INTERNATIONAL JOURNAL OF AUTOMOTIVE AND MECHANICAL ENGINEERING (IJAME)
ISSN: 2229-8649 e-ISSN: 2180-1606
VOL. 19, ISSUE 4, 10050 – 10062
DOI: https://doi.org/10.15282/ijame.19.4.2022.02.0776

ORIGINAL ARTICLE

Performance of Autonomous Vehicles in Mixed Traffic under different Demand Conditions

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ABSTRACT – Autonomous Vehicles (AVs) are considered one of the potential solutions to future urban mobility with several promised benefits regarding safety and traffic operation. Despite of expected benefits, these vehicles will take decades to have full market penetration and before that, AVs will co-exist with Conventional Vehicles (CVs), which may affect the performance of AVs owing to different driving logic than CVs. The aim of this study is to quantify the impacts of varying penetrations of AVs when introduced in mixed traffic conditions. The study employed simulation environment VISSIM to study the different scenarios based on the percentage of AVs in mixed traffic, category of AVs and varying demand levels. The findings show that at lower demand levels (1000 veh/hr and 2000 veh/hr), CVs and three categories of AVs produced similar results. However, cautious and normal AVs negatively affect traffic operations when the demand level is increased. At demand-3 (3000 veh/hr), the penetration rates of cautious AVs greater than 50% shows negative impact on performance. At demand-4 (4000 veh/hr), even a small proportion (25%) of cautious AVs can negatively affect performance, and a similar effect is observed for normal AVs with a penetration rate greater than 75%. For speed, the minimum reduction with the increase in demand is observed for aggressive AVs, followed by conventional vehicles, normal AVs and cautious AVs. It can be concluded that the aggressive AVs produced better delays, queue length, speed and conflicts than CVs, cautious AVs and normal AVs at the highest demand levels.

ARTICLE HISTORY
Received: 25th June 2022
Revised: 31st Aug 2022
Accepted: 25th Nov 2022
Published: 28th Dec 2022

KEYWORDS
Autonomous vehicles; Mixed traffic; Traffic performance; Simulation model; Penetration rate

INTRODUCTION

Autonomous Vehicles (AVs) are expected to improve future urban mobility by alleviating safety, operational and economical aspects of urban traffic [1]. According to National Highway Traffic Safety Administration (NHTSA), AVs are vehicles which perform the steering, acceleration and braking operations without the direct involvement of drivers. The sensors and technology help the AVs to perform certain environment sensing and navigating tasks without human input [2]. Studies have endorsed the efficiency of AVs in improving traffic congestion by enhancing road capacities and safety margins [3]. From the literature, AVs have been considered effective in improving traffic conditions by reducing the overall traffic volume on roads [4], [5], minimizing the need for parking spaces [6], improving throughput and stability [7], reducing the environmental impacts [8] and reducing delays [9], [10]. In addition to the aforementioned aspects, the key benefit of AVs is to eliminate accidents caused by human errors.

According to World Health Organization (WHO), each year, around 1.3 million people lose their lives due to road accidents and 93% of fatalities are reported in low to middle-income countries [11]. Among the factors contributing to road crashes, human error is considered as leading, and studies have shown that human error was a contributory factor in 93% of the accidents [12], and most of the accidents were caused by loss of control by human drivers [13]. The discrete nature of AVs will be able to eliminate such human errors. However, the actual impacts of this technology are still unknown and researchers, enterprises and policymakers are keen to know the future of these advanced vehicles [14], [15].

The Market Penetration Rates (MPRs) of AVs have been predicted by many researchers [16], [17]. The MPR of AVs is estimated to be between 24% and 87% by 2045 [18]. The major benefits of AVs are associated with full market penetration, but there is a long way to reach 100% market penetration [19]. During the transition period, the AVs will interact with Conventional Vehicles (CVs). The complicated environment created by these vehicles of different autonomy is expected to affect the driving behaviour patterns in traffic streams [20]. Keeping in view the MPR predictions and expected behaviour of AVs when simulated with CVs, various researchers are working on mixed traffic conditions and are publishing useful literature on the key topic of this era.

Multiple studies involving every possible scenario of the future are in stream of knowledge to provide a factual ground to decision-makers. A significant proportion of the studies discussing the impacts of AVs on mixed traffic conditions have considered the traffic characteristics of developed countries where impacts of AVs were realized on homogeneous traffic conditions [21], [22]. The homogeneous traffic conditions are characterized by fewer vehicular classes coupled with lane-based driving behaviour [23]. Whereas few studies have studied AVs in the context of heterogeneous traffic

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conditions representing vehicles with varying static and dynamic characteristics. Such traffic streams represent a sufficient proportion of Two-Wheelers (2W) and Three-Wheelers (3W), coupled with non-lane-based driving behaviour. This study has been undertaken to assess the impacts of various penetration rates of AVs into mixed traffic streams having cars, Heavy Vehicles (HVs), 2W and 3W. The study employed a simulation environment to study the operational impacts of AVs on a hypothetical 4-legged signalized intersection under mixed traffic conditions. Several scenarios have been conducted to study different possible combinations of AVs and CVs at varying traffic flow conditions. The study has assumed four different traffic flow conditions to reflect the peak and off-peak flow levels that happen at an urban intersection during daily traffic operations.

Despite the real-world testing of AVs, the data on the driving behavior of AVs are not easily available. In the literature, the simulations studies involving AVs have been conducted by adopting driving behavior parameters based on evidence from the test beds as well as from the capabilities of AVs as identified by manufacturers [10], [24]. Out of the available simulation packages, VISSIM has been considered as the most viable option to simulate AVs. Two different car-following models are available in VISSIM, i.e., Wiedemann 74 and Wiedemann 99. Both these models are helpful in modeling driving behavior for different types of facilities. In the context of human drivers, the Wiedemann 74 model can be used for urban traffic and merging areas, and Wiedemann 99 is more suitable for freeway with no merging areas [25]. However, Wiedemann 99 is considered more suitable to model the deterministic driving behavior of AVs since the model allows the modifications of various parameters [26], [27]. In order to prepare the cities for the transition phase when AVs and CVs share the road space, European Union started CoEXist project in 2017 with the aim to provide data on driving characteristics and impacts of AVs in mixed traffic environments [28]. Based on the experiences in the CoEXist project, VISSIM provided three driving logics of AVs to model the behavior of AVs in a simulation environment. These driving logics include cautious, normal and aggressive, and each represents its own driving behavior characteristics in longitudinal and lateral directions [29]. A brief description of the three AV-ready driving logics avaiable in VISSIM simulation tool has been discussed here [30]:

