Modeling Connected and Autonomous Vehicles in Heterogeneous Traffic Flow

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Abstract

The objective of this study was to develop a heterogeneous traffic-flow model to study the possible impact of connected and autonomous vehicles (CAVs) on the traffic flow. Based on a recently proposed two-state safe-speed model (TSM), a two-lane cellular automaton (CA) model was developed, wherein both the CAVs and conventional vehicles were incorporated in the heterogeneous traffic flow. In particular, operation rules for CAVs are established considering the new characteristics of this emerging technology, including autonomous driving through the adaptive cruise control and inter-vehicle connection via short-range communication. Simulations were conducted under various CAV-penetration rates in the heterogeneous flow. The impact of CAVs on the road capacity was numerically investigated. The simulation results indicate that the road capacity increases with an increase in the CAV-penetration rate within the heterogeneous flow. Up to a CAV-penetration rate of 30%, the road capacity increases gradually; the effect of the difference in the CAV capability on the growth rate is insignificant. When the CAV-penetration rate exceeds 30%, the growth rate is largely decided by the capability of the CAV. The greater the capability, the higher the road-capacity growth rate. The relationship between the CAV-penetration rate and the road capacity is numerically analyzed, providing some insights into the possible impact of the CAVs on traffic systems.

Keywords: Multi-model, connected and autonomous vehicles, cellular automaton, heterogeneous flow model

1. Introduction

Recent developments in information and communication technology have resulted in significant advancements in intelligent transportation systems (ITSs). Because of the latest developments in the automobile industry, connected and autonomous vehicles (CAVs) are coming to the fore. It is widely expected that CAVs will be available on the mass market by 2022 or 2025. Connected systems such as the vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) systems will be introduced in the transportation system along with the deployment of CAVs. These significant developments will change the highway-driving environment. Equipped with computer sensors that can help detect near objects, along with the capability of communicating with other autopilot vehicles, the driving characteristics of the CAVs will be different from those of the conventional vehicles. The CAVs are able to obtain more precise driving-condition parameters compared to human perception; thus, they are capable of instantly reacting to the changes in driving conditions unlike the delay observed in human reaction time or the negative effects of human error. Moreover, the CAVs can be driven in close proximity via the adaptive cruise control (ACC) technology; thus, the distance between two successive CAVs is considerably shorter than that between two conventional vehicles. In addition, inter-vehicle connections via dedicated short-range communications (DSRC) are able to enlarge the detection range of the distance sensors, and allow CAVs a greater capability. The potential merits such as improvement in road capacity, traffic safety, and efficiency are expected through the deployment of CAVs. However, before the CAVs are fully deployed, a heterogeneous traffic flow comprising the conventional vehicles and CAVs will exist for a long period, which may bring uncertainty in the current transportation system. The extent to which the current transportation system can be improved through the deployment of this new technology is unknown. Moreover, the relationship between the CAV-penetration rates and the possible improvement in the road capacity need to be analyzed. In this study, some insights are provided regarding the aforementioned parameters through simulation with the help of a multi-model approach. The known characteristics of the CAVs can be used to model the driving behavior. The simulation approach will be helpful in addressing the problems numerically.

2. Literature review

In recent studies, the possible impact of the CAVs on the current transportation system was discussed such as impact on traffic safety, congestion, travel behaviors, parking, and vehicle ownership. Fagnant and Kockelman summarized the potential benefits of autonomous vehicles with respect to traffic safety, congestion, and travel behaviors [1]. They presented several implementation methods along with some policy recommendations. Gruel and Stanford analyzed the long-term effects of autonomous vehicles using a speculative approach [2]. In these studies, the impact of CAVs was largely addressed using analytical approaches. However, a traffic-flow model can be used to solve this problem by using a computational approach via simulation, which may be able to provide more accurate results.

