QUANTIFYING THE SAFETY IMPACT OF CONNECTED AND AUTONOMOUS VEHICLES IN MOTORWAYS: A SIMULATION-BASED STUDY

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ABSTRACT

Connected and Autonomous Vehicles (CAV) is the developing summit of the integration between artificial intelligence (AI), robotics, automotive design and information technologies. Many researchers are investigating their effects on traffic safety. This study tries to quantify the volume of incidents when sharing the road human-driven vehicles and fully CAV. After modeling the geometry of 4.5 km of motorway and the parameters of connectivity and automation using Aimsun Next platform, several scenarios of the percentages of CAV (0%, 25%, 50%, 75%, and 100%) were driven in microsimulation runs. Then the microsimulation generated vehicles trajectories that are used to identify conflicts using the Surrogate Safety Assessment Model (SSAM). The results of this analysis confirm previous research in that the reduction of number of conflicts will be up to 35% with low and moderate penetration rates of CAV and more than 80% if the road is operated only with CAV.

1. INTRODUCTION

The proposed advances in Connected and Autonomous Vehicles (CAV) will widely change the traffic system to make it more efficient. CAV's most common positive effects discussed in the literature are reducing traffic congestion, delay time, and vehicles emissions (Poczter & Jankovic, 2014; Fagnant & Kockelman, 2015) to the way in which CAV are expected to operate in traffic flow. In addition, ongoing CAV manufacturers' field trials expect that CAV are capable to enhance traffic safety. Theoretically, NHTSA (2008) expected that vehicle automation (i.e. limiting human controls and performing the bulk of driving tasks without the need for a human) can play an important role in achieving the target of zero collisions as the majority of traffic conflicts are due to human errors. Connectivity goes besides and strengthens automated vehicle capabilities by enabling them to share their location and other relevant data with nearby vehicles and infrastructures for safer repositioning and streaming (Petit & Shladover, 2015).

The Society of Automotive Engineers (SAE, 2014) developed a scale for manufacturing levels of CAV from zero to five to define their progression. Level 0 indicates that there is no driving automation. Level 1 is equipped with lateral or longitudinal system for driver assistance. Level 2 uses partial driving automation upon driver request. Level 3 represents the conditional driving automation (i.e. the car transfers the control to the driver and the driver should respond to the car request). Level 4 is with high driving automation and full responsibility for driving task. Finally, Level 5 is with full driving automation and able to operate the car everywhere.

In the last five years, the volume of work evaluating the safety gain hypothesis has increased (e.g. Xie et al., 2019; Papadoulis et al., 2019, Morando et al., 2018). Almost all the related research contend that the safety impact is primarily governed by market penetration rates of CAV. Due to a lack of enough real data, simulation-based microscopic, stochastic methods have been used. These methods involve the CAV penetration rates in car-following and lane changing driving models to reflect the individual vehicles interaction with other vehicles, geometry, and other road elements (HCM, 2016). Consequently, the potential traffic conflicts resulting from vehicles interaction is the measure to evaluate the safety impacts of CAV involved in microsimulation.

Traffic conflicts are situations in which vehicles travel close in time and space in such a way that they could potentially end up in a crash (Hydén & Linderhonm, 2012). To identify these risky situations (traffic conflicts), the vehicle trajectories resulting from simulation are scrutinized using surrogate safety measures indicators (e.g. time-to-collision (TTC), post-encroachment time (PET), etc.).

This study expands the insight into the dynamics of CAV and their impact on safety. It provides a connectivity and automation modeling with the microsimulation platform that enables the modeler to deal with driving dynamics with more details, control, and reliability. In this platform (Aimsun Next platform with V2X extension) many penetration rates of CAV are operated on the case study (motorway segment). Later, the Surrogate Safety Assessment Model (SSAM) is used to quantify the effect of CAV on the corridor safety and compare the results with previous research.

The paper is organized as follows: next section, identifies the most relevant literature on CAV safety evaluation. A detailed description of the motorway segment drawn in Aimsun Next platform guided by Open Street Map, and modeling the car-following and lane-change behavior of the CAV are introduced in section three. The fourth section of the paper presents the results obtained from the simulation, and discusses them with previous literature. Finally, the last section summarizes the conclusions of the research, presents the study limitations and proposes future directions for CAV simulation research.

2. LITERATURE REVIEW

Most prior research performed traffic efficiency assessment of connected and/or automated vehicles (e.g. Guériau et al. 2016; Talebpour & Mahmassani, 2016; Stanek et al., 2018; Makridis et al., 2018) , but few safety evaluation studies exist (e.g. Morando et al., 2018; Papadoulis et al., 2019; Rahman; 2019). To these studies: introduction of CAV would increase the throughput of highway facilities and improve traffic flow stability (Talebpour & Mahmassani, 2016). CAV can also make about 20% of speed improvement (Stanek et al., 2018) and increase the road capacity with the increase in the CAV-penetration rate within even a heterogeneous flow (Ye and Yamamoto, 2018).

The initial work on CAV was based on stability analysis and simulating CAV using a proposed simulation framework (e.g. Talebpour & Mahmassani, 2016, Pereira & Rossetti, 2012). These studies created an integrated multi-level simulation framework that includes traffic, sensors (robotics), and network simulators in order to achieve detailed CAV simulation. Nevertheless, the results of these one-of-a-kind models were less reliable and difficult to compare.