i. Cautious AVs: The vehicle maintains larger headways and maneuvers in a more conservative manner than a conventional human driver. The cautious AVs have been developed as the most conservative and safest among other AV driving logics with an intention to establish the confidence of the public towards an accident-free AV;
ii. Normal AVs: The vehicles behave very similar to conventional human drivers with some additional sensor capabilities to measure the distances and speeds of surrounding vehicles. The vehicles are also capable of having shorter reaction times; however, these vehicles are restricted by the range of their sensors to only perceive the vehicles in their surroundings. In contrast, human drivers are often aware of the vehicles beyond their surroundings;
iii. Aggressive AVs: Aggressive AVs, also known as all-knowing AVs, are well-aware of their entire surrounding due to their perfect perception and prediction abilities. The vehicles can practice smaller headways and more aggressive acceleration and deceleration while providing cooperative behaviour for surrounding vehicles.

The AVs have been categorized into six levels as defined by the Society of Automotive Engineers [31]. These levels are based on the involvement of human efforts while driving. Level 0 needs complete human driving interaction, whereas Level 5 refers to zero input by a human driver. From Level 0 to Level 2, human drivers monitor and execute the driving task and they need to keep their hands on the driving controls. At Level 1, AV can perform either the longitudinal control task or lateral control task at a time. Whereas Level 2 AV can perform both longitudinal and lateral control tasks at the same time. At Level 3, driver monitoring is not required all the time, but still, a driver needs to resume monitoring when requested by driving system. At Level 4, human drivers are not required to monitor or control the vehicle at all. The highest of the automation levels is Level 5, which refers to the driving of autonomous vehicles in all conditions involving incident and weather conditions. This study assumed that AVs are fully automated with level 4 automation and can perform all the driving tasks without the involvement of a human driver [32].

In literature, AVs have been simulated by adopting either the default parameters as given by VISSIM for three categories of AVs or these parameters have been modified by the authors for certain types of traffic and geometric conditions. This study employed the default parameters available in PTV VISSIM 2022 to represent AVs. The remaining of this paper contains three sections. Section 2 presents the method adopted to develop the base simulation model, parameters identification for CVs and AVs and preparation of simulation scenarios and runs. In section 3, results have been presented based on the simulation output obtained from VISSIM. The discussion points based on the variations in output have been given in section 4. In section 5, conclusions have been presented based on the findings of this study.

METHODS

The method involves three phases, including 1) development of the base model, 2) mixed traffic scenario and 3) simulation output and comparison. Figure 1 shows the three aforementioned main phases along with the steps involved in each of the phases.

The first phase refers to the application of VISSIM software to develop a simulation model of a hypothetical 4-legged signalized intersection. The four approaches of intersection were having same characteristics, including the number of lanes, lane widths, turning configurations and signal timings. In the second phase, various scenarios were created based on different proportions of AVs and CVs. All the scenarios were conducted by employing a base model. The third phase involves the simulation output on specific performance measures. These results were utilized to produce graphs to assess the impacts of varying MPR of AVs.

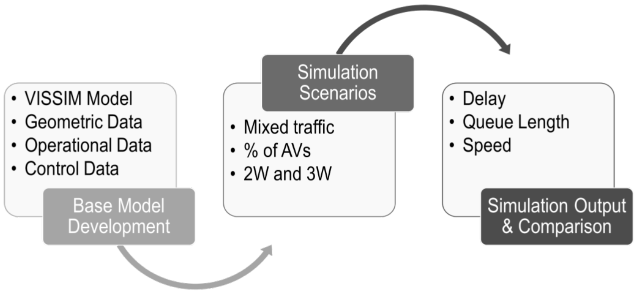


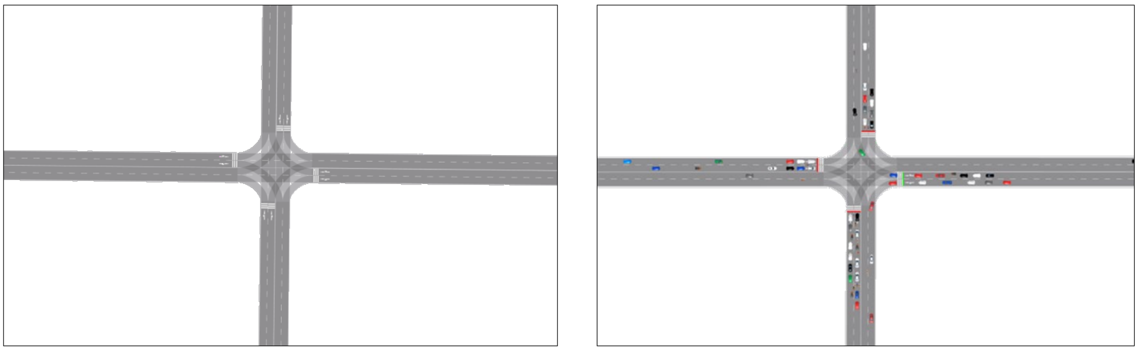
Figure 1. Phases of methodology

Base Model Development

The VISSIM 2022 software was employed to develop the base model and to run various considered scenarios. Scenarios were prepared based on varying demand levels, the proportion of AVs in the vehicle composition and the category of AVs. The output from simulations was obtained for three performance measures; delay, speed and queue length through node evaluation and network performance options in VISSIM. In the absence of enough empirical data on various performance and behaviour aspects of AVs, many studies have considered hypothetical conditions to study various scenarios involving AVs [10], [33], [34]. In this study, a hypothetical 4-leg signalized intersection (Figure 2) was considered with the following assumptions;

i. All four approaches of intersections were having similar characteristics.
ii. The approach length was taken as approximately equal for each approach.
iii. Same traffic volume and vehicular composition was used for a particular scenario.
iv. Identical signal timings were assigned to each of the approaches.

A typical signalized intersection was assumed with varying demand levels ranging from 1000 vehicles per hour to 4000 vehicles per hour. A similar strategy of using different assumed demand levels has been adopted in literature [10], [35]. The objective of using various demand levels ranging from lower level to high demand levels is to reflect the possible peak and off-peak traffic conditions that happen during a full day length. For the base model, the vehicle composition involved only CVs, and subsequent scenarios were conducted at 25%, 50%, 75% and 100% penetration rates of AVs. At intersection, each approach produced three movements including left, through and right. Among the two lanes at each approach, one is shared with left turns and the other with right-turning vehicles. A cycle length of 90 seconds was assumed with equal green, amber and red timings for all approaches. All-red time of 2 seconds was assumed at the end of each cycle.



