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Studying traffic safety during the transition period between manual driving and autonomous driving: A simulation-based approach

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***Abstract*— Connected and Autonomous Vehicles (CAVs) are becoming a reality and are progressively penetrating the markets level by level. CAVs are a promising solution for traffic safety and are expected to eliminate human driving errors. However, robust studies are needed to explore and assess the expected behavior. This study attempts to evaluate traffic safety resulting from the penetration of CAVs with different levels of automation (from Level 1 to Level 4) and the corresponding impact of the near-real introduction of CAVs into the traffic flow, considering that Level 4 vehicles will not be immediately introduced into the traffic. The investigation consisted of the modeling of different CAV levels using Gipps' model calibration, followed by the simulation of nine mixed fleets of CAV levels at a modeled motorway segment. Subsequently, the Surrogate Safety Assessment Model was used for safety analysis using vehicle trajectories. According to the results obtained: (1) the gradual penetration of CAV levels led to a progressive reduction in traffic conflicts. This reduction ranges from 18.9% when the penetration of high levels of automation (Level 3 and Level 4 vehicles) is 5%, to 94.1% when all the vehicles on the traffic flow are Level 4. And (2) human-driven vehicles and vehicles with low levels of automation (Level 1 and Level 2 vehicles) are more frequently involved in conflicts (as possible inductors of risky situations; as follower vehicles) than vehicles with high automation levels (Level 3 and Level 4 vehicles). In fact, human-driven vehicles are involved in conflicts from 8% to 122% more than its sharing percentage on fleets, while vehicles with high automation levels are involved in conflicts from 80% to 18% less than its sharing percentage on fleets, depending on the combination of different types of vehicles in the traffic flow. In general, this study confirms the theory and the conclusions from previous literature that indicate a safety gain due to CAV penetration. Moreover, it provides a broader perspective and support for the introduction of CAVs levels.**

***Index Terms*— Connected and Autonomous Vehicles, levels of automation, simulation, surrogate safety assessment, traffic safety, V2X.**

I. INTRODUCTION

The projected revolution of Connected and Autonomous Vehicles (CAVs) could widely change traffic streams and transportation in general. The most prevalent benefits reported in the literature as a result of introducing CAVs are the reductions in congestion, delay time, and emissions [1]–[7]. Similarly, CAVs are expected to improve traffic safety. Singh [8] claimed that, because they are designed to eliminate all human driving errors, CAVs could reduce traffic crashes by 94%.

To unify the visions of industry and research, the Society of Automotive Engineers [9] developed a scale for classifying manufactured CAVs into six levels, from zero to five, based on their automation progression. Level 0 (L0) indicates no driving automation. Level 1 (L1) vehicles are equipped with lateral or longitudinal systems for driver assistance. Level 2 (L2) vehicles use partial driving automation upon driver request. Level 3 (L3) vehicles incorporate conditional driving automation (*i.e.,* the vehicle transfers control to the driver and the driver should respond to the vehicle request). Level 4 (L4) vehicles have high driving automation and are fully responsible for driving tasks under certain circumstances. Finally, Level 5 (L5) vehicles boast full driving automation and can operate the vehicle everywhere. In addition, connectivity adds other capabilities to autonomous vehicles when transmitting their locations and other useful information to the surrounding vehicles or infrastructure.

Many research projects regarding the introduction of CAVs are being conducted worldwide. In some of them, different stakeholders are testing recent advances in the CAV industry within small networks, while other researches are more oriented toward improving all CAVs introduction processes, including technology efficiency, infrastructure, and social acceptance. In Europe, a new partnership called Cooperative, Connected, and Automated Mobility was formed within the Horizon Europe framework program (2021-2027) to organize and concatenate the efforts on CAVs and address their future challenges (*e.g.,* AutoMate, AVENUE, Drive2TheFuture, ENSEMPLE, INFRAMIX, interACT, Levitate, SUaaVE, etc.) [10].

As a consequence of the rapid evolution in manufacturing, the interest in research on the impact of CAVs on traffic safety has increased in recent years (*e.g.,* [1], [6], [11]–[17]). However, the lack of real CAV performance data (both driving behavior and crash data) has led researchers to use stochastic modeling and traffic simulation to investigate traffic safety problems. Consequently, potential traffic conflicts resulting from mixing streams of CAVs and human-driven vehicles (HDVs) are the main measure to assess traffic safety in the literature. Vehicle trajectories resulting from simulation were analyzed using surrogate safety measures (*e.g.,* time-to-collision (TTC) and post-encroachment time (PET)) to identify these risky circumstances such as traffic conflicts. Most of these studies determined traffic safety based on the market penetration rate of only L4 vehicles in the analyzed networks. Moreover, although some studies have attempted to include the effect of introducing different CAV levels (*e.g.,* [11], [19]), they neither involve all CAV levels nor discuss their effect separately (*e.g.,* the involvement of each CAV level in conflicts or in inducing conflicts). Thus, a comprehensive study that can extensively present the effect of introducing all CAV levels is essential to understand the transition period between human and autonomous driving.

The novelty of this study is twofold: first, it considers all CAV levels (rather than only one or two) within several mixed traffic streams to reflect the reality of CAV traffic safety during the transition period; and second, it discusses the most frequent vehicle interactions and the involvement of different CAV levels in potential traffic conflicts derived from several mixed modeled streams.

To address these objectives, this study examined traffic safety using a microsimulation platform and subsequently applied surrogate safety measures to identify potential traffic conflicts. The evaluation of safety was carried out on the proposed study network as follows: (i) the traffic dynamics obtained from stream trajectories in different scenarios were examined; (ii) the potential conflicts arising across a spectrum of penetration rates of CAV levels were identified; (iii) the involvement of CAVs in conflicts was determined by individually calculating the involvement ratio of each CAV level and by computing the involvement ratio of the two-by-two interactions of the specific vehicle types; and after all (iv) the amount of responsibility related to each CAV level was underlined to generate conflicts based on the follower vehicle.

The remainder of this paper is organized as follows. Section II presents a literature review of research works that evaluate the effect of the introduction and interaction of CAVs on traffic safety. Section III introduces the study network and the methodology used for both traffic simulation and conflict identification. Section IV presents the results obtained from the simulation-based surrogate safety measures and compares them with those of previous literature. Finally, Section V concludes with summary remarks and recommendations for future research.

II. A REVIEW OF RELATED WORK

This section presents several studies on the traffic safety of CAVs, highlighting the approaches used, the traffic safety aspects discussed, and the extent to which the different levels of CAV were studied in the literature.

A. *Simulation-based Approach*

Over the last decade, researchers have focused on the impact of CAVs on traffic safety. By analyzing open-source historical HDVs crash datasets, researchers have employed different approaches to derive the extent of the effect of CAVs on traffic safety. The first approach was to try to eliminate the effect of human errors by reanalyzing past recorded crash data without this factor [5]. The second was by assuming that the safety benefit of autonomous driving on roads would be similar to that of rail or aviation driving environments [20], [21]. After using these simple approaches to determine the preliminary extent of the safety benefits, the focus has been on CAV modeling and simulation to attain a deeper understanding.

Previous researchers have used customized simulation frameworks or multilevel simulation platforms to simulate CAVs ([2], [22], [23]). Alternatively, other studies have used traffic microsimulation software built with widely known and validated traffic flow models and its extensions [7], [11], [12], [24], [25]. This has become the most widely used approach because of its feasibility and the advantage of operating several future scenarios within short periods. Finally, a few studies have analyzed real data gathered from CAVs driving operations along test beds (*e.g.*, [28], [29]). Although the last approach could seem to be the best one, the question is how reliable it could be, while CAVs deployment is still at an early stage and tested on limited scenarios.

Accordingly, thanks to its robust modeling quality and ability to build several operational evaluation scenarios, the microsimulation-modeling approach has been extensively used in CAV traffic safety studies [16]. Table I summarizes previous studies that have employed simulations to test the impact of CAVs on traffic safety. The table provides the following information: software interface used for simulation, calibrated network, type of vehicle considered, penetration rates defined during the simulation, thresholds of surrogate safety measures used to identify potential conflicts, safety evaluation indicators, and CAV types analyzed.

As shown in Table I, various microsimulation platforms have been employed for modeling CAVs in traffic safety studies. The VISSIM interface is commonly used with different external car-following algorithms (*e.g.,* Intelligent Driver Model and Newell's car-following model) in addition to its internal Wiedemann 99 model calibration. However, several studies have run simulations on other platforms (*e.g.,* Aimsun, PARAMICS, SMART, and SUMO). Recently, Aimsun added more capabilities for modeling CAVs with its internal interface algorithms (both car-following and lane-change Gipps' models) and for modeling the connectivity with well-structured external interfaces (V2X extension, the External Agent Interface and the Driving Simulation Interface). All these platforms are adequate for CAV simulation. For more details about comparisons between different results from these platforms, see [31].

Besides, CAVs traffic safety has been simulated on different types of networks and vehicles. While many researchers have applied their studies to freeways, two-lane highways, or intersections (*e.g*., roundabouts, signalized, unsignalized) [12], [13], [15], [26], [27], others have modeled urban arterials and intersections [19], [25]. However, they have all found that higher CAVs penetration rates enhance traffic safety. Likewise, some studies simulated only passenger cars, whereas others included a percentage of heavy vehicles in their simulated traffic stream to simulate the real traffic composition [7], [12], [14], [19]–[25].

On the other hand, simulating the pattern of CAVs introduction plays an important role in reflecting the implementation process. Although most studies increased the L2 or L4 vehicle penetration rates, the approach by Weijermars *et al.* [7], Guériau and Dusparic [19], and Sharma *et al.* [30], where a mixed fleet comprising vehicles of different automation levels in the same scenario, could better represent the real-world problem.

Considering the above, this study uses the microsimulation approach to model the introduction of different CAV levels, employing the Aimsun API internal algorithms and the external V2X extension. In addition, a motorway network is used to test various mixed fleet operations (*i.e.,* passenger cars and heavy vehicles with varying levels of CAV) to achieve a simulation that is sufficiently close to the actual deployment of CAVs on real roads.

B. *CAV Safety Evaluation Criterion*

The criteria used for safety evaluation in the simulation-based method are the Surrogate Safety Measures (SSM) [16]. SSM were initially developed and validated using human-driven field safety studies manually or computer vision and sensors for motion tracking (*e.g.,* [32], [33]). After verifying the advantages of simulation over field studies on traffic operations (*e.g.,* simulation is easier and quicker in applying traffic scenarios and different strategies under the same traffic input), researchers began conducting traffic safety studies using SSM based on simulations. In the case of CAVs, where it is not currently possible to collect field data for mixed-fleet scenarios, traffic simulation is the only tool to conduct both traffic efficiency and safety studies.

The available research on simulation-based CAV safety modeling using SSM can be classified into two categories [16]: (1) trajectory optimization, to optimize merging and crossing maneuver safety and provide proper safe space between vehicles, using distance and time gap constraints (which contain SSM, such as TTC) in maneuver decisions (*e.g.,* [34]–[38]); and (2) safety evaluation using time-based and deceleration-based SSM, similar to the studies presented in Table I. TTC is the most commonly used SSM in the literature about CAV safety modeling, followed by PET [16]. Time-exposed time-to-collision (TET) and time-integrated time-to-collision (TIT) have been frequently used as well (*e.g.,* [12], [25], [39]). Often, the Surrogate Safety Assessment Model (SSAM), developed by the Federal Highway Administration (FHWA), or other customized tools, are used in safety evaluation by analyzing traffic trajectories and extracting the SSM values [31].

The TTC and PET thresholds in SSAM are the basis for determining risky interactions and the resulting SSM indicators. The default values for these SSM are 1.50 s and 5.00 s, respectively. However, these values were assigned considering HDV crash validation. Table I shows that some researchers have used default values after performing a sensitivity analysis with different values [12], [13]. However, others suggest that it is important to reduce the default TTC threshold when dealing with CAVs because of their shorter reaction times and shorter headways. Morando *et al.* [14] applied three TTC thresholds when they tested the resulting conflicts of L4 vehicle penetration: 1.50 s for any conflict involving HDV, and 1.00 s or 0.75 s for L4-L4 interactions, which showed statistically significant differences. Similarly, Guériau & Dusparic [19] used a value of 0.75 s for conflicts involving CAVs, whereas Virdi *et al.* [26] adopted a value of 0.50s.

