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Research Article

In Search of Severity Dimensions of Traffic Conflicts for Different Simulated Mixed Fleets Involving Connected and Autonomous Vehicles

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This study aims to estimate the severity of conflicts that may arise from the introduction of connected and automated vehicles (CAVs) by examining the vehicle paths generated by microsimulations of mixed fleets of human-driven vehicles and CAVs with different levels of automation (L1-L4 vehicles). The study assesses the severity of conflicts using a holistic approach that considers three dimensions: (1) proximity to collision, via the time-to-collision (TTC) indicator; (2) potential consequences of a conflict, via single surrogate safety measures such as maximum speed (MaxS) and vehicle speed difference (DeltaS); and (3) a combination of both dimensions to assign severity scores, via TTC and velocity vectors. The study's findings suggest that moderate penetration rates of L3 and L4 vehicles (35–55%) show significant differences in the number of traffic conflicts with varying TTC values. Additionally, high penetration rates of L3 and L4 vehicles (above 55%) result in lower values of conflict consequences measures such as MaxS and DeltaS. Furthermore, the study shows that conflict consequences decrease if the follower is a L3 or L4 vehicle. The study's findings also reveal that there is a considerable reduction in high severity conflicts when the penetration rate of CAV levels reaches 50%, and the full operation of L4 vehicles results in a 75.5% reduction in high severity conflicts. Therefore, this study provides valuable insight into the potential severe conflicts during the transition period from manual vehicle operation to full CAV operation. Overall, the study's findings highlight the importance of assessing the severity of potential conflicts arising from the introduction of CAVs. By considering the proximity to collision and the potential consequences of conflicts, the study provides a comprehensive assessment of the severity of conflicts. This information can inform the development of policies and strategies to ensure the safe and responsible introduction of CAVs into our transportation systems.

1. Introduction

The forthcoming introduction of connected and automated vehicles (CAVs) on roads has motivated researchers to investigate their various implications, such as traffic delay, congestion, fuel emissions, and traffic safety. Although CAV manufacturers have progressed from CAV research to vehicle prototype production within several automation levels [1], the available (behavioral and crash) data can not sufficiently clarify the ambiguity surrounding the crash risks involving CAVs.

Accordingly, many studies have used the surrogate safety assessment model (SSAM), developed by the Federal Highway Administration, to analyze the vehicle trajectories gathered from a microsimulation platform to determine traffic safety. Several surrogate safety measures (SSMs) (e.g., time-to-collision (TTC), postencroachment time (PET), and deceleration rate) have been applied to estimate the probability of conflict. A traffic conflict is an evident instance in which two or more road users or vehicles are near each other in terms of space and time to the extent that the risk of collision exists if their movements do not change [2]. In traffic simulation-based studies, traffic conflicts can be determined by modeling traffic flow tracking to extract vehicle pathways over time. Accordingly, SSMs have been extensively employed to identify potential traffic conflicts when CAVs share roads. In most previous studies, CAVs typically have a high automation level (i.e., L4) [3–7]. However, other studies have also included several levels of automation [8–10]. In general, they found that increasing the penetration rates of CAV can significantly reduce the number of potential conflicts.

Although the impact of CAVs on traffic safety has been widely studied, to the best of the authors' knowledge, no study has thoroughly assessed the severity of conflicts in traffic streams resulting from the progressive introduction of CAVs. The novelty of this study is its comprehensive analysis of conflict severity involving CAVs under different simulated mixed fleets (i.e., human-driven vehicles (HDVs) and CAVs of different levels). In a review conducted by Zheng et al. [11], they highlighted that it is necessary to establish an adequate traffic conflict technique for measuring traffic conflict severity, applying a sensitivity analysis to select SSMs threshold and the utilization of a multidimensional definition of severity. Thus, this study considers these two research directions to devise a reliable technique for assessing the traffic conflict among CAVs. The present approach uses three dimensions for analyzing conflict's severity: (1) the proximity to a collision; (2) potential conflict consequences; and (3) a combination of proximity and consequences. The TTC threshold is considered the margin value for serious conflicts [12–14]. So, initially different TTC thresholds are tested in this study with the introduction of CAVs of various levels on roads. After identifying the key values for different TTC thresholds, the study examines the consequences of conflict severity using some SSMs, namely maximum speed (MaxS) and vehicle speed difference (DeltaS). The study then compares these values in various scenarios and types of vehicle interaction to gain insight into the impact of CAVs on traffic safety. Finally, a time-to-collision (TTC) to velocity change at collision (DeltaV) diagram (i.e., TTC/DeltaV chart) is developed for each automation level to derive a conflict severity score.

The remainder of this paper is organized as follows. In Section 2, the analysis of traffic safety and conflict severity of CAVs and manually driven vehicles reported in the existing literature is discussed. The study context modeled by Aimsun [15] and the CAV control algorithms and validation processes used are presented in Section 3. In Section 4, the severity analysis and its results are discussed. Finally, Section 5 summarizes the conclusions and limitations of the study as well as the recommended future directions for CAV traffic safety research.

2. Literature Review

This section presents the SSMs used to identify traffic conflict severity. Afterwards, the extent to which the conflict severity in the CAV field can be predicted is discussed.

2.1. SSMs and Conflict Severity. Crash rate and severity are direct indicators of traffic safety performance. However, crashes are rare, and data on aleatory events leading to crashes are not always statistically sufficient for studies. Because of this, SSMs are used to identify traffic conflicts and estimate their severity by analyzing recorded videos or a real-time analysis [16, 17], and/or traffic simulation outputs. In fact, by extracting vehicle pathways over time and evaluating their proximity and movements, vehicles close to collisions and with jerky movements are considered to be involved in more severe conflicts [18].

Most studies that used SSMs as traffic safety assessment tools implied that a substantial correlation exists between serious conflicts and crash severity [19–24]. However, deriving conflict severity from SSMs as an indicator has been widely debated, and several traffic conflict techniques have been developed over the decades.

Previous research has proposed several SSM thresholds to delineate risky/nonrisky conflicts. Uniform and nonuniform conflict severity zones were also created following various traffic conflict techniques and SSM indicators [25]. To predict conflict severity, time-based SSMs (e.g., TTC [26], PET [27], time-integrated TTC (TIT), and time exposed TTC (TET) [28]), deceleration-based SSMs (e.g., deceleration rate to avoid crash [29], maximum deceleration rate [30], and rear-end collision risk index [31]), and energy-based SSMs (e.g., DeltaV, extended DeltaV [32, 33], and conflict index [34]) have been used [35]. Accordingly, traffic conflict severity has been defined in terms of three different types of SSM.

Time-based and deceleration-based SSMs define severity as the proximity with respect to a crash. This is the most prevalent indication for studying traffic accidents and conflict severity [33]. However, the early decision-making criteria for severe/nonsevere conflicts mainly depended on the assessment of human observers by identifying severe events based on their proximity to a collision [19, 23]. Moreover, a time or space threshold that is commonly employed to align severe conflicts has multiple assumptions and validation values.

Energy-based SSMs define severity by another dimension: the consequences of the risk resulting from an interaction (conflict). The idea is that high kinematic forces resulting from vehicle interactions considerably affect road users and probably result in severe injuries and fatalities [2]. Over the years, researchers have indicated their high confidence in this type of indicator for predicting crash severity. Carlson [36] attempted to develop models for estimating the probability of injuries or fatalities in a crash based on variables, such as impact speed and vehicle mass; hence, DeltaV was used to predict injuries and fatalities. Evan [37] subsequently fitted several models using DeltaV to predict injuries and fatalities arising from conflicts. Nevertheless, because this indicator was not used for traffic conflict analysis until its recent incorporation into SSAM [2], the development of new equations was not distinctly pursued. Consequently, the classical Evan models [37] remained in use.

Finally, the third definition of traffic conflict severity is related to the concurrent proportioning of values to proximity and propensity dimensions and generating different severity levels. Conflicts with potentially high consequences

Table 1: Summary of previous studies about severity within CAV's analysis.

References	Data source	CAV considered	Context	Severity dimension	Severity measures
Sinha et al. [6]	Simulation	L4	2-Lane motorway	Proximity and consequences	TTC, Delta S
El-Hansali et al. [43]	Simulation	L4	6-Lane freeway	Consequences	MaxS, MaxD, MaxDeltaV
Rahman et al. [44]	Simulation	L1, L2	Arterial (61.15 km)	Proximity and consequences	TET, TIT, TERCRI, LCC, and NCJ
Zhang et al. [45]	Simulation	L4	4-Lane freeway (7 km)	Proximity and consequences	TET, TIT, TERCRI, and LCC
Laureshyn et al. [32]	Video analysis	—	Urban intersection	Proximity, consequences and levels of severity	T, DeltaV, extended DeltaV (T/DeltaV)
Souleyrette and Hochstein [38]	Simulation	—	Expressway intersections	Levels of severity	TTC/MaxDeltaV
van der Horst and Kraay et al. [39]	Manual conflict' observation	—	Various	Levels of severity	TTC and speeds at conflict
Sinha et al. [46]	Field data (crash data)	L4	Urban network	Consequences	Machine learning classifiers
Chen et al. [47]	Field data (crash data)	L4	Urban network	Consequences	Machine learning classifiers

TTC: time-to-collision, 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, DeltaV: velocity change at collision, MaxDeltaV: maximum DeltaV value of either vehicle in the conflict, 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, T: the expected time for the second (latest) vehicle to arrive at the conflict point, and extended DeltaV: models of the integration of T/DeltaV data.

