Simulation-based impact projection of autonomous vehicle deployment using real traffic flow

Eleonora Andreotti, Selpi and Pinar Boyraz

***Abstract*—In this work we focus on future projected impacts of the autonomous vehicles in a realistic condition representing mixed traffic. By using real flow and speed data collected in 2002 and 2019 in the city of Gothenburg, we replicated and simulated the daily flow variation in SUMO. The expansion of the city in recent years was reflected in an increase in road users, and it is reasonable to expect it will increase further. Through simulations, it was possible to project this increase and to predict how this will impact the traffic in future. Furthermore, the composition of vehicle types in the future traffic can be expected to change through the introduction of autonomous vehicles. 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, we focus 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.**

***Index Terms*—automated driving, mixed-traffic, traffic simulations, realistic conditions**

I. Introduction

In this work, we bring forward the study of the projected impact that autonomous vehicles (AVs) will have on real city traffic. It is well-known that car manufacturers and newly launched high-tech companies are working on AVs and introducing different levels of automation in new vehicles. Therefore, it is a valid research question to investigate the impact of these new technologies in real traffic conditions and how much the current city infrastructure and traffic management systems are ready for this gradual change. In fact, 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 [1]. Therefore, the ground is being prepared for a future in which more and more AVs will exist. In [2], 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 evaluations of the sub- and the macro-categories, a ranking is compiled, in which Sweden occupies the fifth place. In light of this gradual but continuous process, it is important to understand the effects of mixed traffic, in which two or more driving styles (e.g. autonomous and manual) will interact among them. Hence, in order to improve safety and efficiency, our aim is to identify which are the driving characteristics (i.e. parameters' values) that allow a safer and more efficient interaction with manually driven vehicles (MVs). To this end, we have reproduced the topology of the south-east part of the city of Gothenburg, for a total of more than 20km of high-speed road and on and off ramps, and its daily traffic flow through Open Street Map and data from the Swedish Transport Administration (Trafikverket) [3], respectively. We simulated the daily traffic with SUMO (Simulation of Urban MObility [4]) in the years 2002 and 2019, taking into account the changes in posted speed limits on the roads. As for the choice of the car following model, in [5], the IDM and Krauss car following models were compared ([6] and [7], respectively), 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 during vehicles' lane changing. For these reasons, we simulate both autonomous and manually driven vehicles using the Krauss model. In order to represent the behaviour of MVs as close as possible to the real traffic, we used the values of the parameters for lane change and Krauss car following models calibrated in [8] on the roads of Gothenburg. Once the daily traffic is simulated for MVs, we introduce several percentages of AVs. Initially, we consider the values of the AV parameters proposed in [8], subsequently we analyze, in real traffic simulations, the improvements in the values suggested for ideal traffic in [9]. Finally, other parameters' values are analyzed in this paper (on the *apparentDecel*, *lcStrategic* and *decel* parameters). In [9], 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 improve the measure's value. In accordance with the approach introduced in [9], 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. In Section IV we focus on simulations with different percolation percentages of AVs (AV simulations). We investigate the effects of parameters in AV behavior, reflected on these three main outputs: fundamental diagrams (IV-A), number of lane changes (IV-B) and number of conflicts (IV-C). Finally, in Section V, we outline the future work based on our main observations from this analysis.

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II. Description of the simulation setting

By using SUMO, we simulate the daily traffic flow variation in the city of Gothenburg, comparing the real and simulated data of 2002 and 2019. More precisely, we compare the two flows (i.e. the number of vehicles that passes a certain cross-section per time unit, [10]) that passes through three detector devices (red devices in Fig. 1). In SUMO, the flow detectors are called *Induction Loop Detectors* ([11]), for this reason, to distinguish the real devices (those used by Trafikverket) and those placed in SUMO we will call the real detectors as *detector loops* and those in SUMO as *simulated detector loops*. In both loops the information collected are flow and time-mean speed (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 (average speed of vehicles traveling a given segment of roadway during a specified period of time). The authors refer to [12] for an in-depth theoretical and empirical analysis on time-mean speed and space-mean speed.

A. 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, we have placed, in SUMO, 4 simulated loops that inject flow of traffic (blue points in Fig. 1) and the 3 *simulated detector loops* that detect flow, time-mean speed and space-mean speed. 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. We note that, 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, [12]. 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), hence we have considered these detected types in our simulations as well. Therefore, we can say that our simulations have a characteristic representing both mixed (i.e. cars, trucks) and heterogeneous traffic (i.e. AVs and MVs). The SUMO parameters used to define the vehicles are in accordance with the parameters calibrated by [8] 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 Fig. 2 and 3 the flows and time-mean speed as the daily hours vary, detected by SUMO loops and Trafikverket devices are compared, respectively.

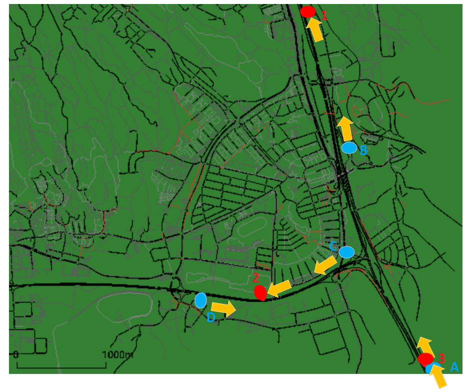

Fig. 1: Portion of Gothenburg in SUMO. Blue loops inject traffic, red loops detect traffic. Traffic detected by the red loop 3 is generated by the blue loop A. Traffic detected by loop 2 is generated by loops A and C. Traffic detected by loop 1 is generated by loops A, B and D.

