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Integrating Autonomous Vehicles (AVs) into Urban Traffic: Simulating Driving and Signal Control

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Abstract: The integration of autonomous vehicles into urban traffic systems offers a significant opportunity to improve traffic efficiency and safety at signalized intersections. This study provides a comprehensive evaluation of how different autonomous vehicle driving behaviors—cautious, normal, aggressive, and platooning—affect key traffic metrics, including queue lengths, travel times, vehicle delays, emissions, and fuel consumption. A four-leg signalized intersection in Balgat, Ankara, was modeled and validated using field data, with twenty-one scenarios simulated to assess the effects of various autonomous vehicle behaviors at penetration rates from 25% to 100%, alongside human-driven vehicles. The results show that while cautious autonomous vehicles promote smoother traffic flow, they also result in longer delays and higher emissions due to conservative driving patterns, especially at higher penetration levels. In contrast, aggressive and platooning autonomous vehicles significantly improve traffic flow and reduce delays and emissions. Mixed-behavior scenarios reveal that different driving styles can coexist effectively, balancing safety and efficiency. These findings emphasize the need for optimized autonomous vehicle algorithms and signal control strategies to harness the potential benefits of autonomous vehicle integration in urban traffic systems fully, particularly in terms of improving traffic performance and sustainability.

Keywords: autonomous vehicles; signalized intersection; PTV VISSIM; microscopic simulation; traffic performance; penetration rate

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1. Introduction

In the ever-evolving landscape of urban transportation, the integration of autonomous vehicles (AVs) stands as a pivotal advancement that holds the promise of reshaping how we navigate our cities [1,2]. Autonomous driving technology has garnered considerable attention for its potential to revolutionize traffic dynamics, enhance road safety, and contribute to sustainable urban living [3,4]. As cities globally explore the possibilities of incorporating AVs into their traffic ecosystems, a critical point of intersection arises at signalized intersections essential nodes in urban traffic management [5,6].

Among the various driving behaviors associated with AVs, platooning has emerged as a particularly promising approach. Vehicle platooning involves a group of AVs traveling in coordinated formations, maintaining short gaps between one another through real-time communication and synchronization. The key benefits of platooning include reduced aerodynamic drag, which improves fuel efficiency, and more coordinated vehicle movements that enhance road capacity and traffic flow [7]. By reducing inter-vehicle gaps, platoons can minimize the stop-and-go behavior common in mixed traffic environments, leading to smoother traffic flow and reduced congestion, especially at intersections. Additionally, vehicle platooning contributes to lower emissions due to more efficient driving patterns, making it a key strategy for promoting sustainable urban mobility.

AVs are heralded as the vanguard of a transformative era in urban mobility, promising to revolutionize transportation systems and redefine the relationship between humans and their vehicles [8]. However, the integration of AVs into existing traffic systems presents unique challenges, particularly in the context of signalized intersections. Previous studies have explored various aspects of AV integration, including their impact on traffic flow stability and throughput on highways [1,2], and the influence of dedicated lanes for connected and autonomous vehicles [3]. Despite these advancements, there remains a significant gap in understanding the effects of AV driving behaviors at urban intersections.

Cautious AVs prioritize safety and adherence to traffic rules [7–9]. Mimicking conservative human driving styles, they are expected to exhibit a restrained approach, avoiding abrupt maneuvers, and ensuring a conservative interaction with the traffic environment. The risk-averse nature of cautious AVs is expected to lead to increased queue lengths and travel times, especially under high-penetration scenarios. Normal AVs, representing a balance between safety and efficiency [10], are anticipated to emulate standard human driving patterns. Their behavior is expected to closely mirror the traffic dynamics observed in a conventional, human-driven scenario. At moderate penetration rates, their influence on key traffic parameters may maintain a neutral impact, aligning closely with the natural flow of traffic. In contrast, aggressive AVs are engineered to prioritize efficiency [11], often characterized by dynamic driving and optimized traffic flow. It is anticipated that their assertive maneuvers and quick decision-making may result in decreased queue lengths, travel times, and delays. However, the potential trade-off could involve an increase in emissions and fuel consumption. Platoon-forming AVs operate in cohesive groups, synchronized for optimal traffic flow [12,13]. Through leveraging communication and coordination, these vehicles aim to reduce gaps between each other, potentially minimizing congestion and improving overall intersection efficiency.

Despite these advancements, there remains a lack of comprehensive studies that address how different AV driving behaviors impact the performance of urban intersections under various traffic signal cycle times. This study aims to fill this gap by investigating the impact of cautious, normal, aggressive, and platoon-forming AV behaviors on traffic performance at a four-leg signalized intersection with heavy traffic volume.

Objectives and Contributions of the Study

- Detailed Analysis of AV Behaviors: This research offers a comparative analysis of the impact of different AV driving behaviors (cautious, normal, aggressive, and platoon-forming) on intersection performance.
- Signal Timing Optimization: This study explores the optimization of traffic signal cycle times (60, 80, 100, 120, 140, 160, 180, and 204 s) to enhance intersection efficiency in the presence of AVs.
- Comprehensive Performance Metrics: This research evaluates multiple performance metrics, including queue lengths, travel time, vehicle delay, and emissions, providing a holistic assessment of AV integration.
- Simulation-Based Analysis: Utilizing the PTV VISSIM traffic simulation model, this study provides insights into the optimal integration of AVs into urban traffic systems.

By addressing these aspects, this study seeks to provide valuable insights into the optimal strategies for integrating AVs into urban traffic systems, thereby contributing to the ongoing discourse on sustainable and efficient urban mobility.

2. Literature Review

The integration of AVs into urban traffic systems has garnered considerable attention, with numerous studies exploring their potential impacts on traffic performance and efficiency. Existing study has predominantly focused on understanding how AVs affect traffic flow, safety, and congestion at signalized intersections and other critical points in urban infrastructure (Table 1).

Table 1. Summary of studies investigating the impact of AV transportation systems.

Reference	Year	The Study Objective	Methodology/Tools Used	Key Findings
[14]	2016	Investigate the impact of CAVs and AVs on traffic flow stability and throughput; optimize AHS performance	Microscopic traffic flow simulation model; developed control schemes and simulation frameworks	CAVs and AVs enhance traffic flow stability and throughput, optimize AHS capacity, reduce congestion, and minimize emissions.
[15]	2016	Investigate the effects of AVs on driver behavior and traffic performance	Literature survey and microscopic traffic simulation using VISSIM	AVs improve average density by 8.09%, travel speed by 8.48%, and travel time by 9.00% during peak hours. AVs reduce congestion and improve safety. CVs near AVs adopt shorter THW. AVs reduce situation awareness and may increase drowsiness.
[16]	2018	Investigate the impact of CAV dedicated lanes on traffic flow throughput	Developed a three-lane heterogeneous flow model; analyzed CAV dedicated lane policy impact on throughput	CAV dedicated lanes achieved higher flow rates. Overall traffic flow throughput increased with higher CAV penetration rates. The optimal strategy is one CAV-dedicated lane above 40% penetration, and two lanes above 60%. Individual CAV performance is crucial for lane effectiveness.
[17]	2018	Investigate how AVs technology can enhance operations and increase capacity of weaving sections	Developed a multiclass hybrid model; calibrated and validated using empirical data from a weaving section; applied in a simulation-based optimization framework	Higher penetration of AVs increases weaving section capacity. Non-linear capacity increase observed. Optimal lane change distributions can prevent capacity reduction. Potential capacity increase of up to 15%.
[18]	2019	Investigate the potential effects of AVs on road transportation	Literature review of existing studies on AV impacts	AVs can improve traffic flow, pedestrian mobility, travel demand, safety, and reduce emissions. Uncertainties exist regarding long-term effects on energy, emissions, pedestrian interaction, and safety.
[19]	2019	Explore the role of CAVs and AVs in enhancing transportation systems' efficiency, safety, and sustainability; assess urban infrastructure's impact on transportation networks and the benefits of integrating CAVs; provide recommendations for policymakers and urban planners	PTV Vissim simulation, data collection points, vehicle travel time, queue counters; statistical analysis and visualization tools; literature review and expert consultations	CAVs improve traffic flow efficiency, reduce queue delays and travel times. The study highlighted the importance of urban infrastructure in supporting CAV integration, providing recommendations for effective transportation planning with CAVs.
[20]	2020	Analyze the impact of CAV clustering strategies on mixed traffic flow characteristics	Analysis of vehicle trajectory data; compared ad hoc and local coordination strategies for CACC	Local coordination outperforms ad hoc in network throughput. Improved network performance and safety. Hard braking events for HVs change significantly under local coordination.
[21]	2020	Investigate how AVs influence road capacity in urban traffic networks	Simulations using SUMO software; analyzed grid and real-world networks with varying AV penetration levels	AVs increase road network capacity. Maximum traffic flows with 100% AVs were 16–23% higher than with only conventional vehicles. Significant capacity improvements were observed around 40–50% AVs penetration.

Table 1. *Cont.*

Reference	Year	The Study Objective	Methodology/Tools Used	Key Findings
[22]	2021	Review of car-following models for human and autonomous driving behaviors	Literature review of car-following models; comparison of traditional cars with human drivers to AVs; discussion on AV-ready tools in micro-simulation platforms	Provides an overview of various car-following models for both human-driven and AVs. Highlights the importance of AV-ready tools in micro-simulation platforms for accurate modeling of vehicle dynamics and environments.
[23]	2021	Identify the impacts of shared AVs on urban parking and space management.	Formulated an estimation method; conducted a case study in a 673,220 m^2 area using real data and previous studies; analyzed parking demand, vehicle ownership, and space reallocation	Shared AVs can significantly reduce parking space demand, allowing reallocation for other uses such as bike-sharing spots, bike lanes, additional traffic lanes, or parklets. Positive implications for urban space management and city planning.
[24]	2022	Analyze the impacts of AV driving logics on traffic performance; assess AV-readiness of infrastructures and changes in driving behaviors	Microscopic traffic simulation using PTV Vissim; various scenarios and simulations to evaluate effects of AVs	AV driving logics and physical interventions improve traffic performance. AV-readiness of infrastructures and change in driving behaviors should be assessed for better performance.
[25]	2023	Evaluate the impact of AV driving logics on traffic performance at a four-leg signalized intersection in a Swedish urban context	Microscopic traffic simulation using PTV Vissim; literature review; developed a model of a four-leg intersection in Norrköping; simulated AV behaviors: cautious, normal, and all-knowing with different penetration rates	AVs improve traffic performance. All-knowing AVs are most efficient. Cautious AVs negatively impact performance. A 50% penetration rate of all-knowing Avs is necessary for significant improvements.

For instance, Peng et al. [14] investigated the influence of CAVs and AVs on traffic flow stability and throughput, highlighting the enhanced performance of automated highway systems (AHS) using control schemes and simulation frameworks [14]. Similarly, a study examined the effects of AVs on driver behavior and traffic performance using VISSIM, finding improvements in average density, travel speed, and travel time during peak hours [15].

Research has focused on the impact of dedicated lanes for CAVs and AVs, demonstrating that higher flow rates and overall traffic throughput are achievable with increased AV penetration rates [16]. Another study explored how AVs technology can enhance the capacity of freeway weaving sections, showing potential capacity increases of up to 15% with higher AV penetration [17].

Recent studies have also delved into the broader implications of AV integration. One literature review conducted on the potential effects of AVs on road transportation emphasized improvements in traffic flow, pedestrian mobility, travel demand, safety, and emissions reduction, while also noting uncertainties regarding long-term impacts [18]. Another study explored the role of CAVs and AVs in enhancing transportation systems' efficiency and sustainability, using PTV Vissim simulation and other tools to provide recommendations for urban planners and policymakers [19].

Zhong et al. [20] analyzed the impact of CAV clustering strategies on mixed traffic flow, comparing local coordination with ad hoc strategies. While this study focused on vehicle coordination strategies, our research addresses how different AV behaviors, including platoon-forming, impact performance at intersections, which presents a unique intersection of traffic signal optimization and driving behavior.

Lu et al. [21] simulated how AVs influence road capacity in urban networks, finding that AVs increase road network capacity by 16–23% at full penetration. However, our research builds upon this by investigating the role of AV penetration rates in mixed-traffic environments and their impact on intersection-specific metrics like delays, emissions, and fuel consumption.

Ahmed et al. [22] provided a review of car-following models for AVs and human-driven vehicles, highlighting the importance of AV-ready tools in simulation platforms. Our study similarly leverages advanced traffic simulation tools (PTV VISSIM) but applies them to specific intersection performance metrics, offering practical insights into AV behavior's effect on urban traffic.

Silva et al. [23] examined the impact of shared AVs on urban parking and space management, showing that shared AVs can reduce parking space demand. Although this study is centered on urban space management, our research is focused on traffic performance and how different AV driving logics affect key metrics at intersections.