and those that are observed close to the occurrence of crashes are found to have a high probability of severity during the interaction [32]. In the past, a simple human decision-making approach was employed to identify two zones distinguishing severe conflicts from the rest of the conflicts considering only the proximity threshold value of time. Subsequently, the International Committee on Traffic Conflict Techniques contributed to the development of several conflict techniques that aided in understanding crash occurrence and its potential severity manually (by observation). The objective was to establish severity in terms of several levels instead of simply splitting it into two categories (severe/nonsevere) [25, 32, 38]. Then, the levels were validated by studies conducted abroad. In the Dutch technique (i.e., DOCTOR), the conflicts in which speed is high and TTC is less than the threshold value are as deemed severe [39]. In addition, both DOCTOR and the Canadian traffic conflict technique [19] incorporate a subjective assessment in which a score (ranging 1–5) determines the probable conflict consequences based on evasive action, maneuvering, observed speed, and objective nearness-in-time indicator. The Swedish traffic conflict technique [21, 40–42] considers both the proximity in time and speed at which the conflict occurs to indicate severity and reflect the potential consequences implicitly. Equidistant parallel severity zones were established by dividing the resulting scores into several levels. The indicators used for deriving the severity levels were varied (e.g., vehicle speed and distance from a conflict site, required deceleration, and friction coefficient) [25]. Moreover, several proximity-to-collision thresholds have been proposed in traffic conflict technique research [33].

Other approaches have been employed by other researchers to indicate severity levels. For example, Souleyrette and Hochstein [38] developed an assessment score by defining and adding TTC and DeltaV scores. Then, some severity lines were fitted by drawing contours for equal assessment score areas. Similarly, Laureshyn et al. [32] incorporated the minimum time leading to an accident and DeltaV in a figure, thus overfitting the extended DeltaV values as severity lines for determining severity levels.

2.2. CAV Crash/Conflict Severity. Table 1 provides a summary of previous studies that discussed the severity terms and traffic conflict techniques, especially, those considering CAVs in their analysis.

There are some undergoing CAVs' tests on public roads in several locations in the United States. In those cases, some studies are able to analyze CAVs' crash severity based on real data. Sinha et al. [46] conducted a detailed safety analysis using the data from the California Department of Motor Vehicles (2014–2019). The reported data were used to develop various automated vehicle crash severity models that focused on the injuries for all crash types. However, owing to insufficient data on crashes involving CAVs, the factors that contribute to the severity of a CAV's crash are not well defined. Nevertheless, various machine learning approaches have been used to better understand CAV crash severity. Chen et al. [47] used a similar approach and found that among all the tested classifiers, Xtreme gradient boosting, a decision tree classification model, performs better in detecting injuries occurring in CAV crashes. Their findings show that if two automated vehicles crash at an intersection or are under adverse weather conditions (e.g., fog and snow), the severity of the crash significantly increases. Furthermore, crashes resulting in injuries are more likely to occur in locations with various land use patterns. Diverse land use (e.g., residential, commercial, and public) results in mixed traffic behaviors and changes in regional traffic flow, substantially affecting traffic safety.

By contrast, as researchers extensively employ SSMs to understand the safety implications of new traffic designs and alternative safety remedies better, modeling the safety consequences of CAVs and their interactions with HDVs is a relevant application of SSMs. In addition, owing to the limited introduction of CAVs, traffic microsimulation outputs have been used to produce SSMs rather than analyzing videos.

Both proximity and consequences dimensions have been used to analyze the severity of CAV conflicts. Several proximity SSM indicators have been employed, with TTC being the most prevalent indicator. TIT and TET have been also widely employed in parallel with TTC [44, 45, 48]. By contrast, the distributions of emergency braking [49], rear-end collision risk index [44, 50, 51], sideswipe (lane-change conflicts) traffic condition [51], and time exposed rear-end crash risk index [51] are all examples of deceleration-based SSMs for evaluating CAV traffic safety [51]. Other surrogate safety indicators, such as standard deviation of speed [51, 52], MaxS, and DeltaS [43, 46, 53], have been used as consequence indicators to assess CAV safety implications. However, to the best knowledge of the authors, no studies have combined all the severity dimensions in CAV traffic safety analysis.

In most previous studies, CAVs and HDVs were assessed using the same SSMs and thresholds (e.g., TTC = 1.5 s), and no specific values were considered for CAVs' conflict analysis [5, 43, 45]. By contrast, some researchers suggest that in dealing with CAVs, the default TTC value should be reduced because of their faster reaction times and shorter headways. For instance, Morando et al. [4] tested the ensuing conflicts of L4 vehicle penetration using three TTC thresholds: 1.50 s for any conflict involving HDVs and two lower values (i.e., 1.00 and 0.75 s) for L4–L4 interactions. They indicated that the TTC threshold is an important factor in demonstrating the benefit of CAV introduction in terms of safety. Guériau and Dusparic [8] and Weijermars et al. [54] proposed 0.75 s for determining conflicts involving CAVs. By contrast, Virdi et al. [7] used 0.50 s, and they claimed that regarding their assumption that the headway kept by CAVs is reduced to one-third, then the threshold defining the conflict should be also proportionally reduced. Evidently, to distinguish between severe and nonsevere safety critical events (conflicts), a sufficient threshold level must be defined. The definition of this value is a current challenge concerning conflicts involving CAVs that must be scientifically addressed.

tAs regards the results of previous studies analyzing traffic conflict severity in CAV areas, Rahman et al. [44] used TTC-derived measures (e.g., TET and TIT) as proximity indicators in addition to evasive action indicators (e.g., number of critical jerks and time exposed rear-end crash risk index) as consequence indicators in estimating traffic conflict severity when L1 and L2 vehicles enter a traffic stream. The results reveal that CAV penetration exceeding 60% significantly reduces the conflict severity at arterial segments and intersections. Sinha et al. [6] studied several SSMs (e.g., TTC, PET, MaxS) by analyzing their distributions at different penetration rates and estimating the corresponding crash rates to assess the conflict severity for L4 introduction. Their findings showed that traffic safety improves, and conflict severity and crash rates decrease when the roads are fully operated with L4 vehicles. However, the conflicts involving HDVs did not decrease in terms of frequency and severity. El-Hansali et al. [43] investigated traffic safety by comparing HDVs and L4 vehicles operating independently at a freeway section (i.e., 100% HDVs vs. 100% L4 vehicles). Contrary to expectations, greater values of severity indicators were observed in the case of L4 vehicles than in the case of HDVs. For example, a higher MaxS was obtained for either vehicle type during conflicts, and a higher MaxD was observed when only L4 vehicles occupied the road. Zhang et al. [45] conducted a study that focused on roadway configuration. Using proximity and consequences indicators (i.e., TTC, TIT, TET, time exposed rear-end crash risk index, and lane-changing conflicts), they investigated the safety of lanes dedicated for L4 vehicles with different penetration rates. They emphasized that establishing even one exclusive lane could increase safety because the conflict severity was significantly reduced in terms of longitudinal and lateral movements.

3. Methodology

Aimsun [15] has been used for microsimulation to estimate trajectories for the different types of vehicles considered. Subsequently, SSAM [18] was applied to extract surrogate safety indicators for the severity estimation process.

3.1. Study Context. As a test corridor, the study area of a three-lane two-way motorway segment (20.27 km of GR-30, an important road leading to Granada City, Spain) (illustrated in Figure 1) was modeled using Aimsun Next. The geometric design characteristics of the segment (e.g., road profile, curves, and lane detailing) were introduced using an imported Open Street Map of the segment. The chosen segment has 14 on-ramps and off-ramps and two major entry points. Traffic flow data were gathered using nine detectors installed in the area by the General Traffic Directorate (Dirección General de Tráfico (DGT)). The detectors register instantaneous speeds, traffic volumes, and vehicle type distributions (heavy vehicles vs. passenger cars) at 15-min intervals.

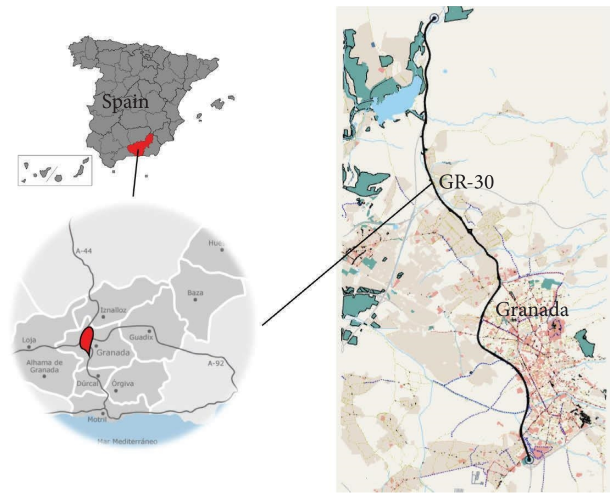


Figure 1: Study area: GR-30 roadway segment in Granada (Spain).

The imported file data from the DGT sensors for validation were selected for a regular day (Tuesday) and off-peak hour (10:00-11:00 am) because this study modeled a free-flow condition. The average instantaneous speed range was 83–118 km/h, and the traffic count was recorded every 15 min: 547−3570 pc/h and 89–260 hv/h were registered for the GR-30 northbound vehicles, and 809–3281 pc/h and 93–499 hv/h were registered for the GR-30 southbound vehicles.

