Safety assessment in future scenarios with Automated Vehicles

Abstract

Nowadays, several Advanced Driving Assistance Systems (ADAS) are installed in vehicles, helping drivers with sevral tasks. Human drivers are evermore less involved in driving thanks to the technological help. According to the automation rate of the vehicles and the human involvment, vehicles can be considered partially or fully automated. The partially automated vehicles (AVs) belong to the SAE level 2-3 and follow a cautious behavior because they are still controlled for some tasks by human drivers. The fully automated ones belong to the SAE level 4-5, and their behavior is thought to be more aggressive since there is no need for human drivers to take over maneuver or manage some driving tasks. The reliability of technologies is considered greater than the ones of men for managing and reacting to any changes in traffic conditions, so the behavior is more assertive, headway between vehicles reduced, and greater acceleration and deceleration.
Starting from these assumptions, in this thesis, three different vehicle typologies are studied, regular vehicles (RVs), Partially AVs (SAE level 2-3), and Fully AVs (SAE level 4-5) for crash assessments in future scenarios (short-term, mid-term, and long-term). This work aims at providing a methodological framework that can be used in every context and for every road type considering the introduction of technologies in traffic for safety assessments. This aspect is crucial since, practically speaking, plans for mobility and road design procedures require safety assessments projected in long temporal horizons. During this considered period there is the great chance that the vehicle types circulating on roads drastically change. Not considering new vehicles and their interactions with RVs in future scenarios can lead to misestimations of safety.
The methodological framework was applied to a real-world case, in the context of the SUMP for the Province of Bari. The main results of this study highlight the importance of automation in traffic. Traffic made just of Fully AVs drastically decrease the crash frequency. Contrary, promiscuity of vehicles in traffic enhances the crash occurrence if compared to the current scenario.
In order to foresee the impact of such changes in traffic, an ad hoc Safety Performance Function for AVs was developed, with the intent of predicting crashes in the future with AVs.

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Coordinator: Prof. Michele Mossa

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ICAR/04 – Roads, Railways and Airports

DICATECh
Department of Civil, Environmental, Land, Building Engineering and Chemistry

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Safety assessment in future scenarios with Automated Vehicles

Prof. Vittorio Ranieri
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Politecnico di Bari

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Al Magnifico Rettore
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Il/la sottoscritto/a Stefano Coropulis nato/a a Bari (BA) il 23/07/1996
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iscritto al 3° anno di Corso di Dottorato di Ricerca in RISCHIO, SVILUPPO AMBIENTALE, TERRITORIALE ED EDILIZIO (Risk and environmental, territorial and building development Ph.D.) ciclo XXXV
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Safety assessment in future scenarios with Automated Vehicles

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XXXV CYCLE
Curriculum: Road Safety

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Coordinatore: Prof. Michele Mossa

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Curriculum: Sicurezza Stradale

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Dipartimento di Ingegneria Civile, Ambientale, del Territorio, Edile e di Chimica

Analisi di sicurezza stradale per scenari futuri in presenza di Veicoli Automatici

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EXTENDED ABSTRACT *(eng)*

Nowadays, several Advanced Driving Assistance Systems (ADAS) are installed in vehicles, helping drivers with different driving tasks. This help makes drivers free of loosening their attention and their involvement in driving, in favor of an increase of automation in accomplishing the driving tasks. According to the automation rate in driving, vehicles can be considered partially or fully automated. The partially automated vehicles (AVs) belong to the SAE level 2-3 and follow a cautious behavior because they are still controlled for many tasks by human drivers. The fully automated ones belong to the SAE level 4-5 (SAE-J3016TM, 30-04-2021), and their behavior is thought to be more aggressive since there is no need for human drivers to take over maneuver or manage some driving tasks. The reliability of technologies is considered greater than the ones of men for managing and reacting to any modifications in traffic conditions, so the behavior is more assertive, headway between vehicles reduced, and greater acceleration and deceleration are allowed. Hence, the terminology Cautious and Assertive is minted by the perception of a human driver, that sees a partially automated behavior as cautious (also because the vehicle has all the motion parameters loosen to allow human interventions and good reactions by other driver actors) and a fully automated vehicle as assertive because it tends to optimize the driving tasks extremizing all the maneuvers to some extent not reachable by humans.

Starting from these assumptions, in this thesis, three different vehicle typologies are studied, regular vehicles (RVs), PAVs (SAE level 2-3), and FAVs (SAE level 4-5) for crash assessments in future scenarios (short-term, mid-term, and long-term). In this work, for Cautious AVs or PAVs will be meant all the partially automated vehicles and for Assertive AVs, or FAVs all the fully automated vehicles. This work aims at providing a methodological framework that can be used in every context and for every road type which takes into account the introduction of technologies in traffic for safety as-

sessments. This aspect is crucial since, practically speaking, plans for mobility and road design procedures require safety assessments projected in long temporal horizons. During this considered period there is the great chance that the vehicle types circulating on roads drastically change. Not considering them in future scenarios can lead to misestimations of safety.

The proposed safety assessment for future scenarios is based on a two-step procedure relying on traffic simulation and Surrogate Safety Assessment. The latter analyzed the trajectories coming from the simulations, extracting conflicts to be converted into crashes (Tarko, 2018). The first step is to decide the road type to analyze (rural roads two-way, two-lane, for this work) for crash assessment related to a certain area (Province of Bari). The second step is to validate the current scenario with the two-step procedure, comparing the simulated and observed crashes available by datasets. Then, according to the hypothetical market penetration curves of AVs in future scenarios, it is possible to set the percentages of RVs, partially AVs, and fully AVs in the decided future scenarios, for the selected roads. The analyses were run, and results were recorded to assess crash variation in future scenarios compared to the current one to understand the impacts of automation on road safety.

Starting from the number of simulated crashes for all the future scenarios, a coefficient, Hazard Index, was calculated. This Index had the scope of converting the number of circulating vehicles in their equivalent number weighted on their safety for crash avoidance. After this conversion of traffic amount for all the scenarios and the analysis of the most crash-related characteristics of the investigated roads, a new Safety Performance Function (SPF), which remarkably considers the introduction of AVs, was calculated apart from the typical variables.

This work provided results for all the mentioned scope of research. The first one was related to the validation of the current simulated scenario with the proposed two-step procedure. The relationship between simulated and observed crashes existed, and it was linear: simulated crashes corresponded to observed by means of a constant scale factor, equal to nine. This result was crucial to show the reliability of the procedure. Then, the same procedure applied to future scenarios suggested that in the case of a great number of fully AVs, as will happen in 2050, crashes will significantly decrease, no matter the type of intersections or traffic and safety of the site. The situation becomes different if talking about 2030 and 2040 scenarios, which are always less safe than 2050. The recorded number of crashes for the mid-term scenario is the greatest for almost all the cases. Starting from these considerations, two other hypothetical scenarios were simulated: a traffic made of 100% of PAVs; a traffic made of 100% of FAVs. The crash recording from these two scenarios, compared to the current situation, made it possible to calculate the Hazard Index associated to the vehicle type. FAVs were found to be 0.76 times dangerous like PAVs, while RVs were found to be 3.59 times dangerous like PAVs.

The SPF was obtained by combining two variables, AV scenarios (including the equivalent AADT, which was calculated by applying the Hazard Index for vehicle type to the available AADT) and road characteristics (intersection types and density over the site extension). The two independent variables were meant to explain the dependent one (the crash frequency) by means of a negative binomial model. The coefficients related to the independent variables in explaining the crash phenomenon were found to be statistically significant. A statistically significant test result ($P \leq 0.05$) means that the test hypothesis is false or should be rejected. The Nagelkerke R^2 was calculated to understand the goodness of fit of the model (0.74)

The simulated scenarios showed a promising situation in which the massive presence of AVs helps road safety in any condition. On the contrary, the mid-term scenario seems more dangerous than the short-term one due to the high promiscuity of vehicular components in traffic and a huge component of humans finalizing driving tasks for RVs and partially AVs (partially AVs will still rely on human drivers). The only sites where the promiscuous traffic is safer than the one in 2030 are characterized by free flow regime or congested flow regime. Two conditions during which the interactions are controlled (or almost null) and the vehicles must follow a certain path. Results showed something strongly debated, i.e., the reduced safety of the transitory phase from no AVs to a great percentage of AVs in traffic. This result is in line with other literature resources. It highlights a strong necessity by a stakeholder to deal with this issue accurately, to make transport safe from RVs to AVs. Two are the possible countermeasures to overcome this issue:

- Introducing dedicated lanes for AVs during the transitory phase, to reduce the interactions between RVs and AVs, in case of new roads. In case of existing roads, the AVs can travel together with Buses and Taxis on reserved lanes for Bus and Taxi, where the traffic volume is low and the drivers are highly skilled.

- Designing fully AVs, at their early stages, with the same motion parameters as partially AVs, in order to make their behavior in traffic more intelligible by human drivers, not used to automation yet.

In addition, the development of an ad hoc SPF for AVs represents a novelty in the safety field that can be used as a base for the new and ever-changing emerging technologies in traffic.

The thesis represents a part of a wider study about the safety of AVs. It can be extended to understand the impacts of AVs in other road and national contexts. In this optic, the variables of the SPF can be adapted and modified to several contexts.

The obtained results are useful for stakeholders and administration because of the proposed methodology framework which can be used for planning and road designing, but also for the development of the SPF. This can be a starting point to think about new countermeasures, like reserved lanes for AVs or the direct implementation of FAVs to avoid a transitory phase, according to the results provided by the SPF.

key words *Road safety; Automated vehicles; Future scenarios; Traffic Simulations; Surrogate Safety Measures; Conflicts-crash; Safety Performance Functions.*

EXTENDED ABSTRACT *(ita)*

Al giorno d'oggi, la maggior parte dei veicoli circolanti è dotata di diversi sistemi avanzati di assistenza alla guida (ADAS), che in maniera più o meno spinta aiutano i conducenti a svolgere i loro compiti. In questa maniera il conducente umano viene sempre più alleggerito nel suo compito di guida, a favore di una vieppiù crescente automazione che compie tutte le mansioni più onerose. In base al tasso di automazione presente su ciascun veicolo, e quindi alla sua capacità di sostituire totalmente o parzialmente il conducente umano, i veicoli possono essere considerati parzialmente o completamente automatizzati. I veicoli parzialmente automatizzati (AV) appartengono al livello SAE 2-3 e seguono un comportamento prudente perché sono ancora controllati per molti compiti da conducenti umani. Quelli completamente automatizzati appartengono al livello SAE 4-5 (SAE-J3016TM, 30-04-2021) e il loro comportamento è ritenuto più aggressivo, poiché non è necessario che i conducenti umani si occupino delle manovre o gestiscano l'esecuzione di alcuna manovra di guida. Questa differenza nei comportamenti di queste due categorie di veicoli automatizzati risiede nella differente affidabilità che si attribuisce agli uomini e alle macchine: si ritiene che una macchina sia più affidabile di un uomo nel gestire qualsiasi situazione e reagire a qualsiasi cambiamento delle condizioni del traffico, quindi il comportamento è più aggressivo, la distanza tra i veicoli ridotta e le accelerazioni e decelerazioni maggiori. Si parla quindi di veicoli Cautious o Assertive in base al loro comportamento visto nell'ottica di un conducente umano, non nell'ottica della sicurezza stradale. Infatti, un veicolo parzialmente automatico ha dei parametri del moto a metà strada tra quelli automatici e quelli umani, parametri che nell'ottica della guida umana fanno risultare il comportamento del veicolo molto più prudente. Questa prudenza è dovuta anche al fatto che è previsto l'intervento dell'uomo per alcune manovre quindi la tecnologia non può essere spinta a tal punto da inibire un corretto intervento e percezione, pre-

cedentemente, da parte del conducente. Inoltre, i veicoli parzialmente automatici sono il primo step per l'introduzione dell'automazione, quindi, necessariamente devono guidare in una maniera che sia più intellegibile da parte dell'utente umano. Al contrario, i veicoli completamente automatici sono quei veicoli che ormai, non necessitando più dell'intervento dell'uomo e subentrati in successione a quelli parzialmente automatici, cercano di ottimizzare il flusso del traffico, seguendo una guida che è settata sulle potenzialità interpretative e correttive delle macchine, quindi vista come aggressive da parte del conducente umano.

Partendo da questi presupposti, in questa tesi si analizza la sicurezza stradale in scenari futuri (breve, medio e lungo termine) per diverse tipologie di veicoli: i veicoli tradizionali (RV), i PAVs (livello SAE 2-3) e gli FAVs (livello SAE 4-5). Nella presente tesi si utilizzerà la terminologia Cautious o PAVs per intendere i veicoli parzialmente automatici e Assertive o FAVs per quelli totalmente automatici. Questa analisi è propedeutica al fornire un inquadramento metodologico al problema dello studio della sicurezza stradale per scenari futuri. Infatti, sia in fase di pianificazione, sia di progettazione delle nuove infrastrutture o di adeguamento di quelle già esistenti, sono richieste, dal punto di vista normativo, delle analisi di sicurezza stradale su ampi orizzonti temporali. Non si considera, però, che nel corso del periodo valutato per l'analisi di sicurezza, il parco veicolare circolante possa contemplare nuove tipologie di veicoli, come quelli automatici.

Il presente lavoro di ricerca mira, pertanto, a colmare questa carenza metodologica, proponendo una procedura da seguire per le analisi di sicurezza stradale per scenari futuri e mostra un esempio applicativo di tale procedura, calata nel contesto del PUMS (Piano Urbanistico della Mobilità Sostenibile) della Città Metropolitana di Bari.

La valutazione della sicurezza per gli scenari futuri proposta, si basa su una procedura in due fasi che si basa sulla simulazione del traffico e sulla valutazione delle Safety Surrogate Measures. Queste ultime analizzano le traiettorie provenienti dalle simulazioni, contando i conflitti, che saranno poi convertiti in incidenti (Tarko, 2018). Il primo passo consiste nel decidere il tipo di strada da analizzare (strade provinciali a doppio senso di marcia, a due corsie, per questo lavoro) per la valutazione degli incidenti relativi a una determinata area (Provincia di Bari). Il secondo passo è quello di validare la procedura proposta per lo scenario attuale, confrontando gli incidenti simulati e quelli osservati disponibili dai dataset. Dopodiché gli scenari futuri sono stati analizzati e il traffico associato ad ogni scenario è stato ricavato grazie alle curve di penetrazione nel parco veicolare circolante dei mezzi a guida automatica: grazie a tali curve è stato possibile ricavare la percentuale di veicoli associata ad ogni tipologia per ogni scenario. Le analisi sono state eseguite seguendo sempre la stessa procedura in due fasi e i risultati sono stati registrati per valutare la variazione degli incidenti in altri scenari rispetto a quello attuale.

Partendo dal numero di incidenti simulati per tutti gli scenari futuri, è stato calcolato un indice di pericolosità, che sinteticamente riassume la pericolosità di una tipologia veicolare rispetto ad un benchmark (i veicoli Parzialmente AVs, sono stati usati come benchmark). Tale Indice di pericolosità è servito per convertire il traffico in traffico pericoloso equivalente, ovvero convertendo il traffico associato ad ogni tipologia di veicolo in un traffico che quantifichi la pericolosità in termini incidentali, di quella tipologia veicolare.

Questa conversione è stata propedeutica per lo sviluppo di una nuova Safety Performance Function (SPF), ad hoc per i veicoli automatici, così con una variabile si potesse tenere conto sia della composizione veicolare che del traffico.

I risultati dello studio sono molteplici, a partire dalla validazione dello scenario attuale simulato. Si è trovata una correlazione lineare tra simulato e osservato che dimostra come gli incidenti simulati siano uguali a quelli 1 osservati grazie ad un fattore di scale pari a 9. Questo risultato è stato fondamentale per dimostrare l'affidabilità della procedura, per poi poterla applicare in tanti altri contesti. I risultati suggeriscono che nel caso di un gran numero di veicoli a guida automatica, come avverrà nel 2050, gli incidenti diminuiranno significativamente, indipendentemente dal tipo di intersezioni o dal traffico e dalla sicurezza di partenza del sito. Diversa è la situazione se si parla di scenari 2030 e 2040, che sono sempre meno sicuri del 2050. Il numero di incidenti registrato per lo scenario a medio termine è il maggiore in quasi tutti i casi.

Partendo dallo studio di questi risultati, e dallo scenario attuale, ipotizzato esclusivamente composto da RVs, si è pensato di simulare altri due scenari ipotetici, in cui il traffico fosse composto esclusivamente da veicoli automatici (100% PAVs; 100% FAVs). La frequenza incidentale registrata per questi due scenari ha reso possibile fare un confronto quantitativo sulla sicurezza associata a ciascuna tipologia di veicolo, a mezzo dell'Indice di pericolosità. Si è trovato che i veicoli FAVs (completamente automatici) sono 0.76 volte pericolosi quanto i PAVs (parzialmente automatici) e che gli RV sono pericolosi 3.59 volte quanto i PAVs.

Con questi indici ricavati si è convertito il traffico in traffico pericoloso equivalente per tutti gli scenari e si è calcolata una SPF che avesse come variabili indipendenti il traffico pericoloso equivalente (quindi lo scenario degli AV) e le caratteristiche geometriche della strada. Le due variabili indipendenti sono state legate a mezzo di una legge binomiale negativa per ottenere la variabile dipendente (la frequenza di incidenti). I coefficienti del modello associati a ciascuna variabile indipendente sono stati considerati statisticamente significativi, in quanto il valore del P-value è risultato minore del 5%. Dopodiché si è calcolata la goodness of fit del modello con il Nagelkerke R^2 (0.74).

Gli scenari simulati hanno mostrato una situazione promettente in cui la presenza massiccia di AV aiuta la sicurezza stradale in qualsiasi condizione. Al contrario, lo scenario a medio termine sembra più pericoloso di quello a breve termine a causa dell'elevata promiscuità dei componenti veicolari nel traffico e dell'enorme componente umana che finalizza i compiti di guida per i veicoli a motore e parzialmente per gli AV (gli AV parzialmente si affideranno ancora ai conducenti umani). I siti in cui il traffico promiscuo è più sicuro di quello del 2030 sono caratterizzati da un regime di veicolo isolato o congestionato. Due condizioni in cui le interazioni sono controllate (o quasi nulle) e i veicoli devono seguire un determinato comportamento.

I risultati hanno evidenziato un aspetto fortemente dibattuto, ovvero la minore sicurezza della fase transitoria in cui c'è elevata promiscuità di veicoli nel traffico. Questo risultato è in linea con altre risorse della letteratura scientifica. Evidenzia, inoltre, la forte necessità, da parte degli stakeholder, di affrontare la questione in modo accurato, per rendere sicura l'introduzione dei veicoli a guida autonoma. In questa ricerca vengono proposte due contromisure per risolvere il problema relativo all'incidentalità nella fase transitoria, ovvero:

- Prevedere delle corsie riservate per i veicoli automatici, in maniera tale da ridurre le interazioni tra diverse tipologie di veicoli, nel caso di strade di nuova costruzione. Per strade esistenti, invece, prevedere la presenza degli AV sulle corsie riservate a Bus e Taxi, che sono caratterizzate da bassi volumi di traffico e sulle quali guidano conducenti altamente specializzati;
- Progettare i veicoli completamente automatici con dei parametri che siano più cautelativi, in linea con quelli dei veicoli parzialmente automatici, in modo tale da aumentare l'omogeneità dei comportamenti delle macchine automatiche e di aumentare l'intellegibilità di questi veicoli da parte dei conducenti umani.

Lo sviluppo di un SPF ad hoc per gli AV, inoltre, rappresenta una novità nel campo della sicurezza che può essere utilizzata come base per future previsioni incidentali per nuove tecnologie emergenti.

La tesi rappresenta una parte di uno studio più ampio sulla sicurezza degli AV. Può essere estesa per comprendere gli impatti degli AV in altri contesti stradali e nazionali. In quest'ottica, le variabili dell'SPF possono essere adattate e modificate a diversi contesti.

I risultati ottenuti sono utili per gli stakeholder e le amministrazioni, in quanto dimostrano la validità dell'assetto metodologico proposto per le analisi di sicurezza. Inoltre lo sviluppo della SPF è un punto di partenza per pensare in maniera rigorosa a contromisure per mitigare l'eventuale impatto negativo delle tecnologie nel traffico.

key words *Sicurezza Stradale; Veicoli automatici; Scenari Futuri; Simulazioni di Traffico; Misure Surrogate di Sicurezza; Conflitti-incidenti; Safety Performance Functions.*

INDEX/INDICE

INDEX OF FIGURES

INDEX OF TABLES

CHAPTER 1

INTRODUCTION

This thesis deals with the road safety assessment for different driving scenarios with Automated Vehicles (AVs). The introduction of AVs in the driving environment has been consistently controversial since their presence could create some issues for the regular human driver in regular vehicles (RVs). They could also not understand the driving environment completely if the infrastructures are not fully intelligible by technologies installed in the vehicles. Considering this ambiguous scenario, the question about the safety consequences of introducing such vehicles arises. The lack of an observed crash dataset could have represented an obstacle to develop a road safety assessment based on the classic approach suggested by the Highway Safety Manual, 2010. In this optic, the idea of creating a new simulated crash dataset thanks to traffic simulations that recreate the desired sites with promiscuous traffic. Having safety assessments adequate for further scenarios and implementations is crucial since regulations or planning require safety estimation of roads for the long term. Starting from this assumption, not considering at all that from now on, the traffic composition will be affected by the introduction of AVs, will lead to inaccurate estimations. For this reason, this work aims at filling this gap, providing a methodological framework to make safety assessment in presence of AVs in future scenario. Since planning procedures requires the safety assessment for long time horizons, the application of this framework was tested in the context of the SUMP (Sustainable Urban Mobility Plan) for the Province of Bari. The selected sites belong to the Province of Bari, on which it is possible to have all the primary input data to make a realistic and precise simulation, like input traffic flow and a dataset with at least five years (2015-2019) of observed Fatal+Injury crashes. The data were extracted by the SUMP. Then the current scenario has been validated to predict the number of crashes in the presence of other traffic with AVs (both fully and partially automated). The next step should have been to rely on the classic road safety approach, based on Safety Performance Functions, to predict the mean crash frequency. However, these functions are estimated and studied for regular actors on roads: human-driven vehicles, infrastructure, and the driving environment. The presence of AVs altered the interaction mechanisms among the traffic components; hence the Safety Performance Functions might be rethought in the optics of new technologies. Another primary variable might be added to the newly developed ad hoc Safety Performance Function (SPF): technology. The development of this new technology-based SPF is the final aim of this manuscript. This concept is crucial since not only will AVs be implemented in the future, but also several other technological things, just thinking about the components of Smart Roads. Thus, creating a new SPF suitable for new scenarios is also a promising idea to be delivered to practitioners and stakeholders to manage how safe their products could be if implemented on existing roads.

The final aim of this research will be achieved through several steps:

- Understanding what AVs are and what are their main features and how they can be categorized into sub-groups (1.1), defining the working environment (1.2), and a road safety assessment (1.3), introducing the concept of traffic simulations and conflicts analysis (1.4).
- Proposing a methodology (Chapter 2):
    - Reproducing the current scenario for the selected area (2.1)
    - Analyzing the traffic models used for traffic simulations to understand the most suitable one to represent both the current scenario and the further ones with AVs. Then, it is necessary to evaluate the performance of the selecting model to understand how to appropriately simulate the current scenario (2.2).
    - Validating the traffic output and filtering the available crash dataset according to the research aim. The validation might be assessed for road safety, too, comparing conflicts (the output of the simulation) to the observed available crashes (2.3)

- Stating the most significant parameters of the selected traffic model through the assessment of a sensitivity analysis propaedeutic to intervene directly on the most influencing parameter when introducing the AVs (2.4).

- Defining the further scenarios, their temporal horizons, and consequently the three different vehicles' market penetration (2.5).

- Developing a new ad hoc SPF for AVs (2.6).

* Showing the results for each part studied in the methodology (Chapter 3).

* Analyzing and making comments on the entire procedure (Conclusions).

1.1 AUTOMATED VEHICLES, NEW ACTORS ON ROADS

The ever-changing innovation and scientific discoveries are profoundly changing current scenarios in daily life. One of the most outstanding and revolutionary improvements in transportation is the introduction of automated and connected vehicles (AVs and CVs, respectively) and smart roads. As with all changes, it cannot be immediate, but it requires some time. The SAE Society of Automotive Engineers developed a classification of the different levels of automation to create a solid base and requirements to target each level and the consequent performance. SAE provided a taxonomy for six levels of automation, ranging from level 0, which corresponds to no automation, to level 5, which stands for full automation. This distinction is useful to state and describes all the driving automation features coherently equipped on motor vehicles. The level of automation strongly and uniquely depends on the features engaged in driving since a vehicle could be equipped with several automated devices that do not perform well or perform partially. The levels also refer to three primary actors in driving: the (human) user, the driving automation system, and other vehicle systems and components. According to them and their dynamic driving task (DDT), the performance is evaluated and assigned to each level. Active safety systems, such as electronic stability control and automated emergency braking, and certain types of driver assistance systems, such as lane-keeping assistance, are excluded from the scope of automation taxonomy because they do not perform part or all the DDT on a sustained basis and, rather, merely provide momentary intervention during potentially hazardous situations. In such cases, driver intervention is still crucial in DDT. On the other hand, full Automated Driving System (ADS) features belong to levels 3-5 since it performs the complete DDT, including crash avoidance capability.

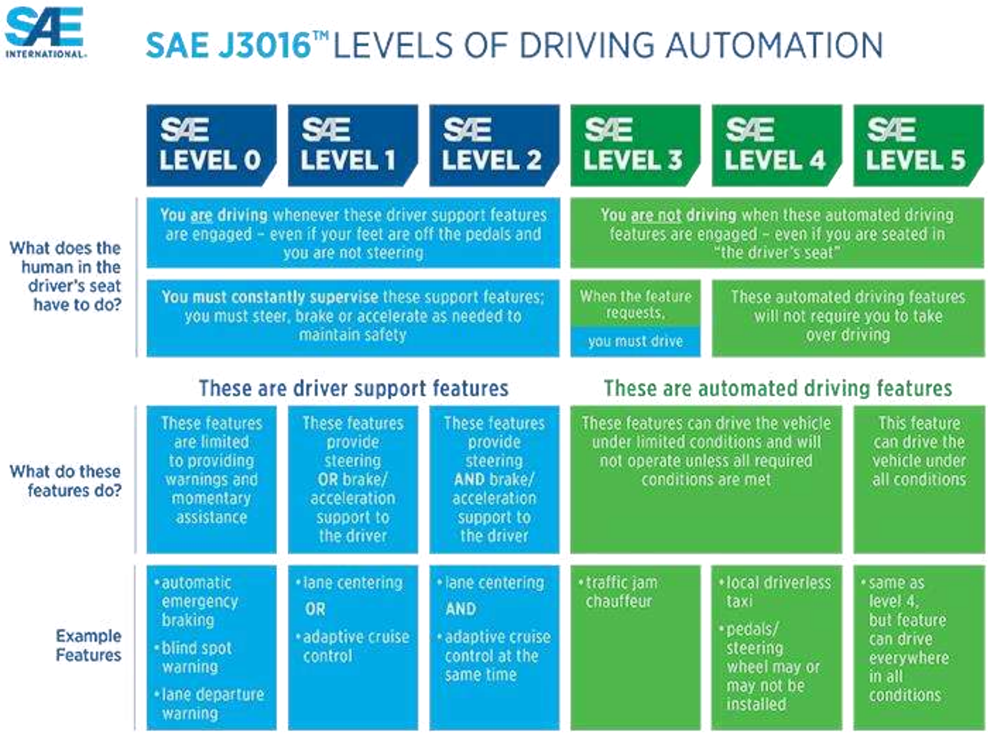

Figure 1:SAE Levels of automation and equipment characteristics (SAE-J3016TM, 30-04-2021).

Based on this taxonomy, nowadays, SAE Levels 0, 1, and 2 are largely deployed on roads because national regulations accept them. SAE level 3 vehicles are slowly introduced in the regular traffic conditions on roads, but authorization is still required to allow them to drive on roads. SAE 4 and 5-level vehicles are still utopistic (Milakis, 2019). These differences are hidden in the state of the art of automation. Now, we are in the infancy of automation, but according to Bertoncello and Wee, 2015 the next future will require at least three stages before fully AVs would be a reality.

On the other hand, there are CVs, which are regular vehicles equipped with instruments that continuously exchange data about traffic, road, and the environment with the road. This kind of vehicle deeply needs the presence of sensors and interfaces on roads, e.g., smart roads. Meanwhile, roads will experience a transition phase during which AVs will travel together with regular vehicles (RVs). This transitory phase will gradually lead to more sustainable cities in pollutant reductions (Salanova Grau et al., 2016; Smith et al., 2018) and more citizen-oriented spaces (WSP, 2017; Hancock et al., 2019). In this optic also, the public means of transportation will be interconnected and automated to reduce parking areas and waiting times, as well as the cities will be affected by fewer crashes (Schoettle and Sivak, 2015; Fagnant and Kockelman, 2015; Salanova Grau et al., 2016; Milakis et al., 2017; Hoadley, 2018; Hyland and Mahmassani, 2019). Despite the optimistic perspective of such implementations, estimates cannot be reliable for a lack of historical data, and, when scenarios are tested, AVs are less exposed to critical events than RVs (Merat et al., 2014; Favarò et al., 2017; Noy et al., 2018). Another important aspect to consider is that maybe the interactions among the vehicles can be potentially more critical than the scenario with only AVs. Hence, the outcome due to crashes and issues related to promiscuous traffic could be easily avoided thanks to a faster rate of implementation of full AVs in the shortest period (Sparrow and Howard, 2017; Kalra and Groves, 2017, Herrmann et al., 2018).