Finally, Ahmed et al. [24] and Desta [25] explored AV driving logics and their impacts on traffic performance. Ahmed et al. [24] analyzed various scenarios using PTV VISSIM, highlighting the importance of assessing AV-readiness in infrastructure. Similarly, Desta [25] focused on traffic performance at a four-leg intersection in Sweden, finding that cautious AVs negatively impact performance. Our study aligns with these insights by evaluating how different AV behaviors, including cautious and aggressive behaviors, influence intersection performance, but we also explore the effects of platooning and signal timing optimization, adding a unique dimension to the analysis.

Despite the extensive research on AVs, there remains a gap in understanding the nuanced effects of different AV driving behaviors—cautious, normal, aggressive, and platoon—at signalized intersections. This study aims to fill this gap by evaluating the impact of these behaviors on traffic performance, including queue lengths, travel times, delays, emissions, and fuel consumption, at a four-leg signalized intersection with heavy traffic volume and different cycle time optimizations. By incorporating these diverse AV behaviors and varying penetration rates, this research provides a comprehensive analysis that enhances the existing body of knowledge and offers practical insights for urban traffic management and AV integration strategies.

This study distinguishes itself from previous research by focusing not only on the individual effects of AV driving behaviors (cautious, normal, aggressive, and platooning) but also on their interaction with signal control optimization at a heavily trafficked urban intersection. This work specifically examines the impact of these behaviors across varying AV penetration rates and cycle times, with a particular emphasis on the role of signal control optimization. By evaluating performance metrics such as queue lengths, delays, emissions, and fuel consumption under these diverse conditions, this research offers a comprehensive perspective on how optimizing signal timing can influence the integration of AVs in urban traffic systems.

3. Methodology

3.1. Study Location

This study was conducted at a signalized traffic intersection located in Balgat, Ankara, Turkey, specifically at the intersection of Kızılırmak, Ufuk Ünv. Cd No:18, 06520 Çankaya/Ankara, as shown in Figure 1. This intersection was chosen based on its representation of typical urban traffic conditions and its suitability for evaluating the impact of AVs on traffic dynamics. The specific location details, including traffic volume, signal timings, and geometric characteristics, were considered to ensure the simulation's accuracy and relevance to real-world scenarios.

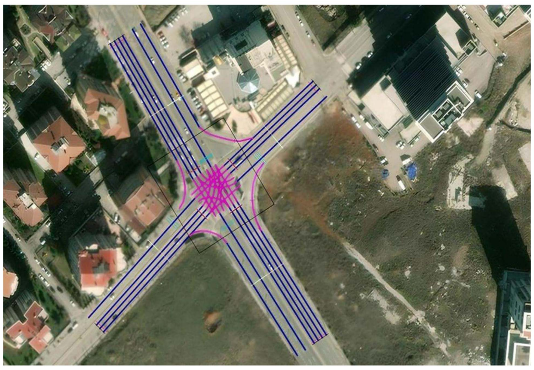


Figure 1. Geographical depiction of the signalized traffic intersection in Balgat, Ankara. Source: PTV VISSIM model.

3.2. Research Methodology Overview

Figure 2 presents a comprehensive overview of the research methodology. The data collection phase involves gathering various traffic metrics, including average travel time, queue lengths, speed observations, and traffic volume with signal timing. The methods section outlines the use of the PTV VISSIM model, focusing on car-following and lane-changing behavior. Model calibration includes adjustments for lane changes and intersection links, followed by validation to ensure accuracy. The validated model is then used for traffic metrics analysis, signal control optimization, and safety assessments. The results are compared before and after optimization to draw conclusions.

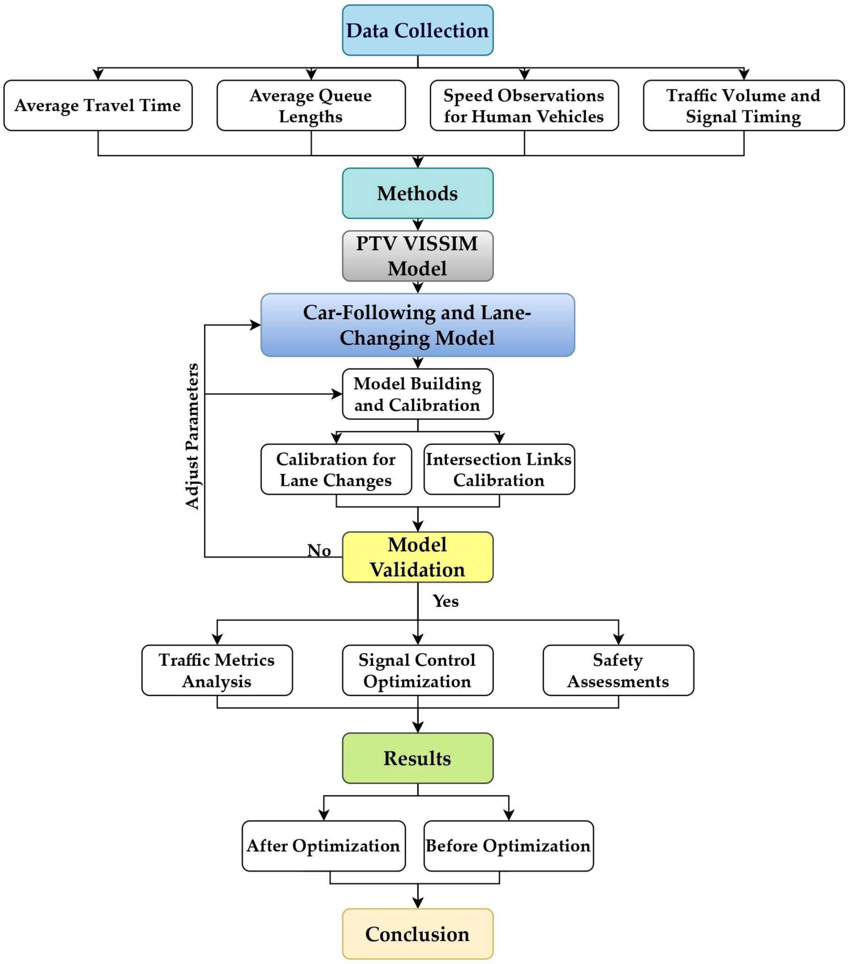


Figure 2. Flowchart of research methodology. Source: processed by authors.

3.3. Data Collection

The traffic volume data were extracted from video analysis conducted during peak morning hours from 7:00 to 8:00 AM, as presented in Table 2. A total of 5386 vehicles were recorded during this period. The 7:00 to 8:00 AM timeframe was chosen as it represents the peak traffic period, capturing the highest levels of commuter traffic and providing a thorough overview of traffic flow and congestion levels, and the cycle time of 204 s as shown in Figure 3.

Table 2. Traffic volume data at the studied signalized intersection.

Bound	Vehicles (Veh/h)	Movement (Veh/h)		
		Right	Straight	Left
North	1793	225	679	889
East	1033	814	157	62
South	1508	244	1228	36
West	1052	28	132	892

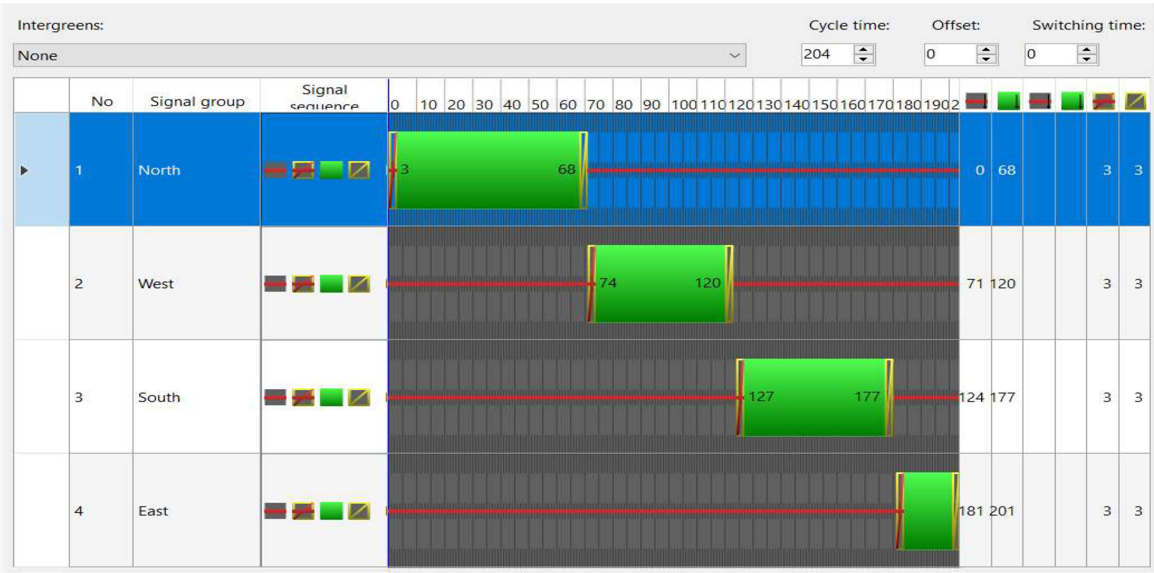


Figure 3. Traffic signal setup of the signalized intersection in Balgat, Ankara. Source: PTV VISSIM model.

The total traffic volume consists of different vehicle types, including buses, passenger vehicles, and trucks. The number of buses has been factored by multiplying 2.25 by the total number of buses, while the total number of trucks has been factored by multiplying by 1.75, according to the guidelines provided in "Arahan Teknik (Jalan) 8/86" by JKR.

3.4. Speed Observation

Speed observations were conducted to analyze the travel behavior of vehicles at the studied intersection. A sample of 20 vehicles was observed for each direction (north and south) during green signal phases. The observations were conducted over a fixed distance of 150 m, and the speed of each vehicle was measured using a stopwatch. The recorded speeds were compiled in Table 3. The analysis revealed that 40% of the observed vehicles traveled within the speed range of 20 km/h to 27 km/h. Additionally, 42.50% of vehicles were observed to be traveling at speeds ranging from 28 km/h to 36 km/h, while 17.5% were traveling between 36 km/h and 39 km/h, as shown in Figure 4.

Table 3. Speed observations during green signal phases.

Vehicle No.	Distance (m)	North-Bound		South-Bound	
		Time (s)	Speed (km/h)	Time (s)	Speed (km/h)
1	150	18.68	28.91	27.69	19.50
2	150	15.61	34.59	22.22	24.30
3	150	25.12	21.49	19.92	27.11
4	150	26.47	20.40	17.31	31.19
5	150	14.52	37.19	23.47	23.01
6	150	19.08	28.30	20.93	25.80
7	150	22.78	23.71	26.08	20.71
8	150	16.82	32.10	18.88	28.60
9	150	20.15	26.78	16.41	32.91
10	150	14.17	38.11	18.18	29.70
11	150	24.00	22.5	17.82	30.30
12	150	16.98	31.80	16.16	33.42
13	150	13.95	38.71	14.28	37.82
14	150	24.43	22.10	20.07	26.91
15	150	16.02	33.71	15.38	35.11
16	150	19.08	28.30	24.32	22.20
17	150	17.71	30.49	15.65	34.50
18	150	14.67	36.81	25.00	21.60
19	150	10.47	51.58	21.51	25.10
20	150	21.42	25.21	17.14	31.51

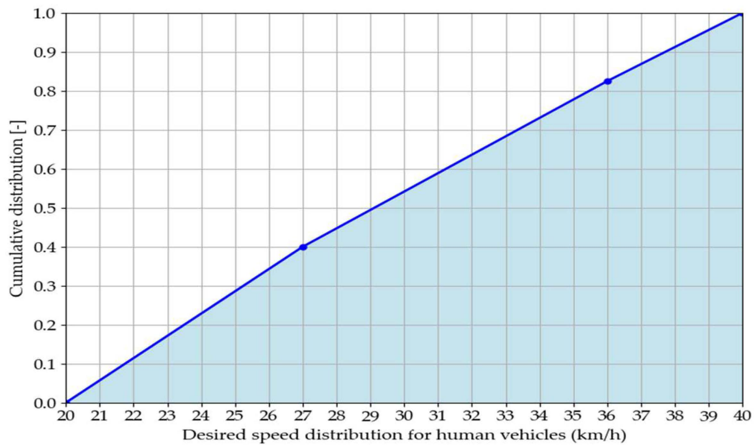


Figure 4. Desired speed distribution of human passenger vehicles. Source: field data collected by authors.

The speed characteristics of AVs were investigated through simulations, considering the full penetration of each autonomous behavior and their interaction with human-driven passenger vehicles. The optimal speed was determined by observing how AVs interacted with human-driven vehicles under different traffic conditions, particularly in a congested environment. Although a desired speed was set in the simulation, the model naturally adjusted the actual speeds of AVs based on the surrounding traffic, considering factors like vehicle acceleration, deceleration, and lane-changing possibilities. This approach allowed us to identify the effective operating speed of AVs in real-world-like traffic scenarios. The analysis revealed that the speed of AVs, both in isolated scenarios and when mixed with human traffic, is within the range of 27 to 31 km/h. These results are depicted in Figure 5.

