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IMPACT OF AUTONOMOUS VEHICLES ON THE PERFORMANCE OF A SIGNALIZED INTERSECTION UNDER DIFFERENT MIXED TRAFFIC CONDITIONS: A SIMULATION-BASED INVESTIGATION

Mohammed Al-Turki[1]*, Nedal T. Ratrout[1], Ibrahim Al-Sghan[2]

[1]Department of Civil & Environmental Engineering, King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia
[2]Ministry of Culture (heritage commission), Eastern province, Saudi Arabia

* moe_kt@hotmail.com

Autonomous driving can overcome the limitations of stochastic human driving behavior. Therefore, implementing autonomous vehicles (AVs) could improve the efficiency of road networks. This study investigates the impacts of AV implementation on the performance of a signalized intersection considering a mixed traffic environment comprising regular vehicles (RVs) and AVs through microscopic traffic simulations. Accordingly, 24 scenarios with different AV implementation rates, AV driving models, and traffic volume conditions, were developed and evaluated using the Vissim simulation software. The results indicated that even partial AV implementation could improve the operational efficiency of a signalized intersection compared to full RV traffic. AV implementation reduced the vehicle delay, stopped delay, and queue length. The expected improvements are primarily based on the implementation rate, and are higher at higher rates (≥50%). The improvements are highest at moderate traffic volumes. Compared to the moderate level, partially replacing RVs with AVs at free-flow conditions does not significantly impact the performance of the intersection. Under congested conditions, the expected improvements from AV implementation are mitigated by the high traffic volumes. Considering the different AV models employed herein, the connected autonomous vehicle (CAV) model exhibited the best performance.

Keywords: autonomous vehicle (AV), connected autonomous vehicle (CAV), mixed traffic environment, signalized intersection, microscopic traffic simulation

1 INTRODUCTION

Traffic problems related to control, safety, and environmental issues are prevalent globally, especially in urban areas. These problems can be primarily attributed to the increased traffic demand [1,2], lack of road infrastructure, inefficient control systems [3], and poor driving behavior [4]. The stochastic human driving behavior associated with regular vehicles (RVs) is a critical factor that affects road capacity [5] and traffic stability [6]. The development of automated driving technologies in recent years has raised the prospect of improving the conventional control of vehicles. Autonomous vehicle (AVs)—a term commonly used to refer to vehicles that are capable of fully automated driving—can replace humans by handling all driving tasks. This can reduce human-related deficiencies and improve the response of vehicles to different control systems. AVs can accurately sense and gather data related to the traffic environment [4]. AVs with connectivity capabilities are commonly referred to as connected autonomous vehicles (CAVs) [7,8]. CAVs are capable of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) interactions that are extremely important for achieving smarter driving behavior [4,9].

AVs occupy the same amount of road space as RVs, but have different and entirely adjustable operational characteristics. Utilizing these characteristics and connectivity capabilities could have significant impacts on future traffic systems. For example, signalized intersection control's design and operational performance could be improved significantly. As AVs have shorter perception and reaction times [10,1], the time lost during the response of a vehicle to traffic signals can be reduced. Consequently, the required yellow change and red clearance intervals can be minimized. As AVs have improved following characteristics, including reduced headways and safe distances [11,1], the road capacity and use of vehicle platooning at intersections can be increased [12]. Considering speed, AVs can maintain the desired design speeds, acceleration, and deceleration rates with low variations [11,13], which can serve to optimize the green phase durations of signal plans effectively. AVs may also perform fewer lane-changing maneuvers in traffic, thereby improving the stability of the traffic flow.

The motivation of the current study is focused on the development and realistic introduction of AVs in the near future. To develop optimal policies for future development of AVs, it is essential to conduct reliable investigations considering various possible scenarios. The expected impacts of AV implementation may be influenced by the AV implementation rate, network-level, and AV characteristics [9]. The related literature indicates that many studies have investigated the impacts of the AV implementation on traffic flow systems. However, the critical analysis of the literature indicates that there is an urgent need for further interpretations to overcome the limitations of the existing research on the expected impacts of AV implementation. The majority of the related studies have primarily assumed fully autonomous traffic environments and few studies have been conducted to evaluate the impacts of partial AV implementation [14]. Although the full implementation of AVs may only occur after several decades, they are expected to gradually enter traffic networks alongside RVs in the near future, resulting in a unique dynamic mixed traffic environment. With respect to traffic network level, most studies have focused on the expected impacts on highway networks and few studies have focused on urban network level. The quality of the traffic flow at signalized intersections may have a significant impact on the level of service across an entire urban traffic network. Evaluating the impacts of AV implementation on signalized intersections could provide valuable insights into the impacts of AVs on the traffic flow characteristics of urban traffic networks [15]. In addition, considering the characteristics of AVs, most studies have focused on the partial automation levels of AV [16,15,17]. Partial automation may help improve human driving behavior using various advanced driver assistance systems [16]. In contrast, full automation can perform all driving tasks without the need for human intervention [9]. The selection of the operational settings is considered a critical factor of the expected impacts of AVs [18,19,20]. Compared to AVs, CAVs may achieve better driving behavior control owing to their ability to acquire data from nearby vehicles.

The literature indicates that investigations focusing on urban networks, primarily under the partial implementation of full automation levels in different traffic conditions, are scarce [9]. To overcome these research limitations, the significant contribution of this study is to investigate and analyze the impacts of introducing AVs in a mixed traffic environment, considering different AV characteristics and gradual implementation rates, under different traffic volume conditions at an urban signalized intersection. It is a more comprehensive study than existing studies and addresses several gaps found in the literature. The expected impacts of partial AV implementation, including high and low rates, are analyzed in addition to its relations with the level of traffic congestion. In addition, the performance of different automated driving capabilities is analyzed and compared.

The real-world implementation of AVs is yet to be realized, and it may be several years before AVs achieve sufficient market penetration and generate enough real-world traffic data to permit detailed studies on AV driving behavior. Consequently, the application of traffic simulation tools is considered to be a suitable alternative for investigating the expected impacts of AVs [21]. Accordingly, a microscopic traffic simulation is performed herein using PTV Vissim (version 11) to evaluate the performance of a signalized intersection considering different performance measures. Studies have shown that the PTV Vissim can accurately mimic the autonomous features of AVs [12,22,17]. So, such a simulator is considered as a reliable alternative that can overcome the absence of real traffic data that represents mixed AV traffic conditions. Therefore, the results presented herein can be treated as a preliminary theoretical experiment with the use of microscopic traffic simulations.

2 RELATED WORKS

Various studies have investigated the potential impacts of AV implementation on traffic flow characteristics [9]. Owing to the lack of real traffic data on AV traffic environments, most of these studies have been modeling or simulation-based studies, considering different AV traffic environments with different AV characteristics, AV implementation rates, and network levels.

Most studies have focused on the expected impacts of different AV models on highway networks, under fully autonomous or mixed traffic environments [23,24,25,26,27,28,29,30,31,32,33,34,35,36,5,37,13,38]. Some studies have also focused on the impacts of AVs on urban networks [9]. Some of these have considered the impacts of partial automation levels, such as adaptive cruise control (ACC) or cooperative adaptive cruise control (CACC). Tientrakool et al. (2011) investigated the impacts of full ACC and CACC implementation on the performance of an urban signalized intersection [39]. They revealed that compared to full RV traffic, full ACC implementation increased the capacity of the intersection by 43%, whereas full CACC implementation increased the capacity by 273%. Bailey and Kroll (2016) observed that different behavioral models and AV parameters, as well as the implementation rate, had different impacts on the traffic flow at an urban signalized intersection [15]. Cao et al. (2021) discovered that increasing the implementation rate of CACC in urban roads can significantly improve the traffic flow efficiency by reducing the queue length and travel time [40].

Some researchers have investigated the impacts of full automation levels of AVs, including CAVs, at the network level [9]. Most of these investigations have been performed considering a full AV implementation environment. Bohm and Häger (2015) investigated the impacts of AVs on the traffic capacity of an urban network [4]. They revealed that when the traffic volume was high, compared to a full RV environment, a full AV traffic environment reduced the delay and number of stops by 56% and 54%, respectively, and increased the speed by 34%. However, when the traffic volume was low, the full AV environment had slightly negative impacts. B. Friedrich (2016) used mathematical modeling and discovered that, compared to a full RV traffic environment, a full AV environment increases the capacity of an urban network increases by 40% [41].

