Transportation Planning and Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/gtpt20

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To cite this article: Li Song, Wei (David) Fan & Pengfei Liu (2021): Exploring the effects of connected and automated vehicles at fixed and actuated signalized intersections with different market penetration rates, Transportation Planning and Technology, DOI: 10.1080/03081060.2021.1943129

To link to this article: https://doi.org/10.1080/03081060.2021.1943129

Published online: 29 Jun 2021.

TRANSPORTATION PLANNING AND TECHNOLOGY
https://doi.org/10.1080/03081060.2021.1943129

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Exploring the effects of connected and automated vehicles at fixed and actuated signalized intersections with different market penetration rates

Li Song, Wei (David) Fan and Pengfei Liu

USDOT Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE), Department of Civil and Environmental Engineering, University of North Carolina at Charlotte, Charlotte, NC, USA

ABSTRACT

To investigate the effects of different market penetration rates (MPRs) of intelligent vehicles – Intelligent Driving Model (IDM) for autonomous vehicles (AVs), Adaptive Cruise Control (ACC) for AVs, and Cooperative Adaptive Cruise Control (CACC) for connected and automated vehicles (CAVs) – in mixed traffic flows with human driving vehicles (HDVs) at intersections, three signalized intersections (fixed signal, gap-based actuated signal, and delay-based actuated signal-controlled intersections) with low, medium, and high traffic demands are investigated. The simulation results indicate that CAVs with the CACC system outperform AVs with ACC or IDM systems and could reduce the average delay under low and high demand scenarios by 49% to 96%. CAVs with the CACC system could also significantly reduce average delay with a 20% MPR, while significant drops could only be observed after 60% and 80% MPRs for AVs with the ACC/IDM system. Gap-based and delay-based actuated signal control schemes are preferred under medium traffic flow demand, and CACC/ACC systems could significantly improve the performance of actuated signal-controlled intersections under high traffic flow demand.

ARTICLE HISTORY
Received 11 October 2020
Accepted 6 April 2021

KEYWORDS
Connected and automated vehicle; market penetration rates; traffic flow; simulation; fixed signal; actuated signal; intersections

1. Introduction

In past decades, emerging technologies that could assist or automatically control the driving process of intelligent vehicles have drawn great interest from researchers and engineers. With the development of Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication technologies, intelligent vehicles could make driving-informed decisions based on multi-source data, such as the speed/location of surrounding vehicles and the signal plans of surrounding intersections. The requirement of the time gap for successive vehicles could also be sharply decreased, and this could significantly change car-following behaviors and impact the performance of transportation systems. However, it is expected to have a long transition period during which human

CONTACT Wei (David) Fan wfan7@uncc.edu USDOT Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE), Department of Civil and Environmental Engineering, University of North Carolina at Charlotte, EPIC Building, Suite 3252, 9201 University City Boulevard, Charlotte, NC 28223-0001, USA

driving vehicles (HDVs) and intelligent vehicles will coexist (Sharon and Stone 2017). Hence, research on the impact of the mixed flow of HDVs and intelligent vehicles is needed.

In addition, there is still a long way to go before intelligent vehicles can be fully applicable in currently used traffic environments, especially for intersections where many conflict points and complex traffic flows coexist (Sharon and Stone 2017). Several proposed intersection control systems require a modification of existing intersections particularly for high market penetration rates (MPRs) of Autonomous Vehicles (AVs) or Connected Vehicles (CVs) (Dresner and Stone 2008; Algomaiah and Li 2019). Reconstruction of those intersections or installing V2I equipment would take a long time. For example, the autonomous interaction management (AIM) system replaces signals with a reservation-based V2I central control system. This V2I communication system requires the AIM to be implemented with more than a 90% MPR of connected and autonomous vehicles (CAVs) (Dresner and Stone 2008).

This paper mainly investigates the effects of CAVs with the Cooperative Adaptive Cruise Control (CACC) system, AVs with the Adaptive Cruise Control (ACC) system, and AVs with the Intelligent Driving Model (IDM) system in a mixed flow with HDVs. Three currently used signalized intersections (fixed signal, gap-based actuated signal, and delay-based actuated signal-controlled intersections) are investigated. A systematic study is conducted regarding the effects of different MPRs of intelligent vehicles at fixed and actuated signal-controlled intersections under different traffic demands. The results of this study can provide a theoretical basis for researchers to investigate intelligent vehicle systems and provide a reference to both transportation engineering researchers and practitioners for better designing, planning and operating intelligent transportation systems.