TABLE I
SUMMARY OF PREVIOUS SIMULATION-BASED STUDIES FOR CAV EFFECT ON TRAFFIC SAFETY

Reference	Simulation platform	Studied network	Vehicle type	Penetration rates	SSM thresholds	Evaluation indicators	Level of CAV
[24]	PARAMICS	Network with work zone	PC	0,20,40,60,80,100	1.5s TTC	Conflict frequency	L2
[14]	PTV-VISSIM	Signalized intersection, roundabout	PC, HV(5%)	0,25,50,75,100	1.5s TTC (HDV-HDV, AV-HDV) 1.0s 0.75s TTC (AV-AV) 5.0s PET	Conflict frequency, Involved vehicles	L4 (2 models)
[6]	Costumized modeling	2-lane road (10 km)	PC	0,25,50,75,100	-	Distripution of TTC, acceleration, and velocity difference	L2
[13]	PTV-VISSIM	3-lane motorway (44.27 km)	PC	0,25,50,75,100	1.5s TTC 5.0s PET	Conflict frequency, Involved vehicles	L4
[25]	PTV-VISSIM	Arterial (61.15 km)	PC, HV (%real data)	30,40,60,80,100 (CV and L2 tested apartly)	1.5s TTC 5.0s PET	Conflict frequency, Severity (TET, TIT, TERCRI, LCC, and NCJ)	L1, L2
[11]	SMARTS	Freeway, CBD, Campus	PC	0,20,40,60,80,100	1.5s TTC	Conflict frequency (sensitivity analysis)	L1,L2, L3, L4
[26]	PTV-VISSIM	Urban intersections	PC	0,10,20,…,90,100	1.5s TTC (?-HDV)* 0.5s TTC (?-CAV) 5.0s PET (?-HDV) 1.65s PET (?-CAV)	Conflict frequency, Involved vehicles	L4
[12]	PTV-VISSIM	4-lane freeway (7km)	PC, HV (0%-30%)	0,10,20,30	2.0s TTC	Severity (TET, TIT, TERCRI, and LCC)	L4
[19]	SUMO	Motorway (7 km), National (5.3 km), Urban (3x3 km)	PC, HV (%real data)	0,2.5,7,20,40,70 (mix of L2 & L4)	1.5s TTC (?-HDV) 0.75s TTC (?-CAV) 5.0s PET (motorway & national) 0.75s PET (urban)	Conflict frequency, Involved vehicles	L2, L4
[15]	PTV-VISSIM	2-lane motorway	PC	0,10,20,…,90,100	1.5s TTC 5.0s PET (?-HDV only)	Crash rate (if PET=0), Severity (TTC, PET, Delta S)	L4
[27]	PTV-VISSIM	6-lane freeway	PC	100	1.5s TTC 5.0s PET	Conflict frequency, Severity (MaxS, MaxD, MaxDeltaV)	L4
[30]	Costumized modeling	-	PC	Mixed fleet of CV levels	-	MTTC, DRAC	L2
[7]	Aimsun	3 tested Networks	PC, HV	Mixed fleet	1.5s TTC (?-HDV) 1.0s (1st generation) 0.5s (2nd generation) 5.0s PET	Crash frequency	L4 (2 driving styles)

Where; PC: passenger car, HV: heavy vehicle, HDV:human driven vehicle, CAV: connected and autonomous
TTC: time-to-collision, PET: post encroachment time, TET: time-exposed-time-to-collision, TIT: time-integrated-time-to-collision, TERCRI: time exposed rear-end crash risk index, LCC: lane changing conflict, NCJ: number of critical jerks, DeltaS: difference in vehicle speeds as observed at tMinTTC, MaxS: maximum speed of either vehicle throughout the conflict, MaxD: maximum deceleration of the follower vehicle, MaxDeltaV: maximum DeltaV value of either vehicle in the conflict, MTTC: modified time-to-collision, DRAC: lower deceleration rate to avoid accident.
**(?-HDV) means the follower vehicle is HDV whatever the first vehicle; (?-CAV) means the follower vehicle is CAV whatever the first vehicle*

C. CAV Levels

Table I also shows that a significant portion of previous studies have investigated the effect of the penetration of L4 vehicles alone [7], [12]–[15], [26], as this is the most awaited stage. Nonetheless, many studies have focused on only low levels of automation and connectivity (L1 and L2 vehicles) (*i.e*., vehicles with one or two advanced systems) [24], [25], [30] to reflect traffic safety expectations for the near future.

Among those who investigated the safety impact of L1 and/or L2 vehicles, Genders & Razavi [24] calibrated L2 vehicles with connectivity between them (Vehicle-to-Vehicle, V2V). Afterward, they tested three behavioral models considering different degrees of driver compliance (high, moderate, and low) with different penetration rates. They found that the change in traffic safety is correlated with driver compliance in terms of how much the driver will follow the data gathered by V2V in the work zone (warnings and information): moderate and low driver compliance are correlated with considerable traffic safety drawbacks, whereas conservative changes in behavior (high driver compliance in interacting with linked data) were correlated with low changes in traffic safety. In addition, this study suggested that L2 penetration rates below 40% contribute to fewer traffic conflicts, whereas high penetration rates decrease network safety. Similarly, Sharma *et al*. [30] implemented a model to test the safety of fleets mixing HDVs and L2 vehicles with high/low-compliant drivers, considering the effect of platoon spatial arrangement. First, by investigating homogenous scenarios (scenarios with only one type of behavior), they found that L2 vehicle platoons with highly compliant drivers achieve a higher level of safety (higher modified time-to-collision (MTTC) and lower deceleration rate to avoid crash (DRAC)) than L2 vehicle platoons with low-compliant drivers, and that L2 platoons with low-compliant drivers still have more safety benefits than HDVs. Second, by considering heterogeneous scenarios, they concluded that the platooning of vehicles, rather than their penetration rates, was the key factor in obtaining safety benefits. Furthermore, their results indicated that the best type of vehicle platoon arrangement consisted of L2 vehicles with high compliance, followed by L2 vehicles with low compliance, followed, in turn, by HDVs. Rahman *et al*. [25] also suggested that the penetration of L1 and L2 vehicles could more significantly reduce traffic conflicts than that of HDVs.

On the other hand, researchers that have assessed the effect of the penetration of L4 vehicles using the SSAM unanimously agree that high penetration rates of L4 vehicles will significantly enhance traffic safety on different roadway sections [12], [13], [15], [27] and at intersections [14], [26], regardless of the network type.

In the case of roadway sections, Papadoulis *et al.* [13] tested motorway safety and examined the number of conflicts resulting from the introduction of L4 vehicles calibrated via the external VISSIM interface. The generated conflicts on different days of the week reduced by 12–47%, 50–80%, 82–92%, and 90–94% for CAV penetration rates of 25%, 50%, 75%, and 100%, respectively. Similarly, El-Hansali *et al.* [27] compared the traffic safety on a 6-lane freeway section fully operated with either HDVs or L4 vehicles (*i.e*., 100% HDVs vs. 100% L4 vehicles). Their results showed a reduction of only 8.6% in the number of conflicts between autonomous and conventional traffic. Although these results showed higher severity values for L4 vehicles (*e.g.,* a higher maximum speed of either vehicle throughout the conflict (MaxS) and higher maximum deceleration of the follower vehicle (MaxD)), they do not necessarily reflect the reality as these severity terms were measured for the conflicts and not for crashes. Sinha *et al.* [15] also considered a motorway section as a case study to apply a traffic safety analysis. They studied traffic flow efficiency and potential conflicts, and estimated potential crash rates from potential conflicts to discuss the severity of L4 vehicle introduction. In general, the results indicated the safety benefit of CAV-HDV interaction over HDV-HDV interaction. Finally, Zhang *et al.* [12] conducted a study on roadway sections. They examined the safety of exclusive lanes for L4 vehicles under different penetration rates. They underlined that setting even one exclusive lane improved safety by decreasing risky situations for both longitudinal and lateral movements. They also highlighted that setting two exclusive lanes was more suitable for high-demand scenarios.

Other researchers analyzed L4 traffic safety at intersections. For example, the reduction in conflicts generated by L4 vehicles for penetration rates between 50% and 100% was estimated in [14] to be between 20% and 65% for signalized intersections and from 29% to 64% for roundabouts. Virdi *et al.* [26] also suggested that the benefits of L4 vehicles will be observed at high penetration rates (particularly for signalized and diverging diamond intersections). Under a L4 vehicle penetration rate of 90%, the reductions in conflicts were estimated to be 48%, 100%, 98%, and 81% for signalized, priority, roundabout, and diverging diamond intersections, respectively.

Nevertheless, L4 vehicles will not operate immediately on the road, and once they do, they will be sharing traffic flow with vehicles with lower automation levels. Thus, to represent reality more closely, scenarios incorporating lower levels should be analyzed. However, very few previous studies have simultaneously modeled more than one CAV level. For instance, Xie *et al.* [11] employed SMARTS to analyze the sensitivity of traffic safety to different levels of automation (L1, L2, L3, and L4 vehicles) by varying the driving parameters (*e.g*., maximum acceleration/deceleration, space/time headway, reaction time), traffic flow (1 000, 3 000, and 5 000 veh/h), and studied area (*e.g.,* urban area, interurban freeway). They found that an increase in the automation level may enhance traffic efficiency but could lead to more potential conflicts. However, this conclusion might be related to some of the limitations that we try to address in this study: first, they did not include the effect of connectivity, which may lead to more adaptation and harmony between vehicles and consequently improve traffic safety; second, they considered the same TTC threshold for HDVs and vehicles with any level of automation, despite the higher capabilities of CAVs; and finally, they considered scenarios that are not very realistic (such as penetration rates of 100% for L1 or L2 vehicles) and which drivers will not see during the transition to fully CAV operation. As a result, these points are highlighted as aspects to be incorporated in the current study to improve the level of reliability.

Guériau and Dusparic [19] tried to include mixed fleets with more than one CAV level (L2 and L4 vehicles) and HDVs. They conducted an extensive study that calibrated real-world traffic (with passenger cars and heavy vehicles) within various types of networks (motorways, national, and urban). They also applied two types of connectivity (V2V and vehicle-to-infrastructure (V2I)). They found that, at low CAV penetration rates, traffic safety was adversely affected and traffic conflicts increased by 30% compared to a human-driven scenario, whereas a high CAV penetration led to improved traffic safety with a 50%-80% conflict reduction. They emphasized that traffic congestion contributes more to potential conflicts than the penetration rates of L2 and L4 vehicles. Therefore, they highlighted the importance of simultaneously ensuring traffic efficiency and safety.

On the other hand, Weijermars *et al.* [7] simulated two styles of CAV driving (*i.e.,* cautious and assertive) with traffic data calibrated from three city networks and eight mixed fleets. However, the main shortcoming of studies [7] and [19] is that the CAV driving styles were not shown or discussed in their results. They only presented the total reduction of conflicts by CAV as one unit rather than showing the involvement of each vehicle type (HDVs, cautious CAVs, and assertive CAVs) in the resulting conflicts among the analyzed scenarios. Indeed, CAV will be introduced during a transition period with several mixed fleets and levels. As a result, it is important to discuss these two aspects simultaneously by presenting the impact of increasing the penetration rates of different CAV levels on traffic safety among multiple scenarios and addressing the participation of each level as involved vehicles in the total resulting conflicts, as well as their contribution as fault vehicles in the resulting potential conflicts or crashes. All the limitations mentioned in this subsection are considered in the current study.

III. METHODOLOGY

This study presents a safety evaluation of the progressive introduction of CAVs into the traffic flow of a freeway segment modeled in Aimsun Next 20 API [40]. This section provides information about the case study freeway segment, calibration of CAV levels, simulation scenarios, and traffic conflict identification procedure to obtain a safety assessment.

A. Case Study

A three-lane 20.27 km road segment of the Spanish GR-30 motorway was considered as a case study. The selected motorway includes two major entrances to the city of Granada and represents a strategic location aligning the city and reaching the main vital points (*i.e.,* city center, hospitals, schools, university, etc.). The motorway segment has 16 access points (see Fig. 1): two major points, one in the north and the other in the south, and 14 weaving segments. An imported Open Street Map was used in the Aimsun platform as a guide to generate the geometry of the segment (*i.e.,* curves of the road segment, lane width, length of sections, and merging and diverging areas) using drawing tools and overlapping the sections created with the imported map.

After including the segment geometry, other network information was defined based on data gathered from several detectors installed by the General Traffic Direction (Dirección General de Tráfico, DGT) along the segment. The DGT data include the speed limit, average instantaneous speed of vehicles passing through a section within 15-min intervals, traffic volume per lane (veh/h/ln), and traffic distribution (passenger cars vs. heavy vehicles). The segment had different speed limits (80, 90, 100, and 120 km/h). Consequently, the reported average instantaneous speed within 15-min intervals varied from 83 to 118 km/h. The traffic flow data used for the calibration of the modeled network correspond to an off-peak hour (10:00-11:00 am) on a regular day (Tuesday), representing free-flow conditions. The traffic counts registered every 15 min by the six detectors in the northbound direction were between 547-3570 pc/h and 89-260 hv/h, whereas those recorded by the four detectors in the southbound direction were between 809-3281 pc/h and 93-499 hv/h. These detectors were used with their anticipated directional hourly volumes to validate the traffic simulations.

B. Simulation

Based on a critical review of several microsimulation platforms used for CAV simulations in both the longitudinal and lateral directions [22], the following conclusions can be drawn: (i) although PTV VISSIM has been widely used for this type of analysis, Aimsun has improved its recent versions (Aimsun Next versions 8.4.3 to 20) providing more specific tools to calibrate CAV behavior as a vehicle type; (ii) Aimsun is considered a user-friendly platform, and it has designed many external API extensions, including the V2X connectivity extension, to correctly represent CAVs.

Accordingly, this study uses Aimsun Next 20 with the V2X extension to calibrate CAV levels. The fleet mixes proposed in this study were simulated for one hour with a 0.1 s time step, following previous studies [13], [14], [41], and an 18-min warming-up period calculated as in [42], considering the length and average speeds of the freeway segment. Based on previous studies (*e.g.,* [43], [44]) each scenario was assigned a total of 15 simulated replications. To achieve a 90% confidence interval level, Shahdah *et al*. [43] defined the number of simulation runs (N) as follows:

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

where σ is the standard deviation of the simulation output sample, t is the Student's t-statistic for the two-sided error $\alpha/2$ with $N-1$ degrees of freedom, E is the allowed error range, $E=\varepsilon*\mu$, μ is the mean of the number of simulated conflicts based on the initial set of simulation runs, and ε is the allowable error specified as a fraction of the mean. For example, in Scenario I, we performed 15 runs with σ=19.54, t=2.14 α=0.05, 14 degrees of freedom, and E=0.10×192, which was a sufficient sample. In addition, in a previous study [44], 30 and 50 runs were tested for each scenario, and the results did not change significantly, indicating that 15 runs were a representative sample.

