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Change in Microscopic Traffic Simulation Practice with Respect to the Emerging Automated Driving Technology

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Abstract
It is believed that autonomous vehicles will replace conventional human drive vehicles in the next decades due to the emerging autonomous driving technology, which will definitely bring a massive transformation in the road transport sector. Due to the high complexity of traffic systems, efficient traffic simulation models for the assessment of this disruptive change are critical. The objective of this paper is to justify that the common practice of microscopic traffic simulation needs thorough revision and modification when it is applied with the presence of autonomous vehicles in order to get realistic results. Two high-fidelity traffic simulators (SUMO and VISSIM) were applied to show the sensitivity of microscopic simulation to automated vehicle's behavior. Two traffic evaluation indicators (average travel time and average speed) were selected to quantitatively evaluate the macro-traffic performance of changes in driving behavior parameters (gap acceptance) caused by emerging autonomous driving technologies under different traffic demand conditions.

Keywords
microscopic traffic simulation, driving behavior, autonomous driving, highly automated vehicles, sensitivity analysis

1 Introduction

The advent of highly automated or fully autonomous vehicles will also entail the change of everyday life, such as the interaction between travelers [1] or the traffic dynamics [2]. The more, the changes will be tangible in the practice of road traffic modeling and simulation.

1.1 Background of microscopic road traffic simulation

Traffic simulation is the mathematical modeling of traffic dynamics through the application of computer software to support the planning, operation, and development of transportation systems. Simulation models can be classified into macroscopic, mesoscopic, and microscopic models according to the level of detail. Macroscopic models [3] have applications when detailed information about a single vehicle's behavior is not required. It only provides a general evaluation of traffic flows in a network. These models are often used for regional transportation planning [4]. Microscopic models describe each vehicle's behavior and interactions in the traffic system, making more detailed modeling for each movement of the vehicle [5]. For this reason, microscopic models can be applied with a much higher level of detail. The microscopic model has the following advantages: by tracking a single vehicle on the road, it can not only reflect the interaction between vehicles but also predict traffic performance indicators such as vehicle travel time, delay and emission while avoiding the impact on actual road traffic; through the microscopic simulation model, the impact of a specific parameter on traffic can be reflected; through the animation interface of the simulator, one can intuitively visualize the changes in road traffic, and provide a good platform for understanding the traffic operation status under different traffic demands. It has superiority that traditional mathematical models cannot match in describing and evaluating the traffic flow of the road network. Microscopic models are becoming an increasingly important and popular tool in the transportation field. It has been used for a wide range of applications in network design, analysis of transportation problems, the evaluation of Intelligent Transportation System (ITS), and traffic management strategies formulation.

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Even though there are a large number of microscopic models, unfortunately, none of them can be considered as an ideal or, at least, a universal one. It is mainly because every model has different parameters to describe a different traffic situation and vehicle behavior. The early research focused on maintaining the existing distance with the vehicle in front [6]. Car-following models [7] are the most popular approach to model the interaction between vehicles. Car-following theories examine the longitudinal movement of each vehicle and are extended by lane-changing maneuver models.

With the development of computer science, the extension extends to the use of cell automation and multi-agent systems. Continuing these efforts, the expansion was being conducted to get a more realistic behavior model by adding a stochastic method for making decisions based on a given environment of the road. Furthermore, the most adopted methodology is to apply the Monte Carlo procedure to generate random values to show the driving behavior in traffic conditions. The basic steps involved in the development are the same irrespective of the type of model described above [7].

1.2 Background of vehicle automation and market penetration

Highly automated or autonomous cars are intelligent vehicles providing automated driving functions through the onboard computer system. It relies on artificial intelligence, computer vision, sensor fusion, monitoring devices, control devices, and high precision positioning to cooperate so that the system can automatically and safely handle the operation of vehicles without human intervention. According to the need of the amount of driver intervention, both the Society of Automotive Engineers (SAE) and the National Highway Traffic Safety Administration (NHTSA) of the United States classify autonomous driving. SAE divides autonomous driving into five levels from 0 to 4, while NHTSA divides it into six levels from 0 to 5. For the definition of the first four levels of autonomous driving, NHTSA and SAE are almost identical. The four levels are in order of no automation vehicles, single-function level automation with driving assistance system, partial automation, and conditional automation. The difference compared with NHTSA's definition is that SAE further refines the full automation based on the limits of roads and environmental conditions divided into high automation and full automation. A fully automated vehicle is not limited by road types and environmental conditions. The specific autonomous driving classification is shown in Table 1.

