Evaluating the impact of connected and autonomous vehicles on traffic safety

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Abstract

This study aims to analyze the impact of connected and autonomous vehicles (CAVs) on traffic safety under various penetration rates. Based on a recently proposed heterogeneous flow model, the mixed traffic flow with both conventional vehicles and CAVs was simulated and studied. The frequency of dangerous situations and value of time-to-collision in the mixed traffic flow under different CAV penetration rates was calculated and used as indicators of CAV's impact on traffic safety. Acceleration rate and velocity difference distribution of the mixed traffic flow was presented to show the evolution of mixed traffic flow dynamics with the increase in CAV penetration rates within the mixed flow. Results show that the condition of traffic safety is greatly improved with the increase in the CAV penetration rate. More cautious car-following strategy of the CAV would contribute to a greater benefit on traffic safety, though less gain in capacity. With the increase in CAV penetration rate, the portion of smooth driving is increased. Velocity difference between vehicles is decreased and traffic flow is greatly smoothed. Stop-and-go traffic will be greatly eased.

Keywords: connected and autonomous vehicles, heterogeneous flow, traffic safety, CAV penetration rate

1. Introduction

Recent advances in automotive technology are about to change the traffic system fundamentally. In particular, the development of connected and autonomous vehicles (CAVs) has attracted amounts of attention from both the public and the research field. People are expecting that with the deployment of this emerging technology, problems such as traffic congestion and accidents would be greatly eased [1]. Other merits such as fuel saving and pollution reduction are also expected. However, to which extent the current transportation system can be improved through the deployment of this new technology is unknown. The gradual adoption of CAV in the vehicle composition indicates that the state of a mixed traffic flow including both conventional vehicles and CAVs on the road simultaneously will last a long time period. Meanwhile, CAV technology is still evolving with time. Varying levels of vehicle automation ranging from partial automation to full automation would exist during this time period. The impact of CAVs on traffic flow during this transition period has not yet been studied thoroughly.

There are many predictions concerning the impact of CAVs on traffic safety. Some researchers argue that CAVs would reduce crashes 90% because more than 90% of traffic accidents are caused by human drivers' error, autonomous vehicles are able to avoid such driving errors [1, 2]. Such prediction may seem too optimistic since it is based on a simple assumption, and it solely concerns about the utopic future but did not pay any attention to the transition period. Other researchers indicate that the introduction of CAVs would smooth the traffic flow, avoid stop-and-go driving and thus result in a significant reduction in fuel consumption and air pollution [3, 4, 5, 6, 7, 8]. However, some researchers hold a quite different point of view over this problem. Their studies demonstrate that low-level automated vehicle in the mixed traffic flow would rather have a negative effect on traffic flow and road capacity. Improvement in traffic flow can only be attained when CAVs reached a high penetration rate in the mixed flow [9, 10].

There is a lot of existing literature addressing the potential impact of autonomous vehicles on traffic flow, most of the work use stability analysis and simulation approach to assess to which extent the mixed traffic flow can be smoothed. Talebpour and Mahmassani studied the potential impact of CAVs on traffic flow using a proposed simulation framework: results show that the introduction of CAV would increase the throughput of highway facilities and improve the stability of the traffic flow [11, 12]. In our previous work, a heterogeneous-flow model was proposed to model CAVs in heterogeneous traffic flow: results show that the increase in capacity is strongly related to the market penetration rate and CAV parameter in the car-following process [13, 14]. In the experimental approach, Stern et al. conducted a car-following experiment on a circuit track: results demonstrate that intelligent control of a single autonomous vehicle is able to dampen the stop-and-go traffic flow [15]. Ge et al. conducted an experimental validation of CAV design among regular vehicles: results show that both safety and energy efficiency can be improved in the mixed flow, and CAV is helpful in mitigating traffic waves [16].

Existing literature also indicates that the implementation of connected vehicle would be beneficial for a safer traffic system [17]. But to which degree of potential benefits can be attained when only a portion of vehicles being CAVs is yet to be studied. Due to a lack of real consequence, it is relatively difficult to find a proper way to estimate the impact of CAVs on traffic safety, especially under varying levels of penetration rate. However, a thorough understanding of the heterogeneous flow dynamics is vital for the making and deployment of future traffic control and management policies. In this regard, this work intends to provide some insights into the heterogeneous traffic flow dynamics during the transition period and to analyze the impact of connected and autonomous vehicles on traffic safety under various CAV penetration rates.

This contribution is a successive study of our previous work on modeling CAVs in heterogeneous traffic flow, which aims to provide a better understanding of the heterogeneous flow dynamics [13]. The methodology for modeling mixed traffic flow is identical with our previous publication, which we included in the appendix of this work. This work focuses on analyzing the safety impact of CAVs on the mixed traffic flow. The methods for evaluating the safety impact is first integrated into this work and the corresponding results are original compared with the former publication. The heterogeneous traffic flow is simulated using a two-lane cellular automaton (CA) model proposed in the aforementioned work. In the mixed flow model, there are two parts for modeling human-driven vehicle and CAV respectively. This model aims to account for the heterogeneity associated with the human-driven vehicles and the CAVs. For molding human-driven vehicles, a refined CA model named TSM was applied. The parameters for modeling the human-driven vehicles in TSM has been calibrated and validated by experimental data, detailed demonstrated in Tian's work [20]. In our previous published work, we also validated that the extended two-lane TSM has a good performance in reproducing the NGSIM traffic data [13].

For modeling CAVs, there are several points that differ from modeling a human-driven vehicle. Firstly, a classical adaptive cruise control model is applied for the autonomous driving. For modeling conventional vehicles, acceleration rate a is a constant value (the acceleration rate a will be further affected in the randomization step which accounts for the uncertainty in human driving). For modeling CAV, its acceleration rate is calculated by the ACC model. Secondly, the randomization step involved in modeling human-driven vehicles is eliminated in the steps of modeling the CAV. Thirdly, in the car-following process of CAV, different following strategies are applied in calculating the anticipated gap according to the type of its preceding vehicle. Namely, a CAV would adopt different strategies between following a human-driven vehicle and following a CAV. when CAVs following a regular vehicle, a more cautious strategy is applied than following a CAV. Besides, connectivity means a better provision of information, we use the average speed of CAVs within connection range as an input parameter in calculating the anticipated speed for a CAV. For conventional vehicles, a reaction time of 1 s was assumed in calculating the safety speed. For CAVs, this reaction time is eliminated, since CAVs could react almost instantly compared to human drivers. This study mainly focuses on analyzing the heterogeneous flow dynamics, the impact of CAV on traffic safety and how would the mixed traffic flow dynamics evolve with the gradual increase in CAV penetration rate in the mixed traffic flow. This work assumed relatively idealized conditions such as a CAV can acquire accurate driving parameters such as the distance between its leading vehicle, the instantaneous speed of its preceding vehicle, and the traffic condition ahead of a distance of connected range, via sensor detection and communication technologies.