3.2. Microsimulation Model and Scenarios. Aimsun was selected to calibrate the different automation levels of vehicles (from L0 to L4) because it provides specialized tools for CAVs. V2X extension was employed to model the connectivity between vehicles. The proposed analytical period for the microsimulation is 1 h; however, for traffic validation (volume and speed), this period was broken down to 15-min intervals to reflect the real traffic data recorded by the DGT's detectors better. Traffic operation data are generated using a small time step (i.e., 0.1 s, following previous studies [4, 5] to increase simulation accuracy and reduce the risk of losing vehicle movement details). The warm-up time was set to 18 min following Wunderlich et al. [55] (based on the road section length and the average speed of vehicles). Furthermore, the model operations were calibrated and validated following the modeling guidelines of Roads and Maritime Services [56]. Miqdady et al. [10] provide more details about this step.

After checking the validity of the modeled network, the "car-following and lane-change models" of Gipps [57, 58] that are variants of each travel condition are calibrated to fall within the proposed stochastic dynamic envelopes of CAVs. For instance, CAVs are supposed to have short reaction times, accept short gaps, cooperate in lane changes, etc. Tables 4 and 5 (in Appendix A) show all the parameters that are affected by different levels of vehicle automation in the car-following and lane-changing models of Gipps based on previous research [4, 5, 8, 43–45, 54, 59] and logic. The parameter definitions are summarized from the Aimsun user manual. The values summarized in Tables 4 and 5 are the inputs for the microsimulation models. They are provided as means and standard deviations and are normally distributed as suggested by Gipps models for both passenger cars and heavy vehicles.

The analysis attempted to cover a gradually introduction of CAVs with various fleet mixes that the real world may encounter. Accordingly, as justified in Miqdady et al. [10], nine mixed fleet scenarios with different CAV penetration rates were suggested. Table 2 lists the combinations of HDVs and vehicles with different automation levels (L1–L4) in each scenario.

Table 2: The studied mixed fleets' simulated scenarios.

Scenarios	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

3.3. Severity Analysis. To evaluate the traffic conflict severity in the simulated scenarios (i.e., the potential market introduction scenarios of CAV), this study considered the three questions presented by Laureshyn et al. [32]: (i) How can the proximity to a crash be measured? (ii) How can the severity of the consequences of a potential crash be measured? (iii) How can both dimensions be merged?

A few studies have analyzed the extent of conflict severity in the CAV context [6, 44]. However, they have neither considered all dimensions of severity combined nor analyzed all levels of automation. For the nine proposed scenarios, several SSM indicators were applied to determine both proximity and consequence dimensions at each conflict. The following section illustrates how this study addresses the previous research questions. The detailed framework is illustrated in Figure 2. The next section explains the approach followed to explore each severity dimension and presents the results obtained after applying these approaches.

4. CAV Severity Dimensions

4.1. Proximity Threshold. The most widely used indicator for investigating traffic proximity and conflict severity in HDV and CAV conflict analysis is TTC [35]. This indicator is defined as "the time that remains until a collision could occur if two successive vehicles maintain a speed difference" [28]. It is given by the following:

$$\mathrm{TTC}_i\,(t) = \begin{cases} \dfrac{x_{i-1}(t) - x_i\,(t) - l_{i-1}}{\mathrm{vi}\,(t) - \mathrm{vi} - 1\,(t)}, & \text{if } \mathrm{vi}\,(t) > \mathrm{vi} - 1\,(t), \\ \infty, & \text{if } \mathrm{vi}\,(t) \leq \mathrm{vi} - 1\,(t), \end{cases} \tag{1}$$

where *TTCi(t)* denotes the TTC value of the following vehicle, *i*, at a time instant; *t*, *x*, and *v* denote the time, position, and velocity of the vehicles, respectively; and l_{i-1} represents the length of the leading vehicle. A small TTC value indicates a high risk of collision at a given time instant.

To assess the severity of vehicle-following events, a TTC threshold must be defined to distinguish between severe and nonsevere conflicts [60]. Setting an universal TTC threshold for assessing conflict severity has become a matter of contention, particularly in the case of CAV introduction. A review of previous research reveals that several thresholds ranging 0.9–5.0 and 0.5–1.5 s have been proposed for various HDV traffic and driving conditions and for CAV scenarios, respectively [60]. Although this study analyzes traffic safety for CAV introduction scenarios, a unique value (i.e., 1.5 s) is proposed for conflicts involving HDVs or vehicles with low automation (L1 and L2) as follower vehicles (low CAVs, LCAV). The most commonly used value for HDV is 1.5 s [18]; and it is also the default value used in the SSAM. Sensitivity analysis was conducted to define a reasonable threshold for conflicts where a high level of automation vehicle (L3 and L4) is the follower (high CAVs, HCAV). Five different values (0.5, 0.75, 1.0, 1.25, and 1.5 s) were examined for the TTC threshold under each scenario to emphasize the appropriate value under various circumstances. Table 3 summarizes the number of conflicts when applying the different TTC values to determine whether there are significant changes by using one-way analysis of variance for each scenario. The changes resulting from applying any value and the base value (1.5 s) are listed in Table 3.

Table 3 shows that

(i) TTC does not present a significant influence on the number of conflicts at scenarios with low penetration rates of HCAV (scenarios D or below)

(ii) TTC presents a very significant influence on the number of conflicts at scenarios with high penetration rates of HCAV (scenarios G or over)

(iii) At intermediate scenarios (E or F), representing moderate penetration rates of HCAV, the number of traffic conflicts starts to present significant differences if the TTC value is below 1.0 s.

These results emphasize the importance of using different TTC values to obtain a reliable assessment of traffic safety related to high penetration of HCAV. Moreover, the results verify the theoretical vision of CAV introduction: when CAV penetration rate is high, traffic flow improves by achieving more harmonized speeds and by reducing reaction times that probably have a direct effect on the TTC threshold. These results agree with the values suggested in previous studies. Morando et al. [4] used two TTC values (0.75 and 1.0 s) to identify conflicts involving CAVs; both values were assumed to be appropriate. Other studies used 0.75 s as the TTC value [8] for fixed conflicts with CAV participation, and other studies reduced this threshold to 0.5 s [7, 61]. Papazikou

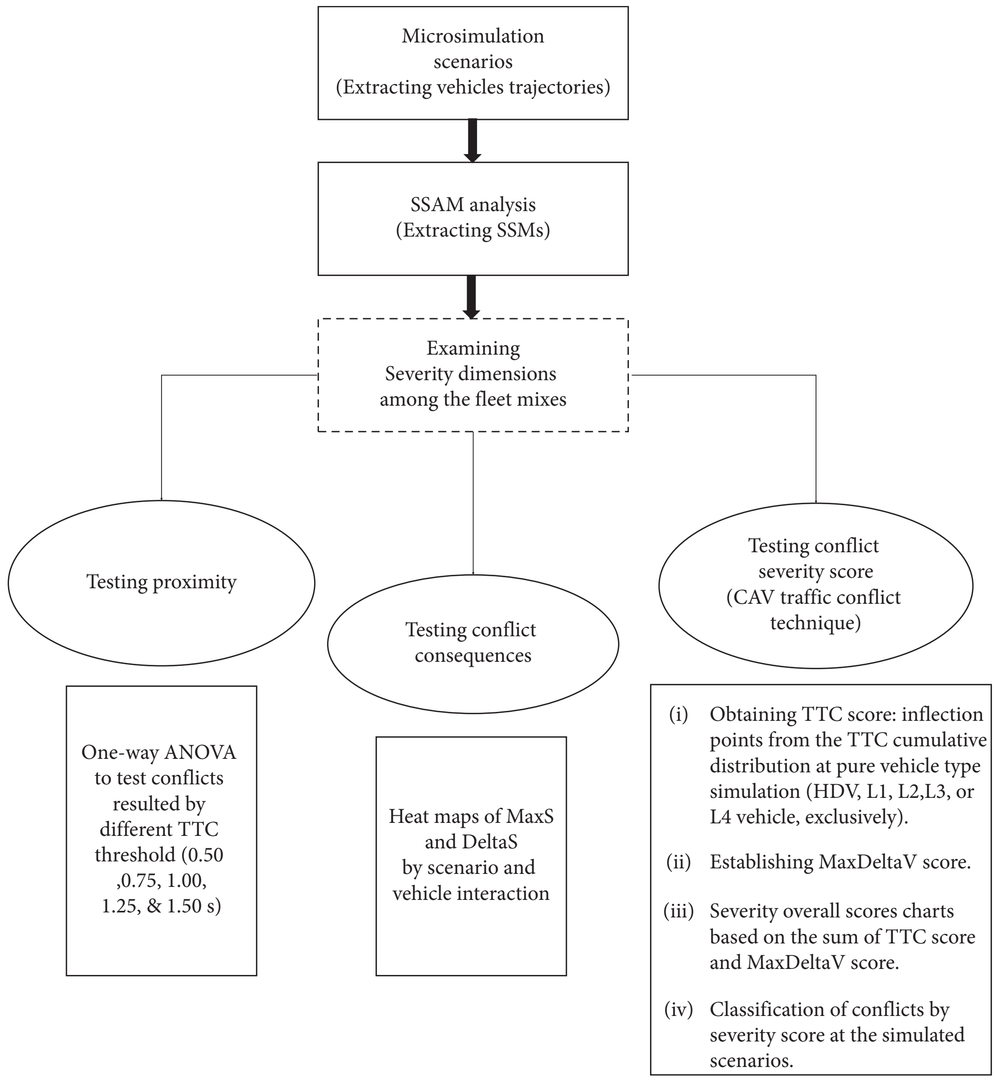


Figure 2: Framework for simulation-based traffic conflict severity estimation for CAV.

et al. [61] claimed that CAVs operating with assertive driving styles could lead to different circumstances resulting in a lower TTC threshold.