Table 1 The levels of vehicle automation

The levels of automation		Classification	Detailed description
SAE	NHTSA		
0	0	No automation	Fully manual operation of the dynamic driving task, the system can only provide warnings (e.g., lane departure warning).
1	1	Driver assistance	The system assists either steering or acceleration/deceleration. The human driver performs all remaining dynamic driving tasks (e.g., cruise control).
2	2	Partial automation	The system automatically operates both steering and acceleration /deceleration according to the driving environment. The human driver performs all remaining dynamic driving tasks (e.g., adaptive cruise control).
3	3	Conditional automation	The system automatically operates all aspects of the dynamic driving task. The human driver must respond appropriately to a request to intervene.
4	4	High automation	The system automatically operates all aspects of the dynamic driving task, even if a human driver does not respond appropriately to a request to intervene.
5	4	Full automation	The system automatically operates all aspects of the dynamic driving task under all roadway and environmental conditions.

In 1977, Tsukuba Mechanical Engineering Laboratory (Japan) developed the first self-driving vehicle that used a camera to detect navigation information based on a large number of experiments, and its speed could reach 30 km/h. In 1984, Carnegie Mellon University developed the world's first self-driving vehicle, which used environmental perception technology to realize automatic decision-making functions. In 1998, an Italian laboratory completed a 2000-kilometer autonomous driving experiment; about 94% of the experimental trip was automated driving, with an average speed of 90 kilometers per hour and a maximum of 123 km/h. In 2009, Google started developing a self-driving car project, using a modified car to drive 14,000 miles in more than a year, and successfully released its self-designed autonomous vehicle in 2014. In January 2016, the new generation autonomous driving platform DRIVEPX2 was officially released by Nvidia; in April, Driver.ai obtained a license to test autonomous cars in California, USA. In the same year, the autonomous vehicle developed by Chang'an Automobile successfully completed the 2000 km long-distance autonomous driving test within six days. In August 2016, the nuTonomy driverless taxi was put into trial operation in Singapore; in September, Uber provided autonomous vehicle travel services to Pittsburgh citizens. In April 2017, Baidu released a project called "Apollo" to provide partners in the automotive industry and autonomous driving field with an open, complete, and safe software platform. In July 2017, the world's first Level 3 self-driving production car, Audi A8, was officially released. In December 2017, the world's first driverless bus, Alphabus, was tested on public roads began trial operation in Shenzhen, China, at the same time.

Technological progress promotes the continuous upgrade of autonomous driving from low-level to high-level. Prior validation to 2015, assisted driving systems were mainly Level 0 and Level 1, and the representative functions were Automatic Emergency Braking (AEB), Lane Keeping Assist (LKA), etc. Autonomous driving technology entered Level 2 in 2016, and its representative functions are Adaptive Cruise Control (ACC) with LKA and Automatic Parking Assistance (APA). In 2020, autonomous driving technology entered Level 3, with representative functions such as Traffic Jam Pilot (TJP), etc., and it will gradually enter Level 4 by 2023, with representative functions such as City Pilot.

At the macro policy level, in February 2020, the National Development and Reform Commission of China issued the "Intelligent Vehicle Innovation Development Strategy", which proposed to realize the mass production of conditional autonomous driving vehicles (Level 3) in 2025 and complete the standard Chinese research and develop systems for autonomous vehicles in 2035. From 2025 to 2030, most vehicles will be fully automated, and more consumers will use shared travel. According to the European Union autonomous driving plan, the automobile industry will be gradually moved towards the autonomous driving society in 2030.

2 Microscopic traffic simulation considering autonomous driving

In the sequel, the traffic simulation is investigated in general, indicating the necessity of applying it for the development of automated/autonomous driving systems.

2.1 The necessity of applying microscopic traffic simulation on the autonomous driving test

Before the autonomous vehicles are officially launched into the market, they must be fully tested in the different traffic environments, thoroughly verify the autonomous driving function, and achieve collaboration with roads, traffic facilities, and other transportation participants. Validation is a necessary step in the development and application of autonomous vehicles. The research and development of autonomous driving systems have been developing rapidly. Still, the industry and the governments have not yet reached a clear consensus on how to conduct safety testing and reliable proving in the real world. Because dangerous traffic scenes are difficult to exhaust, there are technical bottlenecks in scene-based actual vehicle testing methods. According to statistics from the Federal Highway Administration (FHWA) of the United States, a driver needs to travel 850,000 kilometers on average to experience a police report accident and close to 150 million kilometers to experience a fatal accident. The industry generally believes that each autonomous driving system requires 16 billion kilometers of driving data to optimize the system. It would take about 50 years for a fleet of 1,000 autonomous driving test vehicles to complete a sufficient mileage test. Therefore, the general consensus in the industry is that virtual testing and evaluation of autonomous driving systems based on simulation technology is required.