The rest part of this work is organized as follows. Section 2 introduced the indicators for evaluating the safety impact. Section 3 presents the results of this study and followed with discussions. Finally, this work is ended with conclusions in Section 4. For the sake of completeness, the modeling methodology is presented in the appendix.

2. Safety assessment

The model for modeling the mixed traffic flow is a rule-based cellular autonomous model, which is discrete in both time and space. In the simulation, the model does not produce any crashes. Thus, the model cannot be used to measure crashes or traffic safety directly. This work adopted three rules to measure the number of dangerous situation that occurred during the simulation as an indicator for traffic safety evaluation [18]. $d(i, t)$ indicates the space gap ahead of vehicle i at time step t and $v(i, t)$ indicates its velocity. In the model, all variables are integers and measured by units of the cell length. Each cell corresponds to a longitudinal length of 0.5 m. The time step in the simulation equals to 1 s. Thus, at each time step, a vehicle will move forward by a distance of its current speed. The speed of the vehicle in the simulation can be varied at a step of 0.5 m/s.

(1) $v(i+1, t) > 0$, indicating that vehicle i+1is moving at time step t.

(2) $v(i+1, t+1) = 0$, indicating that vehicle i+1 will stop abruptly at time t+1.

(3) $v(i, t)^2/(2^* d(i, t))>10$, indicating that the following vehicle i has to apply a deceleration rate beyond 10 m/s^2 in order to avoid crashing with its stopped leader.

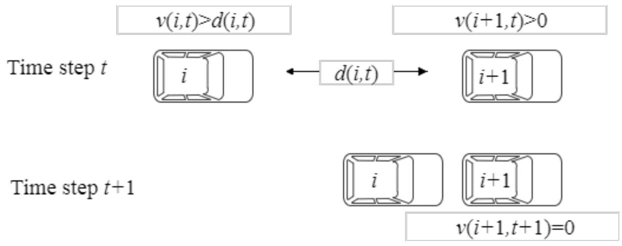


Fig.1. Schematic illustration of the rules for detecting dangerous situation

Fig.1 shows the schematic illustration of an occasion described by the aforementioned three rules. The following vehicle is stopped with a physically impossible deceleration rate beyond 10 m/s^2 due to a stopped leader. Note that these rules are applied when the corresponding simulation is finished, and recorded time-space information of all individual vehicles during the simulation period is available. If the three conditions are met simultaneously, a rear-end accident may occur. The frequency of such occasion is calculated and considered as a negative sign of safety where a potential crash may occur, denoted as N (times/km/h).

The second indicator for evaluating safety impact is the time-to-collision (TTC) [19]. The time-to-collision is defined as the time that remains until a collision could occur if two successive vehicles maintain a speed difference, which has been applied in several studies for identifying safety impacts. The time-to-collision of vehicle i with respect to a leading vehicle i+1 at time step t can be calculated with:

$$TTC(i,t) = \frac{d(i,t)}{v(i,t)-v(i+1,t)} \quad \forall v(i,t) > v(i+1,t) \tag{1}$$

Where $d(i, t)$ and $v(i, t)$ denote the real space gap and the speed of vehicle i at time step t, respectively. A time-to-collision can only be calculated when a positive speed difference exists between two successive vehicles.

Besides, acceleration rates of vehicles in the mixed traffic flow and velocity difference between successive vehicles can be used to indicate to which extent the mixed traffic flow is smoothed under various CAV penetration rates. A smoother traffic flow will contribute to a safer traffic system.

3. Simulation results and discussion

The simulation was conducted on a 10-km two-lane road segment under periodic boundary condition. Initially, regular vehicles and CAVs are randomly distributed in a vehicle fleet on the road segment. The total simulation lasts 20000 time steps, with the initial 10000 time steps eliminated to avoid transition effect. In the simulation, each time step corresponds to 1 s and the longitudinal distance of a cell corresponds to 0.5 m. P_{av} denotes the percentage of CAVs with respect to the total number of vehicles in the traffic flow. T_{ACC} denotes the desired net time gap in the adaptive cruise control (ACC) process of CAVs. A smaller value for T_{ACC} indicates CAV can keep a closer distance when following its preceding vehicle.

Fig.2 shows the relationship between road capacity, the frequency of dangerous situation with regard to density under two scenarios with different T_{ACC} values respectively. Five cases under various CAV penetration rates are included in each scenario. From Fig.2 (a, c) we can directly observe that a smaller T_{ACC} value and a higher penetration rate of CAV corresponds to a higher gain in road capacity. Capacity is equal to the maximal flow rate attained in the free flow phase. It is understandable that a smaller desired net time gap attained by CAVs contributes a larger improvement in capacity. Since CAVs can drive more closely within the traffic flow, and a larger penetration rate of CAV in the mixed flow reinforces this process. Fig.2 (b, d) indicates that the introduction of CAVs in the mixed flow would be beneficial for traffic safety. Generally, the frequency of dangerous situation decreases with the increase in the CAV penetration rate within the mixed flow. The system will attain a considerable gain in terms of safety when CAV penetration rate reaches 25%, and this effect is much more evident when CAVs are under a more cautious strategy in the ACC process. A larger difference in driving behavior between CAVs and regular vehicle shows a negative effect on safety, which can be observed in Fig.2 (b), particular in the case with 75% of CAV in the mixed traffic flow. The difference between the two cases indicates that a more cautious strategy in the ACC performance would contribute to a greater improvement in traffic safety. The simulation results indicate that in the coming future, the trade-off between capacity gain and safety improvement has to be taken into account in the deployment of CAV technology.