(a) (b)

Figure 2. The considered study site; (a) site geometry, and (b) simulations

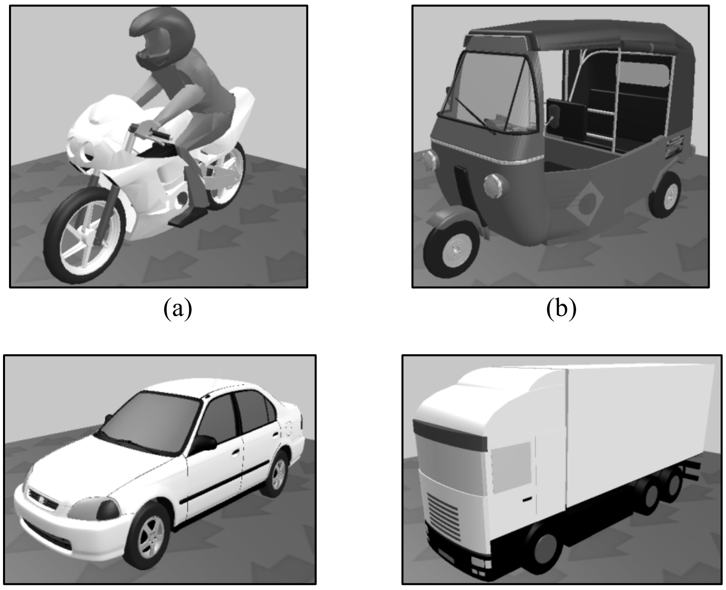
Modeling Vehicle Mix

For traffic mix, two major vehicular categories were considered; Autonomous Vehicles (AVs) and Conventional Vehicles (CVs). Under the AV category, three categories were simulated; cautious, normal and aggressive. All these categories are based on the driving logic in VISSIM, and their parameter values were adopted from the CoEXist project [29]. The values of size, speed and lateral distances for AVs were adopted from the values used for conventional cars. However, the values for other operational characteristics of AVs, such as headway, standstill distance and acceleration aspects, were adopted based on the employed AV driving logic. Although the AV and conventional cars are physically identical, but they behave differently in traffic streams due to different driving logics.

The CV category involved four conventional vehicular classes; 2W, 3W, cars and HVs. For each of the considered scenarios, the mix represents the different proportions of the aforementioned vehicular classes. The details of the considered parameters and their values have been discussed here.

Size of vehicles

The sizes of the considered vehicular classes in terms of length and width were identified from the literature, and the adopted values were used in VISSIM. The software has built-in three-dimensional (3D) vehicular models, which can be modified for any size of vehicle. Similar, strategy was adopted in this study and initially, built-in models for cars, 2W, 3W and HGVs were loaded into software and then these were adjusted for the desired vehicular sizes as shown in Figure 3. The model used for conventional car was adopted for AVs but both vehicular classes were modelled with different driving behaviour. The lengths and widths of built-in 3D vehicular models were modified according to the data given in Table 1.



(a) (b) (c) (d)

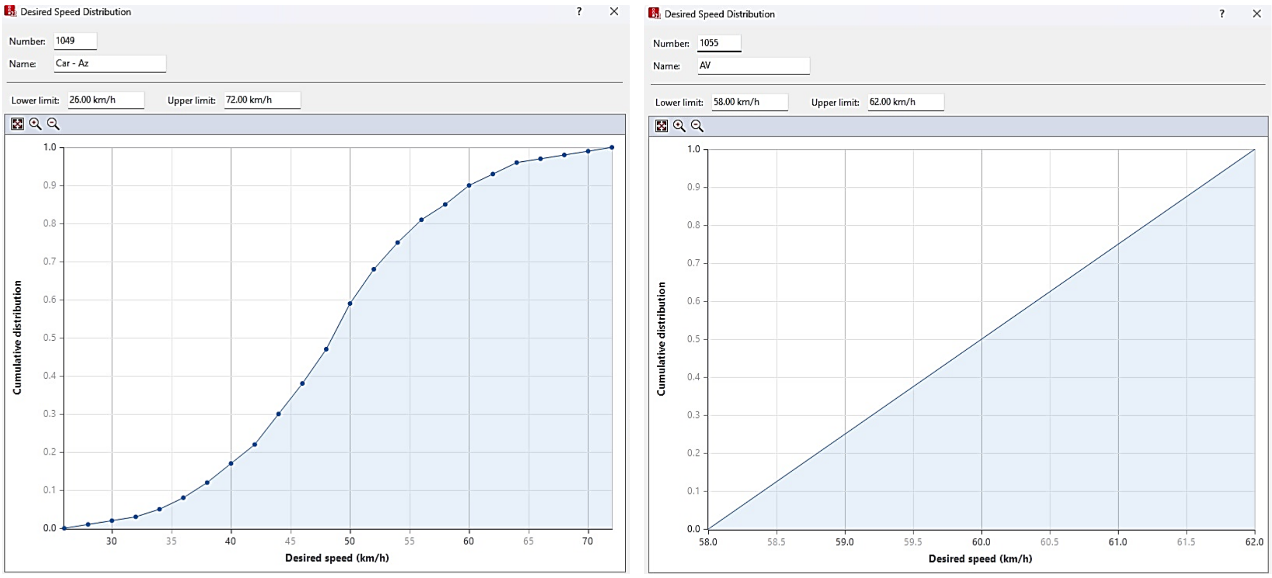
Figure 3. 3D models for considered vehicular classes; (a) 2W, (b) 3W, (c) car, and (d) HGV

Speed

The speed distribution of indiviual vehicular class can also be specified in VISSIM. Since, the intersection has been considered in urban setting, the speeds of each vehiclular class have been assigned accordingly. Some studies conducted in the similar setting were also reviewed and comparable speeds for each of the considred vehicular class were selected [36]–[38]. The highest value of 45 km/h was adopted for conventional cars and AVs, however, comparatively smaller values were used for conventional 2W, 3W and HGVs to reflect the real-world urban traffic conditions as given in Table 1. For CVs, the speed is considered as distribution over a wide range, whereas, minimum variation of ±2km/h in speeds is expected for AVs due to their detreministic behaviour [10], [12]. Several studies have endorsed the narrow range of desired speed distributions for AVs since these vehicles keep their desired speed constant [18], [39], [40]. An example of speed distribution for CVs and AVs is shown in Figure 4.