Further studies started to use a traffic microsimulation platform and its internal/external extensions. This approach showed a considerable ability to model a large scale networks and gave reasonable results (Roncoli et al., 2015; Park et al., 2012). However, since the operational behaviour of CAV is described differently in each study, their results are not always comparable.

Particularly, most of researchers in this approach chose VISSIM to simulate CAV. ATKINS (2016) provided a milestone in simulating the CAV in VISSIM when they use the COM interface to change the CAV-related parameters, penetration rates, time headways that end up with changing driving behaviour when applying the driver model of VISSIM (Wiedemann 99 flow model). Following the criteria of ATKIN (2016) report, Jeong et al. (2017) improved an algorithm to control the longitudinal movement and gave powerful insights with micro safety results. But they still have a weakness since they did not develop a lateral movement control. Meanwhile, Stanek et al. (2018) changed the default VISSIM driver models parameters to show the effect on traffic behaviour. Similarly, Papadoulis et al. (2019) and Gueriau & Dusparic (2020) followed the mentioned approach for analyzing traffic safety.

In microsimulation-based studies, they used to apply the Surrogate Safety Assessment Model (SSAM) developed by the Federal Highway Administration for CAV traffic safety evaluation. Rahman et al. (2019) investigated the safety effect of vehicles with low levels of automation and vehicle-to-vehicle (V2V) and infrastructure-to-vehicle (I2V) connectivity technologies. From SSAM indicators, they integrated several measures (e.g. time exposed time-to-collision (TET), time integrated time-to-collision (TIT), lane changing conflicts

(LCC), etc.) to quantify the conflict risk on an intersection. They found that there is a significant safety enhancement resulting from introducing CAV.

Papadoulis et al. (2019) used the VISSIM API's External Driver Model to develop a decision-making CAV control algorithm and then SSAM time-to-collision indicator was used to measure the number of conflicts. A comprehensive safety evaluation study showed the percentage of conflicts reduction with different CAV market penetration rates: daily, in space, and by conflict type. A fully-CAV-operated motorway showed an extreme reduction in number of conflicts (about 94%) which is very close to the theoretical expectation made by NHSTA (2008).

Moreover, Gueriau & Dusparic (2020) studied the effect of CAV on both efficiency and safety in three types of networks (urban, national, and motorway), simulating different penetration rates of vehicles with various levels of automation. Their results showed that lower penetration rates result in a 30% rise in conflicts, but higher penetration rates result in a 50-80% reduction in conflicts, with steady growth of the increased penetration.

On the other hand, Zhang et al. (2020) developed a platoon control algorithm to represent the cooperation of CAV. To assess the safety impact of setting exclusive lanes for CAV, four surrogate safety indicators were used, including both longitudinal and lateral safety risk indexes. In high-truck ratios scenarios, setting exclusive lanes improves longitudinal and lateral protection up to 55% and 85% respectively.

Finally, it could be shown that safety evaluation of CAV depends primarily on the assumptions of CAV's simulated behaviour in movement. Once there is lack of information about CAV and Human Driven Vehicles (HDV) contact, a special and direct platform of calibrating CAV is need. To this intention this study uses the Aimsun Next API with new versions and extensions that are made especially to model CAV behaviour.

3. METHODOLOGY

The procedure was to design fully CAV (i.e. totally depending on the technology in driving process). This begins with understanding the driving behaviour difference between HDV and CAV. Accordingly, different parameters values affecting car following and lane-changing models used in Aimsun Next platform are applied to CAV and HDV.

3.1 Connectivity between vehicles

Vehicles connection was conducted by building the connection network using V2X Aimsun Next extension. This network includes: On Board Unit (OBU) in each CAV, that represents the receiver and transmitter in a vehicle; Channels, which is the simulated representation of the radio hardware and protocols that provide communication between vehicles; and Cooperative Awareness Messages (CAM), that provide information about the presence, activity and position of CAV. Channel design depends basically on the number of probable CAV in the channel range, their speed, and the channel reliability. This is expressed using three characteristics:

- *Latency*: The delay in packet transmission,
- *Range*: The range of transmission, and
- *Packet Loss*: The percentage of packets which are not received.

Following many research works (Teixeira et al., 2014; Mir and Filali, 2014; Ahmadvand et al., 2016; Chen et al., 2019) and based on our case (higher than 125 connected vehicles in the channel range if the speed is about 100km/h), the selected channel was: *IEEE 802.11p (250 m range) with 2100 ms latency and 0.75 packet loss*.

3.2 Automation parameters

As many studies did, vehicle full automation was modeled by calibration of all needed parameters that control both longitudinal and lateral movements on the road and distinguish the CAV over HDV. The traffic flow model used in Aimsun Next API is Gipps model, so the parameters discussed below are those entering the model' equations.

Specifically, vehicles parameters are modified according to vehicle behavior models: "Car-Following" and "Lane-Changing" as they move through the network.

Gipps (1981) car-following model was created by incorporating the parameters that are influenced by local parameters such as: the "type of driver" (speed limit acceptance of the vehicle), the geometry of the section (speed limits on the section, speed limits on turns, etc.), and the impact of vehicles on adjacent lanes.

However, acceleration and deceleration are the two main elements of Gipps model. The first reflects a vehicle's willingness to reach a certain desired speed, while the second simulates the restrictions imposed by the preceding vehicle when attempting to travel at that speed. The maximum speed that a vehicle (n) can accelerate during a time period (t, t+T) is given by this model:

$$V_a\,(n, t+T) = V(n,t) + 2.5a(n)T\left(1 - \frac{V(n,t)}{V*(n)}\right)\sqrt{0.025 + \frac{V(n,t)}{V*(n)}} \qquad (1)$$

Where:

$V_a(n,t)$ is the speed of vehicle n at time t;
$V^*(n)$ is the desired speed of the vehicle (n) for current section;
a(n) is the maximum acceleration for vehicle n;
T is the reaction time.