All the possible problems related to the interactions among these three types of vehicles (fully AVs, partially AVs, and RVs) can be summarized in an unstable flow because each follows a different path (Calvert et al., 2016; Mahmassani, 2016; Butler, 2020). For instance, fully and partially AVs react earlier than RVs (Calvert et al., 2018). Comparing AVs to CVs, it is possible to assess that they perform better than CVs since they do not need Distance Short-Range Communication (DSRC) and embedded technologies on infrastructures to communicate (Feng et al., 2020). Hence, the market is more prone to go forward with AVs rather than CVs because they can be implemented without intervening in the infrastructures. In the case of equipped infrastructure, AVs are also capable of communicating with it and optimizing behaviors. The performance of such vehicles is subjected to the view of the sensors, Lidars, HD Maps, radars ultrasonic, and cameras (Talebpour et al., 2017). Thus, it is crucial to prevent dangerous situations on roads' regular motion: blind spots must be avoided (Jiménez and Naranjo, 2011). Indeed, road geometry interventions are also necessary to optimize the efficiency of the technologies deployed on the vehicles (Talebpour and Mahmassani, 2016). Only after having adequate infrastructures, which, right now, may seem ideal conditions, AVs can be considered with almost zero reaction time (Talebpour and Mahmassani, 2016) and fully efficient (Jiménez and Naranjo, 2011; Scanlon et al., 2017). The full deployment of smart roads over the entire road network can optimize the communication for the CVs, thanks to the continuous and detailed data exchange between road and vehicle.

Considering AVs, before they will deploy as full AVs, vehicles would be equipped with Advanced Driving Assistance Systems (ADAS) that will integrate the already developed technologies such as lane departure warnings (LD), Forward collision Warnings (FCW), Adaptive Cruise Control (ACC), Pre-crash Brake assistant (PB), Optimal Autonomous Lane Keeping Control (O-ALKC), Active Yaw Control (AYC), and Automated Emergency Braking (AEB). These technologies seem to be effective in improving road safety, as simulation models have been certified (Kusano and Gabler, 2012; Dozza et al., 2016; Jermakian, 2017; Johansson et al., 2017; Yue et al., 2018; Lause III, 2019; Feng et al., 2020; Pipkorn, 2020; Kim et al., 2021) and as results of road safety assessment throughout the use of Crash Modification Factors, CMFs have been made, too (Ma et al., 2016, Deluka Tibljas et al., 2018; Coropulis, 2021). However, some studies (see, e.g., Ranieri et al., 2020) highlight that safety performances may even get worse after AVs deployment, considering the transition phase in which there is mixed traffic between RVs and AVs.

Hence, the AVs would perform differently and have different consequences if they are fully automated or partially automated.

In this case, it is necessary to create a rough distinction, which clusters the 6 AV SAE levels into just 3 categories to be reproduced in the traffic environment. The SAE levels 0 and 1 can be considered RVs.

The SAE levels 2 and 3 can be considered as partially automated with a cautious behavior since there is still the need for a human driver to take over the technology and act the main driving tasks (they will be called from now on or Cautious AVs or Partially AVs, PAVs). They have limited automated tasks, depending on the operational domain design and the performance and reliability of technologies installed at vehicles. The presence of men in driving is crucial, for safety and regulation. Men must complete the tasks that technologies are not set up to do. For this reason, they are thought to be cautious from a human driver perspective, not from a safety one. All the motion parameters of the vehicle are loosened because the vehicle is intermediate between fully automated and human driven. It has to have behaviors that must be understood immediately by the human to take over and by other human drivers travelling on the same roads.

When technologies are modelled to complete all the driving tasks for all the operational domain design, the presence of a human is not considered necessary, also by regulations. These vehicles are the SAE levels 4 and 5, and they can be considered fully automated with more aggressive behavior in terms of reaction time and distance since they rely on technological set performance and no more on the unpredictable human uncertainties. Thus, even if more safe-based and rule-based, their behavior, vehicles will optimize their interactions traveling almost like a platoon. In this sense, they would be considered Assertive (Assertive AVs) from a human driver perspective. The behavior of a fully AV will not be achievable by humans since it relies on perceptions and reactions of technologies, that are more rapid than humans to process information and act consequently. They will be called, from now on or Assertive AVs or Fully AVs, FAVs.

1.2 WORKING ENVIRONMENT

The definition of the working environment is crucial for making all the required analyses. It is possible to define the working environment for road safety assessment, by considering one area, the type of roads that will be investigated, and the geometric characteristics of the selected sites (Highway Safety Manual, 2010; Colonna et al., 2018; Colonna et al., 2019; Intini et al., 2019). Another crucial issue relates to the number of sites to consider (segments and intersections) to obtain a statistically significant sample. For example, the Highway Safety Manual, 2010 (HSM) suggests as a criterion to select and study a number of sites between 30 and 50 to have statistical significance for calibrating safety functions to make crash predictions. This criterion was found to be useful and reliable by multiple studies run through the years (Persaud et al., 2010; Xie et al., 2012; Trieu et al., 2014; Shin et al., 2015).

The road safety assessment needs at least two input data to calculate the safety indicators, like crash frequency or rates:

- the number of crashes that occurred on the road (observed and recorded), at least three years of a crash dataset (Highway Safety Manual, 2010);
- the traffic flow on the selected sites.

Hence, this kind of study must analyze one road type belonging to a selected area (to have constant characteristics as well as homogenous traffic behaviors) and consider the traffic flow, the traffic components operating at these sites (the presence of cyclists or pedestrians make a huge difference from their absence, in terms of risky situations and possible severity of crashes) and the crash dataset.

1.3 ROAD SAFETY ASSESSMENT

1.3.1 GENERAL ISSUES

The promiscuity of vehicles on roads and the different rate of environmental perception among AVs, CVs, and RVs is an issue for road safety assessment. Also, the idea of a smart road is currently well-known and diffused. However, the perfect integration among all the components (new vehicles-roads-regular vehicles) is still far from being determined. While technological discoveries are running fast, the study of road safety is not subjected to any improvement or remarkable modification to consider the new developments in the technological field. The absence of scientifically proven methods strengthens this problem in making road safety predictions in different scenarios from the current one. For road safety assessment, it is fundamental to consider and investigate the interaction between vehicles, infrastructure, and humans. The automation and interconnection of vehicles drastically alter this balance. Hence, finding a relationship between uncertain human and vehicle behavior (in the absence of a dataset) and altered and unpredictable boundary conditions related to the driving environment becomes complex.

Nowadays, widely used tools for safety predictions are the Safety Performance Functions (SPFs) and several CMFs (Highway Safety Manual, 2010; Intini et al., 2019). They are studied both on the vehicle and infrastructure side to make liable estimates on rural and urban roads (Haddon, 1972). The SPFs are functions estimated for a certain type of roads, segments, or intersections, under given ranges of annual average daily traffic (AADT), geometric characteristics, and boundary conditions. Their output is the predicted mean crash frequency. The idea at the base of this study is to adapt the concept of SPFs and CMFs to new hypothetical scenarios, integrating the presence of technology, like AVs, in road traffic to define new ad hoc SPFs. This different approach consistently evaluates the new conditions to be considered for the definition of an SPF, apart from the abovementioned ones, when AVs (both fully automated and partially automated vehicles) are present in road traffic with different penetration rates. The new parameters in the SPFs might be human, vehicle, automation, and infrastructure. The latter is still fundamental because well-designed infrastructure can positively affect the performance of automated vehicles, and poor roads can hardly be perceived by sensors, leading to unsafe driving behavior. In defining the vehicle characteristics, it is necessary, indeed, to consider the fact that RVs and AVs have different perceptions. It means that the perfect infrastructural geometry might be understood adequately by all the vehicle types traveling. This aspect has several implications for the future of road design and road design standards and guidelines, turning to more practical suggestions.

Considering these remarks, the definition of ad hoc SPF for AVs requires some defined scenarios. The absence of a real dataset and observed crashes implies the need to carve them out from other sources. A similar necessity arises from traffic studies, in which the main goal is to assess the performance of road networks.

The need to assess the performance of road networks, design new roads or enhance existing road connections is an everyday problem in transportation engineering. Commonly, transportation analysis relies on traffic simulators to predict traffic conditions in case of significant modifications in the infrastructure system, which may impact travel time and costs. In this latter case, using traffic simulators is crucial since there are no other ways to predict route choice and driving behavior modifications.

Road safety assessments, which should predict the benefits or the potential issues of given future scenarios (i.e., specific countermeasures) on the safety of the analyzed road sites, cannot rely in case of further hypothetical scenarios just on SPFs (which are predictive models based on current conditions). The robustness of predictions is higher if the hypothetical scenarios are precisely described in the simulators. Hence, in this case, the use of traffic simulators can also be crucial to simulate future traffic conditions and perform safety assessments.

Given the previous remarks, in recent years, traffic simulators have been used for predicting traffic improvement schemes (Chimdessa et al., 2013), safety assessments (Guido et al., 2019; Jang et al., 2019), design purposes (Oktech et al., 2004), by providing reliable results (Xue et al., 2019; Chao et al., 2020; Tettamanti et al., 2018). As previously introduced, they can also be used to test hypothetical future scenarios and then make a new input dataset for safety predictions thanks to the SPFs.

1.3.1 SAFETY PERFORMANCE FUNCTIONS (SPFs)

SPFs are introduced in the Highway Safety Manual (HSM). It is important to underline that the main innovation proposed by the HSM method consists not only of a quantitative assessment of the existing safety conditions on-site but also of the different possible scenarios of intervention on existing road sites in the different steps of the road safety management process. Since the SPFs play a consistent role in this research, explaining them, their characteristics, and variables, is required.

The HSM provides an operational framework for each step of the road safety management process. This process requires continuous monitoring of the reference road network, improved site selection, identification, and assessment of possible interventions (Highway Safety Manual, 2010). These operations are closely linked to quantifying the number of crashes and the people involved in fatal and injury accidents occurring during a given period, considering past (observed data) and future (predictions for different project scenarios).

Depending on the objectives set for the road safety study, the analysis of crashes can vary from a purely macroscopic scenario (i.e., an area-wide study) to more microscopic scenarios (a single segment or intersection). However, a baseline SPF is usually formulated by considering the following factors:

$$N_{SPF} = AADT \; x \; L \; x \; e^{k} \qquad \text{(Eq.1)}$$

Where:

- N_SPF = estimation of the predicted mean crash frequency for the SPF related to basic conditions, for a generic road element, segment or intersection (crashes/year);
- AADT = annual average daily traffic (vehicles/day), referring to the analyzed road element (in the case of intersections, traffic volumes on the main and secondary roads may be considered separately);
- L = length of the road segment (miles, in the case of HSM or km), a variable which is absent in the case of intersections;
- k = coefficient to be estimated from the model regression.

The SPF functions can then be adapted to different environmental conditions by the introduction of Crash Modification Factors (CMFs). The SPF is multiplied by the CMFs which consider differences between the geometric and functional conditions of the site under analysis (generic conditions “b”) and the baseline conditions of the functions “a”, specifically defined in the HSM.

Such differences are quantified as the variation of the mean expected crash frequency of a site from condition “a” to condition “b” (Hauer, 2000).

$$\text{CMF} = \frac{(\text{Mean expected crash frequency in condition } \mathbf{b})}{(\text{Mean expected crash frequency in condition } \mathbf{a})}$$

(Eq.2)

The concept of CMFs can also be applied to compare different intervention alternatives (in this case, the conditions “b”) to a specific base condition (of no intervention, conditions “a”). CMFs lower than 1 indicate that the intervention/condition reduces the estimated value of the mean crash frequency compared to the baseline condition.

CMF values greater than 1.00 indicate the opposite, that is an intervention/condition which increases the mean expected crash frequency.

The CMFs can be multiplied to estimate the total effect produced by the combination of different interventions/conditions different than the baseline. This approach does not overestimate the effects since similar effects are not computed multiple times. The predictive method also considers the application of a local calibration coefficient (Cc), which takes into account the different contexts (Intini et al., 2019) in which the SPF is applied (which is referred to both different geographical contexts and different reference periods). After these considerations, it is possible to assess the predicted mean crash frequency, as follows:

$$N_{Predicted\_CMF} = N_{Predicted\_SPF} \times (CMF_1 \times \ldots \times CMF_n) \times C_c \qquad \text{(Eq.3)}$$

As aforementioned, this value must be weighted by the EB-method, which improves the statical reliability of the estimate, using observed crash data too. The EB-method prevents the Regression to the mean (RTM) bias obtaining a value of expected mean crash frequency (NExpected), by assigning a weight (w) to the predicted mean crash frequency, which depends on the overdispersion of the model used, the period of observation, and the number of crashes observed.

$$N_{Expected} = w\, N_{Predicted} + (1 - w) N_{Observed} \qquad \text{(Eq.4)}$$

Where:

- $$w = \frac{1}{1 + k \times (\sum(Years\ of\ observation \times N_{Predicted}))} \qquad \text{(Eq.5)}$$
- k = SPF overdispersion parameter.

The EB method, therefore, succeeds in estimating the mean crash frequency by giving more weight to data that show greater statistical reliability or to relevant values of observed crashes.

It is evident, therefore, that the crash estimation, suggested by the HSM (2010) requires the availability of local SPF functions or at least of suitable calibration coefficients for the types of roads under examination (to be applied to the functions provided in the HSM manual, 2010).

The manual itself encourages the development of local SPFs to be introduced into the predictive method for applications in other contexts because more precise in their estimation than SPFs adapted by CMFs. This is the reason why in the context of new scenarios on roads, with the introduction of AVs and CVs, the first estimation of crash prediction can be made by CMFs, but the development of new SPFs is strongly recommended to improve reliability.

The prediction made by SPFs multiplied by CMFs which consider the introduction of technologies in the driving environment, is supposed to be a preliminary crash prediction. The most useful step to do is indeed the development of an ad hoc SPF.

The SPF is suggested to be developed by counting on at least 30 road elements, for statistical reliability; otherwise, the models could not represent well the incidental phenomenon (Abdel-Aty et al., 2014). In this case, since the goal is to develop a new SPF for AVs and CVs, no matter if for segments or intersections, this study will consider 30 segments and 30 intersections. They will be validated by the comparison between observed crashes and simulated crashes in microscopic traffic simulations. After that, simulations with new scenarios will be run and the results will be analyzed to obtain the SPFs.

1.4 TRAFFIC SIMULATIONS AND CONFLICTS

The need to understand the performance of a road network, design some roads, or make a more efficient connection is an everyday problem in the transportation and infrastructure fields. Transportation analyses commonly rely on traffic simulators to predict road traffic conditions and assess the benefits of some countermeasures. In this field, simulators are crucial since there are no other ways to predict how drivers perceive the roads and how the new road layouts can influence the flow. Sustainable alternatives in terms of time and costs are not present nowadays on the market.

A similar concern to the Transportation analysis is road safety assessment. Road safety is an aleatory problem, and it foresees the benefit or the adversity of some scenarios on road safety in the analyzed site. The scenarios also imply new geometric characteristics of the infrastructure, such as a new road design or the introduction of roundabouts. Road safety assessment can have a deep impact on infrastructure design to make roads safer. To predict the safety performance of the hypothesized countermeasures, it is not always possible to conduct an on-site experiment. Indeed, in most cases, it is almost impossible to directly test the countermeasures. The only possible way to make predictions and analyses supported by strong scientific clues is to rely on simulators. The chance of having simulated scenarios can enable road safety experts to create ad hoc safety performance functions for new and possible scenarios, always starting from a significant crash dataset. The robustness of the mathematical predictions, thanks to the use of safety performance functions, becomes greater if the hypothetical scenarios are precisely described in the simulators. The precision of a simulation depends on the traffic model, for car-following and lane-changing behaviors, used while simulating. Several traffic models exist to depict human-based driving behavior in car-following and lane-changing. The choice of the most accurate one for the specific studies and scenario becomes crucial, as will be explained in the next Chapter.

In recent years the necessity of predicting several conditions for traffic improvement (Chimdessa et al., 2010), safety assessment (Guido et al., 2019; Jang et al., 2019), and designing purposes (Oketech et al., 2004) has drastically moved the focus of infrastructure and transport engineers to the traffic simulator packages. These simulators have been validated through the years in terms of prediction and traffic performance before becoming accepted as reliable for predicting future scenarios (Tettamanti et al., 2018; Xue et al., 2019; Chao et al., 2020). In this way, designers can also count on efficient and smart predictions for further hypothetical scenarios.

This latter is the case of automation in traffic. Moreover, considering not only the unpredictable moment when fully AVs will be deployed on roads, but there are still restrictions for testing them in some countries, like Italy. The Ministerial Decree D.M. 70/2018 assesses the procedure required to make on-site tests, which is still complex. The main on-site tests have been tried in the United States of America, but the failure of some of them has also undermined the trust that people have in the upcoming emerging technologies in traffic (Noah et al., 2017; Adnan et al., 2018; Xu et al., 2021). Thus, it is impossible to count on several real-world studies useful for creating safety performance functions. Indeed, literature is currently developing several studies to predict or foresee the impact of such kinds of technological innovations on traffic (Lee et al., 2019; Liu et al., 2020), sustainability (Dias et al., 2021; Rodriguez-Rey et al., 2021), road efficiency (Shaldover et al., 2012), and safety (Giuffè et al., 2018; Rahman et al., 2019). The unique valid solution to this problem becomes the use of simulators.

Regarding road safety, theoretically speaking, the traffic simulations do not provide an output directly related to the crash. The main results traffic simulators provide are the conflicts extracted by the trajectories. A conflict is defined as an observable situation in which two or more road users approach each other in time and space to such an extent that there is the risk of collision if their movements remain unchanged (Gettman et al., 2008). The trajectories are read by a powerful algorithm, the SSAM (Safety Surrogate Analysis Model) algorithm (Pu et al., 2008; Gettman et al., 2008), capable of detecting dangerous situations according to the conflict definition. Hence, the safety analysis switches to the field of Safety Surrogate Measures (SSM). Safety Surrogate Measures are measures used in the field of crash and conflict analysis to assess the safety of some circumstances. Several SSM exist, like speed difference between two approaching vehicles (to determine the potential severity of their impact), the deceleration, the speed rate, spatial and temporal proximity, and evasive maneuvers. Among them, the most robust ones for safety analysis and conflicts/crash detections are spatial and temporal proximity (PET, Post Encroachment Time; TTC, Time To Collision) because they highlight how much the two vehicles are close and assess their chance of colliding, according to numerical thresholds, if their driving behavior stays unchanged, with very low errors. Evasive maneuvers analysis can be reliable as well, but they can be subjected to recording errors, more easily. All the SSM have been subjected to real data comparisons and tests and they have been widely validated (Ozbay et al., 2008; Yan et al., 2008; Astarita et al., 2012; Yang, 2012; Wang and Stamatiadis, 2013; Astarita et al., 2018; Morando et al., 2018; Guido et al., 2019; Alonso Orena et al., 2020; Astarita et al., 2019; Astarita et al., 2020; Astarita et al., 2021) also for specific cases, like intersections (Vasconcelos et al., 2014) or road users (Johnsson et al., 2018; Johnsson et al., 2021).

The most spread Surrogate Safety Measures to count a conflict, as previously mentioned, are the following two:

- Time To Collision (TTC).
- Post Encroachment Time (PET).

These two measures are indicators of conflict occurrence: for TTC lower than 1.5 s and PET lower than 5 s, a conflict can be counted (Gettman, 2008). The TTC is the most used one (Lu et al., 2005; Laureshyn et al., 2010; KAparias et al., 2010; Ismail et al., 2011; Salamati et al., 2011; Zheng et al., 2014; Morando et al., 2018; Virdi et al., 2019; Astarita et al., 2020; Sinha et al., 2020), and the threshold value can be modified according to the simulated vehicles and dangerousness of the site, but the results were found to be almost stable around the ones found for TTC set equal to 1.5 s (Shaddah et al., 2015; Papadoulis et al., 2019). Analyzing the risk related to two intersecting trajectories unavoidably shows that relying on the SSM makes it possible to calculate the conflict between the two vehicles involved. Hence all the recorded crashes which count just one vehicle involved, like isolated vehicle crashes, or more than two, like multiple vehicle crashes are discharged in the study.

The trajectories recorded and analyzed by the SSAM algorithm are then converted to conflicts according to the SSM chosen to detect a conflict. The conflicts detected are clustered for types, according to the angle of trajectories, α, as stated in Figure 2, and as follows:

- Rear-end conflict for α lower than 30° ($\alpha < 30°$).
- Crossing conflict for α greater than 85° ($\alpha > 85°$), which stands for side-swipe and head-on conflicts (which happens when the angle is 90°).
- Lane-changing conflict for α between 30° and 85° ($30° < \alpha < 85°$), which stands for side conflicts.

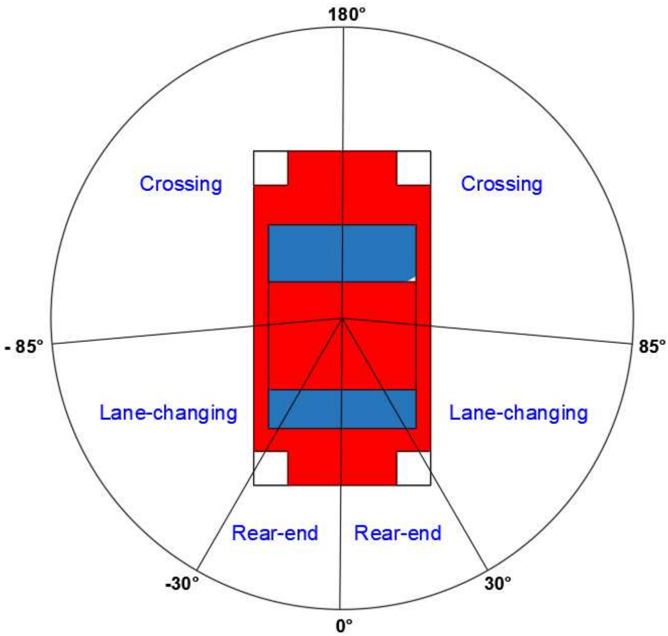

Figure 2: Conflict types according to the angle of possible collision.

Given that the SSAM can work only for conflicts between two different vehicles, as previously stated, single-vehicle conflicts (e.g., run-off road crashes) are out of control. Some other tools were developed, such as the software Zombie Driver (Alonso Oreña et al., 2020; Astarita et al., 2019), used to simulate driver distraction which could be, in turn, a contributory factor for run-off road crashes. However, this procedure partially neglects the run-off road crashes fostered by other conditions such as road geometry, obstacles, etc.

As previously stated, the SSAM output enlightens the number of conflicts. However, the correlation between conflicts and crashes is debatable since not all conflicts become crashes. The relationship between conflicts and crashes can be treated with an extreme value statistical approach (Tarko, 2021). Nevertheless, it is possible to compare the SSAM outputs to real crash data for validation purposes, thanks to several approaches, including simple regressions having linear, exponential, or quadratic forms, depending on the availability of the dataset and the accuracy of the expected conflicts data (Hauer, 1982; Migletz et al., 1985; Hydén, 1987; El-Basyouny et al., 2013; Polders et al., 2018; Johnsson et al., 2021; Glauz et al., 1980; Songchitruska et al., 2006; Zheng et al., 2019; Zheng et al., 2020). Hence traffic simulation outputs must be accurate to obtain accurate and reliable predictions.

CHAPTER 2

METHODOLOGY

In this chapter, all the necessary steps to run the simulations and achieve the final goal are detailed.

2.1 INVESTIGATED AREA

2.1.1 NETWORK DESCRIPTION

In order to perform a safety assessment, it is necessary, as aforementioned, a dataset relative to the crashes that occurred and recorded for at least three years of observation, as well as traffic flow input data in the context of simulations. These data might be obtained thanks to a monitoring phase a priori to make them reliable for the simulation step. These two requirements forced the choice of the investigated area, i.e., the Province of Bari, for which, thanks to the collaboration for the draft of the Sustainable Urban Mobility Plan (SUMP) 2021, all these data were available.

The crash data were relative to Fatal+Injury crashes from 2015 to 2019 (ASSET[1]-ISTAT dataset). On the other hand, the flow data were obtained by previous monitoring of the entire road network belonging to the province.

Analyzing the crash dataset showed how the most crash-affected roads were the two-way, two-lane rural roads, for example because of the exceedance of driveways and minor intersections with low visibility present on straight segments. For this reason, this kind of road was chosen for the study. However, before choosing these

[1] Asset is the Strategic Regional Agency for the Ecosustainable Development of the Territory of the Puglia region. It replaced AREM (Regional Agency for Mobility of the Apulia Region) from 2018, expanding its functions. It is an operational technical body supporting the region in the definition and management of policies for mobility, urban quality, public works, ecology and landscape, prevention and protection of the territory and hydrogeological and seismic risk.

roads, a new analysis was made. The dataset was filtered for just two-vehicle-involved crashes, the only one reproducible by the simulations, representing 65% of the total recorded crashes. Even in the case of two-vehicle-involved crashes, this type of road showed the greatest percentage of crashes.

The choice of the sites to investigate belonging to the entire rural road area was made considering the roads characterized both by a high number of crashes and a low number of crashes. This choice allowed to contemplate all the possibilities happening on roads and analyze the main causes leading to a safe or dangerous site. Moreover, considering this variability, it is possible to make errors in crash frequency prediction. In fact, just choosing the most crashed sites could have led to dramatic predictions about the crash occurrence on the sites. Contrary, this procedure aims at preserving the aleatoric nature of crashes. In this optic and having to consider for the statistical significance of the study at least 30 segments and 30 intersections, 23 sites with multiple segments and intersections were chosen. The extent of the sites (Table 1) was such that a realistic simulation could have been still done; when simulating greater networks, there is the risk of error propagation on the arches of the network, losing the desired accuracy (Li et al., 2013; Jeong, 2017; Rahaman et al., 2018; Stanek et al., 2018; Papadoulis et al., 2019), if the dimensions of the sites are too small or too big to be accurately reproduced. This is the same error also occurring during macroscopic simulations while simulating great areas of interest.

In the figures below, all the selected sites are highlighted in blue. In clear blue are highlighted the sites also used for the sensitivity analysis, as will be detailed in paragraph 2.4.

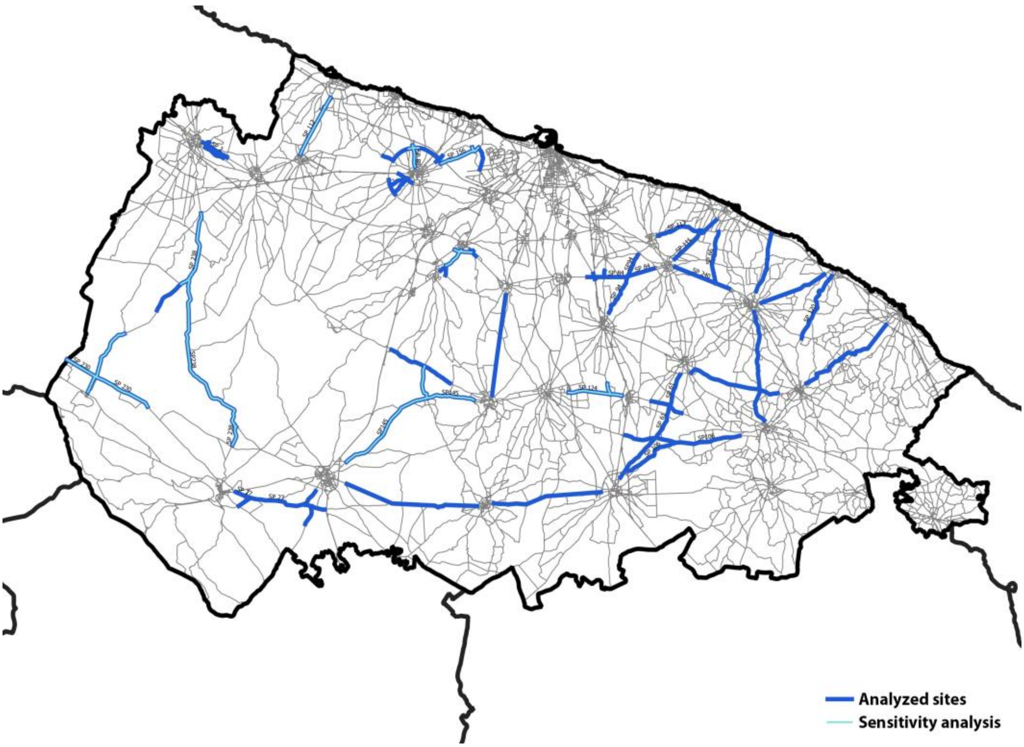

Figure 3: Province of Bari area and its road network. In blue the selected sites are highlighted.