Table 1. Parameters adopted for CVs

No.	Vehicle Type	Size of Vehicle		Speed	Lateral distance (m)	
		Length (m)	Width (m)	(km/h)	0 km/h	50 km/h
1	Two-Wheelers (2Ws)	1.8	0.6	40	0.2	0.5
2	Three-Wheelers (3Ws)	2.6	1.4	35	0.3	0.6
3	Car	4.46	1.86	45	0.5	0.9
4	Heavy Vehicles (HGVs)	11.54	3.17	30	0.5	0.9



(a) (b)

Figure 4. Desired speed distributions for different driving logics; (a) conventional car, (b) AV

Driving behaviour parameters

For CVs, the Wiedemann-74 car following model was adopted; however, Weidemann-99 was used for simulations of AVs. The default model settings were adopted for conventional cars and HGVs. However, the size and parameter values for 2W and 3W were adopted from the literature [36], [41]. Smaller values for headways, standstill distances, lateral distances and safety margins were considered for 2W and 3W [42]–[44]. The 2W and 3W vehicles were allowed to place themselves at any lateral position across the lane width and also, these vehicle classes were allowed to overtake other vehicles from both left and right sides. The remaining all other parameters in the VISSIM model were kept at their default.

For AVs, VISSIM allows users to model different driving behaviors by adjusting the available car following, lane changing, lateral and other important parameters according to the site conditions [45]. Based on the experiences in CoEXist, a European project, VISSIM provided three driving logics for AVs to model the behavior of AVs in a simulation environment. These driving logics include cautious, normal and aggressive and each category represents its own set of behavior parameters [28], [29]. Each driving logic endorses different parameter values for each category of AVs based on how the vehicle perceives and reacts to the surrounding environment. The default values for three driving logics of AVs have been adopted as given in Tables 2, Table 3 and Table 4. The definitions of these parameters can be found in VISSIM user guide [46]. The parameter values were obtained from CoEXist project and are provided as built-in driving logics in VISSIM [46].

Table 2. General following behavior parameters

Parameter	Driving logics for AVs		
	Cautious	Normal	Aggressive
Look ahead distance			
Minimum (m)	0	0	0
Maximum (m)	150	250	300
No. of interaction objects	2	2	10
No. of interaction vehicles	1	1	8
Look back distance			
Minimum (m)	0	0	0
Maximum (m)	150	150	150

The values of parameters endorse the cautious AV as the most conservative driving logic owing to larger values for time headways and smaller values for standstill and driving accelerations. In contrast, aggressive AVs show the smallest values for standstill distance and time headways as compared to other driving logics. From the perspective of information on surrounding vehicles, the aggressive AVs are capable of perceiving information on a higher number of objects and vehicles as compared to other AV driving logics.

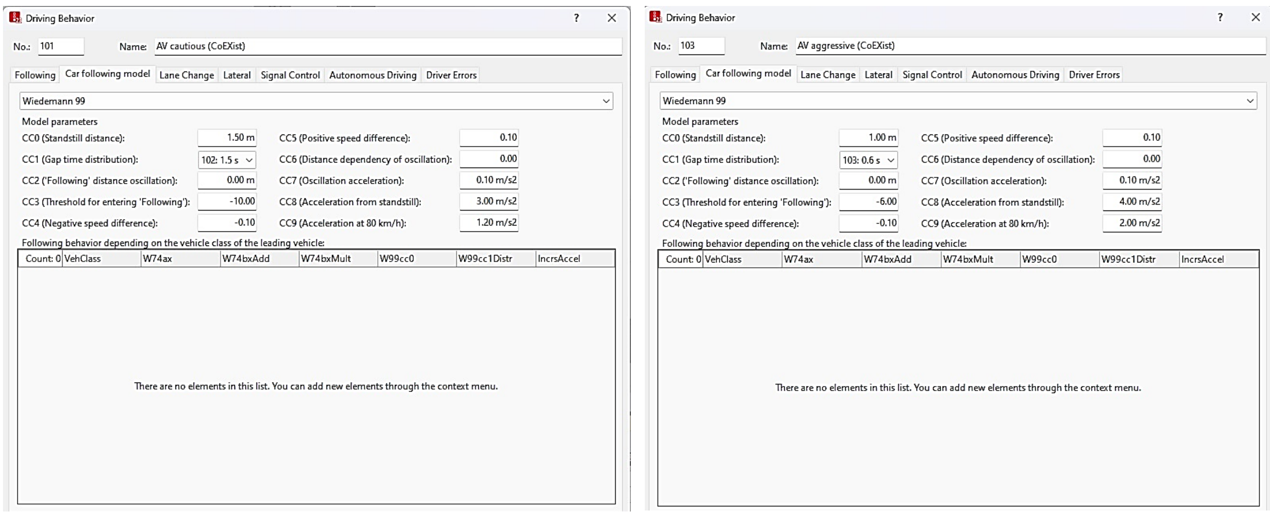
The VISSIM tool offers the flexibility of modifying vehicle-based driving behaviour parameters. After identifying the representative parameter values for size, speed, car-following and lane changing for AVs and CVs, the values were considered into respective car-following models. The car-following parameter settings for cautious and aggressive AVs in Weidemann-99 are shown in Figure 5. In the same way, the values for lane changing and other parameters were adjusted, and then simulations were run to extract the desired output.

Table 3. Weidemann-99 car following parameters

Parameter	Driving logics for AVs		
	Cautious	Normal	Aggressive
CC0 - standstill distance (m)	1.5	1.5	1.0
CC1 - headway time (s)	1.5	0.9	0.6
CC2 - following variation (m)	0.0	0.0	0.0
CC3 - threshold for entering following (s)	-10.0	-8.0	-6.0
CC4 – negative following threshold (m/s)	-0.1	-0.1	-0.1
CC5 - positive following threshold (m/s)	0.1	0.1	0.1
CC6 - speed dependency of oscillation (10^{-4} rad/s)	0.0	0.0	0.0
CC7 - oscillation acceleration (m/s^2)	0.1	0.1	0.1
CC8 - standstill acceleration (m/s^2)	3.0	3.5	4.0
CC9 - acceleration with 80 km/h (m/s^2)	1.2	1.5	2.0