Microscopic traffic simulation is widely used both by the traffic engineering industry and the academic research community. In the traffic engineering industry, a microscopic simulation is a powerful tool in transport development studies, feasibility studies, and concrete development/construction of infrastructures. In research and development, it is used to study traffic management and traffic estimation methodologies. Furthermore, in our days' traffic simulation is also applied in the development of autonomous vehicle systems besides vehicle dynamics simulators.

2.2 Existing microscopic road traffic simulation software tools

Traffic simulation is a mature field; several microscopic road traffic simulators are available. Each simulator has its own advantages and aims to mimic realistic traffic based on car-following models. Typical microscopic traffic simulators applied both in academic and industrial fields are, for instance, Paramics [8], CORSIM [9], PTV VISSIM [10], and Simulation of Urban MObility [11].

It is significant to specify the microscopic modeling issues of autonomous vehicles because automated functions truly affect simulation results. The microscopic simulation software development is inevitable. The traffic impacts of autonomous vehicles should be examined before their implementation. The safety, mobility, and environmental sustainability of the AVs shall be checked. With the emergence of AVs, new vehicle models are needed to simulate them, which means practically new vehicle classes on the simulation software level. Besides, the connected autonomous vehicle (CAV) has a promising prospect. To simulate CAV, Vehicle to Everything (V2X) communications technology also shall be considered [12]. Traffic control features are also expanding. Specific autonomous driver models of different manufacturers should also be implemented in software.

There are currently two ways to develop a microscopic traffic simulation model in software. The first way is that the software developer tries to refine the model and features as much as possible. Another is that the user of the software "develops". For example, they can apply their own vehicle tracking model in traffic simulation applications (e.g., VISSIM API, SUMO TRACI interfaces), or they fine-tune the default driver model to automation properly.

The classical process of traffic control development concludes data collecting, model development, and finally, model calibration. First, traffic engineers make manual traffic counts or get automatically measured traffic data (i.e., detector data). Then, the microscopic simulation model can be created. The last step is to calibrate the model with the data from the reference cross-sections of the test field. When the reference traffic volumes are fixed, one can tune the model by modifying the simulation parameters, such as the car-following model, turning rates, or dynamic traffic inflow. Validation ensures that the software represents reality at a satisfying confidence level by comparing simulation results with real-life observations. Based on reference cross-sections or full network parameters, the GEH-index based validation is applicable. The GEH index is commonly used in traffic engineering, traffic forecasting, and traffic modeling to compare two sets of traffic volumes. The GEH index is classically cross-referenced based on traffic volume.

With the appearance of AVs, the validation methodology should be extended. Appropriate statistical data is required for different automated vehicles. The future outlook for the use of microscopic traffic simulation is also required. In the case of a large number of detectors and automated vehicles (i.e., floating car data (FCD)), there are new possibilities: online calibration [13], simultaneously simulated reality as "virtual twin", application of proactive traffic control, or autonomous vehicle testing [14].