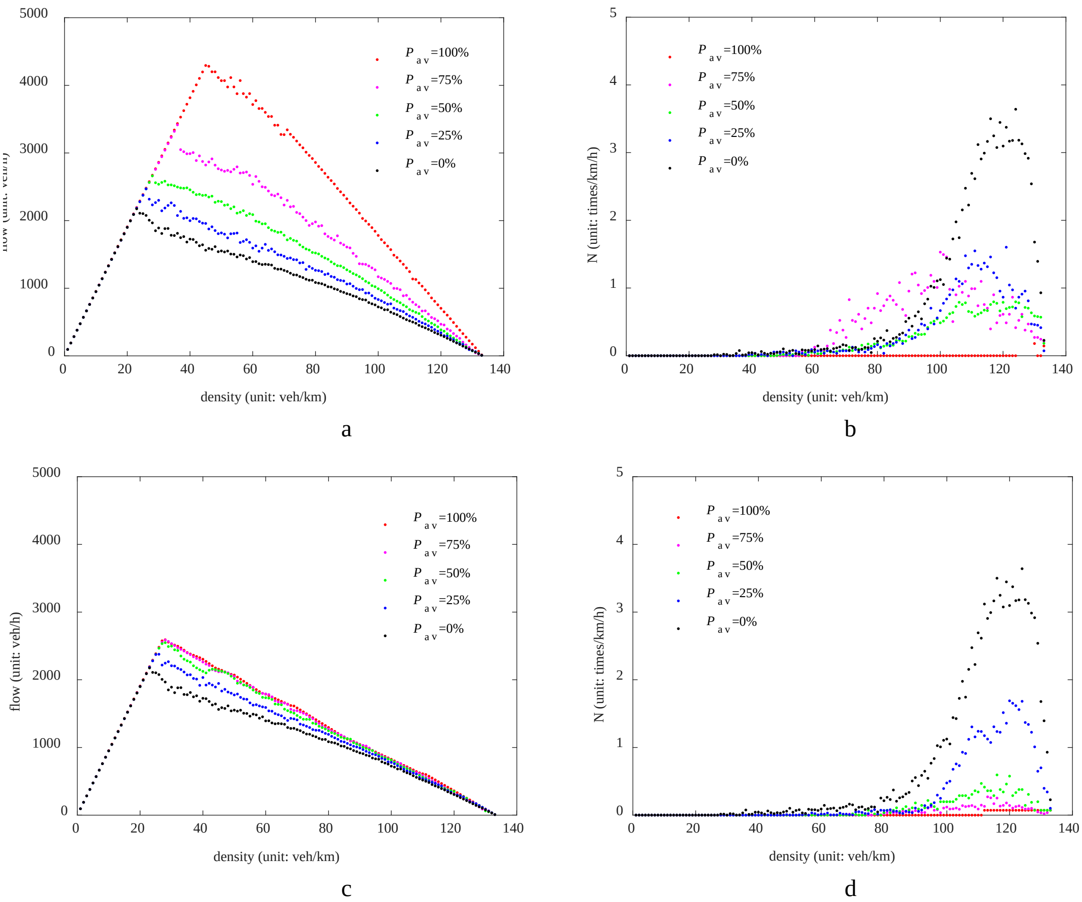
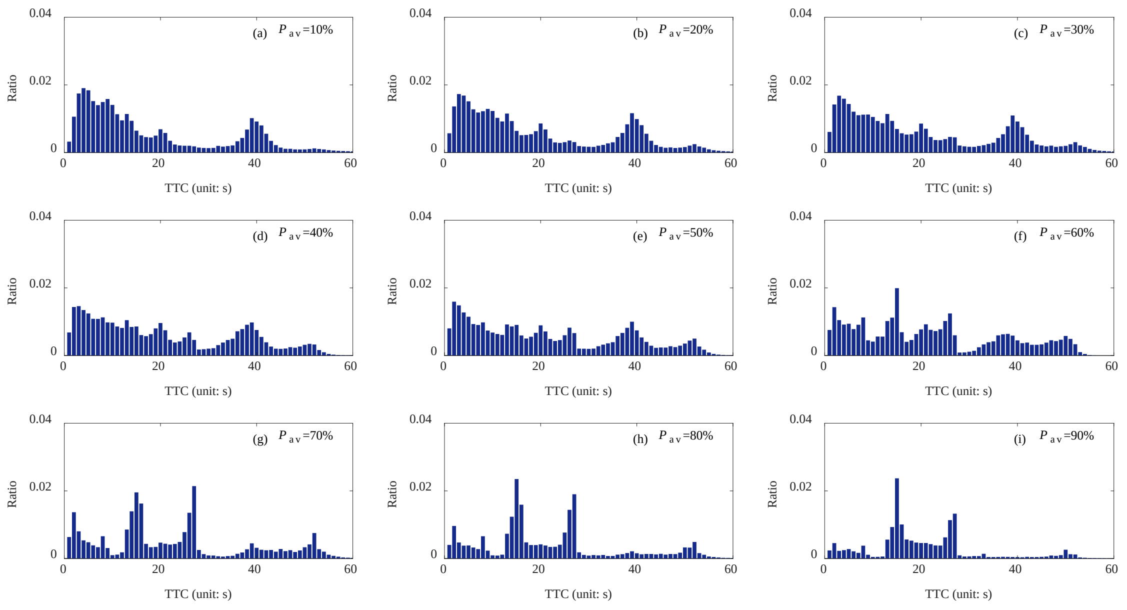
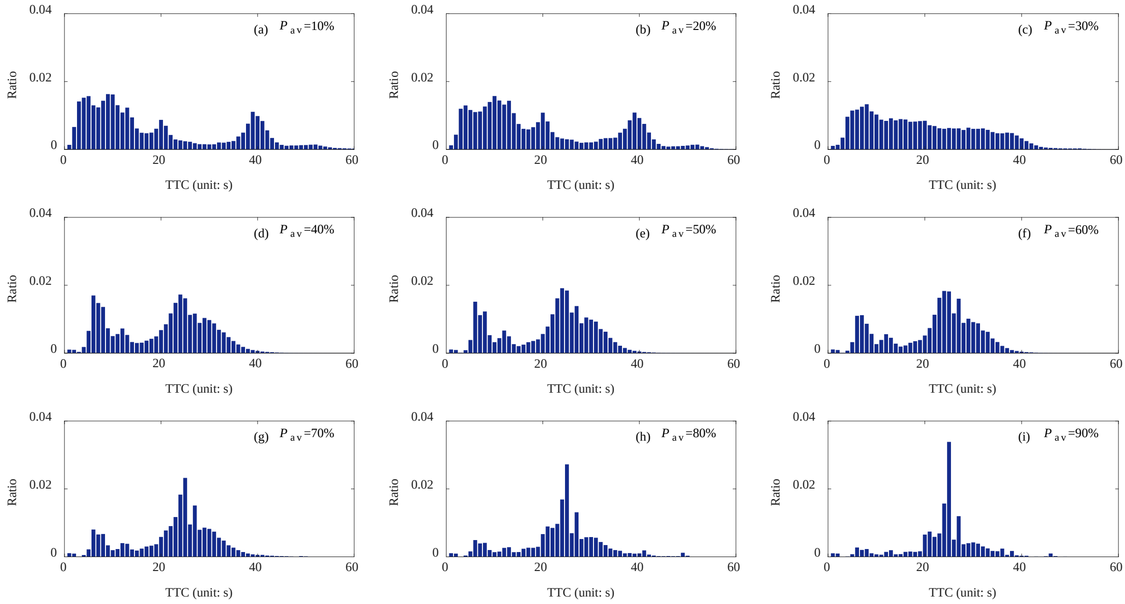


Fig.2. Flow-density diagram and frequency of aggressive vehicle stop with regard to density under various penetration rates of autonomous vehicle P_{av} with T_{ACC} =0.5 s (a, b), 1.1 s (c, d).



