INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 17 No. 9 (2025) 310-325
https://publisher.uthm.edu.my/ojs/index.php/ijie

Impact of Autonomous Vehicles on Control Delay & Safety: A Case Study of Signalized Tight Diamond Interchange at Executive Towers Business Bay, Dubai

Mohammed Arshad[1,2], Sitti Asmah Hassan[1]*, Muhammad Azam[3], Nordiana Mashros[1], Mohd Khairul Afzan Mohd Lazi[1]

[1] *Faculty of Civil Engineering,*
Universiti Teknologi Malaysia, 81310 Skudai, Johor, MALAYSIA
[2] *Department of Traffic and Transportation Studies, Zutari Engineering International (formerly Aurecon),*
8th Floor, Elite Business Center, Al Barsha, Dubai, UNITED ARAB EMIRATES
[3] *Department of Civil Engineering,*
National University of Computer and Emerging Sciences, 54770 Lahore, Punjab, PAKISTAN

*Corresponding Author: sasmah@utm.my
DOI: https://doi.org/10.30880/ijie.2025.17.09.021

Article Info

Received: 5 May 2024
Accepted: 22 August 2025
Available online: 31 December 2025

Keywords

Autonomous vehicles, PTV VISSIM, average delay, surrogate safety assessment model

Abstract

Autonomous Vehicles (AVs) promise to transform urban mobility by improving traffic flow and safety, but their actual impact under varied traffic and geometric conditions remains uncertain, warranting further study. This study evaluates the impacts of AVs on the operational and safety performance of a signalized tight diamond interchange at Executive Towers Business Bay, Dubai, under mixed traffic conditions. Three AV driving logics: aggressive, normal and cautious, were gradually introduced, replacing conventional cars while maintaining a constant mix of 2% heavy vehicles and 1% buses. A calibrated and validated traffic model was developed in PTV VISSIM using site-specific geometric and operational data, with maximum queue length used as the measure of effectiveness (MOE). Thirteen scenarios were simulated to evaluate varying AV penetration levels. Delay outputs were extracted from VISSIM, while vehicle trajectory files were analyzed in the Surrogate Safety Assessment Model (SSAM) using TTC thresholds of 1.5 and 1.0 seconds. Calibration yielded optimal values for VISSIM's car-following parameters: average standstill distance (1.35 m), additive part of safety (0.75 m), and multiplicative part of safety (1.50 m). Results showed that at a demand level exceeding 5,000 veh/hr, AV-Aggressive at 100% penetration reduced average delay by 7.5% and total conflicts by 48.6% compared to conventional vehicles. In contrast, AV-Cautious increased delay by 90.6% and conflicts by 69.2%. AV-Normal caused a modest 3.5% increase in delay but reduced conflicts by 26.7%. Overall, Scenario 13, 100% AV-Aggressive—demonstrated the best operational and safety performance. These results highlight the critical role of AV driving logic in shaping interchange performance, with aggressive AV behavior at full penetration offering the most substantial improvements in delay reduction and conflict mitigation. This suggests that future AV integration strategies should consider behavior modeling as a key factor in optimizing traffic operations and safety in complex urban environments.

1. Introduction

The transport sector is undergoing significant transformation driven by Industry 4.0 and the digitalization of the entire value chain. Globally, road accidents and traffic congestion continue to pose serious challenges, with projections indicating that these issues may worsen over time [1]. The introduction of self-driving cars presents a promising solution, with estimates suggesting they could reduce such incidents by 80% by the year 2040 [2]. In an ideal scenario, an Autonomous Vehicle (AV) or self-driving car, is capable of perceiving its environment and navigating without human intervention [3]. These vehicles are typically equipped with a range of sensors, including video cameras, radars, and GPS, which enable them to detect, interpret and respond to their surroundings effectively.

Research has consistently shown that autonomous driving can help alleviate traffic congestion by increasing traffic capacity, improving safety margins in car following scenarios and reducing time headways between vehicles [4], [5]. In the United States alone, a 2018 reported approximately 6 million traffic incidents, resulting in 3.5 million fatalities and 2.5 million injuries [6]. By gradually replacing human control, AVs have the potential to significantly reduce driver-related accidents.

AVs enhance road safety by addressing key risk factors such as driver error, driver fatigue and impairment due to alcohol or drugs, which are among the leading causes of traffic collisions [7]. Beyond safety improvements, AVs offer a range of additional benefits, including increased productivity, reduced pollution, improved fuel efficiency, and lower parking costs [7]. Their ability to optimize driving patterns contributes to reduced fuel consumption and fewer harmful emissions, helping to mitigate environmental impacts such as ozone layer depletion and the greenhouse effect. Furthermore, AV technology demonstrates significant potential in enhancing mobility for older people and individuals with disabilities, owing to its assistive capabilities that facilitate independent travel and improve accessibility [8].

As AVs become increasingly integrated into urban transportation systems, it is essential to evaluate their impact on key infrastructure components, particularly intersections. The interaction of various AV driving behaviours within mixed traffic environment, especially at varying levels of market penetration, can significantly influence traffic delays and safety outcomes. Research shows the importance of understanding AVs' effect on overall road network performance, highlighting their potential to enhance traffic flow and reduce time losses. Notably, AVs reduce vehicle spacing, maintain stable vehicle columns, and improve manoeuvring safety through appropriate algorithms [9]. The literature further indicates that AVs' consistent headway, speed and spacing, along with shorter reaction times and smoother acceleration and deceleration profiles, positively affect traffic operations [10], [11]. However, the magnitude of these benefits varies depending on geometry and prevailing traffic conditions. For instance, one study reported a delay reduction exceeding 96% at full AVs penetration in a hypothetical urban intersection [12], while another study observed a 12% improvement at a signalized intersection [13].

Despite these promising outcomes, concerns remain regarding AV performance at low penetration rates and their typically cautious driving behaviour [14], [15]. While AVs are expected to improve traffic operations and safety, their performance under different geometric configurations and in mixed traffic conditions remains uncertain. This gap in understanding highlights the need to examine how different AV driving behaviors influence traffic delays and safety at complex urban intersections, particularly as market penetration increases. Dubai has set a target to incorporate 25% autonomous transportation for all trips by 2030, aiming to reduce accidents and losses by 12% and increase individual productivity by 13% [16]. Given these goals, Dubai's road network provides an ideal setting for predicting the impacts of AVs on current geometric and traffic conditions. This study aims to evaluate the impact of varying AV penetration levels at a signalized tight diamond interchange in Dubai. The structure of the paper is as follows: Section 2 outlines the methodological approach used to create the initial simulation model, identify parameters for both CVs and AVs, and prepare simulation scenarios. Section 3 presents the results derived from the simulation output generated by VISSIM and the total conflicts assessed using the Surrogate Safety Assessment Model (SSAM). Section 4 discusses the comparison of the simulation outputs. Finally, Section 5 presents the conclusions drawn from the study's findings.

2. Methodology

The methodology involves three phases as illustrated in Fig. 1. The first phase includes the characterization of the study site, identification of data types, and selection of data collecting methods. In the second phase, a traffic simulation model is developed using PTV VISSIM. This is followed by a calibration and validation process which employs maximum queue length as the primary measure of effectiveness (MOE). The third phase applies the calibrated and validated model to assess the impact of AV's impacts on traffic delay across varying penetration levels AV types. Additionally, traffic conflict analysis is conducted using trajectory data processed through Surrogate Safety Assessment Model (SSAM). The results from VISSIM (delays analysis) and SSAM (conlict analysis) are evaluated and discussed for different scenarios consided in the study.