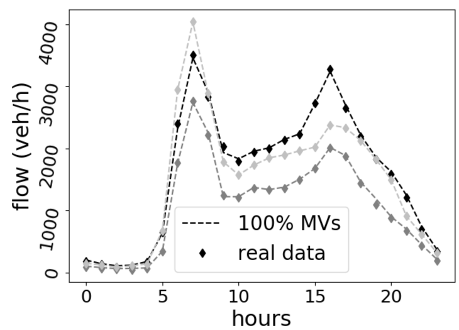

Fig. 2: Flow of vehicles as hours change (on August 29, 2002). The detections of the real devices (markers) are compared with the detections of the loops in SUMO (lines): device 1 (black), 2 (gray) and 3 (light gray).

B. Description of the simulation setting: year 2019

Measurement devices have been placed in different locations in 2002 compared to 2019 according to the dataset collected by Trafikverket. Therefore it is not possible to directly compare the data from 2002 with those from 2019. However, it is possible to derive the daily traffic flows 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 further devices present in the scenery, see [13] for the definition of scenery. For a comparison as precise as possible between the data of 2002 and 2019, we consider week days for both years.

C. On the comparison between 2002 and 2019 data

Fig. 5 shows the traffic densities and flow of one day of 2002 and one day of 2019 passing through loops 1, 2 and 3. We can observe that the number of vehicles passing through the loops is significantly increased in 2019 compared to 2002,

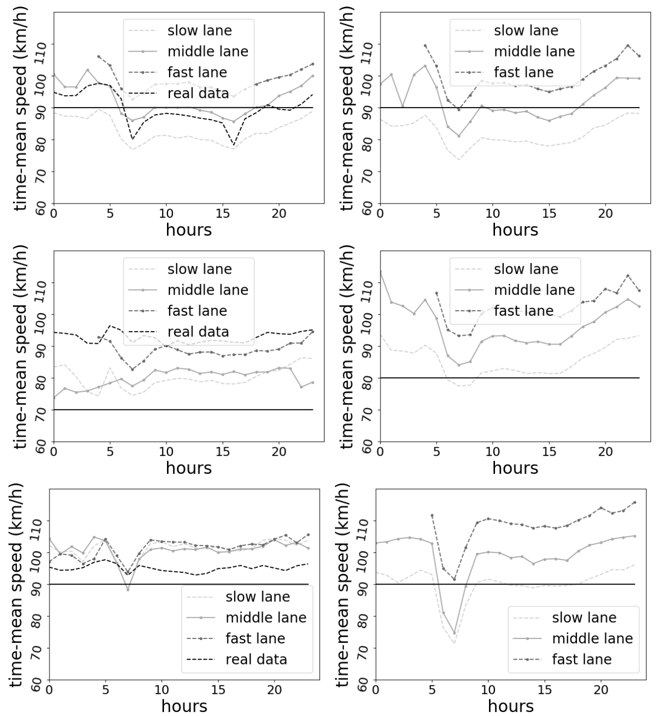

Fig. 3: Time-mean speed of vehicles as hours change, 2002 (left) and 2019 (right). From top to bottom: devices 1, 2 and 3. The solid lines represent the speed limits.

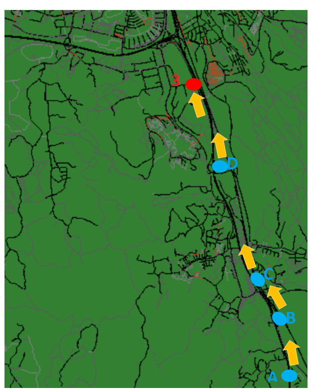

Fig. 4: Portion of Gothenburg in SUMO. The red loop detects traffic injected by blue loops.

for example the number of vehicles that passes through loop 3 has increased by more than 10%. However, the density of the population in the Västra Gotaland region from 2002 to 2019 has increased from 1.5 million inhabitants to more than 1.7 million inhabitants [14]. This would mean that people traveling by car has increased accordingly with the population. 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 in the city. Loop 3, unlike loop 1 and loop 2, is located on an incoming road, thus only detects the incoming flows (see Fig.5). The second observation we can make is that in 2019 most of the increased flow is in the morning, 7-9 a.m., i.e. the flow due to people who live outside the city but who enter the city to work. A further observation is that the average speeds of the vehicles do not seem to have undergone

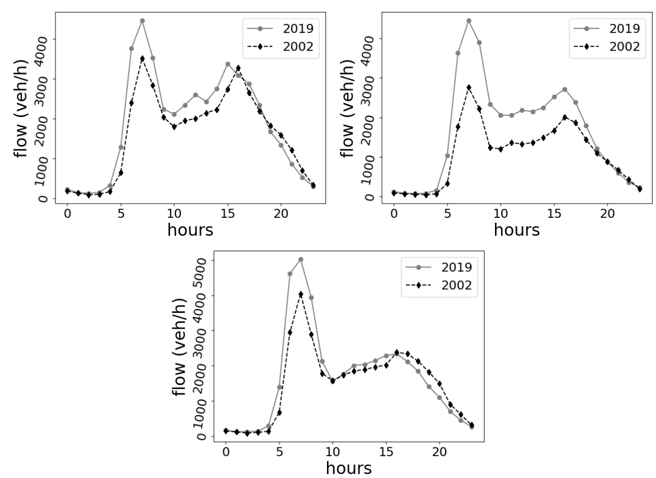

Fig. 5: Comparison of the daily traffic flows in 2002 and 2019 passing through loops 1 (left), 2 (right) and 3.

changes, although the speed limit of the road where device 2 lies has changed from 70 to 80 km/h (Fig. 7). A more detailed analysis of the average speeds will be investigated in the next section.