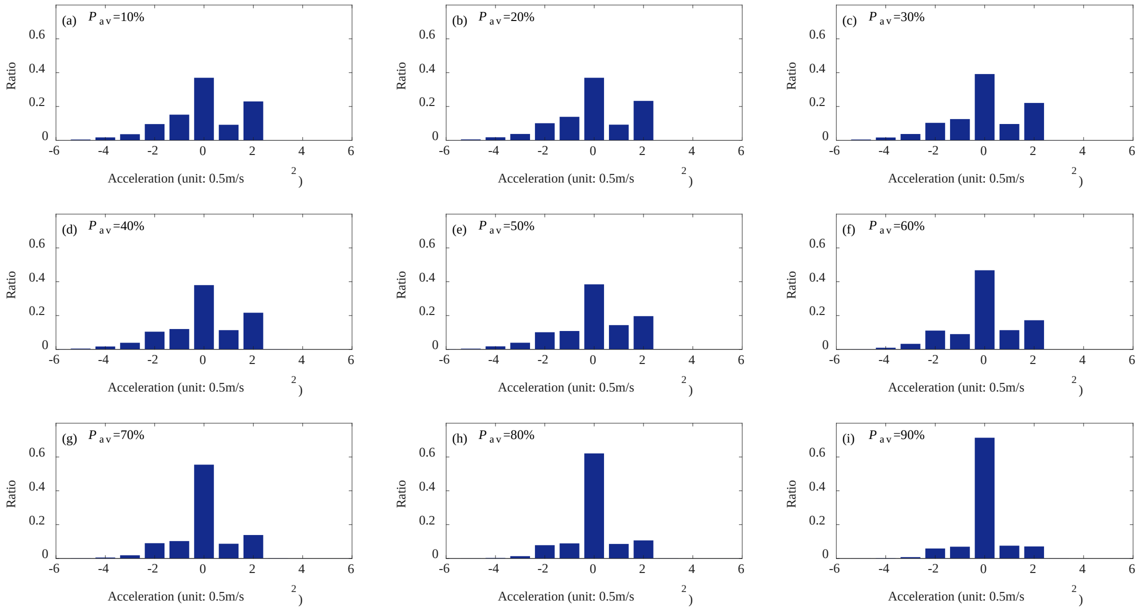
a



b

Fig.3. Time-to-collision distributions under various penetration rates of autonomous vehicle P_{av}, with T_{ACC} =0.5 s (a) and 1.1s (b), density equals to 50 veh/km/lane.

Fig. 3 presents the time-to-collision distributions of two cases with different T_{ACC} values, with P_{av} from 10% to 90%. The ratio of low *TTC*, namely the most left region in the plot, represents the negative effect on traffic safety, which indicates crash is likely to occur if the vehicle is not operated properly under such cases. In contrast, a higher *TTC* indicates the positive performance. In the first case (T_{ACC} =0.5 s), improvement is not obvious at a low CAV penetration rate. Significant improvement on safety can only be observed when CAV reached a major component in the mixed flow. While in the latter case (T_{ACC} =1.1 s), improvement in safety can be observed even CAVs at a relatively lower penetration rate. The difference between the aforementioned two cases indicates that the performance in CAV driving actually has a direct impact on the evaluation of safety effect on the mixed traffic flow. A more cautious strategy on the CAV driving would possess a greater benefit on traffic safety at the beginning of introducing CAVs in the current traffic system. Besides, we can also observe that with the increase in CAV penetration rate, the ratio of large *TTC* values also decreases a lot. Under a lower CAV penetration rate, the traffic flow presents a stop-and-go pattern, which means that both large *TTC* values and small *TTC* values coexist in the system. Large *TTC* values mainly come from the downstream front of traffic wave and small *TTC* values come from the upstream side of the wave. With the increase in CAV penetration rate, traffic flow tends to be smoother, the gap space difference and the speed difference between vehicles are decreased, which results in a decrease in the ratio of both large *TTC* and small *TTC* values.



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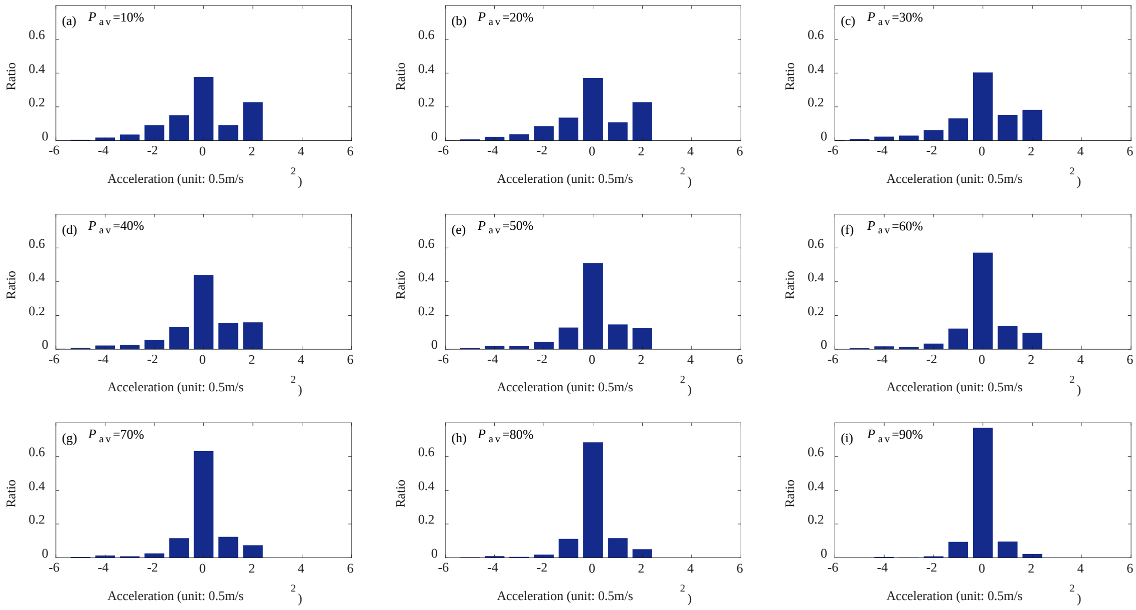
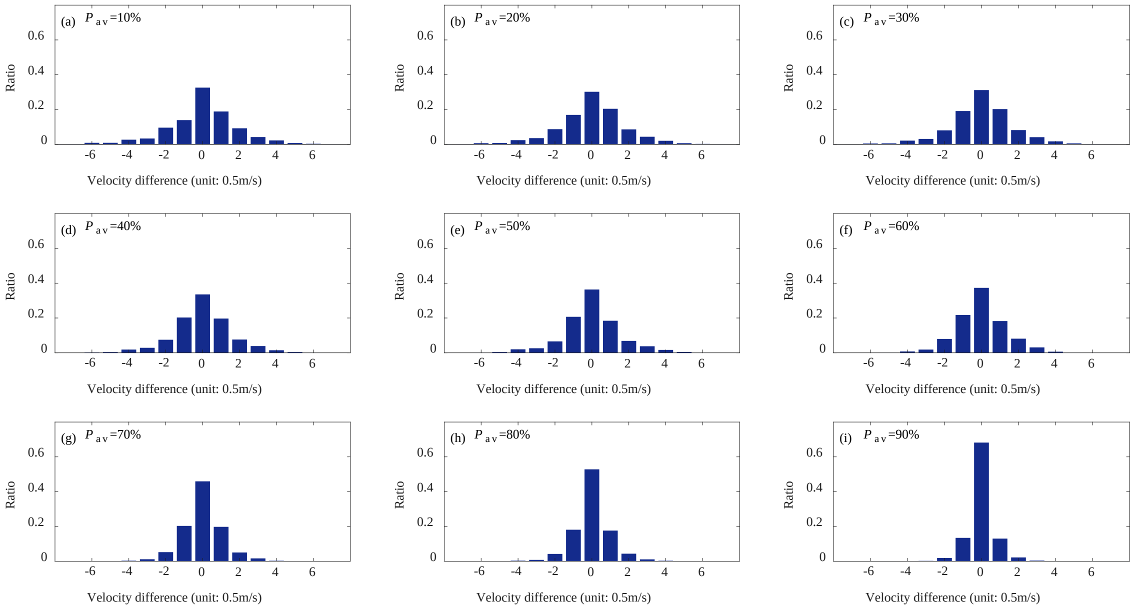