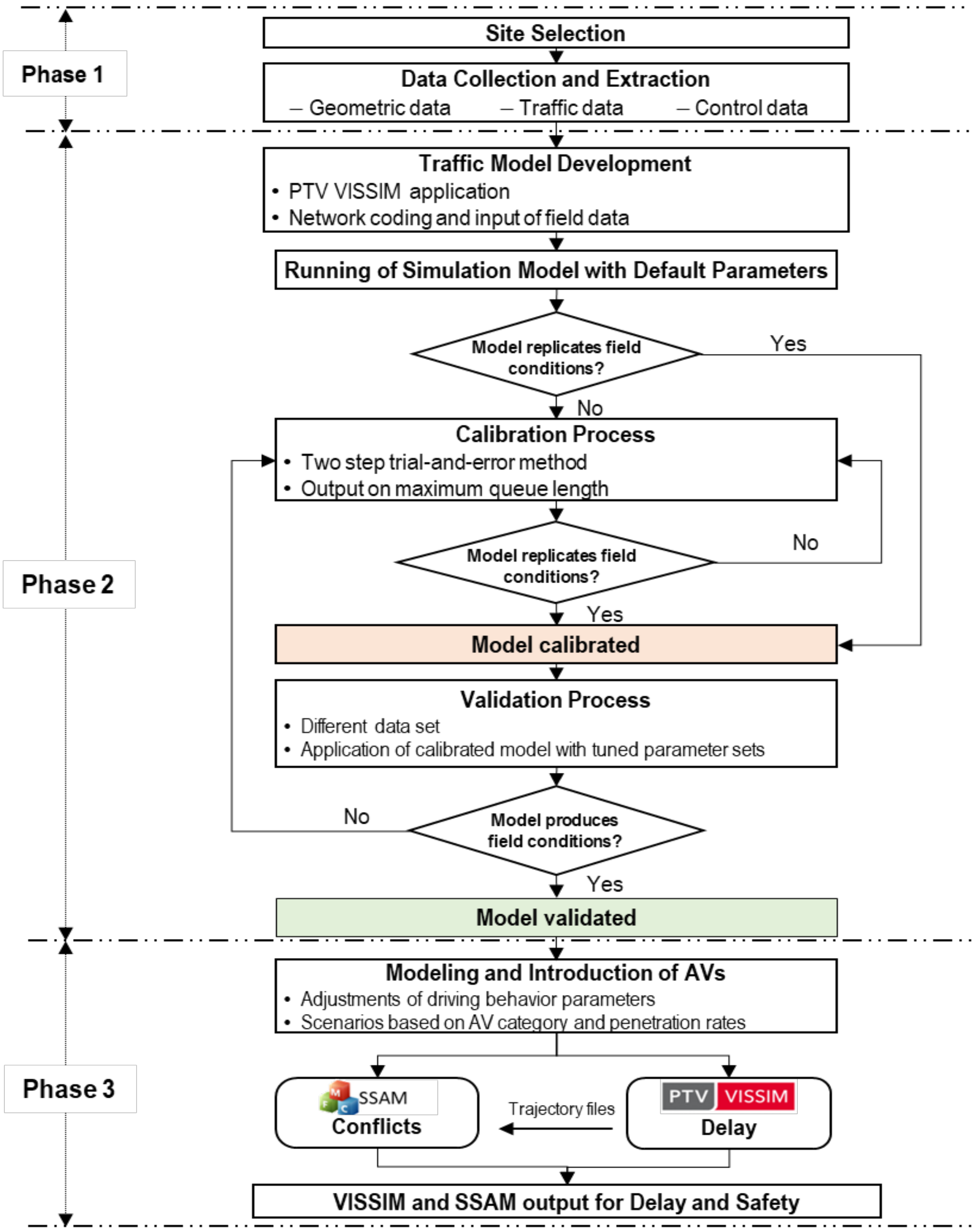


Fig. 1 *Phases of methodology*

2.1 Site Description

The study was conducted at the Executive Towers interchange in Business Bay Dubai, as shown in Fig. 2. The selected site features a tight diamond interchange configuration, comprising two closely spaced at-grade intersections. Its high traffic volumes, diverse mix of road users, complex traffic dynamics, and strategic location within Dubai's central business district, approximately 2.4 km away from Burj Khalifa, make it an ideal setting for evaluating the potential impacts of AVs on traffic delay and safety performance.

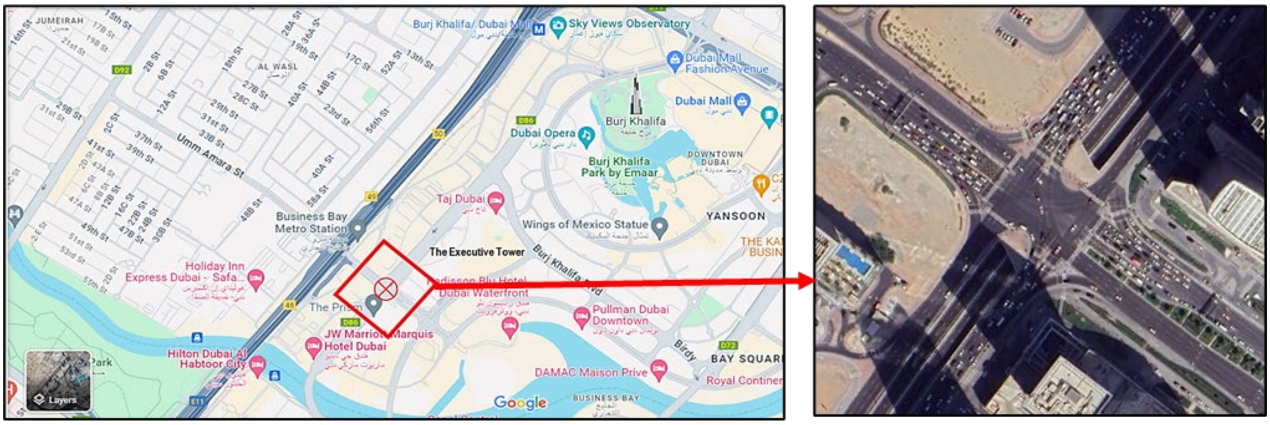


Fig. 2 *Location of the selected study site*

The selected site is situated at the intersection of Al Khaleej Al Tejari 1st Street and Al Mustaqbal Street, with geographic coordinates of 25°11'20"N latitude and 55°15'42"E longitude. Al Mustaqbal Street features grade-separated underpasses that facilitate uninterrupted movement for through traffic. Located in the heart of Dubai's Business Bay District, one of the city's busiest urban areas, the intersection experiences substantial traffic volumes and serves key destinations such as the Executive Towers, Bay Avenue Mall, and a variety of commercial and residential developments. Business Bay's high population density, combined with its concentration of luxury residence and corporate offices, contributes to significant daily traffic congestion. These conditions make the intersection a suitable candidate for evaluating the potential operational and safety benefits of AVs. While AVs are anticipated to mitigate traffic challenges in such high-demand urban environments, simulation-based investigations are essential to understand their potential impacts under existing traffic conditions.

2.2 Data Collection

To facilitate the evaluation, data was collected from the study site and subsequently input into PTV VISSIM for model development, calibration, and validation. The collected data was classified into two distinct types: geometric and traffic data. Geometric data included parameters such as the number of lanes, lane dimensions, and the overall layout of the intersection. Traffic data encompassed traffic volume and turning movement proportions, traffic composition, maximum queue length and the traffic signal timing and phasing. Traffic data was primarily obtained through video recordings conducted at the study site.

Traffic volume data was specifically recorded during the morning peak period, over a one-hour interval from 8:30 AM to 9:30 AM on September 5, 2023. These details are presented in Table 1.

Table 1 *Turning movements critical AM peak time (8:30 AM to 9:30 AM)*

Road/Direction of the Approach	Type of Vehicle	Vehicles Count	Turning Flows (Vehicles)			
			U-Turn	Left	Through	Right
North Bound (To Executive Towers)	Light Vehicles	1295	360	181	380	374
	Heavy Vehicles	39	7	7	13	12
	Total	1334	veh/hr			
South Bound (From Executive Towers)	Light Vehicles	1080	116	141	653	170
	Heavy Vehicles	26	-	4	21	1
	Total	1106	veh/hr			
East Bound (From Dubai Metro)	Light Vehicles	2144	*	777	867	500
	Heavy Vehicles	37	*	11	14	12
	Total	2181	veh/hr			
West Bound (To Dubai Metro)	Light Vehicles	575	10	231	211	123
	Heavy Vehicles	31	0	11	19	1
	Total	606	veh/hr			
	Grand Total	**5227**	**veh/hr**			

Note: *U-turn movement for East Bound movement is blocked.