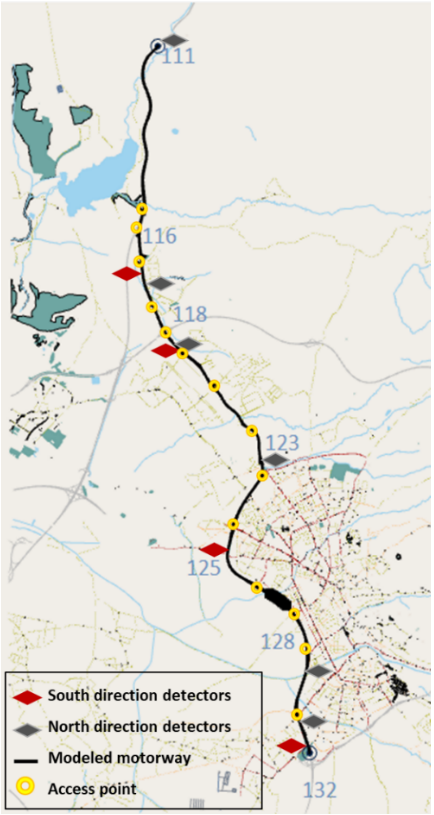


Fig. 1. Modeled study area (GR-30 motorway section)

As a step prior to the traffic microsimulation, a check of the modeled network validity was applied to verify if traffic operations (exposure and arrival) of the network matched the observed traffic operations in the case study. Following previous studies [25]-[27], and applying the modeling guidelines of the Roads and Maritime Services [45], this study applied the following criteria: (1) the Geoffrey E. Havers (GEH) statistic function; which measures traffic volume deviation between networks, 85% and 100% of traffic volumes should render GEH statistics of less than 5 and 10, respectively, (2) R^2 of the observed vs. modeled volumes plot should be over 0.9, and (3) the cumulative average modeled travel times by section (between detectors) should be within 15% or one minute (whichever greater) of the observed travel time. Appendix A exhibits the results of the mentioned criteria, where GEH is less than 5 for 85% and less than 10 for the 100% of traffic volumes (Appendix A, Table A.1). In addition, R^2 of the northbound observed vs. modeled volumes plot was found to be 0.98, and for the southbound was 0.99 (Appendix A, Fig. A.1, A.2). Regarding the average travel times, they were found to be within 15% of the observed cumulative plot for both directions (Appendix A, Fig. A.3, A.4). These results confirm the validity of the modeled network.

In addition, following previous studies [25]–[27], the modeled average travel speed was validated. It was ranging between 86.44% and 90.36% of the speeds registered by the DGT. The mentioned variations in speed (-9.64% and -13.56%) are considered acceptable, because they are below the 15% variation threshold recommended by the Roads and Maritime Services modeling guidelines [45]. The speed per vehicle type was not considered for validation because of the absence of split data.

Table II presents the nine different fleet mixes considered as scenarios for the traffic microsimulation to reflect a closer picture of the introduction of CAV levels. As getting the exact scenarios of CAVs' market penetration rates is unfeasible, this study tried to cover a progressively introduction of CAVs with different fleet mixes that the real world might face. Specifically, Scenario A reflects the base condition in which all vehicles are HDVs; Scenario B represents the first introduction of CAVs, where the road is shared with a low percentage (25%) of mainly L1 and L2 vehicles; in Scenarios C and D the presence of CAVs of various automation levels increases; Scenario E implements a completely mixed fleet with an approximately equal penetration of all vehicle types; scenarios F, G, and H picture fleet mixes of high automation levels; and finally, Scenario I models a situation where all vehicles are L4.

TABLE II
FLEET MIX SCENARIOS CONSIDERED

Scenario	**HDV**	**L1**	**L2**	**L3**	**L4**
A	100%	0%	0%	0%	0%
B	75%	10%	10%	5%	0%
C	50%	10%	25%	10%	5%
D	40%	15%	20%	15%	10%
E	20%	20%	25%	20%	15%
F	5%	10%	30%	30%	25%
G	0%	0%	10%	40%	50%
H	0%	0%	0%	25%	75%
I	0%	0%	0%	0%	100%

C. *CAV Calibration*

The purpose of this part of the study is to calibrate all CAV levels standardized by the Society of Automotive Engineers [9] as distinct vehicle types operated in the microsimulation. L5 vehicles were not considered in this study given that a particular motorway section was analyzed under specific circumstances. Therefore, in the tested context, fully automated vehicles corresponded to level L4. This study aims to model the differences in driving behavior among different CAV levels (*i.e.,* how these vehicles will flow and interact with each other during the transition period) based on literature and manufactural interpretations [1], [11], [19], [41]. These behavioral differences were introduced in Aimsun, considering specific parameters for both car-following and lane-change traffic models.

In particular, the default parameter values in Gipps' model represent HDV behavior. However, they are supposed to have different values for different CAV levels. In addition, according to the viewpoints of both literature and manufacturers [1], [9], [46], CAVs are expected to maintain different standstill distances, accelerate and decelerate faster and more smoothly, maintain constant speed with lower oscillations at free flow, form platoons of vehicles that follow the leader, and change lanes more cooperatively and at a higher speed. Nevertheless, according to the Levitate research project [7], [41], it is expected that the first CAVs introduced into traffic streams will exhibit a cautious driving style, as they will be interacting with HDVs, whereas the second generation will be more assertive [7], [41]. Thus, to achieve a more realistic representation of CAV introduction, this study considered a cautious driving style.

To generate the behavior of each level of automation, the data analysis strategy considered was a type of data mining. First, a previous investigation and analysis of all the parameters used in the empirical and simulation studies were performed to extract the key parameters needing calibration in our models. The key parameters are those that researchers extensively use as the most connected to the behavior of CAVs. Afterwards, the following strategy was used regarding the values of the key parameters for different levels of automation:

- If the parameter was tested within empirical studies (for L1, L2), the value was extracted from these studies (*e.g.,* normal deceleration and maximum acceleration [21]. Sometimes the empirical data were used to obtain the direction of parameter values for different automation levels [47]).
- If the parameter was extensively calibrated in simulations and researchers agreed on its value, then the calibrated value was used. Even though the parameters were not the same in different simulation platforms, an equivalent value for the Aimsun parameters was assigned depending on the scientific definition of each parameter.
- If we assigned values for parameters at specific levels (s) (L2 and L4, for example) based on the previous two conditions, the decision regarding the in-between values (i.e., values related to L1, L3) was based on the interpretation of technology advances for that parameter (*e.g*., reaction time is kept the same in L1 and L2 as the driver is still reacting in both vehicles, whereas speed limit acceptance is represented with some improvement in L2 than L1).
- If the parameter was not extensively calibrated, a sensitivity analysis was performed to determine an appropriate value (*e.g.,* sensitivity factor and aggressiveness level).

In general, as L1 vehicles are defined as those with a driver assistance system, limited changes were expected to model their behavior compared to HDVs' behavior, represented by better speed limit acceptance and more guidance acceptance under the monitoring of a human driver all the time. L2 vehicles, on the other hand, provide more advanced systems (e.g., Cooperative Adaptive Cruise Control, CACC), more regulated acceleration/deceleration, and less aggressive lane changing. Although CACC can control driving sometimes, the driver is the one reacting, and the CACC algorithm can provide control to the human at any time. The behavior of L3 vehicles, which reflect higher automation advances, is characterized by a lower reaction time and a more cautious driving in both car-following (acceleration/deceleration) and lane changing (*e.g.,* cooperating in creating gaps to avoid imprudent lane change). However, CACC still provides control to human drivers to interact with small gaps. Finally, L4 vehicles are totally autonomous vehicles with a very low reaction time, very low aggressiveness, and highly regulated behavior in both the longitudinal and lateral directions.

Appendix B (section *I)* presents a detailed description of the parameters considered in Gipps' car-following and lane-change models for each level of automation, as well as a justification of the values proposed for different automation levels. These values are based on previous literature and depend on the expected advantages of adding advanced technologies. The parameter distribution for both passenger cars and trucks is defined by the mean, standard deviation, and minimum and maximum values. In general, the standard deviation values decrease as the level of automation increases because of its high dependency on technology [46]. The distribution used was the default distribution in the Gipps modeling (normal distribution). Appendix B (section *I)* also shows the definition of each parameter as provided in the Aimsun user manual, as well as previous literature that guided the parameter calibration applied in the current study.

Lastly, connectivity is introduced into the simulated vehicle types as follows: we assumed that HDVs and L1 vehicles are modeled without connectivity; L2 vehicles are connected only with the CACC assistance system; L3 vehicles are connected with both CACC (the whole L3 vehicles) and V2V connectivity (the majority of L3 vehicles, 65% equipped vehicles); and L4 vehicles are entirely connected with V2V connectivity.

More details regarding Gipps' traffic flow theory [48], [49] and connectivity calibration are presented in the Appendix B: sections *II, III,* and *IV*.

D. Safety Evaluation

Microsimulations do not provide direct measures to evaluate traffic safety. The procedure that tends to be used for CAV safety evaluation is based on two approaches: (1) to determine traffic dynamics and behavior by analyzing aggressiveness and jerk interactions in trajectories under different studied scenarios, and (2) to analyze the microsimulation outputs (vehicle trajectories) with the SSAM to identify potential traffic conflicts. The SSAM tracks vehicle positions within sequential time steps while treating a trajectory file. If two vehicles maintain the same speed and projection up to the TTC threshold, they are registered as an overlapping (conflict) [31].

This study uses both approaches: (1) the analysis of trajectory dynamics by drawing their acceleration and velocity-difference distributions among the studied fleet mixes (scenarios A to I), and (2) the analysis of vehicle trajectories using SSAM to first identify potential conflicts registered in each scenario to determine the macroscopic safety effect of the gradual introduction of CAVs, and then to picture the potential conflicts registered by each CAV level.

A two-step process was used to identify conflicts based on TTC thresholds and vehicle type: (1) the vehicle trajectory file was obtained from Aimsun Next 20 (with GetAllInfVeh API extension), and processed by a Python code to extract vehicle type information that is not regularly output; and (2) the trajectory file, containing proper vehicle information, was concatenated with the SSAM output to create a file that contains both conflict data (*i.e.*, SSM, conflict type, the leader and the follower vehicle involved in a conflict) and vehicle data (*i.e.*, vehicle type, speed, acceleration, and position). StataMP 16 was used first for concatenation, and then, to pre-filter and identify the conflicts, setting different TTC thresholds depending on the vehicles involved.

The default TTC and PET values were 1.50 s and 5.00 s, respectively. Table I and Section 2 show that TTC is the most commonly used measure in the literature. In particular, following the concept in literature, which indicates that the shorter reaction times of CAVs could make these vehicles more capable of significantly decreasing the TTC threshold [15], [19], [26], and considering a previously conducted sensitivity analysis [44] that showed a statistically significant difference when examining the change in the frequency of conflicts involving L4 vehicles under several TTC values (0.50, 1.00, 1.50, 2.00, and 2.50 s), this study used two different TTC thresholds:

- TTC=1.50 s to identify HDV-HDV or CAV-HDV conflicts where the follower is an HDV [15].
- TTC=0.75 s to identify CAV-CAV or HDV-CAV conflicts where the follower is the autonomous vehicle.

As L1 and L2 vehicles correspond to low levels of automation and both require human intervention during the driving process, they are included in the first group (TTC=1.50 s), whereas CAVs are related to higher levels of automation (L3 and L4 vehicles). The suggested value of 0.75 s is in line with two previous studies [14], [19]. Although Morando *et al.* [14] tested two TTC thresholds for the identification of CAV conflicts (1.00 s and 0.75 s), the results with 0.75 s showed a better consistency. Virdi *et al.* [26] used a lower value (0.50 s) and found a significant conflict reduction even when the CAV penetration into traffic was very low (only 10%). Moreover, the Levitate project [41] considered two values: 1.00 s for the first generation (cautious driving) and 0.50 s for the second generation (assertive driving), which are convenient for the extreme driving styles modeled. As a result, 0.75 s could represent an average value of all previously proposed values in the literature.

The potential conflicts reported in this study under different scenarios are described in terms of conflict reduction with respect to the base scenario (scenario A) and conflict type (rear-end, lane-change). Moreover, an analysis of variance was conducted between the number of conflicts under different scenarios to measure possible significant changes in safety.

Afterwards, as the pre-filtered conflict file contains the details of the vehicle type (HDV or L1-L4) involved in the conflicts, as well as data regarding which vehicle is the follower in a conflict, this information was used to analyze the vehicles and vehicle interactions involved in the conflicts to further understand the impact of the introduction of different CAV levels on safety. The evaluation was represented by three measures:

1. Vehicle involving ratio was first presented by a ratio computed for each vehicle type among the scenarios as follows:

$$Involving\ ratio_{\ vt\ (i)} = \left[\frac{No.conflicts\ including\ vt\ (i)}{No.conflicts\ (i)}\right] \cdot \frac{1}{\%\ penetration\ vt(i)} \qquad (2)$$

where v_t is the vehicle type (HDV, L1-L4), and i is the scenario (from A to I). Therefore, the involvement ratio of v_t in i is calculated by dividing the number of conflicts that include v_t, whether as a first or second vehicle, by the total number of conflicts in that scenario; then, the ratio is divided by the penetration rate of v_t into the scenario. This measure determines the frequency in which a specific vehicle type is involved in a conflict, normalized for the number of vehicles of that type in the fleet. A value higher than one indicates that the corresponding vehicle type participates in a higher number of conflicts than those corresponding to its penetration rate in that scenario. On the contrary, a ratio lower than one implies that the participation of this type of vehicle in potential conflicts is lower than its presence in the traffic fleet.