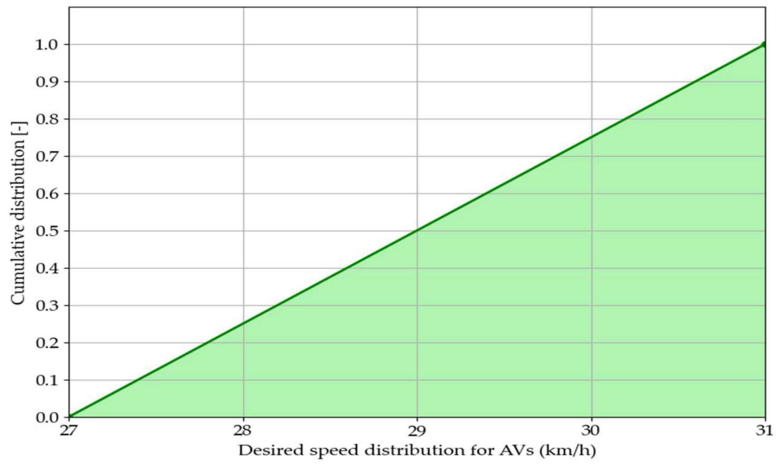


Figure 5. Desired speed distribution of AVs. Source: simulated data processed by authors.

3.5. Car Following Models and Lane Change Models

In the Wiedemann model, human driving behavior is recognized as naturally varying, considering that each driver possesses unique abilities in terms of perception, reaction, and assessing traffic flow [20,25]. The model delineates four driving states: free flow, approaching, following, and critical situation, as illustrated in Figure 6. These states are defined by specific thresholds: ABX and SDX (absolute braking threshold and safe distance threshold in meters) represent the minimum and maximum gap distances during following, respectively; CLDV (closing distance in meters per second) indicates the point at which the driver becomes aware of the narrowing gap; and SDV (sensitive distance in meters) is the critical point when the driver recognizes their proximity to the vehicle ahead. OPDV (opening distance in meters per second) marks the point when the driver realizes they are traveling slower than the vehicle in front.

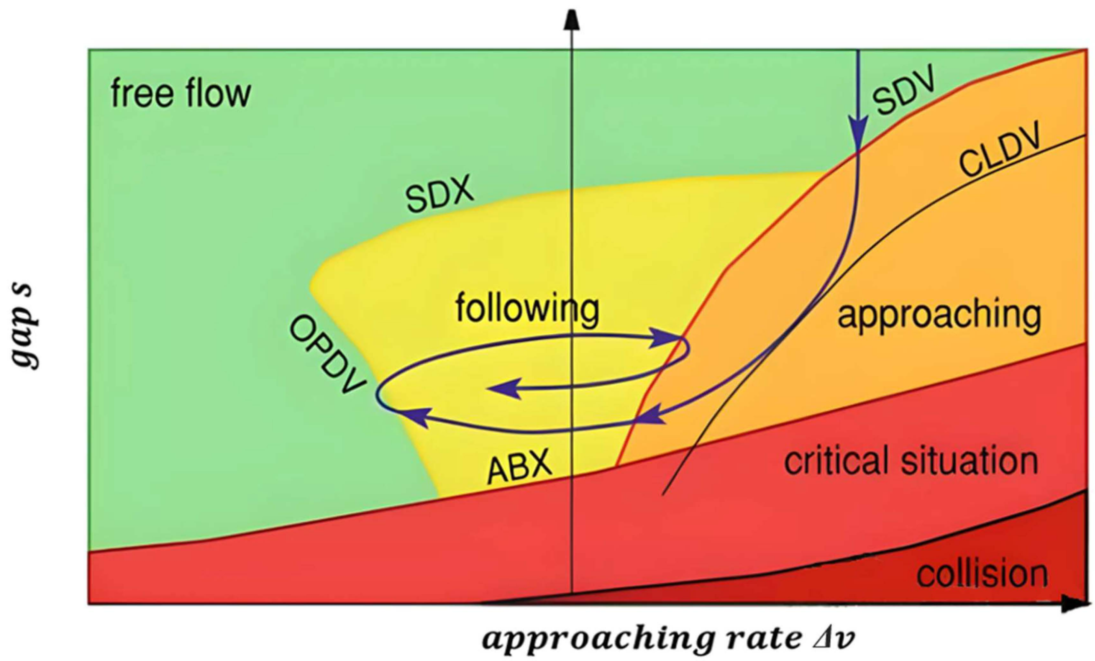


Figure 6. Wiedemann car-following model. Source: [26].

PTV VISSIM incorporates two versions of the Wiedemann car-following model: Wiedemann 1999 and Wiedemann 1974 [22,27,28]. The main distinction between these versions lies in their level of customization, with Wiedemann 1999 offering a greater number of adjustable parameters, making it more suitable for urban and congested traffic scenarios. In contrast, Wiedemann 1974, which was originally designed for freeway conditions, utilizes more rigid, hard-coded parameters [29]. As this study aims to assess the impact of aggressive autonomous vehicles (AVs) at urban signalized intersections, the Wiedemann 1999 car-following model is utilized. The driving behavior parameters (CC) in Wiedemann 1999 are calibrated using threshold values corresponding to different driving regimes. The PTV Group (2018) outlines the definitions and default values of these CC parameters for human-driven vehicles in Table 4. Users have the flexibility to adjust these parameters based on observed vehicle behaviors, including variables such as look-ahead distance, average standstill distance, and desired safety distance components [30].

Table 4. Parameters influencing driving behavior in car following models within PTV VISSIM [25].

Wiedemann 1999 Following Model Parameters	AV Cautious	AV Normal	AV Aggressive	AV Platoon	Human
CC0 Standstill distance (m)	1.50	1.50	1.00	1.00	1.50
CC1 Gap time distribution (s)	1.5	0.9	0.6	0.5	0.9
CC2 "Following" distance oscillation (m)	0.00	0.00	0.00	0.00	4.00
CC3 Threshold for entering "Following" (s)	–10.00	–8.00	–6.00	–6.00	–8.00
CC4 Negative speed difference (m/s)	–0.10	–0.10	–0.10	–0.10	–0.35
CC5 Positive speed difference (m/s)	0.10	0.10	0.10	0.10	0.35
CC6 Distance dependency of oscillation (10^{-4} rad/s)	0.00	0.00	0.00	0.00	11.44
CC7 Oscillation acceleration (m/s^2)	0.10	0.10	0.10	0.10	0.25
CC8 Acceleration from standstill (m/s^2)	3.00	3.50	4.00	4.00	3.50
CC9 Acceleration at 80 km/h (m/s^2)	1.20	1.50	2.00	2.00	1.50

The Wiedemann 1999 model is designed for capture and includes more parameters of driving behaviors:

- CC0: Standstill distance (the desired gap between two stationary vehicles in meters).
- CC1: Following distance (the time-based component of the desired safety distance, dependent on speed in seconds).
- CC2: Longitudinal oscillation (the distance a driver allows before closing in on the vehicle ahead in meters).
- CC3: Perception threshold for following (the point at which the driver initiates deceleration in seconds).
- CC4 and CC5: Negative and positive speed differences (sensitivity to the acceleration or deceleration of the vehicle in front in meters per second).
- CC6: Speed influence on oscillation (how distance affects speed fluctuations during following in 10^{-4} rad/s).
- CC7: Oscillation acceleration (the minimum acceleration or deceleration applied when following another vehicle in m/s^2).
- CC8 and CC9: Desired acceleration from a standstill and at 80 km/h. in m/s^2

The Wiedemann 1999 model determines the acceleration of the following vehicle $\left(a_f\right)$ by considering its speed relative to and the distance from the leading vehicle. This model functions across various driving regimes: free driving, where the vehicle accelerates to reach its desired speed when it is far from the vehicle ahead; approaching, where it modifies its speed to prevent a collision; following, where it keeps a safe distance; and braking, where it slows down to avoid a crash. A central aspect of the model is the desired safety distance $\left(s_f\right)$, which is defined by Equation (1).

$$s_f = s_0 + v_f \cdot T_f + \frac{v_f \cdot \Delta v_f}{2\sqrt{a_b \cdot b}} \tag{1}$$

Here, s_0 denotes the minimum standstill distance (CC0), v_f represents the speed of the following vehicle, and T_f indicates the safe time headway (CC1). The term Δv_f refers to the difference in speed between the following and leading vehicles, a_b is the maximum acceleration capability of the following vehicle, and b represents the comfortable deceleration rate.

Equation (2) outlines how the acceleration of the following vehicle in (m/s^2) $\left(a_{follower}\right)$ is determined by evaluating the current gap between vehicles relative to the desired safety distance, as well as the speed difference between the vehicles [31].

$$a_{follower} = a \cdot \left(1 - \left(\frac{v_f}{v_0}\right)^{\delta} - \left(\frac{s_f}{s}\right)^2\right) \tag{2}$$

In this context, a stands for the maximum acceleration in (m/s^2), v_f refers to the current speed of the following vehicle in (m/s), and v_0 indicates the desired speed in (m/s). The exponent δ, usually set to 4 (unitless), is applied in the calculation. The desired safety distance is denoted by s_f in (m), while s represents the current gap to the vehicle ahead (m).

Table 4 outlines the parameters related to car following model's parameters used in the PTV VISSIM model.

The decision to execute a lane change is determined by the gap acceptance criterion, where a vehicle i assesses the available space g in the target lane to determine if it is adequate for a safe maneuver. This evaluation includes checking the front gap, g_f in (m) (Equation (3)), and the rear gap, g_r in (m) (Equation (4)):

$$g_f = x_{lead} - x_i - l_i, \tag{3}$$

$$g_r = x_i - x_{follower} - l_{follower}, \tag{4}$$

where x_{lead} represents the position of the leading vehicle in the target lane in (m), while x_i denotes the position of the subject vehicle in (m). The length of the subject vehicle is indicated by l_i in (m). Additionally, $x_{follower}$ refers to the position of the following vehicle in the target lane in (m), and $l_{follower}$ is the length of the following vehicle in (m). A vehicle will change lanes if both the front gap (g_f) and the rear gap (g_r) are greater than the respective minimum acceptable gaps ($g_{f,min}$ and $g_{r,min}$). The minimum acceptable gap $g_{f,min}$ is influenced by safety distance, relative speeds, and deceleration.

During the lane change, the deceleration d accepted by the subject vehicle and the trailing vehicle in the target lane can be expressed in Equation (5):

$$d_i = \frac{(v_{lead} - v_i)^2}{2 \cdot \left(g_f - s_0\right)}, \tag{5}$$

$$d_{follower} = \frac{\left(v_i - v_{follower}\right)^2}{2 \cdot (g_r - s_0)}. \tag{6}$$

In this context, v_{lead} refers to the speed of the leading vehicle in the target lane in (m/s), while $v_{follower}$ is the speed of the following vehicle in the target lane in (m/s). A lane change is carried out if both d_i and $d_{follower}$ fall within acceptable limits in (m/s^2), indicating the vehicles' willingness to decelerate. Table 5 provides an overview of the lane change parameters utilized in the PTV VISSIM model.

Table 5. Parameters governing lane change behavior in PTV VISSIM [25].

Parameter's	AV Cautious	AV Normal	AV Aggressive	AV Platoon	Human
Advanced merging	on	on	on	on	on
Cooperative lane change	on	on	on	on	off
Safety distance reduction factor	1.00	0.60	0.75	0.75	0.60
Min clearance (front/rear) in (m)	1.00	0.50	0.50	0.50	0.50
Maximum deceleration for cooperative braking in (m/s^2)	−2.50	−3.00	−6.00	−6.00	−3.00

3.6. Signal Control Optimization

To enhance the performance of the studied intersection, a signal control optimization was conducted using the PTV VISSIM traffic simulation model. The primary goal of this optimization was to evaluate the impact of different cycle times (60, 80, 100, 120, 140, 160, 180, and 204 s) on intersection performance, as shown in Figure 7a–g. This approach aimed to improve the efficiency of traffic flow by adjusting the signal timings and phasing plans to achieve a more balanced and effective distribution of green times across all approaches. Signal control optimization plays a crucial role in managing traffic flow at intersections by adjusting signal timings and phase sequences. This process aims to reduce delays, minimize congestion, and improve the overall efficiency and safety of urban traffic networks [32–34]. The optimization was performed using VISSIM's stage-based signal controller along with priority rules [35]. Additionally, manual signal timing calculations were conducted using Webster's method to identify suitable traffic signal timings. The study initially considered the original signal timings and subsequently investigated the effects of the optimized signal control for each cycle time to assess its impact on intersection performance. The results from the manual calculations were compared with those obtained through the optimization conducted in VISSIM, illustrating the comparative outcomes of these optimizations.