2. Literature review

2.1. Studies on intelligent vehicles

Numerous intelligent control systems have been proposed for intelligent vehicles in previous studies. IDM, ACC, and CACC are the three most used cruise control systems that control the longitudinal movements of intelligent vehicles (Treiber, Hennecke, and Helbing 2000; Milanés and Shladover 2014; Porfyri, Mintsis, and Mitsakis 2018). The acceleration/deceleration of the subject intelligent vehicle is mainly controlled based on the gap distance and speed difference with respect to the preceding vehicle. IDM was first proposed by Treiber, Hennecke, and Helbing (2000). It could be used to describe the longitudinal movement characteristics of HDVs or AVs with a continuously differentiable acceleration/deceleration function (Treiber and Kesting 2013). However, IDM would result in an unrealistically high deceleration rate when the current gap to the preceding vehicle is significantly shorter than the desired gap (Do, Rouhani, and Miranda-Moreno 2019). Hence, IDM was further modified with the Constant Acceleration Heuristics (CAH) to determine different acceleration/deceleration rates in different situations (Kesting, Treiber, and Helbing 2010). Results showed that road capacity is essentially improved, even with only a 50% MPR of intelligent vehicles. In a further study, the IDM model was improved by modifying its minimum gap term to avoid unrealistic deceleration rates (Liu and Fan 2020). The ACC system, which is a variant of the IDM, is proposed and dynamically controlled by four modes, i.e. cruising control, gap control, gap-closing control, and collision avoidance mode (Milanés and Shladover 2014; Xiao, Wang, and Van Arem 2017; Mintsis 2018). The CACC system, which could collect information from V2V and/or V2I communications, is a functional extension of the ACC system. The additional information collected could help CAVs with the CACC system follow their predecessors with higher accuracy, shorter response time, and shorter headway compared to ACC vehicles (Shladover, Su, and Lu 2012). Shladover, Su, and Lu (2012) tested the performance of ACC and CACC vehicles by collecting and analyzing field experiment data. Results showed little increase in roadway capacity when increasing the MPR of ACC vehicles. However, increasing CACC vehicles could significantly increase roadway capacity.

2.2. Studies on mixed traffic of intelligent vehicles at intersections

Many studies designed a control system that assumed 100% MPRs of CVs and/or AVs so that vehicles could obtain full information and be controlled according to the system (Guo, Li, and Ban 2019). Since there is still a long way to achieve high MPRs of CVs or AVs, it is practical and important to investigate the mixed flow of HDVs and intelligent vehicles at currently used intersections. Table 1 summarizes previous studies on intelligent vehicles at intersections considering different MPRs. It is noted that most research studies indicated a positive effect of intelligent vehicles in general, while some others found that intelligent vehicles could improve system performance only after certain MPRs (Algomaiah and Li 2019; Jiang et al. 2017; Lee, Park, and Yun 2013). Also, the interaction between intelligent vehicles with HDVs is found to result in a negative impact on system performance (Du, Homchaudhuri, and Pisu 2017). This is in line with the phenomenon that low MPRs of intelligent vehicles would decrease system performance (Virdi et al. 2019; Yang, Rakha, and Ala 2017).

3. Methodology

3.1. Krauss model

This study uses the Krauss car-following model for HDVs based on safe speed developed by Krauss, Wagner, and Gawron (1997). The desired speed v_d for the subject vehicle is calculated by the minimum value of the maximum speed allowed v_{max}, the acceleration capability of the vehicle, and the safe speed v_{safe}:

$$v_d = \min(v_{max}, v_{i,k} + a\Delta t, v_{safe}) \tag{1}$$

$$v_{safe} = v_{i-1,k} + \frac{g_k - v_{i-1,k}t_r}{\dfrac{v_{i,k} + v_{i-1,k}}{2d_{max}} + t_r} \tag{2}$$

where Δt represents the step duration of the simulation, $v_{i,k}$ indicates the speed of the subject vehicle i at the current time step k, $v_{i-1,k}$ denotes the speed of the leading vehicle in time step k, g_k represents the gap with respect to the leading vehicle in time

Table 1. Summaries of studies for intelligent vehicles at intersections considering market penetration rates (MPRs).