4.2. Severity Consequences Indicators. The proximity to a collision that results in a slight crash must not be equated to a crash with a potentially severe injury. Therefore, the severity measured by the potential consequences of a crash must be accounted by some other means [32]. Several SSMs can be used to extract the dynamic consequences of a conflict [18, 35]. Following previous studies [42, 62], this research uses MaxS and DeltaS to measure the resulting severity of conflicts related to different types of vehicles (HDVs and L1, L2, L3, and L4 vehicles). The former is defined as the maximum speed of any of the vehicles throughout the conflict, whereas the latter is the difference in vehicle speed (i.e., the difference in the velocity of vehicles in conflict) observed at the minimum value registered for TTC. Both indicators are outputs of the SSAM and simulate the resulting dynamics.

Different vehicle interactions can result in varied traffic flow dynamics, and consequently, the severity levels differ. At the end, high MaxS and DeltaS values indicate that the conflicts result in high severity.

The variations in MaxS and DeltaS of different vehicles involved in a conflict within different traffic fleet scenarios are shown in Figure 3. For simplicity and clarity in presenting the results, L1 and L2 vehicles are grouped as low CAVs and L3 and L4 vehicles as high CAVs, shown as LCAV and HCAV in Figure 3, respectively. The shown values (of MaxS and DeltaS) are the mean values of 15 runs in each scenario. The blue-yellow-red scale indicates the increase in severity towards the red color. Lastly, in each figure, the values are categorized by the follower vehicle in the conflict: -HDV, -LCAV, and -HCAV, indicating that the follower vehicle is a HDV, LCAV, and HCAV, respectively. Figure 7 in Appendix B shows an example of the microsimulation results as frequency distributions for MaxS and DeltaS. These distributions show also the heat maps' values (i.e., the mean values exhibited in Figure 3).

Table 3: Sensitivity analysis of different values of TTC threshold for HCAV (-L3 and -L4 vehicles).

Scenario	TTC threshold for HCAV	No. of conflicts	% Change
A (0)*	—	3251	—
	0.50	2636	−0.69
	0.75	2637	−0.68
B (5)	1.00	2637	−0.60
	1.25	2640	−0.56
	1.50	2655	—
	0.50	1671	−6.08
	0.75	1675	−5.86
C (15)	1.00	1697	−4.62
	1.25	1724	−3.11
	1.50	1779	—
	0.50	1131	−11.10
	0.75	1137	−10.61
D (25)	1.00	1156	−8.40
	1.25	1200	−5.64
	1.50	1272	—
	0.50	890a**	−16.85
	0.75	900a	−15.91
E (35)	1.00	935a	−12.69
	1.25	980a,b	−8.50
	1.50	1071b	—
	0.50	628a	−31.22
	0.75	648a	−28.29
F (55)	1.00	709a,b	−22.36
	1.25	770b	−15.66
	1.50	913c	—
	0.50	255a	−66.13
	0.75	298a	−60.46
G (90)	1.00	415b	−44.88
	1.25	528c	−29.99
	1.50	754d	—
	0.50	149a	−79.03
	0.75	198b	−72.02
H (100)	1.00	341c	−51.91
	1.25	467d	−34.06
	1.50	709e	—
	0.50	133a	−82.79
	0.75	192b	−75.12
I (100)	1.00	365c	−52.67
	1.25	517d	−32.99
	1.50	771e	—

*The value in ( ) denotes to the percentages of HCAVs in the scenario. **For each value containing a, b, . . ., letter in a scenario (in the no. of conflicts column), it denotes values of statistically significant differences ($p < 0.05$). Two or more values with the same letter denote a homogeneous subgroup. *Note*. TTC threshold = 1.5 s is established when the follower vehicle is a HDV or a LCAV (L1 or L2 vehicle).

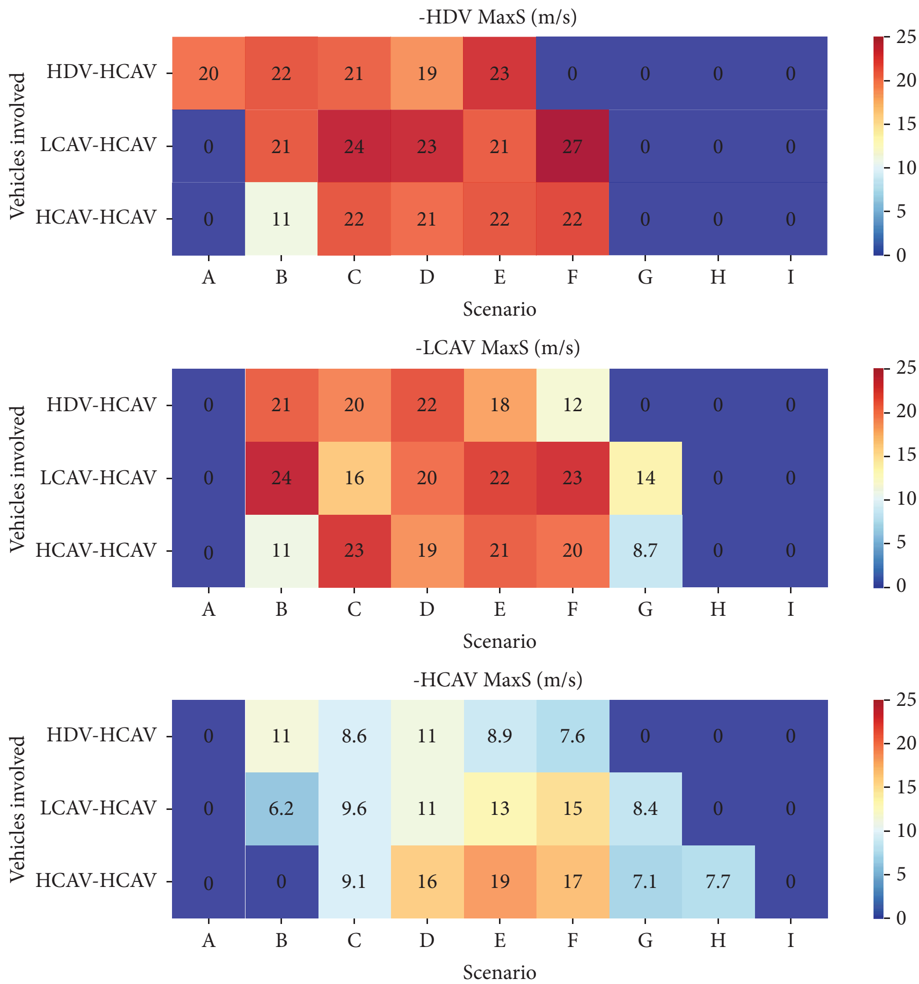
Regarding the conflict consequences extracted at the different scenarios, Figure 3 shows that

(i) The higher MaxS during conflicts is typically observed in scenarios in which the penetration rate of HCAV is from low to moderate (less than 55%, or scenario F) (see Figure 3(a))

(ii) By contrast, high penetration rates of HCAV (scenarios G, H, and I) result in lower MaxS during conflicts (see Figure 3(a))

(iii) Similar conclusions could be obtained from DeltaS's results in Figure 3(b)

Sinha et al. [6] reported a similar pattern. They obtained low crash rates and flat distributions for DeltaS values as the penetration rates of L4 vehicles increased. Rahman et al. [44] observed, using other surrogate safety indicators (e.g., TET, TIT, number of critical jerks, and time exposed rear-end crash risk index), that the increase in the penetration rate of vehicles with low automation levels (i.e., L1 and L2 vehicles) decreased the conflict severity. They found that the highest reduction in severity was achieved when the penetration rate was 100% CAV. By contrast, the reduction was insignificant when the penetration rate was less than 40%.



(a)

Figure 3: Continued.