In the field of traffic modeling, many studies have been conducted concerning the impact of autonomous driving on the flow of traffic. During the early stages of development, the term autonomous driving was largely associated with semi-automatic vehicles having a driving-assistant function known as the ACC. In previous studies, advantages such as smoother traffic flow, improvement in road capacity, and flow stability were presented. Ioannou and Chien developed an autonomous intelligent cruise-control system. They evaluated the performance of the system via a computer simulation and found that the developed system contributes to a faster and smoother traffic flow [3]. Arem et al. studied the impact of a cooperative ACC on the traffic-flow characteristics and found that the traffic-flow stability can be improved along with a slight increase in the flow efficiency [4]. Kesting et al. employed an ACC strategy to improve the traffic stability and increase the dynamic road capacity [5]. In most previous studies on autonomous driving, the possible effects of the ACC technology were analyzed, focusing primarily on the car-following process and single-lane models were used without considering passing behaviors. Although autonomous driving is an important component of the CAV technology, the connectivity was neglected in these studies. Nevertheless, many studies have been conducted on connected vehicles. Lu et al. presented an overview of wireless technologies used in the connected vehicles and discussed the possible pros and cons of vehicular connectivity [6]. Talebpour et al. presented a comprehensive simulation framework to model the behavior of the driver in connected vehicles under a connected environment and found that this technology can be used to improve the efficiency and reliability of a driverless transportation network. Because the connected-vehicle technology and automatic driving are two different emerging technologies, previous studies treated them separately [7].

With the rapid development of CAVs in recent times, fully automated vehicles with connected ability will soon be a reality. Studies are being conducted on this emerging technology. Talebpour and Mahmassni presented a framework used to simulate different types of vehicles including CAVs using different models with some technology-appropriate assumptions [8]. Gora and Rüb presented fundamental concepts and assumptions to model self-driving connected cars [9]. In these studies, fundamental hypothesizes were used to model the CAVs based on the technical characteristics of the CAVs. One such assumption was that the maximum velocity is limited because of the detection range of the sensor. The speed of a CAV should be sufficiently low so that it can react to any event outside the sensor range [10]. These studies serve as the basis for further research on modeling CAVs.

The cellular automaton (CA) model is a type of discrete model, which has been extensively applied in the field of microscopic-traffic modeling in the past few decades. In addition to the capability of describing the vehicular driving behavior, although with relative low accuracy on a microscopic scale comparing to continuous models, advantages such as simplicity and flexibility in adapting to sophisticated characteristics of real traffic have been demonstrated in many previous studies. For example, Tian et al. established a two-state safe-speed model (TSM) to reproduce the metastable state, traffic oscillations, phase transitions, and other real traffic flow dynamics. They compared the TSM with a series of existing models and found that the TSM performs the best [11]. Thus, we choose the TSM as the base of new model in terms of modeling regular vehicles. The CA model was also applied to study the possible impact of the emerging technologies on the traffic flow. Kerner analyzed the shortage of classical traffic theories concerning traffic breakdown, and concluded that the traffic-flow models based on these theories may not be reliable for analyzing the possible impact of autonomous driving or other ITS-applications on the traffic flow. Hence, a traffic-flow model in the framework of the three-phase theory was suggested to analyze the impact of autonomous driving on the traffic flow. The traffic flow model in the framework of the three-phase theory can show and explain traffic breakdown by the F→S transition (free flow to synchronized traffic flow) in the metastable free flow. Kerner further investigated the performance of autonomous driving under mixed-traffic-flow conditions and found that autonomous driving can either decrease or increase the probability of traffic breakdown [12]. Hence, in this study, a heterogeneous flow model was established wherein the conventional vehicles and CAVs were considered simultaneously based on the recent developments in the field of microscopic-traffic modeling. For modeling of regular vehicles, we applied the TSM model. While for modeling the CAVs, new rules were established in the heterogeneous-flow model.

In real traffic, capacity is affected by numerous factors, such as road conditions, road user conditions, driving behaviors of the user, weather conditions and so on. Vehicle composition naturally is a significant factor that affects the capacity. Traffic flow modeling approach enables us to analyze the impact of a certain factor on capacity by conducting simulation under relatively idealized condition. In the field of traffic flow theory, fundamental diagram describes a statistical relation between the macroscopic traffic flow variables of flow, density, and velocity. The term "capacity" used in this work indicates the classical understanding of road capacity. Capacity is equal to the maximal flow rate attained in the free flow phase. The objective of this study was to explore the possible impact of the CAVs on capacity under different penetration rates.