Gathering the required input data for the timing model involves both detection and prediction processes. These data are subsequently fed into the VISSIM simulation software, which is managed using Python. Throughout the optimization process, VISSIM provides critical evaluation metrics, such as delay time and queue length, to the model [36].

In traffic signal control, time delay is a critical element that impacts the evaluation of current traffic flow and is frequently used as a key metric for assessing traffic efficiency. The widely recognized Webster signal cross delay formula, illustrated below, is commonly used to calculate this delay:

$$D_i = \frac{c(1-g_i)^2}{2 \cdot (1-y_i)} + \frac{(y_i)^2}{2q_i g_i (8-y_i)}. \tag{7}$$

In this formula, c represents the cycle time in (sec), g_i denotes the green signal ratio (unitless), q_i is the traffic flow rate for phase in (veh/s), i and y_i (unitless) indicates the saturation level for phase i.

However, because the previous equation is only applicable when saturation is low, Cheng et al. [37] enhanced it by introducing the following equation:

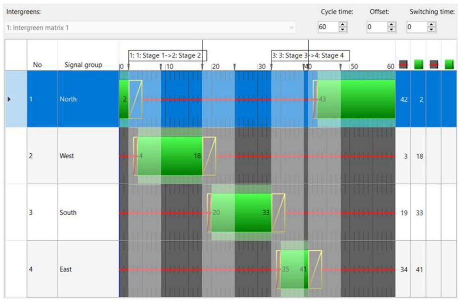
$$D_i = \frac{cq_i(x-y_i)^2}{2x^2(1-y_i)} + \frac{x^2}{2(1-x)}, \tag{8}$$

where x represents the saturation level of the intersection (unitless).

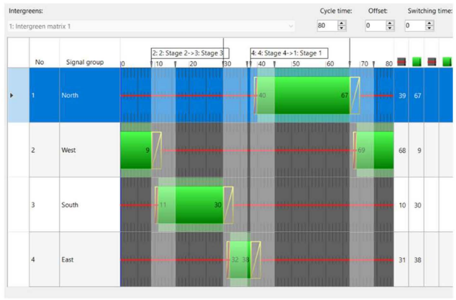
To create an appropriate criterion for the timing scheme, the average vehicle delay time for the cycle is utilized as the primary evaluation metric for optimizing signal timing. The goal of the optimization process is to minimize the following formula [36]:

$$minD = \frac{1}{n}\sum_{i=1}^{n} \frac{D_i}{N_i}. \tag{9}$$

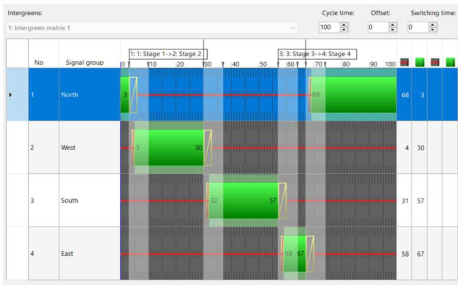
In this formula, n represents the number of lanes, D_i denotes the cycle delay time in (sec) for the ith lane, N_i indicates the cycle flow for each lane, and D is the average vehicle delay time for the entire cycle.



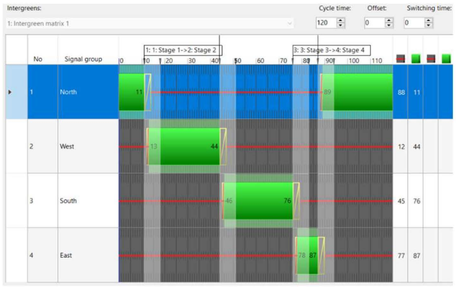
(**a**)



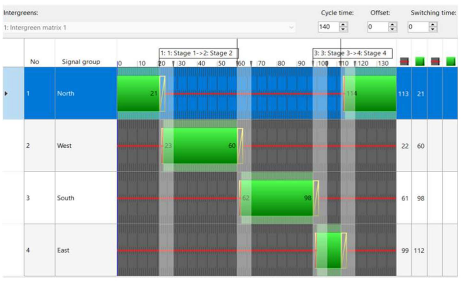
(**b**)



(**c**)



(**d**)



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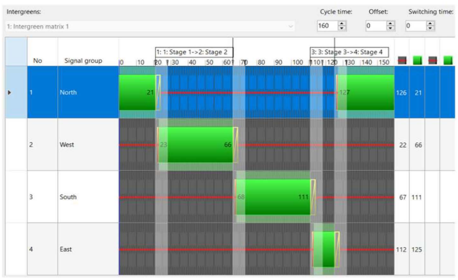

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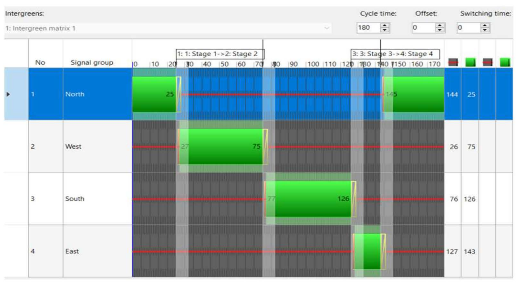

(**g**)

Figure 7. Signal program optimization for the studied intersection at various cycle times: (**a**) 60 s cycle time; (**b**) 80 s cycle time; (**c**) 100 s cycle time; (**d**) 120 s cycle time; (**e**) 140 s cycle time; (**f**) 160 s cycle time; (**g**) 180 s cycle time. Source: PTV VISSIM model.

3.7. Simulation Scenarios

To examine the intricate dynamics between human-driven vehicles and AVs in the intersections comprehensively, this study implemented a meticulously crafted set of 21 scenarios (shown in Table 6), each uniquely designed. These scenarios encompassed a variety of AV behaviors, including aggressive, normal, and cautious behaviors, along with diverse combinations of these behaviors, including AV platoon scenarios.

Table 6. Overview of scenarios with different AV penetration rates and approaches.

Scenarios	AV Penetration Rates				Human
	AV Cautious	AV Normal	AV Aggressive	AV Platoon	
No. 1	0.00%	0.00%	0.00%	0.00%	100.00%
No. 2	25.00%	0.00%	0.00%	0.00%	75.00%
No. 3	0.00%	25.00%	0.00%	0.00%	75.00%
No. 4	0.00%	0.00%	25.00%	0.00%	75.00%
No. 5	0.00%	0.00%	0.00%	25.00%	75.00%
No. 6	6.25%	6.25%	6.25%	6.25%	75.00%
No. 7	50.00%	0.00%	0.00%	0.00%	50.00%
No. 8	0.00%	50.00%	0.00%	0.00%	50.00%
No. 9	0.00%	0.00%	50.00%	0.00%	50.00%
No. 10	0.00%	0.00%	0.00%	50.00%	50.00%
No. 11	12.50%	12.50%	12.50%	12.50%	50.00%
No. 12	75.00%	0.00%	0.00%	0.00%	25.00%
No. 13	0.00%	75.00%	0.00%	0.00%	25.00%
No. 14	0.00%	0.00%	75.00%	0.00%	25.00%
No. 15	0.00%	0.00%	0.00%	75.00%	25.00%
No. 16	18.75%	18.75%	18.75%	18.75%	25.00%
No. 17	100.00%	0.00%	0.00%	0.00%	0.00%
No. 18	0.00%	100.00%	0.00%	0.00%	0.00%
No. 19	0.00%	0.00%	100.00%	0.00%	0.00%
No. 20	0.00%	0.00%	0.00%	100.00%	0.00%
No. 21	25.00%	25.00%	25.00%	25.00%	0.00%

3.8. Model Calibrations and Validation

During the calibration of the intersection links, modifications were required for the east- and west-bound directions due to high traffic volumes. Although the original design included two lanes for each direction, observations indicated that vehicles were queuing as though there were three lanes per link in both the east and west-bound directions, as shown in Figure 8.

Figure 8. Real-world vehicle queuing scenario in east and west-bound lanes. Source: from video records processed by authors.

Since VISSIM allows for only one vehicle per lane, a decision was made to configure both the east- and west-bound directions as having three lanes for each link illustrated in Figure 9. This modification aligns the simulation model more accurately with the observed traffic behavior, ensuring a realistic representation of the flow dynamics at the intersection.

Figure 9. Treating the east-bound and west-bound directions as three-lane roads. Source: PTV VISSIM model.

Additionally, another calibration point was identified, indicating that lane changes should not occur except at exit links. Therefore, it was decided to design each lane as a separate link for each direction, as shown in Figure 10. This decision was influenced by the observation that drivers were selecting their destination lanes early, resulting in no lane changes due to the substantial traffic volume.

Figure 10. Intersection design calibrated for no lane changes: each lane as a separate link. Source: PTV VISSIM model.

3.8.1. Average Queue Length Validation

To validate the accuracy of the simulated average queue in this study, real-world data were collected during the red signal phase at different cycle times. Queue measurements were taken simultaneously across all lanes for each direction. The average queue length was calculated by summing the total number of vehicles across the three lanes, multiplying by the standard vehicle length of 4.481 m, and dividing by 3 to account for the three lanes, as presented in Tables 7–10.

The calculated estimated average queue length was then compared with the simulated average queue from the PTV VISSIM microsimulation platform, as shown in Figure 11. This validation process ensured that the simulation accurately represented real-world conditions, enhancing the reliability of the study's findings and the subsequent analysis of the impact of AVs on traffic dynamics at the signalized intersection. The accuracy difference was calculated using the following formula:

$$Accuracy\ Difference(\%) = \left(\frac{Simulated\ Average\ Queue - Estimated\ Average\ Queue}{Estimated\ Average\ Queue}\right) \times 100. \tag{10}$$

The accuracy difference for the north-bound direction was around 6.30%. For the east-bound direction, the simulated average queue had an accuracy difference of 10.24%. In the south-bound direction, the accuracy difference was about 3.60%, while the west-bound direction showed an accuracy difference of 3.54%.

Table 7. North-bound average queue length real-world data.

Bound	Num. of Lane	Num. of Vehicles at First Lane	Num. of Vehicles at Second Lane	Num. of Vehicles at Third Lane	Estimated Average Queue (m)
North	3	12	11	8	46.303
North	3	11	14	7	47.797
North	3	13	12	6	46.303
North	3	10	11	8	43.316
North	3	16	12	6	50.784
North	3	11	14	9	50.784
North	3	13	13	6	47.797
North	3	11	12	3	38.835
North	3	17	14	4	52.278
North	3	16	11	7	50.784
North	3	13	12	6	46.303
North	3	17	14	2	49.291
North	3	12	11	5	41.822
North	3	16	9	8	49.291
North	3	17	13	4	50.784
North	3	13	11	6	44.81
North	3	13	13	7	49.291
North	3	11	11	4	38.835
North	3	12	11	9	47.797
					47.011

Table 8. East-bound average queue length real-world data.

Bound	Num. of Lane	Num. of Vehicles at First Lane	Num. of Vehicles at Second Lane	Num. of Vehicles at Third Lane	Estimated Average Queue (m)
East	3	5	6	2	19.417
East	3	6	4	1	16.430
East	3	5	4	2	16.430
East	3	6	5	1	17.924
East	3	4	4	1	13.443
East	3	6	5	0	16.430
East	3	5	4	1	14.936
East	3	4	3	1	11.949
East	3	6	5	0	16.430
East	3	5	4	2	16.430
East	3	5	5	1	16.430
East	3	6	2	2	14.936
East	3	4	6	2	17.924
East	3	5	4	1	14.936
East	3	5	4	1	14.936
East	3	5	3	1	13.443
East	3	4	5	0	13.443
East	3	5	4	2	16.430
East	3	6	7	1	20.911
					15.958

Table 9. South-bound average queue length real-world data.

Bound	Num. of Lane	Num. of Vehicles at First Lane	Num. of Vehicles at Second Lane	Num. of Vehicles at Third Lane	Estimated Average Queue (m)
South	3	14	12	6	47.797
South	3	14	12	9	52.278
South	3	11	14	7	47.797
South	3	18	14	4	53.772
South	3	14	13	6	49.291
South	3	16	12	7	52.278
South	3	14	14	5	49.291

Table 9. *Cont.*

Bound	Num. of Lane	Num. of Vehicles at First Lane	Num. of Vehicles at Second Lane	Num. of Vehicles at Third Lane	Estimated Average Queue (m)
South	3	13	13	7	49.291
South	3	15	11	8	50.784
South	3	11	14	9	50.784
South	3	17	14	4	52.278
South	3	13	11	9	49.291
South	3	14	12	7	49.291
South	3	13	14	7	50.784
South	3	14	11	8	49.291
South	3	11	15	7	49.291
South	3	17	14	6	55.265
South	3	14	11	9	50.784
South	3	16	15	3	50.784
					50.548

Table 10. West-bound average queue length real-world data.