2. Interaction involvement ratio. Picturing the most repeated interactions of the vehicles involved in the potential conflicts under each scenario (the leader and follower vehicle of each conflict) is key in illustrating the effect of CAV level penetration on traffic safety during the transition period. It is represented in Eq. 3:

$$Interaction\ involving\ ratio_{\ vc\ (i)} = \left[\frac{No.conflicts\ including\ vc\ (i)}{No.conflicts\ (i)}\right] \frac{1}{\%\ penetration\ vt1(i)\ .\ \%\ penetration\ vt2(i)} \qquad (3)$$

where v_c is the vehicle interaction (*e.g.,* HDV-HDV, HDV-L1, etc.) in a conflict, and i is the scenario (from A to I). The conflict proportion by vehicle interaction (v_c) in i is calculated by dividing the number of conflicts, including v_c, by the total number of conflicts in that scenario. The interaction proportion is normalized then by dividing it on the sharing percentages of both vehicle types in that interaction.

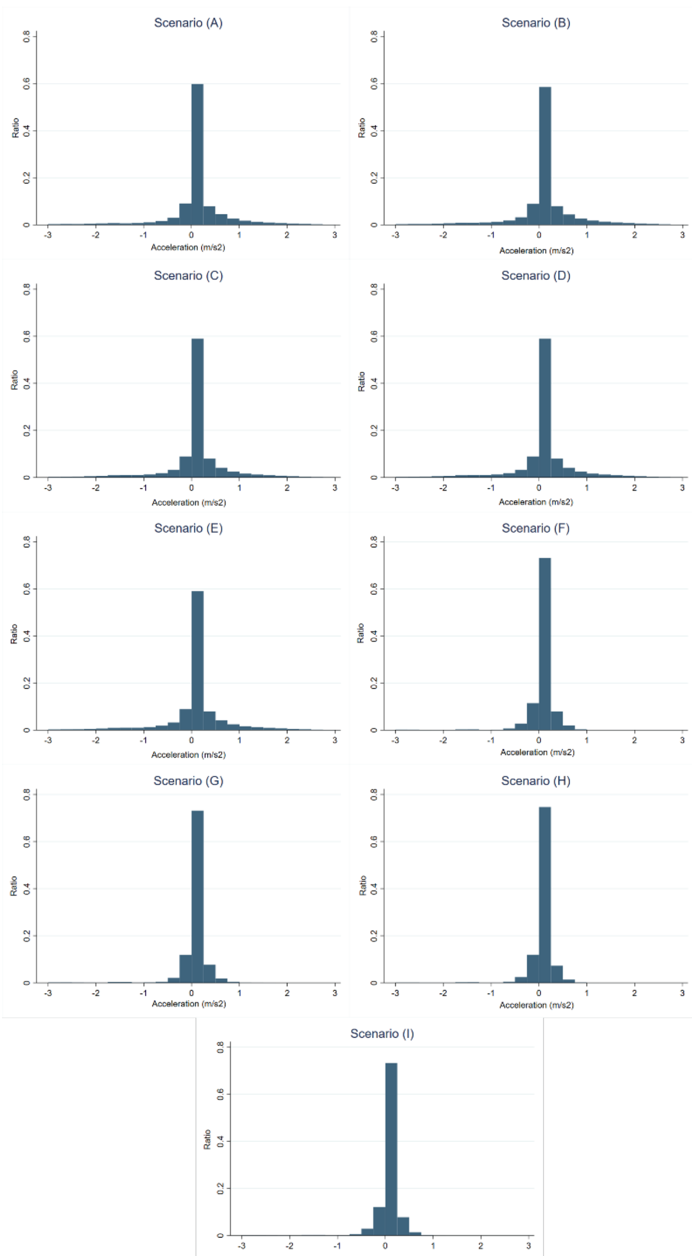
3. Finally, as the follower vehicle in a conflict is considered to be the decision-maker vehicle that can either avoid conflicts or induce them by its errors, the involvement ratio for the follower vehicle at potential conflicts was calculated (Eq. 2) to highlight vehicle types that most frequently induce conflicts. The involvement ratio of the follower in a scenario is calculated by dividing the number of conflicts where the corresponding vehicle type is a follower by the total number of conflicts in that scenario. Then, the ratio is divided by the penetration rate of the follower vehicle type in the scenario for standardization to consider its presence in the studied fleet mix.

IV. Findings and Discussion

Within the framework of investigating the CAV effect on traffic safety, this section presents the microsimulation results for different scenarios of CAV level penetration. These results provide firstly traffic flow dynamics that reflect an indirect traffic safety measure. Later, it presented a direct traffic safety measure represented by potential traffic conflicts depending on the SSAM and analyzed these conflicts.

A. *Traffic flow dynamics*

One of the main traffic safety indicators is to draw clear insight into traffic flow dynamics [1], [2], [46]. This study follows Ye and Yamamoto's [6] approach in analyzing traffic trajectories by their exposure to risky situations, including high acceleration/deceleration or velocity differences between the leader and follower among different fleet mixes. Fig. 2 shows the acceleration distributions of the different scenarios (from A to I).



Note: acceleration values outside the range -3 m/s² to 3 m/s² are negligable and were not represented in these plots

Fig. 2. Acceleration distribution under the proposed scenarios

Even though the distribution patterns exposed for these scenarios are very similar, it is possible to identify two different patterns: one for scenarios A to E, and another one for scenarios F to I. Focusing on the second pattern, when the penetration rate of L3 and L4 vehicles is over 50% (from scenario F onward), the ratio of the acceleration values around 0.00 m/s² increased, diminishing the ratio of acceleration values higher than 1.00 m/s^2 or lower than -1.00 m/s^2. This indicates smoother and harmonized driving patterns. This result is expected given the behavior parameters used for L3 and L4 vehicles design. For example, as imprudent lane changing is banned for them, less extreme acceleration values might be shown. Moreover, as L3 and L4 vehicles are modeled for cooperation in creating gaps, acceleration rates closer to 0 m/s^2 are also expected. Ye & Yamamoto [6] also found that the increase of CAV penetration rate leads to gradual increase of the ratio of 0.00 m/s² acceleration rate. In addition, they pointed out that the aforementioned behavior is expressed by more traffic safety on the road. Sinha *et al.* [15] marked similar results by finding that high variation of acceleration records are decreasing with more CAV in traffic flow.

Regarding the difference in velocity between the leader and the follower vehicles, Fig. 3 shows that for all scenarios, it follows a bell-shaped distribution. However, a closer look to each scenario reveals the gradual change in this shape. The first five scenarios (A-E), where the greatest number of vehicles are HDV, L1 and L2 vehicles, presented a bell shape with a low peak and a wide velocity range. The bell peak starts to increase at high sharing percentages of L3 and L4 vehicles (above 50%), which are scenarios from F to I. At these scenarios, the difference in velocity between vehicles is reduced and tends to cluster around low values. This phenomenon shows that traffic flow homogenizes with high L3 and L4 vehicles penetration rates. According to previous studies [2], [6], velocity difference had a propensity to cluster around 0.00 m/s at high L4 and L2 penetration rates (respectively).

In particular, Ye and Yamamoto [6] emphasized that the anticipated reduction in the frequency of these risky situations, namely, situations with a high velocity difference, would improve traffic safety.

Finally, it should be highlighted, that these more harmonized driving patterns (related to acceleration and velocity-difference distributions) found at scenarios with high proportions of L3 and L4 vehicles, are partly a consequence of a safer and more cooperative behavior of L3 and L4 vehicles.

B. *Traffic Conflicts among Different Scenarios*

Traffic conflict analysis leads us to a better understanding of the safety impact of penetration rates of different levels of CAV at traffic flow. First, using TTC (1.50 and 0.75 s) and PET (5.00 s) thresholds (as discussed in Section III.D), Table III shows the average results of the number of conflicts resulting from our study for each scenario, differentiated by the total number of conflicts and conflict type. In addition, Table III shows the percentage of reduction in the number of total conflicts considering scenario A (where all the vehicles are HDV) as a reference. Moreover, analysis of variance (ANOVA) identifies whether the differences in the number of conflicts between scenarios are statistically significant.

In general, as the CAV penetration rates increase, from B to I scenarios, the number of conflicts decreases. This reduction is higher for higher penetration rates of CAV and for higher automation levels, reaching reductions from 18.9% up to 94.1% from scenario B to scenario I respectively. Moreover, the ANOVA statistical analysis shows statistically significant differences with a 95% confidence level for the average number of conflicts between most of the scenarios.

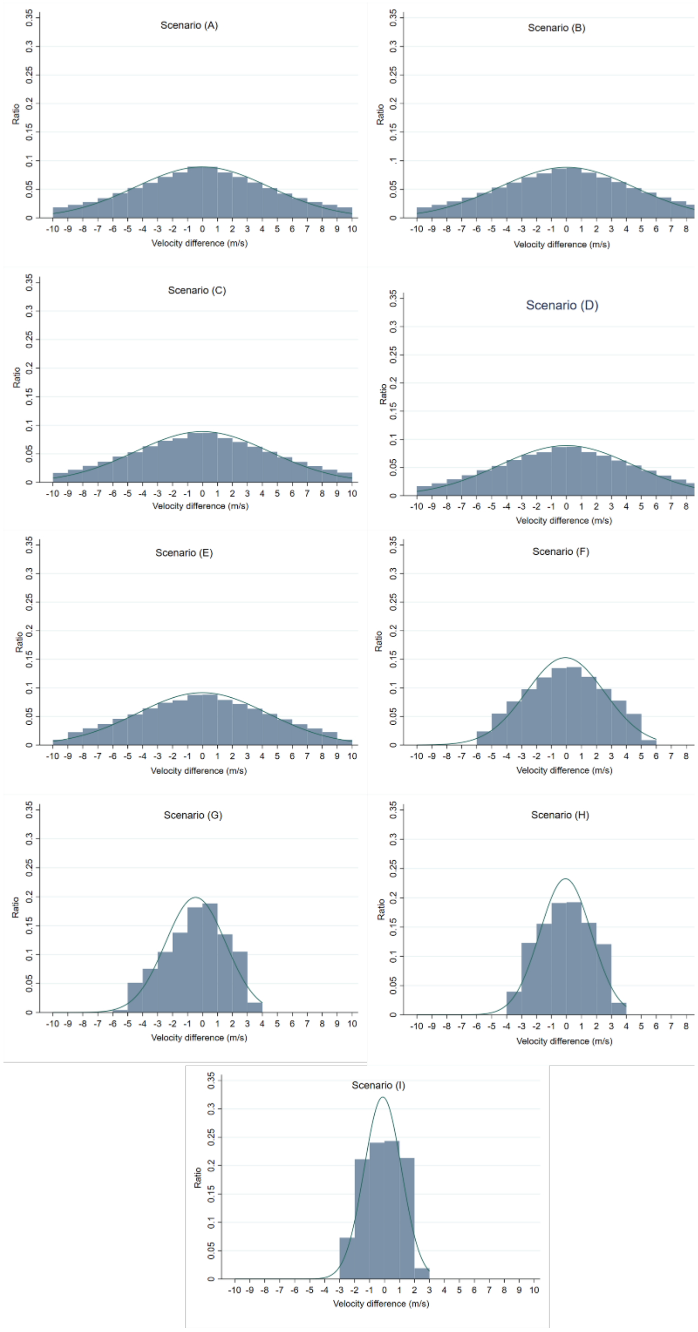


Fig. 3. Velocity-difference distribution under the proposed scenarios

In Table III, from Scenario B to Scenario D, where CAV volume has been progressively increased across the scenarios (from 0% in Scenario A to 25%, 50%, and 60%, respectively), the reduction in the number of conflicts is statistically significant, close to 20 percentage points between them (18.9%, 48.5%, and 65.0%, respectively).

In contrast, when the percentage of vehicles with a high level of automation (L3 and L4 vehicles) is over 35% (*i.e.,* scenario E) and the presence of HDV is low or non-existent, the differences in the number of conflicts are not statistically significant between all these scenarios (scenarios E, F, G, H, and I), but homogenous groups of scenarios are identified with statistical inter-group differences. This indicates that scenario E (with 20% HDV, 20% L1, 25% L2, 20% L3, 15% L4) represents again (as in traffic flow dynamics) the beginning of the saturation level of CAVs penetration gained safety benefits. The results from scenarios D and E (see Table III) shape subgroup *d*, where the composition of vehicles is highly mixed, differ from those of the last three scenarios G, H, and I that conform to subgroup *g*, where the penetration rates of vehicles with a high level of automation (L3 and L4 vehicles) are either 90% or 100%. This suggests that the most significant reductions in the number of conflicts are going to be reached in the first stages of CAV penetration during the transition period, while during later stages, even though the number of potential conflicts continues to decrease, these reductions will not be significant. In the literature, although there was no statistically significant comparison for the safety saturation CAVs penetration level, it can be noted that it was presented at different rates. Papadoulis *et al.* [13] and Morando *et al.* [14], for example, stated that 75% of L4 vehicles should operate the road to obtain the saturation level. In contrast, Virdi *et al.* [26] confirmed the results of the current study, with saturation penetration at 30% of L4 vehicles, particularly at roundabouts and priority intersections (unsignalized intersections). This change in results is related to the different calibrations of L4 behavior.