b

Fig.4. Acceleration rate distributions under various penetration rates of autonomous vehicle P_{av}, with T_{ACC} =0.5 s (a) and 1. 1s (b), density equals to 50 veh/km/lane.

Fig.4 presents acceleration rate distributions of two cases with different T_{ACC} values, with P_{av} from 10% to 90%. Under both cases, a gradual increase in the ratio of the acceleration rate 0 can be easily found, which indicates that the introduction of CAV would boost the portion of smooth driving within the mixed traffic flow. With the increase in CAV penetration rate, the ratio of high deceleration rate is also decreased, which indicates that a smoother traffic flow can be attained. Comparing the results from two cases, we can find that the results of latter case with a higher T_{ACC} value is better than the first case with a lower T_{ACC} value. This indicates that a more cautious car-following strategy of the

CAV would contribute to a greater benefit on smoothing the traffic flow.



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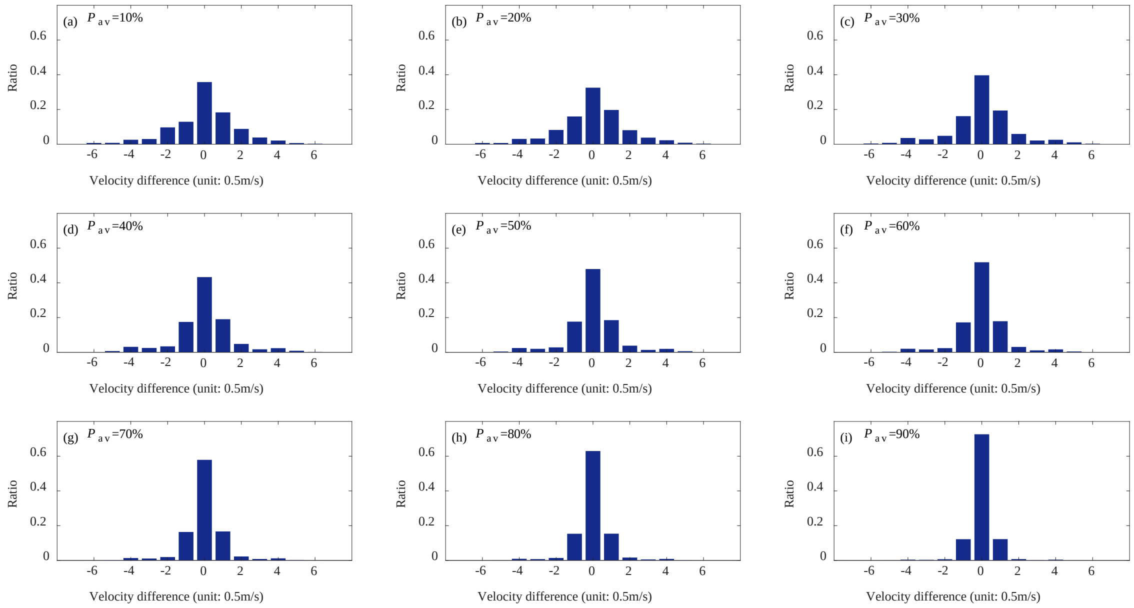
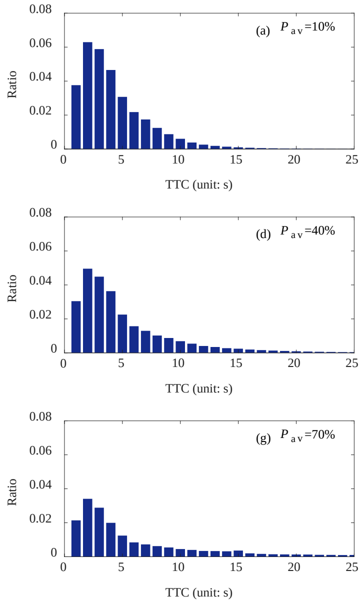


b

Fig.5. Velocity difference distributions under various penetration rates of autonomous vehicle P_{av}, with T_{ACC} =0.5 s (a) and 1. 1s (b), density equals to 50 veh/km/lane.

Fig.5 presents velocity difference distributions of the aforementioned two cases. The distribution is the difference in velocity between each vehicle and its leading vehicle during the simulation period. In general, the velocity difference follows a bell-shaped distribution. However, the shape of the distribution evolves with the increase in the CAV penetration rate in the mixed traffic flow. Under a low CAV penetration rate of 10%, the distribution presents a bell shape with a lower peak and covers a wide range. With the CAV penetration rate increase, the ratio of velocity difference of 0 gradually increase, and the shape of the distribution evolves to a higher peak within a narrow range. The velocity difference has a tendency to cluster around the value of 0. This phenomenon indicates that with the increase in the CAV penetration rate, the velocity difference between vehicles is decreased and traffic flow is smoothed.