The paper is organized as follows. The TSM proposed by Tian et al. is first presented in section 3.1, which is a one-lane homogeneous traffic-flow model in the frame of the three-phase theory. In the subsequent section, we extended the model to a two-lane heterogeneous-flow model by incorporating a classical lane-changing model in the lane-changing process, wherein the CAVs were included in the heterogeneous flow. After having validated the model via the empirical data obtained from Next Generation Simulation (NGSIM) in section 4, the extended model was used in studying the possible impact of the CAVs on the heterogeneous-traffic flow. The simulation results and conclusions are presented in sections 6 and 7, respectively.

3. Model

3.1 The steps involved in the TSM are as follows.

1. Deterministic speed update:

$$v'_{\mathrm{det}} = \min(v+a,\ v_{\max},\ d_{\mathrm{anti}},\ v_{\mathrm{safe}}) \quad (1)$$

2. Stochastic deceleration:

$$v' = \begin{cases} \max(v'_{\mathrm{det}} - b_{\mathrm{rand}}, 0) & \text{with probability } p \\ v'_{\mathrm{det}} & \text{otherwise} \end{cases} \quad (2)$$

3. Position update

$x' = x + v'$ (3)

Here, v (v') and x (x') denote the speed and position at the current and subsequent time steps, respectively. a and v_{max} are the acceleration rate and maximum velocity of the vehicle, respectively. b_{rand} denotes the randomization-deceleration rate. d_{anti} denotes the anticipated space gap, v_{safe} denotes the safe speed, which is defined in the Gipps model [13]. d_{anti} and v_{safe} are defined as follows.

$d_{anti} = d + \max(v_{anti} - g_{safety}, 0)$ (4)

$v_{safe} = [-b_{max} + \sqrt{b_{max}^2 + v_l^2 + 2b_{max}d}]$ (5)

This equation assumes (i) a reaction time of 1 s (which is presumably the time step of the CA model), (ii) no acceleration at the present time.

$d = x_l - x - L_{veh}$ is the real space gap. L_{veh} is the length of the vehicle.

v_{anti} denotes the expected velocity of the preceding vehicle.

$v_{anti} = \min(d_l, v_l + a, v_{max})$ (6)

x_l, d_l, and v_l denote the position, 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, with the constraint $g_{safety} \geq b_{rand}$. b_{max} is the maximum deceleration rate. The round function $[x]$ helps return the integer nearest to x.

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

$$b_{rand} = \begin{cases} a & \text{if } v < b_{defense} + \lfloor d_{anti}/T \rfloor \\ b_{defense} & \text{otherwise} \end{cases} \quad (7)$$

$$p = \begin{cases} p_b & \text{if } v = 0 \\ p_c & \text{else if } v \leq d_{anti}/T \\ p_{defense} & \text{otherwise} \end{cases} \quad (8)$$

where $p_{defense} = p_c + \frac{p_a}{1+e^{\alpha(v_c - v)}}$ 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. $\lfloor x \rfloor$ is the floor function used to return the maximum integer no greater than x. $b_{defense}$ is the randomization-deceleration rate under the defensive state. Under the normal state, the randomization-deceleration rate equals to a.

3.2 Modeling CAV

Compared to the 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 the detection range (DR) of the sensors. Here, the velocity of a CAV is assumed to be sufficiently low such that the vehicle can be completely stopped within the DR, i.e., the maximum velocity of the

CAVs $v_{\max}^{\text{cav}}$, which is defined as follows.

$$v_{\max}^{\text{cav}} = [\sqrt{2b_{\max}DR}] \tag{9}$$

To determine v_{safe} of the conventional vehicles, a reaction time of 1 s for human drivers is incorporated in Equation (5). For the CAV, this reaction time can be neglected. Thus, the following equation can be obtained.

$$v_{\text{safe}}^{\text{cav}} = [\sqrt{v_l^2 + 2b_{\max}\min(d_{\text{anti}}, DR)}] \tag{10}$$

Moreover, for a CAV, based on the capability of obtaining an exact value of the space gap, the anticipation distance can be transformed to the following function.

$$d_{\text{anti}}^{\text{cav}} = \begin{cases} d + v_{\text{anti}} & \text{if } v_l \text{ is a CAV} \\ d + v_{\text{anti}} - b_{\text{defense}} & \text{otherwise} \end{cases} \tag{11}$$

Here, a worst case is assumed to ensure the safety during the operation of the 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. Namely, the result in Eq.(11) will be larger if a preceding vehicle is a CAV. For CAVs, since they can get relatively more precise parameters comparing to regular vehicles, no safety distance is applied. Consequently, Eq.(11) will be larger than Eq.(4).