TABLE III
NUMBER OF CONFLICTS BY SCENARIO AND TYPE OF CONFLICT

Scenario	Total conflicts		Rear-end conflicts		Lane-change conflicts	
	Avg. (St. dev.)	% Reduction	Avg. (St. dev.)	%	Avg. (St. dev.)	%
A	3251 a* (647.26)		3072 (620.72)	94.5	179 (30.35)	5.5
B	2637 b (503.62)	18.9	2473 (482.84)	93.8	164 (25.98)	6.2
C	1675 c (247.79)	48.5	1542 (22.32)	92.1	133 (23.29)	7.9
D	1137 d (135.15)	65.0	1039 (125.93)	91.4	98 (15.42)	8.6
E	899 d, e (103.93)	72.3	818 (96.17)	90.9	81 (12.16)	9.0
F	648 e, f (75.21)	80.1	591 (70.17)	91.2	57 (8.86)	8.8
G	398 f, g (38.43)	87.7	369 (35.94)	92.7	29 (5.33)	7.3
H	199 g (22.92)	93.9	179 (20.89)	89.9	20 (4.73)	10.1
I	192 g (19.54)	94.1	175 (16.04)	91.1	17(4.82)	8.9

**For each value contains a, b…letter, it denotes values of statistically significant differences (p < 0.05). Two or more values with the same letter denote a homogeneous subgroup.*

In particular, in scenario B, where the operating levels of the CAV (almost L1 and L2) represent 25% of the traffic flow, a reduction of less than 20% is obtained for the resulting conflicts with respect to the total human driving scenario (A). This is in agreement with previous studies [13], [19], [25]. However, many of the mentioned studies studied the first introduction of CAV as L4; thus, our results add to the literature that the first introduction of CAV will even provide significant safety improvement even if they have low levels of automation (L1 and L2).

For example, Virdi *et al.* [26] suggested a significant reduction even with a 10% CAV penetration rate. They justified that such a significant reduction was due to a full-scale CAV cooperation that was adopted in their simulation, while other studies adopted low autonomous features, including adaptive cruise control and lane guidance, to simulate the highly promising features of CAV. In addition, they used a TTC threshold of 0.5 s to identify conflicts that involve a CAV, which is a very low value that can identify a low number of conflicts.

In the two suggested scenarios for various automation levels operating almost as the medium of the traffic fleet (scenarios C and D, 50% and 60%, respectively), the results show a significant reduction of 50%-65% with respect to scenario A. This reduction was below the values reported by Papadoulis *et al.* [13] and Virdi *et al.* [26] (93.8% reduction). The corresponding difference in reduction could be justified as both previous studies considered only L4 vehicles, whereas the 50% CAV in the current study is related to L1, L2, L3, and L4 vehicles. This indicates that using mixed levels of automation (closer to reality) does not significantly improve traffic safety, as has been acknowledged in previous studies. In contrast, our value is higher than those in [14] and [25], who analyzed either without connectivity or low levels of automation (L1 and L2 vehicles) alone. Furthermore, several considerations in the model calibration may lead to differences in the results of these research studies, such as the parameters included in the calibration, the magnitude and direction in modifying the default model parameters (increasing/decreasing), and whether the calibration follows the conception of cautious or assertive CAV behavior.

In scenario I, where the traffic flow is composed only of L4 vehicles, the reductions at this level of CAV penetration rate agree with [13] (above 90% of reduction analyzing L4 vehicles) and [26], which upholds a complete removal of conflicts. Indeed, it is the projected benefit of high technological advancement, which all acknowledged studies have highlighted. Nevertheless, these reductions are higher than those identified in previous studies (*e.g.,* [11], [14], [19]). This variation in the results is expected due to the distinct calibration of CAV and the different levels of CAV mixed in traffic within each study.

Table III also shows the effect of the CAV penetration rates on the type of conflict. The resulting conflicts at this motorway are mostly rear-end conflicts in all scenarios (89.9%-94.5%), in accordance with previous studies that have considered different types of conflicts (*e.g.,* [27]). Rear-end conflicts show a slight reduction with respect to scenarios A and B, which are mostly operated by HDV.

Therefore, once the number of HDV is reduced (with a penetration rate equal to or lower than 50%), the percentage of rear-end conflicts diminishes from 1 to 4 percentage points. On the other hand, the opposite effect was observed in the case of lane-change conflicts. When the CAV levels share the road, the percentage of lane-change conflicts may increase, which agrees with El-Hansali *et al.* [27]. In general, the corresponding change in the results within scenarios is related to the distinct behavior of HDV and CAV levels in the car-following and lane-change processes (*i.e.*, imprudent lane change, cooperation in creating gaps, and aggressiveness level) [1], [46].

C. *Vehicles Involved in Traffic Conflicts*

Furthermore, this study analyzes traffic conflicts to examine how often CAV levels or HDV are involved in the conflicts resulting in each scenario by defining an involving ratio (Eq. 2). Conflicts involving ratios for HDV and CAV levels are displayed in Fig. 4. For example, in scenario B, the involving ratios of HDV and L1 vehicles (1.03, 1.04) indicate that these types of vehicles are involved in conflicts 3% and 4% more than the expected values regarding their sharing percentages in the fleet. Alternatively, L2 and L3 vehicles' involving ratios (0.87, 0.66) demonstrate that these types of vehicles are involved in conflicts 13% and 34% less than the expected values regarding their sharing percentages in the fleet.

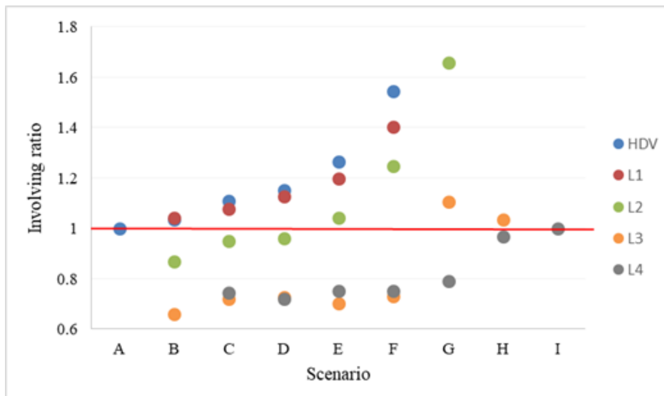


Fig. 4. Conflict involving ratios for CAV levels

Fig. 4 shows that the conflict involving ratios related to HDV, L1, or L2 vehicles are steadily increasing in the totally mixed scenarios (*i.e.,* scenarios C, D, E, and F, that include all types of vehicles) and by increasing CAV penetration rates in general. On the whole, L2 vehicles showed lower involving ratios than HDV and L1 vehicles. However, its involving ratio was below one if the majority of the shared vehicles are HDV and L1 (at scenarios B, C, or D), and started to be over one in scenarios including L3 and L4 vehicles (E and F). Whereas, its involving ratio is suddenly increased in scenario G where they are sharing the road only with L3 and L4 vehicles. In contrary, the involving ratio of L3 vehicles was in the most of cases below one except in G and H scenarios. This could be explained because L3 vehicles in scenarios G and H are sharing the road only with L4 vehicles (which have a more cautious behavior), therefore, it could reveal that L3 vehicles would expose more traffic conflicts than L4 vehicles. This finding agrees with the involving ratio of L4 vehicles that always settles below the value one. Xie *et al.* [11] obtained convergent results as they found that traffic mixed of HDV with L1 or L2 vehicles exposed a higher number of conflicts, while safety benefits come out by high penetration rates of L3 and L4 vehicles.

The distribution of two-vehicle interactions at conflicts was also analyzed (see Eq. 3). Considering that all possible interactions would be difficult to handle, and because of the high similarities identified in conflict involving ratio between L1 and L2 vehicles as well as between L3 and L4 vehicles, the four levels of CAV were merged into two groups: L1 and L2 vehicles as low CAV levels (LCAV), and L3 and L4 vehicles as high CAV levels (HCAV) (see Table IV).

TABLE IV
CONFLICT DISTRIBUTION & INVOLVING RATIO BY TYPE OF INTERACTION

INTERACTION	Scenario					
	B	C	D	E	F	G
HDV-HDV*	0.60** (0.56) ***1.07***	0.29 (0.25) ***1.19***	0.20 (0.16) ***1.28***	0.06 (0.04) ***1.52***	0.01 (0.00) ***1.85***	0
LCAV-HDV	0.16 (0.15) ***1.09***	0.21 (0.18) ***1.17***	0.18 (0.14) ***1.29***	0.13 (0.09) ***1.49***	0.04 (0.02) ***2.16***	0
HCAV-HDV	0.05 (0.04) ***1.30***	0.12 (0.07) ***1.58***	0.17 (0.10) ***1.67***	0.13 (0.07) ***1.83***	0.06 (0.03) ***2.36***	0
Sum –HDV***	0.81 (0.75) ***1.08***	0.62 (0.50) ***1.24***	0.55 (0.40) ***1.38***	0.32 (0.20) ***1.62***	0.11 (0.05) ***2.22***	0
HDV-LCAV	0.13 (0.15) ***0.87***	0.16 (0.18) ***0.91***	0.14 (0.14) ***1.00***	0.10 (0.09) ***1.13***	0.03 (0.02) ***1.39***	0
LCAV-LCAV	0.04 (0.04) ***0.93***	0.12 (0.12) ***1.01***	0.13 (0.12) ***1.05***	0.24 (0.20) ***1.20***	0.25 (0.16) ***1.55***	0.02 (0.01) ***2.25***
HCAV-LCAV	0.01 (0.01) ***1.29***	0.07 (0.05) ***1.32***	0.12 (0.09) ***1.38***	0.24 (0.16) ***1.52***	0.40 (0.22) ***1.80***	0.23 (0.09) ***2.56***
Sum –LCAV	0.18 (0.20) ***0.90***	0.35 (0.35) ***1.00***	0.39 (0.35) ***1.11***	0.58 (0.45) ***1.29***	0.68 (0.40) ***1.70***	0.25 (0.10) ***2.50***
HDV-HCAV	0.00 (0.04) ***0.09***	0.01 (0.08) ***0.16***	0.02 (0.10) ***0.21***	0.02 (0.07) ***0.23***	0.01 (0.03) ***0.34***	0
LCAV-HCAV	0.00 (0.01) ***0.08***	0.01 (0.05) ***0.15***	0.02 (0.09) ***0.21***	0.03 (0.16) ***0.22***	0.06 (0.22) ***0.30***	0.05 (0.09) ***0.61***
HCAV-HCAV	0.00 (0.00) ***0.00***	0.01 (0.02) ***0.23***	0.02 (0.06) ***0.26***	0.04 (0.12) ***0.34***	0.14 (0.30) ***0.46***	0.69 (0.81) ***0.85***
Sum –HCAV	0.00 (0.05) ***0.00***	0.03 (0.15) ***0.20***	0.06 (0.25) ***0.24***	0.09 (0.35) ***0.26***	0.21 (0.55) ***0.38***	0.74 (0.90) ***0.82***

**The second vehicle in the interaction column represents the follower vehicle. E.g., in LCAV-HDV, HDV is the follower.*
****The first value is the conflict distribution by type of interaction, the value in brackets is the probability of that interaction in the fleet, the bolded value is the involving ratio of the vehicle interaction (see Eq. 3)*
*****The gray shaded rows represent the sum of all interactions where the follower vehicle is indicated after Sum-.*

Table IV exhibits the conflict distribution by vehicle interaction as a conflict proportion to the total number of conflicts in the scenario, normalized by the sharing percentages of the vehicle types, obtaining an involving ratio of that interaction (the values in bold). Table IV includes the results along the scenarios B to G (A and I scenarios were excluded because all the vehicles were HDV and L4 vehicles respectively). In general, Table IV shows that when HDV is the follower vehicle (-HDV), the involvement ratio is always larger than one. Moreover, the involvement ratio increases with increasing the penetration rates of CAV (scenarios E, F, G), indicating the higher probabilities of HDV's responsibility in such scenarios. Specifically, it ranges from 1.26 to 2.2 (as shown in the first gray shaded row), indicating that HDV are involved in conflicts as followers between 8% and 122% more than its sharing percentage on fleets. Previous studies have shown similar results. Morando *et al.* [14] found that if the penetration rate of L4 vehicles is 50%, the ratio of HDV-HDV and L4-HDV conflicts by the total conflicts equals to 0.88. In parallel, Sinha *et al.* [15] demonstrated that crash rate of HDV-HDV is much higher than L4-HDV while L4 vehicles penetration rate is up to 50%. A similar pattern is shown in scenarios E, F, and G related to conflicts involving LCAV as a follower (HDV-LCAV, LCAV-LCAV, and HCAV-LCAV). It fact, the highest involving ratio is reached on scenario G for the interaction HCAV-LCAV (2.56). Therefore, when LCAV and HCAV are the unique types of vehicles on the fleet, the LCAV are responsible for most of the conflicts. Additionally, in scenario G, the high penetration rate of HCAV (90%) leads to highly involving them in conflicts (a 74 % of conflicts HCAV is the follower vehicle). This result agrees somehow with Morando *et al.* [14]. When L4 vehicles presented a 75% penetration rate L4-L4 and L4-HDV represented 95% of total conflicts. However, whenever a HCAV in a conflict (interaction) is the follower, the results indicate a considerably low involvement ratio. It ranges from 0.20 to 0.82 (as shown in the last gray shaded row in Table IV), indicating that HCAV are involved in conflicts as followers from 80% to 18% less than its sharing percentage on fleets. The highest involving ratio for HCAV as a follower (0.85) is reached for the interaction HCAV-HCAV in scenario G

D. The Follower Vehicle As A Decision-maker

After looking at vehicles involved in traffic conflicts, the follower (*i.e.,* the second vehicle in a conflict) was considered as the vehicle mostly carrying the load in decision making and presenting proper behavior. Table V presents the follower conflict-involving ratio for each vehicle type in each scenario (see Eq. 2).

