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Research Article

Potential impact of autonomous vehicles in mixed traffic from simulation using real traffic flow

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ABSTRACT: This work focuses on the potential impacts of the autonomous vehicles in a mixed traffic condition represented in traffic simulator Simulation of Urban MObility (SUMO) with real traffic flow. Specifically, real traffic flow and speed data collected in 2002 and 2019 in Gothenburg were used to simulate daily flow variation in SUMO. In order to predict the most likely drawbacks during the transition from a traffic consisting only manually driven vehicles to a traffic consisting only fully-autonomous vehicles, this study focuses on mixed traffic with different percentages of autonomous and manually driven vehicles. To realize this aim, several parameters of the car following and lane change models of autonomous vehicles are investigated in this paper. Along with the fundamental diagram, the number of lane changes and the number of conflicts are analyzed and studied as measures for improving road safety and efficiency. The study highlights that the autonomous vehicles' features that improve safety and efficiency in 100% autonomous and mixed traffic are different, and the ability of autonomous vehicles to switch between mixed and autonomous driving styles, and vice versa depending on the scenario, is necessary.

KEYWORDS: automated driving, autonomous vehicles (AVs), mixed-traffic, traffic simulations, driving style, realistic conditions

1 Introduction

It is well-known that car manufacturers and newly launched high-tech companies have been working on different aspects of autonomous vehicles (AVs). It is expected that 50% of the new vehicles produced and sold in 2040 will be autonomous, and that 10 years later half of the vehicles present on the road will be autonomous (Litman, 2020). Therefore, it is valid to ask what is the potential impact of these new technologies in a mixed traffic with the manually driven vehicles (MVs) and how much the current city infrastructure and traffic management systems are ready for more and more AVs on our roads.

In Threlfall (2019), 4 macro-categories (which includes 25 subcategories) to measure preparedness for AVs made by each country in the world are identified: Policy and Legislation, Technology and Innovation, Infrastructure, and Consumer Acceptance. Based on the evaluations of the sub- and the macro-categories, a ranking is compiled, in which Sweden occupies the fifth place.

In the light of this gradual but continuous process of introduction of AVs on our roads, it is important to understand how two or more driving styles (e.g., for autonomous and manual) will interact with each other in the context of mixed traffic. Based on review of recent works in the field and in this direction, which we briefly summarize in Section 2, it was clear that no study has broadly analyzed the potential impact of different driving styles of AVs in mixed traffic. This paper investigates the potential impact that different driving styles of AVs might have during the transition period from mixed traffic to 100% AVs on city traffic using traffic simulator Simulation of Urban MObility (SUMO). The aim is to identify the driving characteristics (i.e., parameters' values) that allow a safer and more efficient interaction between AVs and MCs.

Through the analysis of simulation results of the impact of different hypothetical AV's driving styles during the transition period, this paper makes contributions to intelligent vehicle design with identification of key parameters of AVs' driving styles, and suggestion that the AVs' driving styles should change over time as the penetration rate increases. Towards the infrastructure, this paper highlights the need to further study if the rules of lanes usage should be adapted during the transition to 100% AVs.

The rest of the paper is organized as follows. Section 2 summarizes recent related work. Methodology is described in Section 3. Section 4 describes the simulation setting. Whether MV simulations in SUMO follow a similar trend as the real traffic flow is briefly assessed in Section 5. Section 6 describes the simulations with different percolation percentages of AVs (AV simulations). Further, the effects of parameters in AV behavior are investigated, reflected on three main outputs: fundamental diagrams (Section 6.1), number of lane changes (Section 6.2), and number of conflicts (Section 6.3). Finally, the future work based on the main observations from this analysis are outlined in Section 7.

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2 Related work

Several aspects of traffic can be affected by the introduction of autonomous vehicles, such as safety, efficiency, and fuel emissions. Milakis et al. (2017) reviewed and classified the potential impacts into a three-fold different stages: first-order (traffic, travel cost, and travel choices), second-order (vehicle ownership and sharing, location choices and land use, and transport infrastructure), and third-order (energy consumption, air pollution, safety, social equity, economy, and public health). The literature suggests that the introduction of AVs is expected to improve many aspects of traffic: in Fagnant and Kockelman (2014) and Liu et al. (2021), the authors showed that AVs could reduce vehicle emissions and increase fuel efficiency, respectively; in Shladover et al. (2012), it was shown that AVs increase road capacity and in Virdi et al. (2019) that AVs increase safety. In Shladover et al. (2012), it was shown that 100% cooperative adaptive cruise control (CACCs) can double the road capacity compared to 100% MVs scenario. In order to evaluate the changes in safety with the introduction of connected and autonomous vehicles (CAVs), Virdi et al. (2019) computed number of potential conflicts at the signalised, priority, roundabout and diverging diamond intersection. It was shown that the potential conflicts in all settings decline, and the reductions are greater in roundabouts and give-way environments, as compared to signalised intersections. However, there is no guarantee that these improvements will also occur in mixed traffic conditions, and further studies have been done in this direction.

Olia et al. (2018) specifically studied the potential impact of mixed traffic for traffic capacity, showing that cooperative AVs can significantly increase highway capacity when their market penetration is higher than 30%, while non cooperative AVs, even at high market penetration, can have only a small impact on highway capacity. Aramrattana et al. (2022) conducted driving simulation experiments to test whether drivers adapt their behavior when driving between automated vehicles (AVs) compared with those driving between manually driven vehicles (MVs) in on-ramp merging scenario. They found that behavioral adaptation can be observed in terms of car-following speed, car-following time gap, number of lane change, and overall driving speed. The adaptations are dependent on the driving scenario and whether the surrounding traffic was AVs or MVs. Arvin et al. (2021) looked at the potential impact from the number of conflicts and driver volatility at an intersection. The results of their work indicate that there is not a significant safety improvement at low market penetration of adaptive cruise control (ACCs), while with higher penetration rates, the number of conflicts and driving volatility decrease considerably. Moreover, a significant safety improvement, in terms of reduction in number of conflicts and driving volatility, is observed by replacing ACCs with CACCs. Others have focused their study in an urban area controlled by static traffic light system (Vaudrin et al., 2017). Here, by simulations, it was shown that traffic lights system has a much greater impact than Avs on waiting time. In Zhao et al. (2018) and Morando et al. (2018), mixed traffic has been studied on signalised intersections and roundabouts, focusing on fuel consumption and total travel time in the first case and safety in the second. The results in Zhao et al. (2018) showed that vehicle coordination yielded significantly improved travel time and fuel consumption under 100% of CAVs. In Morando et al. (2018) the authors show that AVs reduce the number of conflicts by 20%–65% with the AV penetration rates of between 50% and 100% for the signalised intersection, and by 29%–64% with the 100% AV penetration rate for the roundabout. Further studies of mixed traffic simulations have been done focusing on the Advanced Driver Assistance Systems (ADAS), designed to increase road safety and driving comfort (e.g., Guériau and Dusparic (2020) and Mintsis et al. (2018)). In Zhang and Yang (2021), the authors focused on the CAV impact on highway operational performance under a mixed environment. The results of this research revealed that performing optimal speed control to CAVs will concurrently benefit MVs by improving highway capacity. In Zhua et al. (2022) and Wu and Qu (2022), two comprehensive reviews covering both CAVs and mixed traffic scenarios are reported. However, no study has broadly analyzed the potential impact of different driving styles of AVs in mixed traffic. In fact, while the driving styles of manual vehicles cannot be acted upon because they are the driver's own, the driving styles of autonomous vehicles can be modified to improve safety and traffic efficiency. To this end, it is necessary to understand what parameters can improve efficiency and safety in a mixed traffic context.

3 Methodology

For this study, the topology of the south-east part of the city of Gothenburg from Open Street Map was reproduced in SUMO (Krajzewicz et al., 2012) environment, together with its daily traffic flow data from the Swedish Transport Administration (Trafikverket, 2020). This consists of a total of more than 20 km of high-speed road and on- and off-ramps; the different sections of the roads have speed limit ranging from 70 to 90 km/h. The daily traffic in the years 2002 and 2019 was simulated, taking into account the changes in posted speed limits on the roads. As for the choice of the car following model, the results reported in Bjärkvik et al. (2017) were taken into account. In there, the Intelligent Driver Model (IDM) (Krauß, 1998; Treiber et al., 2000) car following models were compared, both calibrated on Gothenburg roads. It was shown that SUMO generates results more similar to real measurements when using the Krauß model instead of the IDM model. Moreover, the IDM model generates more conflicts than real-world traffic data during vehicles' lane changing.

For these reasons, both autonomous and manually driven vehicles are simulated using the Krauß model.

In order to represent the behaviour of MCs as close as possible to the real traffic, the values of the parameters for lane change and Krauß car following models calibrated in Nilsson (2019) on the roads of Gothenburg were used. In addition to AVs and MCs, simulated manually driven trucks (MTs) were also simulated, using the default SUMO parameters along with the default car following model, i.e., Krauß model. Once the daily traffic is simulated for MCs and MTs, the AVs were introduced with different penetration rates. Initially, we consider the values of the AV parameters proposed in Nilsson (2019), subsequently we analyze, in simulations with real traffic flow, the improvement on the speedFactor value suggested for mixed and ideal traffic in Andreotti et al. (2020). Finally, other parameters' values are analyzed in this paper (i.e., the apparentDecel, lcStrategic and decel parameters). In Andreotti et al. (2020), the number of lane changes and the number of conflicts were proposed as a measure of traffic efficiency and safety and the parameters' values have been analyzed in order to reduce the number of conflicts, the number of conflicts involving hard braking, and the number of lane changes. In this paper we analyze for different percolation percentages of AVs and different parameters' values, the number of lane changes, the number of conflicts and the fundamental diagram.