At the same time, the maximum speed that the same vehicle (n) can reach during the same time interval (t, t+T), according to its own characteristics and the limitations imposed by the presence of the lead vehicle (vehicle n-1) is:

$$V_b\,(n,\,t+T) = d(n)\,T + \sqrt{d(n)^2T^2 - d(n)\left[2(x(n-1),t) - s(n-1) - x(n,t)) - V(n,t)T - \frac{V(n-1,t)^2}{d'(n-1)}\right]} \quad (2)$$

where:

d(n) (< 0) is the maximum deceleration desired by vehicle n;
x(n,t) is position of vehicle n at time t;
x(n-1,t) is position of preceding vehicle (n-1) at time t;
s(n-1) is the effective length of vehicle (n-1);
d'(n-1) is an estimation of vehicle (n-1) desired deceleration.

Gipps (1986a and 1986b) lane-change is modelled as a decision process, analyzing the *necessity* of lane change (such as for turn maneuvers determined by the route), the *desirability* of lane change (to reach the desired speed when the leader vehicle is slower, for example), and the *feasibility* of lane change (using forward, backward, and adjacent gap evaluation) depending on the position of the vehicle in the road network with respect to the lane geometry and adjacent vehicles.

			HDV		CAV	
Parameters	**Definition**	**References**	**mean**	**s.d.**	**mean**	**s.d.**
Main parameters						
Speed acceptance	How much vehicles could take a speed greater than speed limit	Atkin (2016), Stanek et al. (2018), Ye and Yamamoto (2019)	1.1	0.1	1	0.05
Clearance (m)	Distance that vehicle keeps with the preceding one when stopped	Atkin (2016), Stanek et al. (2018)	1	0.3	0.2	0.2
Max give-way time (sec)	Give-way time at a Yield or stop junction or an on-ramp	Atkin (2016)	10	2.5	7.4	0.5
Guidance acceptance (%)	The probability that a vehicle will follow the recommendations	Stanek et al. (2018)	70	10	100	0
Reaction time (sec)	The time to react in general	Zhang et al., (2020)	0.8	-	0.6	-
Reaction time at stop	The time to react at stop	Zhang et al., (2020)	1.2	-	1	-
Max acceleration (m/s^2)	The highest value that the vehicle can achieve under any circumstances	Atkin (2016), Stanek et al. (2018), Karjanto et al. (2017)	3.28	0.2	3.72	0.15
Normal deceleration. (m/s^2)	The maximum deceleration that the vehicle can use under normal conditions	Atkin (2016), Naujoks et al. (2016), Karjanto et al. (2017) Zhang et al., (2020)	3.27	0.25	4.12	0.18
Max deceleration (m/s^2)	The most severe braking can be applied under special circumstances	Atkin (2016), Naujoks et al. (2016), Karjanto et al. (2017), Zhang et al., (2020)	5.39	0.5	6.2	0.3
Safety margin factor	a multiplier of a normal range of gap acceptance range	-	1	0	1.5	0.2

Table 1- Gipps models parameters affected by the type of driver

			HDV		CAV	
Parameters	**Definition**	**References**	**mean**	**s.d.**	**mean**	**s.d.**
Car-following model						
Sensitivity factor	How much the vehicle could be sensitive to the deceleration of the leader	-	1	0	1.5	0.5
Gap (sec.)	How much override the headway calculated by car following model	Karjanto et al. (2017)	0	0	0.6	0.1
Headway aggressivenes s	How much vehicles could enter with shorter gaps without forcing the rear vehicle to brake	Stanek et al. (2018)	0.8	0.2	0	0
Lane-changing model						
Overtake speed threshold	The threshold that delaminates an overtaking maneuver	Stanek et al. (2018)	90	-	95	-
Percentage staying in overtaking lane	The probability that a vehicle will stay in the faster lane instead of recovering to the slower lane after an overtake maneuvers	Naujoks et al. (2016)	40	-	20	-
Imprudent lane change	Defines whether a vehicle will still change lane after assessing an unsafe gap	Naujoks et al. (2016)	Ticke d	-	Non ticked	-
Cooperate in creating a gap	Vehicles can cooperate in creating a gap for a lane changing vehicle	Stanek et al. (2018)	non ticked	-	ticked	-
Aggressivenes s Level	The higher the level, the smaller the gap the vehicle will accept, being a level of 1 is the vehicle's own length	Stanek et al. (2018)	0-1	-	0-0.75	-
Distance Zone Factor	To modify the distance zones used in the Lane Changing Model to adjust where lane changes start to be considered and, if a range is given, to randomize behavior	Stanek et al. (2018), Talebpour and Mahmassani (2016)	0.8-1.2	-	0.6-1.5	-

Table 1 (cont.) - Gipps models parameters affected by the type of driver

Consequently, while default values in most of the model's parameters are supposed to represent HDV, CAV tend to keep smaller standstill distances, accelerate and decelerate faster and smoother, keep constant speed with no or smaller oscillation at free flow, form platoons of vehicles and follow the leader, perform more co-operative lane change as lane changes could occur at a higher speed co-operatively (Stanek et. al, 2018).