III. On the comparison between real data and MV simulations

In the previous section we showed how, in SUMO, we generated traffic flows equal to the real flows. In this section we focus on the mean speeds, and the question we shall answer is whether the MV simulations follow the same trend of real data. In the simulations, vehicle speeds depend on the maximum speed allowed on the road, on the car following model used and its parameters' values. In Fig. 3, we compare the time-mean speeds, as the daily hours vary, of the real data with those detected by the red loops on the lanes. We note 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. However, the same cannot be said about the average speeds. The roads where devices 1 and 3 have been placed have a speed limit of 90 km/h in both 2002 and 2019, while the speed limit of the road where device 2 has been placed has a limit of 70 km/h in 2002 and 80km/h in 2019. However, the average time-mean speed of real data (2002) passing through the device 2 is the same with the average time-mean speed of real data in 2019, while in our simulations the average speed is significantly lower (in 2002), in accordance with the speed limit. The causes that can lead to such a difference in average speed maybe due to the speed cameras placed near devices 1 and 3 and not near device 2, or because of the speed limit of the road is perceived as too low near the device 2. In fact, in 2019 the limit was raised from 70 to 80 km/h. By comparing the space-mean speeds of the vehicles that pass through the three loops in 2002 and 2019 we notice that the average speeds do not seem to have changed, while the greatest differences we notice is with regard to the lane speeds, Fig.7. In fact, we note that in 2019, the difference between the speeds in the lanes is more noticeable than in 2002. In addition, we note that the fundamental diagrams (Fig. 6 (left)) also show the change of

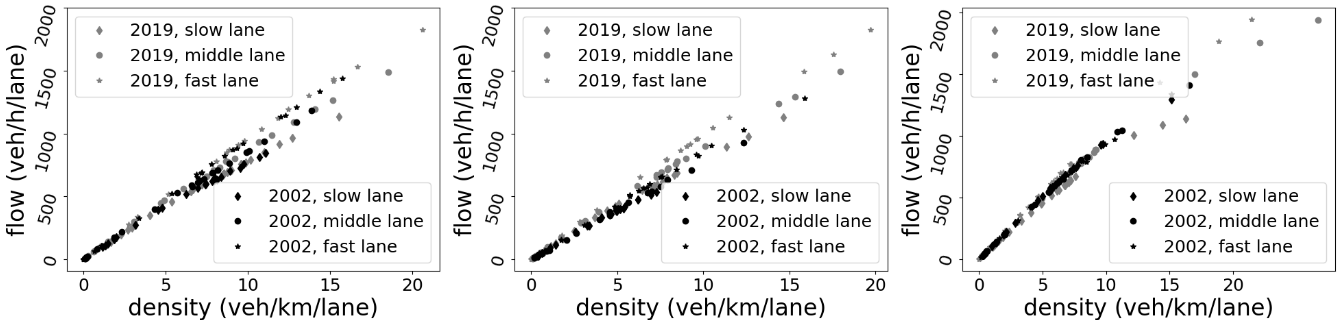

Fig. 6: Comparison of the fundamental diagrams in 2002 and 2019 passing through loops 1 (left), 2 (center) and 3 (right).

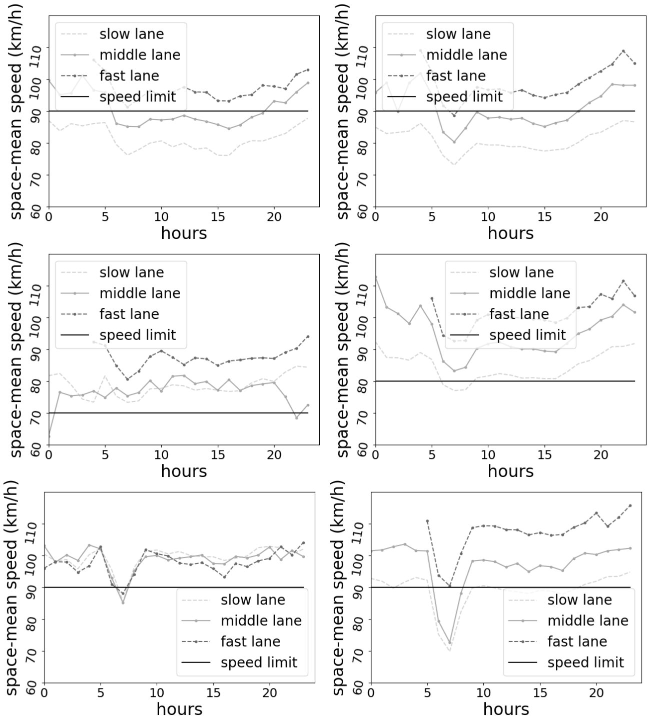

Fig. 7: Speed of vehicles as hours change, 2002 (left) and 2019 (right). From top to bottom: loops 1, 2 and 3.