Besides, simulation results were obtained at a different demand level, with density equals to 100 veh/km/lane, T_{ACC} =0.5 s. Fig. 6 presents the time-to-collision distributions, acceleration rate and velocity difference distributions, respectively. Results show a similar pattern with the aforementioned cases.



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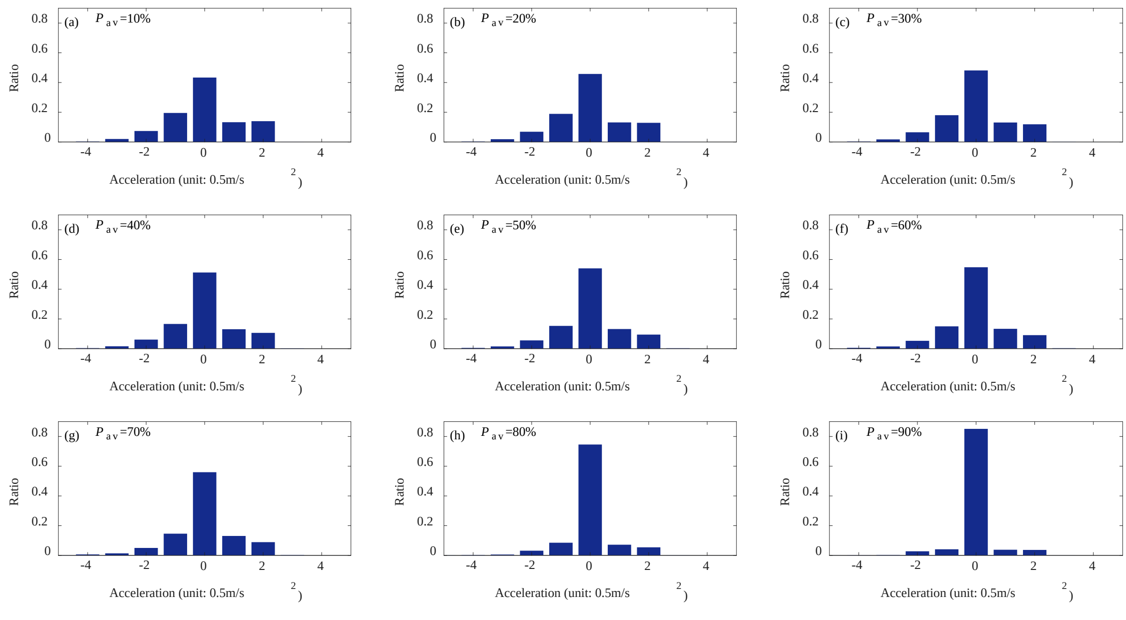

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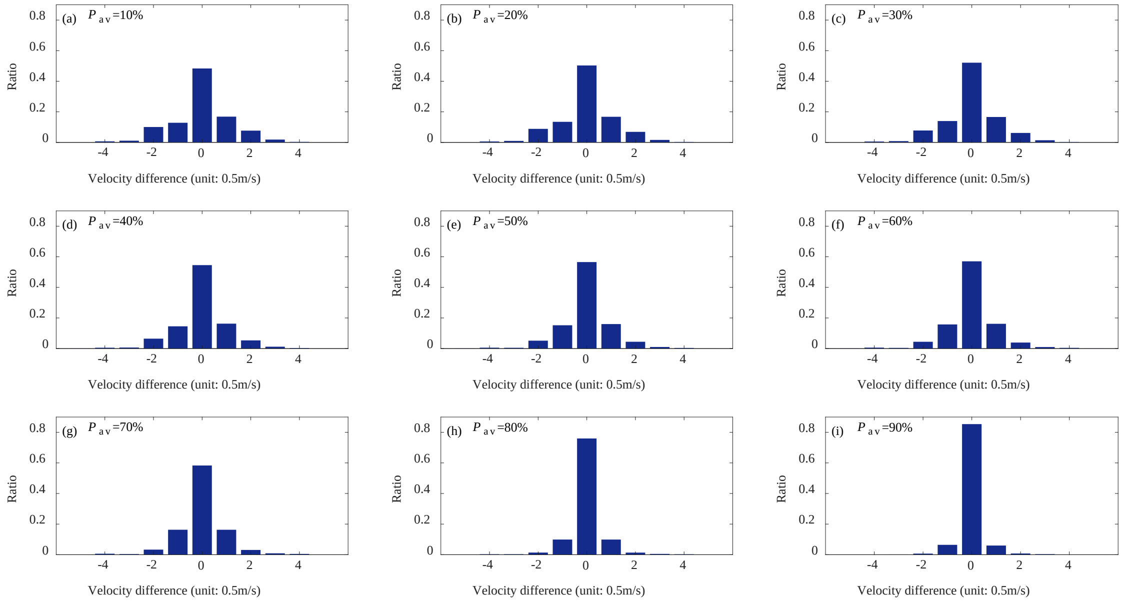

c

Fig.6. Time-to-collision distributions (a), acceleration rate distributions (b) and velocity difference distributions (c) under various penetration rates of autonomous vehicle P_{av}, with T_{ACC} =0.5 s, density equals to 100 veh/km/lane.

4. Conclusions

In this work, we reported a further study of the heterogeneous flow dynamics with both conventional vehicles and CAVs. Simulation results were presented which aims to provide some insights into the impact of CAV on traffic safety and sheds light on how would the mixed traffic flow dynamics evolve with the gradual adoption of CAV under current traffic system.

The frequency of dangerous situations in the mixed flow under different CAV penetration rates indicates that the condition of traffic safety would be greatly improved with the increase in the CAV penetration rate. More cautious car-following strategy of CAV would contribute to a greater benefit on traffic safety, though less gain in capacity. Acceleration rate and velocity difference distribution of the mixed traffic flow indicate that the introduction of CAV would contribute to a higher portion of smooth driving in the mixed traffic flow. Velocity difference between vehicles is decreased and traffic flow is greatly smoothed. Stop-and-go traffic will be eased.

The presented work is just a simulation study on the impact of connected and autonomous vehicles on traffic safety, the effect of CAVs on traffic flow dynamics still needs to be explored from a variety of perspectives.

Acknowledgment

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Appendix A. The heterogeneous flow model

The appendix reviews the methodology for modeling CAVs in the heterogeneous traffic flow [13]. The established model considered both autonomous driving through the adaptive cruise control and inter-vehicle connection via short-range communication. For modeling of regular vehicles, the two-state safe-speed model (TSM) is applied, which is able to reproduce the metastable state, traffic oscillations, phase transitions, and other real traffic flow dynamics [20, 21]. For modeling CAVs, new rules were established in the heterogeneous-flow model. The steps involved in the model are as follows.