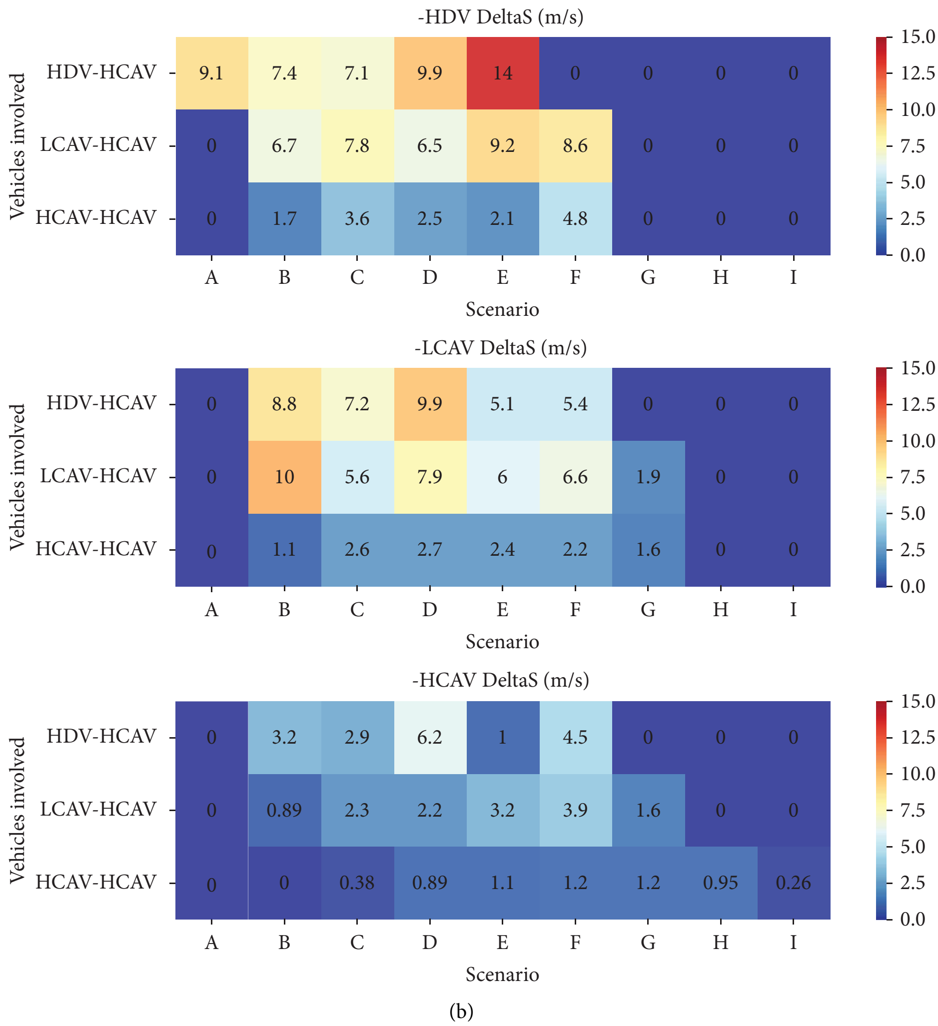


Figure 3: MaxS (a) and DeltaS (b) among several vehicle interactions and scenarios. *Note.* LCAV groups L1 and L2 vehicles; HCAV groups L3 and L4 vehicles. -HDV refers to the conflicts where HDV is a follower vehicle, the same for -LCAV and -HCAV.

The interactions of vehicles within a conflict are also evaluated to determine the effect of CAV introduction on microlevel traffic conflict severity. Consistent with the results of Sinha et al. [6], the conflicts shown in Figure 3 involving CAVs generally have low severity. Severity further decreases if the involved CAVs have high levels of automation (HCAV). This effect is restrictively indicated by MaxS, whereas DeltaS better represents the conflict severity consequences because it is an energy-based indicator [35].

Specifically, DeltaS's results (Figure 3(b)) show that

(i) HDV–HDV interaction presents the highest severity among all vehicle interactions

(ii) In addition, as the supposed behavior of LCAV does not considerably differ from the HDV behavior, the LCAV–LCAV interaction exhibits relatively high severity

(iii) When a HDV is the follower vehicle (such as LCAV–HDV and HCAV–HDV), severity is higher than if the follower vehicle is a LCAV or HCAV

(iv) The largest reduction in severity is achieved when a HCAV is the follower vehicle

This highlights the benefit of increasing the level of automation, as implicitly discussed by Rahman et al. [44]. By contrast, Sinha et al. [6] analyzed the collisions in the HDV–HDV and CAV–HDV interactions based on the effect of the penetration rate of L4 vehicles (not mixed fleets of vehicles with several automation levels were consider, neither HDV–CAV or CAV–CAV interactions were analyzed), and they did not find a significant difference between the severity of both types of interactions.

4.3. Severity Scores (Proximity/Consequences). According to CAV design companies, policymakers, and road planners, they aspire to build a transportation system with CAVs that is free of fatalities and severe injuries. Therefore, the main goal of CAV introduction is to avoid severe crashes, additionally to reduce the number of crashes. As a result, instead of using an indicator that simply expresses the proximity to a crash, a better indicator represents the proximity to a serious (fatal/severe) crash. Evidently, only few traffic conflict indicators and methodologies consider the severity of consequences (e.g., [19, 21, 38, 39]). These traffic conflict techniques (e.g., Swedish, Dutch, and Canadian methods) have been modified and validated for HDVs in different contexts. However, their function is fundamentally the same: to substantially develop a subjective score that can be added to the objective nearness-in-time (proximity) indicator(s) to account for probable consequences (Figure 4).

This study proposes a similar approach for CAVs. We propose a CAV traffic conflict technique that engages the proximity/consequences dimensions to provide various Severity Scores when vehicles with different levels of automation are involved. The proximity to a collision and consequence terms are represented by TTC and MaxDeltaV (in km/h), respectively.

The energy-based term (DeltaV) is referred to a hypothetical collision between two conflicting vehicles that are affected by the vehicle mass and the precollision and postcollision trajectories of a vehicle throughout the considered conflict (Figure 5). The change in precollision and postcollision velocities is defined as DeltaV. Substantial changes in velocity, both in magnitude and direction, imply that large forces impact the vehicle and can be expected to cause considerable injury. Several researchers have presented evidence that DeltaV is the strongest indicator for crash severity [2, 32, 37].

In the SSAM, MaxDeltaV represents the maximum vector magnitude among colliding vehicles. Gettman et al. [18] indicated that FirstDeltaV (Δv1) and SecondDeltaV (Δv2) are calculated based on the difference between the conflict velocity (from FirstVMinTTC (speed) and FirstHeading (heading)) and the postcollision velocity (from PostCrashV (speed) and PostCrashHeading (heading)). The higher value between Δv1 and Δv2 is called MaxDeltaV. The foregoing is defined as follows:

(i) FirstVMinTTC (SecondVMinTTC) is the speed of the first (second) vehicle at tMinTTC, which is the simulation time at which the minimum TTC value for a conflict is observed.

(ii) FirstHeading (SecondHeading) is the heading of the first (second) vehicle during the conflict. This heading is approximated by the change in position from the start to the end of the conflict.

(iii) PostCrashV is an estimate of the postcollision velocity of both vehicles. This estimate assumes that the vehicles crash at the estimated conflict angle and velocities observed at tMinTTC. An inelastic collision between the center of mass of both vehicles is assumed such that both vehicles subsequently move in the same direction and at the same velocity.

(iv) PostCrashHeading is the estimated heading at tMinTTC of both vehicles following a hypothetical collision.

Following the same procedure as Souleyrette and Hochstein [38] for HDVs, the CAV traffic conflict technique was developed by creating two scores: a TTC score (x-axis) and a MaxDeltaV score (y-axis). Both scores are later added to generate the overall score expressed as the Severity Score (SS) by region (see Figure 8 in Appendix C).

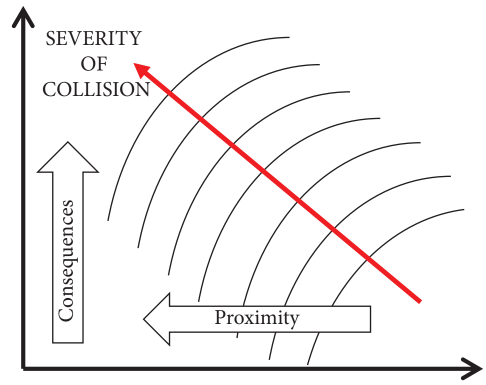


Figure 4: Theoretical concept of severity score.

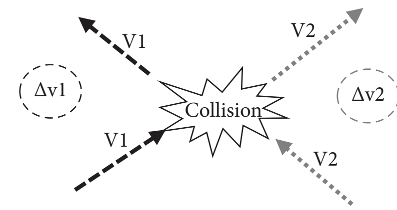


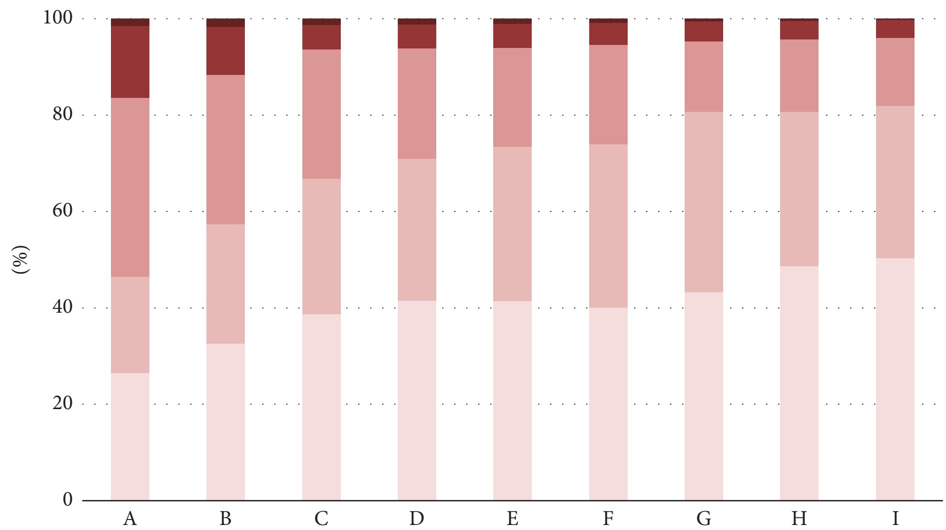
Figure 5: Illustration of DeltaV for two colliding vehicles.