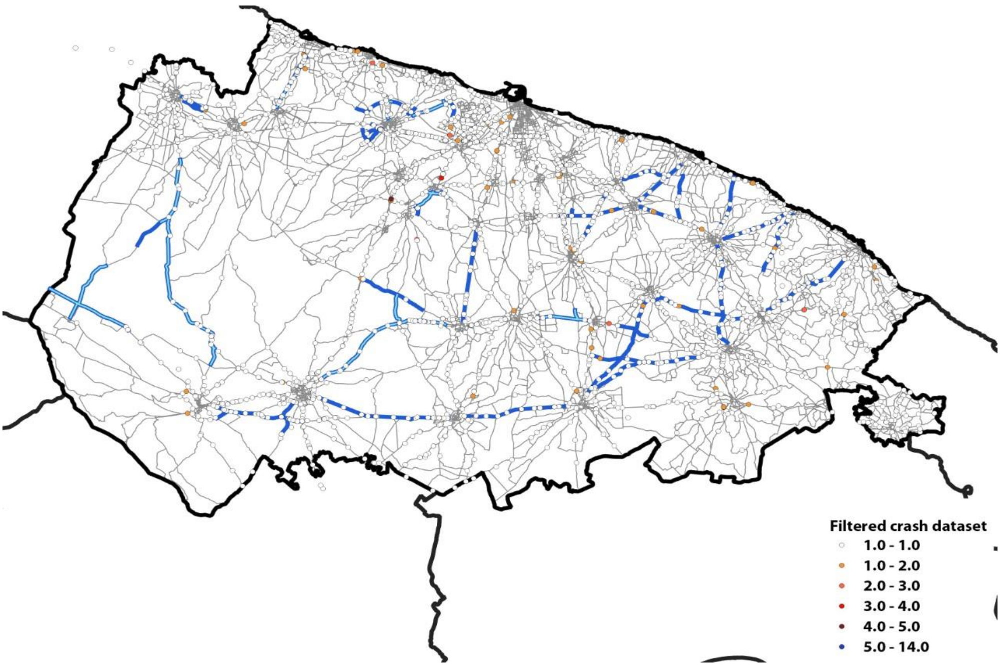

Figure 4: Province of Bari area and its road network. In blue the selected sites are highlighted, and each dot stand for the crashes occurred, clustered by frequency, filtered for the two-vehicles involved crashes only.

2.1.2 DATASET

In the following table, all the characteristics of the investigated sites are detailed, together with the traffic, seen as the Annual Average Daily Traffic. This value was obtained by calculating the total number of vehicles travelling on the site for one day (data about the traffic on segments were available from the SUMP). The crash rate has also been calculated, relying on the equation provided by the HSM 2010, as below:

$$Crash\,rate = \frac{Crashes \times 10^6}{AADT \times 365 \times L} \qquad \text{(Eq.6)}$$

Where L is the length of the segments belonging to the investigated site, the AADT is the average daily traffic, 365 stands for the number of days per year, and crashes stand for the number of observed crashes.

Table 1: Selected sites, their extensions, the number of observed crashes, categorized as the SSAM algorithm does, the traffic (AADT, seen as the average number of vehicles circulating during the day in the entire site), and the Crash rate (Crash/AADT).

Selected Site name	Km	Crash/km	Crossing Crash number	Rear-end Crash number	Lane-changing Crash number	AADT (Veh/day)	Crash/AADT
SP2	6.355	1.73	7	4	0	9674	0.4902
SP27	15.39	2.21	20	9	5	1818	3.3293
SP50	6.39	1.25	5	3	0	5652	0.6069
SP61	35.03	0.83	19	5	5	6604	0.3434
SP84	12.62	4.52	36	12	9	20340	0.6084
SP88	4.47	6.26	19	4	5	10543	1.6278
SP89	7.53	3.59	17	6	4	26400	0.3721
SP111	11.6	1.55	9	6	3	7977	0.5329
SP112	6.66	3.15	12	8	1	14712	0.5872
SP120	7.93	2.14	13	1	3	6645	0.8839
SP121	7.46	2.41	6	4	8	6458	1.0236
SP124	6.96	0.72	3	1	1	5745	0.3426
SP145	27.3	0.95	18	3	5	6413	0.4069
SP156	4.86	6.79	22	4	7	24097	0.7720
SP206	7.98	1.25	6	3	1	12104	0.2836
SP230	17.71	0.11	2	0	0	3142	0.0985
SP235_169	11.74	1.36	8	6	2	5550	0.6728
SP235_177	14.62	1.92	14	10	4	9547	0.5496
SP236	10.58	1.13	7	4	1	8040	0.3865
SP237	11.93	1.93	17	3	3	8309	0.6357
SP238	28.96	0.66	11	3	5	1478	1.2162
SP240_32	22.28	1.26	18	5	5	7430	0.4634
SP240_66	11.87	2.11	12	11	2	18338	0.3147
Mean	12.97	2.17					
Total	**298.22**		**301**	**115**	**79**		

The sites were also characterized by different geometric designs for segments and intersections (3-leg, 4-leg, and roundabout) to account for various situations (Table 2).

This great variability could have also suggested the implication of some road characteristics on crash occurrence if the final value of standard deviation for the average crash recorded for each site had shown high values.

Table 2: Selected sites and their geometric characteristics. The column "Signalized" highlights the typology of signalized intersection for the site. The sites with signalized intersections have just one signalized intersection.

Selected sites name	**Segments**	**Intersections**	**Intersection geometry**			**Signalized**
			3-leg	**4-leg**	**Roundabout**	
SP2	10	5	5	0	1	
SP27	7	3	3	0	0	
SP50	1	0	0	0	0	
SP61	10	4	3	1	0	
SP84	11	4	2	1	1	3-leg
SP88	7	2	0	1	1	
SP89	11	4	1	3	0	4-leg
SP111	4	1	0	0	1	
SP112	4	1	0	1	0	
SP120	1	0	0	0	0	
SP121	1	0	0	0	0	
SP124	3	1	1	0	0	
SP145	8	3	2	0	1	
SP156	11	4	2	1	1	3-leg
SP206	14	5	1	1	3	
SP230	6	3	3	0	0	
SP235_169	8	1	0	1	0	
SP235_177	4	3	2	1	0	
SP236	4	1	0	1	0	
SP237	1	0	0	0	0	
SP238	5	2	2	0	0	
SP240_32	8	2	1	0	1	
SP240_66	7	2	1	1	1	
TOTAL	146	51	29	13	11	

The SUMP database's Annual Average Daily Traffic (AADT) was available for the different Origins and Destinations, after on-site monitoring phases. For this reason, the traffic was considered thanks to OD matrixes.

The first problem related to the selected sites was to recreate in the best way possible the crash-leading conditions, and so, simulating in the best way possible at least one year of traffic. The most common procedure for traffic simulations used for safety assessment is to find a significant number of replications of the peak hour and to average the values obtained by those replications (Shaddah et al., 2015; Papadoulis et al., 2019). In this case, the final aim of creating an ad hoc SPF for AVs, hence the necessity of creating realistic further hypothetical scenarios with almost no comparison to reality, suggest recreating in the simulation environment as well the typical year of traffic. Starting from the AADT available by the SUMP, it was created a multiple-step phase of traffic analysis:

1. Relying on the SIT Puglia 2008 data for the selected rural roads, recreating the traffic vehicle composition, computing the heavy and light vehicle percentages (Table 3). Motorbike number was negligible on this type of road, as well as the number of cyclists.

Table 3: Traffic composition for all the 23 sites.

ID	Investigated Sites	Traffic composition	
		Car (%)	Heavy Vehicle (%)
1	SP2	96.00	4.00
2	SP27	88.85	11.15
3	SP50	91.95	8.05
4	SP61	93.30	6.70
5	SP84	96.90	3.10
6	SP88	95.25	4.75
7	SP89	95.50	4.50
8	SP111	95.95	4.05
9	SP112	95.20	4.80
10	SP120	92.00	8.00
11	SP121	92.20	7.80
12	SP124	94.30	5.70

13	SP145	94.85	5.15
14	SP156	93.00	7.00
15	SP206	97.10	2.90
16	SP230	82.05	17.95
17	SP235_169	92.85	7.15
18	SP235_177	92.85	7.15
19	SP236	94.85	5.15
20	SP237	96.45	3.55
21	SP238	92.40	7.60
22	SP240_32	91.95	8.05
23	SP240_66	91.95	8.05

2. Relying on the SIT Puglia 2008 data for the selected rural roads, the hourly traffic variation law was found, averaging the value obtained for the 23 sites (Figure 5).

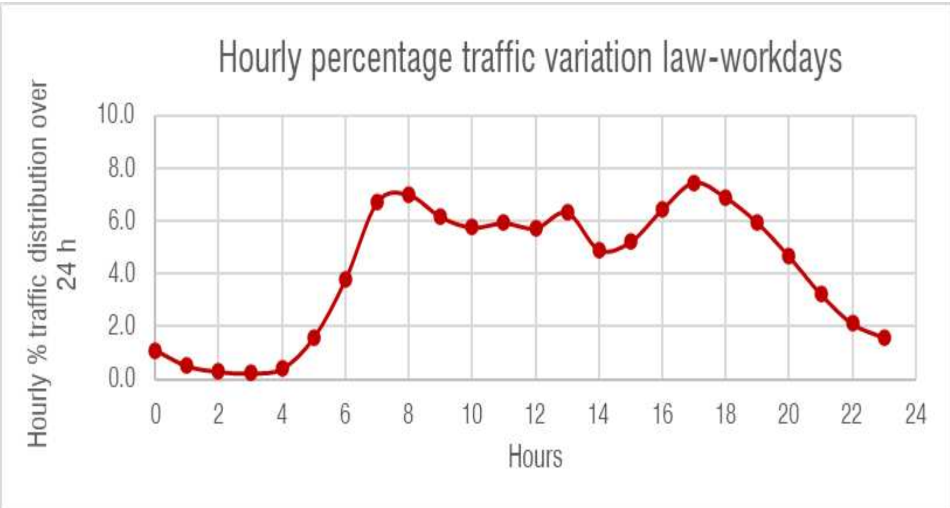

Figure 5: Hourly percentage traffic variation law-workdays for the selected rural roads.

3. Relying on ANAS 2008 traffic data for all the highways in the province of Bari, the hourly traffic variation (averaged over the entire road network managed by ANAS in the Province of Bari) was extracted. Then this variation law was

compared to the ANAS 2015-2019 traffic data to see if some modifications occurred (5 years of traffic data). After it was determined that no modifications occurred between these two datasets for traffic variation, the ANAS 2019 percentage hourly variation was compared to the one obtained by the SIT PUGLIA 2008 dataset. The comparison was made by evaluating the traffic percentage for each hour of the day. The percentages for each hour of the ANAS 2019 dataset and of the SIT PUGLIA 2008 dataset were compared. The correlation was almost perfect (Figure 6). Hence the weekend traffic hourly variation was obtained by ANAS 2019 dataset (always after having compared the ANAS 2008 data to the ANAS 2015-2019 data), and then, thanks to the inverse formula, the weekend hourly percentage variation was calculated for rural roads too (Figure 7).

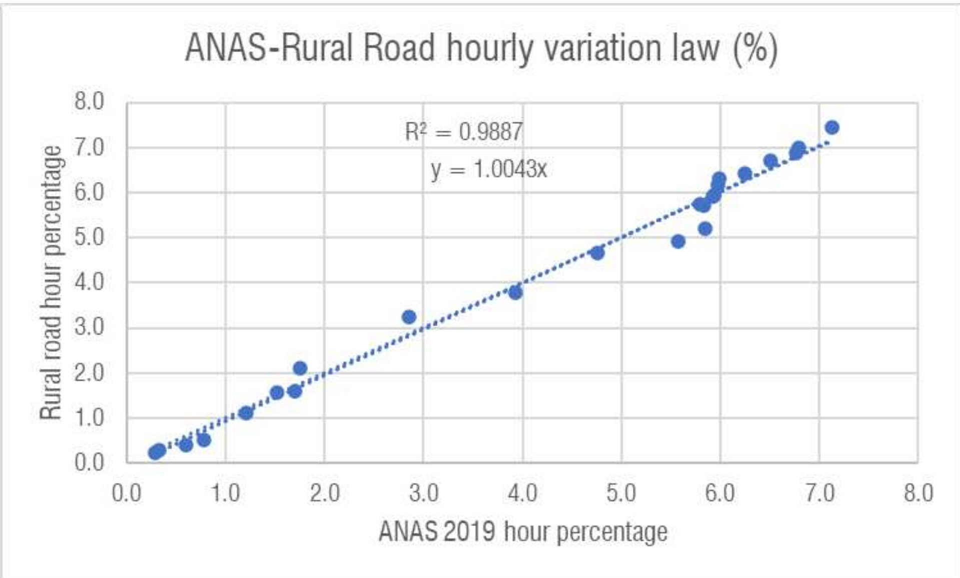

Figure 6: Correlation between ANAS 2019 percentage hourly variation (y-axis) and SIT Puglia 2008 percentage hourly variation (x-axis).

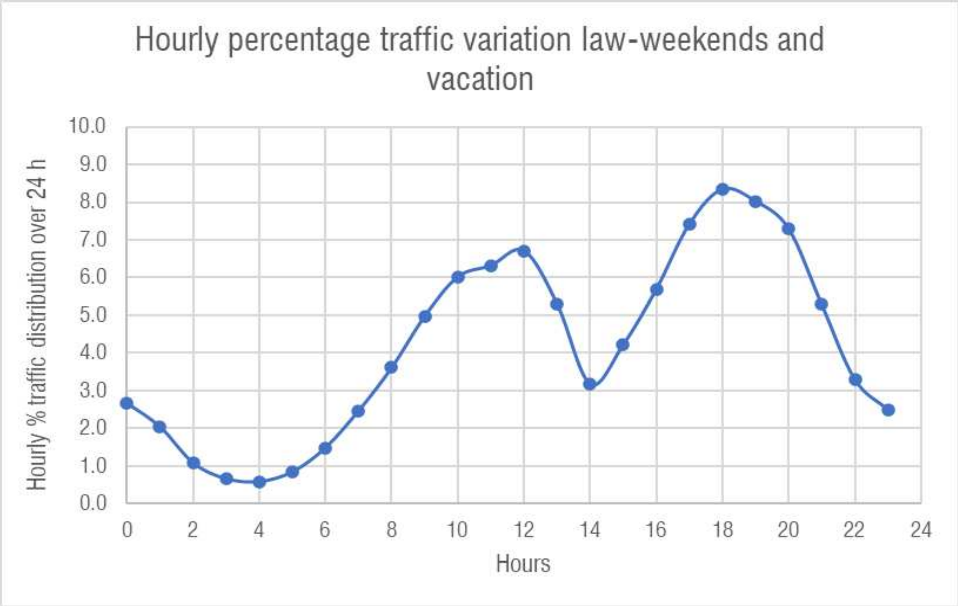

Figure 7: Hourly percentage traffic variation law-weekends and vacation for the selected rural roads.

4. After assessing the good fitting between the SIT Puglia 2008 dataset for rural roads and the ANAS one for the highways of the same area, the ANAS 2015-2019 monthly traffic variation was calculated. In this way, it was possible to determine the seasonal coefficient (Table 4) to adapt the annual average daily traffic to the different seasons (after adapting it to weekdays, vacations, and workdays).

Table 4: Seasonal coefficient for rural roads and the total number of workdays and days off (Weekends and vacations) for each season.

	Seasonal coefficient for rural roads		**Total number of workdays**	**Total number of days off**
	Workdays	**Weekends/Vacations**		
Winter	0.90	0.81	74	17
Spring	0.97	0.97	74	17
Summer	1.03	1.16	77	15
Fall	0.92	0.87	73	18

Working according to these steps make it possible to reproduce accurately what happens during an average year, starting from the available dataset about the vehicle flow for the Province of Bari.

2.2 TRAFFIC MODELS COMPARISON

The choice of the most suitable traffic simulator depends on the analysis of the models implemented in each software. These models are crucial to depict driving behaviors realistically.

Each simulator package aims to virtually reproduce what happens on different types of roads (motorways, rural, urban, and so forth). There are several available simulators and the chance to implement their own codes and algorithms to obtain the desired output parameters for traffic analysis (Rahman et al., 2019). This paragraph mainly focuses on the models used by the most widespread and suitable simulators and their outputs to be used as input for the SSAM analysis. Hence a comparison among all the most common models, car-following and lane-changing, is made to find the most suitable one for the microscopic traffic analysis in rural contexts. The car-following and lane-changing models are the main features that lead the vehicle to behave differently. Each type of model developed belonging to one of those categories contains a different number of parameters, according to the complexity of the model itself. The number of parameters generally affects the accuracy of the output. The greater the number of parameters is, the greater the accuracy and the computational effort become. Despite this correlation, many parameters can also lead to a greater chance of propagation of several inaccuracies (Brackstone et al., 1999). This issue is overcome by reducing the extension of the analysis. Simulating just one segment or one intersection rather than the entire road network is preferable to prevent errors due to the great computational burden (Papadoulis et al., 2019; Li et al., 2013; Rahaman et al., 2018; Stanek et al., 2018; Jeong, 2017).

The car-following models simulate how the vehicles behave in the same lane, interacting with other adjacent vehicles (Brackstone et al., 1999; Olstam et al., 2004), but also in free-flow conditions if the distance between two following vehicles is too large to consider negligible the mutual influence. The lane-changing models simulate how vehicles behave in changing lanes to overtake other vehicles or simply to move from one lane to an adjacent one. This situation is complex since it considers not only adjacent vehicles in the same lane but also the speed, distance, and acceleration of the approaching and existing vehicles in the target lane (Balal et al., 2014). Therefore, a mathematical comparison analyzing the most influential variables among all the simulators has been run to obtain and define the most suitable one for AV simulation purposes.

2.3 TRAFFIC SIMULATOR

After choosing the right model to depict the current scenario and the further ones based on the parameters and the type of car-following and lane-changing models intervening, it is possible to understand how the different simulations work on the software, which is based on the chosen traffic model. The simulator software packages always differ in the type of simulation they can do, like micro, meso, or macro simulation. The idea at the base of this research is to understand the microscopic interactions among the vehicle to analyze their trajectories and represent AVs, intervening on the fundamental parameters of the models rather than on traffic input. A microscopic simulator was used since it was the most suitable for the targeted purpose. The necessity of the microscopic simulator also matched very well with the current scenarios to be tested, characterized by small sites; hence possible to be accurately represented by a microscopic one. When the dimensions of the sites start increasing, the microscopic simulation loses its capability to depict the scenarios, the computational effort becomes huge, and the traffic is not properly represented.

After selecting all the sites useful for the representation, they were represented on the microsimulator based on the Gipps model, AIMSUN Next. This simulator enabled the recreation of the road type and characteristics to represent the input flow data and set the posted speed limit reproduction. Concerning the default parameter to assess a

RV, the values were found to be consistent for the city of Barcelona, where the software was developed (Barcelò et al., 2005). These values were applied to the province of Bari with some modifications (values in Table 5) deriving from studies conducted at European level (Levitate Project D4.4, 2020) due to the slightly different behavior of Italian drivers if compared to the Spanish ones, and according to the Italian regulations for road infrastructures (Ministerial Decree n. 6792, 05/11/2001 and Ministerial Decree n. 170 19/04/2006), as for speed limit, and intersection rules. Design values of acceleration and deceleration are provided by Ministerial Decree n. 6792, 05/11/2001 and they are respectively 1 m/s^2 and 3 m/s^2 but these values cannot be used for simulating maximum deceleration and acceleration.

Hence the RV was modeled according to the values exhibited in the following Table 5. The main parameters used for representing a vehicle are the following:

- Aggressiveness level, which influences the lane-changing gap acceptance; the higher it is, the riskier the lane-changing is.
- Clearance, which stands for the spatial distance, in meters, between two following vehicles (front of the follower and back of the leader).
- Gap, which admits a different time distance, in seconds, between two following vehicles apart from the one calculated by the car-following model.
- Guidance acceptance level stands for the acceptance of road rules and signals.
- Look-ahead distance factor, which is a factor affecting the distance from the intersection that a vehicle considers before signaling or executing a maneuver for the upcoming intersection.
- Maximum acceleration, which stands for the maximum achievable acceleration.

- Maximum deceleration, which stands for the maximum achievable deceleration in dangerous or unexpected situations.

- Maximum desired speed, which is the maximum speed vehicles would reach in the absence of boundary conditions, like posted limits.

- Maximum Yield time is the range of waiting time at intersections that a vehicle could accept before crossing the intersection itself in unsafe situations. The greatest it is, the most aggressive becomes the driver's behavior.

- Normal deceleration, which is the maximum deceleration achievable in regular conditions and not disturbing the driver's comfort.

- Overtake speed threshold is the percentage of the desired speed that a vehicle accepts before starting an overtaking maneuver.

- Reaction time, which is the vehicle's reaction time according to the leader vehicle's behavior, in different situations like at stop, traffic lights and regular traffic.

- Safety Margin Factor is a multiplicator coefficient that intervenes on the calculated gap acceptance during the intersection crossing maneuvers.

- Sensitivity factor, which takes into account the follower vehicle's capability of estimating the deceleration of the follower for a safe driving experience (it is a coefficient).

- Speed limit acceptance which stands for the vehicle's tendency to accept the speed posted limits.

Table 5: RV parameters for the simulation of the current scenario.

Parameters	UoM	Human Driver			
		Mean*	Dev	Min	Max
Aggressiveness level	-	-	-	0.00	1.00
Clearance	m	2.00	0.80	0.50	3.50
Gap	s	1.00	0.50	0.00	2.00
Guidance acceptance Level**	%	50.00	25.00	0.00	100.00
Look-ahead distance factor	s	-	-	0.80	1.20
Maximum acceleration	m/s2	3.00	0.20	2.60	3.40
Maximum deceleration	m/s2	6.00	0.50	5.00	7.00
Maximum desired speed***	Km/h	100.00	10.00	50.00	150.00
Maximum Yield time***	s	10.00	2.50	5.00	15.00
Normal deceleration	m/s2	4.00	0.25	3.00***	5.00
Overtake speed threshold	%	90.00	-	-	-
Reaction time***	s	1.2		-	-
Safety Margin Factor	-	1.00	0.50	0.00	2.00
Sensitivity Factor	-	1.00	0.25	0.00	2.00
Speed limit acceptance***	-	1.10	0.10	0.90	1.30

*Mean, minimum and maximum value have been obtained by at site analysis (Levitate Project, 2020; Ims & Pedersen, 2021).

**Values obtained by data collection run by SIT PUGLIA 2008.

***Values obtained by Ministerial Decree n. 6792, 05/11/2001 and Ministerial Decree n. 170 19/04/2006.

The roads were then designed in the simulator, respecting all the characteristics of the segments and intersections, and creating a project in scale 1:1, i.e., the length of the segments and the dimensions of the roads are the same in the simulator and reality (Figure 8).

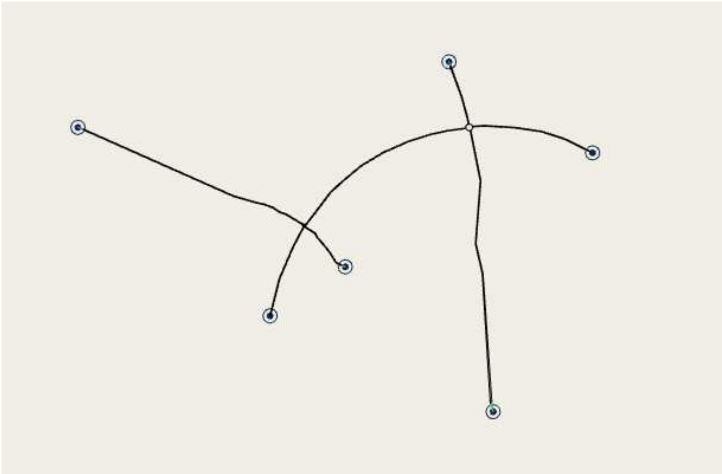

Figure 8: Example of the SP88, one of the selected sites, reproduced in the simulator AIMSUN Next.

One of the first steps to validate the model chosen, thus the simulator, was to validate the traffic output of the simulations. The traffic flow is one of the most significant parameters to be considered, among all the available ones, to validate if the simulation is accurate and if it overlaps the observed data (Guido et al., 2019 b); Papadoulis et al., 2019; Astarita et al., 2020). The check between the simulated scenario and the observed real data about traffic flow is commonly made by the mean of the GEH (Geoffrey E. Havers, 1970) value (Friedrich et al., 2019; Guido et al., 2019 a); Astarita et al., 2020). It is calculated as follows:

$$GEH = \sqrt{2 \text{ x } (\mathrm{M} - \mathrm{C})^2 / (\mathrm{M} + \mathrm{C})} \qquad \text{(Eq.7)}$$

Where:

- M is the value of traffic flow (vehic/hours) obtained by the simulations.
- C is the value of traffic flow (vehic/hours) observed by real monitoring procedures.

A model, indeed, a simulation, is reliable when the GEH is lower than 5. If the GEH is between 5 and 10, the simulation and observed data are not strongly related; if the GEH is greater than 10, there is no correlation between the input data and the simulated ones.

This comparison was made for all the selected sites to assess the reliability of the simulation in terms of traffic flow. If the traffic is not well described, of course, the conflicts too, so the road safety analysis cannot be reliable. This first step was propaedeutic to state that the simulations are correct and that the current scenario can be studied for road safety purposes, starting from the data obtained by the simulations.

The next issue was to understand how to simulate the entire year. Two alternatives were attempted and tested:

- Simulating each day as an individual day, not linked to the others, thus making one simulation for each day;
- Simulating days in continuity for each season, thus making n repeated simulations.

The two approaches were tested on three selected sites to understand their applicability. Three sites were chosen (Figure 9) because they showed different geometric characteristics and different flows. They represented the one with a low number of crashes (SP124 with 5 crashes), the one with an average number of crashes with respect to the sample of sites (SP112 with 21 crashes), and the one with a great number of crashes (SP61 with 29 crashes) among all the selected sites. In this way, it would have been possible to understand the impact of the two proposed alternatives not only on traffic indicators (like flow, density, queue, and total traveled km) but also on the conflicts. The conflict occurrence is also strictly linked to the characteristic of traffic and to the exposure to dangerous situations (Total traveled km). In this way, it was possible to cover a great variability and to understand deeply which one of the alternatives was the most promising. The simulated days were 35 for both alternatives (to have a statistical significance). Hence, for the first alternative 35 single days were simulated (M35); for the second one, 35 consecutive days were simulated (M1). Hence, the Average Annual Daily Traffic (AADT) available from the SUMP for the three sites was used for both conditions. It was distributed over 24 hours following the hourly variation law for rural road workdays. Then, the traffic composition was recreated according to the data in Table 3. The output from the simulations was collected for both the alternatives, and the trajectories were analyzed thanks to the SSAM algorithm to obtain the conflict numbers for both the alternatives proposed. The observed crashes were categorized by the crash type (crossing, lane-changing, and rear-end) to compare the number of conflicts per type with the crashes per type.

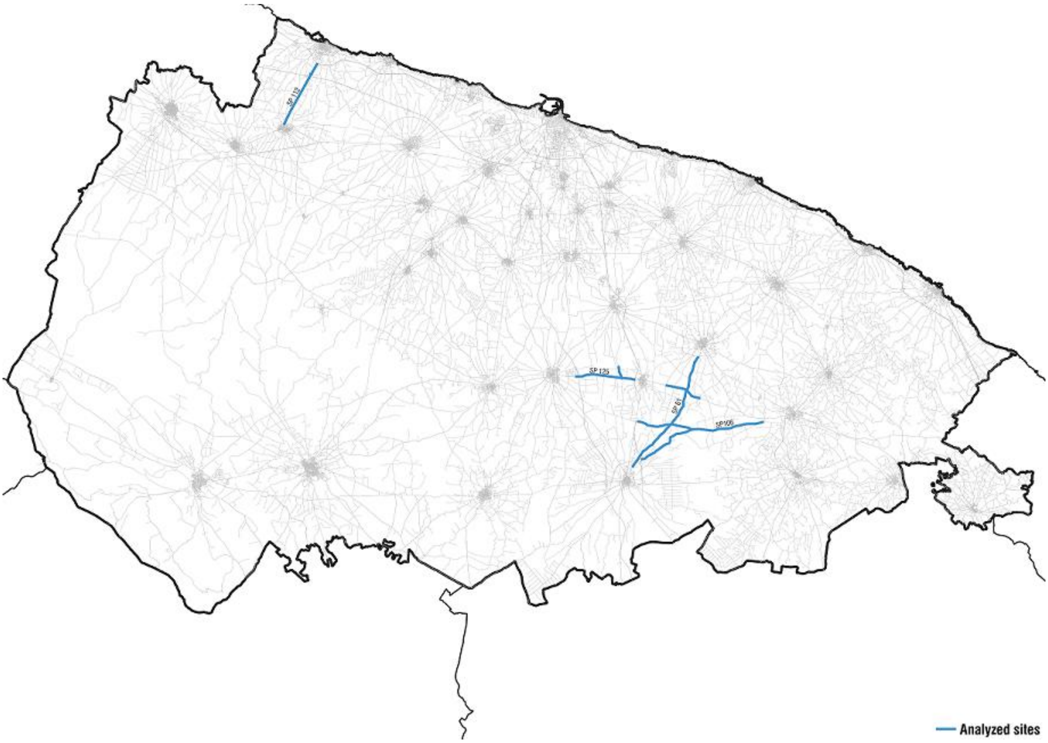

Figure 9: The selected sites for testing the best approach to simulate days in AIMSUN Next.