Table 1 shows the specific parameters that are affected by automation in Gipps' car following and lane-change models depending on previous research (Atkin, 2016; Stanek et al., 2018; Zhang et al., 2020; Karjanto et al., 2017; Naujoks et al., 2016) and logic. Parameters definitions are summarized from Aimsun user manual. Table 1 presents both mean and standard deviation (s.d.) values that were defined before microsimulation. The values follow a normal distribution as it is proposed in Gipps' model. The discussion about the values for both HDV and CAV is provided below.

3.2.1 The main parameters

It is supposed that CAV will respect the speed limits. CAV's clearance is directly adopted from ATKINS (2016) report as minimum space headway. Stanek et al. (2017) showed lower deviation values because of full-dependence on technologies. Maximum give-way time is suggested to be the same to the minimum time gap in ATKINS (2016) report. The report also showed lower deviation for CAV. Guidance acceptance is proposed to be 100% with no deviation in fully CAV.

No previous research has directly detailed CAV's reaction times and it is not a parameter considered in VISSIM car following model (Wiedemann 99). Also, in Aimsun Next old versions, it was considered a global parameter (i.e., with fixed value in the simulation). Recently, since version Aimsun Next 4.3, this parameter is subjected to calibration depending on the type of vehicle that allows the change for CAV. However, Zhang et al. (2020) suggested a hint value that was depending on Adaptive Cruise Control (ACC) platoons applied on the field.

In general, connection-automation technologies are supposed to show higher speed in reaction. Thus, it should be significantly lower when the driving is fully connected and automated (Zhang et al., 2020). The same behaviour will be on unexpected stops, that requires highly connection technology or referring to the driver.

For acceleration and deceleration**,** ATKINS (2016) and Stanek et al. (2017) suggested that CAV will be accelerating and decelerating faster and smoother, resulting in higher values. Besides, the deviation will be lower than in HDV values by 25% according to achieving higher uniformity in dynamic driving process (Stanek et al., 2017).

As CAV will be more cooperative in gap acceptance, a multiplier of 1.5 is proposed for safety margin factor.

3.2.2 Car-following parameters

It is supposed that CAV will be more sensitive to leader action. Thus, a multiplier of 1.5 is proposed for sensitivity factor. In addition, it could override the headway calculated by car following model by 0.6 sec (Karjanto et al., 2017), but without any aggressiveness (Stanek et al., 2017).

3.2.3 Lane-change parameters

As CAV show more co-operation in considering maneuvers, a slight increase of percentage of vehicles that travel at less than Overtake Speed Threshold is suggested. Moreover, they cooperate in creating a gap (Stanek et al., 2018). However, CAV prefer to go back to the original lanes and will not make a lane-change if the gap is not safe (Naujoks et al., 2016). Furthermore**,** in Stanek et al. (2017), CAV showed a reduction of 0.75 of human vehicle driven gap acceptance in lane changing. As a result, the zones that are considered as lane-change distance will be modified by the same factor (Stanek et al., 2017; Talebpour & Mahmassani, 2016).

3.3 Simulated scenarios

After adjusting car following and lane-change models' parameters, five scenarios were considered with different sharing percentages of both HDV and CAV (100/0, 75/25, 50/50, 25/75, and 0/100). The developed models, were calibrated for the times of the real-world trips; between 10:00 and 12:00 am (off-peak hours) in a regular day. The number of replications for each scenario needed in order to achieve a 90% confidence interval level for the simulation output was calculated using Shahdah et al. (2015) equation (Eq. 3). It was shown that 15 runs is a sufficient sample.

$$N = \left(\frac{t_{(1-\alpha/2),N-1} * \sigma}{E}\right)^2 \tag{3}$$

Where, N equals the required number of simulation runs, σ equals the sample standard deviation of the simulation output, t is the student's t-statistic for two-sided error of a $\alpha/2$ with $N-1$ degrees of freedom and E equals the allowed error range, where $E = \varepsilon * \mu$; μ is the mean of the number of simulated conflicts based on the initial set of simulations runs and ε is the allowable error specified as a fraction of the mean For example in 100% CAV scenario we tested a 15 runs trial (with $\sigma = 28.06$, t = 2.14 (with $\alpha = 0.05$ and degree of freedom =14), $E = (0.10*305)$ and it was a sufficient sample. Likewise, 15 runs were a sufficient value for all scenarios.

3.4 Safety evaluation

As expected, the model does not generate any crashes in the simulation. So, the model cannot be used to explicitly calculate collisions or traffic safety. In order to assess the safety, the outputs of vehicles trajectories from Aimsun microsimulation runs have to be analyzed using SSAM. The trajectories at each time step of simulation (0.2 s) are examined to check the existence of traffic conflicts instead of crashes.

The indicator that has been applied in most studies (Gueriau & Dusparic, 2020; Papadoulis et al., 2019; Rahman et al. 2019) to assess traffic safety is the time-to-collision (TTC). It is defined as the time that remains until a collision could occur if two successive vehicles maintain a speed difference (Hayward, 1972). The TTC of vehicle i with respect to a leading vehicle i + 1 at time step t can be calculated with:

$$TTC\,(i,t) = \frac{d\,(i,t)}{v\,(i,t) - v\,(i+1,t)} \quad \forall\, v(i,t) > v\,(i+1,t) \tag{4}$$

Where d(i, t) and v(i, t) denote the real space gap and the speed of vehicle i at time step t, respectively.

Following the recommendation of Papadoulis et al. (2019) and after a sensitivity analysis, we used a threshold value of TTC equal to 1.5 to identify conflicts.