A classical ACC model is employed to determine the acceleration rate a for the autonomous driving of the CAVs [12], which is defined as follows.

$$a_1 = K_1(d - vT_{\text{ACC}}) + K_2(v_l - v),\ a = \lfloor \max(\min(a_1, a_{\max}), b_{\max}) \rfloor \tag{12}$$

Here, K_1 and K_2 are coefficients with respect to the ACC, and T_{ACC} is a desired net time gap of a CAV with respect to the preceding vehicle. The calculated acceleration rate is regulated by the range from $b_{\max}$ to $a_{\max}$, which accounts for the comfort factor. $a_{\max}$ and $b_{\max}$ represent the maximal acceleration rate and maximal deceleration rate, respectively.

Connectivity of the CAVs is another method of obtaining additional road condition from a wider connected range (CR) compared to its sensor-detection range. This characteristic is incorporated in Equation (6),

$$v_{\text{anti}}^{\text{cav}} = \min(d_l, v_l + a, v_{\max}, v_{li}) \tag{13}$$

where v_{li} denotes the average velocity of the preceding connected vehicles within the CR. If there is no CAV within the CR, a default value of $v_{\max}$ is applied for v_{li}. The CAVs are able to obtain the driving condition within the CR via dedicated short-range commutation (DSRC) technology. CR is larger than DR.

3.2 Lane-changing model

A classical lane-changing model is employed to extend the TSM to a two-lane traffic-flow model [14]. 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 $d(i, t)_{\mathrm{back}} > v_{\max}$ 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}.

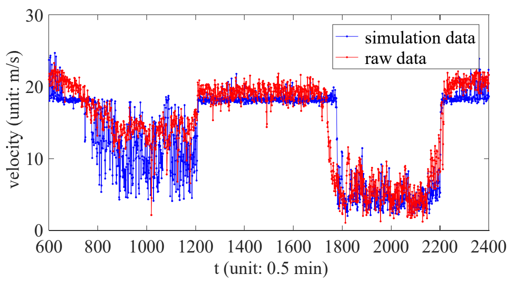
4. Empirical validation

The empirical dataset used to validate this study was presented by NGSIM [15], which was collected using double-loop detectors on eastbound Interstate 80 (I-80) freeway in the San Francisco Bay area in Emeryville, CA, on April 13, 2005. This data set provides 30-s processed, loop detector data. Speed (unit: feet/s), volume (unit: number) and occupancy (unit: percentage) at each detector for the 30-s time step are presented at each detector in each lane. A method proposed by Brockfeld was employed to obtain the effective single lane speeds v_{ave}^{i} and fluxes f_{ave}^{i} over N lanes, which are given below.

$$v_{\mathrm{ave}}^{i} = \sum_{j=1}^{N} w_{ij}\, v_{ij}^{\mathrm{emp}},\; w_{ij} = \frac{f_{ij}^{\mathrm{emp}}}{\sum_{j''=1}^{N} f_{ij''}^{emp}},\; f_{\mathrm{ave}}^{i} = \frac{1}{N}\sum_{j=1}^{N} f_{ij}^{\mathrm{emp}} \tag{14}$$

where f_{ij}^{emp} and v_{ij}^{emp} are the empirical flux and speed in lane j at detector station I, respectively [16].

I-80 is a five-lane freeway, with the left-most lane being a high-occupancy vehicle (HOV) lane. The traffic dynamics on the HOV lane is significantly different from those in other lanes. Thus, to validate the extended model, only the data from lanes 2–5 were used. The loop detector data included in the dataset are separated by lanes. Since the heterogeneous flow model established in our work is a two-lane flow model. We cannot use the empirical data directly in the validation process. In order to take into account the passing behavior, we obtain the effective single-lane data from each two of the original five lanes. Specifically, effective single-lane data from lanes 2–3 and lanes 4–5 are used to validate the extended two-lane model. Tian et al. provided specific simulation setup information [17].