There are many speculations about the impact of autonomous vehicles on the transportation system. Some researchers pointed out that AVs would reduce road congestion, greenhouse gas emissions, economic loss and revolutionize the transportation system. Jadaan et al. [15] proposed in their research that autonomous vehicles can improve road capacity, strengthen road safety, and reduce traffic pollution, but they did not give specific research arguments. Hayes [16] pointed out in his study that AVs can make the parking distance between vehicles smaller, thereby saving urban space resources. Teoh and Kidd [17] compared Google driverless car with conventional vehicles (CV) and found that in most cases, AVs are safer than conventional vehicles, but there is still the possibility of AVs colliding with conventional vehicles. van Arem et al. [18] implemented the traffic flow simulation model MIXIC to study the impact of AVs equipped with Cooperative Adaptive Cruise Control (CACC) on traffic-flow characteristics. The results show that CACC can improve the stability of road traffic flow and improve travel efficiency to a certain extent. Lu et al. [2] investigated how the different percentage of AVs affects the urban macroscopic fundamental diagram (MFD) by using SUMO both with an artificial grid road network and a real-world network in Budapest. Simulation results showed capacity improvement along with AVs penetration growth. Shladover et al. [19] implemented a microscopic simulation model to simulate the impact of ACC (Adaptive Cruise Control) and CACC on freeway capacity under different market shares. Research shows that the use of ACC does not change the freeway capacity much, but when the market penetration of CACC reaches a certain level, it can significantly improve freeway capacity. Wu et al. [20] found that partial autonomous vehicles can reduce fuel consumption by 5% and 7% compared with CVs. van den Berg and Verhoef [21] used dynamic models to study the impact of AVs on traffic bottleneck congestion. They concluded that the existence of AVs could effectively improve road capacity, reduce the value of travel time losses (VOT), and optimize travel efficiency issues caused by travel time loss. Others demonstrated that emerging Autonomous technology would negatively impact the transportation system because it will allow more vehicles to add to the network [22]. Similarly, Szele and Kisgyörgy [23] found that the expected increase of traffic flow through autonomous vehicles is not unequivocal because of the expected increase in motorization.

Based on the above background, to have a deeper understanding of the impact of the emerging autonomous driving technology on the microscopic traffic simulation models, this paper studies the traffic performance in the micro-simulation technology via the gap acceptance model parameter. With the help of VISSIM and SUMO (both well acknowledged, high-fidelity microscopic simulation software), a detailed sensitivity analysis was carried out to quantify the traffic performance under different model parameter settings. The goal of the conducted simulations is to show that the common practice of traffic simulation requires a thorough revision and modification when it is applied with the presence of autonomous vehicles.

3 Simulation-based sensitivity analysis of model parameters

3.1 Related simulators

SUMO is an open-source microscopic continuous traffic flow simulation software developed by the German Aerospace Center in 2001. It comes with a road network editor, which can add roads through interactive editing, modify the connection relationship of lanes, edit signal control schemes. The road network from Vissim, OpenStreetMap, and OpenDrive can also be imported into SUMO through a separate conversion program. One can specify the route of each vehicle by editing the route file or using parameters to generate randomly. It also provides a visualization terminal based on OpenGL to display traffic simulation results in real-time. In addition, SUMO provides convenient MATLAB and Python interfaces, which can be flexibly combined with third-party simulation programs. Recently, SUMO has also been applied to the simulation of autonomous driving, providing random and complex dynamic environments. SUMO is embedded with a variety of car-following models; the default one is the Krauss model [24].

VISSIM is another microscopic traffic simulation tool developed by PTV Group. Using VISSIM can easily construct various complex traffic environments, including highways, roundabouts, intersections, parking lots, etc. It can also simulate the interactive behavior of vehicles, trucks, trams, and pedestrians in a simulation scenario. VISSIM's simulation can achieve high accuracy, including microscopic individual car-following behavior and lane change behavior, as well as group cooperation and conflict. VISSIM has a variety of built-in analysis methods, which can obtain a variety of specific data results in different situations and obtain intuitive displays from a high-quality 3D visualization engine. The traffic flow model in VISSIM is based on the work of Wiedemann, including a psycho-physiological car-following model. The essence of the VISSIM car-following model is to describe the reaction of a driver to the actions of other drivers. The Wiedeman 74 car-following model in VISSIM is suitable for the urban traffic environment, which can be chosen to describe the following behavior of AVs in this paper [25].

3.2 Model assumptions

To simplify the experimental model, optimize the simulation speed, and focus on the problems being explored, we made the following assumptions.

- The traffic flow distribution of the road network remains unchanged. Although AVs can obtain real-time vehicle status information on the road network and optimize vehicle flow distribution on the road network, with the continuous development of intelligent transportation systems, travel information services tend to be intelligent and dynamic. Travelers can also obtain road network outbound information and optimize travel routes based on a series of devices such as onboard networking equipment, smart navigators, and smartphones. Therefore, we ignore the impact of AVs in optimizing travel routes. That is, the distribution of traffic flow in the simulated test network is unchanged.
- To simplify the simulation model, we ignore the impact of other vehicle types in the road network since our study focuses on the urban network, and mainly passenger cars travel on it.
- In order to focus on the research problem, traffic accidents are not simulated, and therefore the impact of accidents is ignored in the simulation.
- Since the current autonomous technology is still developing, and the relevant supporting data is insufficient, the related parameter values in this paper were set based on the current theory of autonomous driving technology.