4. RESULTS AND DISCUSSION

Safety assessment of CAV in this study is conducted on a modeled motorway segment in Aimsun Next platform. Imported Open Street Map was used as a background to create the geometry (i.e. curves of the road segment, lane width and the length of links, merging and diverging areas) of the segment using drawing tools and overlapping the sections created with the map. As case study, a three-lane motorway section was chosen of the GR-30 freeway, close to Granada city in Spain. The designed corridor was 4.57 km long, with fourteen on and off-ramps and nine vehicle input points (seven ramp entrances and two major entrances from south and north) After including the segment geometry, many information from the network has also been modeled, including speed limit, detectors location, and traffic volume. Directional traffic flow (pc/hr) was obtained from several detectors managed by the Dirección General de Tráfico (DGT) in Granada.

Firstly, this section provides a check of the simulation performance by presenting the distribution of TTCs, velocity difference, and acceleration during simulation steps along the five scenarios modeled. Then a sensitivity analysis of TTC thresholds is laid out. Afterwards, the resulted conflicts are discussed among scenarios.

4.1 Traffic flow dynamics

4.1.1 TTC distribution

The introduction of low CAV penetration rates increases both low and high TTC values due to non-consistent flow dynamics (Figure 1). Under high CAV penetration rates, smoother traffic flow reduces large TTC values while reducing the gaps by CAV increasing the ratio of small TTCs. This distribution is logic and agrees with Ye and Yamamoto (2019) research work.

4.1.2 Acceleration distribution

Figure 2 shows that under low penetration rates scenarios, acceleration ratio about 0 slightly decrease due to the lack of harmony in traffic flow, but with high penetration rates the ratio of acceleration rate about 0 increases obviously that indicates smoother dynamic flow. Similarly, this distribution is logic and agrees with Ye and Yamamoto (2019).