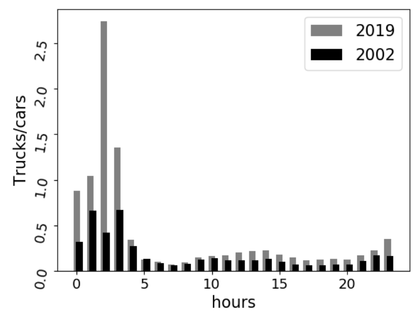

Fig. 8: Ratio between number of truck and number of cars passing through loop 3, [3].

TABLE I: SUMO parameters

Parameter	MVs 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

state (i.e. a change in the slope of the data), from reasonably free flow to congested, in the slow lanes of 2019 already for 10 vehicles per km. The cause of the decrease in speed and density on slow lane in 2019 is attributable to the number of trucks to the number of cars ratio which increased in 2019, Fig.8. 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 reasonably free flow to congested, [15]. We will analyze this aspect in detail in the next section. From here on, unless otherwise specified, the parameters' values of the MVs used in the simulations are those given in Tab. I.

IV. Simulations with different percolation percentages of AVs

In this section, we focus on different AV's percolation percentage. The parameters' values used for MVs are the same as in the two previous sections, while for AVs we consider the values of the parameters introduced in [8] together with improvements analyzed in [9] on *speedFactor* value, and others that we will explore in this work. 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 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 represent 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 MVs 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. We therefore analyze the 4 possible combination cases of AVs and MVs with *apparentDecel* 4 and/or 6$[m/s^2]$. Together with the *apparentDecel* we analyzed the *decel*, being the two parameters closely related, Tab. I. *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, we have carried out a deeper exploration and we have analyzed the default value 1, as well as the one proposed in [8] (*lcStrategic*=10), and the intermediate values between the two, in particular values 3,5 and 7. For more details see Tab. II. From here on we will consider the traffic data of 2019: being composed of higher densities allow us to study in more depth the critical aspects of the parameters, especially in view of an increase of road users towards the future.

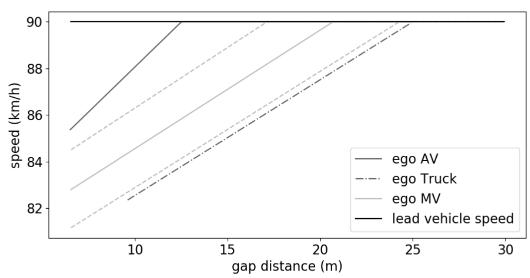

Fig. 9: Ego vehicle speed as the gap distance varies (distance from front bumper of ego vehicle to rear bumper of the vehicle ahead). The dotted lines represent the standard deviation of the gamma distribution that characterizes *tau* for MVs.

TABLE II: Simulations with different 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

A. Fundamental diagram of traffic flow

For representing the heterogeneous and mixed vehicle fleet, we replaced the MVs with different percentages of AVs, while we left the number of trucks unchanged. Let us start by setting the AV parameters as in Tab. I, with the exception of the *speedFactor* (sF) parameter which has been extensively studied in [9] and therefore we set it to 1.2. Comparing the results obtained in 100% MV simulations with those obtained with different percentages of AVs, we observe that the critical point in the fundamental diagram (Fig. 10 bottom) does not seem to occur, or at least not for the densities considered, as the percentage of AV increases. In order to explain the possible explanation for it, we analyze the parameters that characterize the AV and MV. First of all, we observe that the *minGap* (minimum empty space after the ego vehicle) of the AV and MV 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 (1000m/(*minGap*+AV's mean *length*)) while the maximum number of MV is 155 (1000m/(*minGap*+MV'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 the following equation

$$v_{safe}(t) = v_{lead}(t) + \frac{g(t) - v_{lead}(t)\tau_r}{\frac{v_{ego}+v_{lead}(t)}{2decel} + \tau_r}, \quad (1)$$

where t is the time step, $v_{lead}(t)$ 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 MV) have the same speed as the lead vehicle at time t, Fig. 9 compares the speeds of the ego vehicles at the time $t + \Delta t$. We notice that when the ego vehicle is an MV, 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 MV traffic flow. In fact, the mean of gap distance (from front bumper to rear bumper) between MVs of less than 20 m corresponds to a density greater than 40 MVs per km per lane (1000m / (mean distance + MV's *length*)) which correspond to a flow of 3600 MVs per hour per lane (40MVs / 1km * 90km / h), i.e. when more than 1 vehicle is introduced per second per lane, then the MVs start to brake. If we consider the AVs, this mean distance is reduced to 12 m between one vehicle and the next one, which corresponds to a vehicle every 0.7 seconds per lane ((*minGap*+MV's *length*)/(90km/h)). However, the traffic considered is not made up of MVs or AVs only, in fact it is a mixed traffic in which 13% (in 2019) of the vehicles are trucks. Doing the same calculation for trucks, which have reaction times corresponding to 1 s and average length 7.1 m, we get that the distance at which trucks begin to brake is 25 m which corresponds to injections of one truck every 1.3 seconds. 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 we observe that this threshold is considerably lower, Fig. 6, and the cause is the heterogeneity of the vehicles. In fact, not all the vehicles aim to drive at the same speed, the traffic is mixed (we have 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. Fig. 10, Fig. 11, Fig. 12 and Fig. 13 show fundamental diagrams for different percolation percentages of AVs and different parameters' values (*speedFactor*, sF, and AVs' *apparentDecel*, A_AD), respectively. Moreover, in Fig. 10 on the right, we represented the fundamental diagrams per lane. We observe that for different percentages of AVs the vehicles are distributed differently on the lanes: for low percentages of AVs the slow lane is congested at low densities, and therefore the most exploited lanes are middle and fast. On the contrary, for high percentages of AVs the most used lanes are slow and middle, and for the densities considered, the flow does not enter into congested conditions. This aspect is also reflected in the fundamental diagrams (on the left) in which, for high percentages of AVs, the densities are on average lower, but the flow is higher. Fig. 11, Fig. 12 and Fig. 13 show that greater interaction between AVs and MVs (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 [9] 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.