A.1 Deterministic speed update:

$$v'_{\mathrm{det}} = \min(v+a,\ v_{\max},\ d_{\mathrm{anti}},\ v_{\mathrm{safe}}) \tag{2}$$

Here, v and v' denote the speed at the current and subsequent time steps, respectively. a and $v_{\max}$ are the acceleration rate and maximum velocity of the vehicle, respectively. d_{anti} denotes the anticipated space gap, and v_{safe} denotes the safe speed.

For regular vehicles, d_{anti} and v_{safe} are defined as follows.

$$d_{\mathrm{anti}} = d + \max(v_{\mathrm{anti}} - g_{\mathrm{safety}},\ 0) \tag{3}$$

$d = x_l - x - L_{\mathrm{veh}}$ is the real space gap. x and x_l denote the position of the object vehicle and its preceding vehicle. L_{veh} is the length of the vehicle. $v_{\mathrm{anti}} = \min(d_l,\ v_l + a,\ v_{\max})$ denotes the expected velocity of the preceding vehicle. d_l and v_l denote the real space gap and speed of the preceding vehicle, respectively. g_{safety} is a safety parameter that helps in avoiding accidents considering the limitation of human perception.

$$v_{\mathrm{safe}} = \left[-b_{\max} + \sqrt{b_{\max}^2 + v_l^2 + 2 b_{\max} d} \right] \tag{4}$$

$b_{\max}$ is the maximum deceleration rate. The round function $[x]$ helps return the integer nearest to x. This equation assumes (i) a reaction time of 1 s (which is presumably the time step of the cell automata (CA) model), (ii) no acceleration at the present time.

For CAVs, corresponding $d_{\mathrm{anti}}^{\mathrm{cav}}$ and $v_{\mathrm{safe}}^{\mathrm{cav}}$ are defined as follows.

Based on the capability of obtaining an exact value of the space gap, the anticipation distance for CAVs can be transformed to the following function.

$$d_{\mathrm{anti}}^{\mathrm{cav}} = \begin{cases} d + v_{\mathrm{anti}}^{\mathrm{cav}} & \text{if } v_l \text{ is a CAV} \\ d + v_{\mathrm{anti}} - b_{\mathrm{defense}} & \text{otherwise} \end{cases} \tag{5}$$

$$v_{\mathrm{anti}}^{\mathrm{cav}} = \min(d_l,\ v_l + a,\ v_{\max},\ v_{li}) \tag{6}$$

Connectivity is incorporated in Equation (6), where v_{li} denotes the average velocity of the preceding connected vehicles within the connected range (*CR*). If there is no CAV within *CR*, a default value of $v_{\max}$ is applied for v_{li}. CAVs are able to obtain the driving condition within *CR* via dedicated short-range commutation (DSRC) technology. *CR* is larger than the detection range (*DR*). Connectivity of CAVs is another approach of obtaining additional road condition from a wider *CR* compared to its sensor-detection range. b_{defense} is the randomization-deceleration rate under the defensive state. Here, a worst case is assumed to ensure the safety during the operation of CAVs when following a conventional vehicle. Because the driving behavior of humans is unpredictable, a conventional vehicle is always assumed to stay in the defensive state in the operation of a CAV.

In determining safe speed v_{safe} for the regular vehicles, a reaction time of 1 s is incorporated in Equation (4) for human driving. For CAV, this reaction time is eliminated. Compared to conventional vehicles, CAVs are only able to detect vehicles located within the detection range of the sensors. Based on this characteristic, the maximum velocity of a CAV is limited to *DR* of the sensors.

$$v_{\text{safe}}^{\text{cav}} = \left\lfloor \sqrt{v_l^2 + 2b_{\max} \min\left(d_{\text{anti}}^{\text{cav}}, DR\right)} \right\rfloor \tag{7}$$

Here, the velocity of a CAV is assumed to be sufficiently low such that the vehicle can be completely stopped within *DR*, i.e., the maximum velocity of the CAVs $v_{\max}^{\text{cav}} = \left\lfloor \sqrt{2b_{\max} DR} \right\rfloor$.

For regular vehicles, acceleration rate a is a constant value. While for CAVs, a classical ACC model is employed to determine the acceleration rate a_{ACC} for the autonomous driving [9], which is defined as follows.

$$a_1 = K_1(d - vT_{\text{ACC}}) + K_2(v_l - v),\ a_{\text{ACC}} = \lfloor \max(\min(a_1, a_{\max}), b_{\max}) \rfloor \tag{8}$$

Here, K_1 and K_2 are coefficients with respect to ACC, and T_{ACC} is a desired net time gap of a CAV with respect to the preceding vehicle. $\lfloor x \rfloor$ is the floor function used to return the maximum integer no greater than x.

A.2 Stochastic deceleration for regular vehicles:

$$v' = \begin{cases} \max(v'_{\text{det}} - b_{\text{rand}}, 0) & \text{with probability } p \\ v'_{\text{det}} & \text{otherwise} \end{cases} \tag{9}$$

The randomization deceleration b_{rand} and stochastic deceleration probability p are specifically defined as follows:

$$b_{\text{rand}} = \begin{cases} a & \text{if } v < b_{\text{defense}} + \lfloor d_{\text{anti}}/T \rfloor \\ b_{\text{defense}} & \text{otherwise} \end{cases} \tag{10}$$

$$p = \begin{cases} p_b & \text{if } v = 0 \\ p_c & \text{else if } v \le d_{\text{anti}}/T \\ p_{\text{defense}} & \text{otherwise} \end{cases} \tag{11}$$

where b_{rand} denotes the randomization-deceleration rate. $p_{\text{defense}} = p_c + \frac{p_a}{1+e^{\alpha(v_c - v)}}$ is a logistic function used to define the randomization probability p_{defense}. In the function b_{rand}, two different randomization-deceleration values are employed to describe the difference in the driving behaviors under two different states, i.e., the defensive and normal states. b_{defense} is the randomization-deceleration rate under the defensive state. Under the normal state, the randomization-deceleration rate equals to a.

For CAVs, no randomization-deceleration is applied.

A.3 Position update

$$x' = x + v' \tag{12}$$

x' denotes position at subsequent time step. The time step of the model is 1 s and the vehicle will move forward at a distance of its updated velocity.

A.4 Lane-changing rules

A classical lane-changing model is applied to extend the TSM to a two-lane traffic-flow model [22]. It is defined as follows.

Incentive criteria: $d(i, t) < \min\{v + \text{a}, v_{\max}\}$ and $d(i, t)_{\text{other}} > \min\{v + \text{a}, v_{\max}\}$ indicate space ahead of the object vehicle i is not enough for traveling with a higher velocity, and the driving condition in the target lane is better than that in the current lane.