The Severity Score, which detailed procedure is described in Appendix C, is used to classify each conflict at each simulated scenario. For each scenario, the conflicts are divided into subgroups based on the follower vehicle type (i.e., from –HDV to –L4). Later, the chart that should be applied for severity classification is selected based on the follower vehicle type. Figure 9(a) in Appendix C is selected if the follower vehicle in the conflict is a HDV. Figure 9(b) is selected if the follower vehicle is a LCAV, and Figure 9(c) is selected if the follower vehicle is a HCAV.

Figure 6 shows the results of applying these charts for classifying the conflict at each scenario based on TTC and MaxDeltaV. There is a significant reduction in the percentage of high severity conflicts (SS 4 or higher) in the transition between HDVs scenario (A) and 100% L4 vehicles scenario (I).

The reduction in the percentage of conflicts with SS 4 from scenarios A to I is 74.76% (from 14.98% to 3.78% in the total number of conflicts). For SS 5, the reduction in the percentage of conflicts is 86.11% (from 1.44% to 0.2%). The scenarios with considerable fleet diversity (D, E, and F) also exhibit notable reductions compared with scenario A. SS 4 decreases 66.62% (from 14.98% to 5%) at scenario D and 69.82% (from 14.98% to 4.52%) at scenario F. SS 5 decreases 21.52% (from 1.44% to 1.13%) at scenario D and 40.97% (from 1.44% to 0.85%) at scenario F.

Considering the first introduction of CAVs in scenario B where CAVs represent a 25% (with 5% of HCAV), the most severe conflicts (SS 4 and SS 5) are reduced by 29.23% (from (14.98% + 1.44%) to (9.96% + 1.66%)). In scenario C, where



	A	B	C	D	E	F	G	H	I
SS 5	1.44	1.66	1.23	1.13	1.07	0.85	0.52	0.38	0.2
SS 4	14.98	9.96	5.18	5	4.98	4.52	4.19	3.9	3.78
SS 3	37.11	31.04	26.76	22.87	20.52	20.64	14.62	14.98	14.1
SS 2	19.97	24.74	28.15	29.49	31.98	33.96	37.39	32.05	31.58
SS 1	26.48	32.58	38.65	41.48	41.43	40	43.26	48.67	50.31
Total conflicts	8836	7638	5544	4336	3508	3252	2920	3010	2970

Figure 6: Severity scores (SS) frequency (%) among scenarios.

half of the operated vehicles are CAVs (15% HCAV), the reduction in conflicts classified within SS 4 and SS 5 is remarkable (60.96%). This noteworthy reduction in the high severity conflicts at scenarios B and C indicates that scenario C is a significant scenario in CAV introduction with respect to the traffic safety vision of policymakers.

Moreover, Figure 6 shows the reduction in moderate severity conflicts. For example, the number of conflicts with SS 3 gradually decreases by increasing the penetration rates of CAVs. The reduction in scenario I is 62.0% (from 37.11% to 14.1%).

Two scenarios also present significant reductions in moderate severity conflicts. The highly mixed scenarios, D and E, which include more than 50% CAVs, exhibit notable reductions compared with previous scenarios. Scenario G (90% HCAV) shows a distinct reduction of 60.60% (from 37.11% to 14.62%).

Finally, Figure 6 shows that the less severe conflicts are the most representative in scenarios where the fleet consists of HCAV (scenarios G, H, and I). The percentage of conflicts with SS 1 and SS 2 in these scenarios exceeds 80% of the total number of conflicts.

In general, these results agree with those of previous studies that considered the severity term in CAV traffic safety studies. For instance, Rahman et al. [44] claimed that the duration for a vehicle to be under severe conditions decreased with increasing CAV penetration rates. In addition, the number of evasive actions that mitigate severe crashes decreases as the CAV penetration rate increases. Furthermore, Sinha et al. [6] used the crash rate term to express the severity that has also decreased by increasing the penetration rates of CAV scenarios.

Table 4: Automation levels calibration for passenger cars.

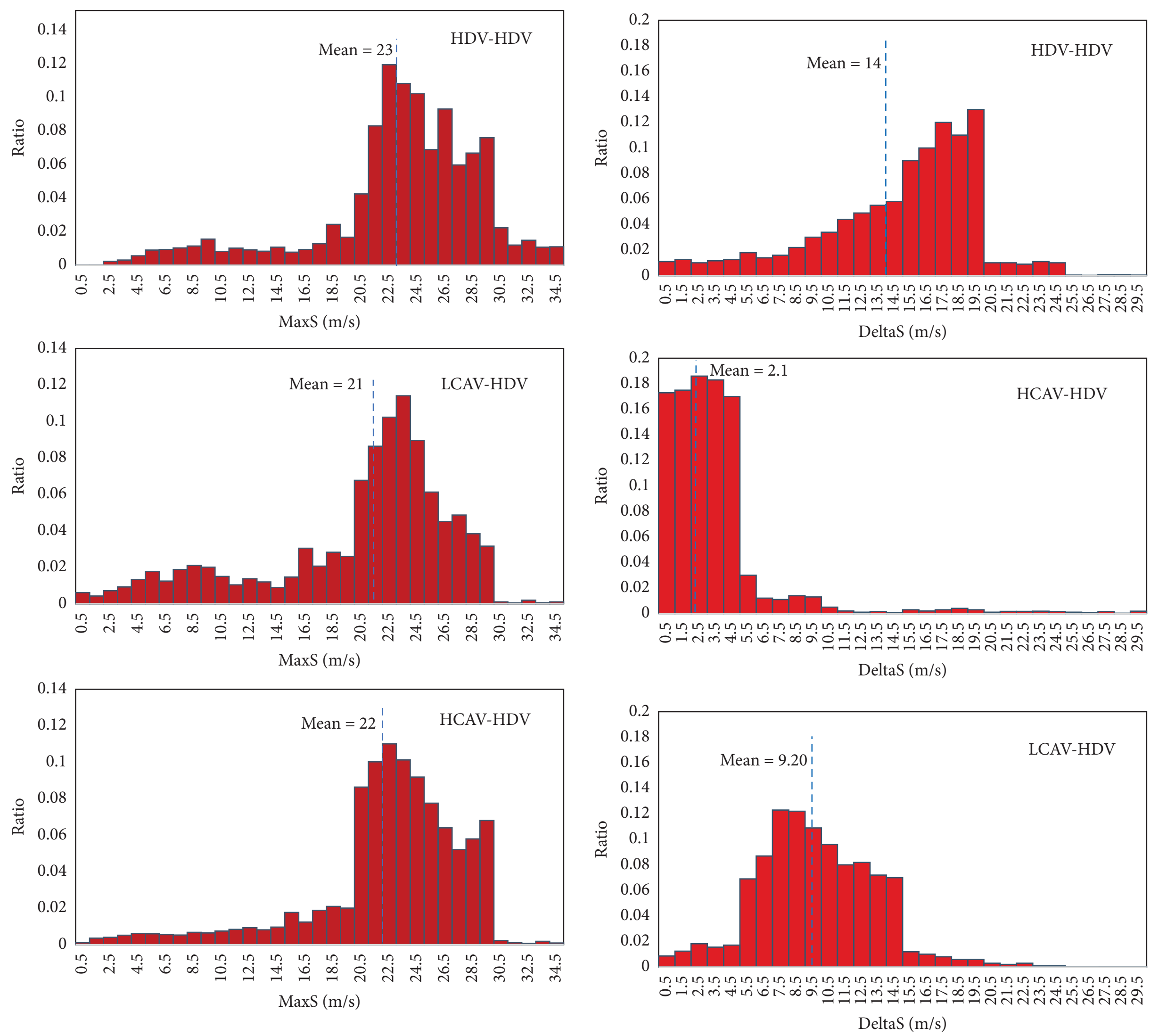
Parameters**	HDV		L1		L2		L3		L4		References
	Mean	SD*	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Speed acceptance	1.1	0.1	1.1	0.05	1.05	0.05	1	0.05	1	0.05	[8, 59, 65, 66]
Clearance (m)	1	0.3	1	0.2	1	0.2	1.5	0.1	1.5	0.1	[4, 8, 9, 54, 59, 67]
Guidance acceptance (%)	70	10	80	10	80	10	90	5	100	0	[67]
Reaction time (sec)	0.8	—	0.8	—	0.8	—	0.5	—	0.1	—	[9, 65]
Reaction time at stop (sec)	1.2	—	1.2	—	1.1	—	1	—	0.1	—	[54, 65]
Max acceleration (m/s^2)	3	0.2	3	0.2	2	0.2	1	0.1	1	0.1	[8]
Normal deceleration (m/s^2)	4	0.25	4	0.25	3.5	0.2	3	0.2	3	0.2	[45, 68]
Sensitivity factor	1	0	1	0	1	0.1	1.1	0.1	1.2	0.1	[61]
Gap (sec.)	1.2	0.2	1	0.2	0.8	0.1	0.8	0.05	0.6	0.05	[8, 49, 65]
Overtake speed threshold (%)	90	—	90	—	90	—	85	—	85	—	[54, 61, 65]
Imprudent lane change	Yes	—	Yes	—	Yes	—	No	—	No	—	[61]
Cooperate in creating a gap	No	—	No	—	No	—	Yes	—	Yes	—	[8, 69]
Aggressiveness level	0-1	—	0-1	—	0–0.5	—	0	—	0	—	[61, 65]
Distance zone factor (look ahead distance factor)	0.8–1.2	—	0.8–1.2	—	0.8–1.2	—	1–1.25	—	1.1–1.3	—	[61, 65]

*SD: standard deviation. **Definition of parameters: speed acceptance: how much vehicles could take a speed greater than speed limit; clearance (m): distance that vehicle keeps with the preceding one when stopped; guidance acceptance (%): the probability that a vehicle will follow the recommendations; reaction time (sec): the time to react in general; 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. Max acceleration (m/s^2): the highest value that the vehicle can achieve under any circumstances; normal deceleration (m/s^2): the maximum deceleration that the vehicle can use under normal conditions; sensitivity factor: how much the vehicle could be sensitive to the deceleration of the leader; gap (sec.): how much override the headway calculated by car following model; overtake speed threshold (%): the threshold that delaminates an overtaking maneuver; imprudent lane change: defines whether a vehicle will still change lane after assessing an unsafe gap; cooperate in creating a gap: vehicles can cooperate in creating a gap for a lane changing vehicle; 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; 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.