Table 4. Lane changing parameters for three driving logics of AVs

Parameter	Driving logics for AVs		
	Cautious	Normal	Aggressive
Maximum deceleration - own (m/s^2)	-3.5	-4.0	-4.0
Maximum deceleration - trailing (m/s^2)	-2.5	-3.0	-4.0
-1 m/s^2 per distance – own (m)	80	100	100
-1 m/s^2 per distance – trailing (m)	80	100	100
Accepted deceleration – own (m/s^2)	-1.0	-1.0	-1.0
Accepted deceleration – trailing (m/s^2)	-1.0	1.0	-1.5
Minimum headway (front/rear) (m)	1.0	0.5	0.5
Safety distance reduction factor	1.0	0.6	0.75
Max. deceleration for cooperative braking (m/s^2)	-2.5	-3.0	-6.0



(a) (b)

Figure 5. Car-following parameter setting for two driving logics; (a) cautious AV, (b) aggressive AV

Simulation Scenarios and Runs

The scenarios were created based on the following three factors;

i. Demand level
ii. Category of AV
iii. Proportion of AV

The four demand levels were considered starting from 1000 vehicles per hour to 4000 vehicles per hour. A similar strategy of using different assumed demand levels has been adopted in the literature [10], [35]. The objective of using various demand levels ranging from lower level to high demand levels is to reflect the possible peak and off-peak traffic conditions that happen during a full day length. For the 1000 vehicles/ hour scenario, 250 vehicles were simulated for each of the four approaches with the same traffic characteristics and vehicle compositions. A similar technique was adopted for other demand levels. As discussed earlier, the VISSIM offers three categories of AVs based on CoEXist project. The scenarios were created by considering all three categories to identify the most efficient driving logic for such mixed traffic conditions. The gradual increase of AVs on roads is considered by including five different AV penetration rates of 0%, 25%, 50%, 75% and 100%. At a 0% penetration rate, there are only CVs, while at a 100% penetration rate, there are only AVs on the road. Table 5 shows the scenarios considered in this study.

Table 5. Scenarios considered for cautious AVs

	Increase in AV Proportion →					
Increase in Demand ↓	Cautious AVs	0%	25%	50%	75%	100%
	Demand-1: 1000	Scenario-1	Scenario-2	Scenario-3	Scenario-4	Scenario-5
	Demand-2: 2000	Scenario-6	Scenario-7	Scenario-8	Scenario-9	Scenario-10
	Demand-3: 3000	Scenario-11	Scenario-12	Scenario-13	Scenario-14	Scenario-15
	Demand-4: 4000	Scenario-16	Scenario-17	Scenario-18	Scenario-19	Scenario-20

In Table 5 above, a total of 20 scenarios have been shown for only the cautious driving logic of AV. Similarly, 20 scenarios were conducted for each of the normal and aggressive driving logics. This amounts to a total of 60 (20×3) scenarios for four demand levels, five proportion levels of AVs and three driving logics.

Operational and Safety Assessment

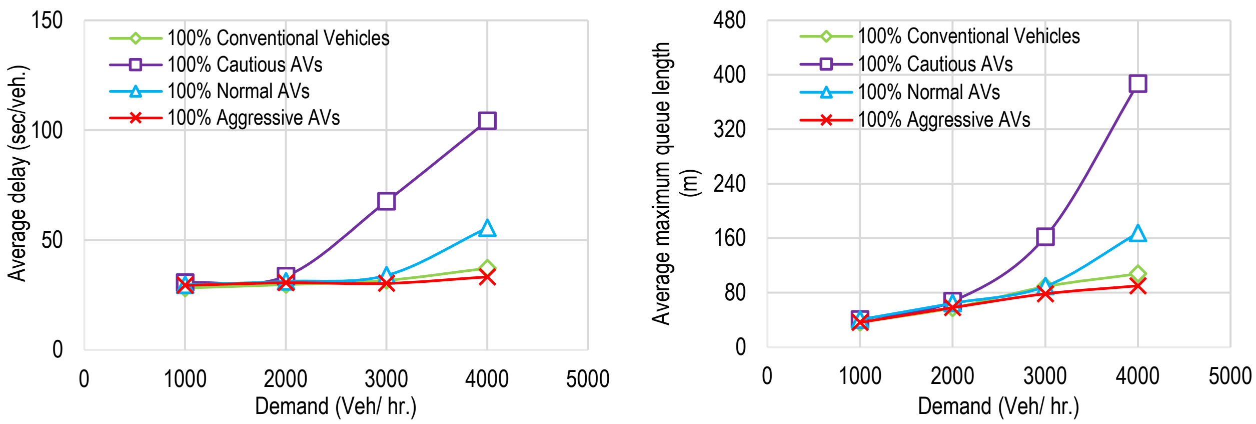
For operational assessment, the output from simulation runs was obtained based on dedicated functions of the software. With the help of node and network evaluation, the data on delays, queue lengths and speed were obtained and summarized for assessment. The simulation runs for each scenario were selected based on a fine review of the literature. Multiple simulation runs are conducted to incorporate the variations in simulation output due to the stochastic nature of the model. Some studies suggested conducting at least 11 simulation runs to record the simulation output for reporting [47]. Some other guiding manuals recommended 10 runs as an acceptable minimum number [48], [49]. Based on evidence from the literature, this study employed 10 simulation runs for each scenario to record output on various performance measures.

For safety assessment, the trajectory files obtained from the VISSIM simulations were used in Surrogate Safety Assessment Model (SSAM) to extract the number of potential conflicts based on surrogate safety measures. Surrogate safety measures, including time to collision (TTC), post encroachment time (PET), deceleration rate (DR), gap time (GT) and proportion of stopping distance (PSD), are considered important measurements of the safety implications [35], [50], [51]. TTC, the most widely used surrogate safety measure, refers to the expected time for two vehicles to collide if they follow the same path and at the same speed [18]. Many studies have considered a value of 1.5 seconds as an unsafe situation [18], [52]. The same value of 1.5 seconds for TTC was adopted in this study for safety assessment in the SSAM tool provided by The Federal Highway Administration (FHWA). All other parameters of the SSAM tool were kept as default. Data on the total number of conflicts for each considered scenario was obtained and analyzed.

RESULTS

The results were obtained from simulations based on three performance measures; delay, queue length and speed. Each simulation run was conducted for a total of 3900 seconds, including a warm-up period of 300 seconds to allow vehicles to reach a stable state. All the aforementioned scenarios were conducted, and results were organized in meaningful charts. Node evaluation and network performance were used to obtain the desired output from simulations.