3.3 Parameter settings

Traffic flow is defined as the interactions between travelers (passenger cars, pedestrians, heavy-duty vehicles, etc.) and road infrastructure systems (traffic lights, traffic signs, etc.). The car-following model describes how the car follows and interacts with others in the lane. Several parameters describe the car-following behavior. AVs have the following obvious advantages: smaller gap acceptance, shorter headway, no reaction time in front of the signal system, maintenance of a constant desired speed, and stable acceleration and deceleration. The main difference between the AVs and CAVs in the simulation is the selected parameters of the car-following model. We chose gap acceptance as the main parameter to be changed due to the emerging autonomous driving technology. Gap acceptance is represented by "minGap" in the Krauss model in SUMO. The default value is 2.5 meters for passenger vehicles. "Standstill Distance" represents the base value for the average desired distance between two stationary cars in Wiedemann 74 model in VISSIM. The default value is 2.0 meters for passenger vehicles. Table 2 shows the detailed setting.

Fig. 1 shows the simulation steps both in SUMO and VISSIM. The detailed setting is introduced in the following sections.

3.4 Case study

To analyze the changes in traffic performance, a typical signalized intersection in the city of Hefei (China) was modeled as a simulation scenario based on an open database OpenITS (www.openits.cn/openData2/710.jhtml). This network contains two arterial roads, Huangshan Road and Kexue Avenue. Fig. 2 shows the generated test network model both in SUMO and VISSIM. The detailed layout of the intersection is shown in Fig. 3. When introducing emerging intelligent technologies, several factors need to be considered, including existing transportation facilities that required a huge investment previously. Straightforwardly, it can be expected that the existing traffic light control system will still be used for many years, even with the mass application of AVs. Table 3 shows the static traffic light control scheme on the intersection.

Considering the different traffic demand distribution, simulations were run with three traffic load conditions as follows:

1. Undersaturated traffic condition:
   Vehicles at the traffic light are not in a saturated state if the cars can always leave the intersection under the current green signal phase. Moreover, the green time is not fully utilized.
2. Saturated traffic condition:
   The green time is fully utilized. The junction is operating at maximum capacity without a residual queue, i.e. the applied green time phase is more-or-less corresponds to the appearing traffic demand.
3. Oversaturated traffic:
   This is the typical congested situation at the intersection, i.e. vehicles must wait for one or more traffic light cycles to leave the junction.

Table 4 shows the traffic inflow of the different traffic demand conditions.

4 Simulation results

To quantitatively analyze how the changes of the parameters due to the emerging autonomous technologies affect the urban road network, signalized intersection scenarios

Table 2 The changes in gap acceptance

Car-following model		Parameter	Description	Values (m)
SUMO	Krauss	minGap	Minimum Gap when standing	0.5, 0.75, 1.0, 1.25. 1.5, 1.75, 2.0
VISSIM	wiedemann74	Standstill Distance	Average standstill distance	0.5, 0.75, 1.0, 1.25. 1.5, 1.75, 2.0