There have been few studies on the impacts of different full automation levels at the networks level with mixed traffic environments [9]. However, these studies have either considered a single AV model or assumed fixed traffic conditions of either traffic volume or implementation rate of AV. Le Vine et al. (2015) observed that AVs with smoother acceleration/deceleration rates had negative impacts on the traffic capacity and increased traffic delays at a signalized intersection [42]. Levin and Boyles (2016) revealed that the implementation of AVs can improve the applied intersection control performance [43]. For a single intersection, the delay decreased linearly with the increase in the AV implementation rate from 0 to 60%; however, above this threshold, the delay remained relatively constant. In contrast, for multiple intersections, higher AV implementation rates (above 80%) were required to improve the control performance. B. Friedrich (2016) discovered that as the AV implementation rate increases, the capacity of the intersection increases [41]. They attributed this to the shorter headways between AVs. A single RV in a mixed traffic environment can decrease the average speed and capacity of the network. Peter Wagner (2016) also investigated the impacts of AVs on a signalized intersection and found that in high volume scenarios, the capacity of the traffic signal doubled [44] . However, at low traffic volumes, the AVs did not offer any improvement. Elvarsson (2017) observed an improvement in the network performance up to an AV implementation rate of 40% [45]. However, above an implementation rate of 60%, the performance of the network decreased. Sukennik et al. (2018) investigated the impacts of AVs on the traffic flow in an urban network comprising single-lane roads without any signalized intersections [12]. They demonstrated that the increase in road capacity in a low-speed environment is moderate and the AV implementation rate has an approximately linear impact on the capacity of the network. Fakhrmoosavi et al. (2020) investigated the impacts of CAVs considering spatially- and temporally-varying distributions of different vehicle types and different CAV implementation rates [14]. They found that higher implementation rates of connected vehicles (CVs) and CAVs led to significant improvements in the flow, capacity, and stability of traffic. Furthermore, AVs had a higher impact than CVs, particularly at lower RV implementation rates. Lu et al. (2020) found that the capacity, stability, and flow of traffic slowly increased with the increase in the CAV implementation rate [1]. Notably, above an implementation rate of 40%, the improvement in the traffic characteristics increased significantly. Maryam et al. (2021) investigated the impacts of AVs on the safety and operation of urban arterial roads [2]. They discovered that the implementation of AVs significantly improves the traffic density, especially at high traffic volumes. The increase in the AV implementation rate significantly reduced the number of rear-end and lane-changing conflicts. P. Liu and Fan (2021) investigated the impacts of CAVs at signalized intersections considering a mixed traffic composed of RVs, AVs, and CAVs [46]. They revealed that the implementation of CAVs with a proposed speed control strategy reduced vehicle delays even at lower CAV implementation rates. Song et al. (2021) investigated the impacts of different AV models on the performance of fixed and actuated signalized intersections [47]. They observed that CAVs with CACC systems can outperform AVs with ACC or intelligent driving model (IDM) systems and could reduce delays in low and high demand scenarios by 49% and 96%, respectively. With CACC systems, a significant reduction in delays was observed at an implementation rate of 20%. However, with ACC and IDM systems, a significant reduction in delays was only observed at high implementation rates. Obaid (2021) found that that AV implementation could significantly reduce the total daily delay and increase the average network speed [48].

These studies indicate that the relationship between the implementation of AVs and their expected impacts in a mixed traffic environment is complex and based on different factors [9]. The implementation rate of AVs has a significant effect on its expected impact [27,43,11,33,1,38,5,37]. Most studies have confirmed that the expected improvement increases with the increase in the implementation rate. The connectivity capabilities of AVs can affect their performance, which in turn affects their impact on the traffic system [30,35,8]. The implementation of CAVs achieves greater improvements than that of AVs owing to their advanced communication capabilities that enable the acquisition of more traffic information, which can be used to improve their driving behavior [9]. The driving behavior models and operational settings of AVs may also affect their performance [15,35,18,30,19,32,42,49]. In addition, the traffic volume conditions may also affect the impacts of AVs [4,50]. Various studies have shown that human driving behavior in mixed traffic environments can also affect the impacts of AVs [35,38,51,37,20]. The findings from different studies have indicated that the network level also affects the expected impact of AV implementation [35,8].

3 METHODOLOGY

The general methodology of the study is shown in (Fig. 1). First, the experimental design was developed based on the objectives of the study. Different traffic volume levels, network configurations, traffic signal plans, and vehicle models were developed for the simulation using Vissim. After setting up the simulation environment, the required inputs were assigned to each simulation scenario. Subsequently, the simulation was performed, and different performance measures were recorded. Finally, the results were summarized, presented, and analyzed, considering the main objectives of the study. Each step of the methodology is explained in detail in the following sub-sections.

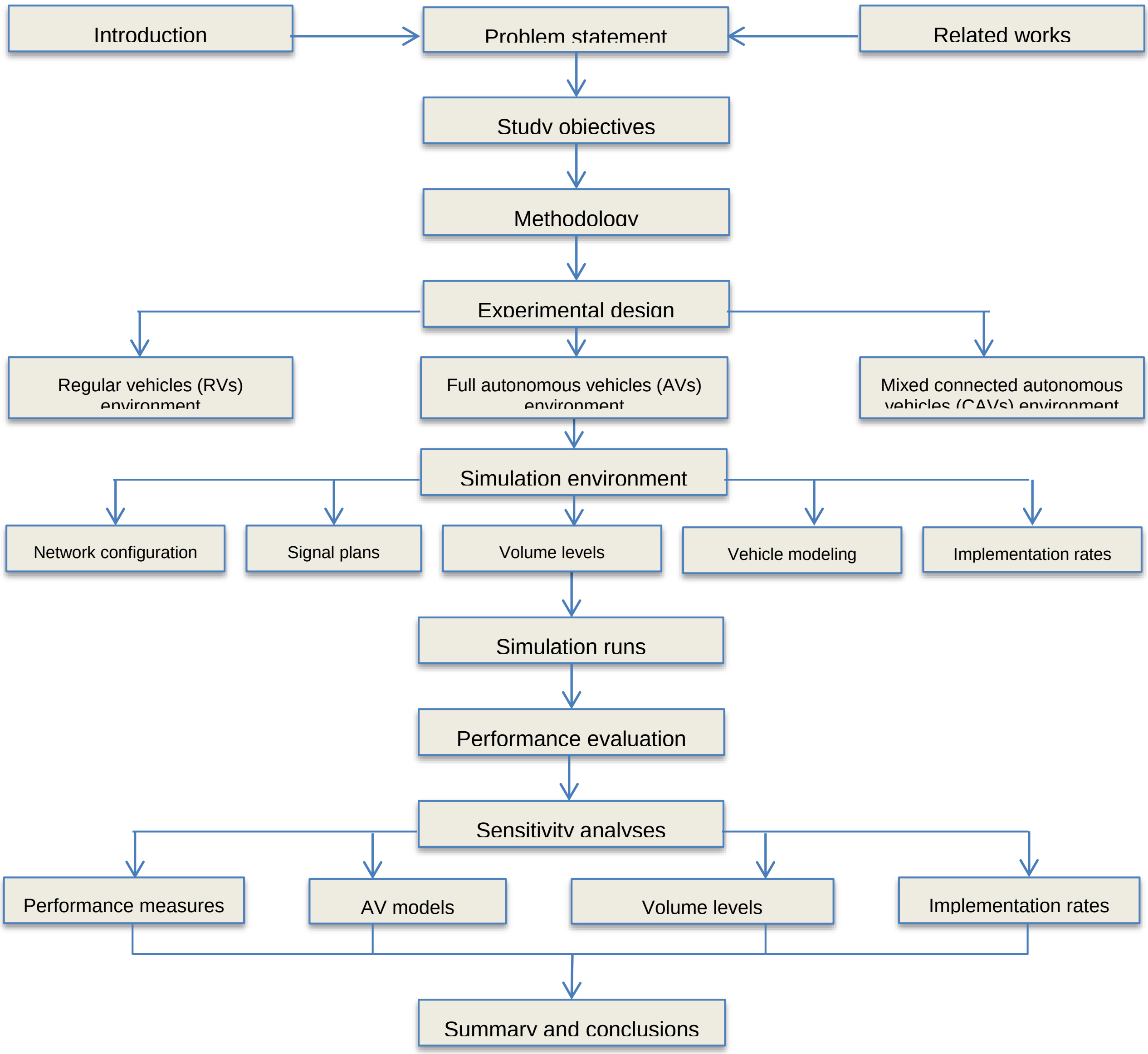


Fig. 1. General methodology of the study

3.1 Experimental design

The aim of this study is to investigate the impacts of AV implementation under different traffic conditions. Accordingly, the experimental design of the simulation scenarios includes three primary inputs. First, three traffic volume levels were considered to represent different traffic volume conditions. Second, three different driving behavior models were considered to represent the different characteristics of AVs. Third, to represent different CAV implementation levels, six different implementation rates (%) were considered herein: 0, 10%, 25%, 50%, 75%, and 100%. A total of eight simulation scenarios were developed and simulated considering the same network. The details of each scenario are listed in (Table 1). Each scenario was evaluated under three different traffic volumes, resulting in a total of 24 simulation scenarios.