Veh.	Aim and method	Software	Criteria	Main result	Cite
CV	Cumulative travel-time responsive (CTR) real-time intersection control algorithm	VISSIM, Matlab	Delay, speed	1. The CTR algorithm improves the system performance after a 30% MPR of CVs. 2. CTR algorithm outperformed the actuated controls after a 70% MPR of CVs.	Lee, Park, and Yun (2013)
CV	Coordinate a CVs passing through multiple interconnected signalized intersections.	–	Fuel	1. Increase the MPRs of CVs would decrease fuel consumption. 2. Fuel consumption will increase if the CV is following an HDV.	Du, Homchaudhuri, and Pisu (2017)
CV	Optimizing the departure sequences	Matlab	Delay	1. CVs with MPRS from 0% up to 60% can significantly reduce the average delay. 2. The average delay could be significantly reduced even with low MPRs (20–40%).	Guler, Monica Menendez, and Meier (2014)
CV, AV, SGV	Jointly optimizing the signal phase and timing (spat) plan along with speed guidance	Java	Delay, stops	1. The average delay and number of stops decrease with higher MPRs of CV, AVs, and SGVs (MV with speed guidance-enabled vehicles). 2. The marginal benefits decrease rapidly when MPRs of the CVs exceed 40%.	Liang, Ilgin Guler, and Gayah (2019)
CV, AV	Optimization of departure sequence and trajectory by maximize the speed entering the intersection	Java	Stops. Delay	1. This algorithm performs better than the actuated signal control after a 50% MPR of CVs. 2. Even a 50% information level for CVs could significantly decrease the delay and stops.	Yang, Ilgin Guler, and Menendez (2016)
AV	Hybrid autonomous intersection management	SUMO	Queue length, Throughput	H-AIM can decrease delays for AVs even at a 1% MPR.	Sharon and Stone (2017)
AV	Headway minimization strategy at a signalized intersection	Matlab	Average travel Time	The average travel time decreases with higher MPRs of AVs.	Pourmehrab, Elefteriadou, and Ranka (2018)
AV	Receding horizon model predictive control (MPC) method to minimize the fuel consumption for platoons	Matlab	Fuel, Travel time	1. Both fuel consumption and travel time decrease with the increasing MPRs of AVs. 2. The benefits of cooperation between AVs and HDVs are most evident for lower MPRs, and a platoon size of 5 can reduce 22% fuel consumption under a 60% MPR of AVs.	Zhao et al. (2018)
CAV	A reservation-based control strategy with a first-come-first-served reservation protocol at intersection	VISSIM	Throughput delay	The proposed control system outperforms traffic signals after a 75% MPR of CAVs.	Algomaiah and Li (2019)
CAV	Optimizing speed of CAVs	VISSIM, Matlab	Fuel, CO2, Throughput	Benefits grow with the MPRs of CAVs until they level off at about 40% MPR.	Jiang et al. (2017)
CAV	Safety assessment of mixed flow with Surrogate Safety Assessment Module (SSAM)	VISSIM	Conflicts	CAVs at low penetration rates increase conflicts at signalized intersections while decrease conflicts at priority-controlled intersections.	Virdi et al. (2019)
CAV	Eco-CACC system that computes the fuel-optimum vehicle trajectory	Integra-tion	Fuel	1. Eco-CACC system produces vehicle fuel savings up to 40% at a 100% MPR of CAVs. 2. Lower MPRs of CAVs increase fuel consumption on multi-lane approaches, and the system decreases the fuel consumption only after a 30% MPR of CAVs.	Yang, Rakha, and Ala (2017)

step k, t_r is the reaction time for the human driver, and d_{max} is the maximum deceleration of the vehicle (m/s^2).

3.2. Intelligent Driving Model

IDM calculates the acceleration rates of the subject vehicle by balancing the ratio of the current velocity versus the desired speed minus the ratio of the desired gap versus the current gap with respect to the preceding vehicle (Treiber, Hennecke, and Helbing 2000):

$$a_{i,k} = a_{max}\left[1 - (\frac{v_{i,k}}{v_d})^{\delta} - \left(\frac{s^*(v, \Delta v)}{s_{i,k}})^2\right]\right. \tag{3}$$

$$s^*(v_{i,k}, \Delta v) = s_0 + max\left[0, \left(v_{i,k}t_d + \frac{v_{i,k}\Delta v}{2\sqrt{a_{max}d_c}}\right)\right] \tag{4}$$

where $a_{i,k}$ denotes the acceleration of the subject vehicle i in time step k, a_{max} represents the maximum acceleration allowed, $v_{i,k}$ is the current speed of the subject vehicle, v_d is the desired speed, δ represents the acceleration exponent, $s^*(v, \Delta v)$ denotes the desired minimum gap, Δv represents the speed difference between the subject vehicle and the preceding vehicle, $s_{i,k}$ is the current distance to the preceding vehicle, s_0 represents the linear jam distance, s_1 denotes the non-linear jam distance, t_d denotes the desired time gap, and d_c is the comfortable deceleration rate.

3.3. Adaptive Cruise Control

3.3.1. Cruising control mode

The cruising controller of the ACC system is triggered if there are no preceding vehicles within the range of 120 m covered by the sensors (Xiao, Wang, and Van Arem 2017; Liu, Xiao, and Kan 2018). This controller aims to keep the ACC vehicle traveling at a desired speed:

$$a_{i,k+1} = k_1(v_d - v_{i,k}) \tag{5}$$

where $a_{i,k+1}$ represents the acceleration recommended for the i-th subject vehicle at the time step $k + 1$, v_d denotes the desired speed, $v_{i,k}$ indicates the speed of the subject vehicle i at the current time step k, and k_1 denotes the control gain parameter determining the acceleration by the speed deviation. Typical values for k_1 range between 0.3 and 0.4 s^{-1} in (Xiao, Wang, and Van Arem 2017), and this study selects 0.4 s^{-1} for k_1.