As part of the traffic survey for base model calibration, a detailed analysis of intersection signal timings and maximum queue lengths was conducted. Fig. 3 and Table 2 depict the phasing layout and the duration of each phase during the critical morning peak period. Table 3 shows the maximum queue lengths recorded at each approach during the morning peak.

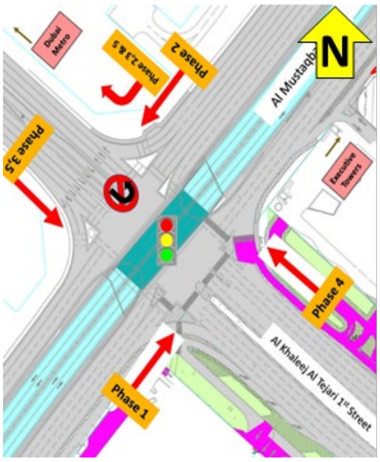


Fig. 3 *Existing signal phasing plan*

Table 2 *Existing signal phasing and timings for the critical morning peak hour*

Phase	Bound	Time in seconds			Allowed movements
		Green	Amber	All-Red	
Phase 1	North Bound	47	3	3	U-Turn, Left, Through
Phase 2	South Bound	45	3	3	U-Turn, Left, Through & Right
Phase 3	East Bound, SB-R*	47	3	5	Left, Through & Right
Phase 4	West Bound	22	3	3	U-Turn, Left, Through & Right
Phase 5	East Bound, SB-R*	27	3	3	Left, Through & Right
		Total Cycle Length:	220 secs		

Note: *SB-R refers to the South bound's right turning movement that is given right of way during East bound's green phase since U-turn movement for East bound movement is blocked. Hence, both the movements don't have conflict.

Table 3 *Maximum observed field queue length during morning peak hour*

Bound	Queue Length (meters)
North Bound	185
South Bound	92
East Bound	208
West Bound	65

2.3 Base Model Development – PTV VISSIM

Several steps were undertaken to develop a realistic traffic simulation model for this study. The model was constructed in PTV VISSIM using geometric and operational data collected from the field. Network links were created and connected using connectors to replicate the actual road layout, with the physical characteristics of the network reflecting the site's geometric features. Once the geometric configuration was established, traffic data was input for each approach, including turning proportions defined through vehicle routing. Vehicle composition for each approach was also incorporated based on field observations. Total approach volumes were assigned to initial links, while vehicle paths were used to distribute relative flows for each turning movement.

Subsequently, traffic control data such as signal phase timings and sequences, were defined in VISSIM based on field measurements. Signal groups were created to manage signal operations, and signal heads were assigned to the appropriate lanes. Data collection points and queue counters were strategically placed within the network.

Simulations were initially run using default parameters to extract outputs related to traffic volumes and queue lengths.

The layout of the study intersection, comprising the major road (Al Mustaqbal Street) and the minor road (Al Khaleej Al Tejari 1st Street), was modeled in VISSIM to replicate the tight diamond interchange, as illustrated in Fig. 4(a). The coded VISSIM model of the intersection is shown in Fig. 4(b).

(a) **(b)**

Fig. 4 *The considered study site; (a) plan layout of the site geometry; (b) simulation ran on base model in VISSIM*

2.4 Model calibration & validation

The calibration procedure aimed to align the simulation model's performance with real-world traffic conditions by minimizing the discrepancy between the model's and field-observed measures of effectiveness (MOEs) to within ±20%, as recommended by the Florida Department of Transportation [17]. This threshold ensures the model's reliability in replicating actual site conditions, thereby supporting accurate operational and safety assessments. Calibration was conducted using maximum queue length as the MOE [18], with two rounds of sensitivity testing involving 15 scenarios. These scenarios varied three key car-following parameters (P1, P2, and P3) across quintile ranges, as detailed in Table 4, and the resulting percentage differences were summarized in Table 5.

To ensure the model reflects local driving behavior, site-specific geometric and traffic data from Dubai were used in the calibration process. This step is critical, as it enables the simulation to produce realistic vehicle interactions for operational analysis. Furthermore, the calibrated model generates vehicle trajectory data that accurately represents local driving dynamics, which is essential for conducting meaningful safety evaluations using the Surrogate Safety Assessment Model (SSAM). By grounding both operational and safety assessments in a validated, context-specific model, the study ensures that its findings are both credible and applicable to real-world conditions.

Table 4 *Calibration parameters and ranges of their values*

Sr. No.	Selected Parameters	Default Value	Range Tested	Variable Values for Calibration (m)				
1	P1 Average standstill distance	2m	1.0 - 3.00 m	1	1.5	2	2.5	3
2	P2 Additive part of safety distance	2m	0.3 - 1.15 m	0.3	0.5	0.75	1	1.15
3	P3 Multiplicative part of safety distance	3m	0.5 - 1.50 m	0.5	0.75	1	1.25	1.5

Based on the parameter values listed in Table 4, Table 5 presents the cumulative percentage differences between field observations and model outputs when each parameter is varied individually, while the other two parameters are held at their default values.

Table 5 *Cumulative percentage difference between model and field values for various parameter values*

Range of Calibration Parameters	Calibration Parameters			Queue Length (m)				Cumulative % Difference
	P1	P2	P2	NB	SB	EB	WB	
	Field Observed			185	92	208	65	
	From Default Parameters			0.16	0.09	0.21	0.07	53%
1.00 - 3.00 m (P1)	1.00	*	*	0.23	0.11	0.16	0.07	57%
	1.50	*	*	0.09	0.08	0.12	0.03	**32%**
	2.00	*	*	0.16	0.09	0.21	0.07	53%
	2.50	*	*	0.09	0.07	0.33	0.14	63%
	3.00	*	*	0.10	0.17	0.32	0.13	72%
0.30 - 1.15 m (P2)	*	0.30	*	0.15	0.06	0.22	0.09	52%
	*	**0.50**	*	0.12	0.01	0.10	0.01	**24%**
	*	0.75	*	0.13	0.01	0.17	0.02	33%
	*	1.00	*	0.15	0.03	0.22	0.03	43%
	*	1.15	*	0.20	0.05	0.27	0.06	58%
0.50 - 1.50 m (P3)	*	*	0.50	0.14	0.02	0.13	0.03	32%
	*	*	0.75	0.13	0.11	0.20	0.04	48%
	*	*	1.00	0.11	0.03	0.15	0.06	35%
	*	*	1.25	0.13	0.02	0.14	0.02	31%
	*	*	**1.50**	0.10	0.01	0.06	0.04	**21%**

Note: Bold value indicates the lowest cumulative percentage difference between model and field values and its corresponding parameter value.

To improve the fit between simulation outputs and field data, the parameter combination yielding the lowest cumulative percentage difference was identified, specifically, P1 = 1.50, P2 = 0.50, and P3 = 1.50, as indicated in Table 5. These values were then refined further by subdividing them into smaller intervals for a second iteration. The results of this refined calibration are presented in Table 6, which demonstrates that a specific combination of the three parameters produces the minimum cumulative percentage difference. The resulting differences between field and simulated queue lengths fall within acceptable thresholds. Therefore, the parameter set that best matched the field data was selected as the final calibrated values.