Bound	Num. of Lane	Num. of Vehicles at First Lane	Num. of Vehicles at Second Lane	Num. of Vehicles at Third Lane	Estimated Average Queue (m)
West	3	14	13	11	56.759
West	3	13	12	12	55.265
West	3	15	12	9	53.772
West	3	13	15	6	50.784
West	3	12	13	11	53.772
West	3	14	15	8	55.265
West	3	17	13	6	53.772
West	3	15	14	8	55.265
West	3	14	13	9	53.772
West	3	13	11	12	53.772
West	3	12	13	9	50.784
West	3	14	15	6	52.278
West	3	13	12	12	55.265
West	3	14	13	11	56.759
West	3	13	11	9	49.291
West	3	12	13	13	56.759
West	3	11	10	9	44.81
West	3	13	11	8	47.797
West	3	12	11	13	53.772
					53.143

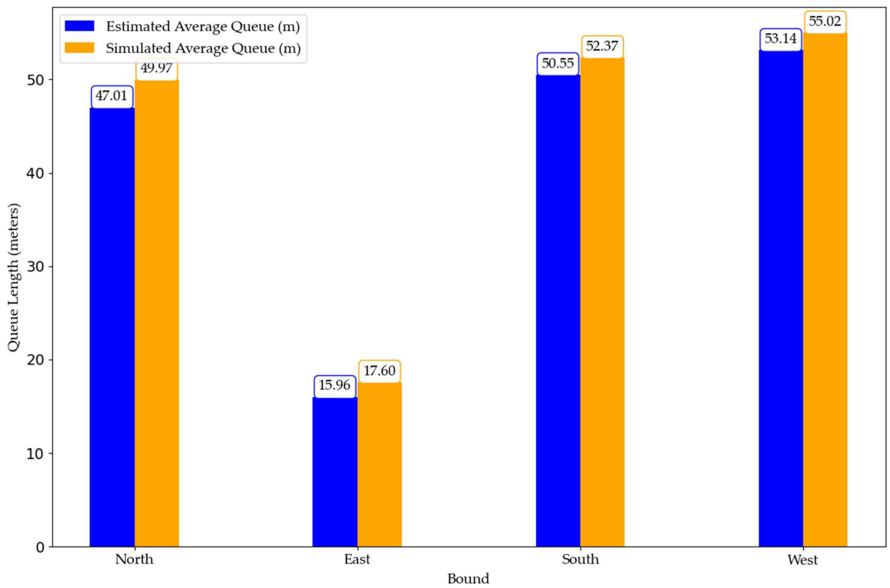

Figure 11. Comparison of estimated and simulated average queue length for all directions. Source: processed by authors.

3.8.2. Average Travel Time Validation

To validate the accuracy of simulated travel times, a sample of 20 vehicles was randomly selected for each direction, considering different signal phases. Unlike the queue validation, these vehicles were chosen randomly during various signal times to capture a more diverse set of traffic scenarios. The travel time for each vehicle was estimated using a stopwatch between two fixed points spaced 150 m apart. The comparison between the estimated and simulated travel times is presented in Table 11 and illustrated in Figure 12.

Table 11. Validation of all directions simulated average travel time against real-world data at different signal phases.

Vehicle No.	Estimated Travel Time (sec)			
	North-Bound	East-Bound	South-Bound	West-Bound
No.1	57.23	79.23	67.23	63.23
No.2	51.37	82.43	55.37	58.37
No.3	47.84	83.81	57.84	62.84
No.4	46.43	74.32	56.43	56.43
No.5	48.22	69.43	68.22	72.54
No.6	51.43	72.54	61.43	64.83
No.7	53.21	71.24	59.21	53.21
No.8	44.83	79.54	64.83	57.45
No.9	53.21	81.43	63.21	47.83
No.10	52.92	84.32	59.92	59.42
No.11	51.29	85.34	51.29	48.82
No.12	48.42	77.32	54.42	47.34
No.13	48.82	69.34	58.82	55.21
No.14	48.82	65.43	59.34	61.21
No.15	49.26	61.43	49.45	49.21
No.16	46.18	68.23	68.45	53.34
No.17	47.34	81.34	57.36	56.33
No.18	43.56	84.39	58.84	62.43
No.19	42.92	67.34	59.54	58.75
No.20	48.07	64.32	68.07	54.92
Estimated Average Travel Time	49.068	75.138	59.963	57.185

The north- and west-bound directions exhibited accuracy differences of approximately 3.87% and 2.84%, respectively, indicating a relatively close alignment between the estimated and simulated travel times. Similarly, the east- and south-bound directions displayed accuracy differences of approximately 4.96% and 4.86%, respectively, as shown in Figure 12. These findings signify the effectiveness of the simulation in replicating real-world travel time dynamics, demonstrating its capability to provide accurate representations of traffic behavior under varying signal conditions.

The contradiction between longer queues and shorter travel times can be explained by differences between real-world human driving and the simulated model. In the simulation, longer queues may form due to conservative driving behaviors, with larger gaps or slower reactions at intersections. However, once vehicles start moving, they tend to accelerate more efficiently in the simulation, leading to smoother traffic flow and shorter travel times. This explains why, despite longer queues, vehicles clear the intersection faster in the model compared to real-world conditions.

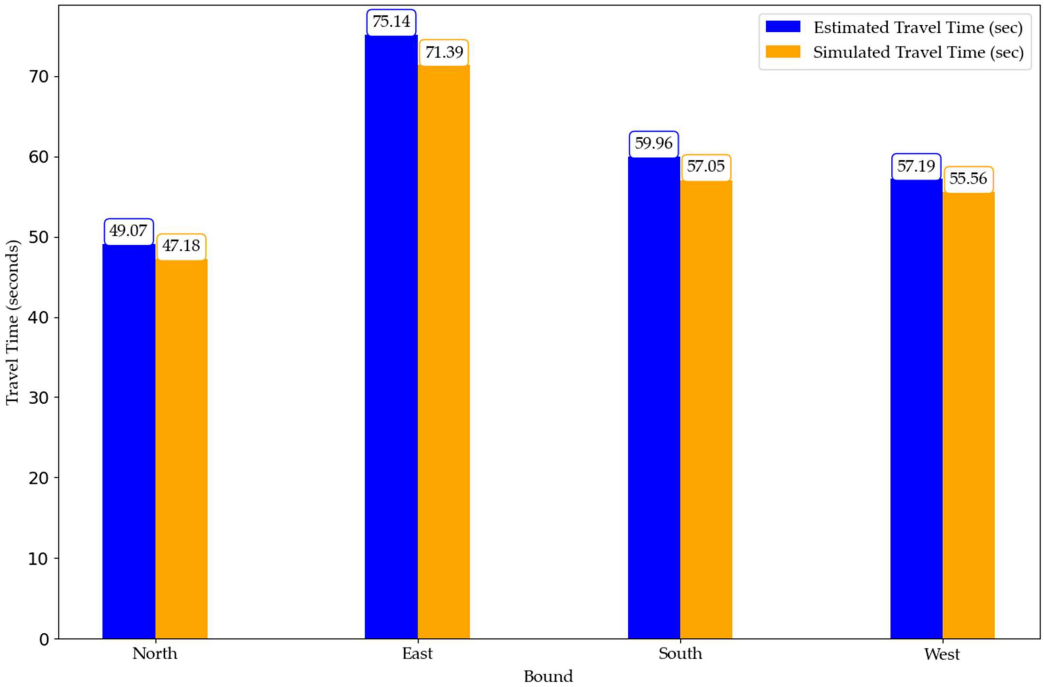

Figure 12. Comparison of estimated and simulated average travel time for all directions. Source: processed by authors.

3.9. Emission Modeling in VISSIM

In assessing the environmental impact of autonomous vehicles (AVs) at urban intersections, accurately quantifying emissions across different traffic conditions is essential. This study employs the emission modeling features of PTV VISSIM, utilizing the Handbook Emission Factors for Road Transport (HBEFA) to simulate and evaluate pollutant emissions such as CO, NOx, and particulate matter (PM). VISSIM calculates emissions using a polynomial function that takes vehicle speed into account, allowing for detailed analysis of the pollutants generated under varying driving behaviors and traffic scenarios.

$$E = \sum_{i=1}^{n} \left(a + b \cdot v_i + c \cdot {v_i}^2 + d \cdot {v_i}^3\right) \cdot \Delta t \tag{11}$$

The total emissions (E) of a specific pollutant (in grams) are calculated using a polynomial function, where v_i represents the speed of vehicle i (in kilometers per hour), and a, b, c, and d are empirical coefficients (unitless) specific to vehicle types and driving conditions. The simulation time step Δt (in seconds) is used to account for emissions generated over time during the simulation. This allows for an accurate estimation of emissions based on real-time vehicle behavior within the VISSIM model.

The coefficients a, b, c, and d are derived from the HBEFA model and are specifically tailored to represent the emission characteristics of different vehicle categories, including both autonomous and human-driven vehicles. These coefficients play a crucial role in modeling the effects of various driving behaviors and traffic conditions on emission levels. They differ based on vehicle type, engine properties, and driving patterns, enabling a realistic evaluation of emissions across different traffic scenarios. The following is a breakdown of these coefficients.

Coefficient a represents the baseline emissions produced when vehicles are idling or moving at low speeds. It tends to be lower for efficient or less aggressive driving behaviors, such as AV platooning, which minimizes idle time and low-speed operations. Coefficient b establishes a linear relationship between speed and emissions, with higher values typically associated with more aggressive driving styles, like AV aggressive, where emissions increase at higher speeds. Coefficients c and d account for the nonlinear effects of speed on emissions, highlighting the significant impact of rapid speed fluctuations, such as during aggressive acceleration or deceleration. These coefficients reflect how dynamic driving behaviors influence overall emissions output.

4. Results

4.1. Average Queue Length Results

Figure 13 presents the average queue lengths across different cycle times (60 to 204 s) for various AV driving behaviors and penetration rates, along with human-driven vehicles. Queue lengths increase with longer cycle times for all scenarios.

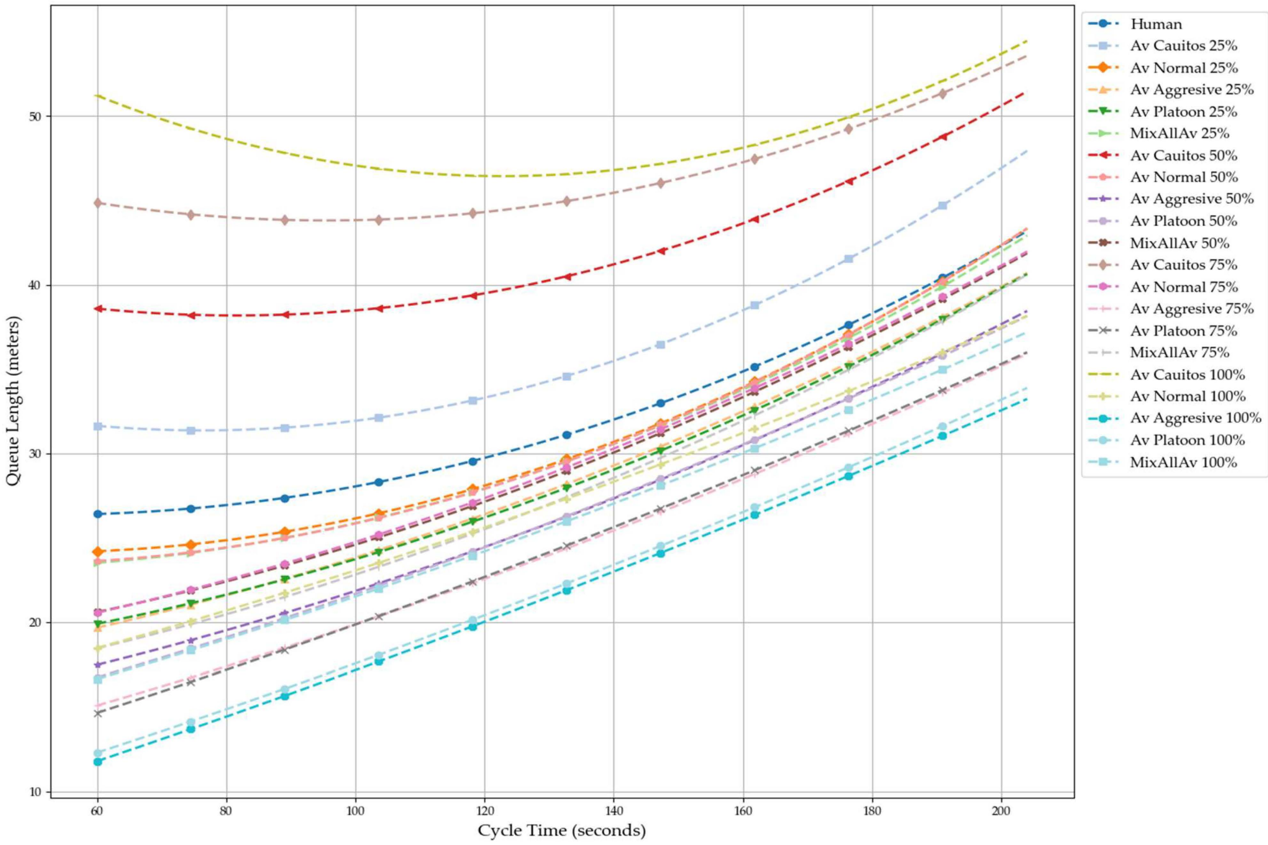

Figure 13. Influence of AV behaviors on average queue lengths at various traffic signal cycle times. Source: processed by authors.