The conflicts where HDV is the follower vehicle is higher than the expected ones in all scenarios, and it increases as the penetration rate of CAV levels increases (*i.e.,* its ratio is always over one and its value increases across the scenarios, ranging from 1.08 to 2.22). This result shows that HDV, that is fully reliant on human's behavior, contributes more in increasing traffic conflicts. L1 vehicles, with limited assistant systems, also present a similar effect on safety and they could be a major inductor to generate conflicts in all scenarios.

On the other hand, L2 vehicles with more driving control in both the longitudinal and lateral directions have a lower propensity to participate as followers at potential conflicts than HDV and L1 vehicles in scenarios B, C, and D, where L2 vehicles are considered more advanced CAV. However, they reach larger values (1.14, 1.59, and 2.56) when they share traffic flow with more advanced CAV (L3 and L4 vehicles) in scenarios E, F, and G, respectively. L3 vehicles show the same pattern as L2, but with much lower conflict ratios, indicating the safety benefit of increasing driving assistance technologies. Lastly, L4 vehicles present ratios below 1 in all scenarios, and they could be considered as the safest vehicles, as they hardly contribute as followers towards causing either rear-end or lane change conflicts.

TABLE V
THE FOLLOWER CONFLICT INVOLVING RATIO FOR SEVERAL VEHICLE TYPES

	Vehicle type				
Scenario	**HDV**	**L1**	**L2**	**L3**	**L4**
A	1 (100%)*	-	-	-	-
B	1.08 (75%)	1.05 (10%)	0.75 (10%)	0.09 (5%)	-
C	1.24 (50%)	1.20 (10%)	0.92 (25%)	0.16 (10%)	0.16 (5%)
D	1.38 (40%)	1.32 (15%)	0.95 (20%)	0.21 (15%)	0.23 (10%)
E	1.62 (20%)	1.48 (20%)	1.14 (25%)	0.25 (20%)	0.27 (15%)
F	2.22 (5%)	1.95 (10%)	1.59 (30%)	0.34 (30%)	0.43 (25%)
G	-	-	2.56 (10%)	1.17 (40%)	0.54 (50%)
H	-	-	-	1.11 (25%)	0.96 (75%)
I	-	-	-	-	1 (100%)

** between ( ) value is the penetration rate of vehicle in that scenario*

These results present evidence about the concept in literature that CAV may increase the safety benefit and enhance driving performance as the level of connection and automation of the vehicles increases. Nevertheless, previous research that examined vehicle engagement in conflicts did not analyze the participation of the follower vehicle as a tentative inductor of traffic conflicts; moreover, they only analyzed L2, L4, or both types of vehicles as a unique type of CAV when they presented results and did not perform a systematic and complete exploration of the outcomes [11]–[15], [19], [26],[30].

V. CONCLUSION

This study examined the impact of the gradual introduction of CAVs on the traffic safety of a motorway using Aimsun Next 20 microsimulation software. Fifteen parameters related to Gipps' traffic model were considered for each CAV level, including the distinct behavior of passenger cars and trucks. In addition, the V2V connectivity network was modeled using the V2X Aimsun API extension. Subsequently, an SSAM was used to compute the potential traffic conflicts generated under nine simulated heterogeneous scenarios combining various vehicle types in different percentages. The TTC threshold for conflict identification in the SSAM was maintained at its default value (1.50 s) for human behavior and low levels of automation (L1 and L2 vehicles), and lowered (0.75 s) for high levels of automation (L3 and L4 vehicles), owing to the higher capabilities expected from these vehicles.

This study resulted in several interesting findings. The traffic flow dynamics obtained by studying the distribution rate of vehicle acceleration/deceleration and velocity difference showed that fleets with high penetration rates of high-level CAVs are, in general, more harmonic. The resulting traffic conflicts tended to decrease as the penetration of CAVs into the road increased. However, this study found that significant conflict reduction could be achieved in the early stages of CAV introduction (up to 60% of CAV participation). Scenarios with further penetration of CAVs on the roads improve safety, but not to the same extent as in scenarios with lower penetration rates. In addition, the vehicle involvement ratio decreases with increasing levels of automation and connectivity. However, this is mainly related to the vehicles shared in the traffic fleet. For instance, L2 vehicles were less involved in conflicts when human control was prevalent, whereas their involvement in conflicts was greater in scenarios where they shared the road with L3 and L4 vehicles only. Likewise, considering the follower vehicle to be regularly responsible for decision-making in a conflict, the main finding was that the involvement ratio of follower vehicles decreases as connectivity and automation levels increase. Moreover, L3 and L4 vehicles exhibited less than the expected responsibility (conflict ratio below 1) in almost all scenarios.

The main contributions of this research as a simulation-based study on the traffic safety of CAV implementation are as follows: (1) a wide range of parameters were calibrated to robustly cover CAV behavior; (2) all CAV levels were modeled, analyzed, and discussed; (3) nine different scenarios with fleets mixing different CAV levels, penetration rates, and vehicle types (passenger cars and heavy vehicles) were considered to present a comprehensive and realistic scheme of CAV introduction; and (4) traffic safety was studied from various perspectives, namely, through traffic flow dynamics, conflict reduction, vehicle involvement, and conflict ratio of the follower vehicle as a decision-maker).

Despite these contributions, the study is limited to one type of road section (motorway) and traffic conditions (free-flow). A similar study but focused on urban roads and/or intersections with different traffic conditions (congestion) could provide complementary results. In addition, although the transition from human to autonomous driving systems is expressed by the CCAV FHWA algorithm parameters, it has not been applied comprehensively for car-following and lane-changing models. Hence, future work could emphasize driving transitions. In any case, more studies are still needed to confirm the CAV traffic flow model calibration. In fact, the parameters used for CAV calibration have a direct influence on the safety analysis herein reported, thus, if other values are assigned to these parameters, the outcomes may change. Future research should focus on a sensitivity and optimization analysis of the parameters used in CAV calibration to achieve the best model performance. Lastly, real CAV data could be employed to explore other traffic safety aspects, such as determining more accurate TTC thresholds and other surrogate measures for different CAV levels.

APPENDIX A
MICROSIMULATION MODEL VALIDATION

This appendix illustrates the results of the followed criteria in this study in traffic volumes and travel time validation of the microsimulation model, following the Roads and Maritime Services modeling guidelines [45]:

1. *Geoffrey E. Havers (GEH) results:*

$$GEH = \sqrt{\frac{2\,(M-C)^2}{M+C}} \tag{A.1}$$

where M is the hourly traffic volume from a link or point of the modeled network and C is the real-world hourly traffic. Traffic volumes were validated using Eq. A.1 at 15 min intervals and per vehicle type. The lowest and highest values of observed (veh/15 min), modeled (veh/15 min), and GEH volumes during the one-hour simulation period at 15-min intervals are shown in Table A.1 for each traffic count location (Fig. 1).

TABLE A.1.Traffic 15 minutes volume validation using GEH statistic

Northbound direction						
Detector	Observed (veh/15minutes)		Modeled (veh/15minutes)		GEH	
	PC	HV	PC	HV	PC	HV
PK-131	577 - 671	21 - 37	494 - 552	19 - 36	**3.59 – 5.42**	**0.17 – 0.86**
PK-129	872 - 941	59 - 68	834 - 890	54 - 62	**0.03 – 1.69**	**0.67 – 1.00**
PK-123	566 - 675	17 - 29	523 - 606	18 - 31	**0.53 – 2.73**	**0.22 – 0.37**
PK-119	250 - 285	21 - 29	195 - 261	19 - 28	**1.09 – 4.49**	**0.40 – 0.80**
PK-117	164 - 212	18 - 27	165 - 209	17 - 27	**0.07 – 0.22**	**0.00 – 0.39**
PK-111	117 - 151	18 - 28	112 - 159	15 - 30	**0.47 – 0.79**	**0.20 – 0.74**

Southbound direction						
Detector	Observed (veh/15minutes)		Modeled (veh/15minutes)		GEH	
	PC	HV	PC	HV	PC	HV
PK-117	176 - 231	20 - 28	168 – 227	21 - 29	**0.26 – 0.77**	**0.19 – 0.58**
PK-119	339 - 386	26 - 32	326 – 390	26 - 30	**0.11 – 0.71**	**0.19 – 0.57**
PK-125	759 - 874	112 - 132	756 – 869	90 - 121	**0.11 – 0.44**	**0.98 – 2.19**
PK-132	262 - 371	83 - 116	271 – 376	86 - 119	**0.22 – 0.55**	**0.28 – 0.88**

The Roads and Maritime Services modeling guidelines [45] suggest that 85% and 100% of traffic volumes should render GEH statistics of less than 5 and 10, respectively. Results in Table A.1 satisfy both conditions, which suggests that the modeled network adequately reflects the real network and it is ready to perform the microsimulation.

2. *R^2 of the observed vs modeled volumes plot:*

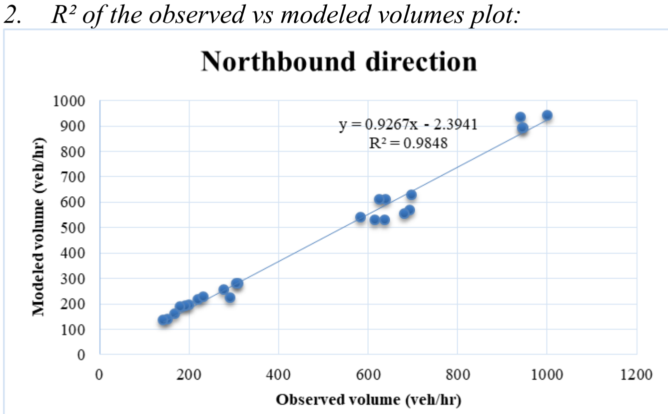


Fig.A.1: Observed volumes vs modeled volumes in northbound route

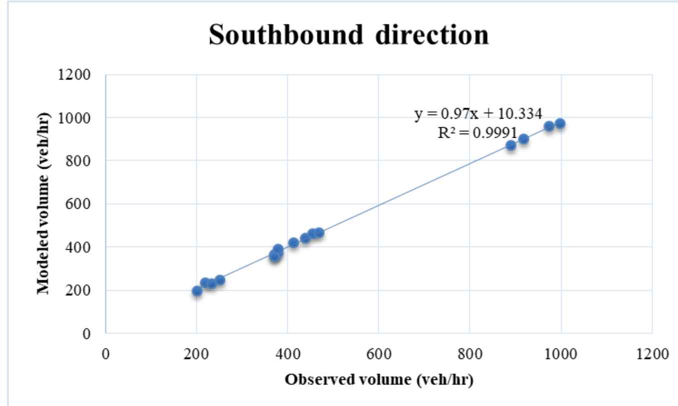


Fig.A.2: Observed volumes vs modeled volumes in southbound route

3. *Average travel times for each route:*

The cumulative graphing of average travel time by section:

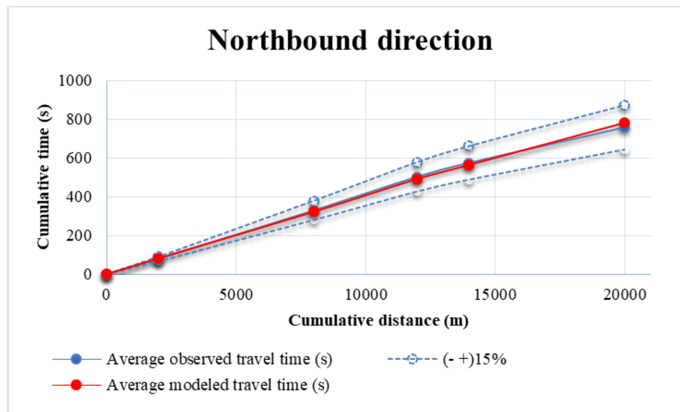


Fig.A.3: Travel time comparison for the northbound route

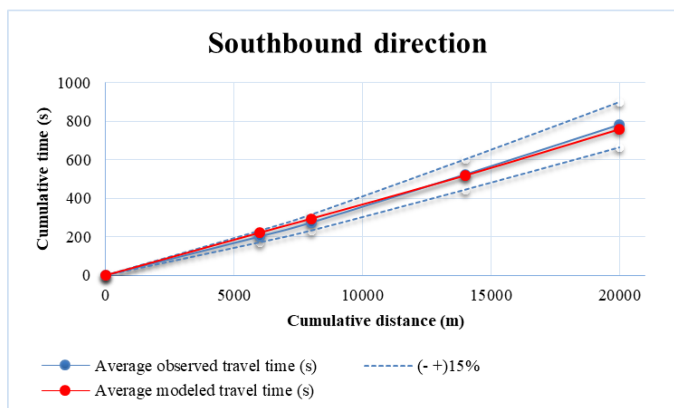


Fig. A.4: Travel time comparison for the southbound route

APPENDIX B

CALIBRATION OF CAV LEVELS (DRIVING PARAMETERS MODELED IN AIMSUN NEXT, GIPPS' MODELS)

I. *Calibration of CAV levels*

I.A. Calibration of car-following model' parameters:

Table B.1 shows the parameters used for calibration of car-following model.