Table 6 *Cumulative percentage difference of the model for all combinations of the values of the chosen parameters*

<table>
<tr><th rowspan="3">Average Standstill distance (P1)</th><th rowspan="3">Additive part of safety distance (P2)</th><th colspan="12">Multiplicative part of safety distance (P3)</th></tr>
<tr><th colspan="4">1.35</th><th colspan="4">1.50</th><th colspan="4">1.60</th></tr>
<tr><th>NB</th><th>SB</th><th>EB</th><th>WB</th><th>NB</th><th>SB</th><th>EB</th><th>WB</th><th>NB</th><th>SB</th><th>EB</th><th>WB</th></tr>
<tr><td rowspan="6">1.35</td><td rowspan="2">0.50</td><td>0.11</td><td>0.06</td><td>0.07</td><td>0.05</td><td>0.11</td><td>0.06</td><td>0.05</td><td>0.05</td><td>0.11</td><td>0.07</td><td>0.12</td><td>0.03</td></tr>
<tr><td colspan="4">29%</td><td colspan="4">27%</td><td colspan="4">33%</td></tr>
<tr><td rowspan="2">0.60</td><td>0.12</td><td>0.08</td><td>0.04</td><td>0.02</td><td>0.12</td><td>0.08</td><td>0.12</td><td>0.05</td><td>0.17</td><td>0.06</td><td>0.16</td><td>0.07</td></tr>
<tr><td colspan="4">26%</td><td colspan="4">37%</td><td colspan="4">46%</td></tr>
<tr><td rowspan="2">0.75</td><td>0.10</td><td>0.05</td><td>0.05</td><td>0.03</td><td>0.09</td><td>0.04</td><td>0.03</td><td>0.02</td><td>0.12</td><td>0.06</td><td>0.10</td><td>0.04</td></tr>
<tr><td colspan="4">23%</td><td colspan="4">18%</td><td colspan="4">32%</td></tr>
<tr><td rowspan="6">1.50</td><td rowspan="2">0.50</td><td>0.13</td><td>0.03</td><td>0.07</td><td>0.06</td><td>0.11</td><td>0.04</td><td>0.18</td><td>0.04</td><td>0.14</td><td>0.04</td><td>0.07</td><td>0.08</td></tr>
<tr><td colspan="4">29%</td><td colspan="4">37%</td><td colspan="4">33%</td></tr>
<tr><td rowspan="2">0.60</td><td>0.10</td><td>0.09</td><td>0.13</td><td>0.10</td><td>0.14</td><td>0.04</td><td>0.15</td><td>0.02</td><td>0.17</td><td>0.08</td><td>0.10</td><td>0.04</td></tr>
<tr><td colspan="4">42%</td><td colspan="4">35%</td><td colspan="4">39%</td></tr>
<tr><td rowspan="2">0.75</td><td>0.11</td><td>0.03</td><td>0.18</td><td>0.07</td><td>0.11</td><td>0.01</td><td>0.09</td><td>0.03</td><td>0.15</td><td>0.05</td><td>0.08</td><td>0.01</td></tr>
<tr><td colspan="4">39%</td><td colspan="4">24%</td><td colspan="4">29%</td></tr>
<tr><td rowspan="6">1.65</td><td rowspan="2">0.50</td><td>0.09</td><td>0.04</td><td>0.17</td><td>0.03</td><td>0.19</td><td>0.03</td><td>0.11</td><td>0.11</td><td>0.10</td><td>0.01</td><td>0.12</td><td>0.03</td></tr>
<tr><td colspan="4">33%</td><td colspan="4">44%</td><td colspan="4">26%</td></tr>
<tr><td rowspan="2">0.60</td><td>0.11</td><td>0.04</td><td>0.13</td><td>0.02</td><td>0.10</td><td>0.04</td><td>0.04</td><td>0.05</td><td>0.09</td><td>0.01</td><td>0.09</td><td>0.02</td></tr>
<tr><td colspan="4">30%</td><td colspan="4">23%</td><td colspan="4">21%</td></tr>
<tr><td rowspan="2">0.75</td><td>0.11</td><td>0.04</td><td>0.11</td><td>0.02</td><td>0.13</td><td>0.04</td><td>0.12</td><td>0.03</td><td>0.09</td><td>0.03</td><td>0.07</td><td>0.01</td></tr>
<tr><td colspan="4">28%</td><td colspan="4">32%</td><td colspan="4">20%</td></tr>
</table>

Following the initial calibration phase, the optimal car-following behavior parameters identified in Table 5 based on 15 simulation scenarios were further refined through a secondary calibration process. This involved conducting 27 additional simulation scenarios by subdividing the selected parameter ranges. The final calibrated parameter set was determined by identifying the combination of values for P1, P2, and P3 that yielded the lowest cumulative percentage difference between simulated and observed field data.

As shown in Table 6 and indicated in blue font, the minimum cumulative difference of 18% was achieved when P1, P2, and P3 were set to 1.35 m, 0.75 m, and 1.50 m, respectively. These results are summarized in Table 8. The absolute percentage error between the simulated and field cumulative maximum queue lengths was 18%, which falls within the acceptable threshold of ±20%, a benchmark commonly used for model calibration accuracy and endorsed by agencies such as Caltrans and the Florida Department of Transportation [17]–[21].

Consequently, the model is considered successfully calibrated and suitable for evaluating design or operational modifications. This calibration criterion, based on FDOT guidelines, stipulates that simulation outputs for key measures of effectiveness such as travel time, delay, and queue length, should fall within ±20% of the observed field data. This threshold is widely adopted in transportation modeling practice, as it accounts for the inherent variability in traffic conditions while recognizing the practical limitations of simulation tools. It ensures that the model reliably represents real-world conditions, thereby supporting informed analysis and decision-making.

2.5 Driving Behavior Parameters for AVs

This simulation study employs PTV VISSIM Version 2020, a CoEXist-recognized platform, to model autonomous vehicle (AV) driver behavior and logic. The CoEXist project, launched in 2017 as a European initiative, aimed to support cities in preparing for the transitional phase in which conventional vehicles (CVs) and AVs coexist on shared roadways [22]. Funded by the European Union, CoEXist focused on characterizing AV behavior in mixed traffic environments and facilitating the integration of AVs into urban mobility systems.

PTV VISSIM Version 11 and later releases incorporate built-in AV driving behaviors derived from the CoEXist project, enabling simulation of various AV characteristics [23]. These behaviors are defined using modified parameters of the Wiedemann 99 car-following model, which has been widely adopted in AV simulation studies due to its robustness and adaptability. CoEXist identified four fundamental AV driving logics: Rail-Safe, Cautious, Normal, and All-Knowing. In the commercial release of VISSIM, the All-Knowing logic was renamed as Aggressive.

In this study, three AV driving logics, Cautious, Normal, and Aggressive were utilized, as provided in VISSIM's built-in behavior profiles. Table 7 presents the driver behavior parameters associated with each AV type, while Table 8 details the corresponding car-following parameters. These predefined logics enable realistic modeling of AV behavior under varying traffic conditions and penetration levels.

Table 7 *Types of AV driving logics established by coexist european project*

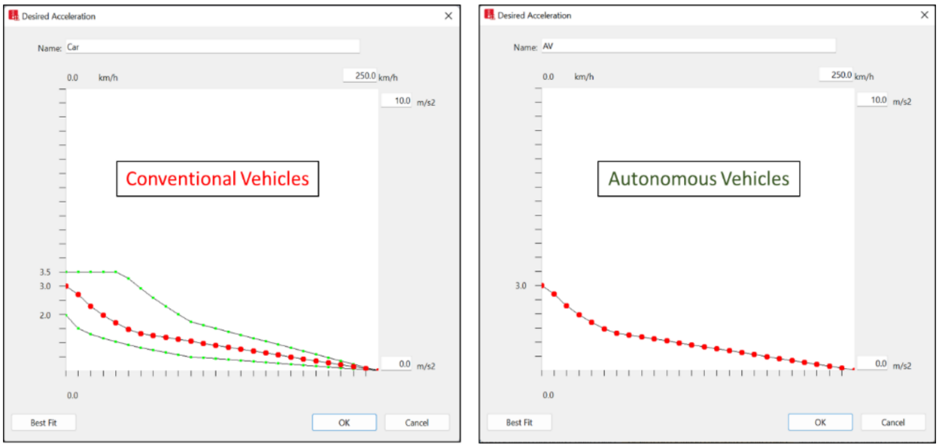
AV cautious (CoEXist)	AV normal (CoEXist)	AV aggressive (CoEXist)
• The AV-cautious car follows road traffic laws and prioritises safety.	• The sensor system in the car detects and tracks nearby vehicles, including their locations and speeds.	• The AV-Aggressive uses equipped equipment to understand and predict traffic conditions, maintaining a minimal space between it and other cars.
• Therefore, the car continually uses the maximum braking distance, allowing it to maintain a greater distance from neighbouring vehicles.	• Thus, the car continually uses the braking distance, maintaining a smaller distance from AV cautious and a larger distance from AV aggressive from nearby vehicles.	• Adopting aggressive autonomous vehicle (AV) driving behaviour is expected to lead to cooperative driving patterns among other cars.