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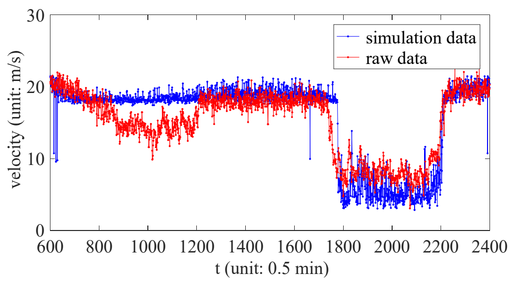

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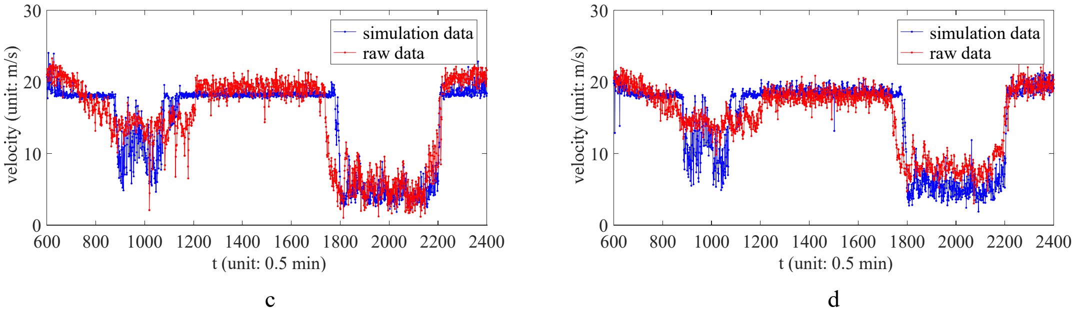

Fig. 1. Comparisons of speed–time series between simulation results and empirical data. Red curves are calculated using Eq. (14) from real data. Blue curves indicate simulation results obtained using the extended model. (a) and (b) are simulation results under condition of no passing behavior on the road segment. (c) and (d) with passing behaviors.

The speed–time series of the real data, indicated in red in Fig. 1, shows a typical pattern of highway-traffic flow during a particular day, wherein a decrease in speed is observed during the peak hours of the morning and traffic breakdown during the peak hours of the afternoon. The original TSM was proved to have the capability of reproducing the lane-average speed–time series through simulation as observed in the study by Tian et al. [17]. However, the speed–time series of each lane are different, i.e., the average speed in the lanes decreases from the left to right. As a one-lane flow model, the TSM is not able to incorporate the passing behaviors, which is a common practice in real traffic flow. This study confirms that the TSM can be extended to a multi-lane flow model by applying the lane-changing model and setting specific speed limits for each lane based on the empirical data. Figs. 1(a) and 1(b) show the simulation results without the passing behavior, which is unsuitable compared to that shown in Figs. 1(c) and 1(d), wherein the passing behaviors are incorporated.

In this section, the simulation result shows that the performance of the extended traffic-flow model is in good agreement with the real traffic data, thus proving the effectiveness of the extended two-lane model. With its capacity of representing the real traffic dynamics of manual driving vehicles, this model is further used in simulating the heterogeneous flow including the CAVs to study the possible impact of the CAVs.

5. Simulation setup

In the CA model, the road segment is subdivided into cells and time into time steps. At each time step, each cell has only two states, which either is occupied by a vehicle or is empty. The simulation was conducted on a 10-km two-lane road segment under periodic boundary condition. First, the simulation involved conventional vehicles and CAVs randomly distributed in a mega-jam on the road segment. Tables 1 and 2 list the parameters of the TSM and parameters for modeling the CAV, respectively.

Velodyne Lidar HDL-64E has a capability of 120 ± 2 m in the detection range. In this study, the detection range DR equals to 120 m. A typical communication range used in the connected vehicles in the DSRC technology is 300 m. The maximum velocity of the CAVs is given by $[\sqrt{2b_{\max}DR}]$. To investigate the difference in the performance between autonomous vehicles and regular vehicles under the traffic-flow conditions, the same $v_{\max}$ is employed for the conventional vehicles in the simulation.