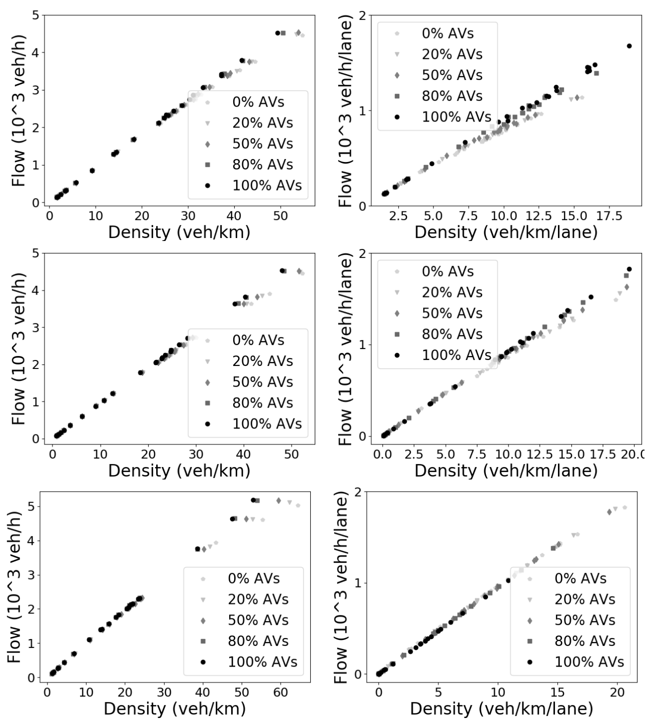

Fig. 10: Fundamental diagram in simulation with different percentages of AV. Left: devices 1 (top), 2 (center) and 3 (bottom). Right: device 1 slow lane (top), middle lane (center) and fast lane (bottom). AV's parameters in accordance with Tab.I and sF=1.2.

In conclusion, if the reaction time of AV is set to on average lower than the reaction time of MV and the AV is set to use speed higher than the MV (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 as a measure of efficiency we consider the number of lane changes proposed in [9].

B. 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 [9], the number of lane changes has been proposed as a measure of driver dissatisfaction in 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

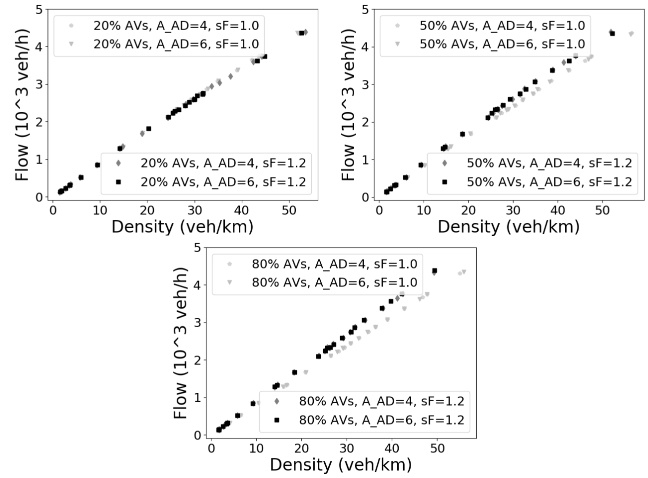

Fig. 11: Loop 1. Fundamental diagram in simulation with different parameters' values. Top Left: 20% of AV. Top Right: 50% of AV. Bottom: 80% of AV.

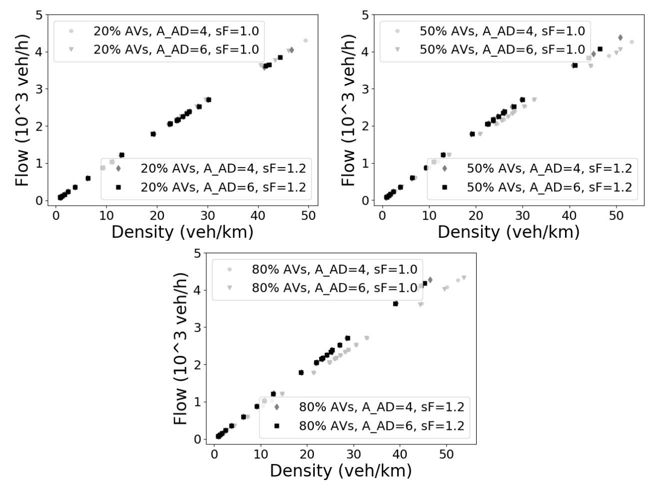

Fig. 12: Loop 2. Fundamental diagram in simulation with different parameters' values. Top Left: 20% of AV. Top Right: 50% of AV. Bottom: 80% of AV.

traffic could allow. However, lane changes are showed to be the cause of stop-and-go waves, [16], [17], and in order to overtake, the speed is usually increased, which increases the risk of accidents. In fact, in [18] it is shown that a 1 % change in speed would lead to a 1.7% change in injury accident on roads with a 120km/h speed limit and 4% on roads with a 50km/h speed limit, while it leads to a 3.3% change in fatal accidents on roads with a 120km/h speed limit and 8.2% on roads with a 50km/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 for changes in driving (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 [9], demonstrate (proposition 3.1) that the number of lane changes increases quadratically as the number of vehicles involved varies. The demonstration is confirmed by simulations on a straight road consisting of three lanes. When traffic condition changes to