Table 8 *Driving car following model assumptions of AVs in VISSIM*

Parameter	Description of the Parameter	Unit	AVs Driving Logic		
			AV - Cautious	AV - Normal	AV - Aggressive
CCO - Standstill distance	The desired spacing between two vehicles is known as the standstill distance.	m	1.5 m	1.5 m	1.0 m
CC1 - Following distance (Gap Time)	The safety distance, as defined by car following models, refers to the minimal distance that a driver maintains while following another vehicle.	sec	1.5 sec	0.9 sec	0.6 sec
CC2 - Longitudinal Oscillation	To determine the appropriate threshold at which a driver purposefully reduces the distance between their vehicle and the one directly ahead, it is necessary to establish a limit on the distance difference.	m	0.0 m	0.0 m	0.0 m
CC3 - Perception threshold for following	More precisely, it denotes the duration required for the driver to attain the appropriate separation distance before to commencing the deceleration procedure. During this stage, the driver is able to identify the car that is travelling at a slower speed ahead.	sec	-10.0 sec	-8.0 sec	-6.0 sec
CC4 - Negative speed difference	The negative speed difference refers to the difference between the initial speed and the succeeding speeds.	m/s	-0.1 m/s	-0.1 m/s	-0.1 m/s
CC5 - Positive speed difference	During succeeding steps, a positive speed differential is established. The positive value of CC5 is associated with the negative value of CC4.	m/s	0.1 m/s	0.1 m/s	0.1 m/s
CC6 - Influence speed on oscillation	The speed oscillations during the procedure are influenced by the distance.	1/ (m*s)	0.0	0.0	0.0
CC7 - Oscillation during acceleration	By assigning a value of '0' to the variable, the oscillation of speed becomes unaffected by changes in distance.	m/s^2	0.1 m/s^2	0.1 m/s^2	0.1 m/s^2
CC8 - Acceleration starting from a standstill	When a motorist is trailing another vehicle, they employ the smallest absolute acceleration or deceleration value.	m/s^2	3.0 m/s^2	3.5 m/s^2	4.0 m/s^2
CC9 - Acceleration at 80 mph	When commencing motion from a state of rest, the intended acceleration is desired.	m/s^2	1.2 m/s^2	1.5 m/s^2	2.0 m/s^2

2.5.1 Base Data - Functions for Acceleration and Deceleration

In VISSIM, the modeling of base data functions for AVs is defined by their discrete operational characteristics, which allow them to maintain consistent behavior across all driving activities. This consistency enables AVs to sustain uniform acceleration and deceleration values throughout their operation [20]. Accordingly, the present study assumes that AVs exhibit standardized acceleration and deceleration patterns. To reflect this, the two stochastic boundary curves typically used to represent variability in driver behavior were removed, ensuring that all AVs maintain fixed values for desired acceleration and deceleration. This adjustment is illustrated in Fig. 5.



Name: Car

Name: AV

Fig. 5 *PTV VISSIM desired acceleration - conventional and autonomous vehicle*

2.6 Simulation Scenarios and Run

The calibrated and validated traffic model was used to simulate a series of proposed scenarios. A total of 13 simulation scenarios were developed, each representing different penetration rates of AVs and conventional vehicles (CVs). Across all scenarios, traffic volume, geometric layout, and control parameters were held constant to ensure consistency. The only variable modified was the proportion of AVs and CVs within the vehicle mix, allowing for an assessment of the most effective combination to address existing traffic congestion while matching actual site conditions.

As previously noted, PTV VISSIM incorporates three AV driving logics based on the CoEXist project: AV-Cautious, AV-Normal, and AV-Aggressive. To identify the most efficient driving logic under mixed traffic conditions, all three AV categories were considered in the scenario development. Each scenario was defined by both the AV category and its penetration rate.

This study evaluated five levels of AV market penetration, ranging from 0% to 100%, while maintaining a constant total vehicle volume. Specifically, buses and heavy trucks were fixed at 1% and 2% of the total volume, respectively, resulting in 3% of traffic being non-passenger vehicles in all scenarios. The remaining 97% of traffic comprising passenger cars was adjusted to reflect varying AV penetration levels: 0%, 25%, 50%, 75%, and 100% [21]. At 0% penetration, all passenger cars are CVs, whereas at 100%, all are autonomous. Table 9 summarizes the simulation scenarios considered in this study.

Table 9 *Scenarios considered in this study*

Types of AVs	Increase in AV Penetration Level / Decrease in CV Proportion				
	0% AV / 100% CV	25% AV / 75% CV	50% AV / 50% CV	75% AV / 25% CV	100% AV
AV-Cautious	Scenario-1	Scenario-2	Scenario-5	Scenario-8	Scenario-11
AV-Normal		Scenario-3	Scenario-6	Scenario-9	Scenario-12
AV- Aggressive		Scenario-4	Scenario-7	Scenario-10	Scenario-13

As outlined in Table 9, a total of thirteen (13) simulation scenarios were analyzed, including the base model (Scenario 1), which represents 0% AV penetration with 100% CVs. Four scenarios (Scenarios 2, 5, 8, and 11) were simulated using the AV-Cautious driving logic across increasing AV penetration levels. Similarly, four scenarios (Scenarios 3, 6, 9, and 12) were developed for the AV-Normal logic, and another four (Scenarios 4, 7, 10, and 13) for the AV-Aggressive logic.

Each scenario was executed ten times, with a simulation duration of 4,200 seconds, including a 600-second warm-up period. The traffic volume composition remained consistent across all scenarios, reflecting the field data presented in Table 1. This approach enabled a systematic evaluation of AV impacts under varying penetration levels and driving behaviors.

2.7 Operational and Safety Assessment

For the operational assessment, delay outputs were obtained from various simulation scenarios involving different proportions of autonomous vehicles (AVs) and conventional vehicles (CVs). Using the node evaluation feature in PTV VISSIM, delay data for each scenario was extracted and summarized for analysis. For the safety assessment, the Time-to-Collision (TTC) metric was employed to evaluate the likelihood of potential collisions. TTC represents the time required for two vehicles to collide if they continue at their current speeds and trajectories [7]. Numerous studies have established critical TTC thresholds to identify potential conflicts, where actual TTC values falling below these thresholds indicate hazardous situations.

In this study, the Surrogate Safety Assessment Model (SSAM) was used to evaluate traffic conflicts in mixed traffic environments. A TTC threshold of 1.5 seconds was applied when a CV was the trailing vehicle. Given the more discrete behavior and faster reaction times of AVs compared to human drivers, a reduced TTC threshold of 1.0 second was used for AVs as trailing vehicles to avoid overestimating conflict frequency [24].

To complement the operational analysis, SSAM, a post-processing tool developed by the Federal Highway Administration (FHWA) was employed to assess safety performance. SSAM analyzes vehicle trajectory data to identify and classify potential traffic conflicts. In this study, trajectory files were generated using PTV VISSIM 2022, which simulates detailed vehicle movements under varying traffic conditions and AV penetration levels. SSAM processes these trajectories to detect surrogate safety indicators such as TTC, enabling the identification and quantification of potential conflicts. These conflicts are categorized into types such as rear-end, lane-change, and crossing conflicts, offering insights into the nature and frequency of safety-critical events.

The integration of VISSIM and SSAM provides a comprehensive framework for evaluating both operational efficiency and safety performance, ensuring a holistic assessment of AV behavior and its impact on urban traffic systems.

3. Results

Following the calibration process, simulation results were analyzed with a primary focus on the key performance metric, average delay at the intersection. All previously defined AV–CV penetration scenarios were executed, and the outcomes were visualized using clear and interpretable graphs. The simulation outputs were obtained using the node evaluation and network performance features in PTV VISSIM.

Fig. 6 illustrates the combined impact of varying AV penetration rates on average delay for all three AV driving logics. The results are presented in a single graph to facilitate direct comparison across AV types.