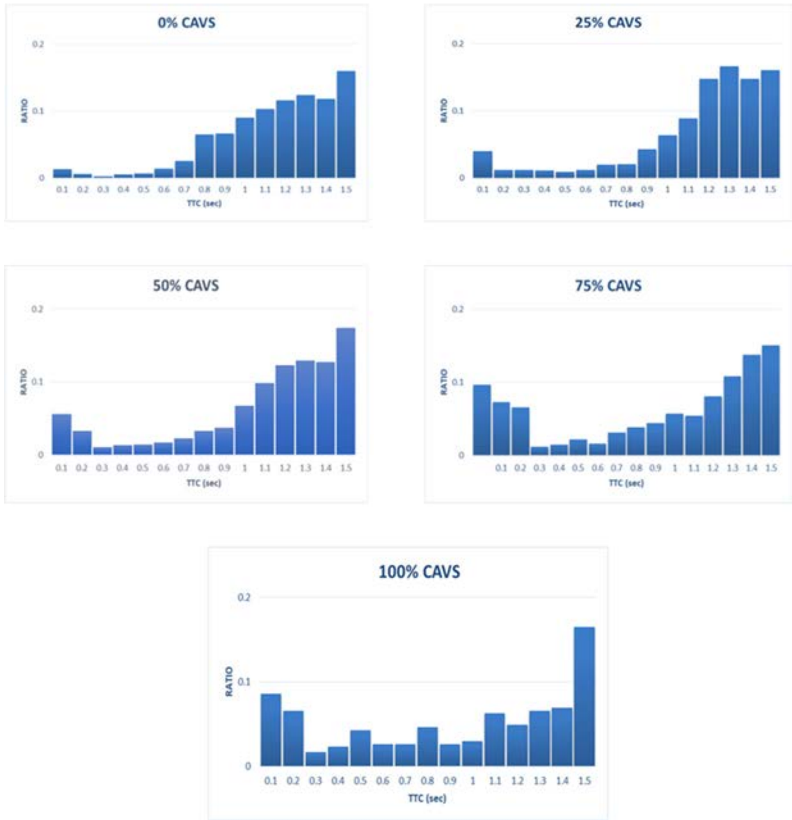


Fig. 1- TTC distribution under the proposed scenarios

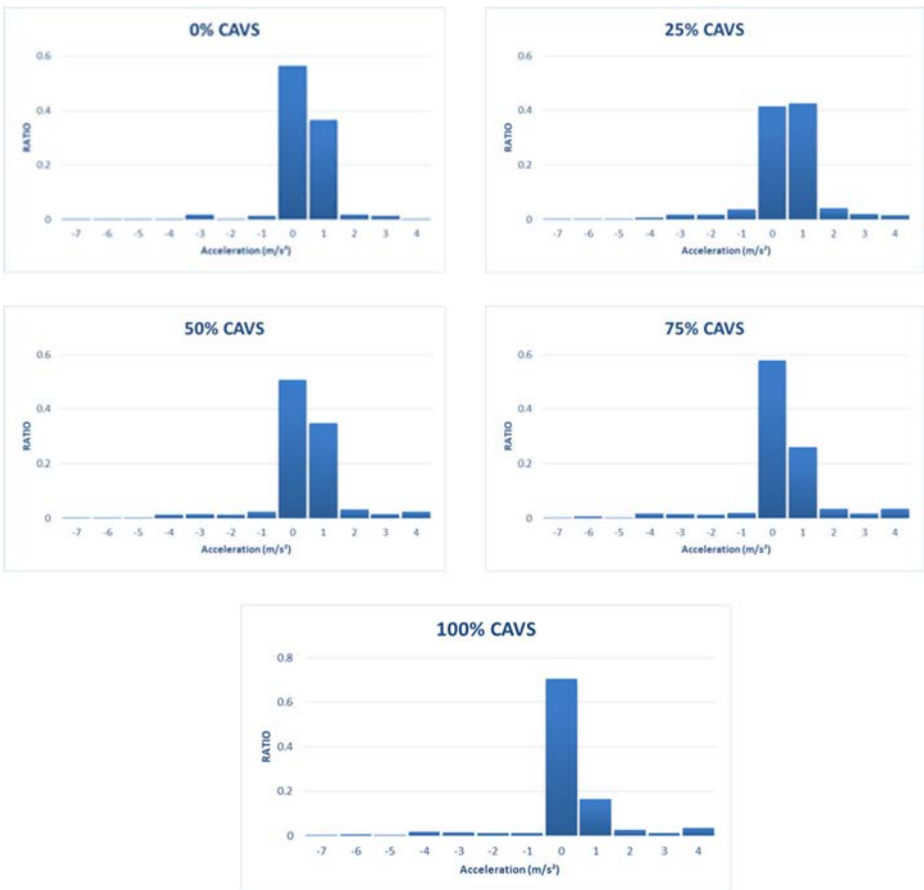


Fig. 2 - Acceleration distribution under the proposed scenarios

4.1.3 Velocity difference distribution

The distribution of difference between the vehicle and its leader velocities for each scenario are shown in Figure 3. A bell shape with a lower peak is present in the distribution of low penetration rates and covers a wider range. The velocity difference ratio of the bell peak slightly increases at high sharing percentages of CAV. The difference in velocity tends to cluster around small values (0, 1). This phenomenon shows that the velocity difference between vehicles is reduced and traffic flow is harmonized with the rise in the CAV penetration rate which is logic and agrees with Ye and Yamamoto (2019).

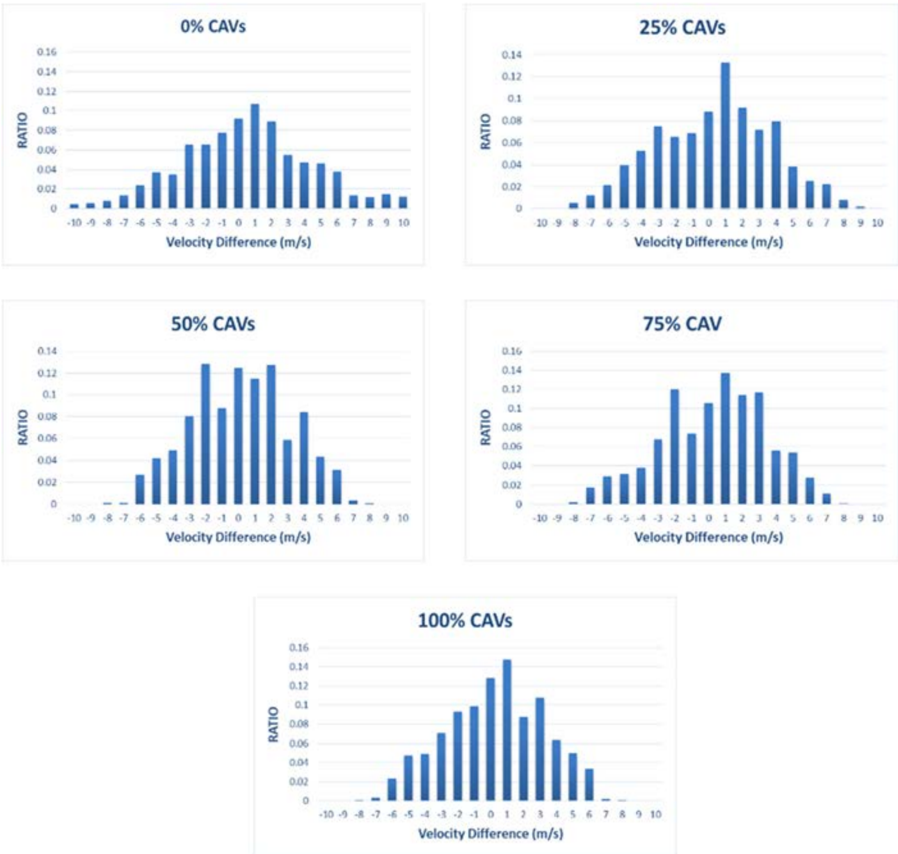


Fig. 3 – Velocity-difference distribution under the proposed scenarios

4.2 TTCs sensitivity analysis

TTC threshold is critical in analyzing traffic conflicts and it is more questionable for CAV. Thus, CAV traffic safety studies used to make a sensitivity analysis to check the effect of changing this value and chose a proper threshold (Zhang et al., 2020; Papadoulis et al., 2019; Morando et al., 2018). In this study, a sensitivity analysis for TTC thresholds of 0.5, 1.0, 1.5, 2.0, and 2.5 seconds has been conducted for CAV introduction scenarios (25% CAV, 50% CAV, 75% CAV and 100% CAV). Using the analysis of variance (ANOVA), the change in percentages of conflicts between each CAV penetration scenario and the HDV scenario was not significantly different in most cases when comparing 1.5 seconds and both 1.0 and 2.0 seconds. But 0.5 and 2.5 seconds (the lowest and the highest thresholds) were statistically significant from the other values (Table 2). Graphical illustration (Figure 4) of mean and standard deviation for the change in percentages of conflicts also showed the same results in variance. The significant values in 0.5 and 2.5 values is normal since the potential conflicts will noticeably change with such extreme time to collision thresholds. Meanwhile Papadoulis et al. (2019) have found non-significant variance even with extreme values; Zhang et al. (2020) have used just 1.0, 1.5, and 2.0 values in their analysis and found the same results of this study. Consequently, both studies used 1.5 seconds as a threshold value.