Figure 6 below shows the comparison of average delay and average maximum queue length for 100% penetration rates of conventional vehicles as well as for three driving logics of AVs with the increase in demand. The lines in the graph are shown in different color codes to represent the impact of 100% penetration rate of different vehicle categories. The 100% conventional vehicle line represents the scenario with 0% penetration rate of any category of AVs.



(a) (b)

Figure 6. Impact of different types of vehicles on (a) average delay and (b) average maximum queue length

Figure 6 shows the impact of full penetration rates of different driving logics on delay and queue length. It can be seen that at demand-1 (1000 veh/hr) and demand-2 (2000 veh/hr), each of the driving logics produced comparable results for the average delay and average maximum queue length. However, the cautious AVs showed a noteworthy increase in delay and queue length values when the demand reached demand-3 (3000 veh/hr). At demand-4 (4000 veh/hr), the value of average delay and average maximum queue length continues to increase for cautious AVs. For demand-4, the normal AVs also produced higher values for both performance measures as compared to conventional vehicles and aggressive AVs. The values of average delay and average maximum queue length for conventional vehicles show a continuous increase when the demand values are changed from demand-1 to demand-4. However, the values are smaller than the values for cautious AVs and normal AVs at every demand point. Aggressive AVs show better performance than conventional vehicles, cautious AVs and normal AVs at higher demand levels. At demand-4 (4000 veh/hr), the aggressive AVs show a decrease of 10.6% and 16.3% in average delay and average maximum queue length, respectively.

Figure 7 shows the percent change in average speed at different demand levels for different driving logics. The demand-1 is considered as the base, and subsequent change in speed is observed with the increase in demand values. All driving logics show comparable values for demand-2 (2000 veh/hr). However, a sharp decline of around 26% in speed is observed for cautious AVs In comparison to base demand (1000 veh/hr) when demand value is increased to demand-3 (3000 veh/hr). A further reduction of 52% in speed is observed for cautious AVs at demand-4 (4000 veh/hr). For normal AVs, a maximum reduction of 20% is observed at the highest demand level. The results for speed are identical to the findings of delay and queue length. It can be observed that the minimum reduction in speed values with the increase in demand is observed for aggressive AVs followed by conventional vehicles, normal AVs and cautious AVs. For aggressive AVs, only a 4% reduction in speed is observed for their 100% penetration rates at demand-4.

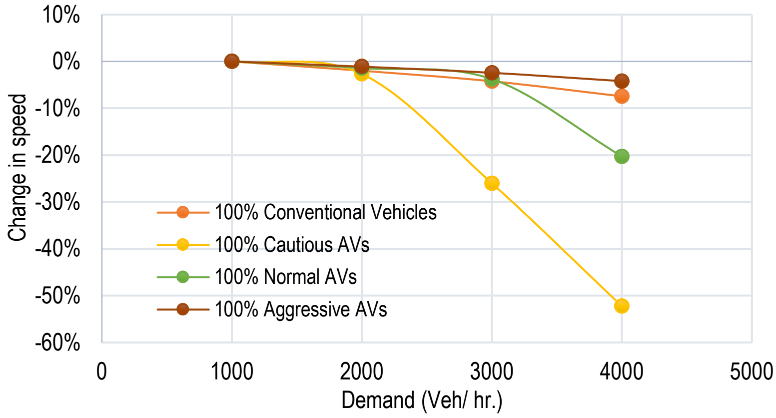
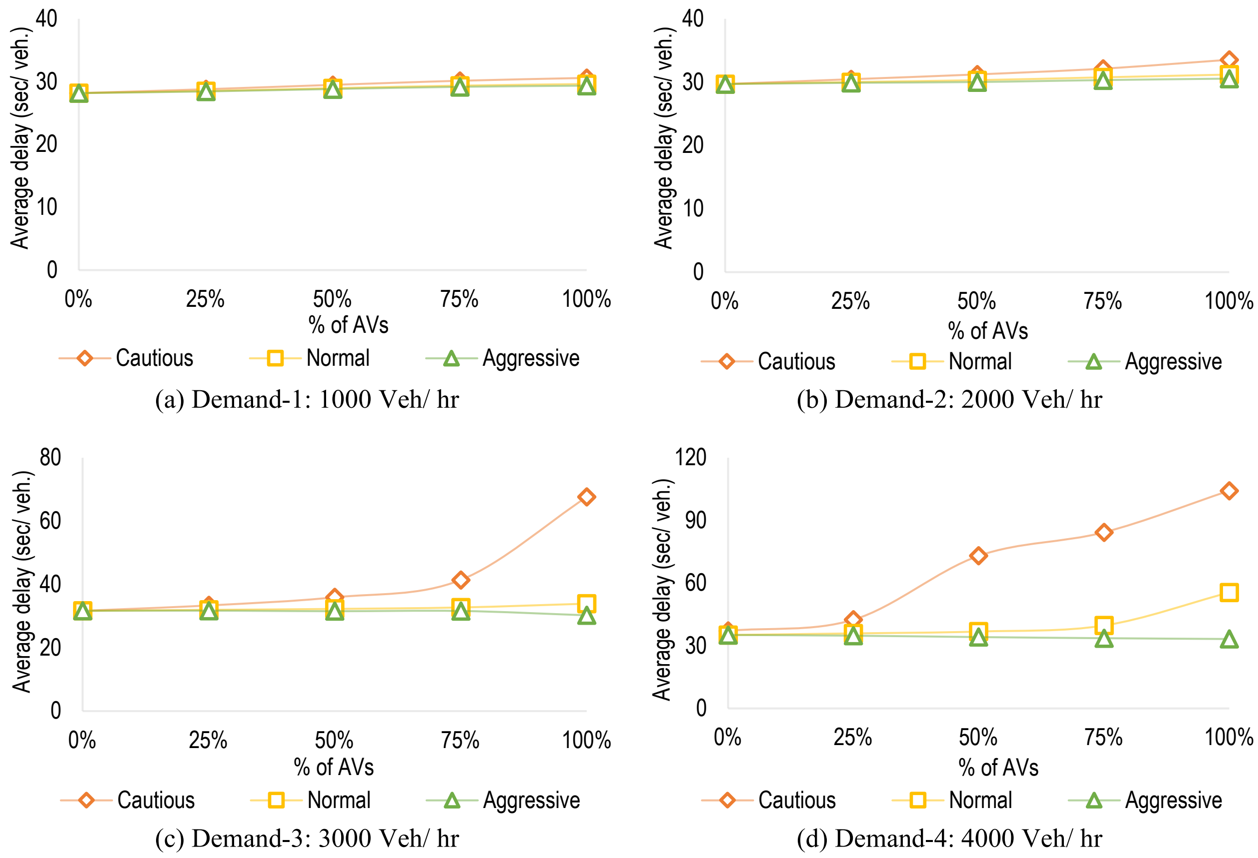