4 Description of the simulation setting

A daily traffic flow variation in the city of Gothenburg, from 2002 and 2019, were simulated in SUMO. A real and simulated data from 2002 and 2019 were compared. The two years were chosen because, it was necessary to find devices positioned in such a way as to give information on the same portions of the roads, either directly or indirectly. More precisely, the two flows (i.e., the number of vehicles that passes a certain cross-section per time unit (Treiber and Kesting, 2013)) that passes through three detector devices (red devices in Fig. 1) were compared.

Fig. 1 A part of Gothenburg in SUMO. Blue loops inject traffic, and red loops detect traffic. Traffic detected by the red loop 3 is generated by the blue loop A. Traffic detected by loop 2 is generated by loops A and C. Traffic detected by loop 1 is generated by loops A, B, and D.

In SUMO, the flow detectors are called *Induction Loop Detectors* (SUMO, 2020a). To distinguish the real devices (those used by Trafikverket) and those placed in SUMO, the real detectors will be called *detector loops* and those in SUMO will be called *simulated detector loops*. In both loops, the information collected are flow and time-mean speed; time-mean speed is defined as the arithmetic average speed of all vehicles for a specified period of time. In addition to those information, the *simulated detector loop* also collects information on space-mean speed; space-mean speed is defined as average speed of vehicles traveling a given segment of roadway during a specified period of time. Please see Knoop et al. (2009) for an in-depth theoretical and empirical analysis on time-mean speed and space-mean speed.

4.1 Description of the simulation setting: year 2002

In order to generate a daily flow of vehicles that is in accordance to the data collected by Trafikverket, four simulated loops that inject flow of traffic (blue points in Fig. 1) and three *simulated detector loops* that detect flow, time-mean speed, and space-mean speed were placed in SUMO. The blue loops will be called *injector loops* (or *injectors*) and they inject traffic flows as such that the flows detected by the *simulated detector loops* are in accordance with the real flows. The *simulated detector loops* have been placed in the same points as the real *detector loops*.

As regards the speeds, we can compare the real time-mean speeds with the simulated ones, but the space-mean speeds are detected only by the simulated devices. Therefore we can compare the resulting simulated fundamental diagrams: once the flows are fixed, the space-mean speeds and the densities depend on parameters' values. Since the vehicle speeds under consideration will not necessarily all be the same, it will not be possible to use the time-mean speed instead of the space-mean speed in the study of the fundamental diagram, Knoop et al. (2009). Each *simulated detector loop* in SUMO is composed of one sub-loop per lane, and since all the roads where we have placed the red loops are formed by 3 lanes, each *simulated detector loop* is composed of three sub-loops. The data provided by Trafikverket are aggregated by hour and by road section. Therefore, it is not possible to determine how many vehicles pass through each lane from the real data, but we can instead get it from the simulated ones. However, by using the real data, it is possible to distinguish the type of the passing vehicles (i.e., cars and trucks), and hence we have considered these detected types in our simulations as well. Therefore, our simulations have a characteristic representing both mixed (i.e., cars, trucks) and heterogeneous traffic (i.e., autonomous and manually driven). The SUMO parameters used to define the vehicles are in accordance with the parameters calibrated in Nilsson (2019) for Gothenburg, where a Metric Stochastic Response Surface Method (MSRSM) optimization algorithm to tune traffic simulation against real world detector data is proposed and used. In Figs. 2 and 3 the flows and time-mean speed as the daily hours vary, detected by SUMO loops and Trafikverket devices are compared, respectively.

4.2 Description of the simulation setting: year 2019

According to the dataset from Trafikverket, measurement devices have been placed in different locations in 2002 compared to 2019. Therefore, to be able to compare the data from 2002 with those from 2019, the daily traffic flows were derived indirectly through other devices. For example, the traffic detected by device 3 has been simulated considering the flow of traffic passing through device A, minus the outgoing traffic from device B, plus the incoming traffic from devices C and D in Fig. 4. However, for a direct verification of the flow data we have compared farther devices present in the scenery, see Andreotti et al. (2021) for the definition of scenery. For a comparison as precise as possible between the data from 2002 and 2019, we consider week days for both years.

4.3 On the comparison between 2002 and 2019 data

Fig. 5 shows the traffic flows of one day in 2002 and one day in 2019 passing through loops 1, 2, and 3. It was observed that the number of vehicles passing through the loops is significantly increased in 2019 compared to 2002, for example the number of vehicles that passes through loop 3 has increased by more than 10%. At the same time, the population in the Västra Götaland region (the county where Gothenburg belongs to) has increased from 1.5 million inhabitants to more than 1.7 million inhabitants from 2002 to 2019 SCB (2020). This suggests that the people traveling by car has increased accordingly with the population

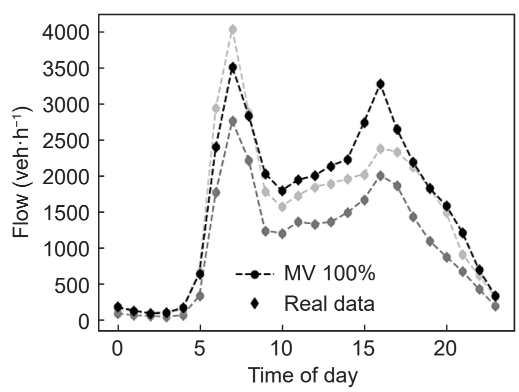

Fig. 2 Flow of vehicles as hours change (on August 29, 2002). The detections of the real devices (markers) are compared with the detections of the loops in SUMO (lines): device 1 (black), 2 (gray), and 3 (light gray).

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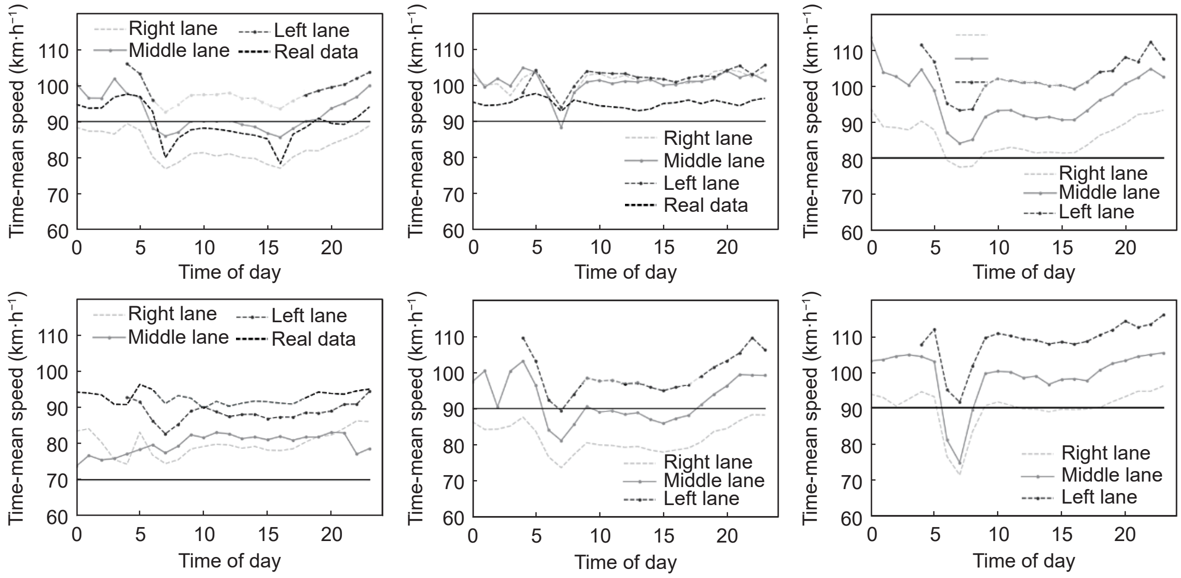

Fig. 3 Time-mean speed of vehicles as hour changes: 2002 (top) and 2019 (bottom). From left to right: devices 1, 2, and 3. The solid lines represent the speed limits.

increased. Furthermore, the increase in flow is evident in all three loops. Loops 1 and 2 are located in the ring road of Gothenburg, therefore they detect both the outgoing and the incoming traffic, as well as the traffic of those who move from one point to another within the city. Loop 3 is located on an incoming road, thus only detects the incoming flows (Fig. 5). It was observed that the highest increase in flow in 2019 happened in the morning, 7–9 a.m., i.e., the flow was due to people commuting to work in the city. Although in loops 1 and 3, the speed limits are the same (90 km/h), the weighted average speed in loop 1 is about 90 km/h, while in loop 3 it is 100 km/h, both in 2002 and 2019 (Fig. 6). The weighted average speed (V_{ave}) is calculated as Eq. (1):

$$V_{\text{ave}} = \frac{\sum_{i=1}^{3} v_i d_i}{\sum_{i=1}^{3} d_i} \tag{1}$$

where i = 1, 2, and 3 are the right, middle, and left lanes, respectively; and v_i and d_i are the speed and density on the lane i, respectively. Since the vehicle parameters and topology did not

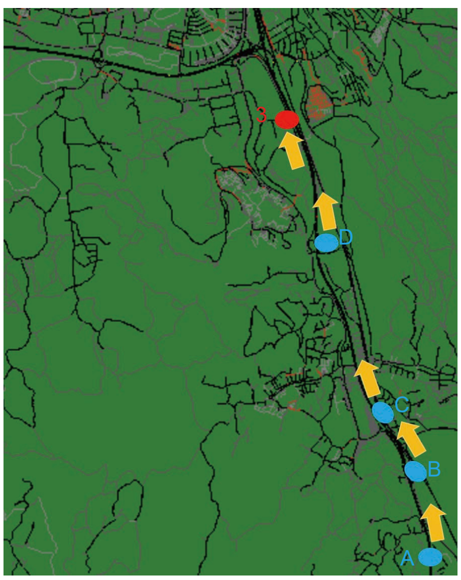

Fig. 4 A part of Gothenburg in SUMO. The red loop detects traffic injected by blue loops.