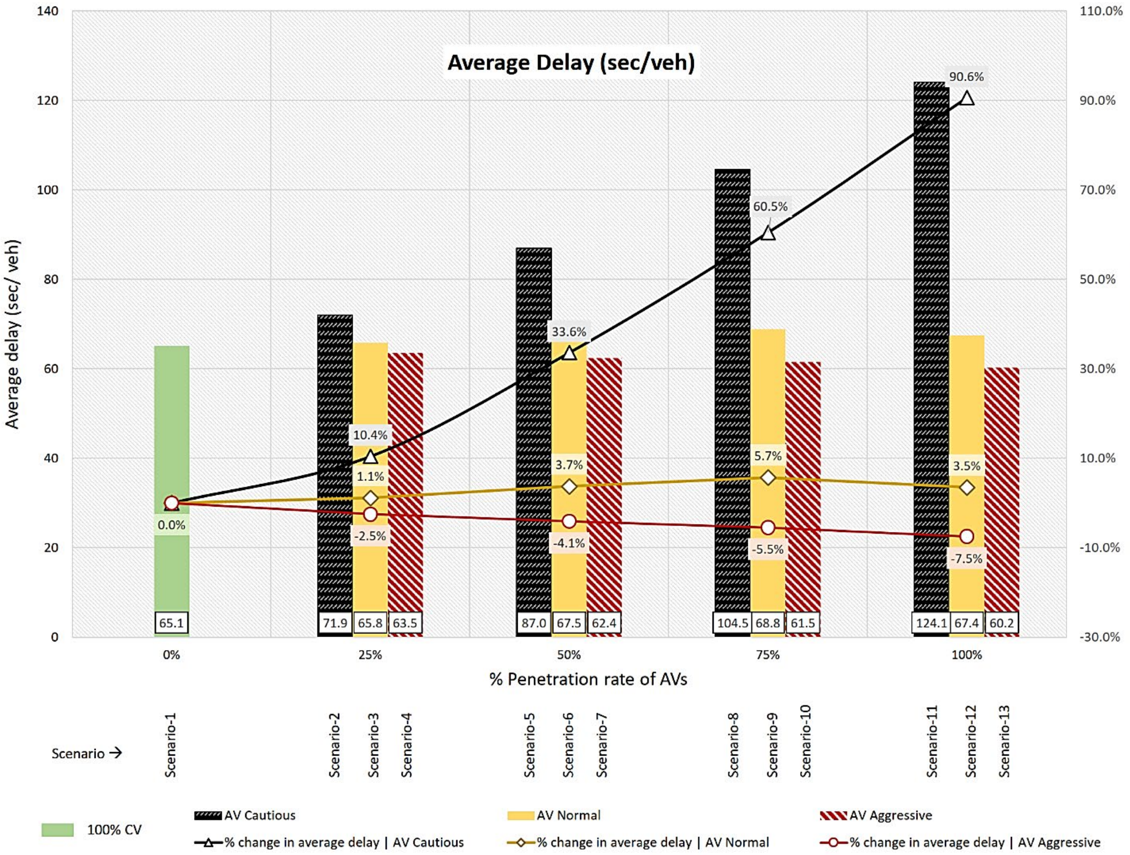
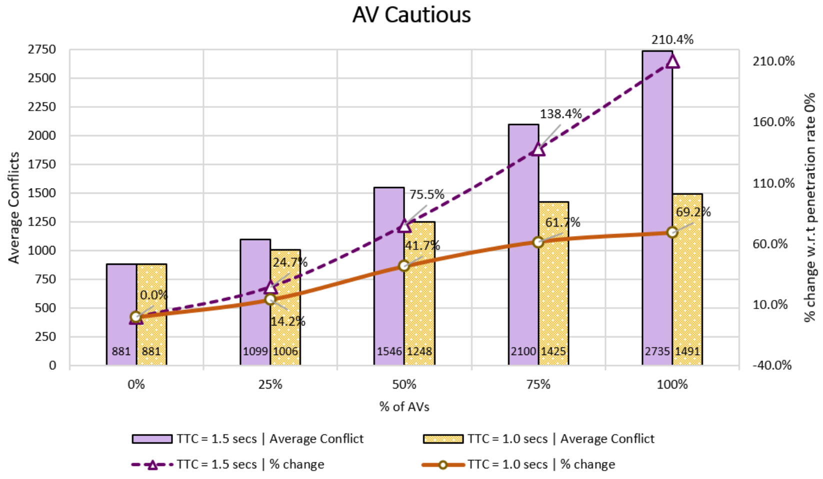


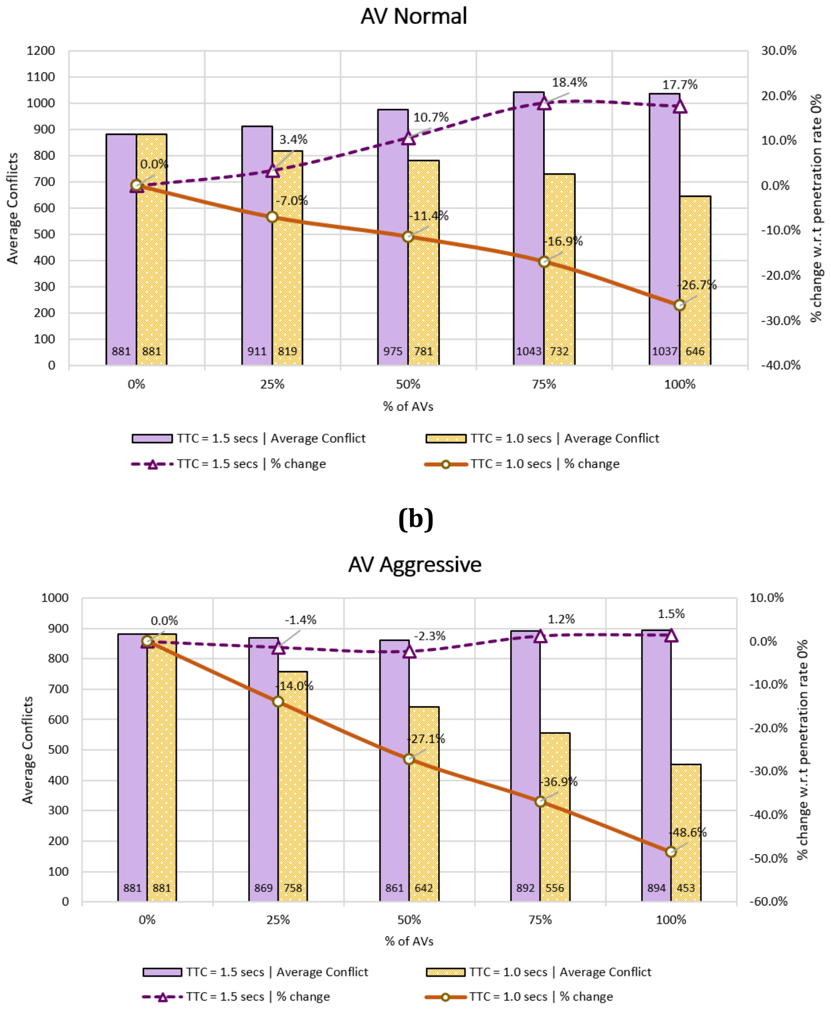
Fig. 6 *Variations in average delay based on different autonomous vehicle driving behaviour*

The simulation results obtained from PTV VISSIM, as illustrated in Fig. 6, demonstrate the impact of varying penetration rates of three autonomous vehicle (AV) driving logics on average delay. At 100% penetration of AV-Cautious vehicles, the average delay increased significantly by 90.6%. In contrast, conventional vehicles and AV-Normal vehicles showed similar performance at lower penetration levels, with only a modest increase of 3.5% in average delay observed at higher penetration rates. Notably, a complete replacement of conventional vehicles with AV-Aggressive vehicles resulted in a 7.5% reduction in average delay, indicating improved operational efficiency.

In addition to the operational assessment, the study also evaluated safety performance under mixed traffic conditions. Fig. 7(a), 7(b), and 7(c) present the total number of traffic conflicts identified from vehicle trajectory data, using two different Time-to-Collision (TTC) thresholds tailored to AV driving logics. These figures provide insight into the safety implications associated with varying AV behaviors and penetration levels.