The safety criteria $d(i, t)_{\text{back}} > v_{\max}$ indicates that, when changing the lanes, the vehicle immediately behind the object vehicle moving on the target lane will not crash the object vehicle after changing lanes. When the two conditions are fulfilled simultaneously, the object vehicle will move onto the target lane with a lane-changing probability P_{lc}.

The lane-changing model adopted here is a classical lane-changing model which is widely applied in cellular automata traffic flow models. The purpose of introducing the lane-changing is for better modeling the human-driven traffic flow. Since one-lane traffic flow model is not able to account for the passing behavior, and passing behavior is a common practice in real traffic flow. A single-lane model can only model the car-following process. By introducing the lane-changing model, the system can be closer to real traffic system and the result of this work would be more reliable. What is more, if using a single lane model, the system is not able to evolve spontaneously. Since no vehicle can pass. And the simulation result would overly rely on the initial distribution of the mixed vehicle fleets. However, this problem can be solved by introducing the lane-changing model. In the simulation of the two-lane freeway, the system can evolve spontaneously.

Tables 1 and 2 list the parameters of the model for modeling the mixed traffic flow.

Table 1 Parameters for modeling regular vehicles [20]

Parameters	L_{cell}	L_{veh}	$v_{\max}$	T	a	$b_{\max}$	b_{defense}	P_{a}	P_{b}	P_{c}	g_{safety}	v_{c}	α
Units	m	L_{cell}	m/s	s	m/s^2	m/s^2	m/s^2	-	-	-	L_{cell}	L_{cell}/s	s/L_{cell}
Values	0.5	15	27	1.8	0.5	−3	1	0.85	0.52	0.1	20	30	10

Table 2 Parameters for modeling CAV [13]

Parameters	DR	CR	P_{lc}	K_1	K_2	$a_{\max}$
Units	m	m	-	s^{-2}	s^{-1}	m/s^2
Values	120	300	0.2	0.14	0.9	3

References

[1] Fagnant, D. J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice, 77, pp.167-181.*

[2] National Highway Traffic Safety Administration, 2008. National Motor Vehicle Crash Causation Survey. *U.S. Department of Transportation, Report DOT HS 811 059.*

[3] Ioannou, P.A. and Chien, C.C., 1993. Autonomous intelligent cruise control. *IEEE Transactions on Vehicular technology, 42(4), pp.657-672.*

[4] Davis, L. C., 2004. Effect of adaptive cruise control systems on traffic flow. *Physical Review E, 69(6), 066110.*

[5] Marsden, G., McDonald, M., and Brackstone, M., 2001. Towards an understanding of adaptive cruise control. *Transportation Research Part C: Emerging Technologies, 9(1), pp.33-51.*

[6] Van Arem, B., Van Driel, C.J. and Visser, R., 2006. The impact of cooperative adaptive cruise control on traffic-flow characteristics. *IEEE Transactions on Intelligent Transportation Systems, 7(4), pp.429-436.*

[7] Kesting, A., Treiber, M., Schönhof, M. and Helbing, D., 2008. Adaptive cruise control design for active congestion avoidance. *Transportation Research Part C: Emerging Technologies, 16(6), pp.668-683.*

[8] Shladover, S., Su, D. and Lu, X. Y., 2012. Impacts of cooperative adaptive cruise control on freeway traffic flow. *Transportation Research Record: Journal of the Transportation Research Board, (2324), pp.63-70.*

[9] Calvert, S. C., Schakel, W. J. and van Lint., J.W.C., 2017. Will automated vehicles negatively impact traffic flow?. *Journal of Advanced Transportation, 2017, Article ID 3082781, 17p.*

[10] Kerner, B.S., 2016. Failure of classical traffic flow theories: stochastic highway capacity and automatic driving. *Physica A: Statistical Mechanics and its Applications, 450, pp.700-747.*

[11] Mahmassani, H. S., 2016. Autonomous vehicles and connected vehicle systems: Flow and operations considerations. *Transportation Science, 50(4), pp.1140-1162.*

[12] Talebpour, A. and Mahmassani, H.S., 2016. Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transportation Research Part C: Emerging Technologies, 71, pp.143-163.*

[13] Ye, L. and Yamamoto, T., 2018. Modeling connected and autonomous vehicles in heterogeneous traffic flow, *Physica A: Statistical Mechanics and its Applications, 490, pp. 269-277.*

[14] Ye, L. and Yamamoto, T., 2018. Impact of dedicated lanes for connected and autonomous vehicle on traffic flow throughput. *Physica A: Statistical Mechanics and its Applications, 512, pp. 588-597.*

[15] Stern, R.E., Cui, S., Delle Monache, M.L., Bhadani, R., Bunting, M., Churchill, M., Hamilton, N., Haulcy, R., Pohlmann, H., Wu, F., Piccoli, B., Seibold, B., Sprinkle, J. and Work, D.B., 2018. Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments. *Transportation Research Part C: Emerging Technologies, 89, pp. 205-221.*

[16] Ge, J.I., Avedisov, S.S., He, C.R., Qin, W.B., Sadeghpour, M. and Orosz, G., 2018. Experimental validation of connected automated vehicle design among human-driven vehicles. *Transportation Research*

Part C: Emerging Technologies, 91, pp. 335-352.

[17] Rahman, M. S., and Abdel-Aty, M., 2018. Longitudinal safety evaluation of connected vehicles' platooning on expressways. *Accident Analysis & Prevention. 117, pp.381-391.*

[18] Boccara, N., Fuks, H. and Zeng, Q., 1997. Car accidents and number of stopped cars due to road blockage on a one-lane highway. *Journal of Physics A: Mathematical and General*, 30(10), pp.3329.

[19] Minderhoud, M. M. and Bovy, P. H., 2001. Extended time-to-collision measures for road traffic safety assessment. *Accident Analysis & Prevention*, *33*(1), pp.89-97.

[20] Tian, J., Li, G., Treiber, M., Jiang, R., Jia, N. and Ma, S., 2016. Cellular automaton model simulating spatiotemporal patterns, phase transitions and concave growth pattern of oscillations in traffic flow. *Transportation Research Part B: Methodological, 93, pp.560-575.*

[21] Tian, J., Treiber, M., Ma, S., Jia, B. and Zhang, W., 2015. Microscopic driving theory with oscillatory congested states: model and empirical verification. *Transportation Research Part B: Methodological, 71, pp.138-157*.

[22] Rickert, M., Nagel, K., Schreckenberg, M. and Latour, A., 1996. Two lane traffic simulations using cellular automata. *Physica A: Statistical Mechanics and its Applications*, *231*(4), pp.534-550.