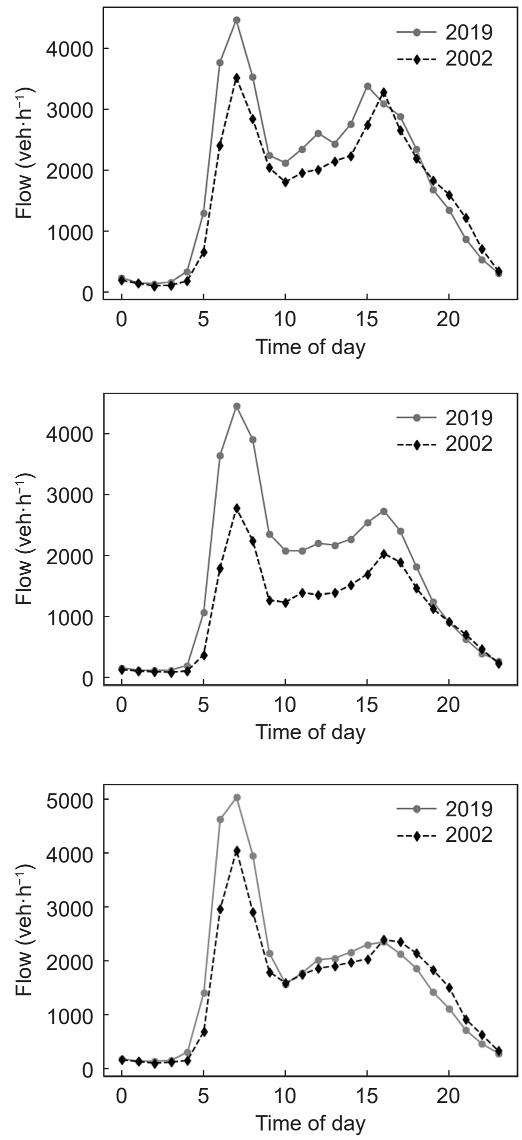

Fig. 5 Comparison of the daily traffic flows in 2002 and 2019 passing through loops 1 (top), 2 (middle), and 3 (bottom).

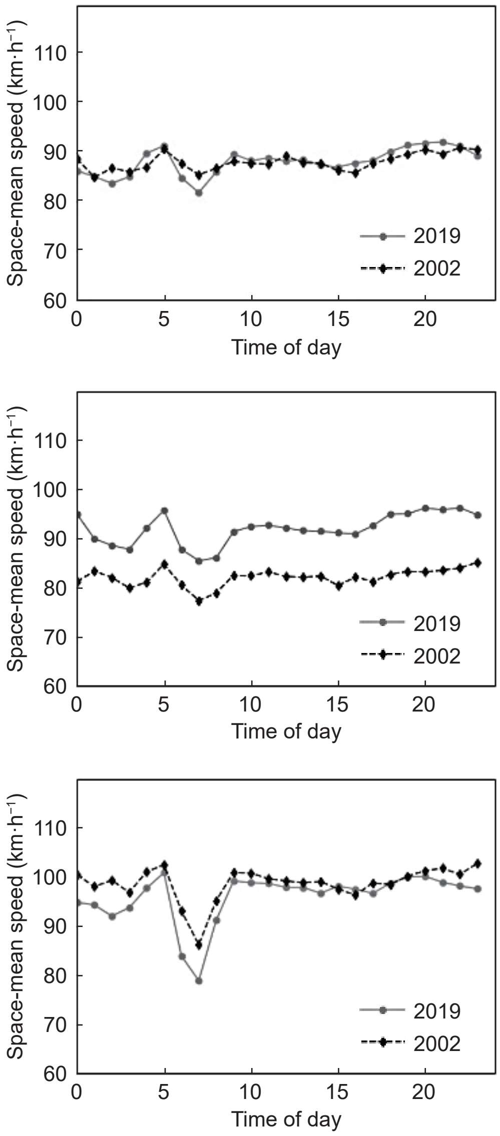

Fig. 6 Flow per lane-weighted average speed of vehicles as time changes through a day in 2002 and 2019: loops 1 (top), 2 (middle), and 3 (bottom).

change in the two years, a likely cause could be the structure of the two road sections, the placement of the loops, or a higher average flow in loop 1 than in loop 3. While in loop 2, where the speed limit increased from 70 km/h in 2002 to 80 km/h in 2019, the weighted average speed also increased from about 80 to 90 km/h. A more detailed analysis of the average speeds will be investigated in Section 5.

5 On the comparison between real data and manually driven vehicle simulations

In order to analyze and compare the relations between macroscopic quantities of traffic, such as the fundamental diagram, in the real and simulated case, it is necessary to calculate the three quantities: mean speed, density, and flow. It was observed that the flow generated by the simulations and the real one is equal. Therefore, in this section, mean speeds will be analyzed to assess whether the MV simulations (manually driven vehicle simulations, i.e., manually driven car and truck simulations) follow the same trend of real data. Then we can derive the density and compare the fundamental diagrams. If the two (i.e., flow and speed), and therefore three (flow, speed, and density), macroscopic quantities are related by the same relations, we can then consider our MV' simulations as a good starting point for mixed simulations.

In the simulations, vehicle speeds depend on the maximum speed allowed on the road, on the car following model used and its parameters' values. Fig. 3 shows a comparison of the time-mean speeds from the real data with those detected by the red loops on the lanes as the time changes through the day. It was noted that although no constraints have been given on the speed of the injected vehicles, the speed detected by the red loops in SUMO varies similarly as the real data varies. By comparing the space-mean speeds of the vehicles that pass through the three loops in 2002 and 2019, one can notice that the average speeds do not seem to have changed, while the greatest differences were observed with regard to the lane speeds, Fig. 7. In fact, the difference between the speeds in the lanes is more noticeable in 2019 than in 2002. In addition, the fundamental diagrams (Fig. 8 (left)) also show the change of state (i.e., a change in the slope of the data), from a reasonably free flow to congested, in the

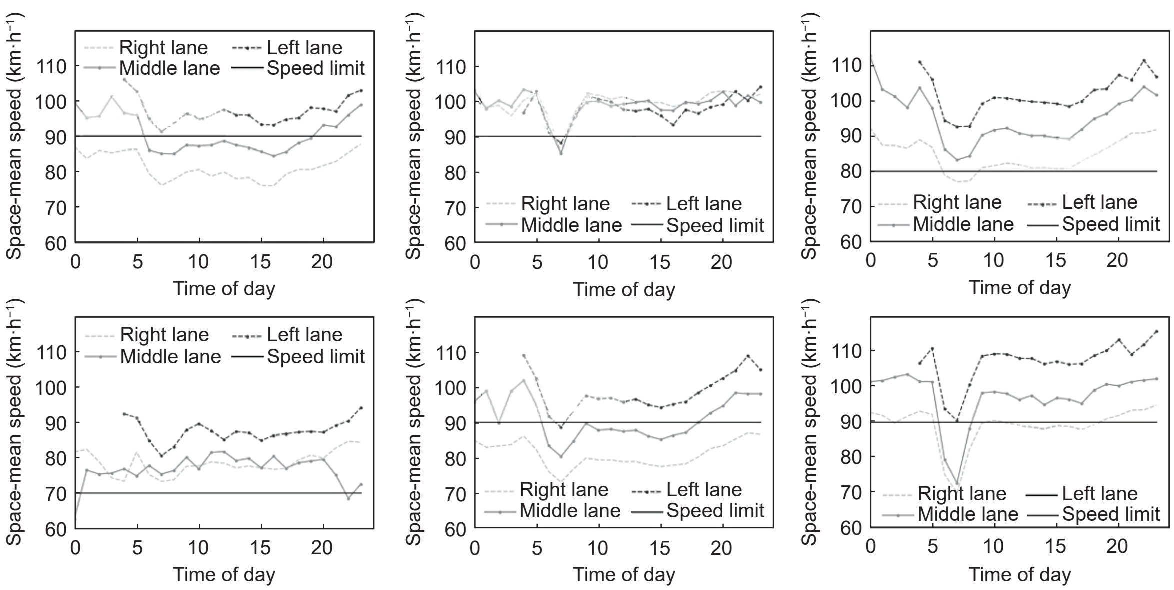

Fig. 7 Speed of vehicles as time changes through a day in 2002 (top) and 2019 (bottom). From left to right: loops 1, 2, and 3.