Table 1. Description of the simulation scenarios

Scenario No.	Traffic composition	Scenario Description
1	100% RV	Full regular traffic
2	100% AV (aggressive)	Full AV (aggressive) traffic
3	100% AV	Full AV traffic
4	100% CAV	Full CAV traffic
5	90% RV–10% CAV	Mixed traffic environment with low CAV implementation rate
6	75% RV–25% CAV	Mixed traffic environment with low CAV implementation rate

Scenario No.	Traffic composition	Scenario Description
7	50% RV–50% CAV	Mixed traffic environment with equally shared traffic
8	25% RV–75% CAV	Mixed traffic environment with high CAV implementation rate

3.2 Traffic volume levels and turning options

The three traffic volume levels considered herein are Low, Med, and High. The High level represents traffic conditions with a moderate level of traffic congestion (level of service (LOS) = E) at a signalized intersection. The LOS levels defined herein are based on the results of the average vehicle delay and are comparable to the LOS defined in the American Highway Capacity Manual of 2010. The Low level represents almost free-flow conditions (LOS = B). The total traffic volume in the Low level was 10% of that in the High level. The Med level represents a moderate level between the High and Low levels, with a total traffic volume of 50% of that of the High level (LOS = C). These levels were implemented using different traffic approaches, with different hypothetical traffic volumes for a given level. However, the movement and lane distribution rates were similar for each approach. The details of the traffic volume levels (vehicles/h) are shown in (Table 2). The number of vehicles used to represent the three volume levels, in addition to the movement and lane distributions, were selected based on the volume data recorded at a similar intersection in a previous study [3].

Table 2. Traffic volumes (vehicles/h) at the intersection

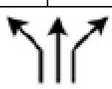
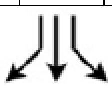
Volume level	Movement	Approach			
		Eastbound	Westbound	Northbound	Southbound
High	Left	300	264	312	288
	Through	600	528	624	576
	Right	100	88	104	96
	Total	1000	880	1040	960
Med	Left	150	132	156	144
	Through	300	264	312	288
	Right	50	44	52	48
	Total	500	440	520	480
Low	Left	30	26	31	29
	Through	60	53	62	58
	Right	10	9	10	10
	Total	100	88	104	96

3.3 Simulation environment

3.3.1 Signalized intersection configuration and control

The primary aim of this study is to investigate the impacts of AV implementation at an urban signalized intersection. To represent a typical common signalized intersection, a hypothetical isolated four-leg signalized intersection was created in Vissim. Each road approaching the intersection comprises three lanes in each direction. The roads were connected using suitable connectors to replicate all the movements that occur at a typical signalized intersection. The signalized intersection is controlled by a traffic signal with a four-phase fixed plan with protected left turns. To ensure the safe operation, vehicles are allowed to move through from any lane, turn left only from the left lane, and turn right only from the right lane. To reliably evaluate the impact of AVs on the signal performance, three signal plans were created for each of the three volume levels. Each signal plan included four signal groups with the same phase sequence. The cycle length for each plan was optimized using the empirical equation developed by the Transport Research Laboratory (TRL) considering the critical-lane traffic volumes [52]. The effective green times were calculated based on the degree of traffic in each approach [52]. The detailed signal plans are shown in (Table 3).

Table 3. Detailed signal plans

Signal group	Northbound			Southbound			Westbound			Eastbound		
Phase	R	G	A	R	G	A	R	G	A	R	G	A
Phase sequences												
Traffic volume level/Phase duration												
Low (C = 32)	0	6	3	0	5	3	0	4	3	0	5	3
Med (C = 42)	0	9	3	0	8	3	0	6	3	0	7	3
High (C = 210)	0	51	3	0	50	3	0	48	3	0	49	3

* C: Cycle length (s), R: Red (s), G: Green (s), A: Amber (s)

3.3.2 Performance measures

The performance of the signalized intersection was evaluated using four performance measures that are reported by Vissim as node evaluation attributes. These are, the average vehicle delay (s), average stopped delay (s), average number of stops, and average queue length (m). The average vehicle delay, which has been widely used in previous studies to measure the LOS, is defined as the additional time required for a vehicle to cross the intersection. It is obtained by subtracting the theoretical travel time from the actual travel time. The average stopped delay (per vehicle) is defined as the waiting time spent in the queue from the instant a vehicle is stopped by a red signal till the signal turns green.

3.3.3 Simulation set-up and parameters

The traffic simulations were conducted using PTV Vissim, which is a microscopic traffic simulation software package. The Vissim software includes the mathematical models required to run traffic flow models [53]. A recent version (Version 11) of Vissim, which includes advanced built-in features such as AV modeling [21], was used herein. Considering the modeling of automated driving behavior, Vissim offers a significant advantage as it includes several adjustable parameters that can be effectively used to simulate different AV models [4]. Each simulation scenario was run for 5400 s (1.5 h). To saturate the system and eliminate the start-up period, the results were only recorded after 3600 s (1 h). The final results of the recorded performance measures for each scenario were based on the average of the simulation runs.

3.4 Vehicles and driving behavior models

In microscopic traffic simulations, the driving behavior is represented and governed by various functions, distributions, and driving parameters [15,21]. Accordingly, different functions of the desired acceleration and deceleration were created and assigned to the RVs and AVs. Also, three desired speed distributions were created and assigned to the RVs and AVs. The acceleration, deceleration and speed values are stochastically selected for the RVs, whereas for the AVs, considering their deterministic behavior and ability to maintain the desired settings, the values are constant. The different speed distributions of the RVs and AVs are shown in (Fig. 2).

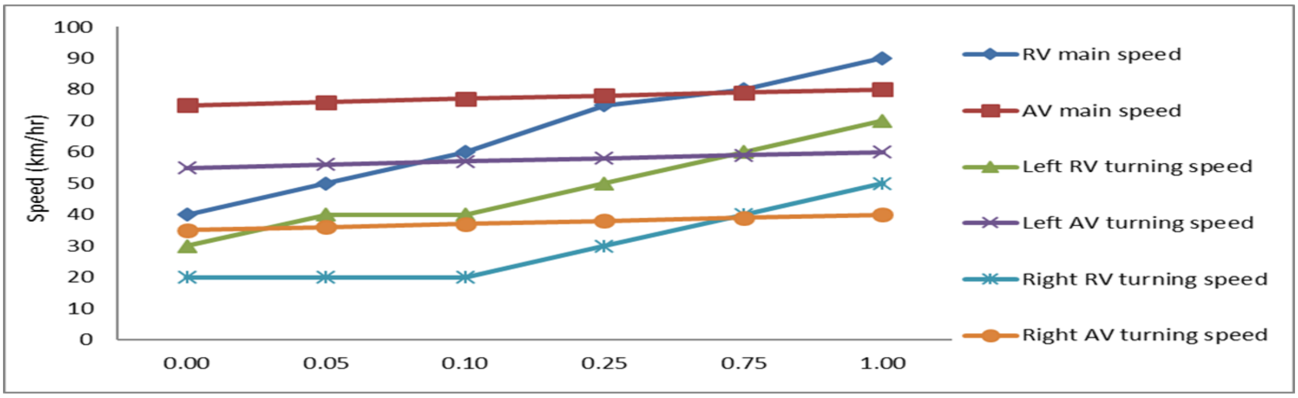


Fig. 2. Probability of different speed distributions of the RVs and AVs

The driving models control the different driving behaviors of the vehicles such as car following, lane changing, gap acceptance, and vehicle behavior at a traffic signal. One driving behavior model was considered herein to represents typical human driving behavior (RV model). The default settings of the default urban driving behavior in Vissim were used for the RV model. However, the reaction time distribution was adjusted to more realistically simulate human driving behavior at a traffic signal. Compared to the RV, the AV are expected to maintain shorter space and time headways [1] between vehicles with no oscillations in its following behavior [12,17]. Considering reaction times, AVs have more accurate and faster reactions than RVs [43,12,50]. Overall, they are expected to have better and more stable driving behavior than RVs.