Speed acceptance: CAVs are predicted to achieve more speed uniformity and speed acceptance of speed limits with increasing CAV levels [1], [6], [46]. The default values for the HDV are 1.1 for PC and 1.05 for HV (both operate at speeds greater than the speed limit), whereas Mesionis *et al.* [50] used a value of 1.0 for L4 vehicles, whereas Guériau and Dusparic [19] used 1.05 for L2 vehicles and 1.0 for L4 vehicles, respectively. Therefore, the same values were used, while in the cases of L1 and L3 vehicles, we kept the HDV's value with lower deviation for L1 vehicles, and we kept the same values of L4 vehicles for L3 vehicles, as they operate approximately with the same advanced systems.

Clearance (m): The clearance that a vehicle maintains with the preceding vehicle in the traffic stream is adopted mainly from the ATKINS [1] report and other studies (*e.g.,* [7], [11], [14], [19], [46]) based on minimum space headway values. In addition, following cautious driving behavior, the clearance increases with increasing automation level.

Guidance acceptance (%): increases as the CAV level increases from 70% for HDV to 100% for L4 vehicles following Stanek *et al.* [46] assumption that L4 vehicles could have about 25% better detection system. In the case of trucks, driving operations are generally more homogenous and follow the leaders, as they must adhere to other restrictions (other laws and speed limits) [51]. Therefore, 100% guidance acceptance was maintained at all the levels.

Reaction time (s): The default value for HDV is 0.8 s. Most previous studies that used other software in calibration did not consider this parameter. However, Zhang *et al.* [12] addressed the value extracted from adaptive cruise control real data (*i.e.,* L1 or L2) to be 0.50 s. Other authors [11], [50] suggested that this value should be lower in L2 and L3 vehicles and approximately zero for L4 vehicles to reflect the effect of connection-automation technologies. However, as L1 and L2 vehicles operate under human driver control, they maintained the same value as for HDV in their study. The same behavior will occur on unexpected stops, which require highly connected technology or referring to the driver.

Acceleration and deceleration (m/s²): Their values are discussed in abundance in CAV calibration [1], [41], [46]. For acceleration, some of these studies proposed to maintain the same values [3], [4], [46], and represent the change between vehicles only with headway values. However, the others either increased or decreased the acceleration of L4 vehicles. [1], [11], [14] followed an increasing argument for CAV. Stanek *et al.* [46] mentioned this scenario if the driving behavior is suggested to be assertive. Other studies [19], [41], [52] considered a lower value for L4 vehicles than for HDV, with lower deviations. As this study considers the cautious CAV driving hypothesis, it follows [12], [19] values in decreasing both maximum acceleration and normal deceleration with increasing CAV levels. However, it also follows these studies [12], [19], [46] in keeping the same value of maximum deceleration for all levels, indicating that this parameter is used in emergence situations and it could be reflected by the same magnitude regardless of the driving style, as it is related more to the vehicle motor capacity, not to driving behavior.

Sensitivity factor: In cautious driving, CAV are supposed to be more sensitive to leader deceleration to maintain a safe distance (clearance higher than that kept in HDV-HDV interaction). Thus, the value of the sensitivity factor is expected to be higher than 1.00 (the vehicle overestimates the leader deceleration) for high levels of automation (L3 and L4 vehicles) and 1.0 for levels that are still under human control all the time (L1 and L2 vehicles). Practically, a sensitivity analysis for the potential conflicts resulting from applying the values 0.5, 0.75, 1.0, 1.25, 1.5 in L4 vehicles was used to analyze this factor. The values 0.5 and 0.75 (if the follower underestimated the leader deceleration) have shown 31.5% and 33.7% more potential conflicts than the default value (1.0) without significant difference between them but with significant differences with the other values (1.0, 1.25, and 1.5). The values 1.25 and 1.5 (if the follower overestimated the leader deceleration) showed a decrease in the potential conflicts by about 21.2% and 24.1% respectively, indicating the safety benefit of CAV. Again, these values (1.25 and 1.5) did not show significant differences. Our decision for this value was to increase the value above 1.0 for high automation CAV levels, as the considered driving style is cautious.

Gap (s): Previous studies [4], [19], [50] have used the values of 1.2 and 1.5 s for HDV (for PC and HV, respectively), 0.8 s for L2 vehicles, and 0.6 s for L4 vehicles. These values were used, and in-between values were adopted for the L1 and L3 vehicles.

I.B. Lane-change model parameters:

Table B.1 shows the parameters used for calibration of lane-change model.

Overtake speed threshold (%) is the percentage of the desired speed of a vehicle below which the vehicle may decide to overtake. This means that whenever the leading vehicle drives slower than the overtake speed threshold (in percentage) of its desired speed, the vehicle will try to overtake [50]. Papazikou *et al.* [41], Mesionis *et al.* [50], and Weijermars *et al.* [7] (conducted within the Aimsun API) proposed lower values for L4 vehicles (80% or 85%) than for HDV. In this study, we used the proposed value of 85% for L3 and L4 vehicles and maintained 90% for all levels of automation that are still under human control (HDV, L1, and L2 vehicles) because this parameter is related to driver decision.

Imprudent lane changing: This study followed [41] argument in that HDV could still change lanes even after assessing an unsafe gap (the same for L1 and L2 vehicles that are still under human control), while high automation levels (L3 and L4 vehicles) will not show this imprudent behavior, especially in the cautious mode.

Cooperate in creating a gap: Multiple assumptions have been made for this parameter. Stanek *et al.* [46] ticked the choice just for AV, indicating that vehicles of this type can cooperate in creating a gap for lane changing. Guériau and Dusparic [19] modeled a value of 0.5 (50% cooperation) for HDV and L2 vehicles and a value of 1.0 (always cooperate) for L4 vehicles (for both PC and HV). On the other hand, for the studies that used Aimsun API, Mesionis *et al.* [50] ticked the parameter for HDV and both L4 vehicle driving styles, whereas Papazikou *et al.* [41] supposed that cooperation will be present in HDV but not in L4 vehicle driving styles. In this study, we believe that one of the technological benefits could be the ability of CAV to be more cooperative in creating gaps [19], [52]. Thus, we followed the logic of ticking cooperation behavior for vehicles L3 and L4.

Aggressiveness level: in-gap acceptance to make a lane change. Papazikou *et al.* [41] proposed values of 0-0.25 for L4 assertive driving and the value 0.0 (without any aggressiveness level) for cautious driving. Mesionis *et al.* [50] assumed that L4 vehicles should show 0.0 aggressiveness whatever the driving style. This study assumed that the aggressiveness level would still be 0-1 for L1 vehicles, and it would decrease with more assistance advance systems (L2 vehicles) to 0-0.5. Afterward, it should show 0.0 aggressiveness for high technologies in L3 and L4 vehicles, particularly as we modeled the cautious driving style.

Distance zone factor (Look ahead distance factor): As CAV are supposed to cooperate in creating gaps, it leads to improvements in their maneuvers [41], [50]. Therefore, the zones that are considered as lane-change distances are modified to larger zones following [41] values for L4 cautious driving and in-between values for L3 vehicles. On the other hand, for HDV, L1, and L2 vehicles, the value was kept the same as that of the main controller in the driving process.

II. Gipps' Car-following model

Vehicle driving behavior related to each CAV level is modified using the Aimsun Next API Gipps model. The Gipps [48] model is used to control the parameters of the car-following algorithm. This control is achieved by calibrating various local parameters within the microsimulation, such as the type of driver (*i.e.,* speed limit acceptance of the vehicle), the geometry of the section (*i.e.,* speed limits on the section, speed limits on turns, etc.), or the impact of vehicles on adjacent lanes. However, acceleration and deceleration are the two main elements in the Gipps model. The first reflects a vehicle's willingness to reach a certain desired speed, whereas 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 attain during period (t,t+T) is given by:

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

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

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

$$V_b\,(n,t+T) = d(n)\,T$$
$$+\sqrt{d(n)^2T^2 - d(n)\left[2(x(n-1),t) - s(n-1) - x(n,t)) - V(n,t)T - \frac{V(n-1,t)^2}{d^{\prime}(n-1)}\right]} \qquad \text{(B.2)}$$

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

The minimum of these two speeds is the speed of vehicle *n* during interval *(t, t+dt)*:

$$V(n,t+dt)= min\{V_a(n,t+dt),\ V_b(n,t+dt)\} \qquad \text{(B.3)}$$

The integration of speed is then used to update the position of vehicle n along the current lane. Different methods have been used to integrate acceleration and deceleration phases. The rectangular method is used to integrate the acceleration phase, which corresponds to the following equation:

$$x(n,t+dt) = x(n,t) + V(n,t+dt)dt \qquad \text{(B.4)}$$

The trapezoid method is used for deceleration phase integration as follows:

$$x(n,t+dt) = x(n,t) + 0.5(V(n,t) + V(n,t+dt))\times dt \qquad \text{(B.5)}$$

The estimated deceleration of the leader is a function of the Sensitivity Factor (α), which is defined per vehicle type:

$$d'(n-1) = d(n-1) \times \alpha \qquad \text{(B.6)}$$

When $\alpha < 1$, the vehicle underestimates the leader's deceleration, becoming more aggressive and shortening the distance between itself and the leader. When $\alpha > 1$, the vehicle overestimates the leader's deceleration; as a result, the vehicle becomes more cautious, increasing the gap in front of it. As a constraint of the deceleration component, the model also includes the minimum headway between the leader and follower, which is applied before updating position *x(n,t+T)*. The minimum headway constraint is expressed as follows:

If x*(n-1, t+T) – [x(n,t) + V(n, t+T)T] V(n, t+T) . MinHW(n)*

Then

$$V(n,\ t+T) = \frac{x(n-1,t+T)-x(n,t)}{MinHW(n)+T} \qquad \text{(B.7)}$$

where *MinHW(n)* is the minimum headway between vehicle *(n)* and vehicle *(n+1).*

III. Gipps' Lane-changing model

On the other hand, lane-changing is incorporated as a decision process in Gipps' model [49], analyzing the *necessity* (e.g., for turn maneuvers determined by the route), *desirability* (to reach the desired speed when the leader vehicle is slower), and *feasibility* (using forward, backward, and adjacent gap evaluation) of a lane change depending on the position of the vehicle in the road network with respect to the lane geometry and adjacent vehicles.

Consequently, the lane-changing of each vehicle *i* in section *s* has five aspects to model:

			HDV				L1				L2				L3				L4			
Parameters	**Definition**	**Hint work**	**Mean**	**dev**	**Min.**	**Max**	**Mean**	**dev**	**Min.**	**Max**	**Mean**	**dev**	**Min.**	**Max**	**Mean**	**dev**	**Min.**	**Max**	**Mean**	**dev**	**Min.**	**Max**
Speed acceptance	How much vehicles could take a speed greater than speed limit	[1], [6], [19], [50]	**1.1 (1.05)***	0.1 (0.1)	0.9 (0.85)	1.3 (1.25)	**1.1 (1.05)**	0.05 (0.1)	1 (0.85)	1.2 (1.25)	**1.05 (1.05)**	0.05 (0.05)	0.95 (0.95)	1.15 (1.15)	**1 (1)**	0.05 (0.05)	0.9 (0.9)	1.1 (1.1)	**1 (1)**	0.05 (0.05)	0.9 (0.9)	1.1 (1.1)
Clearance (m)	Distance that vehicle keeps with the preceding one when stopped	[1], [7], [11], [13], [14], [19], [46]	**1 (1.5)**	0.3 (0.5)	0.5 (1)	1.5 (2.5)	**1 (1.5)**	0.2 (0.5)	0.6 (1)	1.4 (2.5)	**1 (1.2)**	0.2 (0.3)	0.6 (1.2)	1.4 (2.1)	**1.5 (2)**	0.1 (0.1)	1.3 (1.9)	1.7 (2.2)	**1.5 (2)**	0.1 (0.05)	1.3 (1.95)	1.7 (2.1)
Guidance acceptance (%)	The probability that a vehicle will follow the recommendations	[46]	**70 (100)**	10 (10)	50 (80)	90 (100)	**80 (100)**	10 (10)	60 (80)	100 (100)	**80 (100)**	10 (10)	60 (80)	100 (100)	**90 (100)**	5 (5)	80 (90)	100 (100)	**100 (100)**	0 (0)	100 (100)	100 (100)
Reaction time (sec)	The time to react in general	[41], [50]	**0.8 (0.8)**	-	-	-	**0.8 (0.8)**	-	-	-	**0.8 (0.8)**	-	-	-	**0.5 (0.5)**	-	-	-	**0.1 (0.1)**	-	-	-
Reaction time at stop (sec)	This is the time it takes for a stopped vehicle to react to the acceleration of the vehicle in front.	[41], [50]	**1.2 (1.3)**	-	-	-	**1.2 (1.3)**	-	-	-	**1.1 (1.2)**	-	-	-	**1 (1)**	-	-	-	**0.1 (0.1)**	-	-	-
Max acceleration (m/s²)	The highest value that the vehicle can achieve under any circumstances	[19],[21]	**3 (1)**	0.2 (0.5)	2.6 (0.6)	3.4 (1.8)	**3 (1)**	0.2 (0.5)	2.6 (0.6)	3.4 (1.8)	**2 (1)**	0.2 (0.5)	1.6 (0.6)	2.4 (1.8)	**1 (0.8)**	0.1 (0.3)	0.8 (0.6)	1.2 (1.2)	**1 (0.8)**	0.1 (0.3)	0.8 (0.6)	1.2 (1.2)
Normal deceleration. (m/s²)	The maximum deceleration that the vehicle can use under normal conditions	[12],[21]	**4 (3.5)**	0.25 (1)	3.5 (2.5)	4.5 (4.8)	**4 (3.5)**	0.25 (1)	3.5 (2.5)	4.5 (4.8)	**3.5 (3)**	0.2 (1)	3.1 (2)	3.9 (4.3)	**3 (2.5)**	0.2 (1)	2.6 (1.5)	3.4 (3.8)	**3 (2.5)**	0.2 (1)	2.6 (1.5)	3.4 (3.8)
Max deceleration (m/s²)	The most severe braking can be applied under special circumstances	[12], [19], [46]	**6 (5)**	0.5 (0.5)	5 (4)	7 (6)	**6 (5)**	0.5 (0.5)	5 (4)	7 (6)	**6 (5)**	0.5 (0.5)	5 (4)	7 (6)	**6 (5)**	0.5 (0.5)	5 (4)	7 (6)	**6 (5)**	0.5 (0.5)	5 (4)	7 (6)
Sensitivity factor	How much the vehicle could be sensitive to the deceleration of the leader	[41]	**1 (1)**	0 (0)	1 (1)	1 (1)	**1 (1)**	0 (0)	1 (1)	1 (1)	**1 (1)**	0.1 (0.1)	0.8 (0.8)	1.2 (1.2)	**1.1 (1.1)**	0.1 (0.1)	0.9 (0.9)	1.3 (1.3)	**1.2 (1.2)**	0.1 (0.1)	1 (1)	1.4 (1.4)
Gap (sec.)	How much override the headway calculated by car following model	[4], [19], [50]	**1.2 (1.5)**	0.2 (0.2)	0.8 (1.1)	1.6 (1.9)	**1 (1.5)**	0.2 (0.2)	0.6 (1.1)	1.4 (1.9)	**0.8 (1)**	0.1 (0.1)	0.6 (0.8)	1 (1.2)	**0.8 (1)**	0.05 (0.05)	0.7 (0.9)	0.9 (1.1)	**0.6 (0.8)**	0.05 (0.05)	0.5 (0.7)	0.7 (0.9)
Overtake speed threshold (%)	The threshold that delaminates an overtaking maneuver	[7], [41], [50]	**90 (90)**	-	-	-	**90 (90)**	-	-	-	**90 (90)**	-	-	-	**85 (85)**	-	-	-	**85 (85)**	-	-	-
Imprudent lane change	Defines whether a vehicle will still change lane after assessing an unsafe gap	[41]	**Yes (Yes)**	-	-	-	**Yes (Yes)**	-	-	-	**Yes (Yes)**	-	-	-	**No (No)**	-	-	-	**No (No)**	-	-	-
Cooperate in creating a gap	Vehicles can cooperate in creating a gap for a lane changing vehicle	[19], [50]	**No (No)**	-	-	-	**No (No)**	-	-	-	**No (No)**	-	-	-	**Yes (Yes)**	-	-	-	**Yes (Yes)**	-	-	-
Aggressiveness level	The higher the level, the smaller the gap the vehicle will accept, being a level of 1 is the vehicle's own length	[41], [50]	**0-1 (0-1)**	-	-	-	**0-1 (0-1)**	-	-	-	**0-0.5 (0-0.5)**	-	-	-	**0 (0)**	-	-	-	**0 (0)**	-	-	-
Distance zone factor (Look ahead distance 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	[41], [50]	**0.8 - 1.2 (0.8 - 1.2)**	-	-	-	**0.8 - 1.2 (0.8 - 1.2**	-	-	-	**0.8 - 1.2 (0.8 - 1.2)**	-	-	-	**1 - 1.25 (1-1.25)**	-	-	-	**1.1 - 1.3 (1.1-1.3)**	-	-	-

**values in ( ) are related to heavy vehicles (HV) calibration*

TABLE B.1. Parameters used for calibration of car-following model and lane-change model.

- Lane-changing zone distance calculation
- Target lanes calculation
- Vehicle behavior considering the target lanes
- Gap acceptance for changing lane
- Target gap and cooperation

Lane-changing zones are restricted by two parameters: look-ahead distance and critical look-ahead distance. Look-ahead is the upstream distance to the point where the vehicle is aware of its target lanes, where it is looking for a gap (downstream or adjacent) and trying to adapt their speed. The critical look-ahead is the upstream distance to the start of lane-changing, where vehicles are urgently trying to reach their valid lane, looking for gaps upstream, and reducing speed if necessary. The parameters were calculated by Liu *et al.* [53] by multiplying the time required for each zone by the speed limit of the section. In the Aimsun API, the perception of the look-ahead and critical look-ahead is provided as a factor range. For example, if the look-ahead distance is defined as 200 m, the minimum look-ahead factor is 0.9, and the maximum look-ahead factor is 1.2, the perceived distance will range from 180 m (0.9x200) to 240 m (1.2 x 200) using a uniform random distribution.

The microscopic model generates two sets of valid lanes considering the "Visibility distance" of all obstacles identified within the look-ahead and critical look-ahead distances. Then, the behavior of vehicles trying to reach the set of target lanes is defined by the following strategy:

- *If the current lane of the vehicle is not within the subset of valid lanes determined by the critical look-ahead zone, the behavior of the vehicle is determined by the critical look-ahead zone.*
- *If the current lane of the vehicle is within the subset of valid lanes determined by the critical look-ahead zone but outside that determined by the look-ahead distance, the behavior of the vehicle is determined by the look-ahead distance zone.*
- *If the current lane of the vehicle is within the subsets of valid lanes of both zones, the behavior of the vehicle is governed by the traffic conditions on that lane by applying the "overtaking maneuver model".*

Afterwards, the gap acceptance model is applied with the consistency of the car-following model. Two main constraints have been applied by Gipps to avoid artificial breakdown situations: (1) the Gipps car-following model is stable (*i.e.,* it does not require decelerations above the maximum desired deceleration); (2) the gap and speed remain positive throughout the deceleration process and at the end of it to avoid crashes and to follow a new leader in the target lane. According to the Gipps gap acceptance model, the two constraints can be achieved by fulfilling the following condition for both the upstream and downstream gaps at time *t*:

$$Gap_{\,Up} \geq max\,\{0, \frac{V^2\,k(t)}{2b\,k} + 0.5\,Vup(t)Tup + \max\left[0, (-\frac{V^2up(t)}{2b\,up} + \alpha\,up\,(1-0.5\alpha\,up)b\,up\,T^2up + (1-\alpha\,up)Vup(t)Tup)\right]\} \tag{B.8}$$

And

$$Gap_{\,Dw} \geq max\,\{0, \frac{V^2\,Dw(t)}{2b\,Dw} + 0.5\,Vk(t)Tk + \max\left[0, (-\frac{V^2k(t)}{2b\,k} + \alpha\,Dw\,(1-0.5\alpha\,Dw)b\,k\,T^2k + (1-\alpha\,Dw)Vk(t)Tk)\right]\} \tag{B.9}$$

where $Gap_{\,up}$ is the calculated upstream gap, $Gap_{\,Dw}$ is the calculated downstream gap, v_k is the speed of the subject vehicle, $v_{\,Up}$ and $v_{\,Dw}$ are the speeds of the preceding and following vehicles, α is the sensitivity factor, and T is the reaction time. The acceptance of the gap in the lane-changing model can be modified by defining the following parameters in the Aimsun API [40]: aggressiveness (allowing vehicles to enter shorter gaps without forcing the rear vehicle to brake) and imprudent lane-changing (vehicles can enter gaps that do not ensure car-following stability). Finally, the percentage of upstream vehicles that cooperate in the lane-changing model is defined for each automation level using the lane-changing cooperation parameter. An overtaking maneuver can also occur when the vehicle is in its set of valid lanes and changes lanes to pass another vehicle. The overtake speed threshold parameter was evaluated to promote or discourage overtaking. This means that whenever a vehicle is constrained to drive slower than the overtake speed threshold, which is expressed as a percentage of its desired speed, it will attempt to overtake. The default value was set to 90%. Appendix A demonstrates all the discussed parameters regarding the automation levels.

IV. Vehicles connectivity: CCAC and V2V network

Vehicle connectivity was modeled by designing a Vehicle Ad Hoc Network (VANet) using the V2X Aimsun Next extension (V2X Software Development Kit (SDK)) in addition to the driving assistance system built in Aimsun API (CACC). Only V2V connectivity is considered because V2I is predicted to cover the networks in the farthest future, whereas this study endeavors to capture a sooner reality.

The CACC model applies a forward collision warning algorithm proposed by the FHWA [53], where the simulated vehicles have a dynamic cruise control status using the gap regulation mode in platooning

Specifically, the CACC gap regulation mode works by assessing the gap-to-leader ratio at each time step and comparing it with lower/upper gap thresholds, which enables the vehicles to change between CACC and manual driving modes if the algorithm shows a potential collision.

CACC was applied by defining the percentage of vehicles equipped with this assistance system, keeping the default gap thresholds defined by the FHWA algorithm [53], and setting speed gain = 0.0125, distance gain = 0.45/s, time gap for leader = 1.5 s, time gap for follower = 0.6 s, lower gap threshold = 1.5 s and upper gap threshold = 2.0 s.

Regarding V2V connectivity, the V2X framework in Aimsun enables the modeler to implement connected VANets in the simulation. A VANet is a fleeting network formed by a collection of connected vehicles in close proximity to one another or a similarly connected roadside unit (RSU) (Fig. B.1). Aimsun [40] offers V2X extensions that make vehicles more aware of the presence and intentions of other nearby vehicles and assess the changes in vehicle behavior in response to that information. In addition, connectivity simulation can be used to investigate various communication quality and range scenarios, as well as different levels of connectivity penetration across the fleet of vehicles [40].

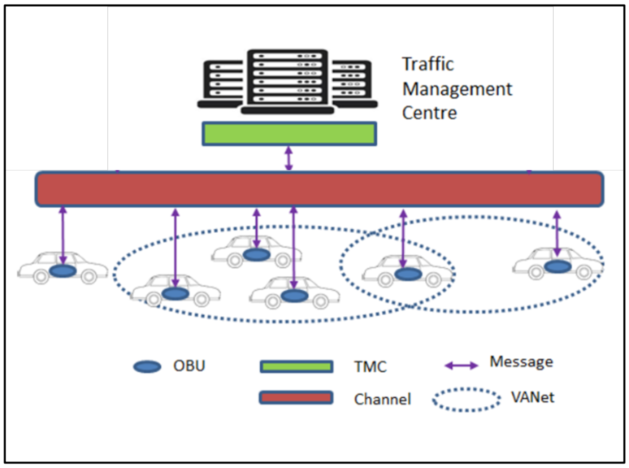


Fig. B.1 V2V connectivity network components and process [40]

V2V network consists of: (1) an onboard unit (OBU) equipped in CAV, which represents the receiver and transmitter of the vehicle; (2) channels that simulate the radio hardware and protocols providing communication among vehicles; (3) cooperative awareness messages, providing information about the presence, activity, and position of CAVs; and (4) a traffic management center (TMC), which combines the previous protocols and controls the entire connectivity process. Fig. 2 illustrates the V2V connectivity network components and process.

Vehicles transfer data within a space using defined messages over a communication channel connected to the OBUs on the vehicles. The vehicle-oriented communication channel issues messages to the TMC dedicated to managing communication in its local area. The TMC evaluates the information, and its actions are forwarded back to the equipped vehicles in the traffic network via channel signals. Finally, the vehicle rules engine, i.e., the class of rules used in simulation to evaluate and perform actions (before and after the time step, respectively), takes the V2X data from other vehicles and adds them to the vehicle's existing knowledge of the traffic in the space. The rules engine then adjusts vehicle behavior and decision-making by changing its longitudinal and lateral clearance, speed, acceleration, deceleration, and lane change process.

Considering the importance of channels in this process as a type of communication protocol used to transfer data between vehicles, channel design is acknowledged as a significant step in modeling V2V connectivity networks [54]-[57]. This is typically accomplished through the design of short-range Wi-Fi channels, such as IEEE 802.11p, or long-range LTE cell-based transmission channels [54]. In practice, there are specific protocols for each type of channel dealing with joining and leaving a data network, as well as dealing with the channel congestion that a network member (*i.e.,* vehicle in a VENet) must follow.

The V2X SDK Aimsun extension provides a default objected coded channel that simplifies the design of the significant characteristics of the channel protocol: the *latency,* which indicates the reliability and range of communication in a channel reflected by the delay in packet transmission, the *range* of transmission, and the *packet loss*, which is the percentage of non-received packets.

According to [54] and [57], the implementation of V2V connections requires a short-range connection channel; therefore, IEEE 802.11p was chosen in our VaNets design as the dedicated short-range communications (DSRC) protocol. This type of channel has shown (experimentally [56]) its greatest efficiency up to 250-300 m, thus a range of 250 m was chosen in this study. Furthermore, many experimental studies [54]–[57] have shown that the channel efficiency (latency and packet loss) depends on the probable number of vehicles connected to the channel range and their speed. The range in our case study could accomplish the largest studied category of connected vehicles (125 vehicles), and the registered speeds were 83-118 km/hr. Thus, the selected channel (IEEE 802.11p /250 m) was suggested to allow 2100 ms latency and 0.75% packet loss following the experimental data from the aforementioned studies.

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