3.3.2. Gap control mode

The gap control mode of the ACC system is triggered when the gap and speed deviation with respect to the preceding vehicle are less than 0.2 m and 0.1 m/s, respectively (Xiao, Wang, and Van Arem 2017). The acceleration of the subject vehicle i at the next time step $k + 1$ is calculated based on the gap and speed deviations:

$$a_{i,k+1} = k_2 s_{i,k} + k_3(v_{i-1,k} - v_{i,k}) \tag{6}$$

where $s_{i,k}$ denotes the gap deviation of the subject vehicle i at the current time step k, $v_{i-1,k}$ represents the current speed of the preceding vehicle (index in $i - 1$), and k_2 and

k_3 denote the control gains on the gap and speed deviations, respectively. Typical values for the optimal gains are $k_2 = 0.23\ \text{s}^{-2}$ and $k_3 = 0.07\ \text{s}^{-1}$ (Xiao, Wang, and Van Arem 2017).

The gap deviation of the subject vehicle is defined according to Milanés and Shladover (2014):

$$s_{i,k} = x_{i-1,k} - x_{i,k} - d_0 - t_d v_{i,k} \tag{7}$$

where $x_{i-1,k}$ and $x_{i,k}$ represent the current positions of the preceding vehicle and the subject vehicle, respectively, $v_{i,k}$ is the current speed of the subject vehicle, and t_d indicates the desired time gap for the ACC vehicle.

3.3.3. Gap-closing control mode

The gap-closing control mode was proposed in Milanés and Shladover (2016) and is activated when the gap to the preceding vehicle is less than 100 m. When the gap is between 100 m and 120 m, the subject vehicle retains the previous control mode to provide hysteresis in the control process and perform a smooth transfer between two modes (Xiao, Wang, and Van Arem 2017; Liu, Xiao, and Kan 2018). The formula of the gap-closing control mode is calculated by recalibrating the parameters of control gains in Equation (6), and this study utilizes $k_2 = 0.04\ \text{s}^{-2}$ and $k_3 = 0.8\ \text{s}^{-1}$ according to Xiao, Wang, and Van Arem (2017).

3.3.4. Collision avoidance mode

The collision avoidance mode aims to avoid imminent rear-end collisions, and it is activated when the gap to the preceding vehicle is less than 100 m, and the gap and speed deviations are less than 0 and 0.1 m/s, respectively (Mintsis 2018). If the gap is between 100 m and 120 m, the subject vehicle retains the previous control mode to provide hysteresis in the control process and performs a smooth transfer between the two modes (Xiao, Wang, and Van Arem 2017; Liu, Xiao, and Kan 2018). The collision avoidance control mode was also derived by calibrating the parameters of gap control gains in Equation (6), and this study sets $k_2 = 0.8\ \text{s}^{-2}$ and $k3 = 0.23\ \text{s}^{-1}$ according to Mintsis (2018).

3.4. Cooperative Adaptive Cruise Control

3.4.1. Cruising control mode

The speed controller for the CACC system is the same as that for the ACC system. The cruising control mode is triggered when the time-gap with respect to the preceding vehicle is greater than 2 s, and the gain k_1 in Equation (5) is set as $0.4\ \text{s}^{-1}$ (Xiao, Wang, and Van Arem 2017; Liu, Xiao, and Kan 2018).

3.4.2. Gap control mode

The gap control mode for the CACC system is activated when the gap and speed deviations are less than 0.2 m and 0.1 m/s, respectively (Xiao, Wang, and Van Arem 2017). Compared to the gap control mode of the ACC vehicle, the speed of the subject

CACC vehicle at the next time step $k+1$ is calculated by:

$$v_{i,k+1} = v_{i,k} + k_4 e_{i,k} + k_5 \dot{e_{i,k}} \quad (8)$$

$$\dot{e_{i,k}} = v_{i-1,k} - v_{i,k} - t_d a_{i,k} \quad (9)$$

where $\dot{e_{i,k}}$ is the first-order derivative of the gap deviation $e_{i,k}$. The values of the control gains k_4 and k_5 in Equation (8) are calibrated as 0.45 s^{-2} and 0.25 s^{-1}, respectively (Xiao, Wang, and Van Arem 2017).

3.4.3. Gap-closing control mode

The gap-closing control mode in CACC is activated when the time-gap is less than 1.5 s. If the time-gap is between 1.5 and 2 s, the subject vehicle would retain the previous control mode as a transition process (Xiao, Wang, and Van Arem 2017; Liu, Xiao, and Kan 2018). The Gap-closing control function is also calculated by calibrating the optimal gains in Equation (8), and are set as $k_4 = 0.01$ s^{-2} and $k_5 =$ s^{-1} (Xiao, Wang, and Van Arem 2017).