Cautious AVs consistently show the highest queue lengths across all cycle times and penetration rates, reflecting inefficiencies due to their conservative driving behavior, which leads to underutilization of road capacity. Human-driven vehicles also exhibit high queue lengths, though they perform slightly better than cautious AVs.

Aggressive AVs, across all penetration rates, demonstrate the best overall performance, achieving the lowest queue lengths. While queue lengths increase at higher cycle times, aggressive AVs maintain better performance compared to other behaviors. Their ability to exploit smaller gaps and maintain faster acceleration helps keep queue lengths lower than cautious and normal driving behaviors at all penetration rates.

Platooning AVs also show highly efficient queue length reduction due to their coordinated driving, with performance nearly identical to aggressive AVs at full penetration. The difference between the two is minimal, with aggressive AVs showing only a slight improvement in queue lengths.

Normal AVs exhibit moderate increases in queue lengths, striking a balance between cautious and aggressive behaviors. In mixed AV environments, queue lengths are more stable, falling between the extremes of cautious and aggressive behaviors, promoting balanced traffic flow.

4.2. Average Travel Time Results

Figure 14 presents the average travel times across different cycle times (60 to 204 s) for various AV driving behaviors and penetration rates, along with human-driven vehicles. Travel times generally increase with longer cycle times for all scenarios.

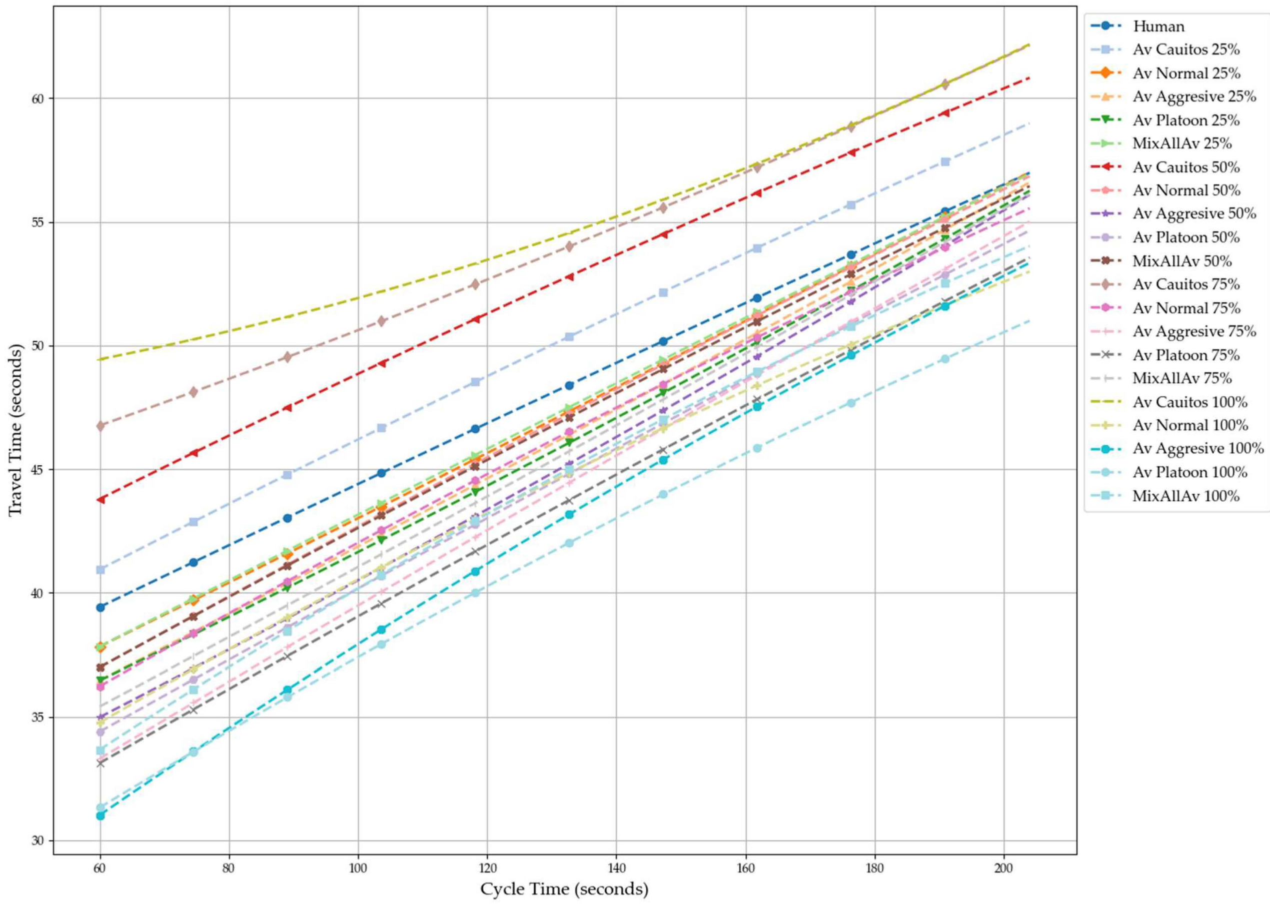

Figure 14. Influence of AV behaviors on average travel time at various traffic signal cycle times. Source: processed by authors.

Cautious AVs consistently show the highest travel times across all cycle times and penetration rates, due to their conservative driving behavior, which underutilizes road capacity and leads to inefficiencies. Human-driven vehicles also exhibit high travel times but perform slightly better than cautious AVs, particularly at higher cycle times.

Platooning AVs with 100% penetration demonstrate the best overall performance, achieving the lowest travel times. Their coordinated driving minimizes stop-and-go waves, resulting in highly efficient traffic flow. Aggressive AVs, while showing slightly higher travel times than platooning AVs, still perform well with lower travel times across all penetration rates. The differences between aggressive AVs and platooning AVs are slight, particularly at lower cycle times.

Normal AVs exhibit moderate increases in travel times, offering a balanced performance between cautious and aggressive behaviors. In mixed AV environments, travel times are more stable, falling between the extremes of cautious and aggressive behaviors, providing smoother and more predictable traffic flow.

4.3. Average Vehicles Delay Results

Figure 15 presents the vehicle delays across different cycle times (60 to 204 s) for various AV driving behaviors and penetration rates, along with human-driven vehicles. Vehicle delays increase with longer cycle times for all scenarios.

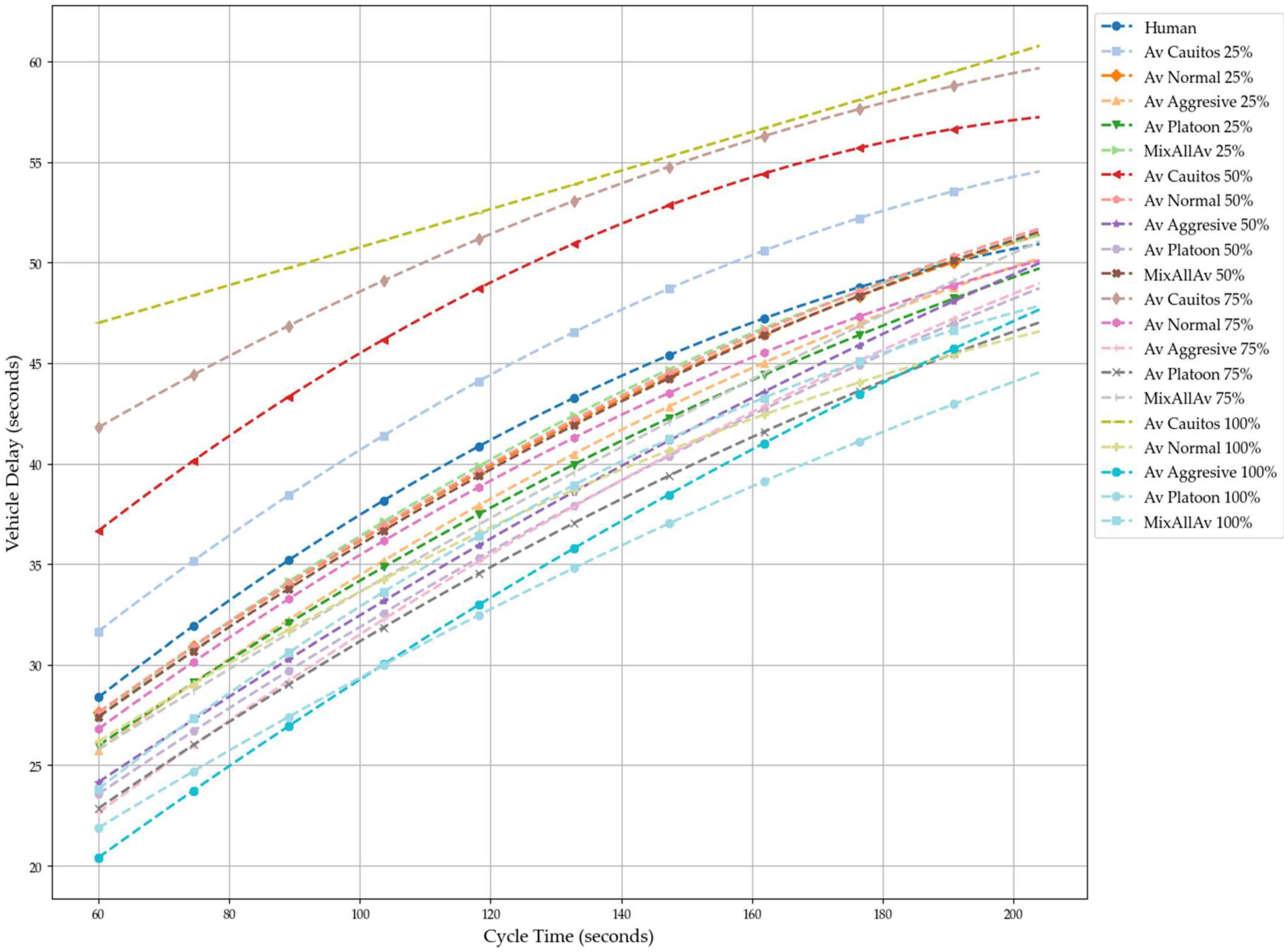

Figure 15. Influence of AV behaviors on average vehicle delay at various traffic signal cycle times. Source: processed by authors.

Cautious AVs consistently show the highest delays across all cycle times and penetration rates due to their conservative driving behavior, which underutilizes available road capacity. Human-driven vehicles also exhibit high delays, though they perform slightly better than Cautious AVs at longer cycle times.

Aggressive AVs and platooning AVs with 100% penetration demonstrate the best overall performance, achieving the lowest delays. Aggressive AVs reduce delays by exploiting smaller gaps and accelerating quickly, although delays increase slightly at higher cycle times due to traffic instability. Platooning AVs, with their coordinated driving, also achieve low delays, showing a similar performance to aggressive AVs, with only slight differences.

Normal AVs show a moderate and steady increase in delays with longer cycle times, providing a balanced performance between cautious and aggressive behaviors. In mixed AV environments, vehicle delays are more stable, falling between the extremes of cautious and aggressive behaviors, leading to more-consistent and predictable traffic flow.

4.4. Average Vehicle Gas Emissions and Fuel Consumption Results

Figures 16–19 present the impact of different autonomous vehicle (AV) behaviors and penetration rates on carbon monoxide emissions (CO), nitrogen oxides emissions (NOx), volatile organic compounds emissions (VOC), and fuel consumption across various traffic signal cycle times (60 to 204 s). Emissions and fuel consumption generally decrease with shorter cycle times across all driving behaviors and AV penetration rates.