(a)



(b)

(c)

Fig. 7 *Comparison of total conflicts between default & lowered TTC values; (a) AV cautious; (b) AV normal; and (c) AV aggressive*

The data presented in Fig. 7(a)–(c) were generated using the Surrogate Safety Assessment Model (SSAM) and illustrate the impact of varying AV penetration rates on traffic conflicts. At a traffic demand exceeding 5,000 veh/hr, and using the default Time-to-Collision (TTC) threshold of 1.5 seconds, a consistent increase in the total number of conflicts was observed as AV penetration rates rose across all driving logics. The only exception occurred at a 50% penetration rate of AV-Aggressive, where a slight reduction in conflicts, approximately 2.3% lower than the baseline (0% AV penetration) was recorded.

When the TTC threshold was reduced to 1.0 seconds for AVs as trailing vehicles, the safety performance improved significantly. At 100% AV-Aggressive penetration, the number of conflicts dropped to 453, compared to 881 for conventional vehicles, representing a 48.6% reduction relative to the baseline scenario. In contrast, full penetration of AV-Cautious resulted in the highest number of conflicts (1,491), exceeding those of conventional vehicles (881), AV-Normal (646), and AV-Aggressive (453). This indicates that AV-Cautious generated 69.2% more conflicts than conventional vehicles under the same demand conditions.

Based on the analysis of all thirteen (13) scenarios, the optimal performance was achieved in Scenario 13, which involved 100% penetration of AV-Aggressive. This scenario resulted in a 7.5% reduction in average delay and a 48.6% reduction in total conflicts, demonstrating superior operational and safety outcomes.

4. Discussion

The operational assessment results indicate that the AV-Aggressive driving logic can significantly enhance intersection performance under current high-demand conditions. In contrast, when AV-Cautious vehicles reached 100% penetration, a substantial decline in performance was observed, marked by a notable increase in average delay. This outcome is attributed to the higher CC0 and CC1 values associated with cautious AVs, which result in greater headways and more conservative driving behavior. Their careful lane-changing maneuvers and frequent stops to maintain safe distances tend to disrupt traffic flow, causing delays for surrounding vehicles [25].

AV-Normal vehicles demonstrated performance similar to conventional vehicles, with only a slight decline in efficiency. This is primarily due to their slightly larger standstill distances compared to CVs. On the other hand, AV-Aggressive vehicles, characterized by shorter CC0 and CC1 values, facilitated smoother traffic flow and increased road capacity [7], thereby improving overall operational performance.

From a safety perspective, AV-Aggressive also proved to be the safest under high-demand conditions. This was particularly evident when the TTC threshold was reduced from 1.5 seconds to 1.0 second, which significantly lowered the number of detected conflicts. The aggressive driving logic allows AVs to maintain shorter gaps and react more quickly, reducing the likelihood of collisions. While AV-Normal vehicles contributed to safety by maintaining greater longitudinal spacing, AV-Cautious vehicles, despite similar spacing, exhibited overly conservative behavior and abrupt braking, leading to frequent stops and increased rear-end collision risks.

In addition to operational and safety evaluations, the study emphasizes the importance of exploring signal optimization strategies. Previous research has highlighted the effectiveness of both vehicle-based and movement-based approaches in mitigating delays and improving traffic efficiency, particularly under high-demand conditions [26]. These strategies, often supported by advanced technologies, enable dynamic signal timing adjustments based on real-time traffic data, thereby enhancing intersection throughput [27].

Contrary to common assumptions, movement-based strategies rooted in traditional signal timing logic remain highly effective and irreplaceable in high-demand scenarios [26]. Their advantages are largely attributed to reduced cycle lengths achievable with AVs. As supported by Lu, *et al.* [28], vehicle-based strategies tend to mimic signal-like behavior by grouping vehicles from different movements to enter intersections in coordinated turns. Moreover, advancements in adaptive signal control systems have demonstrated substantial improvements in signal phasing and coordination, contributing to better traffic flow and safety outcomes [29].

Overall, the findings of this study confirm that AVs, particularly those with aggressive driving behavior, offer a promising solution for enhancing traffic efficiency and safety. Their flexible and responsive nature enables them to reduce congestion, shorten queues, and minimize the risk of collisions.

5. Conclusions

This study aimed to forecast the potential impacts of AVs on the operational and safety performance of a signalized urban intersection located at Executive Towers in Business Bay, Dubai, under mixed traffic conditions. The diverse static and dynamic parameters of different vehicle types, along with their respective driving behaviors, can significantly influence AV performance and lead to outcomes that differ from those observed in homogeneous traffic environments. To evaluate these effects, AVs were modeled using three distinct driving logics: Cautious, Normal, and Aggressive.

In the simulation setup, conventional passenger cars were progressively replaced with AVs, while maintaining a constant proportion of heavy vehicles (2%) and buses (1%). AVs were introduced at incremental penetration levels of 25%, 50%, 75%, and 100%. Multiple scenarios were developed for each AV type and executed in PTV VISSIM to assess operational performance. For safety evaluation, vehicle trajectory files generated in VISSIM were analyzed using the Surrogate Safety Assessment Model (SSAM), applying two Time-to-Collision (TTC) thresholds: the default 1.5 seconds and a reduced 1.0 second, as supported by prior research.

The results revealed that increasing the penetration of AV-Aggressive vehicles led to significant improvements in intersection efficiency, as measured by average delay. In contrast, higher proportions of AV-Cautious and AV-Normal vehicles resulted in reduced performance. Specifically, AV-Cautious at 100% penetration caused a 90.6% increase in delay, while AV-Normal showed a modest 3.5% decline. AV-Aggressive achieved the best operational outcome, reducing delay by 7.5%. From a safety perspective, AV-Aggressive also demonstrated superior performance, reducing total conflicts by 48.6% compared to conventional vehicles.

This study provides valuable insights into how varying proportions of AV driving logics affect traffic performance in mixed environments. However, several limitations should be acknowledged for future research. The AV behaviors used in this study are based on the CoEXist project, which offers a standardized framework for simulating AVs in microscopic traffic models. While CoEXist provides a practical and widely accepted approach, future studies may benefit from incorporating more adaptive and context-sensitive driving logics that reflect ongoing advancements in AV technology and decision-making capabilities.

Moreover, the scope of this study was limited to passenger car-based AVs. As AV technologies evolve, it will be important to include other vehicle types, such as autonomous buses and trucks, to gain a more comprehensive understanding of AV impacts across different transportation modes. Additionally, SSAM relies on predefined thresholds for surrogate safety measures like TTC, which may not fully capture the complexity of real-world driver behavior or AV decision-making. SSAM also does not account for environmental factors, human reactions, or vehicle dynamics beyond trajectory overlaps. Future safety assessment tools should aim to incorporate more advanced behavioral and contextual data to enhance the accuracy of conflict analysis.

Acknowledgement

The authors would like to extend their gratitude to the academic and support personnel at the Faculty of Civil Engineering, Universiti Teknologi Malaysia, for their unwavering assistance during the course of this research. Additionally, Zutari Engineering International deserves high praise for their valuable support in providing various types of traffic data information necessary for this research.

Conflict of Interest

The authors declare that they don't have any competing personal or financial interests that might have influenced the work reported in this manuscript.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Mohammed Arshad, Sitti Asmah Hassan;* ***data collection:*** *Mohammed Arshad;* ***analysis and interpretation of results:*** *Mohammed Arshad, Sitti Asmah Hassan, Muhammad Azam;* ***draft manuscript preparation:*** *Mohammed Arshad, Sitti Asmah Hassan;* ***draft review:*** *Nordiana Mashros, Mohd Khairul Afzan Mohd Lazi. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Kaur, K. & Rampersad, G. (2018) Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. *Journal of Engineering and Technology Management*, *48*, 87-96, https://doi.org/10.1016/j.jengtecman.2018.04.006

[2] Bertoncello, M. & Wee, D. (2015) Ten ways autonomous driving could redefine the automotive world. McKinsey & Company, 6, 1-5.