3.4.4. Collision avoidance mode

The collision avoidance mode helps the CACC vehicles to change velocity more smoothly and carefully when the time-gap to the preceding vehicle is less than 1.5 *s* and the gap deviation is negative (Mintsis 2018). The collision avoidance controller is also derived by calibrating the parameters of the gap control gains in Equation (8), and this study sets $k_4 = 0.45$ s^{-2} and $k3 = 0.05$ s^{-1} (Mintsis 2018).

4. Simulation experiments

A typical four-leg intersection with three-lane approaches is set for the simulation and is shown in Figure 1. Three different traffic demands for the approach are determined by the critical intersection volume-to-capacity (v/c) ratio (Transportation Research Board 2010), i.e. v/c = 0.4 for low-demand (512 *vph*), v/c = 0.8 for medium-demand (1024 *vph*), and v/c = 1 for high-demand (1280 *vph*). The proportions of left-turn, straight, and right-turn rates are set as 15%, 65%, and 20%, respectively. CAVs with the CACC system, AVs with the ACC system, and AVs with IDM system are investigated separately in the mixed flow with HDVs. The MPRs of intelligent vehicles increase from 0% to 100% by 20% per step. To study the effects of intelligent vehicles at present intersections, each demand scenario encompasses three currently used signal control schemes, i.e. fixed control, gap-based actuated control, and delay-based actuated control schemes. The fixed signal scheme with four phases is optimized by the performance index approach in Synchro. Two actuated signal schemes are controlled based on the fixed signal scheme while setting 5 *s* for the minimum duration and 20 *s* for the maximum extension of the green phase. For the gap-based actuated control, the green phase is prolonged when the maximum time gap between successive vehicles is less than 3 *s*. For the delay-based actuated control scheme, a prolongation of the green phase would be activated when the delay (i.e. cumulative time loss) of a vehicle is greater than 1 *s* within the detector/communication range of 300 *m*.

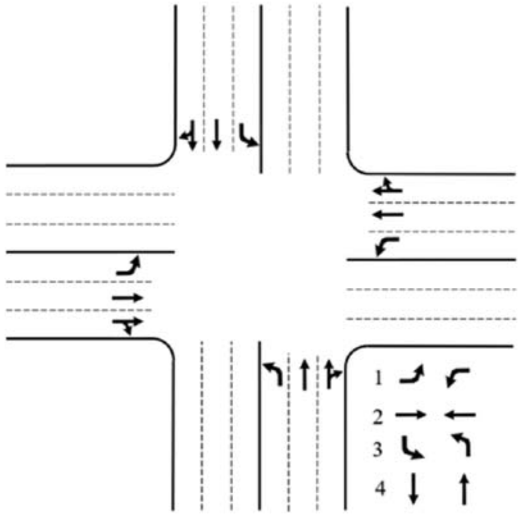

Figure 1. Intersection Configuration and Basic Signal Phase.

All simulation scenarios were processed in the Simulation of Urban MObility (SUMO) and the TraCI-Python interface. The simulation time for each case was 3600 *s* with a 0.1 *s* time step. The speed limit of the road is 50 *km/h*. To avoid identical driving behavior, the initial speed and departure lane of a vehicle are generated randomly. Also, to avoid homogeneous speeds, the desired speed for each vehicle is calculated by the product of the speed factor and speed limit. The speed factor in this paper obeys a normal distribution of $N(1.2,\ 0.1)$. Meanwhile, the driver's capability in holding the desired speed (between 0 and 1) is determined by the speed control factor according to Mintsis (2018). The LC2013 model is set as the lane-changing model for all vehicles (Erdmann 2015). The parameters for the car-following models are as given in the methodology section above and shown in Table 2 (Porfyri, Mintsis, and Mitsakis 2018; Xiao, Wang, and Van Arem 2017; Mintsis 2018).

5. Results and discussions

5.1. Effects of the AVs with the IDM system

The average delay of all vehicles, which is calculated by the average travel time minus the desired travel time of the trip, is used to measure the performance of the intersection system under fixed, gap-based actuated, and delay-based actuated signal scenarios. The results of the average delay for AVs with the IDM system under three traffic demands

Table 2. Basic Factors in Car-Following Models.