	Time-to-Collision (TTC)				
	0.5 s	1.0 s	1.5 s	2.0 s	2.5 s
Scenario 25% CAV	39.50 a	-21.54 b	-2.56 c	1.84 c	34.08 a
Scenario 50% CAV	11.39 a	-39.26 b	-35.90 b	-29.81 b	-3.67 c
Scenario 75% CAV	-9.57 a	-54.53 b	-60.83 b	-55.75 b	-29.01 c
Scenario 100% CAV	-47.07 a	-77.16 b	-82.66 c	-80.53 b,c	-68.42 d

For each scenario, a, b and c values denote differences statistically significant ($p < 0.05$). Two or more TTC values with the same letter denote a homogeneous subgroup.

Table 2-The percentage of change in the number of conflicts for each TTC value

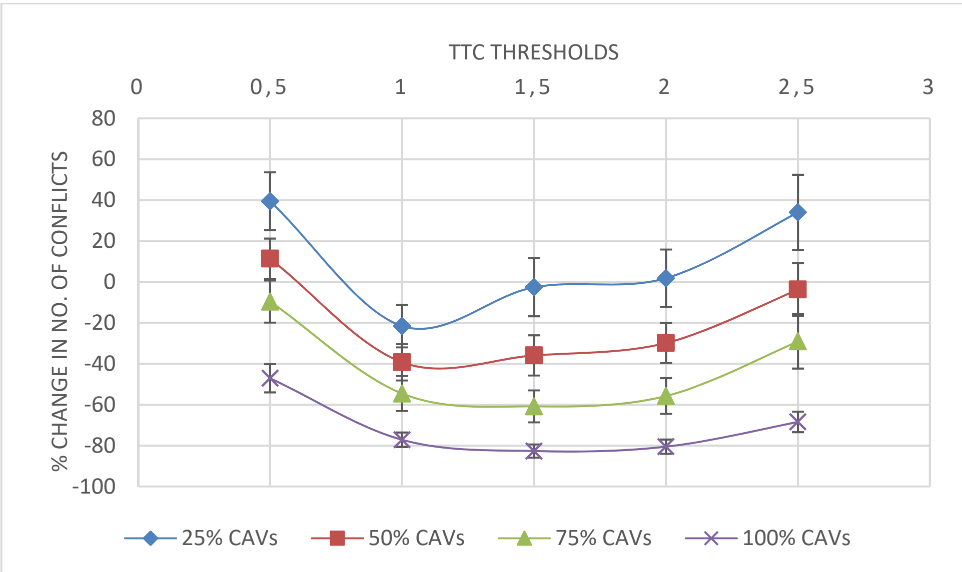
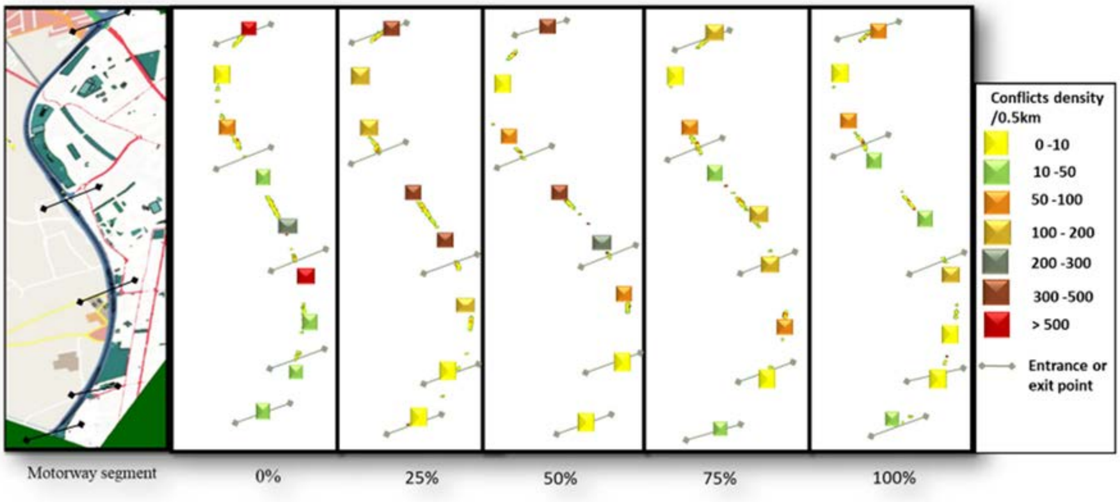