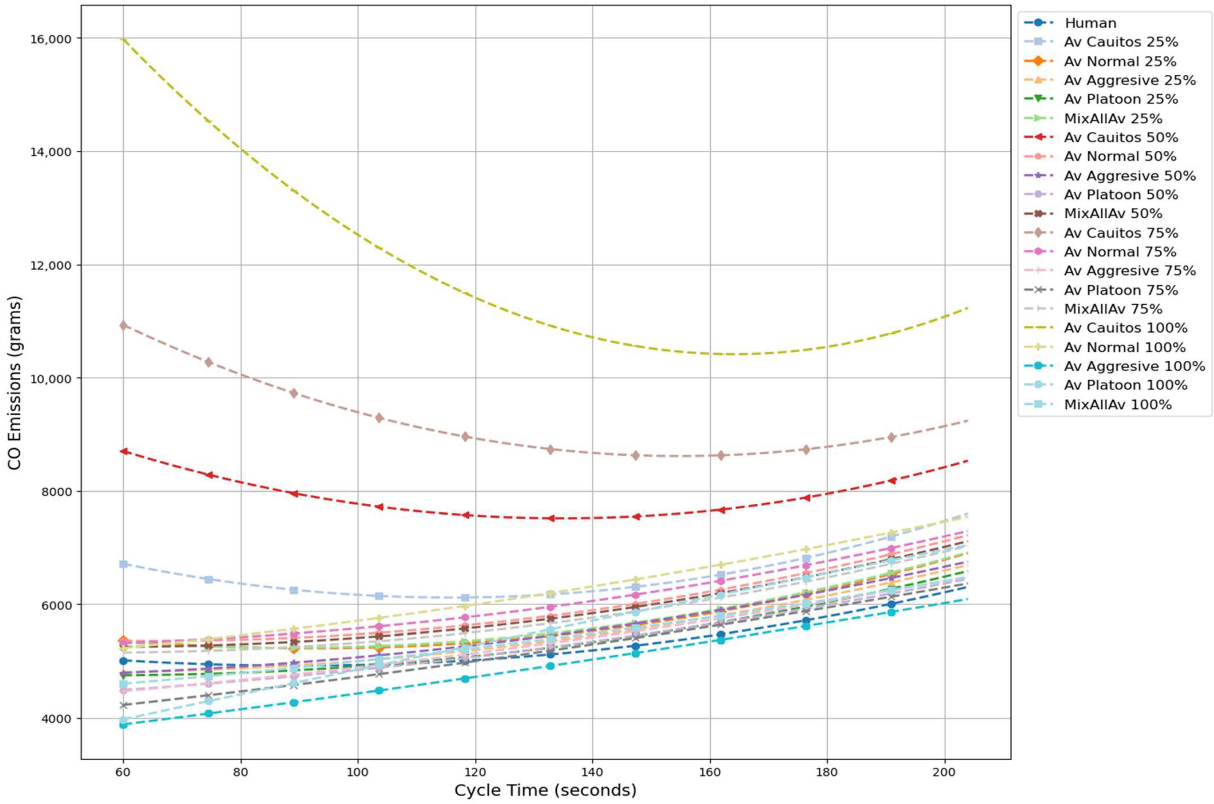

Figure 16. Influence of AV behaviors on average CO emissions at various traffic signal cycle times. Source: processed by authors.

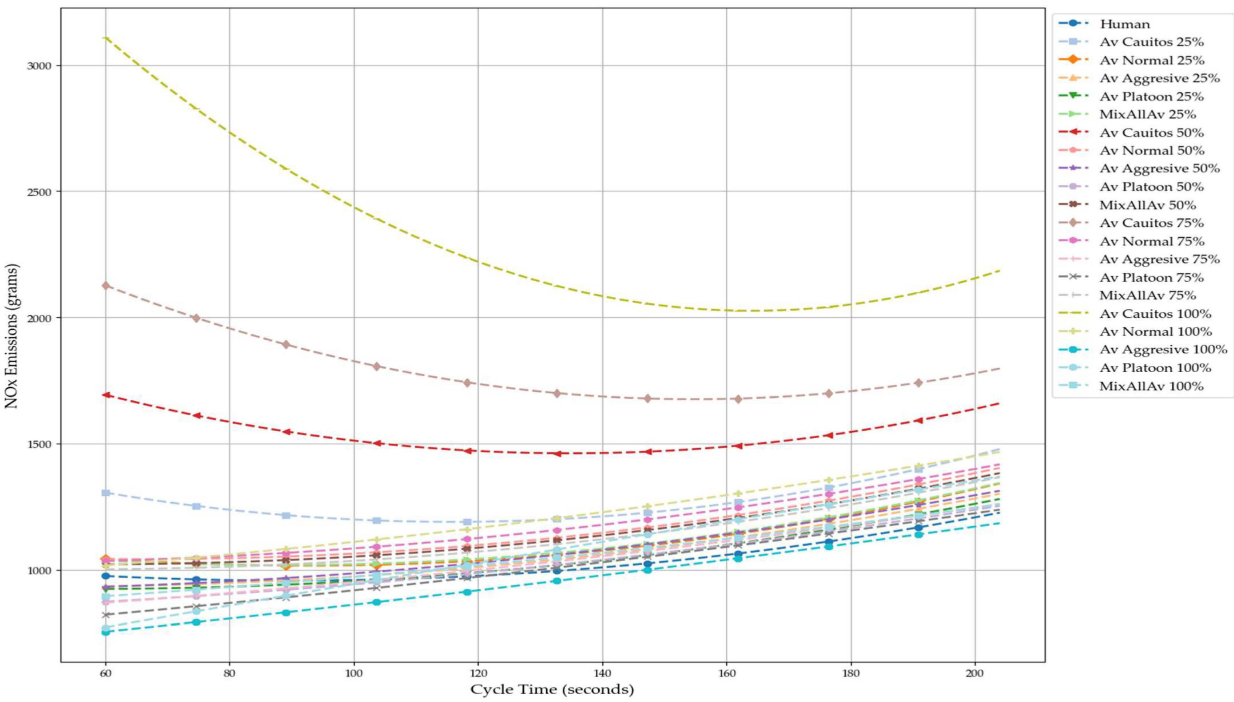

Figure 17. Influence of AV behaviors on average NOx emissions at various traffic signal cycle times. Source: processed by authors.

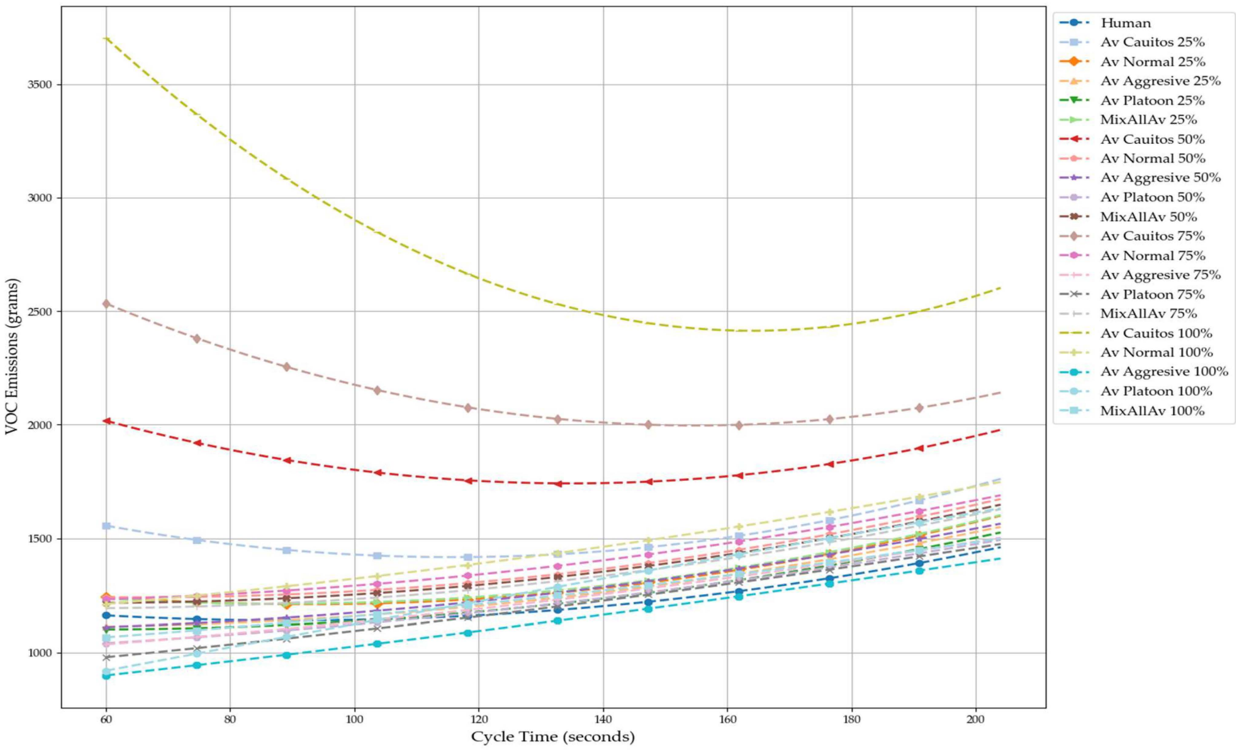

Figure 18. Influence of AV behaviors on average VOC emissions at various traffic signal cycle times. Source: processed by authors.

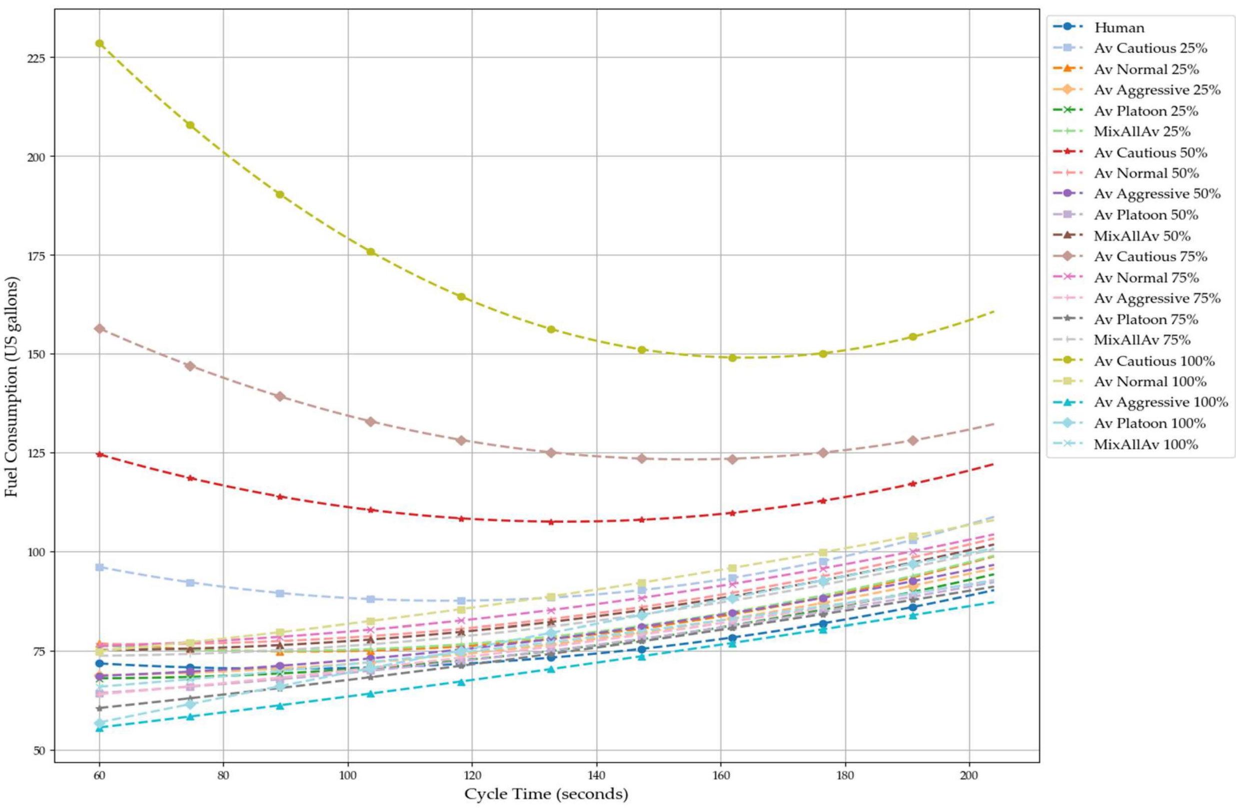

Figure 19. Influence of AV behaviors on average fuel consumption at various traffic signal cycle times. Source: processed by authors.

Cautious AVs consistently exhibit the worst performance, with the highest emissions and fuel consumption across all cycle times. Although emissions and fuel consumption for cautious AVs start to decrease as cycle times increase, they remain the least efficient scenario compared to other AV behaviors.

Aggressive AVs, especially at 100% penetration, demonstrate the lowest emissions and fuel consumption. While other AV behaviors show slight increases in emissions and fuel consumption at higher cycle times, aggressive AVs with 100% penetration achieve the best results by maintaining lower emissions and fuel consumption throughout all cycle times.

Normal AVs with high penetration show improved emissions and fuel consumption compared to human-driven vehicles, particularly at shorter cycle times. However, as cycle times increase, emissions and fuel consumption for normal AVs begin to rise.