Vehicle Type	Control Mode	Acceleration (m/s^2)	Deceleration (m/s^2)	Desired headway (s)	Speed control factor	Reaction time (s)
HDV	Krauss	1.25	3	1.64	0.5	0.7
AV	IDM	2	4	1.4	0.1	0.1
AV	ACC	2	4	1.1	0.1	0.1
CAV	CACC	2	4	0.6	0.1	0.1

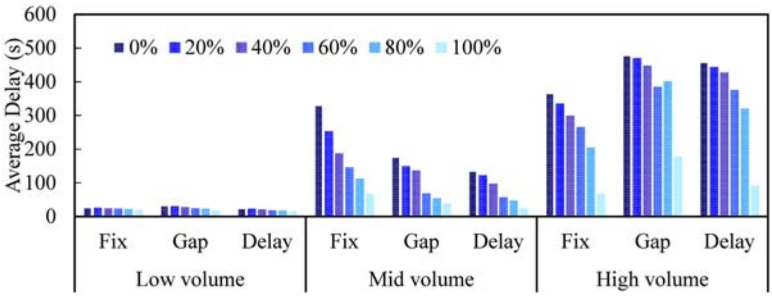

Figure 2. Average Delay under Different Market Penetration Rates of AVs with the IDM System.

with different MPRs are shown in Figure 2. Table 3 also includes the change rate of the average delay compared to the result of the 100% HDVs scenario. For the low traffic demand and 100% IDM controlled AVs scenario, the average delay decreases by 28%, 45%, and 36% for fixed, gap-based, and delay-based signalized intersection, respectively.

For the medium traffic demand scenarios, the average delay decreases significantly in all three signalized intersections as the MPR of IDM controlled AVs increases. When the MPRs of the IDM controlled AVs exceed 60%, both actuated signalized intersections reduce about 50% of the average delay compared to those in the fixed signal scenario. With a 100% MPR of IDM controlled AVs, about 79% and 82% decrease of the average delay could be observed at gap-based and delay-based actuated signalized intersections, respectively.

When the traffic is sufficiently high and reaches the saturated flow, significant drops of the average delay could only be observed after an 80% MPR of the IDM controlled AVs. With a 100% MPR of IDM controlled AVs, the fixed signal scheme outperforms two actuated signal schemes and decreases about 81% of the average delay. Hence, the actuated signal scheme may not be suitable for peak hours or other high traffic demand circumstances when using IDM controlled AVs. Also, there is an increase in the average delay when the MPR of the IDM controlled AVs increases from 60% to 80% in the scenario of high traffic demand and gap-based signalized intersection. This indicates the unstable delay at the intersection in the mixed flow of HDVs and IDM controlled AVs.

5.2. Effects of AVs with the ACC system

The results of the average delay and corresponding change rate of the average vehicle delay for ACC controlled AVs under different scenarios are shown in Figure 3 and Table 4. The results of ACC controlled AVs are similar to the results of the IDM system in low and medium traffic demand scenarios. With a 100% MPR of ACC controlled AVs, the average delay decreases by 85% at the delay-based signalized intersection under medium traffic demand. Also, a slight increase in average delay is observed when the MPR of the ACC controlled AVs increases from 60% to 80% at the fixed signalized intersection under medium traffic demand. This further proves the instability interaction between HDVs and ACC controlled AVs. For the high traffic demand scenarios, the average delay decreases more quickly when the MPRs of the ACC controlled AVs exceed 60% compared to IDM controlled AVs. Different from the IDM scenario, the

Table 3. Average Delay and Change Rate of Average Delay (in brackets) for AVs with the IDM system compared to 100% HDVs Scenario (unit: s).

IDM	Low volume			Medium volume			High volume		
MPRs	Fix	Gap	Delay	Fix	Gap	Delay	Fix	Gap	Delay
0	27.1	32.6	24	330	176.7	134.9	365.6	478	457.7
0.2	26.1(0.04)	30.9(0.05)	22.9(0.05)	253.2(0.23)	149.5(0.15)	123.1(0.09)	334.7(0.08)	470.6(0.02)	443.6(0.03)
0.4	24.8(0.09)	28(0.14)	21.2(0.12)	187.8(0.43)	137.1(0.22)	98.3(0.27)	299.6(0.18)	449.4(0.06)	428(0.06)
0.6	23.4(0.14)	24.5(0.25)	18.8(0.22)	145.4(0.56)	68.5(0.61)	57(0.58)	265.8(0.27)	386.1(0.19)	375.8(0.18)
0.8	22.1(0.18)	22.7(0.3)	17.8(0.26)	112.9(0.66)	54.8(0.69)	47.8(0.65)	204.6(0.44)	402(0.16)	321.1(0.3)
1	19.6(0.28)	18(0.45)	15.4(0.36)	67.2(0.8)	38(0.79)	24.1(0.82)	68(0.81)	178.3(0.63)	91.7(0.8)