Table 1 Parameters of TSM

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	1	−3	1	0.85	0.52	0.1	20	30	10

Table 2 Parameters for modeling CAV

Parameters	DR	CR	P_{lc}	T_{ACC}	K_1	K_2	$a_{\max}$
Units	m	m	-	s	s^{-2}	s^{-1}	m/s^2
Values	120	300	0.2	1.1	0.14	0.9	3

Because of the lack of real data regarding the CAVs, the parameters required for the ACC process follow the ones in the study conducted by Kerner [12]. Specifically, T_{ACC} = 1.1 s with coefficients of ACC adaptation K_1 = 0.14 and K_2 = 0.9. Moreover, two comparison experiments are conducted simultaneously with T_{ACC} set as 0.8 s and 0.5 s, representing more advanced capabilities of the CAV. This also helps provide additional information on the impact of the CAVs on the traffic flow. Lane-changing probability is a parameter, which incorporates randomness in the lane-changing process. In this work, the lane-changing probability is set as 0.2, which is a typical value used in CA model for the lane-changing probability. We compared the performance of several values for the lane-changing probability, including 0.1, 0.2, and 0.3. Value of 0.2 has the best performance among these three values, with its result presented in Fig.1 (c) and (d). Still, we fail to find any reference for determining some parameters in CAV driving, such as the lane-changing probability for CAVs. For these parts, we did not differ CAVs from regular vehicles in the modeling process. Generally, lane-changing probability would have a direct impact on traffic safety. While the impact of lane-changing probability on road capacity would not be so significant as improvement in individual vehicle performance.

6. Simulation results and discussion

The simulation was conducted under periodic boundary. P_{av} denotes the percentage of the CAVs with respect to the total number of vehicles in the traffic flow.