In Table 6 the results from this comparison are presented. The comparison among the traffic outputs and the observed scenario is neglected since the sites have been already validated and the results from the validation will be shown in detail in Chapter 3: Results (3.3).

Table 6: Comparison among the output from the two tested alternatives and the ratio calculated between observed crashes and recorded conflicts from the simulations (Sites SP61, SP112, SP124).

		Traffic Output								Safety output		
		Density (veh/km)		Flow (veh/h)		Maximum queue (veh)		Tot. Km travelled		Number of simulated conflicts		
		Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Crossing	Rear end	Lane changing
SP61	Mean 35 single day simulations (M35)	0.98	0.03	278.40	4.18	1.82	0.46	41250.15	639.83	44	967	40
	Mean 35 consecutive days simulations (M1)	0.99	0.02	278.71	3.39	1.74	0.44	41366.8	616.19	52	1086	40
	Variation (M35-M1)/M1%	-0.9	35.3	-0.1	23.2	4.8	4.2	-0.3	3.8	-15.4	-10.9	0.0
	Total Observed Crashes from database									*10*	*5*	*5*
	Ratio Observed/M35									*0.227*	*0.005*	*0.125*
	Ratio Observed/M1									*0.192*	*0.005*	*0.125*
SP112	Mean 35 single day simulations (M35)	4.43	0.03	602.36	5.10	3.57	0.61	76660.55	700.20	108	116	32

	Mean 35 consecutive days simulations (M1)	4.43	0.04	602.39	4.74	3.49	0.56	76709.2	631.13	114	120	37
	Variation (M35-M1)/M1%	-0.1	-15.3	0.0	7.6	2.3	8.6	-0.1	10.9	-5.3	-2.9	-13.5
	Total Observed Crashes from database	[redacted]								*10*	*8*	*1*
	Ratio Observed/M35	[redacted]								*0.093*	*0.069*	*0.031*
	Ratio Observed/M1	[redacted]								*0.088*	*0.067*	*0.027*
SP124	Mean 35 single day simulations (M35)	1.86	0.03	248.98	3.34	2.20	0.41	31172.47	428.49	4	6	1
	Mean 35 consecutive days simulations (M1)	1.87	0.03	249.38	3.21	2.17	0.38	31234.4	408	4	5	1
	Variation (M35-M1)/M1%	-0.4	-9.8	-0.2	4.1	1.4	6.8	-0.2	5.0	0.0	20.0	0.0
	Total Observed Crashes from database		[redacted]							*1*	*2*	*1*
	Ratio Observed/M35		[redacted]							*0.250*	*0.333*	*1.000*
	Ratio Observed/M1		[redacted]							*0.250*	*0.400*	*1.000*

From the results of the standard deviation (which highlights the dispersion of the values around the mean), traffic output, and conflicts, it is blatant that the continuative-days simulations are likely to create a learning mechanism for the vehicles which tend to optimize vehicle paths. Indeed, the total traveled km is always greater, as well as the flow and the density, but not the queue, which is always lower. It means that vehicles start driving as familiar humans do during their path, avoiding the more congested roads, preferring alternatives with lower waiting times. This situation is closer to what happens during the average travel on roads, especially on rural roads where usual drivers are the most frequent ones, driving with more aggressive behaviors (Colonna et al., 2021). This aspect is also highlighted by the slightly increased number of conflicts recorded during the continuative days' simulations compared to the ones recorded by the single-day simulations.

Under this light, the consecutive-days simulation was chosen to represent the traffic flow most realistically. One year of traffic was simulated, divided into seasons, workdays, weekends, and vacations. This 365-day simulation was propaedeutic to obtain the trajectories and conflicts, thanks to the SSAM algorithms. The correlation between conflicts and observed (filtered) crashes might be validated for the current scenario to assume that the predicted conflicts for further scenarios with AVs realistically reproduce crashes.

The SSAM algorithms extracted the trajectories and provided the number of conflicts for each site. The sites were evaluated one per time, and the chosen surrogate safety measure to detect conflicts was the Time To Collision (TTC), set equal to 1.5 s, as already justified in chapter 1.4. The conflicts for each site were categorized for different conflict typologies, then compared to the observed crashes. The observed crashes were divided by 5 to have the comparison conflicts/year – crash/year. The first attempt was to correlate conflicts and crashes by mean of a factor (Hauer 1982; Gettman, 2008; El-Basyouny and Sayed, 2013), but it was found to be hard to have a good fitting between these data. The next approach was to rely on the Extreme Values distribution, converting simulated conflicts into simulated crashes, as suggested by

Tarko (2018). This approach was chosen since it was proposed for predicting crashes for future scenarios like AVs, especially at intersections. Hence, the starting conditions overlap the aim of this present research. This method uses the Lomax distribution. This distribution depends on the surrogate safety measure used (TTC, for this study) and its threshold value (in this case, 1.5 s for the TTC) and on the difference between this threshold value and the surrogate safety measure chosen value (TTC) of each recorded conflict. The characteristics parameters of the distribution are k and θ, defined as follows:

$$k = \frac{-\sum \log\left(1 - \left(\frac{i - 0.5}{n}\right)\right) \log\left(1 + \theta x_i\right)}{\sum\left[\log(1 + \theta x_i)\right]^2} \quad \text{(Eq.8)}$$

$$\theta = \frac{1}{TTC_{max}} \quad \text{(Eq.9)}$$

Where:

- x_i is the difference between the TTC $_{max}$ and the i-esim TTC for the i-esim conflict.
- i is the number of the recorded conflict, after having ordered all the conflicts in descending order according to the recorded TTC.
- n is the total number of conflicts.

This procedure requires the calculation of the composed probability to have crash from the recorded conflicts, P (C|N). Multiplying this probability to the number of recorded conflicts, n, it is possible to obtain the simulated crashes Q_c.

$$Q_c = P(C|N) \times n = 2^{-k} \times n \quad \text{(Eq.10)}$$

This value was reduced to 20% since the observed crashes are only Fatal and Injuries crashes, which statistically represent, for the rural environment, 20% of the total amount of observed crashes (Vernon et al., 2004; Colonna et al., 2021).

After that, the simulated crashes for the entire site (without distinctions of the type, as suggested by Tarko, 2018) were compared to the observed ones employing a linear correlation, which was the only one acceptable to reduce the error propagation in this two-phase correlation, as it will be deeper discuss in paragraph 3.3. The correlation was found to be acceptable for an R^2 greater than 0.3 (Ng et al., 2004; Giuffrè et al., 2007; Cafiso and Lagrazia, 2010; Intini et al., 2021). A possible interpretation for the acceptance of these results in road safety analysis is that the correlations are always subjected to the aleatory of the accidental phenomenon, so they are weaker than the one possibly found for laboratory experiments, for instance.

The validation of the model made it possible to run all the other research steps, which is useful for reproducing the scenarios with AVs.

2.4 SENSITIVITY ANALYSIS

The influence of some parameters can be greater than others on the safety assessment results. Hence, a case study scenario was investigated after having determined the most suitable software tool for the simulation of AV scenarios. The rural roads in the Bari Province (Italy) were tested, within the framework of the SUMP (Sustainable Urban Mobility Plan) for the Province of Bari, since the further development of this study will consist in simulating the most vulnerable rural roads in the Province of Bari from a safety perspective, to determine whether the AVs introduction could lead to safety benefits.

A sensitivity analysis of the most influencing parameters for the chosen simulators can highlight which of the main variables are the most effective in safety assessment. Thus, it would be possible to understand which variables can be suitable for the automation simulation considering the entire driving environment.

The sensitivity analysis included 8 road sections of the Bari Province, made by secondary and local roads, as shown in the figure (Figure 10). The networks are selected among the most dangerous rural roads in the province of Bari (see Table 7).

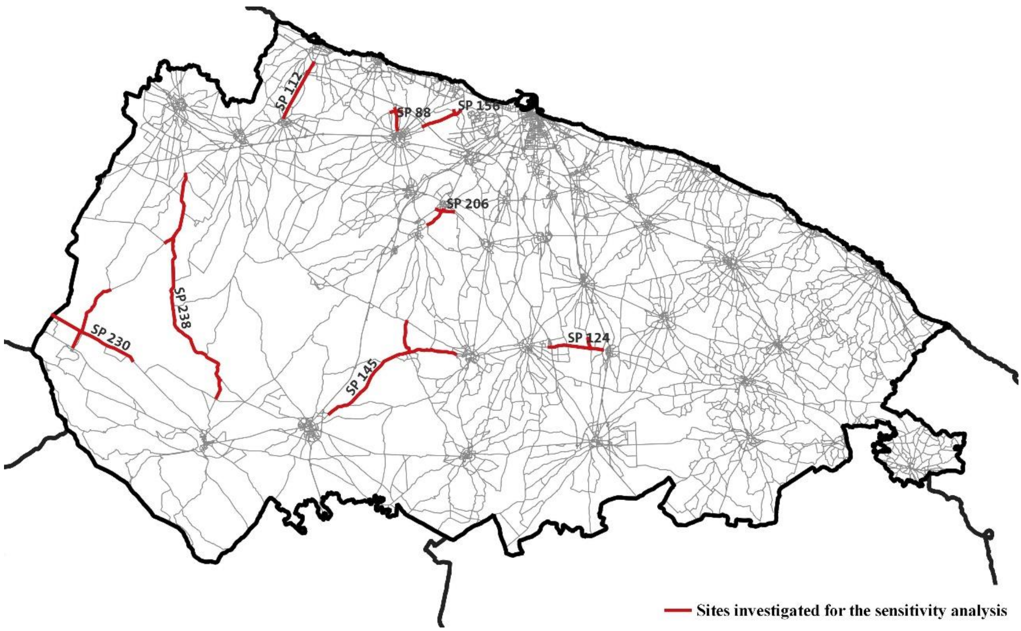

Figure 10: Bari Province (CMB) area: the 8 sites investigated for the sensitivity analysis in red.

These roads belong to the same category (two-way, two-lane rural roads) but with different geometric features to account for the possible effect of different geometric configurations. The investigated road network includes the following basic elements: two-way, two-lane segments, 3-legged and 4-legged signalized and unsignalized intersections, and roundabouts (Table 7).

Table 7: Selected roads and their characteristics (*The AADT stands for the average number of vehicles circulating during the day in the entire site).

Sites	Length (Km)	*AADT (Veh/day)	Crash rate	Crash/year	Observed crashes (5 years)
SP88	4.47	10543	1.6278	5.6	28
SP112	6.66	14712	0.5872	4.2	21
SP124	6.96	5745	0.3426	1	5
SP145	27.3	6413	0.4069	5.2	26
SP156	4.86	24097	0.7720	6.6	33
SP206	7.98	12104	0.2836	2	10
SP230	17.71	3142	0.0985	0.4	2
SP238	28.96	1478	1.2162	3.8	19

The sensitivity analysis was run for the parameters of the selected model (Table 8). Each parameter was set with a different value, one per time with ceteris paribus. Since each parameter of the model follows a truncated normal distribution to contemplate the human driver differences in driving, the parameters varying between a minimum, and a maximum value, also show an average value and a standard deviation. It was also calculated to assume a great variability of the chosen parameter, starting from the truncated distribution, the 5th and the 95th percentile of the associated normal distribution. Thus, this procedure led to 5 different values to test for each parameter: the minimum, the 5th percentile, the average, the 95th percentile, and the maximum. In this way, the sensitivity analysis for each parameter could have deeply investigated the effects of each parameter on the global model output. Each value was tested 10 times for each site and averaged to have a statistical significance of the results. Otherwise, the result obtained by just one simulation for each value could have been affected by single environmental issues, as the order of vehicle appearance in the site.

The main parameters chosen for the sensitivity analysis are the following:

- Aggressiveness level
- Clearance
- Gap
- Guidance acceptance level

- Look-ahead distance factor
- Maximum acceleration
- Maximum deceleration
- Maximum desired speed
- Maximum Yield time
- Normal deceleration
- Overtake speed threshold
- Reaction time
- Safety Margin Factor
- Sensitivity factor
- Speed limit acceptance.

Starting from these parameters, whose values have already been calibrated for the safety purposes (Casas et al., 2010; Levitate Project, L4 2020; Ims & Pedersen, 2021), the analysis was run. The sensitivity analysis results for all 8 sites have been recorded and averaged in terms of conflicts. These results were then compared, for each type of conflict (rear-end, crossing, and lane-changing), to the baseline condition, counting as a reference the default parameters considered by the models in the case of 100% human (regular) drivers.

The main importance of this sensitivity analysis consists in providing results for the impacts of the parameters of the Gipps model on road safety assessments. This also represents a discrimen compared to previous studies about sensitivity analysis of traffic models or simulators, because they were made just for traffic outputs or, relying on other models or simulators (Cunto & Saccomano, 2008; Habtemichael & Picado-santos, 2013; Xu et al., 2014; Azevedo et al., 2015; Cascan et al., 2019).

The relative conflict ratio in recorded conflict for each of the simulated scenarios has been calculated concerning the default baseline simulation (scenario with all human drivers/RVs), as shown by Eq.11:

$$R\ conflict_{\ j} = \left(\frac{N_{sa\ ij}}{N_{b\ j}}\right) \quad \text{(Eq.11)}$$

Where:

- $N_{sa\ i}$ is the number of conflicts recorded for the i-esim simulation run during the sensitivity analysis, for a selected conflict type -j;
- $N_{b\ j}$ is the number of conflicts recorded for the baseline condition, for a selected conflict type $-j$;
- $R\ conflict_{j}$ is the calculated relative conflict ratio for a selected conflict type -j (rear-end, crossing, and lane-changing).

Then, the comparison among the results was made and different thresholds were set to consider the different rates of parameters influencing the conflict recording. The significance was assessed according to the following thresholds, decided to have homogeneity among all the intervals (in base of the frequent distributions of results):

- $R\ conflict_{\ j} < 0.2$ means that the number of conflicts is drastically reduced; its significance is great in the overall analysis. In Figure 16-17-18, it is marked by a red circle on the x-axis, and in Table 14-15-16 it is highlighted by red colored boxes and numbers.
- $0.2 < R\ conflict_{\ j} < 0.5$ means that the number of conflicts decreases. In Figure 16-17-18, it is not marked, and in Table 14-15-16 it is highlighted by red contour boxes and numbers.
- $0.5 < R\ conflict_{\ j} < 1.2$ means that the number of conflicts does not vary remarkably. In Figure 16-17-18, it is not marked, as well as it is not highlighted in Table 14-15-16.
- $1.2 < R\ conflict_{\ j} < 1.5$ means that the number of conflicts increases, but in a reduced way. In Figure 16-17-18, it is not marked, and in Table 14-15-16 it is highlighted by blue contour boxes and numbers.
- $R\ conflict_{\ j} > 1.5$ means that the number of conflicts increases significantly; the significance is great in the overall analysis. In Figure 16-17-18,

it is marked by a blue circle on the x-axis, and in Table 14-15-16 it is highlighted by blue colored boxes and numbers.

After this analysis, two other steps were run, as control tests to assess the reliability of the sensitivity analysis run. These control tests aim at verifying the fluctuation of the results changing the parameters, giving a practical sense to the used values. In this optic the control tests provide different scenarios, and the analysis of the relative conflict ratio according to its set thresholds. The two control tests are the following:

1. Knowing the values of the parameter to use for representing PAVs (or Cautious AVs) and FAVs (or Assertive AVs), the analysis was made changing one per time the values accounting for these vehicle types. The results might assess the importance of the parameters analyzed with the sensitivity analysis, in a real-case scenario. The test gives an insight into the significance of a single parameter on the global conflict detection, for the AVs. The obtained results were compared to the baseline scenario ones, to always rely on the same benchmark (results are highlighted in 3.2).
2. Knowing all the values for all the parameters of the model, to represent AVs and RVs, this test aims at checking the impact of a vehicle type over the global conflict count. In this light, different scenarios were tested, changing the penetration of the vehicle type. The representation of each vehicle was obtained by changing all the parameters according to the decided values to depict that specific vehicle type. Different scenarios, also include the one in which all the most influencing parameters obtained by the sensitivity analysis are modified simultaneously (results are shown in 3.2). The tested scenarios are:
    - 100% RVs (baseline condition).
    - 100% PAVs (considering all partially automated vehicles as cautious AVs and thus setting all the accountable parameters for AVs accordingly).
    - 100% FAVs (considering all fully automated vehicles as assertive AVs and thus setting all the accountable parameters for AVs accordingly).

- 50% regular vehicles (RVs, with default parameters) and 50% PAVs (Cautious AVs).
- 50% RVs (RVs, with default parameters) and 50% FAVs (Assertive AVs).
- 50% FAVs (Assertive AVs) and 50 % PAVs (Cautious AVs).
- 100% vehicles whose some variables were modified simultaneously using the values found to be crucial by the previous analysis for each kind of conflict. The most influencing parameters for the j-esim conflict type ($R\ conflict_j > 1.2$ and $R\ conflict_j < 0.5$) were collected and modified all at once in the simulation to be aware of their significance when combined. This scenario is called “Main Variable Car”.

Regarding the first control test, some values used for representing FAVs or PAVs were already considered among the five alternatives chosen for the sensitivity analysis. Hence the ones not already chosen are highlighted in the table (Table 8). These values listed for the two different typologies of AVs were then used, all together, for simulating the AV scenarios in traffic for the second part of the control tests.

Table 8: Parameters of the Gipps Model and their variability for human driving, according to truncated normal distribution and values for the Automated vehicles, fully and partially (FAVs and PAVs).

Parameters	UoM	Human Driver						PAVs	FAVs
		Mean	Dev	Min	Max	95 Perc	5 Perc		
Aggressiveness level	-	0.50	0.25	0.00	1.00	0.87	0.13	0.00	0.25
Clearance	m	2.00	0.80	0.50	3.50	3.14	0.86	2.00	1.00
Gap	s	1.00	0.50	0.00	2.00	1.74	0.26	2.00	1.00
Guidance acceptance Level	%	50.00	25.00	0.00	100.00	86.81	13.19	75.00	100.00
Look-ahead distance factor (LAF)	s	1.00	0.10	0.80	1.20	1.15	0.85	1.1-1.3	1-1.25

Maximum acceleration (Max acc)	m/s2	3.00	0.20	2.60	3.40	3.29	2.71	3.00	3.00
Maximum deceleration (Max dec)	m/s2	6.00	0.50	5.00	7.00	6.74	5.26	6.00	6.00
Maximum desired speed (Max speed)	Km/h	100.00	10.00	50.00	150.00	116.45	83.55	110.00	50.00
Maximum Yield time (MYT)	s	10.00	2.50	5.00	15.00	13.68	6.32	12.00	8.00
Normal deceleration (Ndec)	m/s2	4.00	0.25	3.50	4.50	4.37	3.63	2.00	2.00
Overtake speed threshold	%	80.00	5.00	30.00	99.00	88.22	71.78	85.00	85.00
Reaction time*	s	1.60		0.10	2.40	1.80	1.20	0.10	0.10
Safety Margin Factor	-	1.00	0.50	0.00	2.00	1.74	0.26	1.25-1.75	0.75-1.25
Sensitivity Factor	-	1.00	0.25	0.00	2.00	1.41	0.59	0.3-0.7-0.9	0.1-0.5-0.9
Speed limit acceptance	-	1.10	0.10	0.90	1.30	1.25	0.95	1.00	1.00

*Reaction time did not follow a truncated distribution; hence the attributed values are either calculated according to the Italian regulation for the minimum and maximum design speed (respectively 1.8 s and 2.4 s), or taken by literature (Casas et al., 2010) or equal to the simulation step.

2.5 AV SCENARIOS DEFINITION

The definition of the further scenarios with AVs might follow the hypothetical trends studied for the penetration in the market of such technology. According to Lause III (2019), the penetration of AVs in the market would follow a sigmoidal trend (Figure 11), like with the introduction of mobile phones.

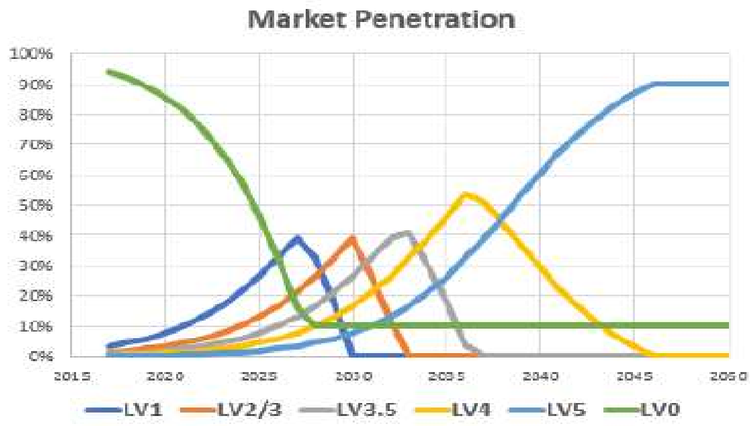

Figure 11: Curves of AV penetration in the market according to Lause III (2019) Prediction.

However, this trend seems utopistic, considering that in Italy, the regular driving of SAE level 3 vehicles is still not allowed, which, according to this prediction, might have already been deployed (3-5%). For this reason, the market penetration was selected according to another study, more recent than 2019, by Garcia et al., for Austroads (2022). This study hypothesis is that there are three different curves for transit AV penetration, one more realistic and two that consider the limit conditions, i.e., the worst-case scenario of slow implementation and the best-case scenario of a rapid implementation of them in traffic. The chosen curve, among the three, is the realistic one, with a gradual market penetration rate in the traffic, projected from now to 2050.

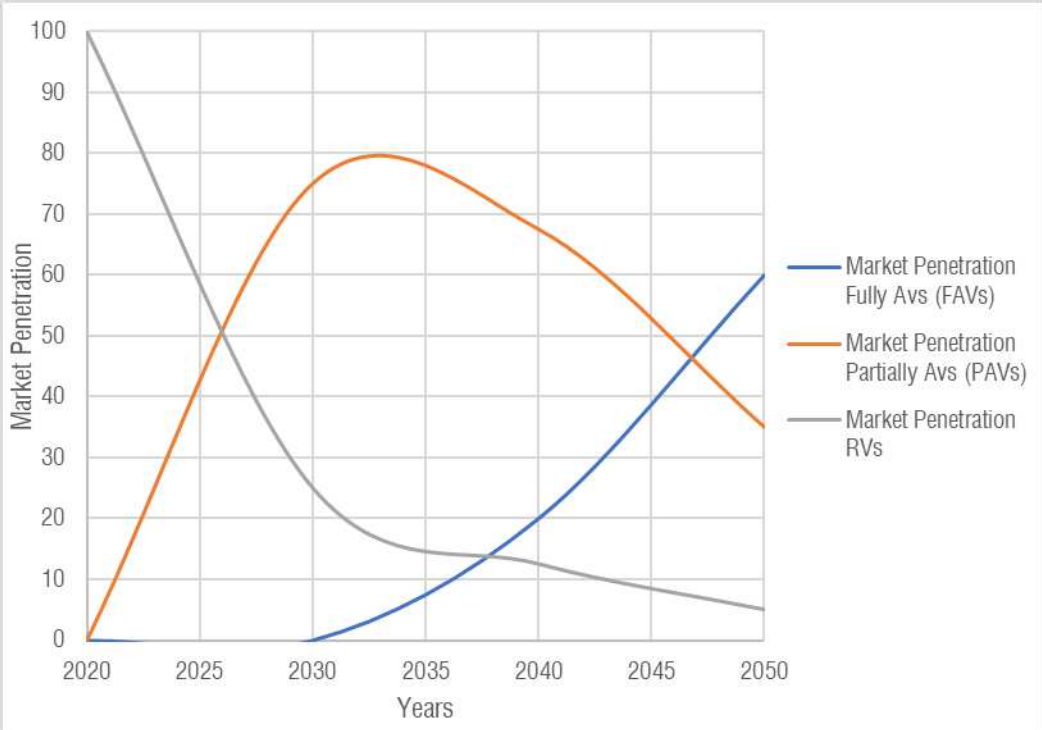

Figure 12: Market penetration of different type of vehicles (2020-2050), based on Garcia et al., 2022.

The tested scenarios are three, with the temporal horizons chosen accordingly to Garcia et al. (2022):

- Short-term scenario (2030)
- Mid-term scenario (2040)
- Long-term scenario (2050)

For each of these scenarios, the market penetration of the AVs and RVs was found. The selected penetration rates are shown in the following table.

Table 9: Market penetration of different type of vehicles for the three simulated scenarios.

Further Scenarios	Target Year	Vehicles (%)		
		FAVs	PAVs	RVs
Short-term	2030	0	75	25
Mid-term	2040	20	67.5	12.5
Long-term	2050	60	35	5

The simulations were run for all the selected sites, which have previously been validated by the correlation conflicts-crash and simulated crashes-observed crashes. The 1-year simulation was maintained, as well as the seasonality and the distinction among workdays and weekends, and vacation days. The traffic composition was modified according to the mentioned percentages. They were applied to Car and Heavy vehicles to still simulate the difference between transit vehicles and freight ones.

The simulation output was collected and then analyzed through the SSAM algorithm to understand the number of conflicts for each site. The conflicts are evaluated for conflict types to be aware of the most recurrent typology, but then analyzed in an aggregate way, as suggested by Tarko, 2018. They were studied with the Extreme value distribution (Tarko, 2018), as already made for the current scenario. The Long-term scenario was the only one to be tested with TTC equal to 0.5 s (Papadoulis et al., 2019), since the dangerous situations for AVs interacting among them are more likely to happen with TTC closer to 0 s. This assumption is crucial because it considers the fact that FAVs travel with a greater spatial and temporal proximity than RVs or PAVs (in fact, they are called Assertive AVs), because they do not rely on human perceptions and mistakes, but only on sensors and algorithms. The strict rule-based behavior of FAVs also makes safe this kind of proximity. For these reasons, almost all vehicles are closer than 1.5 s. Hence, the TTC threshold of 1.5 s can induce errors in conflict analysis, labeling as a dangerous situation a regular platoon made of FAVs. From the literature, as highlighted, the most representative threshold for TTC under the mentioned conditions is 0.5 s, which labels as dangerous only situations of potential danger for FAVs.

The analyzed sites were investigated for the three scenarios and the comparison between the further ones and the current one was made by the following equation, calculating the C_V, Crash variation:

$$C_v = \frac{SC_{ij} - SC_{current}}{SC_{current}} \tag{Eq.12}$$

Where:

- SC_{ij} is the simulated crash number for the i-esim site and j-esim scenario (2030, 2040, 2050)
- $SC_{current}$ is the simulated crash number obtained for the current scenario.

2.6 SPF DEVELOPMENT FOR AVs

After having collected the results of the simulations for the AV scenarios, it is possible to be aware of the number of probable crashes predicted for each site and each scenario. The investigated sites were 16 and 3 market penetration scenarios for all the investigated sites. The number of predicted crashes is the output of the SPFs; thus, combining the independent variables makes it possible to create SPFs specific to AVs. It is possible to reach this goal by considering the different traffic penetration rates for all the analyzed sites. Relying only on 16 sites, it was possible to correlate only two independent variables and the intercept to obtain the SPF. This is because of the statistical procedures, which suggest counting on a limited number of independent variables related to the number of measurements. It is commonly used to limit the number of independent variables if the sample is not that big. In this case, the sample dimension was 16; thus, the maximum number of independent variables must be small. In this specific analysis, the number of independent variables to correctly depict the scenarios was 2.

The SPFs are usually estimated for intersections or segments. In this study, the entire site has been analyzed since the output of the SSAM algorithm is comprehensive and allows this kind of procedure. This approach is in line with new ideas related to SPF that account for macro-SPF to make predictions (Intini et al., 2022). The use of macro-SPF or a site-based SPF, rather than a specific one for the single geometrical element of the road, is suitable for this study, accounting in this way for all the characteristics of the analyzed site. In this way, it is possible to highlight all at once the crash-leading factors, having a realistic prediction of crashes for further scenarios. Moreover, the necessity to develop an ad hoc SPF for AVs, necessarily required the investigation of the overall environment at a macro-scale rather than focusing just on one road elements, to consider in a more extensive way the interactions among vehicles and the impact of intersections (different types and layout) and road characteristic on crashes.

The development of an ad hoc SPF for the AVs has the ambitious goal of creating a tool useful for all practitioners and stakeholders to foresee the road safety implications of such a new implementation. Also on a practical side, providing macro-SPF makes their use easier for non-expert used, and they can be extensively used for planning at a large level. In this way, the prediction can be comprehensive, and the main goal of knowing the safety of AVs can be easily achieved.

Hence, combining the variables affecting the crash occurrence in future scenarios (dependent variable) was necessary to have a function, SPF, just on two independent variables and the intercept.

The main variables affecting the crash are the intersections (typology and number for each site), the traffic, the extension of the site itself, and the different typology and penetration of vehicles (Partially and Fully AVs and RVs). As for the intersections, it was possible to create a variable that counted the intersection typology and density, I_j

(intersection/km of the site) and the combination of different intersection typologies in each site. A coefficient taken by CMFclearinghouse[2] and Pract-repository[3] was assigned to each type of intersection. The coefficients were set as the first attempt equal to the CMFs, even if the CMFs have been studied for the current scenario, to provide a piece of information about the significance of the intersection typology on crash occurrence. In the case of roundabouts, the coefficient was 0.13 (Rodegerdts et al., 2007), calculated as the benefit introduced by a roundabout if compared to the 4-leg intersection in rural roads for severe crashes. This value was considered adequate even if it did not account for fatal crashes too, because all the CMFs for roundabouts for fatal crashes highlighted greater reduction than the one used with this CMF, which can be considered cautionary. Regarding the 3-leg intersections and 4-leg intersections, a calculation of the safety was made relying on two equations of the HSM (2010) retrieved by the Pract-repository for two-way two-lane rural roads, and Fatal and severe crashes only.