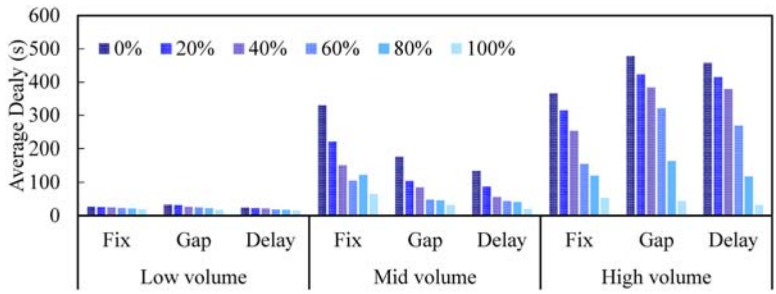

Figure 3. Average Delay under Different Market Penetration Rates of AVs with the ACC System.

average delay for two actuated signal-controlled intersections under high traffic demand with a 100% MPR of ACC controlled AVs is less than that for the fixed signal scenario. The average delay is decreased by 93% at the delay-based signalized intersection with a 100% MPR of ACC controlled AVs, while the fixed signal scenario only decreases 85% of the average delay. These results indicate that ACC controlled AVs outperform the IDM controlled AVs. Also, the implementation of ACC controlled AVs could better cooperate with gap-based and delay-based actuated signal schemes under high traffic demand.

5.3. Effects of CAVs with the CACC system

Figure 4 and Table 5 present the average vehicle delay and the corresponding change rate of the average delay for CACC controlled CAVs under different scenarios. The average delay decreases with the increase of CACC controlled CAVs, and CACC controlled CAVs outperform IDM and ACC controlled AVs in all scenarios. For medium traffic demand scenarios, the average delay drops significantly after a 20% MPR of CACC controlled CAVs for all signal schemes. The average delay drops by 94% at the fixed signalized intersection with a 100% MPR of CACC controlled CAVs. The results of two actuated signalized intersections indicate that actuated signal schemes are more suitable under medium traffic demand compared to the fixed signal scheme. For high demand

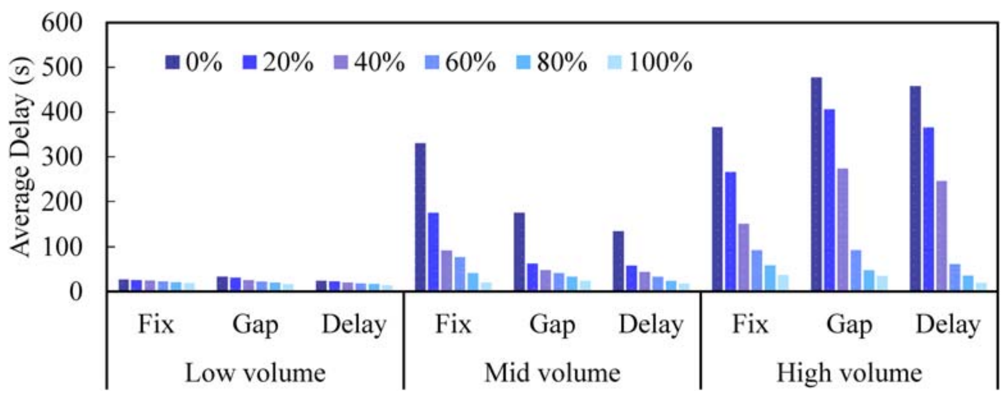

Figure 4. Average Delay under Different Market Penetration Rates of CAVs with the CACC System.

Table 4. Average Delay and Change Rate of Average Delay (in brackets) for AVs with the ACC system compared to 100% HDVs Scenario (unit: s).

ACC	Low volume			Mid volume			High volume		
MPR	Fix	Gap	Delay	Fix	Gap	Delay	Fix	Gap	Delay
0	27.1	32.6	24	330	176.7	134.9	365.6	478	457.7
0.2	25.7(0.05)	31.3(0.04)	22.9(0.05)	220.6(0.33)	104.4(0.41)	87.6(0.35)	314.5(0.14)	424.1(0.11)	414.7(0.09)
0.4	24.5(0.1)	26.5(0.19)	21.4(0.11)	151.6(0.54)	85.1(0.52)	56(0.59)	253.3(0.31)	384.1(0.2)	379.1(0.17)
0.6	22.9(0.16)	24.2(0.26)	19.1(0.21)	105(0.68)	47.8(0.73)	43.6(0.68)	155.1(0.58)	322.1(0.33)	268.8(0.41)
0.8	21.1(0.22)	22.7(0.31)	17.5(0.27)	122.9(0.63)	45.6(0.74)	41.1(0.7)	120.1(0.67)	164.5(0.66)	117.8(0.74)
1	19.4(0.28)	17.5(0.46)	15.1(0.37)	64.9(0.8)	32.1(0.82)	19.6(0.85)	53.4(0.85)	43.8(0.91)	32.1(0.93)

Table 5. Average Delay and Change Rate of Average Delay (in brackets) for CAVs with the CACC system compared to 100% HDVs Scenario (unit: s).