Table 5: Automation levels calibration for heavy vehicles.

Parameters**	HDV		L1		L2		L3		L4		References
	Mean	SD*	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Speed acceptance	1.05	0.1	1.05	0.1	1.05	0.05	1	0.05	1	0.05	[8, 59, 65, 66]
Clearance (m)	1.5	0.5	1.5	0.5	1.5	0.3	2	0.1	2	0.05	[4, 8, 9, 54, 59, 67]
Guidance acceptance (%)	100	10	100	10	100	10	100	5	100	0	[67]
Reaction time (sec)	0.8	—	0.8	—	0.8	—	0.5	—	0.1	—	[9, 65]
Reaction time at stop (sec)	1.3	—	1.3	—	1.2	—	1	—	0.1	—	[54, 65]
Max acceleration (m/s^2)	1	0.5	1	0.5	1	0.5	0.8	0.3	0.8	0.3	[8]
Normal deceleration. (m/s^2)	3.5	1	3.5	1	3	1	2.5	1	2.5	1	[45, 68]
Sensitivity factor	1	0	1	0	1	0.1	1.1	0.1	1.2	0.1	[61]
Gap (sec.)	1.5	0.2	1.5	0.2	1	0.1	1	0.05	0.8	0.05	[8, 49, 65]
Overtake speed threshold (%)	90	—	90	—	90	—	85	—	85	—	[54, 61, 65]
Imprudent lane change	Yes	—	Yes	—	Yes	—	No	—	No	—	[61]
Cooperate in creating a gap	No	—	No	—	No	—	Yes	—	Yes	—	[8, 69]
Aggressiveness level	0-1	—	0-1	—	0–0.5		0	—	0	—	[61, 65]
Distance zone factor (look ahead distance factor)	0.8–1.2	—	0.8–1.2	—	0.8–1.2		1–1.25	—	1.1–1.3	—	[61, 65]

*SD: standard deviation. **Definition of parameters: speed acceptance: how much vehicles could take a speed greater than speed limit; clearance (m): distance that vehicle keeps with the preceding one when stopped; guidance acceptance (%): the probability that a vehicle will follow the recommendations; reaction time (sec): the time to react in general; 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. Max acceleration (m/s^2): the highest value that the vehicle can achieve under any circumstances; normal deceleration. (m/s^2): the maximum deceleration that the vehicle can use under normal conditions; sensitivity factor: how much the vehicle could be sensitive to the deceleration of the leader; gap (sec.): how much override the headway calculated by car following model; overtake speed threshold (%): the threshold that delaminates an overtaking maneuver; imprudent lane change: defines whether a vehicle will still change lane after assessing an unsafe gap; cooperate in creating a gap: vehicles can cooperate in creating a gap for a lane changing vehicle; 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; 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.



(a) (b)

Figure 7: Fractional distribution of MaxS (m/s) (a) and DeltaS (m/s) (b) outputs from microsimulation at scenario E. *Note*. the values indicated as the mean values are those represented in Figure 3 (Section 4.2).

Table 6: The assigned TTC score by vehicle type.

	HDV		L1		L2		L3		L4	
TTC score	Thresholds	Sample size (%)	Thresholds	Sample size (%)	Thresholds	Sample size (%)	Thresholds	Sample size (%)	Thresholds	Sample size (%)
0	$4.0 < TTC \leq 5.0$	30.0	$4.2 < TTC \leq 5.0$	28.9	$4.2 < TTC \leq 5.0$	30.4	$4.3 < TTC \leq 5.0$	29.9	$4.3 < TTC \leq 5.0$	32.8
1	$2.5 < TTC \leq 4.0$	26.9	$2.5 < TTC \leq 4.2$	31.9	$2.5 < TTC \leq 4.2$	31.1	$2.6 < TTC \leq 4.3$	33.6	$2.6 < TTC \leq 4.3$	31.1
2	$1.5 < TTC \leq 2.5$	27.6	$1.0 < TTC \leq 2.5$	32.4	$1.0 < TTC \leq 2.5$	32.3	$0.75 < TTC \leq 2.6$	31.5	$0.75 < TTC \leq 2.6$	31.5
3	$TTC \leq 1.50$	15.3	$TTC \leq 1.0$	6.6	$TTC \leq 1.0$	6.1	$TTC \leq 0.75$	4.8	$TTC \leq 0.75$	4.4

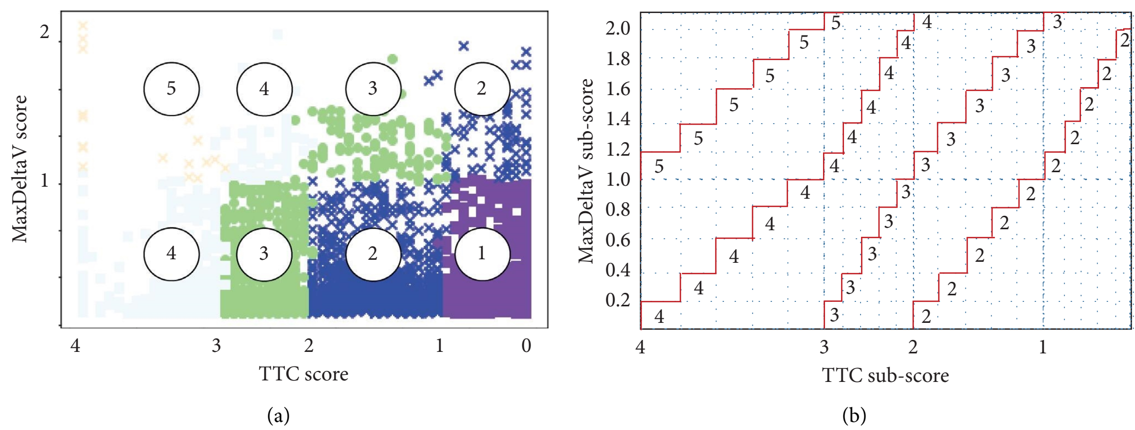


Figure 8: Conceptual illustration of conducting the overall severity score: (a) overall score by regions and (b) step-graded lines from the subscores.