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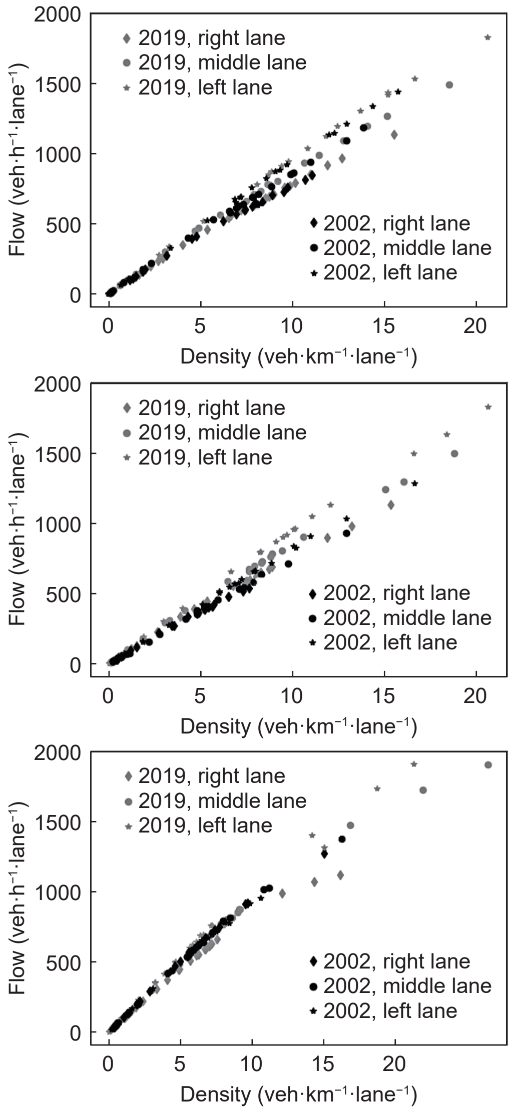

Fig. 8 Comparison of the fundamental diagrams in 2002 and 2019 passing through loops 1 (top), 2 (middle), and 3 (bottom).

rightmost lanes of 2019 for a density of 10 vehicles per km. The cause of the decrease in speed and density of the rightmost lane in 2019 is attributable to the ratio between the number of trucks and the number of cars which increased in 2019 (Fig. 9, the ratio is only shown for loop 3 here, but the ratios for the other loops are similar). In fact, it is well known that trucks may not be allowed to use as high speed as cars (because of law/safety reasons) and take up more space. In general, the lowering of the flow in the fundamental diagrams (over 20 vehicles per km per lane) reflects the change of state from a reasonably free flow to congested (Garber, 2002). This aspect will be analyzed in detail in the next section.

From here on, unless otherwise specified, the parameters' values of the MCs used in the simulations are those given in Table 1. The value for acceleration for AVs that we used here is reasonable considering that acceptable longitudinal accelerations that was reported by Hoberock (1977) for public transport is 1.47 m/s^2, an acceptable acceleration threshold based on an experiment studying passenger comfort for AVs was reported to be 1.23 m/s^2 by de Winkel et al. (2023), and the 99th percentile of acceleration events in real urban driving data collected by de Winkel et al. (2023) was 2.2 m/s^2.

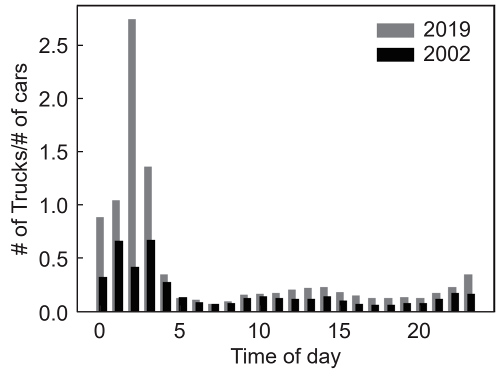

Fig. 9 Ratio between number of trucks and number of cars passing through loop 3 (Trafikverket, 2020).

6 Simulations with different percolation percentages of AVs

The purpose of this section is to deeply investigate macroscopic quantities through a study of microscopic quantities to improve safety and efficiency in mixed traffic conditions. In this regard, we analyze the potential impact of different AV percentages that vary from 0 to 100%, and different driving parameters.

The parameters explored are *speedFactor* (sF, the factor by which the driver multiplies the road speed limit and result represents the maximum speed used in the simulation), *apparentDecel* (AD, the value used as the expected maximum deceleration of the lead vehicle), *decel* (the maximum deceleration of the ego vehicle), *lcStrategic* (i.e., driver's eagerness to perform strategic lane changing), and *Driver state Device* (i.e., the perception errors related to the distance with the lead vehicle and the relative speed). By default, the *apparentDecel* is equal to the *decel*, which means that each vehicle expects the lead vehicle to decelerate like it does. In a context of mixed traffic where MCs have an average *decel* equal to 4 m/s^2 and AVs equal to 6 m/s^2, this assumption is very strong and deserves to be studied in detail. Therefore the 4 possible combination cases of AVs and MCs with *apparentDecel* 4 and/or 6 m/s^2 were analyzed. The parameter *decel*, which is closely related to the *apparentDecel* was also analyzed (Table 1).

lcStrategic is a parameter concerning the lane changes model and as we will see later, it has a strong impact on traffic safety conditions. For this reason, a deeper exploration was conducted. The default value 1, as well as the value proposed in Nilsson (2019) (i.e., *lcStrategic* = 10), and the intermediate values between the two (i.e., the values 3, 5, and 7) were analyzed. For more details see Table 2.

Only the traffic data from 2019 is used from here onward: being composed of higher densities allows us to study in more depth the critical aspects of the parameters, especially in view of an increase of road users towards the future.

6.1 Fundamental diagram of traffic flow

For representing the heterogeneous and mixed vehicle fleet, the MCs was replaced with different percentages of AVs, while the number of trucks was left unchanged. Initially the AV parameters are set as in Table 1, with the exception of the *speedFactor* (sF) parameter which has been extensively studied in Andreotti et al. (2020) and therefore was set to 1.2.

Comparing the results obtained in 100% MC simulations with those obtained with different percentages of AVs, it is observed that the critical point in the fundamental diagram (Fig. 11, bottom) does not seem to occur, or at least not for the densities

Table 1 SUMO parameters

Parameter	MCs value	AVs value
length	norm(4.9, 0.2); [3.5, 5.5]	norm(4.9,0.2); [3.5, 5.5]
accel	norm(1.4976, 0.0555)	1.5000
decel	norm(4.0522, 0.9979)	6.0000
apparentDecel	decel	decel
sigma	norm(0.7954, 0.1615)	0.5000
tau	gamma(33.6166, 40.6236)	0.5000
minGap	norm(1.5401, 0.2188)	1.5014
lcStrategic	norm(0.0122, 1.6575)	10
lcCooperative	norm(0.9978, 0.1)	0.9999
lcSpeedGain	1	1
lcSpeedGainRight	1	1
lcKeepRight	1	1
lcAssertive	1.3	1
speedFactor	norm(1.2081, 0.1425)	1
lcOpposite	1	1
lcLookAheadLeft	2	3
lanechange-duration	1.1362	0

Table 2 Simulations with different parameters of AVs. Values in bold are default values

Parameter	*speedFactor*	*apparentDecel*	*lcStrategic*	*decel*
AVs value	**1**, 1.2	4, 6	**1**, 3, 5, 7, 10	4, 6

considered, as the percentage of AV increases. In order to explain the possible explanation for it, the parameters that characterize the AV and MC were further studied.

First of all, the *minGap* (minimum empty space after the ego vehicle) of the AV and MC is not different enough to compromise the result. In fact, the maximum estimated number of AVs in a stretch of 1 km road segment is 156 (1,000 m/(*minGap*+AV's mean *length*)) while the maximum number of MC is 155 (1,000 m/(*minGap*+MC's mean *length*)). The parameter that most influences the result is the driver's desired (minimum) time headway, *tau*, of the two vehicle types in the car following model. In fact, the parameter *tau* is also used in the implementation of the Krauß model instead of the reaction time τ_r. More precisely, the safe speed, in Krauß model implementation, of the ego vehicle is computed using Eq. (2):

$$v_{\text{safe}}(t) = v_{\text{lead}}(t) + \frac{g(t) - v_{\text{lead}}(t)\,\tau_r}{\dfrac{v_{\text{ego}} + v_{\text{lead}}(t)}{2decel} + \tau_r} \tag{2}$$

where t is the time step, $v_{\text{lead}}(t)$ is the speed of the leading vehicle in t, $g(t)$ is the gap between ego vehicle and leading vehicle in t, and $\tau_r = tau$. Assuming that the ego vehicle (AV or MC) has the same speed as the lead vehicle at time t, Fig. 10 compares the speeds of the ego vehicles at the time $t + \Delta t$. We notice that when the ego vehicle is an MC, the vehicle brakes at much longer distance to the lead vehicle compared to when the ego vehicle is an AV, thus an AV traffic flow will enter in critical regime with higher densities than an MC traffic flow. In fact, the mean of gap distance (from front bumper to rear bumper) between MCs of less than 20 m corresponds to a density greater than 40 MCs per km per lane (1,000 m/(mean distance + MC's *length*)) which correspond to a flow of 3,600 MCs per hour per lane (40 MCs/1 km × 90 km/h), i.e., when more than 1 vehicle is introduced per second per lane, then the MCs start to brake. If we consider the AVs, this mean distance is reduced to 12 m between one vehicle and the next one, which