Unlike RVs, there is a lack of real data relating to AV driving behavior. Consequently, the behavioral models of the AVs in the simulations are hypothetical and primarily determined from various logical assumptions available in the literature [22]. To model the car-following behavior of the AVs in Vissim, Wiedemann 99 model was selected as the base model [4,54,12]. The Wiedemann 99 model is a psycho-physical model that assumes a linear relationship between speed and following distance [22,53]. The parameters of the model can be adjusted to model the AV car-following behavior at different network levels including urban network [12,17]. Zeidler et al. (2019) analyzed the real data of the standstill distances (CC0) and headway (CC1) used in ACC and CACC models operating in real-world scenarios [22]. The following behavior of these models was compared to the simulated following behavior of the Wiedemann 99 model in Vissim. The results indicated that the behavior of the CACC model is reproduced well in Vissim. Several AV-related features in Vissim have been implemented within CoEXist project. The results, from the field data, showed that there is a linear relationship between headway and speed when the AV is following RVs or AVs [17]. Sukennik et al, (2020) recommended different settings to model the AV-related features and it`s driving behavior [17]. Different studies have used Wiedemenn 99 car-following model to model AV behavior at signalized intersections of mixed traffic environment [55,56,57].

To represent different autonomous driving characteristics, three AV models were considered herein as representative models: AV (aggressive), AV, and CAV. The AV (aggressive) model is a default AV model present in Vissim 11. The different settings of this model were proposed by PTV based on empirical studies and co-simulation data recorded in a mixed traffic environment under the CoExist project [17]. The AV and CAV models were new models that were created by adjusting the default settings of the driving behavior parameters, based on the autonomous features of full AV obtained from the literature [4,29,15,43,50,55,22,56,1,21]. The AV model represents unconnected AV driving behavior, which is similar to the RV driving behavior, but with improved and deterministic operational behavior. The CAV model represents connected AV driving behavior, which is similar to the AV driving behavior, but with improved operational behavior owing to its connectivity capabilities. Table 4 shows the main settings of the driving behavior models employed herein.

Table 4. Driving behavior settings of the driving models

Attribute	Driving model			
	RV	AV (aggressive)	AV	CAV
Following Behavior				
Max look-ahead distance (m)	250	300	250	300
Number of interaction objects	4	10	2	10
Number of interaction vehicles	99	8	1	8
Use implicit stochastics	On	Off	Off	Off
Car following behavior (based on the Wiedemann 99 model)				
CC0: Standstill distance (m)		1.00	0.50	0.50
CC1: Headway time (s)		0.60	0.90	0.50
CC2: Following distance oscillation (m)		0.00	0.00	0.00
CC3: Perception threshold for following (s)		−6.00	−8.00	−6.00
CC4: Negative speed difference (m/s)		−0.10	−0.10	−0.10
CC5: Positive speed difference (m/s)		0.10	0.10	0.10
CC6: Speed dependency of Oscillation (1/(m/s))		0.00	0.00	0.00
CC7: Oscillation acceleration (m/s^2)		0.10	0.10	0.10
CC8: Standstill acceleration (m/s^2)		4.00	3.8	3.8
CC9: Acceleration at 80 km/h (m/s^2)		2.00	1.50	2.00
Behavior at traffic signal				
Desired position at free flow	Continuous checking	One decision	One decision	One decision
Behavior at red/amber signal	Go	Stop	Stop	Stop
Reaction time distribution (s)	0.50–2.00	0.00	0.00	0.00

4 RESULTS

The simulation results of the signalized intersection performance are presented in this section. The performance measures recorded for each simulation scenario under each volume level (Low, Med, and High) are the average vehicle delay, average stopped delay, average number of stops, and average queue length. These measures are key indicators of the impacts of AV implementation on the performance of the intersection. First, we evaluated the performance with the full implementation of the RV and AV models (four scenarios). The results at different volume levels are shown in (Table 5). Subsequently, we evaluated the performance considering different implementation rates of the CAV model in a mixed traffic with RVs (four scenarios). The results at different volume levels are shown in (Table 6).

Table 5. Results of signalized intersection performance with full implementation

Performance measure	Low volume	Med volume	High volume
100% RV			
Vehicle delay (s)	13.42	23.79	78.54
Stopped delay (s)	5.61	13.05	65.78

Performance measure	Low volume	Med volume	High volume
Queue lengths (m)	0.29	3.51	29.94
Number of stops	0.56	0.86	0.93
Level of service (LOS) (A–F)	B	C	E
100% AV (Aggressive)			
Vehicle delay (s)	11.48	16.50	69.12
Stopped delay (s)	4.11	8.09	57.95
Queue lengths (m)	0.23	2.00	24.14
Number of stops	0.49	0.65	1.08
LOS (A–F)	B	B	E
100% AV			
Vehicle delay (s)	11.49	17.47	66.61
Stopped delay (s)	4.08	8.49	55.57
Queue lengths (m)	0.23	1.94	20.64
Number of stops	0.49	0.72	1.30
LOS (A–F)	B	B	E
100% CAV			
Vehicle delay (s)	11.41	16.14	66.68
Stopped delay (s)	4.03	7.68	56.46
Queue lengths (m)	0.23	1.80	21.22
Number of stops	0.48	0.65	0.95
LOS (A–F)	B	B	E

Table 6. Results of signalized intersection performance with different CAV implementation rates

Performance measure	Low volume	Med volume	High volume
90% RV–10% CAV			
Vehicle delay (s)	13.12	22.85	78.04
Stopped delay (s)	5.37	12.56	65.39
Queue lengths (m)	0.27	3.06	29.43
Average number of stops	0.54	0.83	0.95
LOS (A–F)	B	C	E
75% RV–25% CAV			
Vehicle delay (s)	12.87	21.48	75.23
Stopped delay (s)	5.22	11.62	62.98
Queue lengths (m)	0.27	2.78	27.39
Average number of stops	0.55	0.80	0.94
LOS (A–F)	B	C	E
50% RV–50% CAV			
Vehicle delay (s)	12.27	18.94	72.32
Stopped delay (s)	4.83	9.81	60.96
Queue lengths (m)	0.26	2.31	25.14
Number of stops	0.52	0.73	0.95
LOS (A–F)	B	B	E
25% RV–75% CAV			
Vehicle delay (s)	11.41	17.17	69.02

Performance measure	Low volume	Med volume	High volume
Stopped delay (s)	4.27	8.57	58.21
Queue lengths (m)	0.23	2.02	23.01
Number of stops	0.49	0.67	0.94
LOS (A–F)	B	B	E

5 DISCUSSION

5.1 Impacts of full AV implementation

A sensitivity analysis was performed to investigate the impacts of full AV implementation by analyzing the obtained results. Accordingly, the effectiveness of each designed AV model was evaluated relative to the base scenario (100% RV). The impacts of the different AV characteristics were compared as well. Figures 3–6 depict the vehicle delay, stopped delay, number of stops, and queue length, respectively, after the full implementation of the models under different volume levels.