Figure 7. Impact of different types of vehicles on speed

Figure 8 shows the impact of varying penetration rates of three categories of AVs on average delay at four demand levels. The penetration rates for each category of AV vary between 0% to 100%, where 0% refers to CVs-only conditions and 100% refers to AVs-only conditions. The focus of the graphs in Figure 8 is to compare the performance of cautious, normal and aggressive AVs with the change in traffic mix and demand levels. At lower demand levels (demand-1 and demand-2), it can be observed all three categories of AVs have shown comparable performance for all penetration levels. At demand-3, the penetration rates of cautious AVs higher than 50% showed a negative impact on performance. The negative impacts continue to increase with the increase in penetration rates and demand values. However, normal and aggressive AVs show a similar trend with an increase in penetration rates at demand-3. At demand-4, even a smaller proportion (25%) of cautious AVs can negatively affect the performance. Whereas normal AVs show a negative impact with a penetration rate of 75%, which further worsen the conditions at a 100% penetration rate at demand-4. The 100% penetration rates of aggressive AVs produced better results than 100 CVs (0% AVs). It can be concluded that with the increase in demand levels, aggressive AVs perform better than CVs followed by normal AVs and cautious AVs.

In addition to the operational assessment, the study also considered the safety aspect of mixed traffic conditions. The total number f conflicts obtained from the trajectory files based on varying demand levels and different driving logics are given in Figure 9. The data shown in Figure 9 are based on the output of the SSAM tool. It is evident that at lower demand levels, the cautious AVs are safest with a minimum number of conflicts than normal AVs, aggressive AVs and CVs. The aggressive AVs showed a higher number of conflicts than cautious and normal AVs at lower demand levels. With the increase in demand level to 3000 veh/hr, the cautious AVs and CVs showed comparable performance, whereas normal AVs and aggressive AVs produced better safety conditions as endorsed by a smaller number of conflicts. At the highest demand level of 4000 veh/hr, the aggressive AVs produced 183 conflicts in comparison to 363 conflicts by CVs, reducing the number of conflicts by 49.6%. In contrast, cautious AVs produced the highest number of conflicts of 558 in comparison to 363, 198 and 183 conflicts by CVs, normal AVs and aggressive AVs, respectively. The cautious AVs produced 53.7% more conflicts than CVs at the highest demand level.



(a) Demand-1: 1000 Veh/ hr

(b) Demand-2: 2000 Veh/ hr

(c) Demand-3: 3000 Veh/ hr

(d) Demand-4: 4000 Veh/ hr

Figure 8. Impact of varying penetration rates of cautious, normal and aggressive AVs on average delay at four demand levels

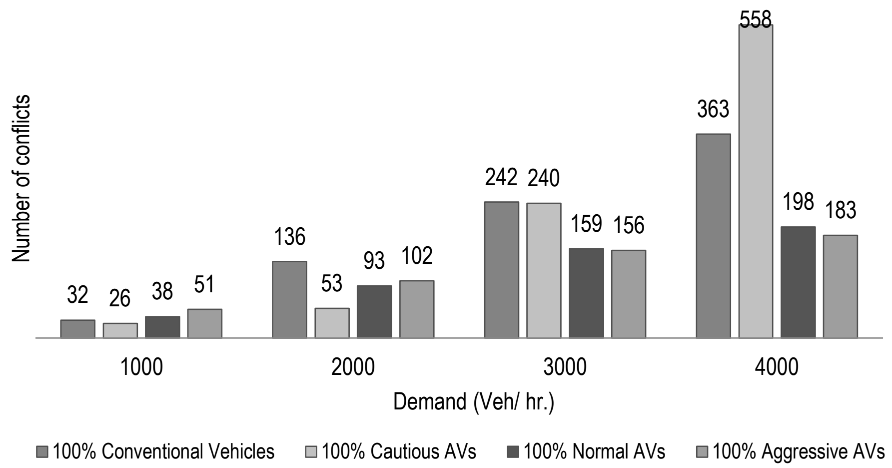


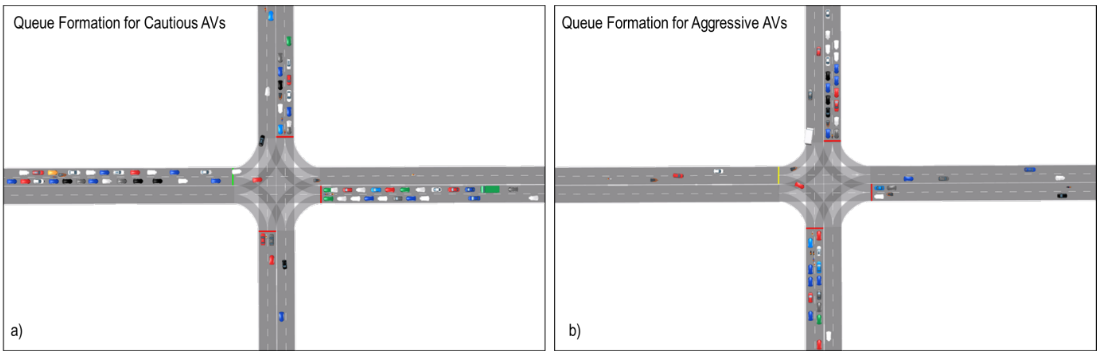
Figure 9. Number of conflicts for different driving logics at varying demand levels

DISCUSSION

The results of the operational assessment indicate that the aggressive AVs have potential to improve the intersection's performance even at higher demand levels. The findings show that at low demand levels, the three driving logics of AVs give an identical performance. A noticeable change in performance can be observed when the demand level is increased to 4000 veh/hr. The 100% penetration rate of cautious AVs deteriorated the performance and showed an increase in delay and queue length values. A similar trend is observed for normal AVs and their 100% penetration rate shows an increase of 49.4% in average delay and 55.8% in average maximum queue length, and 20% reduction in speed at demand-4 (4000 veh/hr). The aggressive AVs produced better delays, queue length and speed than CVs, cautious AVs and normal AVs at higher demand levels. The findings of the operational assessment are identical to the published literature. The value of time headways showed a significant impact on traffic flow and capacity. With the larger values of time headway, automation affects traffic operations negatively [53], [54]. Another study showed that the cautious AVs deteriorated the operational performance of highways [55]. In contrast, the shorter headway time of AVs improves the traffic flow and capacity [18], [56], [57]. The difference in performance by different driving logics of AVs is associated with their parameter settings in VISSIM. The more aggressive and accurate driving ability of AVs results in better performance for aggressive AVs.