Fig. 4 – Sensitivity analysis of TTCs thresholds under the proposed scenarios

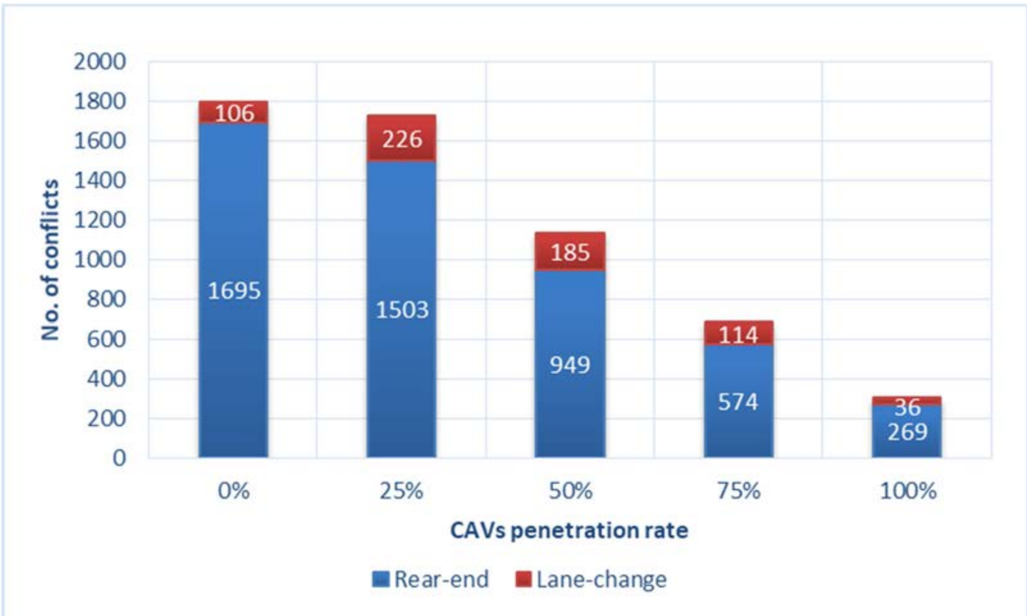
4.3 Quantifying the safety impact of CAV penetration

Using 1.5 s as TTC threshold, the average results of the conflicts tried out of microsimulation runs are shown in Figure 5. Increasing the penetration rates of CAV has positive effect on decreasing the number of possible conflicts. The reduction percentages of conflicts for 25%, 50%, 75% and 100% CAV scenarios are 2.56%, 35.9%, 60.83%, and 82.66% respectively. These results agree with Papadoulis et al. (2019) for motorways and Morando et al. (2018) for intersections. On the other hand, Gueriau & Dusparic (2020) and Xie et al. (2019) have shown that low levels of automation could increase the potential conflicts especially in low penetration scenarios.

Figure 5 (a) shows the previous main result by density of resulted conflicts within the segment at the conflicts distribution map. The density representative points of each 500 m range show decreasing in the number of conflicts by increasing the percentages of shared CAV that agrees Papadoulis et al. (2019) results. In addition, the figure shows that the probable conflicts are near to the entrances and exits of the motorway as it was observed in Gueriau & Dusparic (2020). This is due to speed differences at these points that affect the possibility of resulting conflicts.



(a)



(b)

Fig. 5 – Conflicts resulted by the proposed scenarios: (a) Conflicts density representative points. (b) Number of conflicts by type

Figure 5 (b) shows the effect of penetration rates of fully CAV on conflict type. The resulting conflicts at this motorway are mostly rear-end conflicts in the base scenario (only HDV scenario). While rear-end conflicts are probably to be 93.95%, 86.9%, 83.64%, 83.37%, and

88.12% of overall conflicts, lane-change conflicts will be of much lower percentages (5.96%, 13.09%, 16.32%, 16.59%, and 11.89%).

Whereas rear-end conflicts had the same direction of reduction of the total conflicts, the effect was different in the case of lane-change conflicts. Even sharing just 25% of CAV can over duplicate the percentage of lane-change conflicts. This is related to the significant difference in behaviour between HDV and fully CAV in lane-change process (imprudent lane change, cooperation in create gap, and aggressiveness level) (ATKINS, 2016; Stanek et al., 2018). After that the percentage of lane-change conflicts was not affected significantly with increasing CAV ratios.

5. SUMMARY, CONCLUSIONS AND LIMITATIONS

In this paper, it was applied a simulation-based safety assessment of introduction of fully connected and automated vehicles. It was conducted on a motorway segment with free flow condition. The modeling of CAV was done using Aimsun Next API by building connection network and calibration the automation behaviour of both longitudinal and lateral movements. This platform enables the user to calibrate the behaviour parameters with a range rather than fixed value (i.e. mean, min, max, deviation values) that improve the calibration to be realistic and reliable. Moreover, the used models (Gipps models) in this platform deal with parameters that reflect a direct and explicit driving behaviour such as reaction time, speed and guidance acceptance, driving aggressiveness.

Traffic flow dynamic was configured by drawing the distribution of some indicators (TTCs, acceleration and velocity-difference) resulted after traffic microsimulation. These distributions demonstrate that increasing the penetration rates of CAV will make the flow dynamics more harmonized and smooth.

The potential conflicts were detected by calculating the time to collision (TTC) indicator using SSAM. To test the proposed value of TTC threshold (1.5 s), a sensitivity analysis was applied for a range around this value (between 0.5 and 2.5 seconds) and the results showed a significant difference in case of extreme values (0.5 s and 2.5 s) but non-significant difference between the values 1.0, 1.5, and 2.0 seconds on the impact of CAV.

The effect of introducing the fully CAV is through with the theoretical and experimental exist research. The positive effect (i.e. the reduction in the total number of conflicts) reached about 35% for medium penetration rates and 80% for fully operated motorway of CAV.

This work is limited to various circumstances: it considers only HDV and fully CAV vehicles, while in the real world several type of vehicles, with several automation levels will be circulating simultaneously; and it considers only one type of road section. Further studies could deal with different levels of automation. Also, many types of road sections, traffic conditions, and vehicles could be simulated.

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