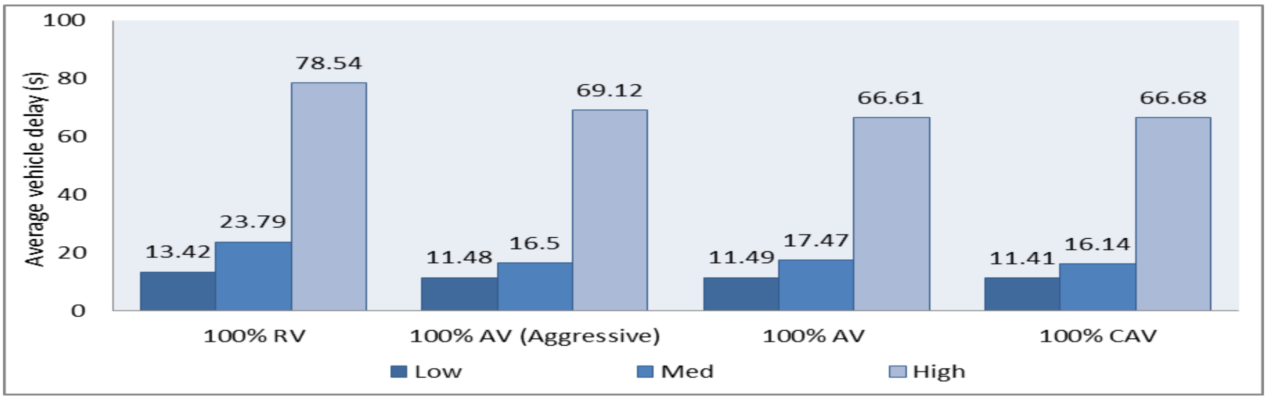


Fig. 3. Average vehicle delay with full implementation under different volume levels

Considering the vehicle delay, as shown in (Fig. 3), at the Low volume level, the three AV models performed better than the RV model, with an average delay of 11.46 s. At the Med volume level, the performance of the three AV models differed slightly, with an average delay of 16.70 s. At the High volume level, the three AV models exhibited an average vehicle delay of 67.47 s. Considering the stopped delay, as shown in (Fig. 4), at the Low volume level, the three AV models had almost the same positive impact. At the Med volume level, the three AV models significantly reduced the stopped delay. At the High volume level, all three AV models exhibited improved performance compared to the base scenario. Considering the number of stops, as shown in (Fig. 5), at the Low volume level, the three AV models performed better than the RV model, exhibiting almost the same values, with an average of 0.49. At the Med volume level, the three AV models reduced the number of stops compared to the RV model. At the High volume level, the implementation of the three AV models did not reduce the number of stops, which is an unexpected result. Considering the queue length, as shown in (Fig. 6), at the Low volume level, the three AV models performed better than the RV model, with the same value of 0.23 m. At the Med volume level, the performance of the three AV models differed slightly, with an average value of 1.91 m, which represents a significant improvement compared to the base scenario. At the High volume level, the three AV models had almost similar impacts on the queue length.

In summary, the queue length experienced the highest positive improvement after full AV implementation under all volume conditions; in contrast, the number of stops experienced the least positive impact. Full AV implementation reduced the number of stops at the Low and Med volume levels, whereas at the High volume level, full AV implementation slightly increased the number of stops. At the Low and Med levels, the stopped delay experienced the second highest improvement after the queue length.

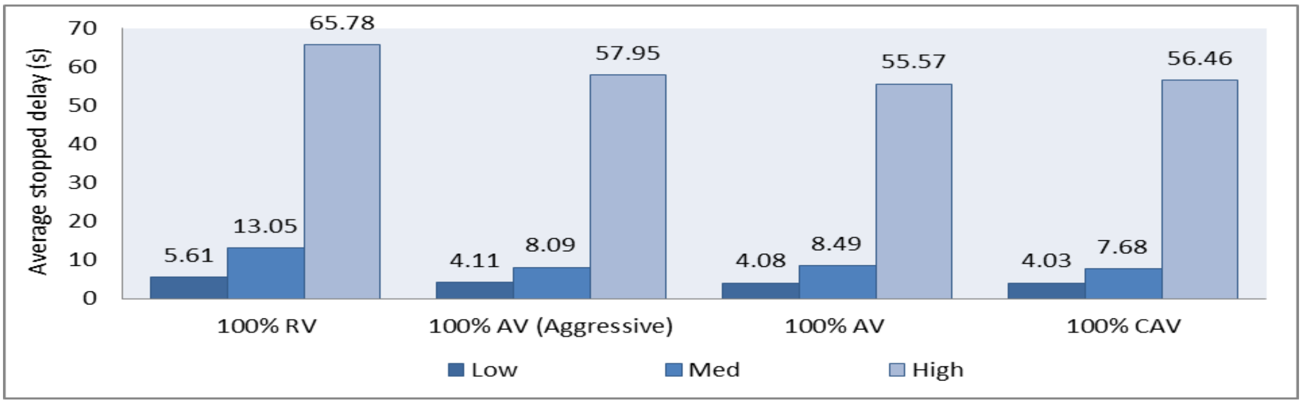


Fig. 4. Average stopped delay with full implementation under different volume levels

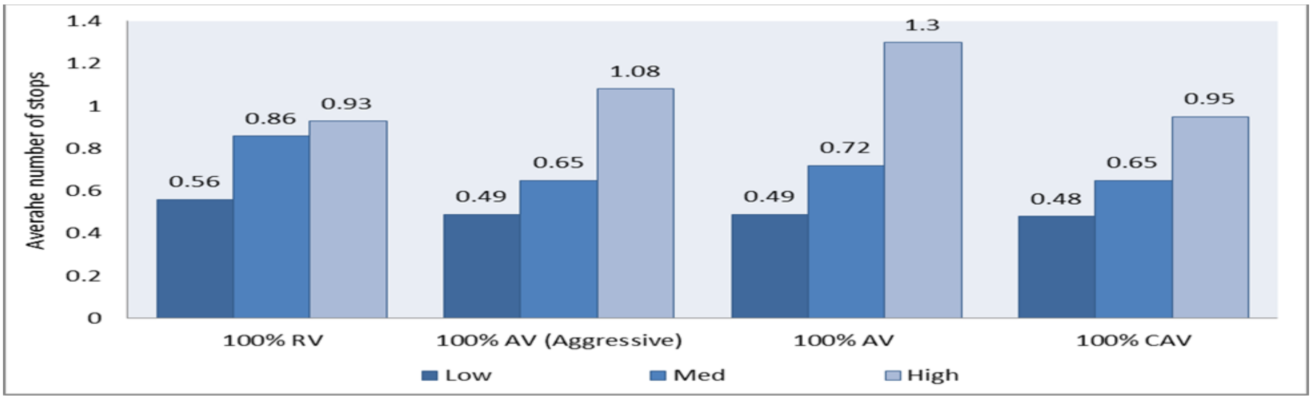


Fig. 5. Average number of stops with full implementation under different volume levels

The level of improvement derived from full AV implementation depends on the traffic volume conditions. The expected improvement was higher at the Med volume level compared to the Low of High volume levels. At the Low volume level, full AV implementation reduced the vehicle delay, stopped delay, number of stops, and queue length by 14.60%, 27.45%, 12.50%, and 20%, respectively; at the Med volume level, the corresponding reductions were 29.80%, 41.21%, 24.42%, and 48.72%, respectively; at the High volume level, the corresponding reductions were 14.10%, 13.86%, −2.00%, and 31.02%, respectively. Comparing the Low and High volume levels, the extent of positive improvement varies. The stopped delay and number of stops experienced higher improvement at the Low level, whereas the queue length experienced higher improvements at the High level. Both these volume levels lead to similar improvements in the vehicle delay.