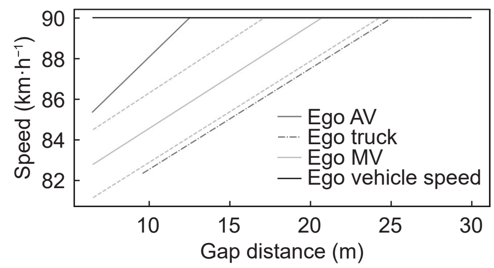

Fig. 10 Ego vehicle speed as the gap distance varies (distance from front bumper of ego vehicle to rear bumper of the vehicle ahead). The dotted lines represent the standard deviation of the gamma distribution that characterizes *tau* for MCs.

corresponds to a vehicle every 0.7 seconds per lane ((*minGap*+MC's *length*)/(90 km/h)). However, the traffic considered is not made up of MCs or AVs only, in fact it is a mixed traffic in which 13% (in 2019) of the vehicles are MTs. Doing the same calculation for MTs, which have reaction times corresponding to 1 s and average length of 7.1 m, we get that the distance at which MTs begin to brake is 25 m which corresponds to injections of one truck every 1.3 s. In correspondence with these thresholds (from 25 of trucks to 40 of AVs veh/km/lane) the state of the system changes from a regime of reasonably stable to a congested regime, therefore, shorter τ leads to higher speeds for higher densities. However, in our simulations this threshold is observed considerably lower than the computed ones (Fig. 6) and the cause is the heterogeneity of the vehicles. In fact, not all of the vehicles aim to drive at the same speed, the traffic is mixed (with cars and trucks together), vehicles change lane and enter and exit the road through on- and off-ramps and therefore interact more than simply adapting to the speed of the lead vehicle.

Figs. 11–14 show fundamental diagrams for different percolation percentages of AVs and different parameters' values (*speedFactor*, sF, and AVs' *apparentDecel*, *A AD*), respectively. Moreover, in Fig. 11 on the bottom, the fundamental diagrams per lane were shown. It is observed that for different percentages of AVs the vehicles are distributed differently on the lanes: for low percentages of AVs the rightmost lane is congested at low densities, and therefore the most used lanes are the middle and the leftmost. On the contrary, for high percentages of Avs, the most used lanes are the rightmost and the middle, and for the densities considered, the traffic does not enter into congested conditions. This aspect is also reflected in the fundamental diagrams (on the top of Fig. 11) in which, for high percentages of AVs, the densities are on average lower than for lower percentages of AVs, but the flow is higher.

Figs. 12–14 show that greater interaction between AVs and MCs (sF equals to 1.2) increases traffic flow, i.e., for the same densities the vehicles drive faster on average. In this sense, we could deduce an improvement in the efficiency of the traffic flow, which would confirm the results obtained in Andreotti et al. (2020) with respect to the value of the sF.

As for the AV's *apparentDecel*, it does not significantly affect the fundamental diagram, therefore we will deeply analyze this parameter in the following sections.

In conclusion, if the reaction time of AV is set to on average lower than the reaction time of MC and the AV is set to use speed on average equal to that of the MC (i.e., *speedFactor* of AV is 1.2), then we can expect that the increase in the percentage of AVs increases the efficiency of road traffic, where efficiency is measured by the number of lane changes proposed in Andreotti et al. (2020).

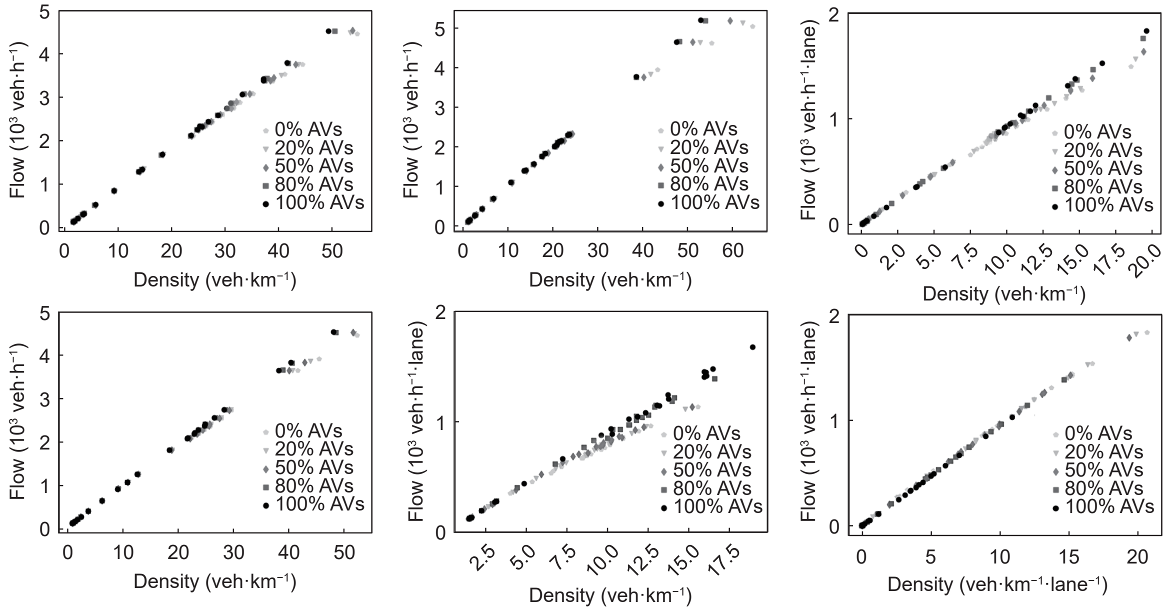

Fig. 11 Fundamental diagram in simulation with different percentages of AV. Top: devices 1 (left), 2 (center) and 3 (right). Bottom: device 1 slow lane (left), middle lane (center), and fast lane (right). AV's parameters in accordance with Table 1 and sF = 1.2.

6.2 Results about lane changes

In this section we will investigate the number of lane changes for different parameters' values and different percentages of autonomous/manually driven vehicles. In Andreotti et al. (2020), the number of lane changes has been proposed as a measure of driver dissatisfaction in a reasonably free flow condition. In fact, "being able to change lanes" means having margin to reach the desired speed, something that only a state of uncongested traffic could allow. However, lane changes are showed to be the cause of stop-and-go waves (Cassidy et al., 2009; Zheng et al., 2011), and in order to overtake, the speed is usually increased, which increases the risk of crashes. In fact, in Aarts and van Schagen (2006) it is shown that a 1% change in speed would lead to a 1.7% change in injury risks on roads with a 120km/h speed limit and 4% on roads with a 50 km/h speed limit, while it leads to a 3.3% change in fatal crashes on roads with a 120 km/h speed limit and 8.2% on roads with a 50 km/h speed limit. Safe and efficient traffic is therefore traffic in which it is possible to overtake (reasonably free flow conditions) and at the same time such that the number of overtaking is as small as possible. This condition can be reached with all AVs and in segments of roads that do not require changes in driving maneuver (there are no on-/off-ramps, intersections, traffic lights, ...). It is clear that these are totally ideal conditions. However, our aim is to get as close as possible to traffic conditions of this type. The authors, in Andreotti et al. (2020), demonstrated (proposition 3.1) that the number of overtakes increases quadratically as the number of vehicles involved varies. The demonstration was confirmed by simulations on a straight road consisting of three lanes. When traffic condition changes to an approaching unstable flow and unstable flow state occurs, the number of lane changes increases linearly. Through simulations, this section will show that the same behavior also occurs in real roads topology. However, overtaking is not the only reason for changing lanes, in fact in SUMO, the reasons that lead to a lane change can be divided into four categories: cooperative, strategic, keep right and speed gain. During an overtaking each vehicle makes two lane changes: the first one due to the "speed gain" reason and the second one due to the "keep right" reason. However, in overtaking, re-entry into the starting lane does not always occur, e.g., sometimes there is no room. Figs. 15 and 16 show the number of lane changes for different parameters' values and different percentages of autonomous/manually driven vehicles, respectively. The analysis was made by varying the number of vehicles involved, i.e., the number of vehicles injected into the network per hour, in accordance with the flow data collected by Trafikverket in the roads where the detector loops have been placed.