The equation for calculating the safety performance of a 4-leg intersection is the following one:

$$N_{SPF} = 43.1\% \times e^{-8.56+0.6\ln(AADT_{maj})+0.61\ln(AADT_{\min})} \qquad \text{(Eq.13)}$$

Where $AADT_{maj}$ stands for the AADT on the main roads of the intersection, and $AADT_{min}$ for the one related on the minor roads converging into the intersection. The safety performance was calculated for 4-leg intersections and for 3-leg intersections, assuming them as previously been 4-leg intersections. The same approach was used for the 3-leg intersections. The safety performance was calculated thanks to Eq.14 for both 3-leg intersections and 4-leg intersections assumed to have been 3-leg intersections in the past. Making this assumption makes it possible to calculate the benefit of

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[2] https://www.cmfclearinghouse.org/
[3] https://www.pract-repository.eu/

a 3-leg intersection if compared to a 4-leg. Hence, making the ratio of the safety performance of a 3-leg over a 4-leg for all the intersections and averaging this result it is possible to obtain a CMF for the 3-leg intersection.

$$N_{SPF} = 41.5\% \times e^{-9.86+0.79\ \ln(AADT_{maj})+0.49\ \ln(AADT_{min})} \quad \text{(Eq.14)}$$

The obtained CMF was 1.872 for a 4-leg intersection compared to a 3-leg intersection. Then, the CMF for the roundabout was calibrated using the 3-leg intersection as the reference. In this way the safety improvement calculated by the CMF was 0.243. These coefficients were multiplied respectively by the intersection density for each type of intersection. Then the products were summed to obtain an indication of their combination. The obtained variable was called Com2 since it is the combination of 2 factors regarding the intersections (density and typologies). In this way, it was possible to consider the influence and significance of intersections on crash occurrence.

$$Com2 = 0.243 \times I_{Roundabout} + 1 \times I_{3-Leg} + 1.872 \times I_{4-Leg} \quad \text{(Eq.15)}$$

Then, the market penetration of vehicles needed to be considered thanks to a different variable. The variable was called Tr1 and it takes into account the traffic for the three different scenarios, as equivalent traffic. This equivalent traffic was calculated by means of a coefficient, Hazard Index (HI). The HI was obtained considering the three types of vehicles (FAV, PAV, and RV) and their impact on safety. Thanks to the simulations run for all the sites for scenarios with just one vehicle category travelling (100% FAVs; 100% PAVs; 100% RVs), the crash frequency related to each specific category was calculated and averaged over all the investigated sites. Using the PAV as the benchmark, the HI was calculated as the ratio between the j-esim crash frequency related to the j-esim vehicle type (in the 100% scenario) and the crash frequency recorded for 100% PAVs. Two HIs were calculated, one for FAVs and one for RVs. Then, thanks to the HIs, the AADT of each site was converted into an equivalent safety AADT, assigning to each vehicle category the impact on safety by multiplying by HI.

$$AADT_{equivalent} = HI_{FAV} \times \ FAVs_{AADT} + 1PAVs_{AADT} + HI_{RV} \times RVs_{AADT}$$

(Eq.16)

In this way, the market penetration and the safety impact of vehicles were considered by one variable at once. The equivalent AADT became the independent variable called Tr1 in the model.

The SPF for AVs was calculated by combining the two independent variables (Tr1 and Com 2) by means of the negative binomial general linear model, glm.nb, as suggested by the HSM, 2010. The dependent variable was the crash frequency, N, calculated as the number of crashes (obtained by simulations), per year. The equation of the SPF was the following one:

$$\begin{aligned} N_{SPF\_AVs} &= L \ \times e^{\beta_0 + \beta_1 Tr1 + \beta_2 (0.243 \times I_{Roundabout} + 1 \times I_{3-Leg} + 1.872 \times I_{4-Leg})} \\ &= L \ \times e^{\beta_0 + \beta_1 Tr1 + \beta_2 Com_2} \end{aligned}$$

(Eq.17)

Where L stands for the length of the i-esim road network site, and β_0 (it is the intercept), β_1 and β_2 are the coefficients of the variables.

The model was considered good whether the coefficients, β_1 and β_2, linked to the independent variables, were statistically significant. In accordance with the conventional acceptance of statistical significance at a P-value of 0.05 or 5%, the significance of the coefficients was calculated and verified. If an observed result is statistically significant at a P-value of 0.05, then the test hypothesis is false or should be rejected.

After assessing the statistical significance, the goodness of fit of the model was verified by calculating the Nagelkerke R^2. The threshold set to consider the SPF with an acceptable fit was 0.25. Only the results above 0.25 (Intini et al., 2021) were considered good.

The fact that the determination of the SPF is based on a few cases and limited to the Area of Bari makes it possible for further research to calibrate the coefficient to use in Com2, Tr1 to better represent other scenarios or other technological devices.

In the table below, there are the parameters used for the study.

Table 10: Dependent (N, predicted crash frequency) and independent variables for the SPF. The values shown in the table will be better explained in 3.5 and 3.6 paragraphs.

Scenario	SP	Com2	Tr1	L (Km)	N
2030	2	0.83	15932	6.35	14
	27	0.19	2996	15.39	1
	61	0.14	10874	35.03	17
	88	0.47	17361	4.47	6
	111	0.02	13135	11.60	4
	112	0.28	24226	6.66	24
	124	0.14	9459	6.96	1
	145	0.08	10559	27.30	8
	206	0.45	19931	7.98	24
	230	0.17	5176	17.71	2
	235_169	0.11	9141	11.74	1
	235_177	0.26	15721	14.62	74
	236	0.18	13239	10.58	1
	238	0.07	2436	28.96	0
	240_32	0.09	12237	22.28	8
	240_66	0.26	30199	11.87	34
2040	2	0.83	12332	6.35	15
	27	0.19	2317	15.39	1
	61	0.14	8421	35.03	17

	88	0.47	13442	4.47	4
	111	0.02	10168	11.60	6
	112	0.28	18756	6.66	24
	124	0.14	7324	6.96	2
	145	0.08	8177	27.30	11
	206	0.45	15431	7.98	28
	230	0.17	4006	17.71	2
	235_169	0.11	7076	11.74	1
	235_177	0.26	12169	14.62	70
	236	0.18	10250	10.58	1
	238	0.07	1886	28.96	0
	240_32	0.09	9473	22.28	9
	240_66	0.26	23377	11.87	33
2050	2	0.83	9519	6.35	9
	27	0.19	1789	15.39	0
	61	0.14	6496	35.03	12
	88	0.47	10373	4.47	4
	111	0.02	7849	11.60	2
	112	0.28	14476	6.66	12
	124	0.14	5652	6.96	1
	145	0.08	6311	27.30	6
	206	0.45	11907	7.98	18
	230	0.17	3091	17.71	1
	235_169	0.11	5463	11.74	0
	235_177	0.26	9391	14.62	22
	236	0.18	7910	10.58	0
	238	0.07	1454	28.96	0
	240_32	0.09	7313	22.28	5
	240_66	0.26	18043	11.87	17

CHAPTER 3
RESULTS

In the next paragraph, all the results are shown. The first part was related to the choice of the most suitable simulator to run the test for further scenarios with AVs (3.1). Then the sensitivity analysis was run for all the different scenarios tested in terms of conflicts to assess the most influential parameters for the simulations (3.2)

After that, the validation process was shown, starting from the GEH (Geoffrey E. Havers statistics) to the relationship between conflicts-simulated crash-observed crashes (3.3). The scenarios with AVs are presented with all their results related to the conflicts and then to the simulated crash output according to the selected procedure with Extreme Value distribution.

3.1 TRAFFIC MODELS

In order to select the proper traffic model for the main purposes of this research, the characteristics of both the car-following models and the lane-changing models, more widespread, were investigated, as shown below.

3.1.1 Car-following models

Before explaining each car-following model, it is necessary to introduce the different types of models belonging to this macro-category of models, as shown in the figure below (Figure 13), where the considered car-following models are listed, together with their independent variables.

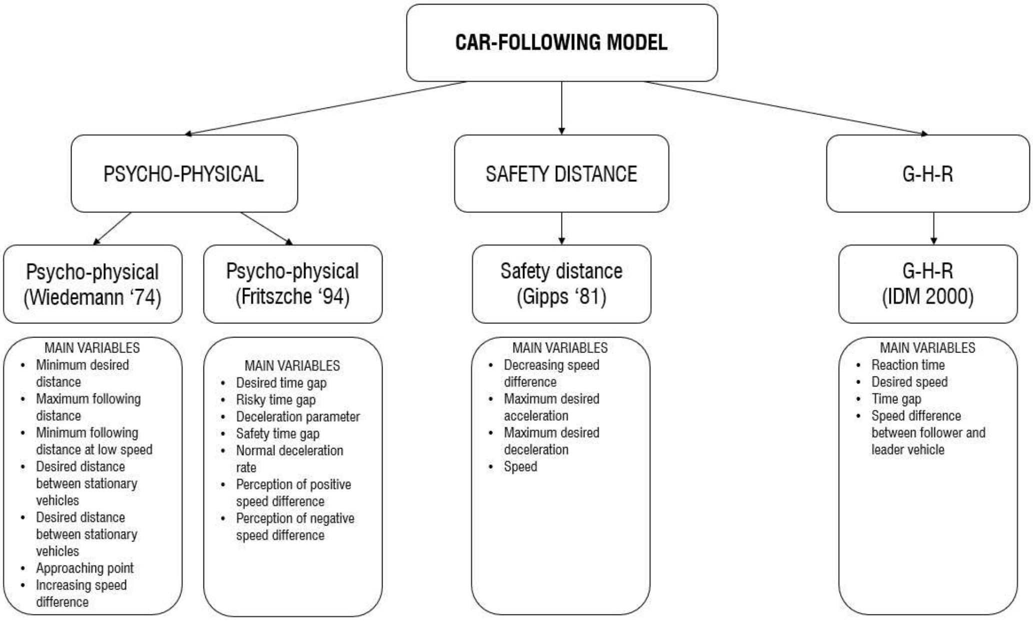

Figure 13: Comparison of the car-following models.

Table 11: Comparison of the car-following models.

Car-following model	Type	Main Variables	Regimes	Software package
Wiedemann '74 (Wiedemann et al., 1992; PTV, 2018)	Psycho-physical	Minimum desired distance	Free flow	VISSIM
		Maximum following distance	Emergency	
		Minimum following distance at low speed	Closing in	
		Desired distance between stationary vehicles	Deceleration	
		Approaching point	Following	
		Increasing speed difference		
Gipps '81 (Gipps,	Safety distance	Decreasing speed difference	Free flow	AIMSUN

1981)		Maximum desired acceleration Maximum desired deceleration Speed	Constrained	
IDM 2000 (Treiber et al., 2000)	G-H-R	Reaction time Desired speed Time gap Speed difference between follower and leader vehicle	Free flow Cooperative	AIMSUN and VISSIM
Fritszche '94 (Duncan, 1997)	Psycho-physical	Desired time gap Risky time gap Deceleration parameter Safety time gap Calibration parameter Normal acceleration rate Perception of positive speed difference Perception of negative speed difference	Free flow Closing in Danger Following I Following II	PARAMICS

The study of the different baseline equations, variables, and parameters helps understand the different potentialities of models and of the corresponding software. For the aims of this study, it is crucial to identify the most appropriate models for safety assessments related to future automation/connection scenarios.

In summary, two of the shown models (Wiedemann ’74 and Fritzsche ‘94) are Psycho-physical models, which mainly rely on different flow regimes (as shown in Fig. 14) according to the set thresholds. This kind of model depends on the desired driving behavior, being able to simulate precisely and reliably what currently happens on roads due to the mental decision process of the human driver.

Psycho-physical models consider vehicle velocity as a variable dependent on the perceptive thresholds, such as the minimum velocity difference between follower and leader. These models are based on two key assumptions:

- for large distances, the following driver is not influenced by the speed difference
- for a small distance, for a specific speed or distance that marks a threshold, the following driver may not react.

The following driver monitors changes in the leader's behavior and will react by modifying his/her kinetic variables only if thresholds are reached.

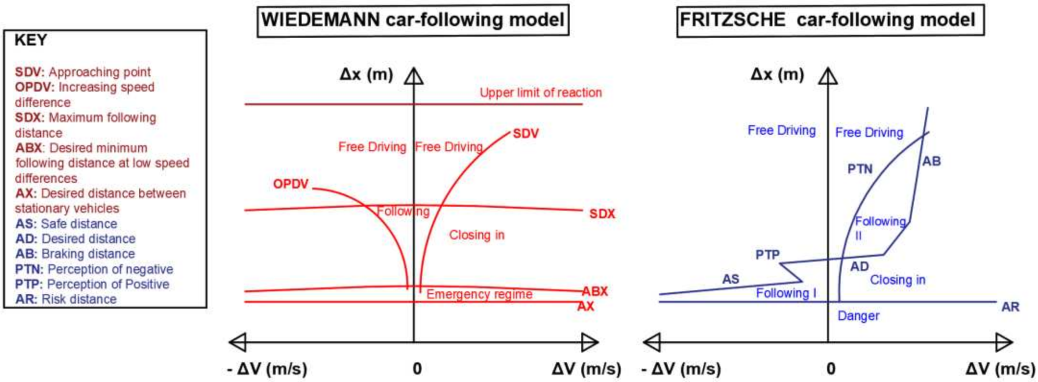

Figure 14: Wiedemann and Fritzsche car-following models according to their thresholds.

In the following regime, the acceleration is a function of the normally distributed driver-dependent variable according to a linear relation. In the free driving regime, the acceleration is proportional to the exponential of the desired speed. Considering the closing-in regime, the deceleration of the follower vehicle varies quadratically with the speed difference, while it is inversely proportional to ABX (t) and the distance. The emergency regime links the squared speed difference to the deceleration and the inverse of the distance.

The Fritzsche model has the same structure as the Wiedemann one, and it simulates five different flow regimes according to exceeding the thresholds. In particular, it sets two thresholds for the perception of negative (PTN) and positive (PTP) speed differences. Drivers are assumed to be more inclined to observe positive speed differences, so PTP is greater than PTN. In the danger regime, the driver uses maximum deceleration because it has no space to modify maneuvers. Contrary, in the closing-in regime, the acceleration is directly proportional to the squared difference between the vehicle speed and inversely proportional to the imposed distance between the two vehicles. The following behavior (both I and II, as shown in the figure) relates the deceleration to the speed and distance between vehicles. The free driving regime relates the acceleration to the desired speed but also contemplates the chance of not maintaining the fixed desired speed as constant since the driver is not affected by any external constraint by taking into account a determined value of regular deceleration.

The psycho-physical models were introduced to overcome the issues aroused by the different behavior a human driver can follow according to the several situations it faces while driving. They can simulate this aspect thanks to the different threshold values, which aim at recreating the mental decision workload of the driver whose final decision is affected by the willingness to be safe. Hence in each flow regime, all the parameters, including acceleration, standstill distance, and time headway, are typical of different driver behavior.

On the contrary, the other two models, the Intelligent Driver Model, IDM, and the Gipps model, are related to the vehicle kinematic characteristics and their interactions in the traffic flow, focusing on the following vehicle behavior according to the input provided by the leader. Such models are implemented in some of the more diffused commercial simulation software, which also allows the user to modify the set of variables of the model to address, more specifically, some requested scenarios.

The Intelligent driver model (IDM) belongs to the family of those derived from the Gazis-Herman-Rothary model (GHR) (1959). This model has been optimized at microscopic and macroscopic levels several times over the years (Brackstone et al., 1999). In these models, the acceleration is a function of the velocity of the front vehicle and the distance to the front vehicle. The IDM 2000 parameters, updated at each step of the simulation, are $a_{max}, b_{max}, s_0, and\ T$ (respectively, the maximum acceleration and deceleration, the distance to the front vehicle, and the time headway).

The Gipps model (Casas et al., 2010) belongs to another type of model, called the safety distance or collision avoidance model, which essentially relies on a safe following distance from the leader that the follower must comply with for the entire path. The safety distance is calculated by manipulating Newton's equation of motion. The safety distance is always achieved by updating, in each simulation step, the deceleration and the speed according to the calculated time gap between the leader vehicle and the leader's deceleration. The aim of this model is not to reproduce the human mind's work process, as the Psycho-physical ones do, but to consider the vehicle motion according to the safest behavior, measuring the kinematics of the vehicle. Hence, it is more reasonable to consider this model for analyses that strictly disregard human behavior and mental processes while driving.

The Gipps model simulates not only the constrained flow regime, in which the follower follows the leader, but also the free flow one, in which the leader is too far from the follower so that its influence on the follower's behavior is negligible. This car-following model considers only the speed of the leader and follower vehicles, their acceleration, and deceleration on a single lane, not calculating thresholds to simulate the mental decision process as the psycho-physical models do. In this sense, the safety distance models, as the Gipps one, aim at simulating human behavior, not replicating the human approach and mental workload, but just intervening on some specific parameters of their equations, like the Safety Margin Factor, the Speed limit acceptance, the non-lane-based behavior (the one usually followed by moped, bicycles, and motorcycles, or by uncertain drivers which moves laterally in a less cautious way), the aggressiveness.

The IDM and the Gipps car-following models depend on the same main variables and provide comparable results (Ims et al., 2021).

Moreover, other car-following models exist and are used for commercial purposes: for instance, the TEXAS (Lee et al., 1977) intersection model, embedded in the TEXAS software, uses an ad-hoc model belonging to the GHR family, which is applicable for the analysis of intersections only. This model investigates the variation of acceleration and deceleration rates of the two involved vehicles. The minimum deceleration of the following vehicle depends on the speed difference and distance between the two vehicles. The distance between vehicles can vary according to a linear relationship between the distance itself and the leading vehicle speed.

3.1.2 Lane changing models

The lane-changing models works on vehicle lateral movement and possible vehicle interactions. In this sense, the lane-changing models must consider the total time gap between two vehicles that allow a possible lane-changing maneuver by one vehicle travelling on adjacent lanes. If this gap is not enough, the vehicle will not change lane, except for the cases of aggressive and imprudent behaviors. These kinds of behavior are more common in real cases than in simulated traffic environments since the models tend always to be rule-based (Figure 15).

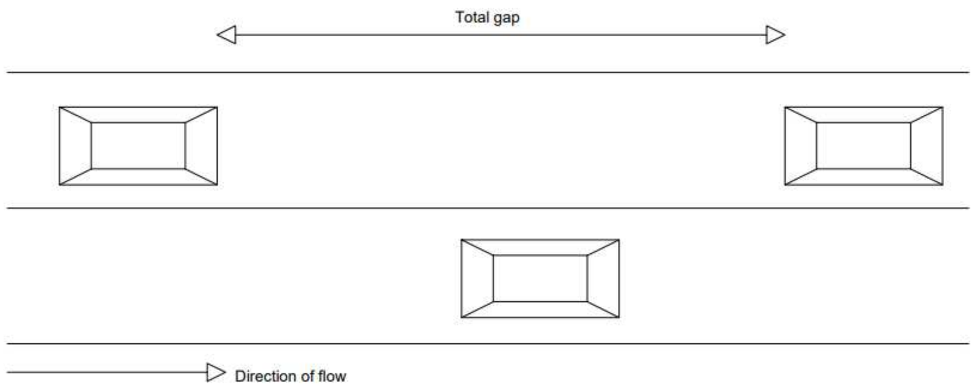

Figure 15: Gap Acceptance (inspired by Hill et al., 2015).

In the following table (Table 11) all the main variables for the most diffused Lane-changing models.

Table 12: A comparison of the lane-changing models.

Lane changing model	Perceived Flow Types	Variables	Software package
Wiedemann and Reiter '92 modified (Oketch et al., 2004; Moridpour et al., 2010)	Free	Available time lag to collision	VISSIM
	Necessary	Safety distance	
		Minimum time headway	
		Lead time to collision	
		Speed of the vehicle in the target lane	
		Speed of the lane changing vehicle	
Gipps '86 modified (Chao et al., 2020) (Tettamanti et al., 2018; Lee et al., 2019)	Discretionary	Desired speed	AIMSUN
	Mandatory	Front gap	
	Forced	Speed of the follower vehicle	
		Rear gap	
Fritszche '94 modified (Cameron and Duncan, 1996; Liu et al., 2020)	Free	Front gap	PARAMICS
	Necessary	Rear gap	
		Reaction Time	

As shown in the table, models differ in the type of lane changing, in the factors that make it necessary, and consequently in the characteristic variables of each model.

Most of those models constitute the base of the more widespread commercial software packages (AIMSUN, VISUM, PARAMICS), but a traffic modeling tool that fully describes lane-changing is still lacking. Gipps (Gipps, 1986) proposed a lane-changing model based on the decision-making process considering the potentially conflicting points and assuming a logical driver behavior. The model highlights the urgency of the lane-changing maneuver, always according to the kinematic parameters, such as the deceleration and the time gap, which aim at reproducing the drivers' gap acceptance and braking behavior.

Yousif and Hunt (Yousif et al., 1995) investigate the lane-changing behavior on multi-lane unidirectional roadways. The model assumes that if the available gap is smaller than the expected acceptable one, no lane changing process will occur.

Wagner (Wagner et al., 1997) defines a set of rules for a car that wants to change lane, emphasizing the need not to obstruct the car behind in the other lane. The model reproduces the lane usage characteristics satisfactorily on multi-lane roads under incident-free conditions.

The comparison is shown in the previous table, and the above-reported remarks pave the way for highlighting some serious issues in recently developed lane-changing models, which should be solved before any improvement can be achieved. In particular:

- Models are largely based on how the modelers themselves would make lane-changing decisions, rather than on the general driving experience. For the existing lane-changing decision models, only a few have identified factors and developed lane-changing rules based on video evidence (Hidas, 2002; Hidas, 2005), or by interviewing drivers (Sun et al., 2011; Sun et al., 2012).
- In the few models where driver characteristics are considered, this crucial dimension is over-simplified, with only one or two parameters accountable for capturing the total impact of drivers' characteristics and interpersonal interactions. Examples of these parameters are: the impatience factor, the speed indifference factor (Yang et al., 1996); a driver-specific random term that represents unobservable characteristics of the driver and correlations between observations of the same driver over time (Toledo et al., 2003); and ε, the speed

difference that the vehicle i + 1 is willing to accept during the driving process (Laval et al., 2008). These parameters are often assumed to be constant across individuals in calibration and validation.

- The driver's role in lane-changing is often over-simplified. Lane-changing is a typical choice-making process in which the choice maker (the driver) plays the main role. However, this role is more active than the one that is presumed in the existing models, where only one distance gap – the one nearest to the lane changer – is evaluated (Wang et al., 2021).
- A lane-changing decision is often modeled as a one-driver (the lane changer) decision-making process. However, in heavy traffic, a typical lane-changing decision-making process closely involves at least two drivers – the lane changer and the follower in the target lane. This is because the follower often also requires making decisions because of other drivers' lane-changing decisions (Wang et al., 2021).
- Failed lane-changing attempts are often ignored in calibrating and validating lane-changing models due to a lack of observed data; thus, they are likely to have significant impacts on surrounding traffic and have important safety-related implications (Ali et al., 2020).
- There is a different interest in the lane-changing decision-making process (i.e., how a driver reaches the decision when facing conflicting goals) and lane-changing impacts (the decision-making is not specifically considered). The current studies are dominated by lane-changing decision modeling. Models that ignore lane-changing impacts on surrounding vehicles are incapable of reproducing lane-changing related traffic phenomena (e.g., anticipation, relaxation, and capacity drop). Compared with the long history and vast family of lane-changing decision models, only two types of lane-changing impact models have been proposed and tried in literature research (Laval et al., 2008; Jin, 2010).

During years of research in this field, most models were widely either numerically tested or validated by demonstrating their potential to produce outcomes consistent with certain macroscopic traffic flow features.

3.1.3 AVs in traffic models

Several software packages are available that use combinations of the models above. Among the most diffused software, there are AIMSUN, VISSIM, and PARAMICS, as aforementioned. All the software integrates car-following and lane-changing models to represent the driving task in several conditions accurately. These software packages strongly depend on their baseline models, but the user can interact with the models by modifying some parameters to represent better the desired scenarios (Lee et al., 2019; Ims et al., 2021; Mesionis et al., 2020; Bailey, 2016; Morando et al., 2018; Atkins, 2016; PTV, 2018). Another way of modifying the software model is to write its code that can interact with the baseline equations of the software through the use of Application Programming Interfaces (APIs). This is the case of the IDM 2000 model that can be implemented by scripting into the VISSIM and AIMSUN software.

The mentioned models are globally set to the specific presence of human drivers. Thus, the question is to verify if all of them are still reliable in the case of vehicle automation. The simulation of fully automated vehicles, which undoubtedly will follow different behaviors from the human one, maybe less precise if based on the psychophysical car-following and lane-changing models since their goal is to reproduce the human decision process correctly. Acceleration, speed, time, and deceleration drastically change their meaning in the case of not-human drivers if the model is set to reproduce the human driver behaviors reliably and so the common laws of vehicle interactions could not be applied (Shladover et al., 2012; Ims et al., 2021; Morando et al., 2018). This is the reason why, in the case of fully automated vehicles, especially in VISSIM (Papadoulis et al., 2018; Kockelman et al., 2016) and in PARAMICS (Olia et al., 2018; Rezaei et al., 2021) the AVs are simulated thanks to the use of ad hoc scripts in APIs (Application Programming Interfaces). In the case of the safety distance model, like the Gipps one, the focus of the algorithms for the driving behavior is on physics parameters: their dependency on the type of driver can be adjusted just by modifying the values of some crucial parameters. Changing these parameters means accounting for different behaviors (for instance, cautious, PAVs, or assertive AVs, FAVs) from the human ones. This is the case with AIMSUN, which used the Gipps Model. Intervening on parameters like Reaction time, Guidance acceptance level, maximum acceleration, deceleration, and so forth deeply modifies the "safety" of the car-following and lane-changing model. Vehicles would react differently to any modification in the flow conditions, bringing to a more risky or less risky situation, always following the imposed rule of the governing model.

Among all the simulators, AIMSUN is the only one to provide microscopic, mesoscopic, and macroscopic models all at once. Despite this capability, it is possible to intervene in the influencing parameters of the base model for all three types of simulations to test different conditions of driving and different scenarios from the standard one. VISSIM, on the other side, provides just a microsimulation tool, but it is still possible to work on some of the parameters of the model (Vrbanić et al., 2021). The IDM was considered reliable in previous research, but it is used more for simulating cooperative driving behavior (like platoons) than for fully automated driving (Li et al., 2017; Treiber et al., 2000; Wang et al., 2010).

The main characteristics of the AVs, when implemented in already existing codes, are accounted for by the modification of values of the main variables of the car-following and lane-changing model, as mentioned above. These variations are summarized in the following tables for both the AIMSUN and the VISSIM software in case of the absence of APIs. These two software applications are the most used for AVs safety analysis due to both the reliability of results and the possibility of interconnecting the results with other models which can study the interaction between vehicles on which the SSAM software is based (as it will be discussed in the next paragraph). The parameters shown in Table 12 are all modifiable and labeled as "vehicle type" parameters to intervene on. There is a huge difference in simulating human-driven cars and automated ones. There is also a difference according to the rate of automation of the AV, because a semi-automated car still relies on humans for some maneuvers. Hence, it must be more cautious in all driving tasks, because it needs the exchange between man and technology in a short time and it must prevent at the same time all the dangerous situations deriving from a possible failure (for this reason, PAVs are simulated as Cautious AVs). A different approach can be done considering the fully automated vehicles that can be more aggressive in virtue or their full reliability on technologies. The fact that technology can also prevent dangerous situations due to mechanical failure without human interventions makes possible to set more aggressive parameters in their algorithms (for this reason, FAVs are simulated as Assertive AVs). The default value for human driving is stochastic since not all drivers follow the same behavior. In the case of AVs, the lack of experience and real-world dataset made the idea of creating a range of statistical variability of the parameters difficult. Hence the values presented in the table (Ims & Pedersen, 2021) are deterministic since they are just considered the probably reasonable values attributable to the AV. In this way, an automated (SAE level 4-5) or semi-automated (SAE level 2-3) vehicle is subjected just to following the determined behavior. This consideration can also be justified by considering that the AVs might work ceteris paribus, with no distinctions among the vehicles. Despite this assumption, current studies (Herrmann et al., 2018) have demonstrated great variability in AVs behavior depending on the manufacturers. Thus, further improvements of this research might consider statistical truncated normal distribution for the values related to the AVs, especially those Cautious (Levitate Project, 2020, suggests some distributed parameters, as it was shown in Table 8). Cautious AVs (PAVs), in fact, still partially depend on human intervention, and there is no certainty as well as uniformity in the driving behavior of a human during the takeover phase. Hence, considering deterministic, some parameters could not depict the real traffic conditions in a promiscuous driving environment.

A different approach is the one used for the VISSIM simulator, where all the different vehicles, RVs, PAVs, and FAVs are modeled with deterministic parameters, as shown in the table. This different approach to defining the parameters' variability is due to the different car-following and lane-changing models.