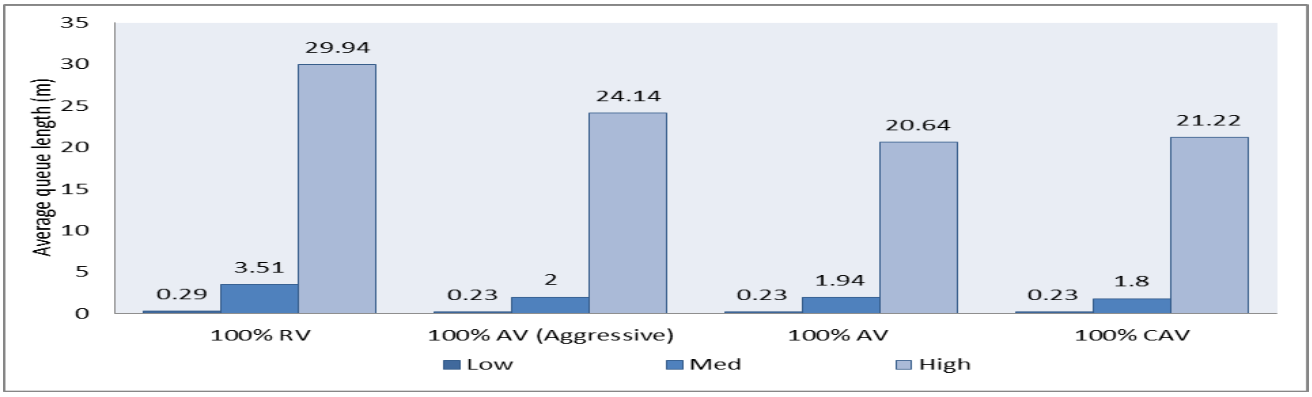


Fig. 6. Average queue length with full implementation under different volume levels

Comparing the impacts of the three AV models applied herein, in general, they had comparable performance with no significant differences between them. At the low volume level, the three models almost showed similar performance. At the Med and High volume levels, their performance differed slightly. The CAV model slightly outperformed the other two AV models. The superiority of the CAV model in terms of the reduction in the vehicle and stopped delays and queue length were significant at the Med volume level. At the High volume level, the AV model provided a higher reduction in the stopped delay and queue length, whereas the CAV model provided a higher reduction in the number of stops. At this level, all three AV models had similar impacts on the vehicle delay.

Compared to the RV model, the improvements offered by the three AV models can be primarily attributed to their deterministic driving behaviors and the lack of variation in their driving settings. The constant speed distributions and uniform deceleration and acceleration functions of the AV models did not influence their performance. However, the operational driving settings had a significant effect on their performance. In particular, the results indicated that the following longitudinal distance oscillation and the reaction time distribution at a signal made the highest contributions to the performance of the AV models.

5.2 Impacts of partial AV implementation

The results of the full implementation indicated that, in general, the applied AV models have similar impacts on the intersection performance. However, the CAV model performed slightly better than the others. Consequently, the CAV model was used to investigate the impacts of different AV implementation rates. A sensitivity analysis was performed to investigate the impacts of partial AV implementation on the performance measures. Specifically, the effectiveness of different CAV implementation rates, compared to the base scenario, under different volume levels, was evaluated herein. The implementation rates of 10% and 25% represent low implementation rates, a 50% implementation rate represents an equally shared traffic environment with RVs, and a 75% implementation rate represents a high implementation rate. Figures 7–10 depict the vehicle delay, stopped delay, number of stops, and queue length, respectively, considering different CAV implementation rates, under different volume levels.

Considering the vehicle delay, as shown in (Fig. 7), at the Low volume level, the delay decreased slightly (from 13.42 s to 11.41 s) as the CAV implementation rate increased from 0 to 100%. At an implementation rate of 25%, the delay was 4% lesser than that of the base scenario. At rate of 75%, the CAV model provided an improvement of 15%. At the Med volume level, the vehicle delay decreased significantly (from 23.79 s to 16.14 s) as the CAV implementation rate increased. At an implementation rate of 25%, the delay decreased by approximately 10% compared to the base scenario, however, at rate of 75%, the delay decreased by approximately 28%. At the High volume level, the delay decreased from 78.54 s to 66.68 s as the CAV implementation rate increased. At an implementation rate of 10%, the reduction in the delay was minimal. At rates of 25% and 75%, the delay decreased by approximately 4% and 12%, respectively, compared to the base scenario. Considering the stopped delay, as shown in (Fig. 8), at the Low volume level, the delay decreased from 5.61 s to 4.03 s as the CAV implementation rate increased from 0 to 100%. At an implementation rate of 75%, the delay decreased by approximately 24% compared to the base scenario. At the Med volume level, the delay decreased significantly (from 13.05 s to 7.68 s) as the CAV implementation rate increased. At low implementation rates, the improvement derived from CAV implementation compared to the base scenario was small. In contrast, at high rates, the implementation of the CAV provided significant improvement. At an implementation rate of 75%, the improvement was approximately 34%. At the High volume level, the delay decreased from 65.78 s to 56.46 s as the CAV implementation rate increased. At an implementation rate of 10%, the reduction in the delay was small, however, at higher rates, the reduction increased significantly. At an implementation rate of 75%, the reduction in the delay was approximately 11.50%.

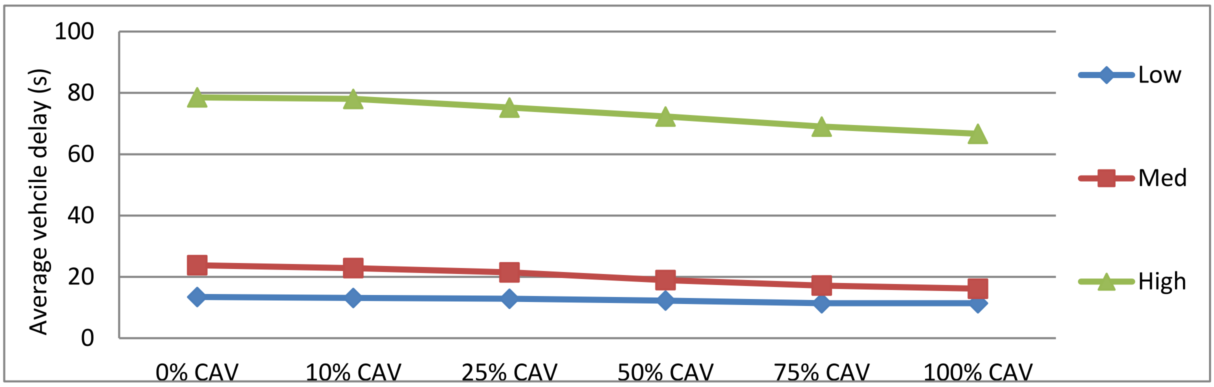


Fig. 7. Average vehicle delay with different CAV implementation rates under different volume levels

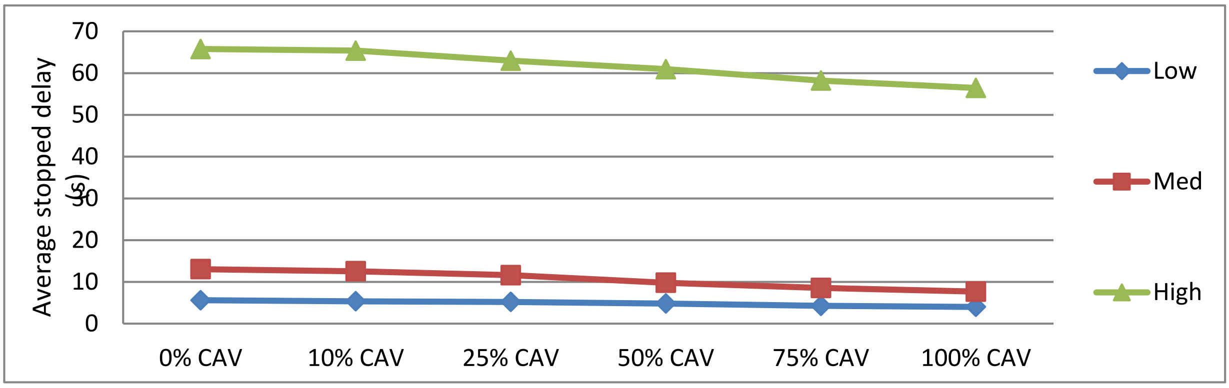


Fig. 8. Average stopped delay with different CAV implementation rates under different traffic volume levels

Considering the number of stops, as shown in (Fig. 9), at the Low volume level, the number of stops decreased slightly (from 0.56 to 0.48) as the CAV implementation rate increased from 0 to 100%. At low implementation rates

(10% and 25%), the number of stops were similar, with an average value of 0.545. At a rate of 75%, the number of stops decreased by approximately 12.5% compared to the base scenario. At the Med volume level, the number of stops decreased from 0.86 to 0.65 as the CAV implementation rate increased. At low implementation rates, the improvement derived from CAV implementation, compared to the base scenario, was minimal. At high implementation rates, the improvement derived from CAV implementation was more significant. At a rate of 75%, the improvement was approximately 24.50%. At the High volume level, the number of stops did not decrease regardless of the implementation rate, which is an unexpected result. As the CAV implementation rate increased, the number of stops varied between 0.95 and 0.94. At an implementation rate of 75%, the number of stops increased by 1% compared to the base scenario. Considering the queue length, as shown in Figure 10, at the Low volume level, the queue length decreased slightly (from 0.29 m to 0.23 m) as the CAV implementation rate increased from 0 to 100%. At low implementation rates, the queue lengths decreased by approximately 7% compared to the base scenario. At a rate of 75%, the queue length decreased by approximately 21% compared to the base scenario. At the Med volume level, the queue lengths decreased significantly from 3.51 m to 1.80 m as the CAV implementation rate increased. At an implementation rate of 75%, the reduction in the queue length was approximately 42.5% compared to the base scenario. At the High volume level, the queue lengths decreased from 29.94 m to 21.22 m as the CAV implementation rate increased. At an implementation rate of 10%, the reduction in the queue length was minimal. Above a rate of 25%, the reduction became more significant. At a rate of 75%, the improvement compared to the base scenario was 23%. Figures 11–14 depict the improvement (%) in the vehicle delay, stopped delay, number of stops, and queue length, respectively, with different CAV implementation rates, under different volume levels, compared to the base scenario.