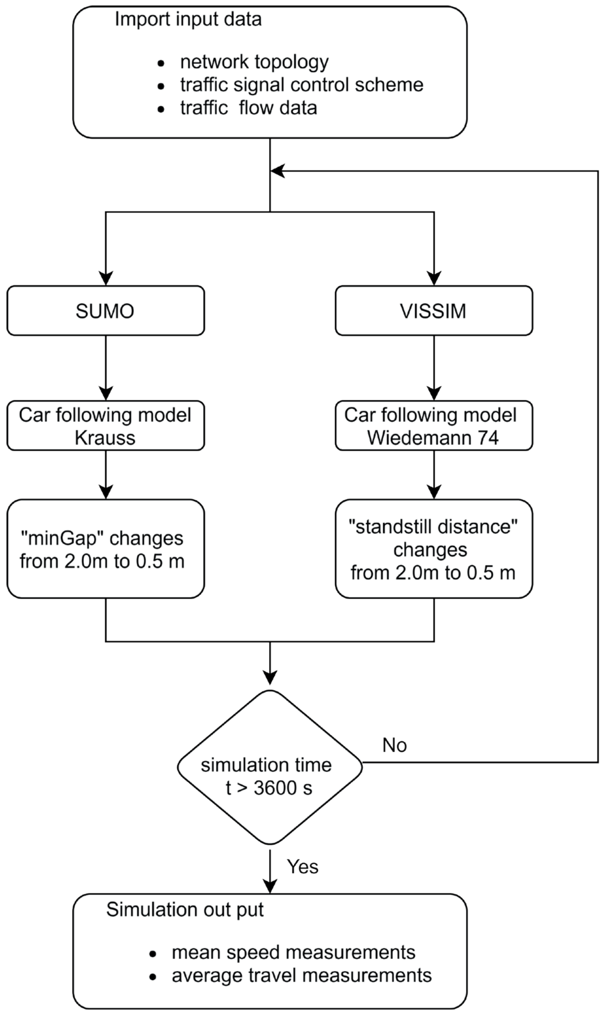

Fig. 1 Simulation steps in SUMO and VISSIM

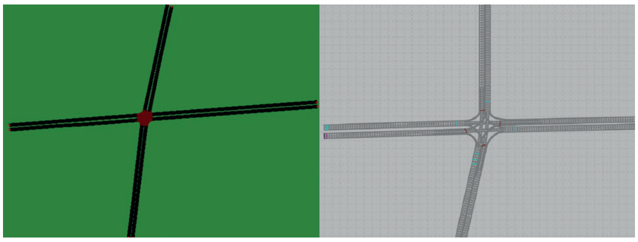

Fig. 2 Microscopic traffic simulation road network in SUMO (left) and VISSIM (right)

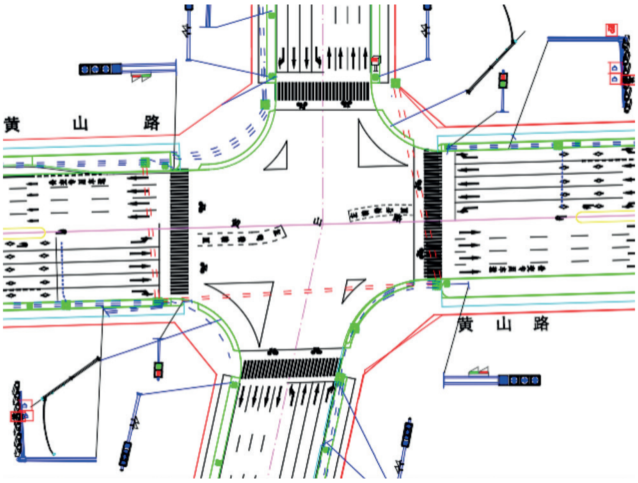

Fig. 3 The layout of the intersection

Table 3 Static signal control scheme

Phase	Traffic direction	Green time (s)	Yellow time (s)	Phase difference	Cycle time
1	East-west straight	45	3	4	147
2	East-west turn left	34	3		
3	South-North straight	34	3		
4	South-North turn left	22	3		

were simulated based on the different traffic demand conditions both in SUMO and VISSIM as mentioned in the previous section. The simulation time was set to 3600 seconds. The sensitivity analysis of the different gap acceptance was carried out in the simulations. As commonly used indicators, mean speed and average travel time were selected as evaluation indexes of traffic efficiency.

In the edge-based traffic measurement of SUMO output, mean speed refers to the speed on edge within the reported interval. The unit is meter per second. In the vehicle network performance evaluation results of VISSIM, the mean speed is defined as total travel distance divided by total travel time. The unit is kilometers per hour.

In SUMO edge-based measurement, the definition of "overlapTraveltime" refers to the time needed to completely pass the edge. The unit is second. The average of

Table 4 Traffic flow of different traffic demand conditions

Type of traffic	Approach	Movement	Flow (vehicles/h)
Undersaturated traffic	Eastbound	Left-turn	289
		Through	823
		Right-turn	741
	Southbound	Left-turn	252
		Through	754
		Right-turn	754
	Westbound	Left-turn	266
		Through	929
		Right-turn	929
	Northbound	Left-turn	289
		Through	722
		Right-turn	722
Saturated traffic	Eastbound	Left-turn	458
		Through	915
		Right-turn	823
	Southbound	Left-turn	280
		Through	839
		Right-turn	838
	Westbound	Left-turn	295
		Through	1032
		Right-turn	1033
	Northbound	Left-turn	321
		Through	802
		Right-turn	803
Oversaturated Traffic	Eastbound	Left-turn	480
		Through	960
		Right-turn	865
	Southbound	Left-turn	294
		Through	880
		Right-turn	880
	Westbound	Left-turn	310
		Through	1084
		Right-turn	1084
	Northbound	Left-turn	338
		Through	842
		Right-turn	842

"overlapTraveltime" of each edge is, therefore, the average travel time within the network. In VISSIM, the average travel time can be calculated from total travel time divided by the total number of vehicles in the network. The unit is second. Tables 5 and 6 show the mean speed and the average travel time measurements under different gap acceptances both in SUMO and VISSIM. To make the unit equal, the unit of mean speed in SUMO output is converted to kilometers per hour.