CACC	Low volume			Mid volume			High volume		
MPR	Fix	Gap	Delay	Fix	Gap	Delay	Fix	Gap	Delay
0	27.1	32.6	24	330	176.7	134.9	365.6	478	457.7
0.2	25.7(0.05)	31.1(0.05)	22.3(0.07)	175.5(0.47)	62(0.65)	58.2(0.57)	265.8(0.27)	407(0.15)	365.5(0.2)
0.4	24.2(0.11)	25.2(0.23)	20(0.17)	92.2(0.72)	47.9(0.73)	43.5(0.68)	151.9(0.58)	273.9(0.43)	246.1(0.46)
0.6	22.5(0.17)	22.1(0.32)	18.6(0.23)	77.3(0.77)	41.4(0.77)	32.7(0.76)	92.9(0.75)	92.7(0.81)	61.2(0.87)
0.8	20.8(0.23)	20(0.39)	16.8(0.3)	41.1(0.88)	32.7(0.82)	23.6(0.82)	58.5(0.84)	47.3(0.9)	35.4(0.92)
1	19(0.3)	16.5(0.49)	13.9(0.42)	20.2(0.94)	24(0.86)	17.2(0.87)	37.1(0.9)	35.2(0.93)	19.4(0.96)

scenarios, the average delay drops significantly with the increase of CACC controlled CAVs. About 87% and 96% drops in the average delay at the delay-based intersection are observed when the MPRs of CACC controlled CAVs reach 60% and 100%, respectively. All these indicate the superiority of the CACC system since the communication function of the CACC controlled CAVs could further decrease the headway and help the fleet to react cooperatively.

6. Conclusions

As the technologies of intelligent vehicles and infrastructures are still under study, it is expected to have a long transition period during which human driving vehicles (HDVs) and autonomous vehicles will coexist (Sharon and Stone 2017). Hence, there is a need to study the effects of introducing intelligent vehicles on currently used transport infrastructures. This paper has studied the effects of three typical intelligent vehicles: Intelligent Driving Model (IDM) controlled autonomous vehicles (AVs), Adaptive Cruise Control (ACC) controlled AVs, and Cooperative Adaptive Cruise Control (CACC) controlled connected and automated vehicles (CAVs) on three currently used signalized intersections (i.e. fixed signal, gap-based actuated signal, and delay-based actuated signalized intersections).

The main results and contribution of this research to currently used signalized intersection systems are as follows: firstly, CACC controlled CAVs outperformed IDM/ACC controlled AVs in all scenarios. A 96% drop on average was observed at the delay-based signalized intersection under high traffic demand with a 100% MPR of CACC controlled CAVs; secondly, CACC controlled CAVs could significantly decrease the average delay under medium and high demand scenarios after the MPRs exceed 20% and 40%, respectively. For high demand scenarios, significant drops of the average delay could only be observed after an 80% MPR of the IDM controlled AVs, while significant drops in the average delay could be obtained after a 60% MPR of ACC controlled AVs or a 40% MPR of CACC controlled CAVs; thirdly, gap-based or delayed-based actuated signal schemes are preferred when traffic demand is low or medium (v/c ratio less than 0.8). An increase in the average delay could be found in the scenario of IDM controlled AVs at gap-based actuated signalized intersections under high demand; fourthly, CACC and ACC systems outperformed the IDM system at actuated signalized intersections under high traffic demand. Also, high MPRs of ACC controlled AVs or CACC controlled CAVs at actuated signalized intersections performed better than the fixed signalized intersection scenario; and finally, unstable delay results were found in the mixed flow of HDVs with AVs controlled by the IDM and ACC mode, which have also been observed in previous studies (Yang, Rakha, and Ala 2017; Du, Homchaudhuri, and Pisu 2017).

These results could provide a foundation for researchers to investigate the impact of intelligent vehicles on currently used intersections and provide a reference for better signal control and intelligent vehicle operations. Also, the results could give a solid reference to researchers/engineers for better planning and operating of future intelligent transportation systems. Meanwhile, considering the unstable results found in the mixed flow of HDVs with IDM and ACC controlled AVs, a further study on the interactions between intelligent vehicles and HDVs is needed.

Acknowledgements

The authors want to express their deepest gratitude to the financial support by the US Department of Transportation, University Transportation Center through the Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE) at The University of North Carolina at Charlotte (Grant Number: 69A3551747133).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The authors want to express their deepest gratitude to the financial support by the US Department of Transportation, University Transportation Center through the Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE) at The University of North Carolina at Charlotte (Grant Number: 69A3551747133).

ORCID

Li Song http://orcid.org/0000-0002-4888-6045
Wei (David) Fan http://orcid.org/0000-0001-9815-710X
Pengfei Liu http://orcid.org/0000-0001-7217-151X

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