According to literature, the greatest difference between FAVs and PAVs stands in the aggressivity of the vehicle, in terms of the reduced time of maneuvering: FAVs are more prone to be aggressive in case of full automation, while the PAVs are simulated in a cautionary way.

Table 13:Input parameters a) for AIMSUN software package; b) for VISSIM software package.

a)

Input parameters of the Gipps '81 model used in AIMSUN (Ims et al.. 2021)	UoM	Human Driver				PAVs (Cautious AVs)	FAVs (Assertive AVs)
		Mean	St. Dev.	Min	Max		
Normal deceleration	m/s^2	4.00	0.25	3.50	4.50	2.00	2.00
Safety Margin Factor (Rahman et al..2019)	-	1.00				2.00	1.00
Sensitivity Factor	-	1.00				1.50	1.00
Overtake speed threshold	%	90.00				80.00	90.00
Gap (Giuffrè et al.. 2018)	s	0.00				2.00	1.00
Look-ahead distance factor (Giuffrè et al.. 2018; Kim et al.. 2021)	s			0.80	1.20	1.50	1.25
Aggressiveness level	-			0.00	1.00	0.00	0.00
Maximum desired speed	Km/h	110.00	10.00	80.00	120.00	110.00	50.00
Speed limit acceptance (Giuffrè et al.. 2018)	-	1.00	0.10	0.90	1.10	1.00	1.00

Maximum giveway time	s	10.00	2.50	5.00	15.00	12.00	8.00
Clearance (Kim et al.. 2021)	m	2.00	0.80	0.50	3.50	2.00	1.00
Reaction time	s	0.90				0.10	0.10
Reaction time at stop	s	1.20				0.10	0.10
Reaction time at traffic light	s	1.35				0.10	0.10
Guidance acceptance Level	%	50.00	25.00	0.00	100.00	75.00	100.00
Maximum acceleration (Kim et al.. 2021)	m/s2	3.00	0.20	2.60	3.40	3.00	3.00
Maximum deceleration (Kim et al.. 2021)	m/s2	6.00	0.50	5.00	7.00	6.00	6.00

All the parameters shown in tables are taken from Ims & Pedersen, 2021, but some values adopted for simulations are taken from other studies, highlighted in brackets, closer to the Italian case or coming from deeper analyses.

b)

Input parameters of the Wiedemann '74 model used in VISSIM (Morando et al.. 2018)	**UoM**	**RVs**	**PAVs - Cautious AVs (Atkins 2016)**	**FAVs- Assertive AVs (PTV 2018)**
Standstill distance CC0	m	1.50	0.5	0.75
Headway time CC1	s	0.9	0.5	0.45
Following variation CC2	m	4.00	0.00	2.00
Negative following threshold CC4	-	-0.35	0.00	-0.1

Positive following threshold CC5	-	0.35	0.00	0.1
Speed dependency of oscillation CC6	-	11.44	0.00	0.00
Acceleration during oscillation CC7	m/s^2	0.25	0.45	0.25
Desired acceleration from standstill CC8	m/s^2	3.5	3.9	3.5
Look-ahead distance	n of vehic.	2.00	10.00	2.00

The increase in automation penetration and, respectively, the lack of human interventions seem to lead to more aggressive vehicle behaviors. The cause of this modification is directly related to the technological performance of sensors which might be more reliable than the human ones and not governed by instantaneous unpredictable behavioral changes. The difference between cautious (PAVs), and assertive AVs (FAVs), stands for this difference between the SAE level 2-3 vehicle and the SAE level 4-5 vehicle. The presence of the human driver makes the semi-automated vehicle less "aggressive" in driving performance because it has not full control of the driving task and so has just to mitigate the aberrant behavior of the drivers. When there is full or almost full automation, the vehicle can be more "aggressive" since it can rely on predictable technological performance.

The fact that the models at the base of the software packages are different clearly implies relying on different parameters. In the Wiedemann '74 model, the values adopted for AVs seem less cautious than those used in the Gipps '81 model since the former was studied to represent human behavior well. Apart from AIMSUN and VISSIM software, which have been used for these applications, PARAMICS has been widely used until now only for calculating atmospheric emissions and traffic congestion related to automation (Gao et al., 2016; Olia et al., 2018), more than for safety purposes, because of the nature of the Fritzsche model which is based on.

Despite the different nature of the models implemented in AIMSUN and VISSIM, and so the general number of variables of the model, both can precisely represent the automated vehicles just varying 16 parameters.

3.1.4 Safety Surrogate Measures

Previous studies (Gettman et al., 2008) aimed to compare the applicability of the results of the different model mixes adopted by the several commercial software packages described above to the SSAM analysis. Strong differences were highlighted in the crash prediction in RV's environment. Most of the detected conflicts for all the simulators were rear-end conflicts; on the other hand, crossing conflicts were very low. Crossing conflicts had a smaller TTC value than rear-end conflicts which had a larger TTC value.

The main differences between software applications are as follows:

- VISSIM had the least number of conflicts across all categories for all cases. This seems to create a stable condition for recording conflicts but is independent of traffic variability (a crucial aspect as it will be shown for other results).
- When traffic volume increased, the related conflicts detected by VISSIM proportionally increased with respect to those detected by the other codes.
- The accuracy of the prediction of the number of conflicts was in the following descending order for high and medium volume ranges (three ranges of volume for single direction were considered, low with around 100 veh/h; medium with around 300 veh/h; high with around 500 veh/h): VISSIM, AIMSUN, PARAMICS. The ranking order for a decreased traffic volume (low volume range) was VISSIM, PARAMICS, and AIMSUN.
- AIMSUN led to a higher percentage of low-speed conflicts than PARAMICS, while PARAMICS led to a higher percentage of severe conflicts than AIMSUN.
- AIMSUN records precisely the conflicts at high speeds and is not subjected to unreliable conflict detection increases due to low speed (results obtained with low speeds are not affected by noise and are in line with the expected conflict count).

- VISSIM and AIMSUN led to fewer low-speed or crash events than PARAMICS.
- Most conflicts in VISSIM, and AIMSUN, were less severe conflicts (conflicts with TTC $\geq$ 0.5), while in PARAMICS, most conflicts were severe conflicts (conflicts with TTC $<$ 0.5).

These findings highlight blatantly how the simulators practically show similar performance and that in each different scenario, the reliability of a simulator can increase or decrease. The same conclusion was also found and supported by the results of other researchers (Ims et al., 2021), which assess that the simulator choice highly depends on the simulated scenario.

The highlighted results are just found for the RV environment neglecting the chance of using the same simulator for analyzing AV scenarios, which require a different approach, as already presented. Moreover, the results provided might be validated for real datasets in different contexts since the driving behavior of human drivers differs a lot according to the country of investigation. Some traffic simulation models can be highly reliable for some geographical areas and less for others.

In light of the consideration of the different predictability of the simulation for AV scenarios, the Levitate Project (2020) was launched with the aim of predicting future scenarios with Connected and automated vehicles (CAVs) by collecting the results of analyses carried out by researchers to obtain dose-response curves for crash reduction predictions. This approach, considered valid for road safety analysis, focuses on the percentage reduction in accident rates as a function of AV level 5 penetration, thanks to the trends provided by dose-response curve beams. The studies conducted rely on VISSIM + API or AIMSUN in the absence of APIs since its base model is considered suitable also for automation.

Five different approaches can be used to estimate the road safety impacts of AVs:

- In-depth approach that assesses the accident rate according to the various factors that determine it. In a mixed context, the most demanding doubt is the human adaptation to technology and its velocity of adaptation to the change.

- Epidemiological approach which evaluates a risk coefficient, the value of which indicates the concomitance of several factors for the occurrence of accidents.
- Technology extrapolation approach in which benchmark values set at either the maximum or minimum penetration of technologies must be chosen so that intermediate situations can be assessed. Leslie et al. (2019) identified a 46% reduction in buffering by evaluating the Autonomous Emergency Braking system (AEB) and camera-based Forward Collision Warning (FCW) alone. Wang et al. (2020) established an accident reduction range of 41-55% for Adaptive Cruise Control (ACC) and AEB. The number of driver support devices installed before full automation will inevitably lead to lower percentage accident reductions with the introduction of automation.
- Comparative reliability approach evaluates the difference in reliability between man and machine: despite a high number of accidents human reliability is considered extremely high (in terms of accidents/million km traveled). For example, reliability is studied by using naturalistic data from the SHRP2 program (Favarò et al., 2017; Papazikou et al., 2019; Osman et al., 2018).
- Accident rate comparison approach evaluates RV and AV's difference in accident rates. Noy et al. (2019) found that accidents with AVs are higher than with RVs but based on a statistically insignificant sample. Their result is statistically insubstantial, according to Kalra and Paddock (2016), because AVs have to travel at least 8.8 billion miles before a meaningful comparison can be made; however, the results of the previous study are for 3 years of investigations (2012-2015) and only 11 reported accidents with AVs.

The choice of the most suitable simulations depends on the boundary conditions, for sure, but it is also crucial to simulate accurately the scenario according to the vehicle type. Simulating AVs with psycho-physical models can require several modifications, because it implies adapting a simulation made to reproduce the human driving workload to driverless cars. Contrary, a safety distance model, like the Gipps one, that tries to simulate traffic flow as a fluid, with particles at safe distance one to the other, can be optimal for AVs and a bit simplistic for RVs.

3.2 SENSITIVITY ANALYSIS RESULTS

In the following paragraph, a sensitivity analysis is presented, performed on the AIMSUN software, which is preferred because of the characteristics of the analyzed road networks, as the previous section results highlighted. One of the most promising considerations for using the Gipps Model (at the basis of AIMSUN) is to work on the safety distance model, which is more suitable than a psycho-physical one, to represent vehicles as automated. Moreover, by intervening directly on some of the parameters at the basis of the simulation model, it is possible to manage different possible scenarios and control what happens on the network. Using a limited number of parameters allows a precise representation of a wide road network (Papadoulis et al., 2019; Li et al., 2013; Rahaman et al., 2018; Stanek et al., 2018; Jeong, 2017). Furthermore, according to the previous comparison of software performance in terms of safety, AIMSUN simulates less severe conflicts than the other software packages. This characteristic is compatible with the low percentage of severe and fatal crashes recorded in the available dataset for the analyzed sites. The parameters used in the sensitivity analysis are the ones presented in table 8.

As mentioned in the previous paragraph, the performance of the simulation model implemented in AIMSUN is good at different speeds, especially at high ones. This is the other important peculiarity of the tested sites, where the recorded speeds are high, most often much greater than the posted speed limit, 50 Km/h (up to 118% increase for the average recorded speed). The great variability of traffic demand (AADT ranging from 1400 veh/day to 14000 veh/day) and the high crash frequency for all the sites (4.5 crash/year) in the available dataset suggested that AIMSUN could potentially be the best software for the safety assessment. This is justified by the conditions mentioned above (3.1.4) and by its flexibility, which is greater than the other codes in detecting conflicts in high traffic volume variability conditions.

Varying the boundary conditions (traffic, speeds, and so forth) of the investigated sites, the choice of the most suitable simulation model can vary accordingly.

Thus, the analysis was performed with AIMSUN, according to the methodology stated above, by varying the values of the parameters listed in table 8. In general, results show that the most influencing parameters vary according to the conflict type.

The averaged results for the relative conflict ratio for the j-esim type of conflict are listed in the table below (Table 13) for each of the tested possible alternatives.

Table 14: Tested parameters for the sensitivity analysis with the mean and the standard deviation calculated over the 8 sites compared to the baseline which is the calculated conflict frequency for the current scenario.

Tested parameters	Mean			St. Deviation		
	Conflict Ratio (Analysis/Baseline)			Conflict Ratio (Analysis/Baseline)		
	Crossing	Rear-end	Lane-changing	Crossing	Rear-end	Lane-changing
Aggressiveness Level 5 Percentile	0.82	0.80	0.71	1.09	0.76	0.90
Aggressiveness Level 95 Percentile	1.08	1.43	0.57	0.92	1.29	0.53
Aggressiveness Level Avg	0.64	1.11	0.50	0.91	0.75	0.48
Aggressiveness Level Max	0.80	0.96	0.68	0.84	0.76	0.56
Aggressiveness Level Min	0.75	0.86	0.53	0.96	0.72	0.59
Clearance 5 Percentile	0.75	1.43	0.81	0.84	1.07	0.70
Clearance 95 Percentile	0.26	0.18	0.16	0.26	0.18	0.22
Clearance Avg	0.59	0.79	0.80	0.81	0.58	0.63
Clearance Max	0.37	0.38	0.34	0.33	0.34	0.35
Clearance Min	1.46	1.40	1.30	1.98	1.00	1.83
Gap 5 Percentile	0.56	0.93	0.32	0.68	0.78	0.37
Gap 95 Percentile	0.48	0.73	0.33	0.59	0.51	0.37
Gap Max	0.82	0.87	0.60	1.27	0.65	0.74
Gap Avg	0.83	0.90	0.73	1.28	0.51	0.54

Gap Min	0.69	0.85	0.59	0.54	0.59	0.65
Guidance Acceptance 5 Percentile	0.74	1.02	0.51	0.51	0.49	0.51
Guidance Acceptance 95 Percentile	0.70	0.78	0.61	0.62	0.56	0.44
Guidance Acceptance Avg	0.40	0.84	0.45	0.53	0.62	0.48
Guidance Acceptance Max	0.60	0.87	0.59	0.69	0.67	0.53
Guidance Acceptance Min	0.77	0.91	0.58	0.79	0.61	0.41
LAF (Look-Ahead Factor) 5 Percentile	0.89	0.80	0.49	1.10	0.39	0.43
LAF 95 Percentile	0.69	0.77	0.28	0.56	0.38	0.31
LAF Avg	0.30	0.61	0.40	0.42	0.47	0.46
LAF Max	0.64	0.74	0.46	0.97	0.39	0.48
LAF Min	0.45	0.87	0.33	0.39	0.40	0.45
Max Acc 5 Percentile	0.92	1.03	0.58	1.03	0.52	0.46
Max Acc 95 Percentile	0.70	0.80	0.57	0.70	0.74	0.56
Max Acc Avg	0.60	1.02	0.65	0.50	0.73	0.54
Max Acc Max	0.75	0.87	1.06	0.87	0.66	1.06
Max Acc Min	0.59	0.81	0.53	0.51	0.65	0.55
Max Dec 5 Percentile	0.45	1.02	0.69	0.59	0.58	0.47
Max Dec 95 Percentile	0.54	1.07	0.73	0.50	0.82	0.70
Max Dec Avg	0.89	0.76	0.55	0.89	0.55	0.63
Max Dec Max	0.68	0.93	0.85	0.71	0.63	0.85
Max Dec Min	0.50	0.83	0.46	0.55	0.74	0.38
Max Speed 5 Percentile	0.89	0.81	0.47	0.54	0.63	0.52
Max Speed 95 Percentile	0.56	1.06	0.56	0.67	0.77	0.46

Max Speed Avg	0.59	0.94	0.53	0.48	0.73	0.53
Max Speed Max	0.43	0.93	0.48	0.45	0.82	0.45
Max Speed Min	0.57	0.73	0.41	0.50	0.63	0.42
MYT (Maximum Yield Time) 5 Perc	0.58	0.80	0.55	0.82	0.59	0.52
MYT 95 Perc	0.52	0.60	0.61	0.56	0.55	0.66
MYT Avg	0.71	0.91	0.49	0.43	0.52	0.78
MYT Max	0.78	0.79	0.49	1.12	0.63	0.42
MYT Min	0.79	0.69	0.70	0.82	0.64	0.43
Ndec (Normal deceleration) 5Perc	0.54	0.78	0.44	0.63	0.71	0.51
Ndec 95Perc	0.49	0.96	0.49	0.45	0.69	0.44
Ndec Avg	0.92	0.83	0.78	0.83	0.56	0.70
Ndec Max	0.37	0.83	0.56	0.40	0.67	0.46
Ndec Min	1.16	0.64	0.50	1.41	0.57	0.47
Overtake Speed Threshold 30	0.59	0.93	0.59	0.70	0.52	0.54
Overtake Speed Threshold 72	0.84	0.86	0.43	0.81	0.81	0.45
Overtake Speed Threshold 80	0.45	0.79	0.45	0.53	0.69	0.47
Overtake Speed Threshold 90	0.55	1.18	0.81	0.50	0.56	0.59
Overtake Speed Threshold 99	0.63	0.96	0.52	0.82	0.77	0.36
Reaction Time* 0.1	0.60	0.75	0.71	0.60	0.51	0.60
Reaction Time 1.2	0.53	1.36	0.55	0.46	1.40	0.72
Reaction Time 1.6	0.56	0.65	0.44	0.70	0.45	0.48

Reaction Time 1.8	0.43	0.61	0.41	0.47	0.41	0.47
Reaction Time 2.4	1.28	0.67	0.63	1.27	0.45	0.53
Safety Margin Factor 5 Percentile	0.70	0.79	0.48	0.67	0.58	0.50
Safety Margin factor 95 Percentile	0.66	1.17	0.53	0.58	0.65	0.41
Safety Margin Factor Avg	0.71	0.85	0.63	0.59	0.57	0.88
Safety Margin Factor Max	0.50	0.82	0.61	0.56	0.61	0.52
Safety Margin Factor Min	1.06	0.61	3.11	0.80	0.43	5.89
Sensitivity Factor 5 Percentile	0.28	2.47	0.64	0.30	2.63	0.84
Sensitivity factor 95 Percentile	0.60	0.66	0.48	0.66	0.68	0.40
Sensitivity Factor Avg	0.85	1.33	0.57	0.65	0.83	0.53
Sensitivity Factor Max	0.63	0.76	0.27	0.47	0.64	0.28
Sensitivity Factor Min	1.04	2.12	3.06	1.25	1.50	4.26
Speed Limit Acceptance 5 Percentile	1.05	0.93	0.75	0.75	0.42	0.78
Speed Limit Acceptance 95 Percentile	0.46	0.62	0.32	0.39	0.58	0.38
Speed Limit Acceptance Avg	0.63	0.88	0.51	0.55	0.59	0.41
Speed Limit Acceptance Max	0.49	0.60	0.40	0.45	0.39	0.43
Speed Limit Acceptance Min	0.52	0.85	0.44	0.57	0.46	0.44

(*Reaction time did not follow a truncated distribution; hence the attributed values are either calculated according to the Italian regulation for the minimum and maximum design speed (respectively 1.8 s and 2.4 s) or taken by literature (31) or equal to the simulation step).

The results suggest that not all the parameters are influencing, making a categorization for the type of conflict. The graphic criterion used to highlight the significance of a parameter has been explained in Paragraph 2.4.

Table 15: Sensitivity analysis results for Conflict ratio (R) -Crossing conflict (the blue-colored boxes represent R greater than 2; the blue-edged boxes represent R between 1,2 and 2; the red-edged boxes represent R between 0,5 and 0,2; the red-colored boxes represent R lower than 0,2).

	Conflict Ratio (Analysis/Baseline)				
	Crossing				
Main Variable	**Min**	**5th Percentile**	**Avg**	**95th Percentile**	**Max**
Aggressiveness level	0.75	0.82	0.64	1.08	0.80
Clearance	1.46	0.75	0.59	0.26	0.37
Gap	0.69	0.56	0.83	0.48	0.82
Guidance Acceptance Level	0.77	0.74	0.40	0.70	0.60
Look Ahead Factor	0.45	0.89	0.30	0.69	0.64
Max Acceleration	0.59	0.92	0.60	0.70	0.75
Max Deceleration	0.50	0.45	0.89	0.54	0.68
Max Desired Speed	0.57	0.89	0.59	0.56	0.43
Max Yield Time	0.79	0.58	0.71	0.52	0.78
Normal Deceleration	1.16	0.54	0.92	0.49	0.37
Overtake Speed Threshold	0.59	0.84	0.45	0.55	0.63
Reaction Time	0.60	0.60	0.56	0.43	1.28
Safety Margin Factor	1.06	0.70	0.71	0.66	0.50
Sensitivity Factor	1.04	0.28	0.85	0.60	0.63
Speed Limit Acceptance	0.52	1.05	0.63	0.46	0.49

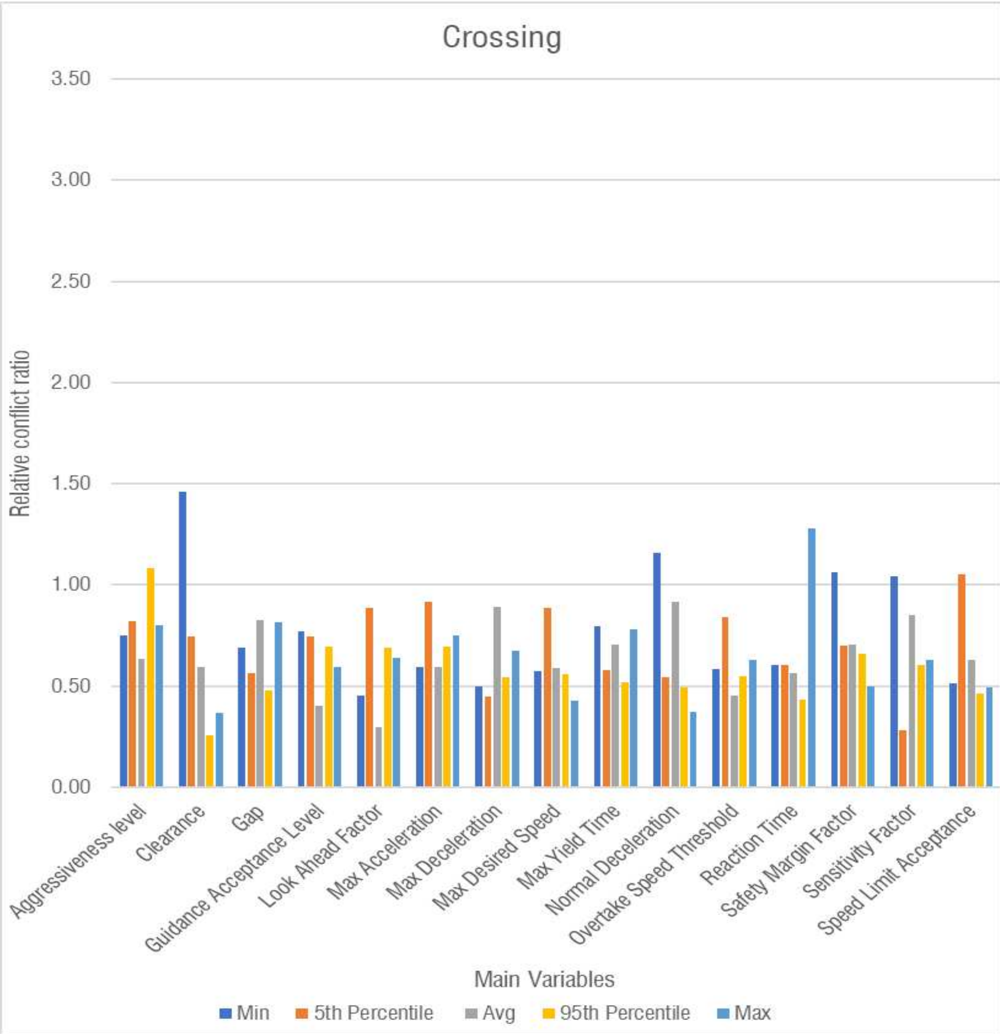

Figure 16: Conflict ratio sensitivity analysis for crossing conflicts.

Table 16: Sensitivity analysis results for Conflict ratio (R) - Rear-end conflict (the blue-colored boxes represent R greater than 2; the blue-edged boxes represent R between 1,2 and 2; the red-edged boxes represent R between 0,5 and 0,2; the red-colored boxes represent R lower than 0,2).

	Conflict Ratio (Analysis/Baseline)				
	Rear-end				
Main Variable	**Min**	**5th Percentile**	**Avg**	**95th Percentile**	**Max**
Aggressiveness Level	0.86	0.80	1.11	1.43	0.96
Clearance	1.40	1.43	0.79	0.18	0.38
Gap	0.85	0.93	0.90	0.73	0.87
Guidance Acceptance Level	0.91	1.02	0.84	0.78	0.87
Look Ahead Factor	0.87	0.80	0.61	0.77	0.74
Max Acceleration	0.81	1.03	1.02	0.80	0.87
Max Deceleration	0.83	1.02	0.76	1.07	0.93
Max Desired Speed	0.73	0.81	0.94	1.06	0.93
Max Yield Time	0.69	0.80	0.91	0.60	0.79
Normal Deceleration	0.64	0.78	0.83	0.96	0.83
Overtake Speed Threshold	0.93	0.86	0.79	1.18	0.96
Reaction Time	0.75	1.36	0.65	0.61	0.67
Safety Margin Factor	0.61	0.79	0.85	1.17	0.82
Sensitivity Factor	2.12	2.47	1.33	0.66	0.76
Speed Limit Acceptance	0.85	0.93	0.88	0.62	0.60

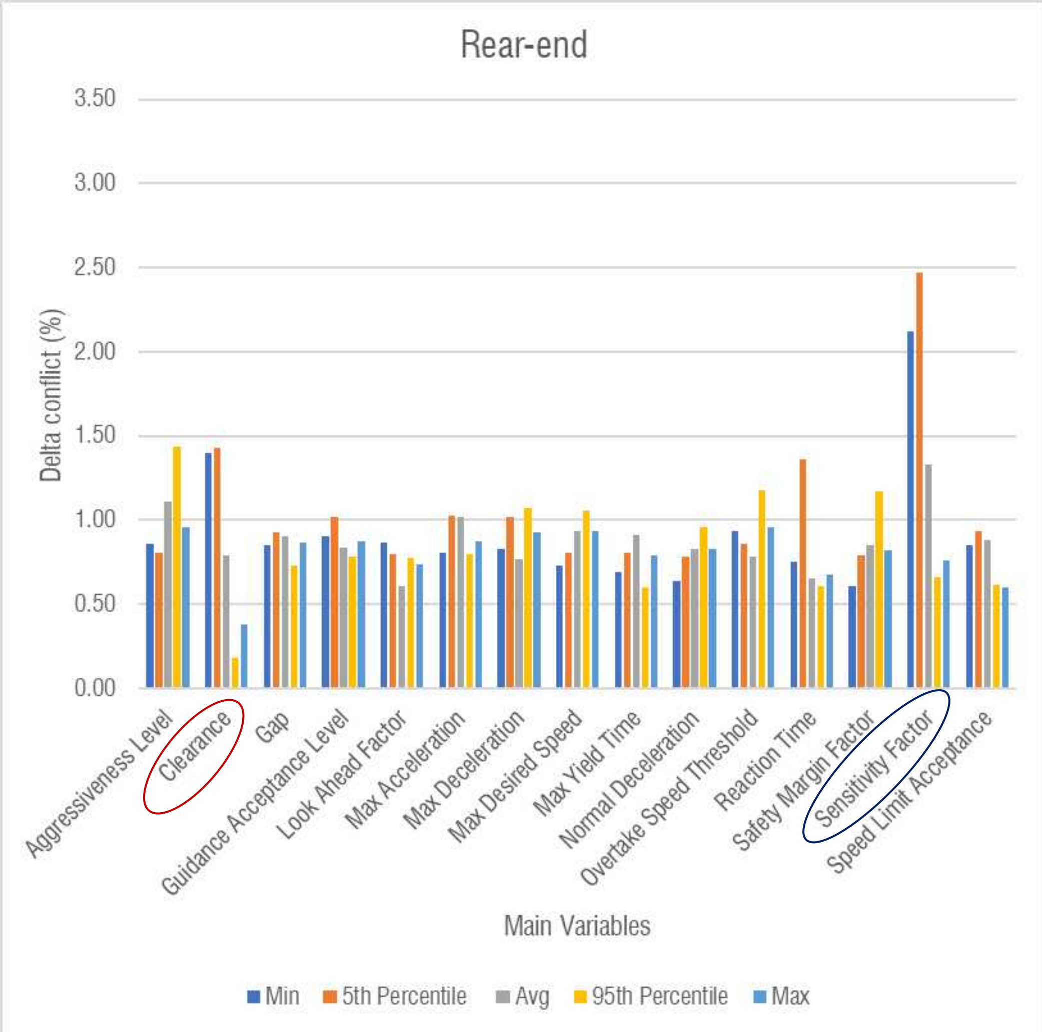

Figure 17: Conflict ratio sensitivity analysis for Rear-end conflicts (the red circle for the parameters which show the conflict ratio lower than 0,2 and the blue circle for the parameters which show the conflict ratio greater than 2).

Table 17: Sensitivity analysis results for Conflict ratio (R) - Lane-changing conflict (the blue-colored boxes represent R greater than 2; the blue-edged boxes represent R between 1,2 and 2; the red-edged boxes represent R between 0,5 and 0,2; the red-colored boxes represent R lower than 0,2).