On the other hand, the cautious AVs produce larger gaps and perform the following and lane-changing maneuvers more cautiously, resulting in deteriorated performance [58]. The deteriorated performance of cautious AVs can be realized by the change in arrival pattern, queue formation and queue discharge due to larger values of standstill distances and headway time and smaller values of standstill acceleration and driving acceleration. The normal AVs yet show better performance compared to cautious AVs due to smaller values for standstill distance and headway and more aggressive standing and driving acceleration. The aggressive AVs showed the most competitive performance in improving the performance when simulated in mixed traffic conditions. The aggressive AVs keep the smaller headways which helped the tighter queue formation, and higher values of standstill and driving acceleration helped to discharge the queue in a quick manner allowing the next platoon to be served at signal. Figure 10(a) and 10(b) below show a comparison of queue formation by for two different vehicle compositions containing cautious AVs and aggressive Avs, respectively. It can be observed that aggressive AVs form tighter queues and follow the other vehicles in a closer manner as compared to cautious AVs.

From the perspective of safety assessment, the cautious AVs were considered the safest driving logic at lower demand levels, while aggressive AVs were observed as the safest at the highest demand level. At lower demand levels, the cautious AVs and aggressive AVs produced the smallest and highest number of conflicts, respectively. Whereas an opposite situation was observed at the highest demand level, where aggressive AVs produced around 67% lesser conflicts than cautious AVs. The cautious AVs, with their conservative driving behaviour deteriorated the operational and safety conditions at higher demand levels. The poor safety performance associated with cautious AVs is due to the slower process of merging to avoid other vehicles [59]. This slow process of merging produces a queue of vehicles waiting for a safe situation and in turn, causes rear-end conflicts. A similar trend of rear-end conflicts between actual AVs and human-driven cars in the real world [60]. In contrast, the lesser conflicts by aggressive AVs are associated with higher acceleration and lower deceleration values [61]. These vehicles are considered more flexible in avoiding crashes due to their aggressive driving behaviour. Also, better operational conditions produced by aggressive AVs encourage shorter queues and lesser congestion. The improved operational performance results in better safety conditions [62]. Although aggressive AVs have shown better operational and safety performance for congested mixed traffic conditions, however, more testing by considering different network settings and varying penetration rates is needed to draw a more reliable conclusion.



(a) (b)

Figure 10. Queue formation for two vehicle compositions containing; (a) cautious AVs and (b) aggressive AVs

CONCLUSIONS

The study investigated the impacts of different penetration rates of AVs on an urban signalized intersection under mixed traffic conditions. The study employed the VISSIM simulation tool and considered a hypothetical 4-legged signalized intersection with assumed geometric, control and varying demand levels. For the base case, the study assumed a heterogeneous vehicular mix containing 2W, 3W, conventional cars and HVs. Three categories of AVs, i.e., cautious, normal and aggressive were considered to study their impacts on mixed traffic conditions. A total of 60 simulation scenarios were conducted based on varying input demand, proportion and category of AVs. The input demand was varied from 1000 veh/hr to 4000 veh/hr, whereas the penetration rate of each of the AV category was varied from 0% to 100% with an increment of 25%.

The findings show an improvement in the intersection's performance in terms of delay, queue length and speed for higher penetration rates of aggressive AVs, while the conditions get deteriorate with the higher penetration rates of normal and cautious AVs. At lower input demands, all three categories of AVs produced identical results. At demand-3, the penetration rates of cautious AVs greater than 50% show a negative impact on performance. At demand-4, even a small proportion (25%) of cautious AVs can negatively affect the perfomrance, and a similar effect is observed for normal AVs with a penetration rate greater than 75%. A noticeable change in performance can be observed for higher demand levels. The 100% penetration rate of cautious AVs deteriorated the performance and showed an increase in delay and queue length values. A similar trend is observed for normal AVs, and their 100% penetration rate shows an increase of 49.4% in average delay and 55.8% in average maximum queue length and 20% reduction in speed at demand-4 (4000 veh/hr).

For speed, a sharp decline of around 26% in speed is observed for cautious AVs in comparison to base demand (1000 veh/hr) when demand value is increased to demand-3 (3000 veh/hr). A further reduction of 52% in speed is observed for cautious AVs at demand-4 (4000 veh/hr). For normal AVs, a maximum reduction of 20% in speed is observed at the highest demand level. The results for speed are identical with the findings of delay and queue length. It can be observed that the minimum reduction in speed values with the increase in demand is observed for aggressive AVs followed by conventional vehicles, normal AVs and cautious AVs. At demand-4 (4000 veh/hr), the aggressive AVs show a decrease of 10.6% and 16.3% in average delay and average maximum queue length respectively. The aggressive AVs produced better delays, queue length and speed than CVs, cautious AVs and normal AVs at the highest demand levels. In addition to the operational performance, the study also assessed the safety impacts of AVs on mixed traffic. The study concluded that cautious AVs are safest among CVs, normal AVs and aggressive AVs at lower demand levels. Whereas aggressive AVs produced around 67% lesser conflicts than cautious AVs at the highest demand level (4000 veh/hr).

Although this study provided a basis to understand how different proportions of three driving logics of AVs can affect the performance under mixed traffic conditions, there were some limitations that need to be considered for future studies. This study considered hypothetical geometric conditions with the assumption that all the approaches have similar characteristics. The findings of this study need to be validated based on a real-world case having similar characteristics. For each of the considered scenarios, only one category of AV was involved and there were not any considerations for the cases when different proportions of all three driving logics will co-exist in the real-world. Future studies can explore more cases considering the different combinations of cautious, normal and aggressive AVs and CVs. More testing by considering various network settings and varying penetration rates is needed to draw a more reliable conclusion on the safety performance of different driving logics of AVs.

ACKNOWLEDGEMENT

The authors would like to thank the academic and the support staff at the Faculty of Civil Engineering, Universiti Teknologi Malaysia for their continuous support throughout this research

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