Table 5 Mean speed measurements

Gap acceptance (m)	Mean speed (km/h) traffic demand conditions					
	undersaturated		saturated		oversaturated	
	SUMO	VISSIM	SUMO	VISSIM	SUMO	VISSIM
2.0	54.014	41.275	54.122	38.374	54.027	29.840
1.75	53.928	41.286	53.946	38.551	53.919	36.039
1.50	53.757	41.838	53.735	39.417	53.739	36.787
1.25	53.670	41.974	53.681	40.932	53.645	38.051
1.0	53.721	42.470	53.649	40.914	53.757	39.356
0.75	53.708	42.683	53.433	41.437	53.415	39.784
0.5	53.622	42.786	53.339	42.060	53.145	40.803

Table 6 Average travel measurements

Gap acceptance (m)	Average travel time (s) traffic demand conditions					
	undersaturated		saturated		oversaturated	
	SUMO	VISSIM	SUMO	VISSIM	SUMO	VISSIM
2.0	76.658	51.069	76.356	53.511	76.581	62.996
1.75	76.699	51.057	76.626	53.573	76.764	56.143
1.50	77.050	50.584	77.023	52.629	77.064	55.220
1.25	77.195	50.449	77.086	51.226	77.266	54.173
1.0	77.119	50.046	77.190	51.289	77.023	52.831
0.75	77.113	49.874	77.586	50.802	77.623	52.495
0.5	77.213	49.760	77.726	50.293	78.099	51.483

To intuitively show the variation of these changes, Figs. 4, 5, and 6 were drawn based on the above measurement data.

In SUMO, as the gap acceptance decreases, the average travel time of the road network gradually increases, and the average speed gradually decreases. However, VISSIM tends to give opposite results. This result means that the sensitivity of the two car-following models (SUMO and VISSIM) to the different gap acceptance settings is not the same. VISSIM is much more sensitive to gap changes in the oversaturated traffic situation, especially when the gap changes from 2.0 meters to 1.75 meters. Both mean speed and average travel time show significant fluctuation. Unlike the basically linear change in VISSIM, the average travel time changes in steps in SUMO, too large and too small gap acceptance has a greater impact, and there is nearly no change when the minimal gap changes from 1.5 meters to 1 meter. Another fact that needs to be noticed is that no matter what traffic demand situation is applied, SUMO has a greater measure of mean speed and average travel time.

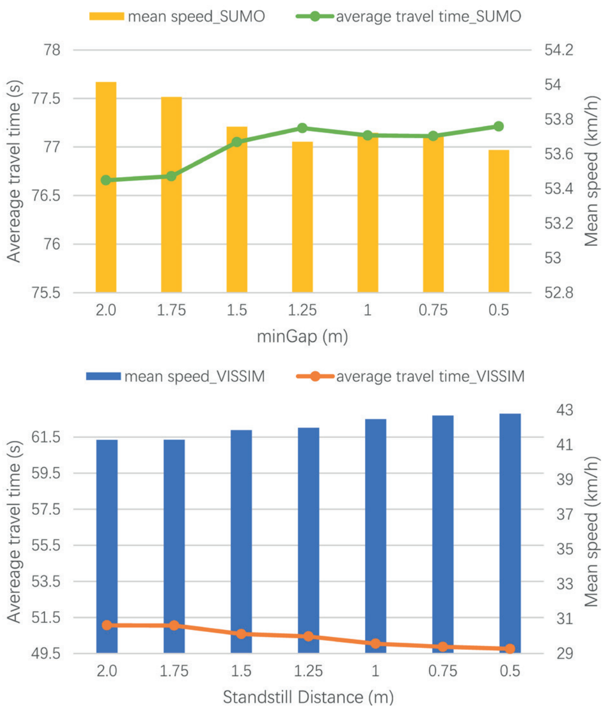

Fig. 4 Variations of mean speed and average travel time in the undersaturated traffic situation