By comparing the different parameter's values for the *apparentDecel* of AVs ($A\ AD$), it is observed that the number of lane changes increases quadratically as the number of vehicles increases, please see Fig. 15 (top) for the comparison between $A\ AD = 4$ and $A\ AD = 6$ in 50%AV mixed traffic and Fig. 16 (top and middle) for a comparison between different percolations of AV ($A\ AD = 4$ on the left and $A\ AD = 6$ on the right). Moreover, in the histograms of Figs. 15 and 16 it is shown that the vehicles that mostly change lanes are AVs, for all the parameters examined. This is due to *lcStrategic* parameter, which for AVs is considerably higher than the values of MCs (Table 1). The reasons why vehicles perform the maneuver depend 50% (in simulations with 0% AVs) to 40% (in simulations with 100% AVs) on speed gain and 25% (in simulations with 0% AVs) to 40% (in simulations with 100% AVs) on keep right, while strategic and cooperative account for about 20% and 2%, respectively. We highlight that the *lcStrategic* parameter does not affect the "strategic" reason, but how early the lane change maneuver is performed. For this reason, in simulations with higher percentages of AVs, which have higher *lcStrategic* than MVs, we have an increase in the number of lane changes, and in particular the increase is because of the reason "keep right". It is also noticed that, in simulations with equal percentage of AVs, the proportion of the reasons why vehicles perform the maneuver are not significantly dependent of the *apparentDecel* parameters. Hence, when both populations (AV and MC) need to change lanes less, it means that both vehicles are more satisfied with the speed of their lead vehicles, whether they are autonomous or manual. From Figs. 15 and 16 one can see that the number of lane changes by MCs is greater when $A\ AD = 4$, while the least number of total lane changes is achieved when both vehicles have apparent deceleration parameter equal to 6. These

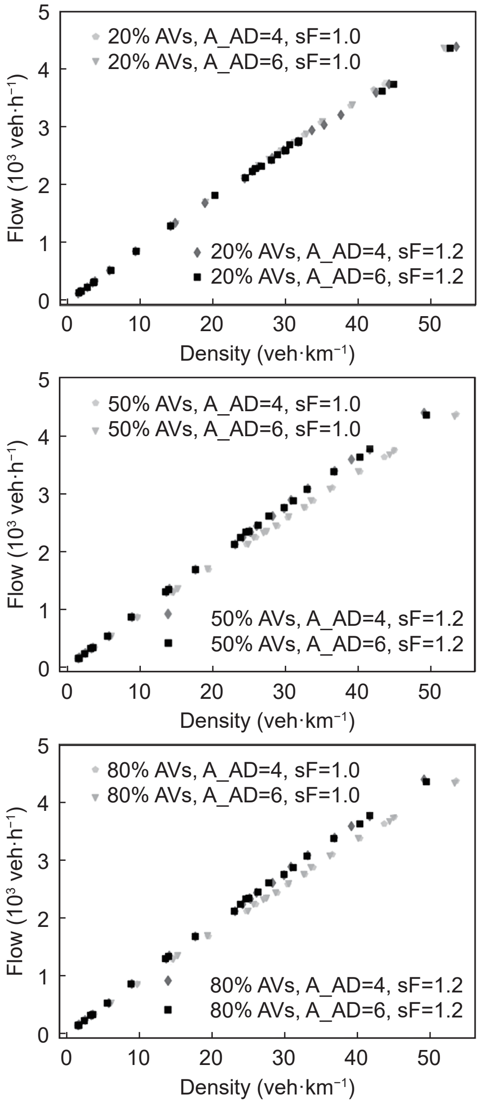

Fig. 12 Loop 1. Fundamental diagram in simulation with different parameters' values. From top to bottom: 20% of AVs, 50% of AVs, and 80% of AVs.

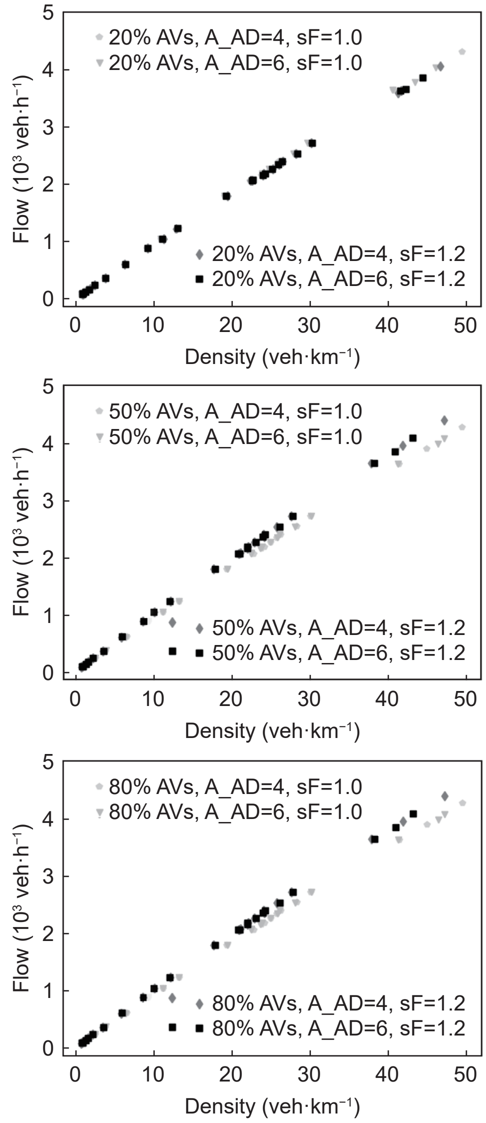

Fig. 13 Loop 2. Fundamental diagram in simulation with different parameters' values. From top to bottom: 20% of AVs, 50% of AVs, and 80% of AVs.

results allow us to identify the best, in terms of efficiency given by fewer lane changes, *apparentDecel* 's values even when we do not consider the type of lead vehicle.

The number of lane changes for different percentages of AVs are compared in Fig. 16. The increase is initially quadratic for all of the percentages analyzed, and then becomes linear, exactly as observed in Andreotti et al. (2020). However, unlike on straight roads, by inserting a more complex topology, it is observed that the breaking point (i.e., when the increase changes from quadratic to linear) depends on AV's percentage considered. As one can see in Fig. 16 (top and middle), the higher the percentage of AVs, the higher the breaking point.

6.3 Results about conflicts

This section discusses the number of conflicts occurred in the simulations, for the same parameters and percentages of AV as in Section 6.2. In order to detect the conflicts between vehicles, SSM devices (Safety Surrogate Measures) were placed on 1% of the vehicles injected.

In SUMO, conflicts are detected when one of the following conditions occurs: TTC (Time To Collision) lower than 3.0 s, DRAC greater than 3.0 m/s^2, PET lower than 2.0 s, maximum brake greater than 0.0 m/s^2, SGAP lower than 0.2 m and TGAP lower than 0.5 s. For more details about SSM device, readers are referred to SUMO (2020b). In Xu et al. (2022) some adjustment on SSM for the mixed traffic flow are suggested. In addition to the conflicts identified by SSM, conflicts as a result of uncomfortable braking, i.e., brakes greater than 4 and 6 m/s^2 for MCs and AVs, respectively, will also be discussed.

Fig. 17 (top) showed the number of conflicts detected (which is expected to be 1/100 of the real ones) for a mixed population consisting of trucks and cars, and the cars are composed of 50% of AVs, 50% of MCs, for the different *apparentDecel* 's values and time of day. The total number of vehicles during the one-day simulations is shown in the same figure with gray dashed line. It is interesting to note that the greatest number of conflicts occurs when the *apparentDecel* of AVs and MCs are equal, i.e., when one of the two types of vehicles has *apparentDecel* different from *decel*. While, the least number of conflicts occurs when each vehicle expects the lead vehicle to behave as itself, i.e., when *A AD* equals the AV's *decel* and *M AD* equals the MC's *decel*. Fig. 17 (bottom) shows the number of conflicts with uncomfortable braking detected in the 4 simulations. Fewer uncomfortable brakings, as

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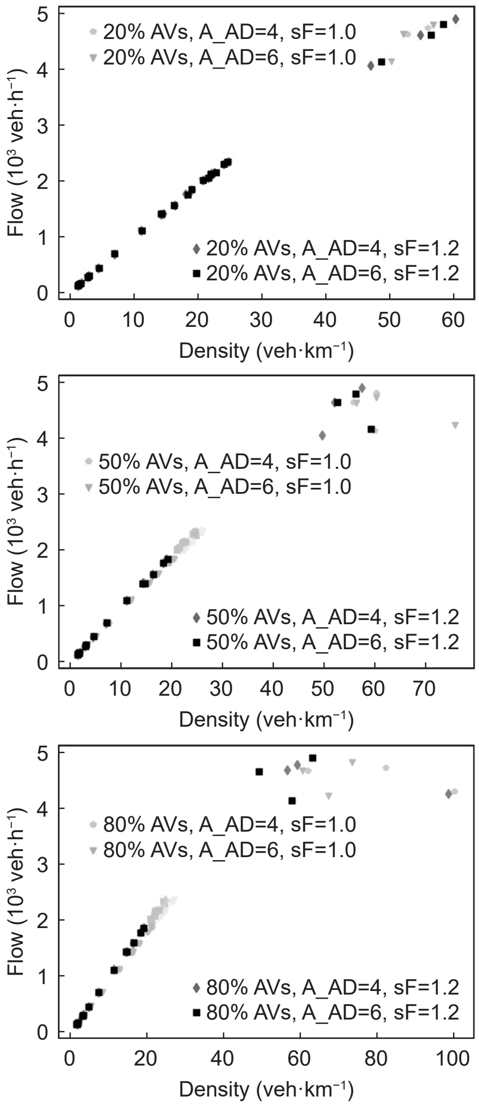

Fig. 14 Loop 3. Fundamental diagram in simulation with different parameters' values. From top to bottom: 20% of AVs, 50% of AVs, and 80% of AVs.