[3] Kumar, G., James, A. T., Choudhary, K., Sahai, R. & Song, W. K. (2022) Investigation and analysis of implementation challenges for autonomous vehicles in developing countries using hybrid structural modeling, *Technological Forecasting and Social Change*, *185*, 122080, https://doi.org/10.1016/j.techfore.2022.122080

[4] Azam, N. M., Hassan, N. S., Puan, N. O., Azhari, N. S. & Faiz, N. R. (2022) Performance of Autonomous Vehicles in Mixed Traffic under different Demand Conditions. *International Journal of Automotive and Mechanical Engineering, 19(4)*, 10050–10062, https://doi.org/10.15282/ijame.19.4.2022.02.0776

[5] Huang, C.-K., Li, J. Q., Liu, W., & Yang, X. (2022) Evaluating the Impact of Autonomous Vehicles on Traffic Flow at a Stillwater Intersection, *International Conference on Transportation and Development 2022*, https://doi.org/10.1061/9780784484326.006

[6] Shi, Y., Liu, Y., Qi, Y. & Han, Q. (2022) A Control Method with Reinforcement Learning for Urban Un-Signalized Intersection in Hybrid Traffic Environment, *Sensors*, 22(3), 779, https://doi.org/10.3390/s22030779

[7] Morando, M. M., Tian, Q., Truong, L. T. & Vu, H. L. (2018) Studying the safety impact of autonomous vehicles using Simulation-Based Surrogate Safety Measures, *Journal of Advanced Transportation,* 1–11, https://doi.org/10.1155/2018/6135183

[8] Shaik, I (2022) Micro-Simulation of Autonomous Vehicles in Mixed Traffic and Its Impact at an Urban Setting Signalized Intersection. Edinburg Napier University.

[9] Neuendorf, N., Bruns, T. & Luckel, J. (2004) The vehicle platoon controller in the decentralised, autonomous intersection management of vehicles, *Proceedings of the IEEE International Conference on Mechatronics*, 375–380, https://doi.org/10.1109/icmech.2004.1364468

[10] Aria, E., Olstam, J. & Schwietering, C (2016) Investigation of automated vehicle effects on driver's behavior and traffic performance, *Transportation Research Procedia*, *15*, 761–770, https://doi.org/10.1016/j.trpro.2016.06.063

[11] Overtoom, I., Correia, G., Huang, Y., & Verbraeck, A. (2020) Assessing the impacts of shared autonomous vehicles on congestion and curb use: A traffic simulation study in The Hague, Netherlands, *International Journal of Transportation Science and Technology, 9(3)*, 195–206, https://doi.org/10.1016/j.ijtst.2020.03.009

[12] Budan, G., Hayatleh, K., Morrey, D., Ball, P. & Shadbolt, P. (2018) An analysis of vehicle-to-infrastructure communications for non-signalised intersection control under mixed driving behaviour, *Analog Integrated Circuits and Signal Processing*, *95(3)*, 415–422, https://doi.org/10.1007/s10470-018-1152-2

[13] Almobayedh, H. B., Eustace, D. & Appiah-Kubi, P. (2019) Simulation of the Impact of Connected and Automated Vehicles at a Signalized Intersection, *Civil and Environmental Engineering and Engineering Mechanics Faculty Publications*, *70*, https://ecommons.udayton.edu/cee_fac_pub/70/

[14] Tomás, R. F., Fernandes, P., Macedo, E., Bandeira, J. M. & Coelho, M. C. (2020) Assessing the emission impacts of autonomous vehicles on metropolitan freeways, *Transportation Research Procedia*, *47*, 617–624, https://doi.org/10.1016/j.trpro.2020.03.139

[15] He, S., Guo, X., Ding, F., Qi, Y. & Chen, T. (2020) Freeway Traffic Speed Estimation of Mixed Traffic Using Data from Connected and Autonomous Vehicles with a Low Penetration Rate, *Journal of Advanced Transportation*, *2020*, 1–13, https://doi.org/10.1155/2020/1361583

[16] The United Arab Emirates' Government Portal. (2023) Dubai Autonomous Transportation Strategy, https://u.ae/en/about-the-uae/strategies-initiatives-and-awards/strategies-plans-and-visions/transport-and-infrastructure/dubai-autonomous-transportation-strategy (accessed May 02, 2024).

[17] Florida Department of Transportation (FDOT) (2021) Traffic Analysis Handbook. Tallahassee, Florida.

[18] Azam, M., Puan, O. C., Hassan, S. A. & Mashros, N. (2019) Calibration of microsimulation model for tight urban diamond interchange under heterogeneous traffic, *IOP Conference Series Materials Science and Engineering*, *527(1)*, 012077, https://doi.org/10.1088/1757-899x/527/1/012077

[19] Virginia Department of Transportation (VDOT) (2020), Traffic Operations and Safety Analysis Manual (TOSAM).

[20] Manjunatha, P., Elefteriadou, L., Hunter, M., Duan, X., Letter, C., Roy, S., White, C.C., Postma, D. & Guin, A. (2021) Evaluation of Advanced Vehicle & Communication Technologies through Traffic Microsimulation. Technical Report Project D. Southeastern Transportation Research, Innovation, Development and Education Center (STRIDE), University of Florida, Transportation Institute, United States.

[21] Kockelman, K., Boyles, S., Stone, P., Fagnant, D., Patel, R., Levin, M. W., Sharon, G., Simoni, M., Albert, M. Fritz, H. Hutchinson, R., Bansal, P., Domnenko, G., Bujanovic P., Kim, B., Pourrahmani, E., Agrawal, S., Li, T., Hanna, J., Nichols, A. & Li, J. (2017) An assessment of autonomous vehicles: traffic impacts and infrastructure needs, *Technical Report 0-6847-1* (Report No.: FHWA/TX-17/0-6847-1), University of Texas at Austin. Center for Transportation Research, United States.

[22] Olstam, J. J. & Johansson, F. (2018) *D1.3: Use Case Specifications*. CoEXist Project Deliverable, European Union's Horizon 2020 Programme, Grant Agreement No. 723201. Retrieved from https://www.diva-portal.org/smash/get/diva2:1330025/FULLTEXT01.pdf

[23] Atkins, Department for Transport (2016): Research on the impacts of connected and autonomous vehicles on traffic flow. Stage 2: Traffic Modelling and Analysis, *Technical Report*, Version 2.1: Department of Transport (5145311).

[24] Mousavi, S. M., Osman, O. A., Lord, D., Dixon, K. K. & Dadashova, B. (2021) Investigating the safety and operational benefits of mixed traffic environments with different automated vehicle market penetration rates in the proximity of a driveway on an urban arterial, *Accident Analysis & Prevention*, *152*, 105982.

[25] Kaltenhäuser, B., Hamzehi, S., & Bogenberger, K. (2023) The Impact of Autonomous Vehicles and Their Driving Parameters on Urban Road Traffic, In *Proceedings of the 12th International Scientific Conference on Mobility and Transport: Mobility Innovations for Growing Megacities*. *Lecture Notes in Mobility*, pp. 3-19. Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-19-8361-0_2

[26] Yang, C., Lin, X., Li, M. & He, F. (2022) Simulation comparisons of Vehicle-Based and Movement-Based traffic control for autonomous vehicles at isolated intersections, *IEEE Transactions on Intelligent Transportation Systems, 23(12),* 22954–22970, https://doi.org/10.1109/tits.2022.3210772

[27] Li, D., Zhu, F., Chen, T., Wong, Y. D., Zhu, C. & Wu, J. (2022) COOR-PLT: A hierarchical control model for coordinating adaptive platoons of connected and autonomous vehicles at signal-free intersections based on deep reinforcement learning, *Transportation Research Part C Emerging Technologies, 146*, 103933, https://doi.org/10.1016/j.trc.2022.103933

[28] Lu, G., Shen, Z., Liu, X., Nie, Y. & Xiong, Z. (2021) Are autonomous vehicles better off without signals at intersections? A comparative computational study. *Transportation Research Part B Methodological, 155*, 26–46, https://doi.org/10.1016/j.trb.2021.10.012

[29] Wang, Y., Yang, X., Liang, H. & Liu, Y. (2018) A review of the self-adaptive traffic signal control system based on future traffic environment, *Journal of Advanced Transportation*, *2018(1)*, 1096123, https://doi.org/10.1155/2018/1096123