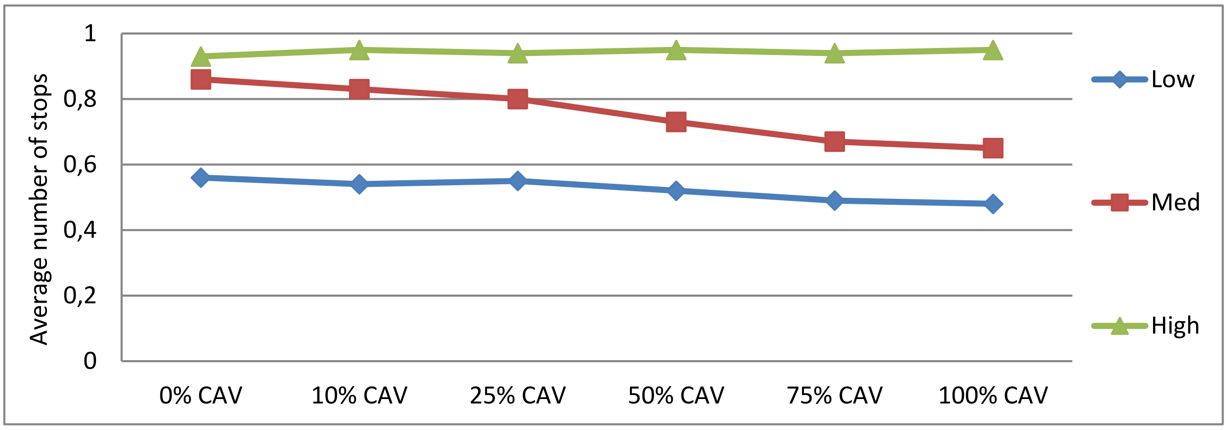


Fig. 9. Average number of stops with different CAV implementation rates under different traffic volume levels

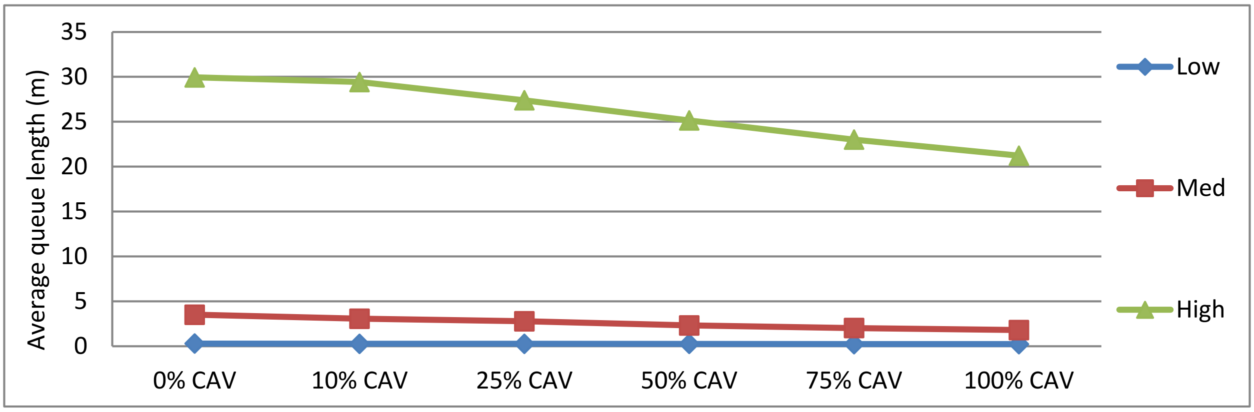


Fig. 10. Average queue length with different CAV implementation rates under different traffic volume levels

In summary, in general, partial AV implementation reduced the vehicle delay, stopped delay, and queue length, regardless of the traffic volume level. However, the number of stops only reduced at the Low and Med volume levels, and increased at the High volume level, regardless of the AV implementation rate.

The level of improvement in performance increases with the increase in the AV implementation rate, and becomes significant at higher implementation rates (50% and above). For example, the results of the vehicle delay at the Med volume level shows that an implementation rate of 50% doubled the improvement achieved at low implementation rates, and a further increase in the implementation rate to 75% provided an additional improvement of 8%. The level of improvement also depends on the traffic volume conditions. The level of improvement is more significant at the Med volume level compared to the other two volume levels. For example, the 75% CAV implementation rate reduced the vehicle delay by almost 28% at the Med volume level, whereas at Low and High levels, the reductions in the delay were only 15% and 12%, respectively. Compared to the Med level, the AV implementation at free-flow conditions indicate that changing the driving behaviors, from RV to AV, of a small number of vehicles does not significantly impact the performance of the intersection. At congested conditions, the expected impacts of the improved driving behavior of AVs are mitigated by the high traffic volumes. The level of positive improvements at the Low and High volume levels varies. Considering the stopped delay and number of stops, the improvement derived from AV implementation is higher at the Low volume level. Considering the queue length, the improvement derived from AV implementation is higher at the High volume level. Considering the vehicle delay, both Low and High volume levels provide similar improvements.

Partial AV implementation has a more significant impact on the queue length compared to the other measures at the Med and High volume levels. In contrast, at the Low volume level, partial AV implementation has a stronger impact on the stopped delay. At the Med volume level, the stopped delay experiences the second highest improvement, whereas the vehicle delay experiences the least improvement.

Considering the impacts of AV implementation on the LOS of the signalized intersection at the Low volume level, increasing the implementation rate from 10% to 100% did not improve the LOS compared to the base scenario (LOS remained constant at B). At the Med volume level, at low implementation rates, the LOS did not improve (LOS remained constant at C). However, at higher rates (50% and above), the LOS improved from C to B. At the High volume level, increasing the implementation rate did not improve the LOS (LOS remained constant at E). These findings confirm that AV implementation offers significant improvements at the Med volume level.