	Conflict Ratio (Analysis/Baseline)				
	Lane-changing				
Main Variable	**Min**	**5th Percentile**	**Avg**	**95th Percentile**	**Max**
Aggressiveness level	0.53	0.71	0.50	0.57	0.68
Clearance	1.30	0.81	0.80	0.16	0.34
Gap	0.59	0.32	0.73	0.33	0.60
Guidance Acceptance Level	0.58	0.51	0.45	0.61	0.59
Look Ahead Factor	0.33	0.49	0.40	0.28	0.46
Max Acceleration	0.53	0.58	0.65	0.57	1.06
Max Deceleration	0.46	0.69	0.55	0.73	0.85
Max Desired Speed	0.41	0.47	0.53	0.56	0.48
Max Yield Time	0.70	0.55	0.49	0.61	0.49
Normal Deceleration	0.50	0.44	0.78	0.49	0.56
Overtake Speed Threshold	0.59	0.43	0.45	0.81	0.52
Reaction Time	0.71	0.55	0.44	0.41	0.63
Safety Margin Factor	3.11	0.48	0.63	0.53	0.61
Sensitivity Factor	3.06	0.64	0.57	0.48	0.27
Speed Limit Acceptance	0.44	0.75	0.51	0.32	0.40

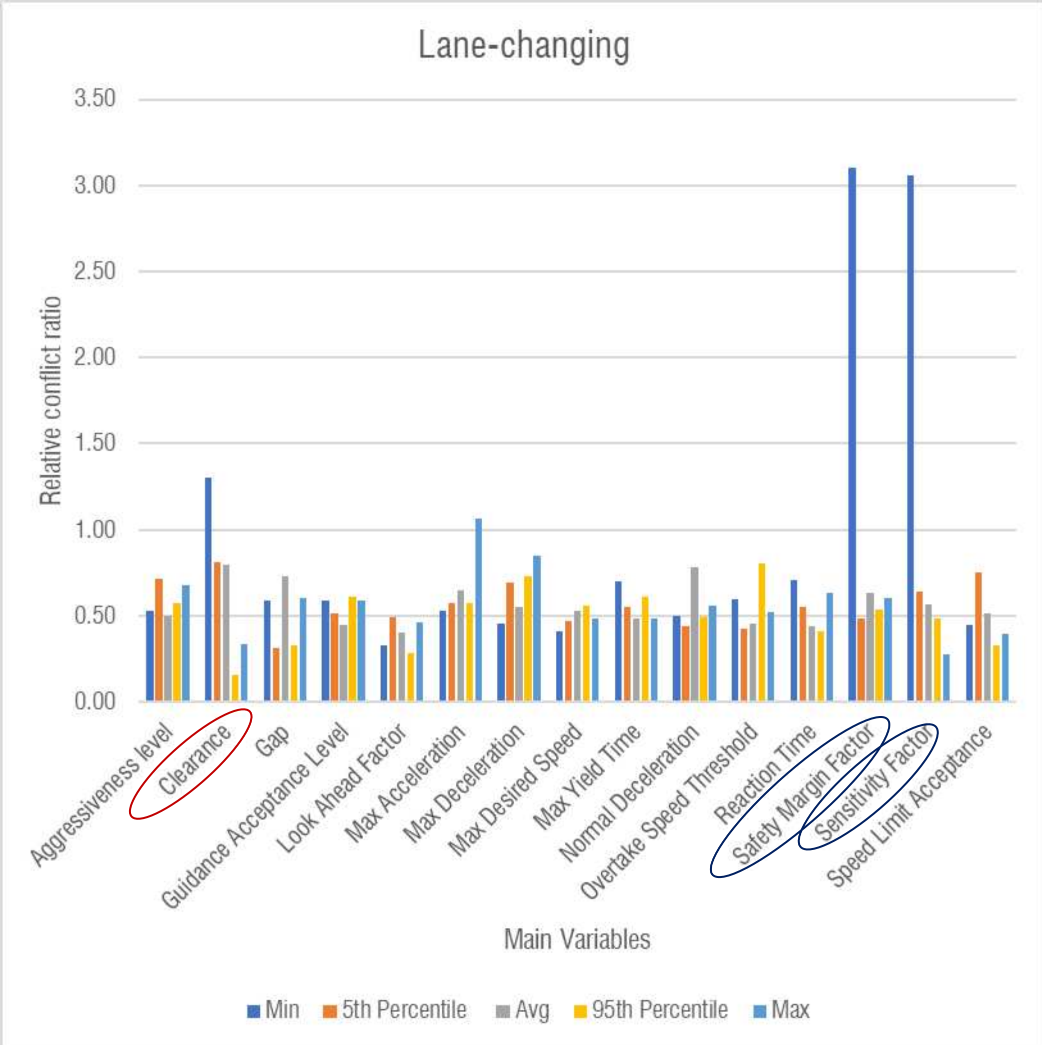

Figure 18: Conflict ratio sensitivity analysis for Lane-changing conflicts (the red circle for the parameters which show the conflict ratio lower than 0,2 and the blue circle for the parameters which show the conflict ratio greater than 2).

Results show dramatic variations of conflict numbers for almost all the values, even if the sensitivity implies the replacement of just one parameter per time. This is justifiable by the fact that in ordinary conditions, the simulation aims at reproducing the current scenario with a variability also of the parameters to consider everything. Contrary, setting just one parameter fixed without variability forces the simulated behavior to be far from the current situation. The models are based on mathematical equations that explain the physics of the vehicles. Forcing one parameter with a fixed value and a different nature (no more stochastic but deterministic) in one equation can deeply modify the outcome even if all the other parameters are unchanged. The nature of the reproduced behavior in this sense can be less realistic than in the regular scenario. Moreover, the scenarios present a great variability of boundary conditions. In this sense, the impact of one parameter can be more or less important according to the boundary conditions of the site. For this reason, the values of the analysis fluctuate not around 1, but around other values, greater or lower than ones according to the danger expressed by the modified parameter.

Each type of conflict is affected differently by all the parameters. The lane-changing conflict is the most sensitive to the variation of the parameters, followed by the rear-end and then by the crossing. All these conflicts have been recorded at intersections. The effect of each parameter on the conflict recording depends on the number of conflicts recorded. The rear-end conflicts are the most detected, hence the ones with the greatest number of conflicts, followed by crossing and lane-changing. While crossing and rear-end conflicts seem stable in the recordings, the lane-changing ones are the rearrest ones, so they vary greatly.

Crossing conflicts are particularly sensitive to clearance, normal deceleration, reaction time, safety margin factor, sensitivity factor, and speed limit acceptance. These parameters are directly linked to the chance of being aggressive while crossing an intersection and following a vehicle. Thus, this behavior leads to less distance (spatial and temporal) among the crossing vehicles at intersections. So, it is more probable to record a potentially unsafe situation than the usual ones.

Crossing and lane-changing relative conflict ratios are always below 1, meaning that changing the parameters leads to a decrease in conflict, averaging over the 8 sites. The rear-end conflicts decreased in 81% of the analyzed cases (61 out of 75). Aggressiveness level, clearance, max acceleration, deceleration, overtake speed threshold, reaction time, safety margin factor, and sensitivity factor lead in some cases to the increase of rear-end conflicts. This result was expected since a variation in these parameters unavoidably impacts the safety distance calculated by the model. Thus, situations detected become less safe than the ones usually provided by the safety distance model. The most sensitive parameters for rear-end reduction are clearance and sensitivity factor which directly work on the following vehicle distance.

Lane-changing conflicts are particularly sensitive to clearance, safety margin factor, and sensitivity factor. The reason can be found in the same details explained and highlighted for crossing conflicts.

This analysis was propaedeutic to determine the main influencing parameters for all the conflict types. After that, the two-control tests to investigate the influence of these parameters' influence on AV scenarios have been proposed, compared to the current one. The first control test aimed at understanding the impact of each of the parameter values chosen for AVs on the conflict records compared to the baseline scenario (100% RV).

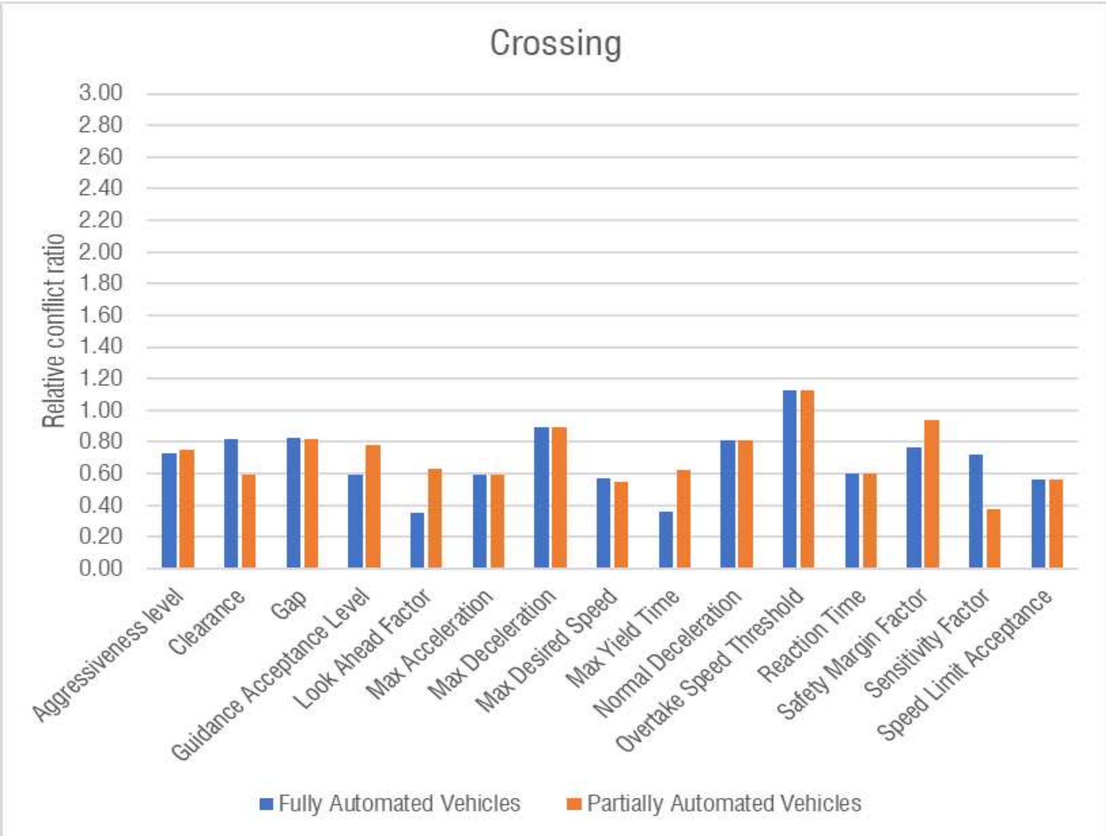

Figure 19: Control test about relative conflict ratio for crossing conflicts with parameters for AVs.

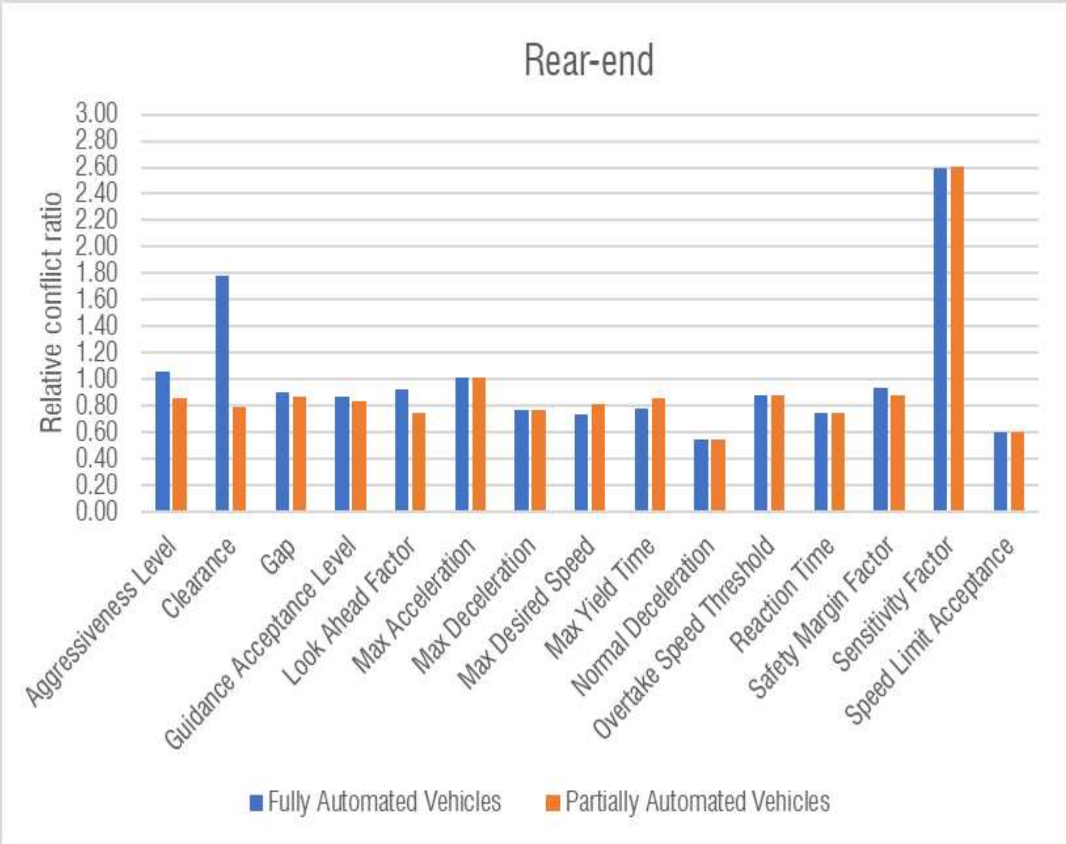

Figure 20: Control test about relative conflict ratio for rear-end conflicts with parameters for AVs.

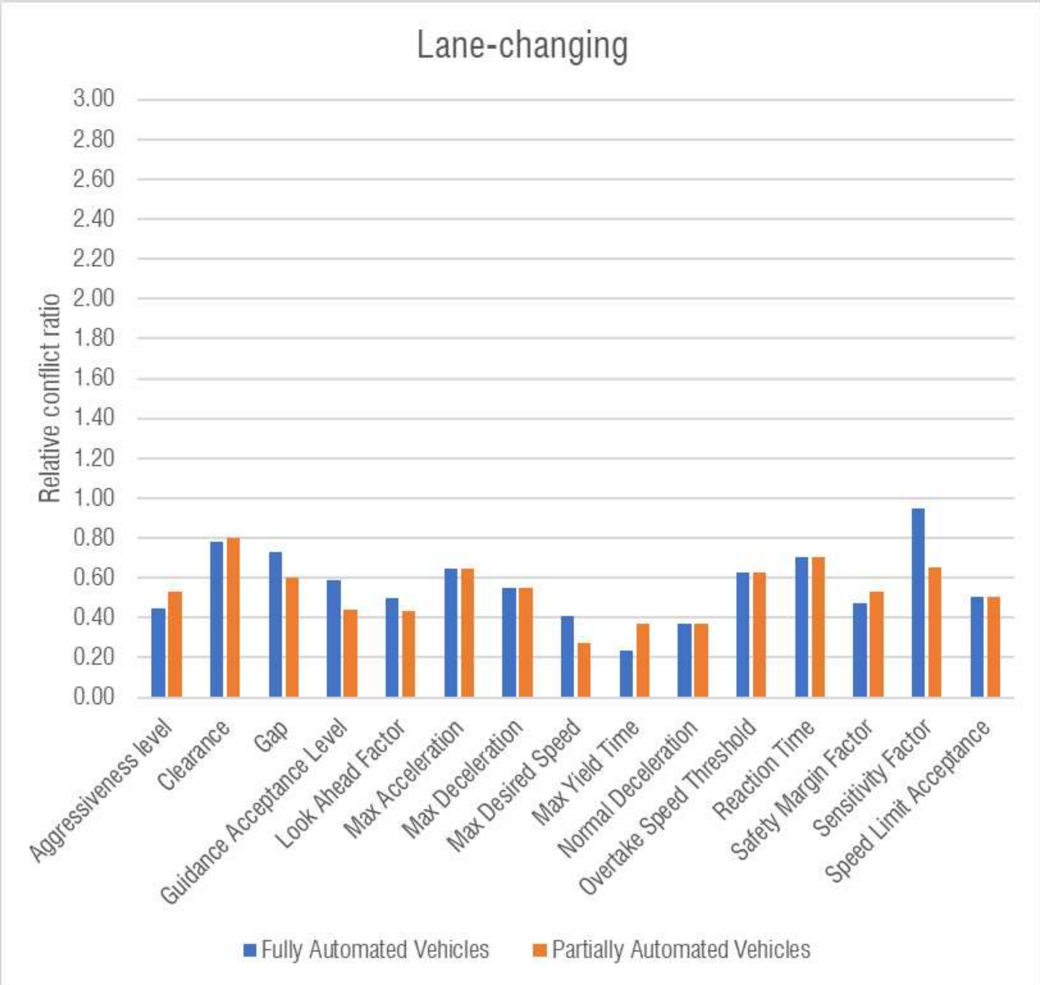

Figure 21: Control test about relative conflict ratio for lane-changing conflicts with parameters for AVs.

The parameters are presented twice to represent the case of the PAVs and FAVs. Thus, the parameter has been inserted into the graph with the indication Partially or Fully Automated Vehicles to address them differently.

The results show how the parameter set for AVs leads to a decrease in conflict recording for almost all the analyzed scenarios except for the Overtake speed threshold for crossing conflict. The values used for AVs (both, fully and partially automated) for aggressiveness level, clearance, safety margin factor, and sensitivity factor (Table 8) increase rear-end conflicts if compared to the baseline scenario. This is justifiable because the parameters set for the AVs might be more cautious in all the crossing situations and more prone to respect the rules, but also to optimize the traffic flow, reducing the gaps. Hence the rear-end conflicts are the ones that are more likely to be detected compared to the baseline condition. All the other parameters show the benefits in conflict reduction brought by the AVs.

To certify this assumption, the second control test has been made. The different scenarios have been tested, including the one created by considering all the influencing parameters of the sensitivity analysis, called “Main Variable Car”. All these influencing parameters, no matter the conflict type, have been set all at once in one simulation to understand the impact of their combination on the different conflict types (crossing, rear-end, and lane-changing), as shown in the table below (Table 17). It can be supposed that the parameters put together mitigates the dangerousness of this kind of vehicle “Main variable Car”. This result can confirm the importance of the parameters and can provide an insight about how alle the maximum effects interact with them. It is a car made just to understand this interaction among all the parameters.

Table 18: Most influencing parameters obtained by the sensitivity analysis, useful to define the “main variable Car” scenario.

Parameters	UoM	Value	Most influencing value	Type of conflict mostly affected	Effects on conflict number recording
Aggressiveness level	-	0.87	95th percentile	Rear-end	Increase
Clearance	m	3.14	95th percentile	Rear-end	Decrease
Gap	s	0.26	5th percentile	Lane-changing	Decrease
Guidance acceptance Level	%	50	Average	Crossing	Decrease
Look-ahead distance factor	s	1.15	95th percentile	Lane-changing	Decrease
Maximum deceleration	m/s2	5.26	5th percentile	Crossing	Decrease
Maximum Yield time	s	10	Avg	Lane-changing	Decrease

Overtake speed threshold	%	71.78	5th percentile	Lane-changing	Decrease
Reaction time	s	1.8	95th percentile	Lane-changing	Increase
Safety Margin Factor	-	0	Minimum	Lane-changing	Increase
Sensitivity Factor	-	0	Minimum	Lane-changing	Increase
Speed limit acceptance	-	1.25	95th percentile	Lane-changing	Decrease

The results of the scenario analysis are presented as relative conflict ratio setting the baseline scenario (100% RVs) as the benchmark.

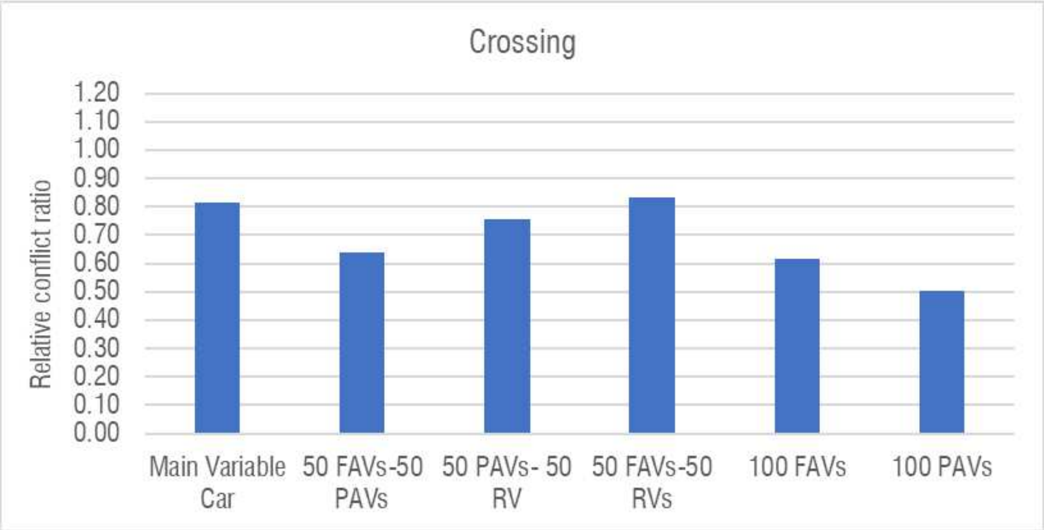

Figure 22: Relative conflict ratio-crossing conflicts for different scenarios - second control test.

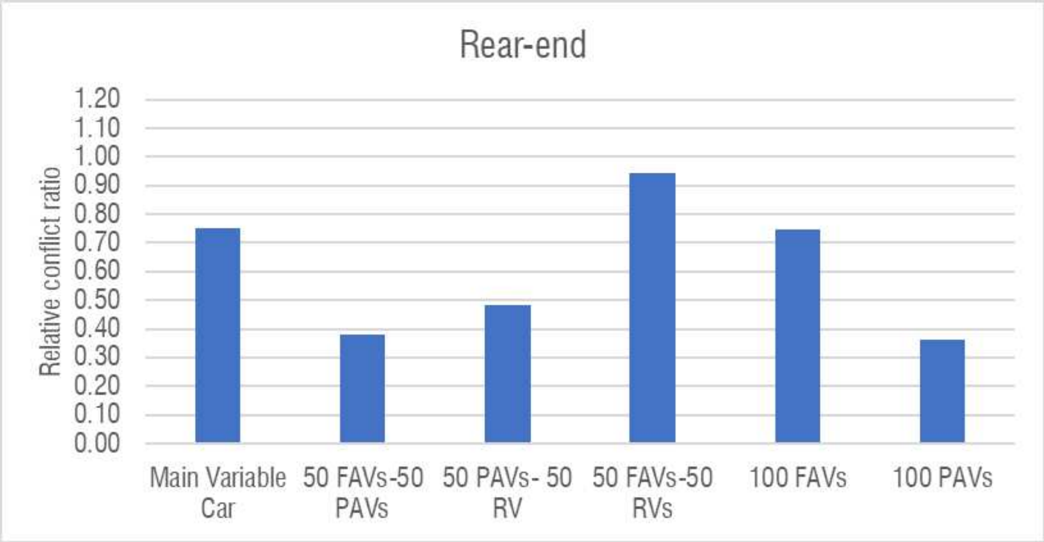

Figure 23: Relative conflict ratio-Rear-end conflicts for different scenarios - second control test.

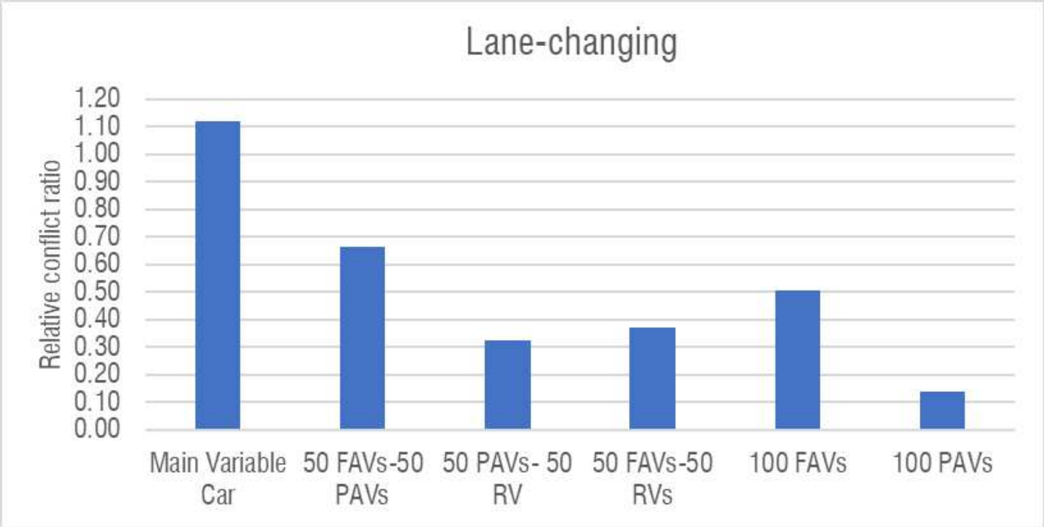

Figure 24: Relative conflict ratio-Lane-changing conflicts for different scenarios - second control test.

It is blatant from the graphs how all the scenarios, except for the one "Main Variable Car", lead to a decrease in conflict recorded. The most promising scenario is the one with PAVs since it is the one that reduces the most conflicts for all the three-conflict types. The FAVs are more aggressive if compared to RVs to avoid possibly dangerous situations, even if it is clear how among all the recorded conflicts, just a small part can become a crash (Tarko 2018). Thus, it is possible that converting conflicts to crash scenarios with 100% FAVs is the safest one since the interactions can be perfectly managed by the vehicles that will behave like fluid particles in an ordinated flow. The promiscuous scenarios are not always as safe as the ones with just one category of vehicles driving. The only cases of a dramatic reduction in recorded conflicts are the 50 PAVs-50 RV for lane-changing conflicts and 50 FAVs-50 PAVs for rear-end conflicts. This suggests that vehicle interactions can differ considering other traffic situations and conflict types. The main Variable Car scenario is the one that varies the most because of its unrealistic simulated driving behavior. Its impact on conflict counts is negligible when considering conflict reduction (Crossing and rear-end) or increase (lane-changing).

It was blatant that each conflict type was sensitive to a specific set of characteristic parameters. It must be noted that not all the tested values for the parameters have a positive impact on the safety performance of road sites. The main result was that only some values led to a dramatic conflict reduction (less than 0.2 or greater than 2). The greatest number of conflicts detected, also in the baseline condition, was for the rear-end, followed by crossing and lane-changing. This is because the safety distance model highlights the issue related to a lack of safety distance between two vehicles while they are approaching the intersections, which is more likely than all the other unsafe conditions.

Considering the crossing conflicts, the most influencing parameters for conflict reduction are the clearance (0.26), the sensitivity factor (0.28), and the look-ahead distance factor (0.30). The parameters which seem to have a direct effect on the conflict increase are 8 out of 15 and are related to unsafe situations, like the reduction of the clearance (1.46), the increase of reaction time (1.28), or the reduction of the normal deceleration (1.16). The AV parameters impact overtake speed threshold (1.13) and the Maximum Yield time for FAVs (0.36).

Regarding the rear-end conflicts, the parameters not involved in conflict increase compared to the baseline scenario are 5 out of 15: Gap, Look Ahead Factor, Maximum Yield Time, Normal Deceleration, and Speed Limit Acceptance. The variation of these parameters makes the scenarios always safer than the baseline conditions. The most significant parameter in conflict increase is the Sensitivity factor (2.61), with the

PAV value, followed by the Clearance (1.78), with the FAV value, and the aggressiveness level (1.43). Parameters like Clearance (0.16), Maximum yield time (0.23), and look ahead factor (0.28) also account for the most promising conflict decrease compared to the baseline conditions for lane-changing. The first and last variables are also the most significant for crossing conflict reduction, highlighting how these parameters can influence a lot the lateral safety of a vehicle, especially during crossing the intersection maneuvers.

After the sensitivity analysis results, it was useful to understand not only which were the main influencing parameters but also the significance of the parameters useful to simulate the two different types of AVs on the simulation output. Thus, this AV parameters sensitivity analysis was used as a control test to check the reliability of the previous analysis.

Compared to the sensitivity one, the results from this analysis are shown in the following tables, clustered for different conflict types. The greatest conflict reduction for each parameter is highlighted in red; meanwhile, the greatest increase in conflict is highlighted in blue. There are some parameters whose only effect is to reduce the conflict number compared to the baseline scenario.

Table 19: Sensitivity analysis results and control test results for crossing conflict.