Platooning AVs consistently exhibit low emissions and fuel consumption, with performance almost as efficient as aggressive AVs, particularly at higher penetration rates. In mixed AV environments, emissions and fuel consumption levels remain stable, balancing the various driving behaviors and leading to more efficient and predictable traffic flow.

5. Discussion

The integration of autonomous vehicles (AVs) into urban traffic systems has been a focal point in recent transportation research, primarily due to the potential benefits AVs can offer in improving traffic efficiency, reducing congestion, and minimizing environmental impacts. This study evaluates the impact of different AV driving behaviors (cautious, normal, aggressive, and platooning) on traffic performance at a signalized intersection. The discussion below provides a detailed comparison of our findings with previous research, highlights the implications of the results.

5.1. Traffic Efficiency and Flow

The findings from this study support the growing body of literature indicating that AVs can enhance traffic flow efficiency, particularly under specific driving behaviors and penetration rates. Aggressive and platooning AVs significantly reduced queue lengths, travel times, and delays compared to human-driven vehicles. For instance, at a 60 s cycle time, aggressive AVs reduced queue lengths by up to 56.62%, travel times by up to 21.15%, and vehicle delays by up to 27.59%. Similarly, platooning AVs at 100% penetration achieved comparable reductions, highlighting their efficiency in streamlining traffic flow.

However, the aggressive AV behavior introduced instability at higher signal cycle times, leading to increased vehicle oscillations and traffic disturbances, particularly at a 204 s cycle time where the reductions in queue lengths and travel times dropped to about 23.14% and 6.63%, respectively. This phenomenon aligns with the findings of [11], who highlighted trade-offs between aggressive AV driving patterns and traffic flow stability, especially in dense urban settings. To mitigate these issues, adaptive traffic signal control systems that dynamically adjust to real-time traffic conditions and AV behaviors could be implemented. Moreover, integrating cooperative AV algorithms that enable vehicle-to-vehicle and vehicle-to-infrastructure communications could further reduce traffic oscillations.

On the contrary, cautious AVs, while enhancing safety and promoting smoother traffic flow, resulted in longer queue lengths and higher delays, particularly at higher penetration rates. At 100% penetration and a 60 s cycle time, cautious AVs increased queue lengths by up to 82.30% and delays by up to 59.03%. This supports research by [4,15,38], which suggests that risk-averse AVs may induce traffic inefficiencies due to larger gaps and slower acceleration rates, especially in interactions with human drivers.

Normal AVs provided a more balanced performance, mitigating extremes in traffic behavior by reducing queue lengths by up to 33.91% and delays by up to 15.26% at 60 s. This balance suggests that normal AVs may offer an optimal compromise between efficiency and safety in mixed-traffic environments as they navigate between the conservative and aggressive extremes.

In mixed AV environments, vehicle delays and queue lengths were more stable, generally falling between the extremes presented by cautious and aggressive behaviors. This mixed strategy led to reductions ranging from about 14.34% to 38.82% in queue lengths and from 0.85% to 16.98% in vehicle delays at 60 s. This demonstrates that a diversified approach to AV behavior can provide smoother and more predictable traffic flow, ensuring broader benefits across different traffic scenarios.

5.2. Environmental Impacts: Emissions and Fuel Consumption

The results demonstrated that platooning AVs can significantly reduce emissions (CO, NOx, VOC) and fuel consumption, particularly at shorter cycle times. For example, platooning AVs showed a reduction in CO emissions by up to 22.9% at 60 s and decreased fuel consumption by up to 22.85% at the same cycle time. This aligns with reductions in NOx and VOC emissions, which further underscore the efficiency of platooning AVs in optimizing traffic flow and reducing environmental impacts.

While the reduction in emissions and fuel consumption is notable, it is essential to assess whether these environmental benefits justify the cost of implementing platooning technology. Studies show that over time, the savings from reduced fuel consumption and lower emissions, especially in high-traffic urban areas, can offset the initial investment in AV technology [39]. Furthermore, as the technology matures and adoption rates increase, the cost of implementation is expected to decrease, making it a more viable option for sustainable urban transportation systems.

However, aggressive AVs consistently showed the best performance across all cycle times, achieving the lowest emissions and fuel consumption compared to human-driven vehicles and other AV behaviors. For instance, aggressive AVs at 100% penetration demonstrated a reduction in CO emissions by 23.3% at 60 s, and fuel consumption decreased by up to 23.31% at the same cycle time. These results highlight the potential of aggressive driving algorithms to maximize efficiency and minimize environmental impacts effectively. Although a 100% AV scenario may seem distant, evaluating it provides crucial insights into the maximum potential of AVs to reduce emissions and fuel consumption. These benchmarks serve as a guide for optimizing future AV driving algorithms and traffic systems. As the vehicle fleet evolves potentially incorporating more electric or hybrid AVs this methodology can adapt, making the findings valuable for long-term urban transportation planning. This study helps cities prepare for increasing AV penetration and develop strategies to maximize environmental and operational efficiencies.

However, the results also revealed that cautious AVs, despite their smoother driving patterns, can paradoxically increase emissions and fuel consumption in scenarios with longer cycle times. This occurs because their conservative driving behaviors lead to underutilization of road capacity, resulting in more idling and slower speeds, as noted in the work of [18,40]. For example, cautious AVs at 100% penetration increased CO emissions by 220.6% at 60 s and fuel consumption by 220.53% at the same cycle time. This finding highlights a critical challenge for AV deployment: ensuring that overly cautious driving algorithms do not negate the environmental benefits of AV integration, particularly in high-traffic urban environments.

These insights provide a comprehensive view of the impact of different AV behaviors on environmental and operational efficiencies, underlining the importance of balanced algorithm development to harness the full potential of autonomous vehicle technologies.

5.3. Optimization of Traffic Signal Control

One of the key contributions of this study is the exploration of signal timing optimization in conjunction with AV penetration rates. Our results show that optimized traffic signal control, particularly at cycle times between 60 and 100 s, can substantially improve both traffic flow and environmental outcomes. This observation is in line with the work of [5], who demonstrated that coupling AV technology with signal control optimization can enhance traffic performance by reducing vehicle delays and improving throughput at intersections.

This study used Webster's method and PTV VISSIM simulation software to optimize signal timings, and the results suggest that coordinated AV movements, particularly under platooning conditions, can further enhance the benefits of optimized signal control strategies. These findings complement the research of [26], who found that integrating AV control algorithms with signal optimization can minimize delays, CO emissions, and fuel consumption in urban traffic networks.

Despite these benefits, our findings also suggest that traffic signal optimization alone may not be sufficient to mitigate the inefficiencies introduced by cautious AVs, particularly at high penetration rates. This underscores the importance of developing more adaptive and flexible signal control strategies that can dynamically adjust to different AV behaviors and penetration levels, as noted by [37] in their study of adaptive signal control systems.

5.4. Mixed Environments: The Role of AV–Human Interactions

The mixed-traffic scenarios simulated in this study, where different AV behaviors coexist with human-driven vehicles, produced interesting insights into the interactions between human and autonomous drivers. In particular, the balanced driving patterns of normal AVs and the coordinated movements of platooning AVs helped mitigate the traffic inefficiencies introduced by aggressive and cautious driving styles. This is consistent with the findings of [27,29,38,40–44], who noted that mixed-traffic environments with diverse AV behaviors can stabilize traffic flow by balancing the extremes of cautious and aggressive driving.

5.5. Infrastructure and Policy Implications

The integration of AVs into urban traffic systems will likely require significant modifications to existing infrastructure, particularly at intersections. Studies by [21,23,45] have emphasized the need for AV-ready infrastructure, such as enhanced traffic signal systems, dedicated AV lanes, and communication networks to support the efficient coordination of AVs. Our study's findings further highlight the importance of infrastructure readiness, particularly in supporting platooning AVs, which showed the greatest benefits in terms of traffic efficiency and environmental outcomes.

From a policy perspective, the results of this study underscore the need for regulatory frameworks that can guide the integration of AVs into urban traffic systems. This includes the development of safety standards for AV driving behaviors, as well as guidelines for optimizing traffic signal control in AV environments. Research by [8] has similarly highlighted the importance of developing policies that balance the trade-offs between safety and efficiency in AV deployment, particularly as AV technology becomes more widespread.

6. Conclusions

This study provides a comprehensive analysis of the impact of different autonomous vehicle (AV) driving behaviors on urban traffic performance at a signalized intersection. The simulation results demonstrate that AV behaviors have varying effects on traffic efficiency, emissions, and fuel consumption. Cautious AVs, despite promoting smoother traffic flow, led to significant increases in queue lengths and delays, particularly at higher penetration rates. For instance, at 100% penetration and a 60 s cycle time, cautious AVs increased queue lengths by up to 82.30% and delays by 59.03%. Additionally, emissions and fuel consumption saw dramatic rises, with CO emissions and fuel consumption increasing by 220.6% and 220.53%, respectively, at shorter cycle times. This indicates that overly conservative driving behaviors can hinder road capacity utilization, leading to negative environmental impacts. In contrast, aggressive AVs showcased significant benefits, particularly at 100% penetration. Aggressive AVs reduced queue lengths by up to 56.62%, travel times by 21.15%, and vehicle delays by 27.59% at a 60 s cycle time. They also decreased CO emissions by 23.3% and fuel consumption by 23.31%. However, at longer cycle times, such as 204 s, the benefits diminished due to increased traffic oscillations, reducing queue length savings to 23.14% and travel time improvements to 6.63%. Platooning AVs exhibited strong performance, especially at shorter cycle times, where CO emissions were reduced by up to 22.9% and fuel consumption by 22.85%. Their coordinated driving behavior effectively optimized road usage, minimizing inter-vehicle gaps and enhancing overall traffic flow. Normal AVs provided a balanced performance, reducing queue lengths by up to 33.91% and delays by up to 15.26%, offering an optimal compromise between aggressive and cautious driving behaviors. Mixed AV environments, featuring a blend of AV behaviors, demonstrated stable performance, with reductions in queue lengths ranging from 14.34% to 38.82% and vehicle delays decreasing by 0.85% to 16.98%. This approach mitigated the extremes of individual AV behaviors, resulting in smoother and more predictable traffic flow.

These findings underscore the transformative potential of AVs to improve traffic efficiency and environmental sustainability. However, they also highlight the importance of optimizing AV algorithms and traffic signal control strategies to realize the benefits of AV integration in urban traffic systems fully. Balancing aggressive and cautious behaviors while leveraging platooning technology could be key to maximizing the operational and environmental advantages of AVs.

For future research, it is recommended to undertake the following:

- Investigate the long-term impacts of mixed driving scenarios on traffic patterns and urban mobility.
- Explore necessary infrastructure modifications to support AV integration.
- Study the behavioral nuances of platooning at higher penetration rates.
- Focus on designing energy-efficient AV systems to minimize environmental impacts.
- Develop comprehensive policy and regulatory frameworks for AV deployment.
- Conduct real-world pilot studies to validate simulation results and gather empirical data.
- Examine the potential for extrapolating and modeling various performance metrics (queue lengths, travel times, delays, emissions, and fuel consumption) to enhance understanding of AV impacts.

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List of Abbreviations

AVs	Autonomous Vehicles
CAVs	Connected Autonomous Vehicles
AHS	Automated Highway Systems
CV	Conventional Vehicle
THW	Time Headway
CACC	Cooperative Adaptive Cruise Control
ABX	Absolute Braking Threshold
SDX	Safe Distance Threshold
CLDV	Closing Distance
SDV	Sensitive Distance
OPDV	Opening Distance
CO	Carbon Monoxide
NOx	Nitrogen Oxides
VOC	Volatile Organic Compounds

List of Symbols (Nomenclature)

Symbol	Description	Unit
g_f	Front gap between the subject vehicle and the leading vehicle	m
g_r	Rear gap between the subject vehicle and the following vehicle	m
X_{lead}	Position of the leading vehicle in the target lane	m
x_i	Position of the subject vehicle	m
l_i	Length of the subject vehicle	m
$x_{follower}$	Position of the following vehicle in the target lane	m
$l_{follower}$	Length of the following vehicle	m
v_{lead}	Speed of the leading vehicle	m/s
$v_{follower}$	Speed of the following vehicle	m/s
d_i	Deceleration of the subject vehicle	m/s^2
$d_{follower}$	Deceleration of the following vehicle	m/s^2
a_f	Acceleration of the following vehicle	m/s^2
s_f	Desired safety distance	m
s_0	Minimum standstill distance	m
T_f	Safe time headway	s
a_b	Maximum acceleration capability	m/s^2
b	Comfortable deceleration rate	m/s^2
E	Total emissions of a pollutant	g
v_i	Speed of vehicle $_i$	km/h
a, b, c, d	Empirical coefficients for emission calculation	—

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