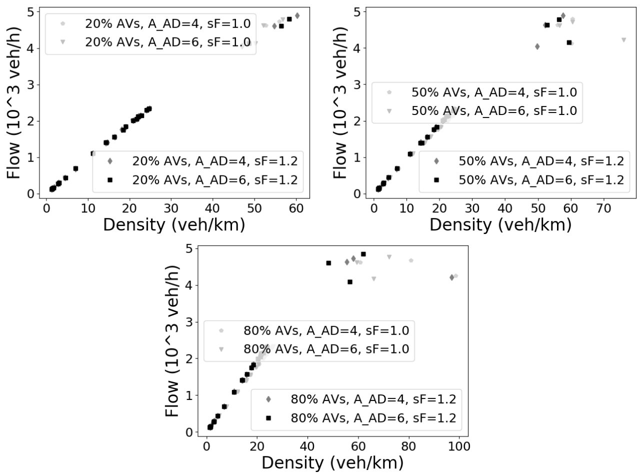

Fig. 13: Loop 3. Fundamental diagram in simulation with different parameters' values. Top Left: 20% of AV. Top Right: 50% of AV. Bottom: 80% of AV.

an approaching unstable flow and unstable flow state occurs, the number of lane changes increases linearly. In this section we show through simulations that the same behavior also occurs in real roads topology. Fig. 14 and Fig. 15 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 different parameter's values for the *apparentDecel* of AVs (A_AD) we observe that the number of lane changes increases quadratically as the number of vehicles increases, please see Fig. 14 (top) for the comparison between $A\_AD = 4$ and $A\_AD = 6$ in $50\% AV$ mixed traffic and Fig. 15 (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 Fig. 14 and Fig. 15 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 MVs, Tab.I. The number of overtaking by MVs is greater when $A\_AD = 4$, while the least amount of total overtaking is achieved when both vehicles have apparent deceleration parameter equal to 6. When both populations (AV and MV) need to overtake less means that both vehicles are more satisfied with the speed of their lead vehicle, whether they are autonomous or manual, and that therefore this result allows us to identify the best, in terms of efficiency given by fewer lane changes, *apparentDecel*'s values even when we don't consider the type of lead vehicle. In Fig. 15 we compare the number of lane changes for different percentages of AVs. The increase is initially quadratic for all the percentages analyzed, and then becomes linear, exactly as observed in [9]. However, unlike on straight roads, by inserting a more complex topology, we note 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. 15 (top and middle), the higher the percentage of AVs, the higher the breaking point.

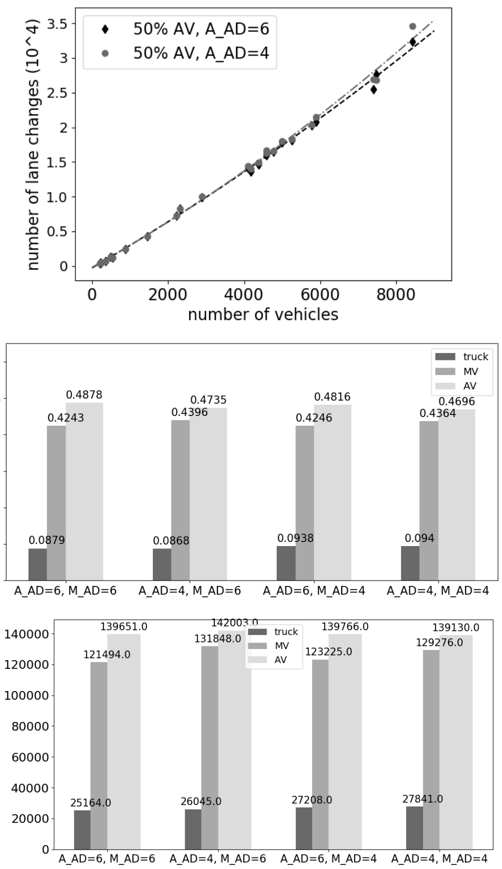

Fig. 14: Number of lane changes in simulations with different parameters' values. Top: number of lane changes as the number of vehicles varies. Middle and bottom: relative density (middle) and number of lane changes (bottom) for each type of vehicle (truck, AV and MV) for different values of the *apparentDecel* of MV (M_AD) and AV (A_AD).

C. Results about conflicts

In this subsection we investigate the number of conflicts for the same parameters and percentages of AV as in the previous subsection. In order to detect the conflicts between vehicles, we have placed an SSM device (Safety Surrogate Measures) on 1% of the vehicles injected. The SUMO conflicts are detected when one of the following conditions occurs: TTC 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 [19]. However, as in [9], we will focus on conflicts (those identified as conflicts by SSM) and on conflicts in which uncomfortable braking occur, i.e. brakes greater than $4m/s^2$ and $6m/s^2$ for MVs and AVs, respectively. Fig.16 (top) showed the number of conflicts detected (which we expect 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 MVs, for different *apparentDecel*'s values, as the hours of the day vary. In the same figure we also represent the total number of vehicles during the daily simulation (gray dashed line). It is interesting to note that the greatest number of conflicts occurs when the *apparentDecel* of AVs and MVs are equal, i.e. when

