particularly if overly cautious driving behaviors or induced demand leads to increased travel. These findings highlight the importance of coordinated planning, where technological advances in automation are integrated with traffic management strategies, upgrades to both physical and digital infrastructure and built environment, and policies that prevent rebound effects. Furthermore, the consistency of Bosch ESTM emission estimates in AV-integrated networks with previous studies; reporting similar reductions on both congested and uncongested roadways using alternative simulation models[34], [35]; underscores the reliability of Bosch ESTM. This provides a robust foundation for future research to apply and extend this approach in broader contexts.

Future work will extend the analysis to multiple intersections and scenarios and will include comparisons of Bosch ESTM+VISSIM with alternative tools, such as VISSIM+MOVES to provide insights. Furthermore, future research will develop a digital twin of the modeled intersection to enhance validation. Although current low AV market penetration limits direct validation at higher adoption levels, this approach will improve calibration of baseline and early-stage scenarios, strengthening the reliability of projected mobility and emission results. Future work should also evaluate human comfort in relation to the AV calibration used in this study. As a complement to Winkel et al. [36], real-world experiments or simulators with larger motion envelopes are needed to capture a wider range of motion pulses, including abrupt braking and acceleration events. This would overcome the limitations of restricted simulators and allow refinement of AV calibration parameters to balance traffic efficiency with passenger comfort.

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