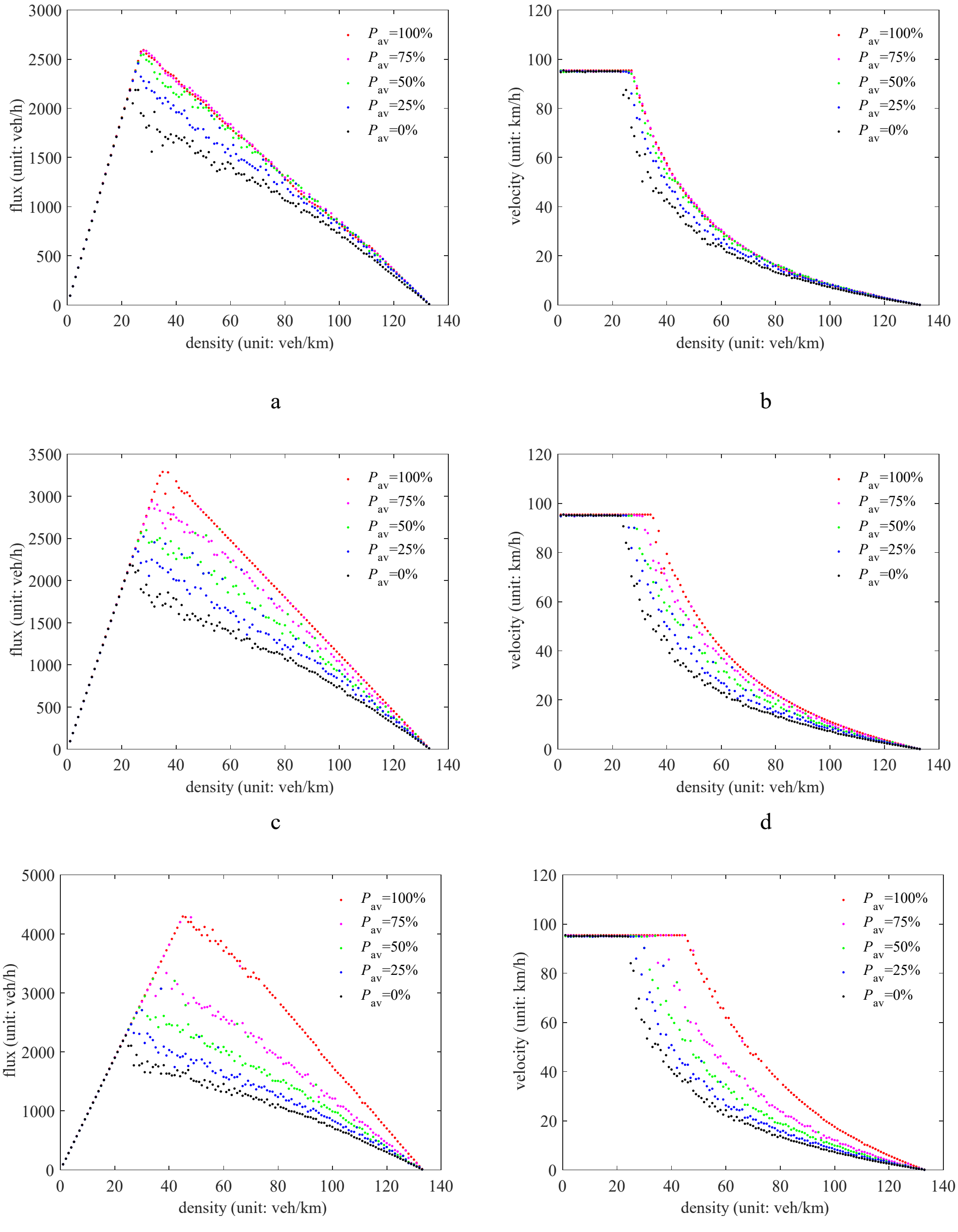

Fig.2. Flow-density diagrams and speed-density diagrams of the presented model under different penetration rates of autonomous vehicle P_{av} with T_{ACC} = 1.1 s (a, b), 0.8 s (c, d), and 0.5 s (e, f).

Fig. 2 shows the relationship between the traffic flow and velocity with respect to the density. First, the traffic flow increases with a linear function until it reaches the road capacity. Subsequently, the flow decreases with further increase in the density. The diagram can be divided into two parts: the free flow phase and congested-flow phase. The maximum flow rates, shown in Figs. 2(a), 2(c), and (e), helps in reflecting the road capacity. Under different P_{av}, the road capacity varies. In other words, a higher penetration rate P_{av} corresponds to a higher capacity, indicating that the presence of CAVs can increase the road capacity. In the free-flow phase, the effect of the CAVs on the performance of the system is negligible. The conventional vehicles and CAVs are able to operate at maximum velocity, without interacting with other vehicles. In the congestion phase, the CAVs are more advantageous than the conventional vehicles. A smaller gap between a CAV and its preceding vehicle could be achieved, further increasing the road capacity. Moreover, situations with a higher penetration rate P_{av} results in a longer free-flow phase, which is a direct effect of the increased road capacity.

Comparing the results of Figs. 2(a) and 2(b) with those of Figs. 2(c) and 2(d) and Figs. 2(e) and 2(f), we can find that the capability of the CAVs in terms of the desired net time gap plays a decisive role in the process, which can be understood easily. When it comes to connectivity, it is not so plausible that connectivity results in an increase in the capacity directly. Since the increase in capacity is largely based on the improvement of individual vehicle performance, in terms of a decrease in the average time gaps. Still, connectivity actually is a part of the reasons that contributes to the decreased average time gaps and helps to avoid potential crashes at the same time. Further improving the capability of the CAVs compared to the conventional vehicles will lead to a greater improvement in the road capacity. However, the growth pattern in each situation seems different.

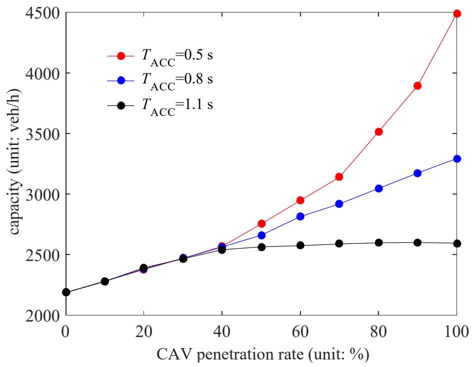

Fig.3. Relationship between road capacity and CAV-penetration rate in the heterogeneous traffic flow with different T_{ACC}.