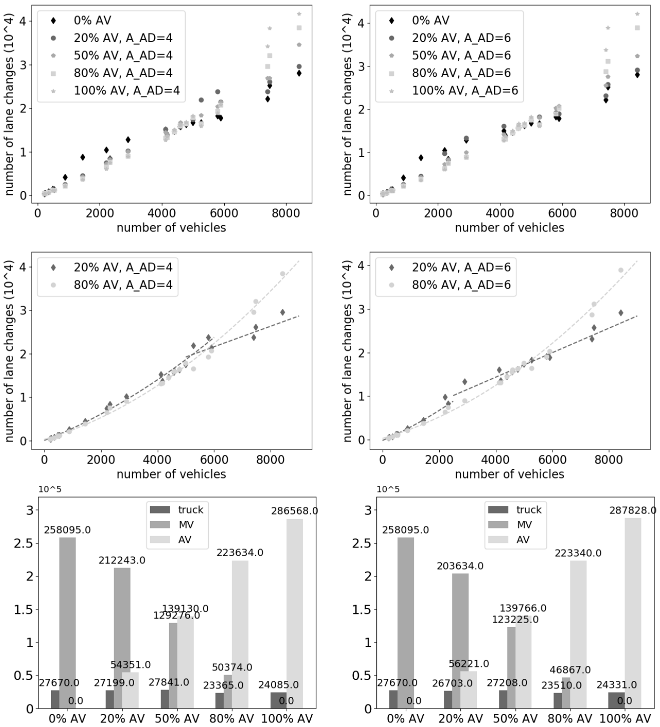

Fig. 15: Number of lane changes in simulations with different percentage of AV. The value of *apparentDecel* for AVs is set to $4m/s^2$ for the left figures and $6m/s^2$ for the right figures.

one of the two types of vehicle 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 MV's *decel*. Fig. 16 (bottom) shows the number of conflicts with uncomfortable braking detected in the 4 simulations. We observe that fewer uncomfortable brakings, as well as number of lane changes, are resulted for *apparentDecel*'s values equal to the *decel*'s values. Therefore, we will consider these values from here on. Tab. III shows the number of conflicts with varying AV percentages. Unlike what was observed in [9], the flows closely homogeneous (low AV percentages or low MV percentages) do not lead to a decrease in conflicts. In fact, in our simulations we note that for high flows we get the greatest number of conflicts for high AVs' percentages. However, when flows are low, high percentages of AV bring less conflict. We also observe 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 8am to 9am the flow is greater than the flow from 6am to 7am, however the number of conflicts is greater in the second case than in the first one, for all the percentages of AV analyzed. We can therefore deduce that the more complex topology and the change in traffic flow lead to different results. 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, we have identified *lcStrategic* as the parameter that most affects the increase in conflicts. From Fig.17, we can note 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' *lcStrategic* which decreases when the percentage of AVs on the roads increases. By placing the *Driver State*

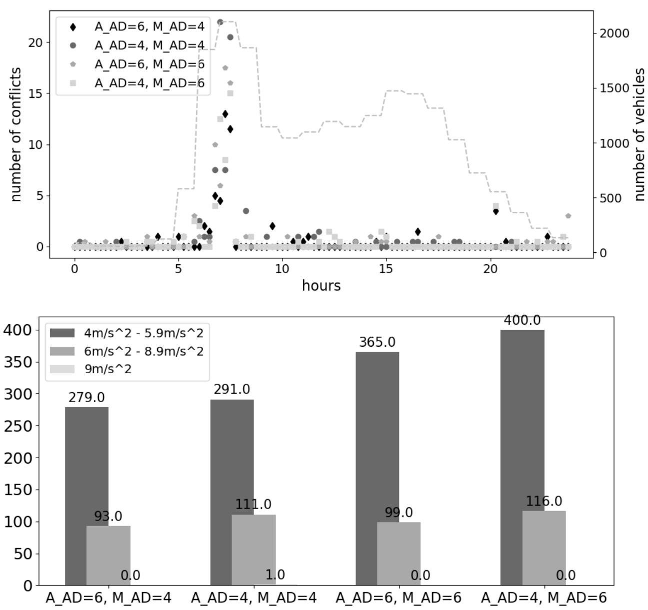

Fig. 16: Conflicts in a 50% AV and 50% MV population for different values of the *apparentDecel* parameter. Top: number of conflicts as daily hours vary. Bottom: Number of conflicts that bring to uncomfortable braking.

TABLE III: Number of conflicts in simulations with different percentage of AV. *apparentDecel*'s values equal to the *decel*'s values.

Hour	**Number of vehicles**	**Number of conflicts**				
		0%	20%	50%	80%	100%
2-3	213	0	0	1	2	1
1-2	222	1	0	0	0	0
3-4	233	0	1	0	0	1
0-1	347	0	0	0	1	0
4-5	487	0	0	2	1	1
23-0	534	0	1	2	1	4
22-23	881	0	0	0	1	1
21-22	1451	0	1	1	0	0
20-21	2213	2	3	7	0	1
5-6	2319	0	1	2	1	0
19-20	2896	0	0	0	0	0
18-19	4109	1	2	0	2	0
10-11	4173	0	5	1	0	0
11-12	4389	2	0	3	1	0
9-10	4580	0	4	4	1	0
13-14	4588	1	0	0	3	0
14-15	4992	6	0	1	0	1
12-13	4774	3	3	0	3	0
17-18	5260	0	0	0	1	0
16-17	5784	0	4	3	0	0
15-16	5892	0	4	2	2	0
6-7	7401	9	5	7	30	58
8-9	7465	8	4	0	4	16
7-8	8415	19	43	68	103	137
Tot.	83618	52	81	104	157	221