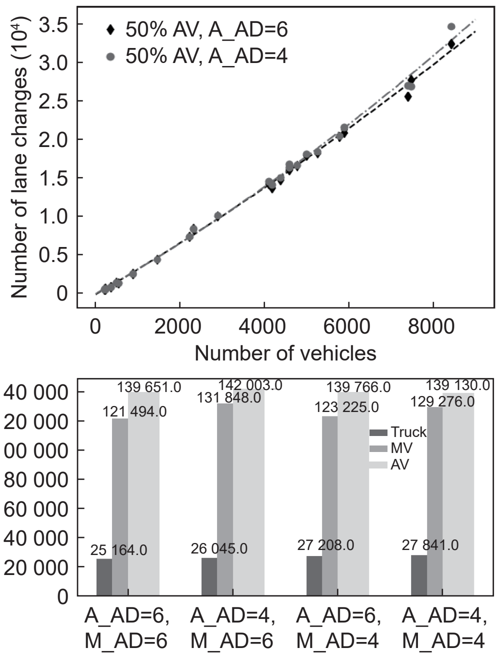

Fig. 15 Number of lane changes in the simulations with different parameters' values. Top: number of lane changes as the number of vehicles varies. Bottom: density of number of lane changes for each type of vehicle (MT, AV, and MC) for different values of the *apparentDecel* of MC (*M AD*), and AV (*A AD*).

well as fewer number of lane changes, are observed when *apparentDecel* 's values are equal to the *decel* 's values (i.e., when *A AD* = 6, *M AD* = 4). Therefore, these values will be considered from here on.

Table 3 and Fig. 18 show the number of conflicts with varying AV percentages. It is noted that for high flows (rush hours), the greatest number of conflicts are observed for high AVs' percentages. However, when flows are low, high percentages of AV bring less conflict. It can be observed that the number of conflicts grows more when the transition is from a low flow to a higher flow compared to the transition from high flow to a lower flow. For example, from 8 am to 9 am, the flow is greater than the flow from 6 am to 7 am, however the number of conflicts is greater in the second case than in the first one, for all the percentages of AV analyzed. We therefore investigate what is the cause of an increase in the number of conflicts.

Through simulations with the different values of the AV parameters introduced in this work, *lcStrategic* was identified as the parameter that mostly affects the increase in conflicts. From Fig. 19, one can see that for high *lcStrategics* (equal to 10 and 7) the higher the percentage of AVs, the greater the number of conflicts that occur. However, as the value of *lcStrategics* decreases the number of conflicts is reduced: with *lcStrategics* equal to 5, the combination in which the least conflicts occur is 50% of AVs, while for *lcStrategics* equal to 1, the best combination turns out to be 80% of AVs. From these results, it seems safer to set the AVs' with decreasing *lcStrategic* values (which means less eagerness for performing strategic lane changing) as the percentage of AVs on the roads increases.

Similar results and the same trend were obtained by placing the *Driver State Device* on each vehicle. Since not all AVs will be identical and have the same perceptions with respect to the strategy to be adopted, for example as a result of being produced by different manufacturers, an experiment was conducted to investigate how the number of conflicts would change if eagerness of AVs to conduct lane changes is changed by generating the *lcStrategic*'s values from a normal distribution with mean in 1, 3, 5, 7, and 10 and variance 1. By comparing the results with those obtained with variance 0, a decrease in the number of conflicts was noticed only for low AV percentages, an example is shown in Fig. 20. From these observations one can deduce that low *lcStrategic* values guarantee an overall reduction in the number of conflicts, however constant *lcStrategic* values allow a better interaction between AVs and low percentages of MCs, while in mixed traffic with higher percentages of MCs it is safer to have AVs with non-constant *lcStrategic*. It is also interesting to note that for scenarios totally consisting of only AVs (and MTs), the number of conflicts does not vary regardless if *lcStrategic* is constant or not.

A further parameter that distinguishes the two types of vehicles is *decel*, i.e., the maximum deceleration for comfort braking. In our simulations, the values of MCs'*decel* are normally distributed around average of 4, and the value of this parameter in AVs is set fixed at 6. In reality, this parameter has effects not only on the driving style, but also on the safety and interaction with the vehicles that follow it. In fact, a vehicle that performs a rapid braking requires greater attention to the vehicles that follow it: the

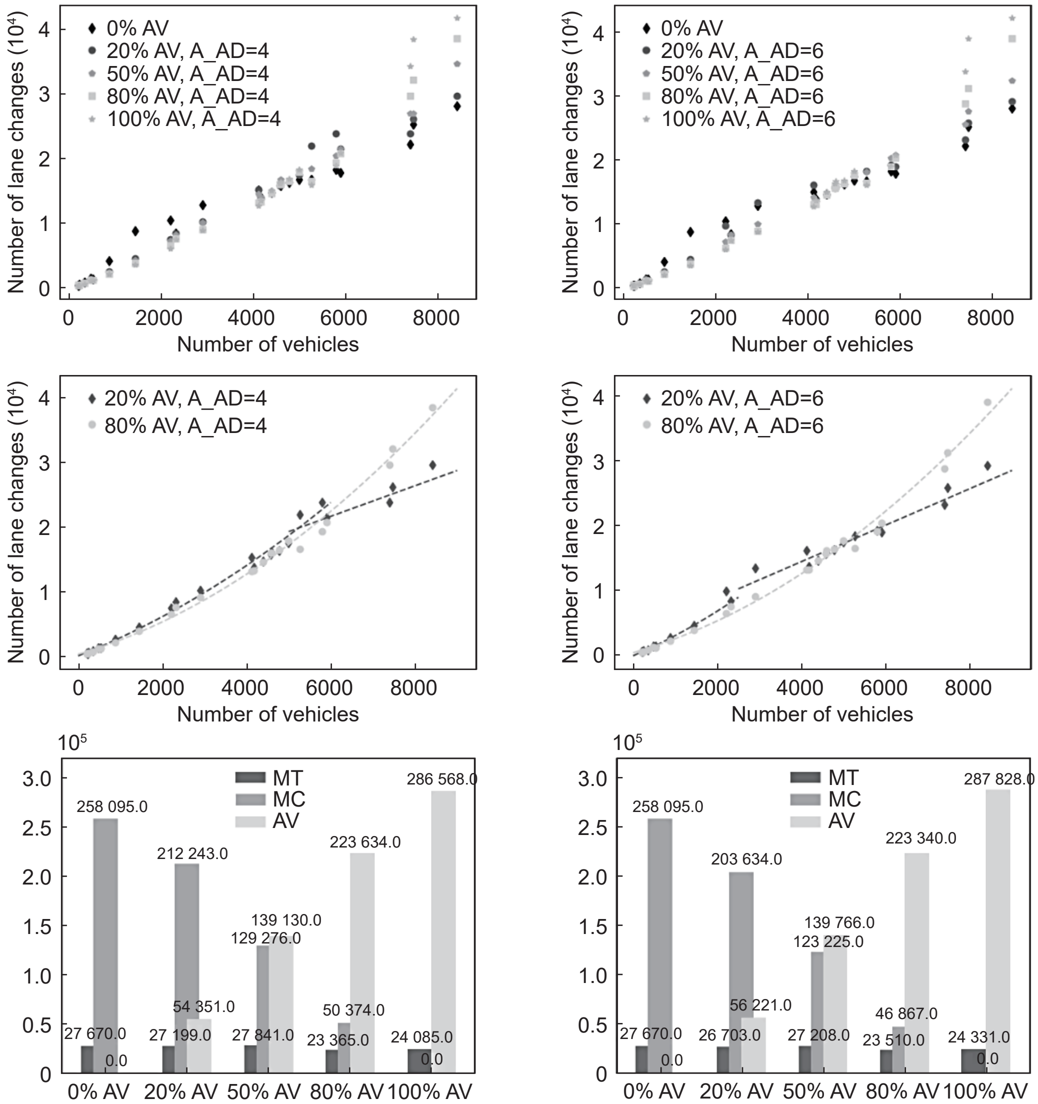

Fig. 16 Number of lane changes in the simulations with different percentages of AV. The value of *apparentDecel* for AVs is set to 4 m/s² for the left figures and 6 m/s² for the right figures.

braking of a vehicle with *decel* 6 can be done later than the braking of a vehicle with *decel* 4. We therefore replaced the *decel* of AVs

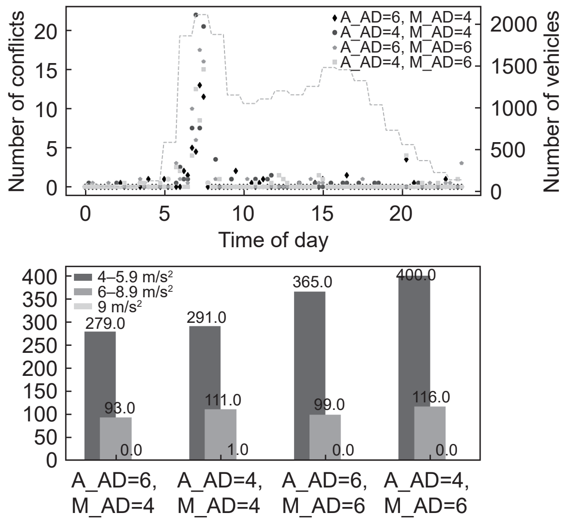

Fig. 17 Conflicts in a 50% AV and 50% MC population for different values of the *apparentDecel* parameter. Top: number of conflicts as daily hours vary. Bottom: Number of conflicts that bring to uncomfortable braking.

with the fixed value of 4 and compared the simulations with the default parameter simulations (Fig. 21).