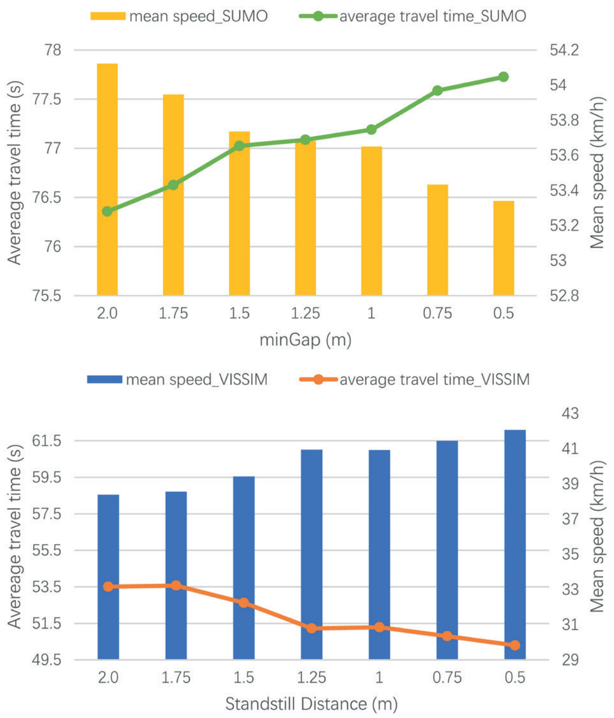

Fig. 5 Variations of mean speed and average travel time in the saturated traffic situation

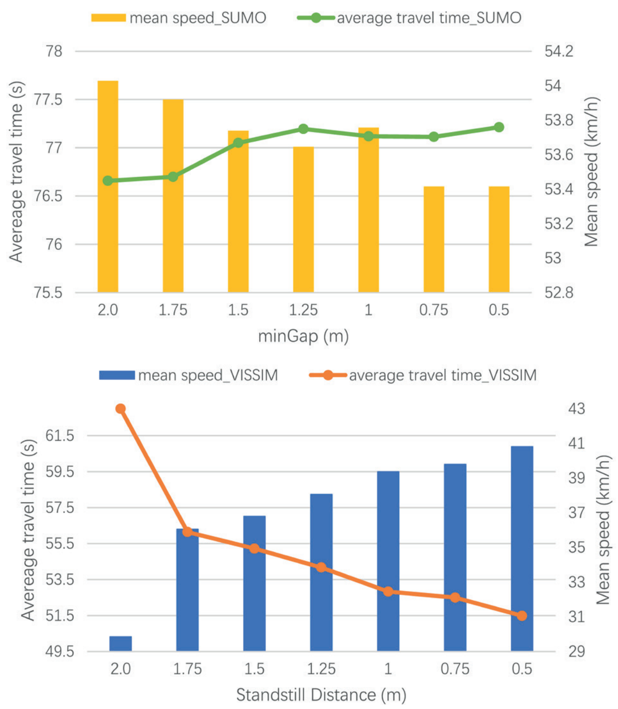

Fig. 6 Variations of mean speed and average travel time in the oversaturated traffic situation

5 Conclusions

Based on the sensitivity analysis of a given test intersection, it has been demonstrated that the current simulation practice of traffic engineering needs change due to the emerging presence of highly automated cars and soon the advent of fully autonomous vehicles on public roads. By reviewing the state-of-the-art papers related to the driving behavior of AVs, it has been selected reasonable driving behavior parameters for analysis. With the help of microscopic traffic simulation software SUMO and VISSIM, an urban junction model was established based on the theoretical and technical basis of AVs and driving behavior. The traffic flow performance (measured as mean speed and average travel time) of different gap acceptances with three different traffic demand situations (undersaturated traffic, saturated traffic, and oversaturated traffic) were quantitatively evaluated. As the main contribution of this work, it has been shown that the microscopic simulation model is strongly sensitive to automated driving functions. The given driving behavior parameter changes had the opposite effect in two microscopic traffic simulation models. The results of this research also show that to precisely model the behavior of the emerging autonomous vehicles, developing a driving behavior model based on the actual autonomous vehicle dynamical model is a promising solution. From the perspective of traffic planning, in order to adapt to the emerging autonomous driving vehicles, the existing traffic networks need to transform intelligence properly.

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