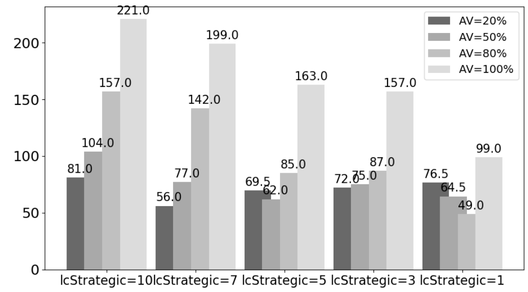

Fig. 17: Number of conflicts in simulations with different percentage of AV and values of *lcStrategic*.

Device on each vehicle we obtain similar results and the same trend. If all vehicles have the same *lcStrategic*'s value, i.e. the same eagerness for performing strategic lane changing, they will try to do the manoeuvres at the same time and therefore create very dense and unsafe zones in the roads. Hence, a possible solution is to generate the *lcStrategic*'s values from a normal distribution. Actually, this assumption is reasonable, in fact not all AVs will be identical (different car manufacturers) and will have the same perceptions with respect to the strategy to be adopted. However, by generating *lcStrategic* with mean in 1,3,5,7, and 10 and variance 1 we have noticed a decrease in the number of conflicts only for low AV percentages and an increase in the number of conflicts when the percentages are higher, an example is shown in Fig.18. From these observations we 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 MVs, while in mixed traffic with higher percentages of MVs 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 trucks) the number of conflicts does not vary regardless if *lcStartegic* is constant or not. A further parameter that distinguishes the

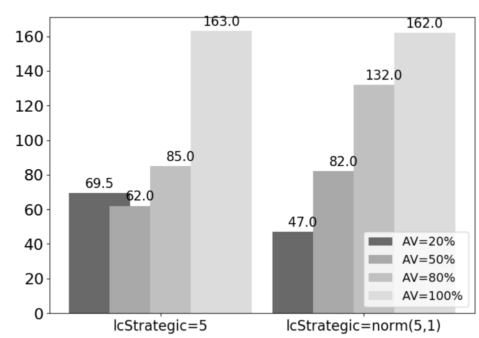

Fig. 18: Number of conflicts in simulations with different percentage of AV and values of *lcStrategic*.

two types of vehicle is *decel*, i.e. the maximum deceleration as comfort braking. In MVs, *decel* is normally distributed around average of 4, in AVs it is 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 rapid braking requires greater attention to the vehicles that follow it. We therefore replaced the *decel* of AVs with the fixed value of 4 and compared the simulations with the default parameter simulations (see Fig.19). We could expect a vehicle with lower deceleration

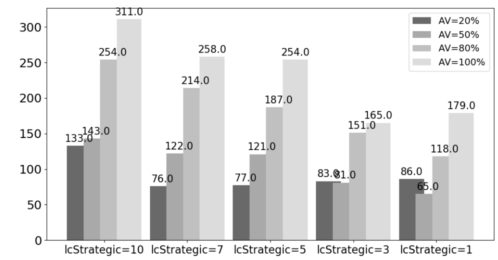

Fig. 19: Number of conflicts in simulations with different percentage of AV and values of *lcStrategic* for AV's *decel* set to 4.

to start decelerating earlier, however, in the Krauss model, the *decel* value only saying what the driver of that car would prefer as a normal deceleration. Therefore, it is clear that an ego vehicle, with $g(t) < v_{lead}(t)\tau_r$ (in Eq.1), approaches the lead vehicle with higher speed if it has low *decel* value. This observation justifies the increase in conflicts for AV's *decel* equal to 4 shown in Fig.19.

V. Discussion and Future Outlook

In this work, we have studied the impact that a future increasing number of AVs will have on safety and efficiency on real roads. For this purpose, firstly, we represented the big scenario of a portion of the city of Gothenburg in 2002 and 2019, the daily traffic flows and calibrated parameters of the MVs. Secondly, in order to include AVs, by starting from the parameters' values proposed in the literature, we have analyzed several values and the effects during interactions with MVs.
We have shown that, as in the ideal case of a straight road, even for complex topologies, in reasonably stable traffic conditions, the number of lane changes increases quadratically as the number of vehicles on the road increases. The number of conflicts also increases as the number of vehicles increases. However, we have shown that although AVs improve the efficiency in terms of the number of lane changes of the road, they significantly increase the number of conflicts for high flow. The parameters that most influence these results are *tau* regarding the efficiency, and *lcStrategic* and *decel* regarding the safety. Moreover, 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. In fact, for low vehicles' densities, the lower the percentage of AVs, the greater the number of lane changes, while for high vehicles' densities, the greater the percentage of AVs, the greater the number of lane changes. On the one hand, this aspect highlights the "dissatisfaction" of MVs, which in conditions of reasonably free flow overtake more, on the other, a greater percentage of AVs is congested with higher densities. We also showed that high *lcStrategic* and low *decel* values reduce safety in terms of the number of conflicts. Therefore, if it is reasonable and safe to set greater *decel*'s values in AVs, the same cannot be said for the lane change strategy. A possible improvement in the SUMO model, and also in the implementation of the real maneuvering strategies of the AVs,

can therefore be 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 MVs, 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.

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