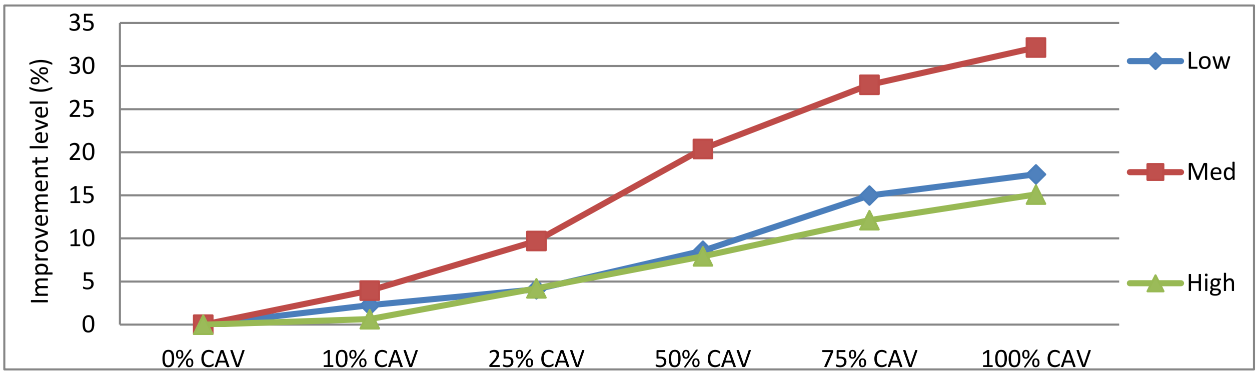


Fig. 11. Improvement in average vehicle delay with different CAV implementation rates under different traffic volume levels

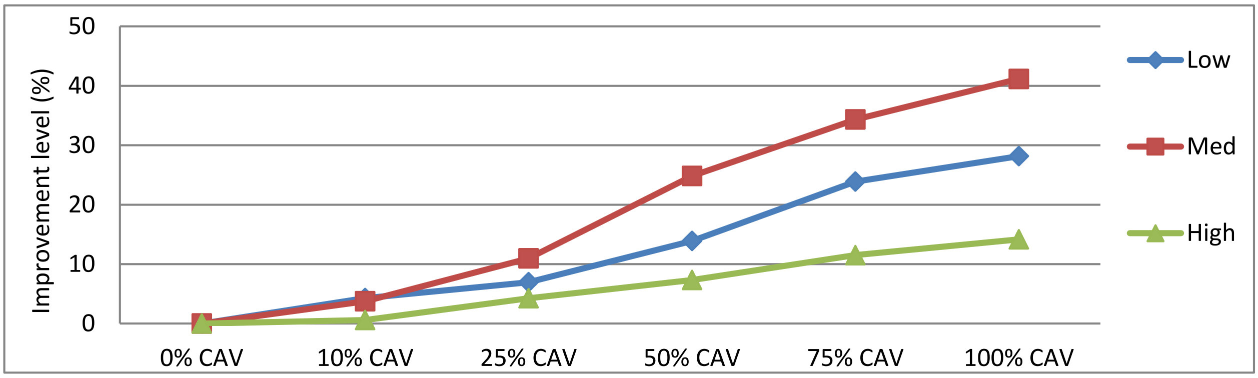


Fig. 12. Improvement in average stopped delay with different CAV implementation rates under different traffic volume levels

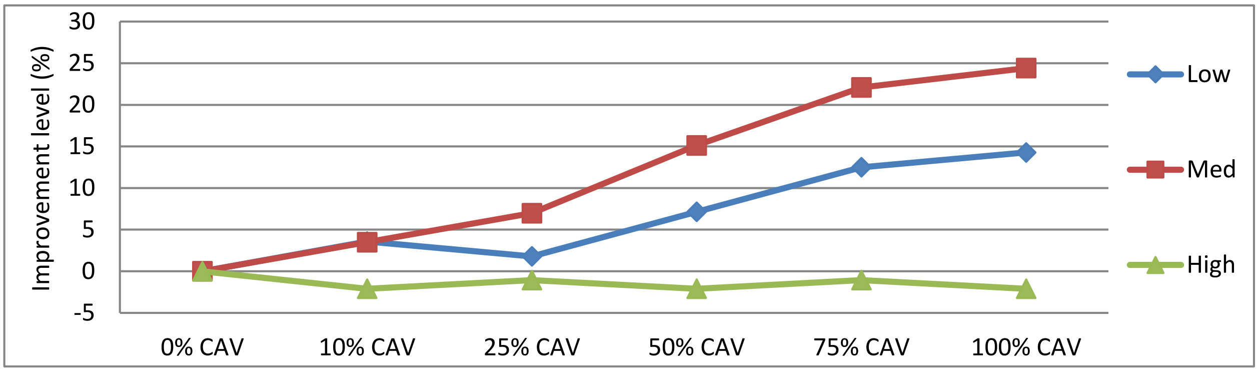


Fig. 13. Improvement in average number of stops with different CAV implementation rates under different traffic volume levels

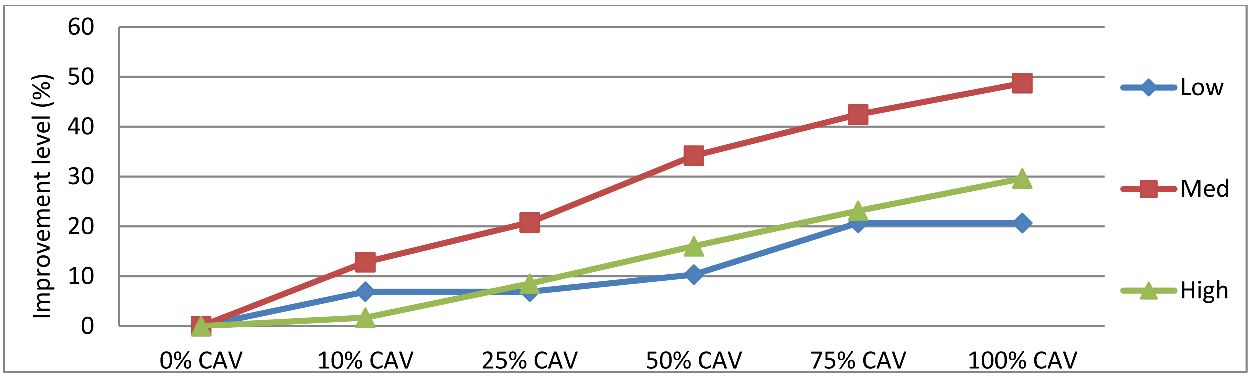


Fig. 14. Improvement in average queue length with different CAV implementation rates under different traffic volume levels

6 CONCLUSIONS

Herein, we performed a simulation-based investigation on the impacts of AV implementation on the performance of an urban signalized intersection under different traffic volume conditions considering a mixed environment comprising AVs and RVs. The results revealed that, compared to full RV traffic, the implementation of different AV models provides significant performance improvements by reducing the vehicle delay, stopped delay, and queue length at a signalized intersection under different traffic volume conditions. Considering different performance measures, the queue length experiences the highest positive improvement; in contrast, the number of stops experiences the least positive impact. The reduction in these key performance measures could reduce pollution, increase safety, and enhance the efficiency of road networks. Even partial AV implementation, including low implementation rates, in a mixed traffic environment provides improvement in the signalized intersection performance. The results revealed that, level of improvement increases with the increase in the AV implementation rate, and becomes significant at higher implementation rates (50% and above). The level of improvement depends on the traffic volume conditions. All the performance measures experienced the highest improvement at the Med volume level. There are no significant differences between the performances of the three AV models especially at the Low and Med volume levels. Nevertheless, the CAV model was slightly superior to the other two AV models particularly in terms of reducing the delay and queue length. This confirms the encouragement of CAV implementation instead of non-connected AVs. Such findings are useful for AV manufacturers or policy makers in order to maximize the AV efficiency.

This study can potentially serve as the starting point for further studies on the impacts of AVs under mixed traffic environments composed of AVs and RVs, which is essential for increasing the efficiency of the AV adoption in the near future. The findings obtained herein can provide new insights into the potential impacts of AV implementation and can be used to design analytical models that incorporate mixed traffic environments in an urban transportation network. These models can be used to improve the efficiency of signalized intersection control by analyzing the relationships between different AV characteristics and traffic signal performance under different traffic conditions. The findings can also be used to compare the behavior of AVs and RVs and their impacts on signalized intersection performance. Furthermore, the findings can help AV manufactures and traffic authorities to program the operational settings of AVs to better optimize AV implementation. However, these findings are based on a single isolated signalized intersection. Consequently, in future studies, the impacts of AV implementation should be evaluated considering different urban network levels, including multiple signalized and non-signalized intersections, as well as other important parameters such as the intersection capacity. The most significant obstacle to AV implementation is the acceptance of fully autonomous driving technologies by human drivers, rather than technical challenges. Although AVs can address several problems associated with RVs, their positive impacts will remain unrealized until they are accepted and trusted by the public. Despite the expected impacts, such as improved traffic flow and reduced environmental emissions [60], drivers may be unwilling to cede control to automated driving systems [61]. Therefore, a high level of trust must be cultivated to ensure the acceptance and widespread use of AVs. The safety of AVs is the biggest concern for most people. Although various studies have demonstrated that AVs can improve safety under mixed traffic conditions [62], further studies are required to highlight this aspect and increase driver acceptance.

7 ACKNOWLEDGEMENTS

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