One could expect that a vehicle with lower deceleration starts decelerating earlier, however, in the Krauß model, the *decel* value only indicates what the driver of that car would prefer as a normal deceleration. Therefore, it is clear that an ego vehicle, with $g(t) < v_{\text{lead}}(t)\tau_r$ (in Eq. (1)), approaches the lead vehicle with higher speed if it has low *decel* value. This observation explains the increase in conflicts for AV's *decel* equal to 4 shown in Fig. 21.

7 Discussion and future outlook

In this paper, experiments are conducted to investigate how the driving styles of AVs might affect safety and efficiency in mixed traffic condition with increasing AV penetration rate until it reaches full 100% AVs. For this purpose, a scenario of a portion of the city of Gothenburg in 2002 and 2019 with the daily traffic flows from real measurements in 2002 and 2019 are represented in traffic simulator SUMO. Starting from the parameters' values proposed in the literature, several parameters and values that represent changes in driving styles and the effects of the changes in driving style during the interactions with MCs were analyzed.

We have shown that, both in the ideal case of a straight road

Table 3 Number of conflicts in simulations with different percentages of AV. *apparentDecel*'s values equal to the *decel*'s values

Time	Number of conflicts	Different percentage				
		0%	20%	50%	80%	100%
0–1	347	0	0	0	1	0
1–2	222	1	0	0	0	0
2–3	213	0	0	1	2	1
3–4	233	0	1	0	0	1
4–5	487	0	0	2	1	1
5–6	2,319	0	1	2	1	0
6–7	7,401	9	5	7	30	58
7–8	8,415	19	43	68	103	137
8–9	7,465	8	4	0	4	16
9–10	4,580	0	4	4	1	0
10–11	4,173	0	5	1	0	0
11–12	4,389	2	0	3	1	0
12–13	4,774	3	3	0	3	0
13–14	4,588	1	0	0	3	0
14–15	4,992	6	0	1	0	1
15–16	5,892	0	4	2	2	0
16–17	5,784	0	4	3	0	0
17–18	5,260	0	0	0	1	0
18–19	4,109	1	2	0	2	0
19–20	2,896	0	0	0	0	0
20–21	2,213	2	3	7	0	1
21–22	1,451	0	1	1	0	0
22–23	881	0	0	0	1	1
23–0	534	0	1	2	1	4
Tot.	83,618	52	81	104	157	221

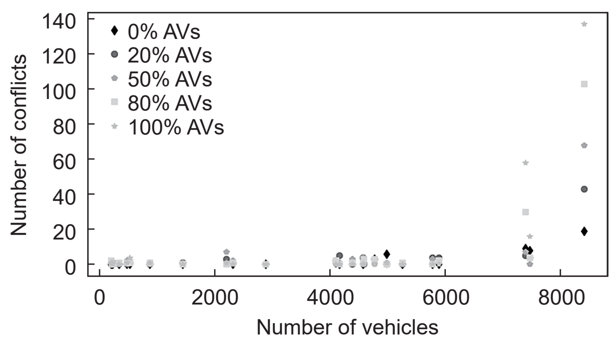

Fig. 18 Number of conflicts in simulations with different percentages of AV. The *apparentDecel*'s values equal to the *decel*'s values.

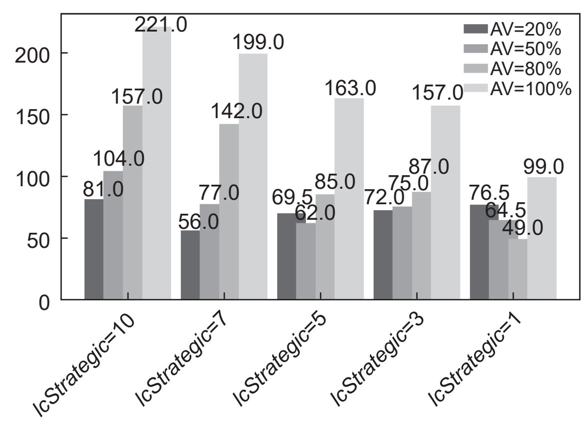

Fig. 19 Number of conflicts in simulations with different percentages of AV and values of *lcStrategic*.

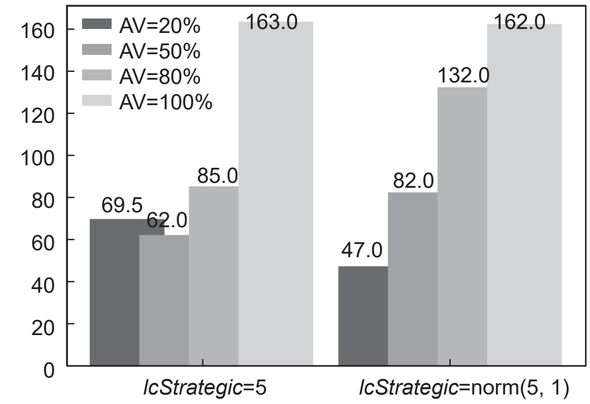

Fig. 20 Number of conflicts in simulations with different percentages of AV and values of *lcStrategic*.

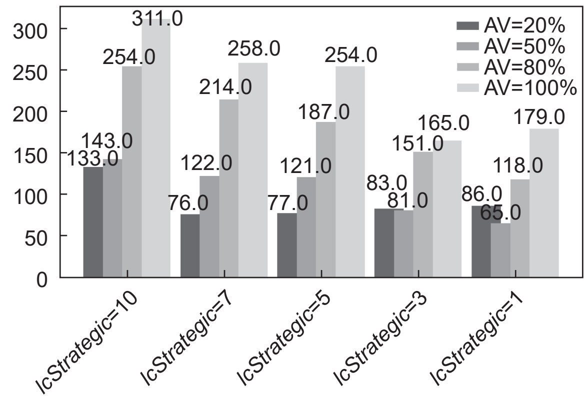

Fig. 21 Number of conflicts in simulations with different percentages of AV and values of *lcStrategic* for AV's *decel* set to 4.

(Andreotti et al., 2020) and for complex topologies (in this paper), the number of lane changes increases quadratically as the number of vehicles on the road increases in reasonably stable traffic conditions. Further, our experiments suggest that the number of conflicts also increases as the number of vehicles increases.

Although AVs improve the efficiency in terms of the number of lane changes, they appear to significantly increase the number of conflicts for high flow in our simulations. The latter was observed mainly because a conflict was still calculated based on the thresholds that were used to compute a conflict for MCs, while AVs' reaction time was shorter and *decel* was higher compared to the respective values for MCs. This points to the need of defining appropriate definition of conflict in the context of AVs.

Our simulations suggest that reaction time, eagerness to do lane changes, and deceleration ability of the AVs should be among the key parameters of the AVs' driving styles.

In general, lower reaction times, *tau*, allow higher vehicle speeds, and the fundamental diagram shows higher flows as the percentage of AVs increases. This observation is also confirmed by the number of lane changes. With the way MCs and AVs are modelled in our simulations, MCs and AVs occupy the lanes in different ways, with the right lane has higher density of AVs. While the real driving styles of AVs could be different compared to the way AVs are modelled here, the potential impact of mixed traffic to lanes usage observed in our simulations highlight the need to further study if the rules of lanes usage should be adapted during the transition to 100% AVs.

Our simulations suggest that the driving styles of AVs should change over time as the penetration of AVs increases until it reaches 100%. In a mixed traffic, it seems important to keep the behaviour of the vehicles more homogeneous/similar to keep the number of conflicts low. This means that keeping AVs' driving style more similar to those of MCs in low AVs penetration rate i.e., by setting the value of AVs' *lcStrategic* non constant with similar mean and variance with those of MCs. While in the mixed traffic with high AVs penetration rate, this means keeping AV behaviour more predictable among AVs, such as setting the value of AVs' *lcStrategic* as constant. Our experiments particularly suggest that as the penetration of AVs increases, it seems safer (less conflict) to have AVs with less eagerness to perform strategic lane changing. When the traffic is 100% AVs (i.e., no MCs), the choice of AVs' driving style can perhaps be more flexible as it was found in the experiments that constant or nonconstant *lcStrategic* do not affect the number of conflicts significantly. However, validation is needed to confirm the conclusions derived here.

This study has limitations. Despite efforts to choose parameters and values for AVs that make sense (i.e., using knowledge from analysis of real human-driver behaviour as well as reasonable expectations that are circulated among the community and/or from the literature), they might differ from real AVs' driving styles. Further, the same definition for conflict (i.e., the same thresholds) is used for both AVs and MCs. This is obviously an oversimplification. A further analysis should therefore be made considering different thresholds for the two categories of vehicles. Hence, a possible improvement in the SUMO model, and also in the implementation of the real maneuvering strategies of the AVs, is to study a model for lane change strategy that improves safety. Considering that it is difficult for any vehicle to know whether it can expect that the lead vehicle will decelerate like AVs or like MCs, the easiest would be for a vehicle to expect the lead vehicle to behave like it does. To reach the ideal case, it is important to make the lead vehicle's strategies recognisable or somehow communicated to the vehicle that follows it.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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