Fig. 3 shows the results under the three situations with various T_{ACC} values. The figure shows that the increase in the road capacity is different for different T_{ACC} values. Before the CAV-penetration rates reaches a rate of 30%, the road capacity increases gradually. The effect of the difference in the CAV capability on the capacity growth rate is negligible. At this stage, with CAVs being the minority in the heterogeneous flow, the connected condition is rarely fulfilled, and only autonomous driving is fully realized. As the conventional vehicles are in majority, the increase in the road capacity resulting from the CAVs is limited. When the CAV-penetration rate exceeds 30%, the growth rate is largely decided by the improved capability of the CAVs in the ACC compared to conventional vehicles. An improved capability corresponds to a higher capacity growth rate and a higher road capacity.

7. Conclusions

In this study, an extended CA model was established incorporating the CAVs in the heterogeneous traffic flow. The possible impact of the CAVs on the road capacity under different penetration rates is numerally investigated. The simulation results indicate that the introduction of CAVs changes the traffic-flow dynamics, increasing the road capacity along with the increase in the CAV-penetration rate within the heterogeneous flow. Before the CAV-penetration rate reaches 30%, the increase in the road capacity is gradual; moreover, the effect of the difference in the CAV capability on the growth rate is insignificant. When the CAV-penetration rates exceed 30%, the growth rate is largely decided by the CAV capability on the desired net time gap. A higher capability corresponds to a higher capacity growth rate. The possible increase patterns are numerally presented, providing some insights into this problem.

The contribution of this study can be summarized as follows. A two-lane heterogeneous flow model is established wherein the possible impact of the CAVs on the current traffic system is analyzed. The possible impact of an increase in the road capacity is verified, with the growth mechanisms demonstrated via simulation experiments. The growth pattern with respect to the capacity relies on the improvements of the individual CAVs compared to the conventional vehicles. To more accurately predict the growth pattern, more accurate empirical data regarding the CAVs are needed. In terms of connectivity, the inter-vehicle connection via short-range communication is only used to enlarge the range of the distance sensor. Only the response to the immediate leader is considered; i.e., no "multi-anticipation" is applied. These are the major limitations of this work. Extending the analysis to multi-anticipation will be a research direction in future studies. The problem of lacking empirical data of CAVs can be solved as and when related data is published along with the development of this emerging technology.

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References

[1] Fagnant, D.J. and 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] Gruel, W. and Stanford, J.M., 2016. Assessing the long-term effects of autonomous vehicles: a speculative approach. *Transportation Research Procedia*, *13*, pp.18-29.

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

[4] 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.

[5] 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.

[6] Lu, N., Cheng, N., Zhang, N., Shen, X. and Mark, J.W., 2014. Connected vehicles: Solutions and challenges. *IEEE internet of things journal*, *1*(4), pp.289-299.

[7] Talebpour, A., Mahmassani, H.S. and Bustamante, F.E., 2016. Modeling driver behavior in a connected environment: Integrated microscopic simulation of traffic and mobile wireless telecommunication systems. *Transportation Research Record: Journal of the Transportation Research Board*, (2560), pp.75-86.

[8] 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.

[9] Gora, P. and Rüb, I., 2016. Traffic models for self-driving connected cars. *Transportation Research Procedia*, *14*, pp.2207-2216.

[10] Reece, D.A. and Shafer, S.A., 1993. A computational model of driving for autonomous vehicles. *Transportation Research Part A: Policy and Practice*, *27*(1), pp.23-50.

[11] 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.

[12] Kerner, B.S., 2016. Failure of classical traffic flow theories: stochastic highway capacity and automatic driving. *Physica A: Statistical Mechanics and its Applications*, *50*, pp.700-747.

[13] Treiber, M. and Kesting, A., 2013. Traffic flow dynamics. *Traffic Flow Dynamics: Data, Models and Simulation, Springer-Verlag Berlin Heidelberg*.

[14] 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.

[15] NGSIM, 2006. Next generation simulation. https://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm

[16] Brockfeld, E., Kühne, R. and Wagner, P., 2005. Calibration and validation of microscopic models of traffic flow. *Transportation Research Record: Journal of the Transportation Research Board*, (1934), pp.179-187.

[17] 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.