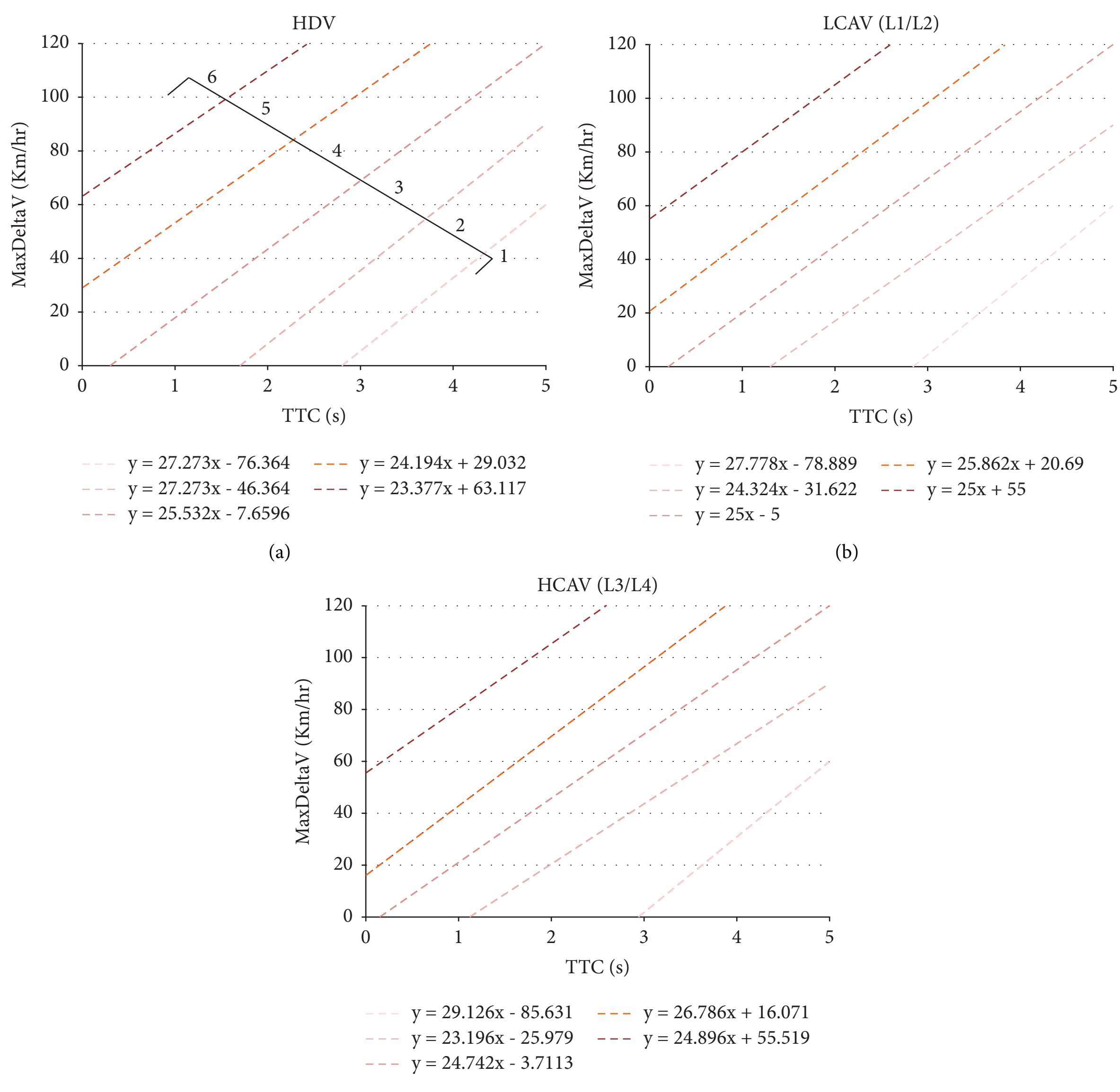


Figure 9: Severity scores (SS) for different types of vehicles: (a) for HDV, (b) for L1 & L2 vehicles (LCAV), and (c) for L3 & L4 vehicles (HCAV).

5. Conclusion

This study investigates the extent of conflict severity resulting from the introduction of CAVs into traffic streams. It presents an analysis of the potential traffic conflicts that occur when roads completely operating with HDVs transition into full L4 vehicle operation. Three dimensions of severity are examined: proximity to collision, consequences of collision, and proximity/consequence of collision classified by severity score. Owing to the lack of crash data involving CAVs, this study implemented a traffic microsimulation approach followed by SSAM analysis. The specific outputs of the SSAM (e.g., TTC, MaxS, DeltaS, and MaxDeltaV) are used to estimate conflict severity. The results of several mixed fleet operation scenarios are compared to determine traffic safety when the real and current extent of penetration of CAVs on roads is exceeded.

The key findings of this study are as follows. The sensitivity analysis of the TTC threshold in scenarios where HCAV is the follower vehicle yields interesting results. If the presence of HCAV on the road is low (less than 35%), the difference in the number of identified conflicts between the applied TTC threshold values (i.e., 0.5, 0.75, 1.0, 1.25, and 1.5 s) is not statistically significant. By contrast, the scenarios where HCAVs have moderate sharing percentages (35%–55%) start to show a significant difference at 1.0 s. The scenarios where the operation percentage of these vehicles is high lead to significant differences in the number of conflicts among all the tested TTC values. Therefore, the importance of applying different TTC threshold values for such scenarios must be recognized. The MaxS and DeltaS values were discussed as conflict consequence indicators within the proposed scenarios and several vehicle interactions. These indicators show that the scenarios where 55% or more HCAV share the road result in conflicts with low severity (low speeds and low speed differences among vehicles involved in conflicts). In addition, the conflicts where HDVs are the follower vehicles yield the highest severity conflicts, followed by the conflicts where the follower vehicles are LCAV.

Finally, proximity/consequence (TTC/MaxDeltaV) charts related to different vehicle types have been developed. These charts have been used to classify the resulting conflicts into severity scores in each scenario. The results indicate that increasing the shared percentages of CAVs operating on the road significantly decreases the number of conflicts with high severity. When approximately 100% of HCAV operate on roads, severe conflicts are anticipated to disappear, and those with low severity are reduced.

This study presented a comprehensive investigation of traffic conflict severity dimensions and analyzed the conflict severity related to several levels of automation within various mixed fleet operation scenarios. Nevertheless, this study presents some limitations that should be considered for future research. Firstly, whether the SSMs thresholds under conventional traffic conditions are applicable when modeling safety in mixed or fully automated traffic remains unclear. Different TTC threshold values have been tested and applied to solve this problem. However, when real data become available, the validity of SSM should be thoroughly reviewed and verified. Therefore, new data sources related to CAV data will be crucial for the development of an universal SSM set that can satisfy all automation levels. Secondly, for particular traffic scenarios, the investigation of SSMs, such as the lateral safety provided by lane changing and merging maneuvers, must be implemented. Both HDVs and CAVs can exhibit different levels of lateral safety, particularly in a mixed autonomy traffic. And finally, the calibration process could be improved with field TTC data [63, 64]. This should be considered in similar future research.

Appendix

A. Behavior Parameters Used for CAV Levels Modeling

This appendix contains the CAV behavior parameter values as indicated in Table 4 (for passenger cars) and Table 5 (for heavy vehicles).

B. A Sample of Microsimulation Results

The following results in Figure 7 represent an example of the microsimulation outputs related to MaxS and DeltaS that were generated at scenario E, when HDV is the follower vehicle in the conflicts. MaxS and DeltaS outputs are presented as distribution charts to reflect the resulted data more descriptively.

C. Severity Charts for HDVs and CAVs

This appendix describes the procedure followed in developing the severity charts (by vehicle type) based on TTC score/MaxDeltaV score.

To obtain the TTC score, different TTC thresholds were established by vehicle type. The procedure looks for the inflection points of the TTC cumulative distribution when pure vehicle type scenarios were modeled (i.e., all the vehicles in the simulation are exclusively HDVs, L1, L2, L3, or L4 vehicles). Specifically, 15 microsimulation runs were executed for each pure scenario, and the TTC cumulative distribution charts were depicted. All the conflicts identified with a TTC value equal to or lower than 5.0 s were considered for the TTC distribution analysis.

According to the Hydén [21] safety pyramid, extremely severe conflicts are considerably limited, whereas less severe traffic conflicts are more frequent. According to Souleyrette and Hochstein [38], these severe conflicts can be obtained based on the inflection points of the TTC cumulative distribution of the pure scenarios for each vehicle type. These points are used as thresholds to delineate the few severe conflicts from nonsevere ones. Later, the nonsevere conflicts were divided into three approximately equal groups. A TTC score was assigned to each group (one severe and three nonsevere), which was later used to obtain the overall score. Table 6 summarizes the proposed TTC scores and thresholds to determine the overall scores of the pure operation scenarios.

As listed in Table 6, the thresholds that identify severe conflicts (with a TTC score equal to 3) differ among the pure vehicle type operational scenarios. Precisely, the inflection point for HCAV (L3 and L4 vehicles) was lower than those of the other vehicles, indicating their improved capabilities. The inflection points for the pure scenarios of HCAV, LCAV, and HDVs were 0.75, 1.0, and 1.5 s, respectively. Table 6 shows the variation in the inflection point affects other thresholds. Moreover, the decrease in a severe conflict region (with a score equal to 3) is clearly achieved by increasing the automation level, affirming the safety benefit of incorporating HCAV.

For the consequence score, Souleyrette and Hochstein [38] used the equation of Evan [37], which employs MaxDeltaV to calculate the likelihood of crash injuries and fatalities. Their results showed that MaxDeltaV values of approximately 30 and 60 km/h are key (inflection) values that significantly increase the propensity for severe conflicts. Because the Evan equation only depends on MaxDeltaV and the consequences of a crash with certain MaxDeltaV values have the same effect on HDVs and CAVs (with different automation levels), these two key values can be considered the same for all automation levels and interactions. Therefore, following Souleyrette and Hochstein [38], the severity value for MaxDeltaV is divided into three scores: (1) score 1, MaxDeltaV ranging 0–30 km/h; (2) score 2, MaxDeltaV ranging 30–60 km/h; and (3) score 3, MaxDeltaV exceeding 60 km/h.

The next step is adding both scores (TTC and MaxDeltaV scores) to obtain an overall severity score. The resulted overall score is represented by regions in Figure 8(a), where each score area represents the severity score. However, severity scores are better identified by lines or curves rather than by square areas [32, 38]. For this reason, these square areas are converted into severity isolines as contour lines (Figure 9). Precisely, each overall square area is reshaped to five subscores (with an increment of 0.2 points) for each major score (in both ranges of TTC and MaxDeltaV scores), see Figure 8(b).

Afterwards, the step-graded lines resulting from the equal overall scores in Figure 8(b) are reshaped into smooth contour lines for HDVs, LCAV, and HCAV, as shown in Figure 9. In the figure, the variation of the red color from light to dark represents the increment in Severity Score (SS).

Data Availability

The data supporting the current study are available from the corresponding author upon request.

Disclosure

This study is part of the Research Project PID2019-110741RA-I00.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors' Contributions

Rocío de Oña and Juan de Oña conceptualized the study; Tasneem Miqdady, Rocío de Oña, and Juan de Oña performed methodology; Tasneem Miqdady, Rocío de Oña, and Juan de Oña did formal analysis and investigation; Tasneem Miqdady wrote the original draft preparation; Rocío de Oña and Juan de Oña wrote the article and reviewed and edited the article; Rocío de Oña did funding acquisition.

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