	Relative Conflict Ratio (Analysis/Baseline)						
	Crossing						
	Min	**5th Percentile**	**Avg**	**95th Percentile**	**Max**	**FAVs**	**PAVs**
Aggressiveness level	0,75	0,82	0,64	1,08	0,80	0,73	0,75
Clearance	1,46	0,75	0,59	0,26	0,37	0,82	0,59
Gap	0,69	0,56	0,83	0,48	0,82	0,83	0,82
Guidance Acceptance Level	0,77	0,74	0,40	0,70	0,60	0,60	0,78
Look Ahead Factor	0,45	0,89	0,30	0,69	0,64	0,35	0,63
Max Acceleration	0,59	0,92	0,60	0,70	0,75	0,60	0,60
Max Deceleration	0,50	0,45	0,89	0,54	0,68	0,89	0,89
Max Desired	0,57	0,89	0,59	0,56	0,43	0,57	0,54

Speed							
Max Yield Time	0,79	0,58	0,71	0,52	0,78	0,36	0,62
Normal Deceleration	1,16	0,54	0,92	0,49	0,37	0,81	0,81
Overtake Speed Threshold	0,59	0,84	0,45	0,55	0,63	1,13	1,13
Reaction Time	0,60	0,60	0,56	0,43	1,28	0,60	0,60
Safety Margin Factor	1,06	0,70	0,71	0,66	0,50	0,76	0,94
Sensitivity Factor	1,04	0,28	0,85	0,60	0,63	0,72	0,38
Speed Limit Acceptance	0,52	1,05	0,63	0,46	0,49	0,57	0,57

Considering the crossing conflicts, the most influencing parameters for conflict reduction are the clearance (0,26), the sensitivity factor (0,28), and the look-ahead distance factor (0,30). The formers impact the safety distance in the following two vehicles, increasing the safety among crossing trajectories. The third one has a direct impact on possible risky situations while crossing since it is strictly related to lane-changing and intersection maneuvers. The parameters which seem to have a direct effect on the conflict increase are 8 out of 15 and are related to unsafe situations, like the reduction of the clearance (1,46), the increase of reaction time (1,28), or the reduction of the normal deceleration (1,16). The AV parameters have the greatest impact on overtake speed threshold (1,13) and for the Maximum Yield time (0,36) for FAVs.

Table 20: Sensitivity analysis results and control test results for rear-end conflict.

	Relative Conflict Ratio (Analysis/Baseline)						
	Rear-end						
	Min	**5th Percentile**	**Avg**	**95th Percentile**	**Max**	**FAVs**	**PAVs**
Aggressiveness Level	0,86	0,80	1,11	1,43	0,96	1,05	0,86
Clearance	1,40	1,43	0,79	0,18	0,38	1,78	0,79
Gap	0,85	0,93	0,90	0,73	0,87	0,90	0,87
Guidance Acceptance Level	0,91	1,02	0,84	0,78	0,87	0,87	0,83
Look Ahead Factor	0,87	0,80	0,61	0,77	0,74	0,92	0,74
Max Acceleration	0,81	1,03	1,02	0,80	0,87	1,02	1,02

Max Deceleration	0,83	1,02	0,76	1,07	0,93	0,76	0,76
Max Desired Speed	0,73	0,81	0,94	1,06	0,93	0,73	0,81
Max Yield Time	0,69	0,80	0,91	0,60	0,79	0,78	0,86
Normal Decelera-tion	0,64	0,78	0,83	0,96	0,83	0,54	0,54
Overtake Speed Threshold	0,93	0,86	0,79	1,18	0,96	0,88	0,88
Reaction Time	0,75	1,36	0,65	0,61	0,67	0,75	0,75
Safety Margin Factor	0,61	0,79	0,85	1,17	0,82	0,93	0,87
Sensitivity Factor	2,12	2,47	1,33	0,66	0,76	2,60	2,61
Speed Limit Ac-ceptance	0,85	0,93	0,88	0,62	0,60	0,59	0,59

Regarding the rear-end conflicts, the parameters not involved in conflict increase compared to the baseline scenario are 5 out of 15: Gap, Look Ahead Factor, Maximum Yield Time, Normal Deceleration, and Speed Limit Acceptance. The variation of these parameters makes the scenarios always safer than the baseline conditions, highlighting that their single impact on the conflict recording for rear-end is not significant. The most significant parameter in conflict increase is the Sensitivity factor (2,61), with the PAV value, the Clearance (1,78), with the FAV value, and the aggressiveness level (1,43). The greatest conflict reductions are highlighted by the Clearance (0,18), the normal deceleration (0,54), and the Speed limit acceptance (0,59), both with the AVs value. The parameters set for AVs are the most significant, for conflict decrease or increase, in 6 cases out of 15 (maximum deceleration and maximum desired speed likewise lead to a conflict reduction, apart from the already mentioned).

Table 21: Sensitivity analysis results and control test results for lane-changing conflict, highlighting in blue the conflict-leading parameters (with great significance greater than 1.0) and in red the conflict-avoiding parameters (with great significance, lower than 0.5).

	Relative Conflict Ratio (Analysis/Baseline)						
	Lane-changing						
	Min	**5th Percentile**	**Avg**	**95th Percentile**	**Max**	**FAVs**	**PAVs**
Aggressiveness level	0,53	0,71	0,50	0,57	0,68	0,45	0,53
Clearance	1,30	0,81	0,80	0,16	0,34	0,78	0,80
Gap	0,59	0,32	0,73	0,33	0,60	0,73	0,60
Guidance Acceptance Level	0,58	0,51	0,45	0,61	0,59	0,59	0,44
Look Ahead Factor	0,33	0,49	0,40	0,28	0,46	0,50	0,44
Max Acceleration	0,53	0,58	0,65	0,57	1,06	0,65	0,65
Max Deceleration	0,46	0,69	0,55	0,73	0,85	0,55	0,55
Max Desired Speed	0,41	0,47	0,53	0,56	0,48	0,41	0,27
Max Yield Time	0,70	0,55	0,49	0,61	0,49	0,23	0,37
Normal Deceleration	0,50	0,44	0,78	0,49	0,56	0,37	0,37
Overtake Speed Threshold	0,59	0,43	0,45	0,81	0,52	0,62	0,62
Reaction Time	0,71	0,55	0,44	0,41	0,63	0,71	0,71
Safety Margin Factor	3,11	0,48	0,63	0,53	0,61	0,47	0,53
Sensitivity Factor	3,06	0,64	0,57	0,48	0,27	0,95	0,65
Speed Limit Acceptance	0,44	0,75	0,51	0,32	0,40	0,50	0,50

Lane-changing conflicts always decrease for every simulated parameter, apart from 4 cases, never involving AV parameters, which are related to Clearance, maximum acceleration, Safety margin factor, and sensitivity factor. These parameters also account for more complex situations while crossing flows at intersections since reducing or accepting a reduced time gap before starting the maneuver at intersections leads to more unsafe conditions. Parameters like Clearance (0,16), Maximum yield time (0,23), and look ahead factor (0,28) also account for the most promising conflict decrease compared to the baseline conditions. The first and last are also the most significant for crossing conflict reduction, highlighting how these parameters can influence a lot the lateral safety of a vehicle, especially during crossing the intersection maneuvers.

The second control test scenario was made to understand the impact of AVs and promiscuous traffic environment on conflict recordings, always compared to the baseline scenario. It was possible to test 6 different situations, either with half RVs and half AVs, or with half PAVs and half FAVs, but also single vehicle type scenario: Main variable car, 100 FAVs and 100 PAVs (Table 15).

Table 22: Second control test-Scenarios analysis results.

Input parameters	**Mean**		
	Conflict Ratio (Analisys/Baseline)		
	Crossing	**Rear-end**	**Lane-changing**
Main Variable Car	0.82	0.75	1.12
50 FAVs - 50 PAVs	0.64	0.38	0.66
50 PAVs - 50 RVs	0.76	0.48	0.32
50 FAVs - 50 RVs	0.83	0.94	0.37
FAVs	0.61	0.75	0.51
PAVs	0.50	0.36	0.14

In red the greatest conflict reduction, lower than 0.5

Per previous literature (Noy et al., 2018; Leslie, 2019; You et al., 2019; Shi et al., 2020), the unpredictable transitory phase, which sees the coexistence of RVs to AVs on the same roads, is not stable for all the kinds of conflict.

The interaction between RVs and PAVs seems safer than the one between RVs and FAVs. This might be justified because a human can understand better cautious behavior and act consequently. Moreover, the main actor in PAVs is still human, and automation helps the human driver reduce mistakes and uncertainties. Hence, the interaction among vehicles seems to be almost safe. The cautious behavior is also useful for the driver in the AV to perform the takeover maneuver accurately in case of automated system failure. FAVs in the 100% and 50% scenarios have a less promising impact on conflict reduction than PAVs, apart from lane-changing conflicts, which seem to be accurately avoided by the precise interactions among all FAVs. This behavior will be further investigated thanks to the three scenarios simulations (for 2030, 2040, 2050), since it highlights similar results to the existing literature (Kockelman et al., 2016; You et al., 2019; Shi et al., 2020). Moreover, this outcome for conflicts does not necessarily imply that traffic made of just FAVs or mixed AVs will be more likely to bring crashes than other scenarios since not all the conflicts become crashes. The gap reduction in FAV assertive behavior is detected as a potentially risky situation by the SSAM algorithm, but possibly converting conflicts to crashes, the potential risk will be assessed as safe and neglected. In fact, the SSAM algorithm detects conflicts according to the set TTC value. The FAV proximity in the scenarios can also be detected and counted as a possible conflict according to the TTC threshold used. In all the analyses, the TTC threshold was set equal to 1.5 s to assess the presence of RVs and create homogeneity in comparing the scenarios. Using this value means detecting conflicts for vehicles with great proximity. Despite this, all the other parameters used to depict AVs can lead to crash avoidance even if there is a chance of a conflict according to the algorithm. In this light, in the case of crash analysis starting from simulated conflicts, a TTC threshold equal to 0.5 s is suggested (Kockelman et al., 2016; Papadoulis et al., 2019) for the scenarios with only AVs because considered more realistic the conflict-to-crash conversion.

The “Main Variable Car” scenario in which all the main variables for each conflict type have been modified all at once shows the worst results in reducing conflict numbers. In some cases, it also led to a conflict recording increase. This scenario is also unlikely to happen on roads since the values used to depict it all together represent a vehicle with unrealistic behavior.

This analysis showed which are the most significant parameters in the Gipps model used by AIMSUN software, for road safety assessment, for three different types of conflicts (crossing, rear-end, lane-changing):

- Clearance.
- Safety Margin Factor.
- Sensitivity factor.

They can reduce or increase the conflict recordings for all three conflict types, up to five times compared to the 100 % RVs scenario, set as baseline conditions.

3.3 VALIDATION OF THE CURRENT SCENARIO

The first results to validate the current scenario come from the GEH test for all the sites. During this calculation, the difference between simulated traffic flow and observed one is counted for all the seasons and the day distinction (workdays- weekend/vacations). The table with the results is shown in Annex B. The results clearly showed a small difference between the simulation and the observation. It means that the chosen simulator can realistically reproduce the real scenario and that the input parameters for simulating RVs are adequate since the simulated behavior is the same that happens on roads.

The GEH values are always below 5, but in 90% of the analyzed case, the GEH was also lower than 1, highlighting an optimal fit between the simulation and the observed data. Some of the GEH values related to the weekend data are greater than 1, and it could be because weekend data hourly variation was obtained employing a correlation from highway data, so the variation law was not directly extracted. Another explanation can be addressed to the fact that the comparison is made on the mean value over the 24 hours, but the variability during the traffic hourly variability on weekend days is greater than during the weekdays. This uncertainty rate is low since the GEH value suggests an optimal match between the input data and the output one.

The reliability of the simulations was the first necessary step in trying to simulate conflicts and extract the crashes.

The first issue in analyzing trajectories came from the SSAM algorithm. It did not find any conflicts in segments. This could be ascribed to the safe and rule-based behavior of the models at the base of each simulator and to the contemporary not perfect reliability of the SSAM algorithm to detect dangerous situations apart from the intersections. Moreover, the observed crashes on the segments were mainly due to secondary accesses, which are neglected in the simulations since the traffic flow is almost null. The SSAM algorithm was validated with high accuracy at intersections (Gettman et al., 2008) and with lower accuracy on segments (Gettman et al., 2008), where the rule-based behavior of the traffic models makes it more difficult to detect conflicting trajectories.

In this research, the conflicts on segments were also tested with different TTC, ranging from 0.5 to 3.5 s as threshold (values extracted by literature, Mahmud et al., 2017), but nothing different happened (conflicts on segments are always null). This outcome suggested that for two-lane, two-way rural roads, where overtaking is less frequent than on two-lane one-way roads, the SSAM algorithm fails in realistically detecting conflicts. After this finding, all the selected sites with only segments were neglected, reducing the overall number of sites to be tested for the correlation and AV scenarios. This choice was made also considering the fact that the intersections represent the most dangerous road element, where the 41% of all the crashes in Italy happen (Berloco et al., 2022). Under this light, the analysis of the intersections constituted a significant portion of the problem, needed to be investigated deeply. As regards to segments, further analyses will deal with the road safety assessment for such elements.

The conflicts were recorded for each site and clustered according to conflict type. The first attempt was to find a correlation between the simulated conflict and the observed crashes for each conflict type, for all the sites. The results were very poor, as the figure below suggests, as well as the physical meaning of the correlations.

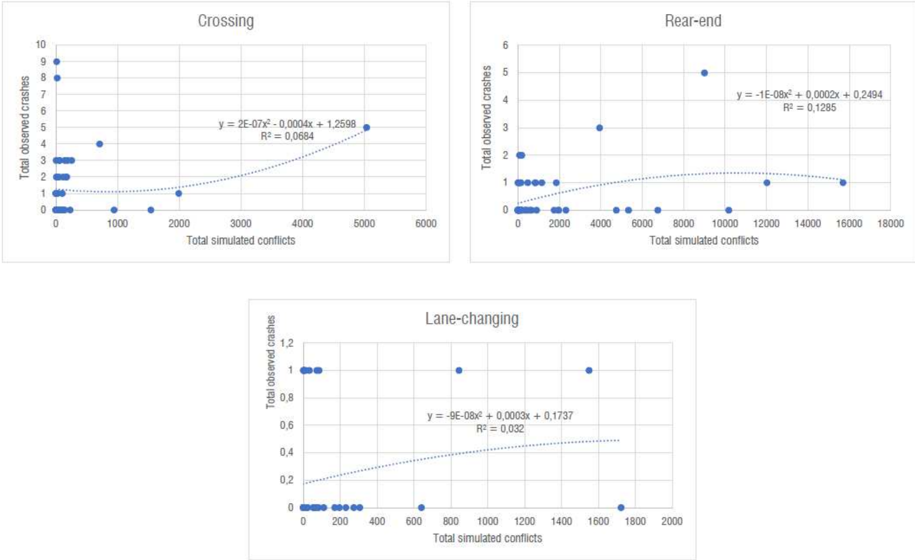

Figure 25: Poor correlation between simulated conflicts and observed crashes clustered for conflict types.

There was no correlation between the two datasets, which was likely because conflicts are more prone to happen than crashes since evasive maneuvers can avoid most of them. It is difficult to understand how many conflicts can become crashes since it depends on human capabilities. Human perception and capabilities are not fixed in the real world. Even if they are depicted in a probabilistic way in the simulator, it is always possible to account for slightly different behaviors in crash avoidance from the real one. Even if the simulator has already been validated for traffic output, the crash statistics are more aleatoric than the traffic one. This caused the first issue, directly relating the two datasets. Another attempt was made by clustering the conflicts for intersection typology rather than for conflict types. The results were poor also in this case, and sometimes the physical meaning was not correct, as shown in Figure 26, for the same reasons mentioned above.

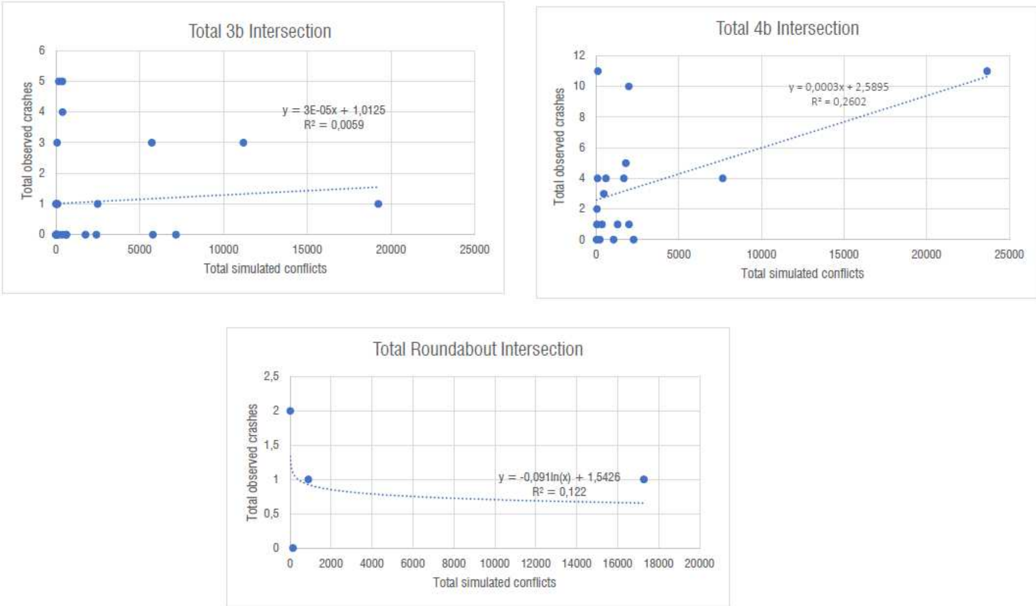

Figure 26: Poor correlation between simulated conflicts and observed crashes clustered for intersection typology (3b and 4b stands respectively for 3-leg and 4-leg intersections).

The normalization of conflicts over the AADT and the contemporary combination of conflict type and intersection type to cluster the simulated conflicts did not improve their correlation, except for roundabout (all three conflict types) and 4-leg intersection (4b) rear-end conflicts. This was because roundabout-detected conflicts and crashes were low, so there was not so much variability in the dataset, enabling an easier correlation. As regards the 4b rear-end conflicts, they were the most numerous also by the observed crash dataset, so the high number of detected conflicts by the SSAM algorithm was better approximated.

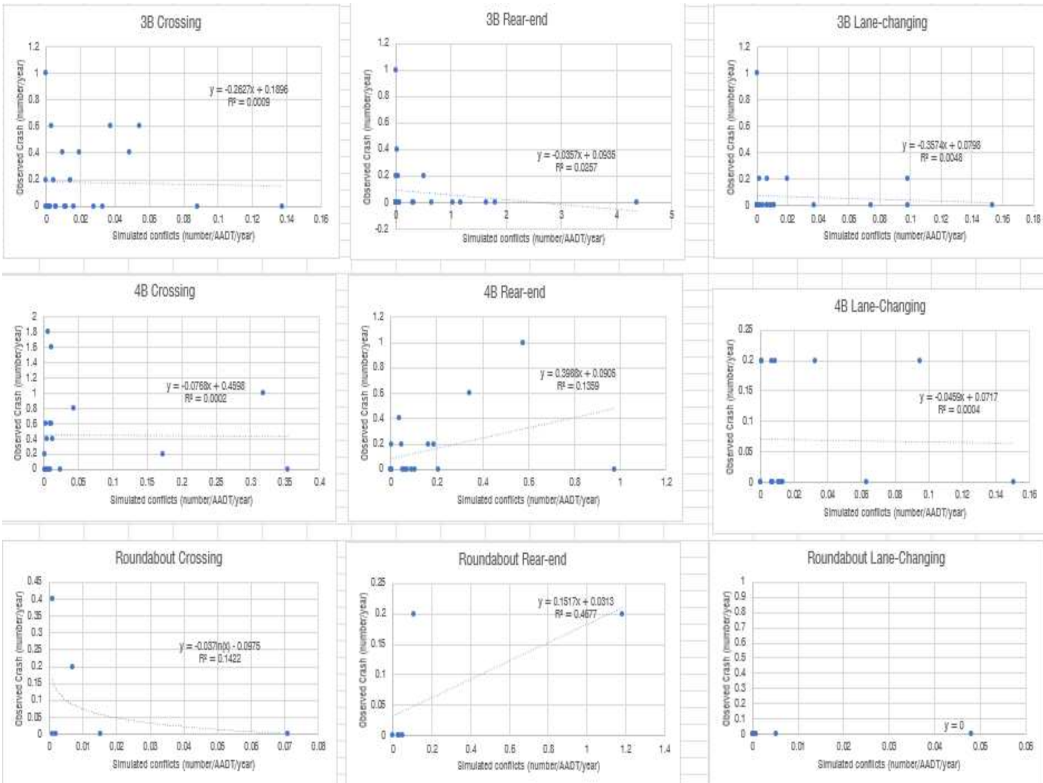

Figure 27: Poor correlation between simulated conflicts and observed crashes clustered for intersection typology and conflict type, with normalized conflicts for 1 year over the AADT (3b and 4b stands respectively for 3-leg and 4-leg intersections).

These results confirm the necessity of relying on other methods to find relationships between conflicts and crashes. It was used the one proposed by Tarko (2018), based on the Lomax distribution. The surrogate safety measure used was the TTC set equal to 1.5 seconds. The detected conflicts were recorded per each site, and then the probable crashes coming from the simulated crashes were calculated.

The results were not clustered for crash types, as the procedure suggested. They were analyzed, and the results are shown in the table below. The SP50, SP120, SP121, and SP237 were neglected in the comparison since they are only composed of segments. The observed crashes were normalized by years of observation (5 years) to compare the two datasets for one year. The last column in the table shows the percentage of probable simulated crashes extracted from the total number of simulated conflicts for each site.

Table 23: Comparison between observed crashes and simulated crashes (obtained following the procedure suggested by Tarko, 2018).

SP	Observed		Simulated		
	Tot	Tot/year	Conflicts	Probable crash	% Probable Crash/Conflicts
2	11	2.2	3309	15.94	0.48
27	34	6.8	196	0.61	0.31
61	29	5.8	8589	13.78	0.16
84	57	11.4	25320	143.33	0.57
88	28	5.6	3953	3.86	0.10
89	27	5.4	25347	125.75	0.50
111	18	3.6	958	3.39	0.35
112	21	4.2	1791	48.92	2.73
124	5	1	61	1.61	2.63
145	26	5.2	13030	6.02	0.05
156	33	6.6	20048	184.21	0.92
206	10	2	5786	44.59	0.77
230	2	0.4	614	1.13	0.18
235_169	16	3.2	39	1.77	4.54
235_177	28	5.6	1504	89.58	5.96
236	12	2.4	44	1.19	2.70
238	19	3.8	31	0.60	1.93
240_32	28	5.6	1062	5.52	0.52
240_66	25	5	11810	20.00	0.17

The sites that show many crashes extracted by the conflicts are those with signalized intersections (SP 84, SP89, and SP156). This result was expected since the time to collision for stopped vehicles at intersections can be close to zero, so it could have been transformed into a crash by the Extreme values calculation of the Lomax distribution. Apart from this exception, all the other calculated crashes from conflicts are comparable to the observed ones.

A correlation between these two datasets was attempted, as shown in the Figure below (Figure 28).

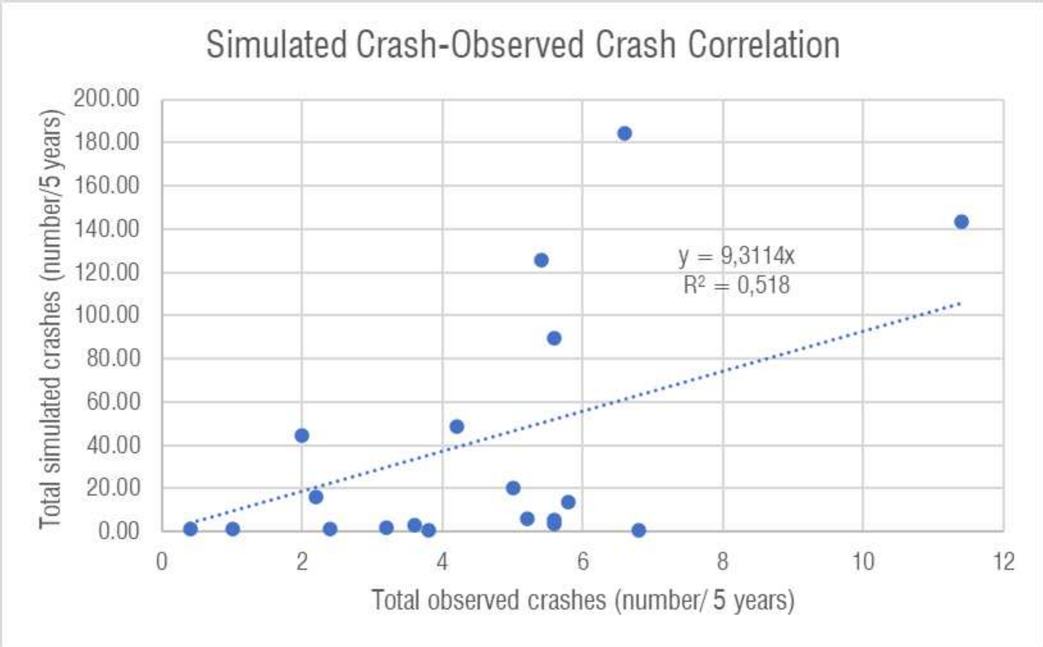

Figure 28: Simulated crash-observed crash Correlation

The figure shows blatantly that a linear correlation between the two datasets exists. This correlation is reliable, R^2 greater than 0.5, considering that the crash phenomenon has been investigated which is a rare and aleatoric event. The linear regression between these two datasets was the only one acceptable since this was the second step of the procedure. Relying on other regressions would have amplified the error coming from the first step and made the correlation less robust. This aspect is crucial because every other regression could have also generated the overfitting error. The found correlation highlights an important fact, i.e., with the two-step procedures of simulation analysis, the simulated crashes are related to the number of the observed ones (only fatal and severe crashes) by mean of a constant scale factor, equal to 9. This result is a milestone for the rest of the research, which aims at finding the crash occurrence of simulated scenarios with AVs.

These considerations are useful to know that just one probable real-world crash will happen over 9 simulated crashes by the two-step simulation procedure, also in the AV scenarios. But at the moment, this assumption cannot be verified by real-world tests for AVs, so the simulated crashes in AV scenarios will not be divided by the scale factor to obtain real-world crashes.

3.4 AV SCENARIOS

The analyses run for the different scenarios highlighted interesting results. As it was aforementioned, the number of selected sites was reduced due to the low accuracy of the SSAM algorithm for depicting the sites with only segments (as it was done for the validation of the current scenario), and for those with signalized intersections, where the TTC threshold made the algorithm counting a conflict even in such case when the vehicles had reduced gaps due to the traffic lights. Hence, the three sites SP84, SP89, and SP156 with signalized intersections were neglected in the analysis of further scenarios.

The scenarios were represented for three realistic conditions of AV market penetration rates, going from the short term (2030) to the long term (2050). In these situations, the number of conflicts and crashes was calculated thanks to the SSAM algorithm and the Lomax distribution to convert conflicts into crashes. For all the analyzed sites, the typology of conflicts was recorded, highlighting that the greatest number of recorded conflicts is Rear-end for the current scenario, 2030 short-term scenario, and 2040 mid-term scenario, followed by Crossing and Lane-changing. For the long-term scenarios, the increased number of FAVs led to increased vehicle gaps. Hence Rear-end conflicts were reduced compared to the Crossing, which became the main conflict typology. This is because the FAVs are more aware of what happens on segments (also while approaching intersections) than at intersections themselves, where their assertive behavior can be seen as risky situations by the algorithm.

Moreover, the available crash dataset for the validation of the current scenario contains only fatal or severe crashes, two typologies more related to Crossing and Rear-end crashes than to Lane-changing. Thus, the conflict recording, as it happened to validate the current scenario simulated realistic situations. The conversion of conflicts into crashes attempted just to have an idea of the crash typology for the analyzed sites highlighted that Crossing is the most frequent one, followed by Rear-end and Lane-changing for all the sites and scenarios. This was the same result found for the current scenarios.

Table 24: Analyzed sites and conflict and crash type rankings (RE stands for Rear-end; CR for Crossing; LC for Lane-Changing).

SP	Conflict Type ranking			Crash Type ranking				
	2030	2040	2050	Observed-Current	Simulated-Current	2030	2040	2050
SP2	RE; CR; LC	RE; CR; LC	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; LC; RE	CR; LC; RE	CR; LC; RE
SP27	RE; CR; LC	RE; CR; LC	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; LC; RE	LC; CR; RE	CR; LC; RE
SP61	RE; CR; LC	RE; CR; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; RE; LC	CR; LC; RE
SP88	RE; CR; LC	RE; CR; LC	CR; RE; LC	CR; LC; RE	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; RE; LC
SP111	RE; CR; LC	RE; CR; LC	CR; LC; RE	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; RE; LC
SP112	RE; CR; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; RE; LC	CR; RE; LC	CR; LC; RE
SP124	CR;RE; LC	RE; CR; LC	CR; LC; RE	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; LC; RE
SP145	RE; CR; LC	RE; CR; LC	CR; LC; RE	CR; LC; RE	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; LC; RE
SP206	RE; CR; LC	RE; CR; LC	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; LC; RE	CR; LC; RE	CR; LC; RE
SP230	RE; CR; LC	RE; CR; LC	CR; LC; RE	CR; RE; LC	CR; LC; RE	CR; LC; RE	CR; LC; RE	CR; LC; RE
SP235_169	RE; CR; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC
SP235_177	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; LC; RE	CR; LC; RE	CR; LC; RE	CR; RE; LC
SP236	RE; CR; LC	RE; CR; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC
SP238	RE; CR; LC	RE; CR; LC	LC	CR; LC; RE	CR; RE; LC	CR; RE; LC	CR; RE; LC	LC
SP240_32	RE; CR;	RE; CR;	CR; RE;	CR; LC; RE	CR; RE; LC	CR; RE;	CR;	CR;

	LC	LC	LC			LC	LC; RE	LC; RE
SP240_66	RE; CR; LC	RE; CR; LC	RE; CR; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC	CR; RE; LC

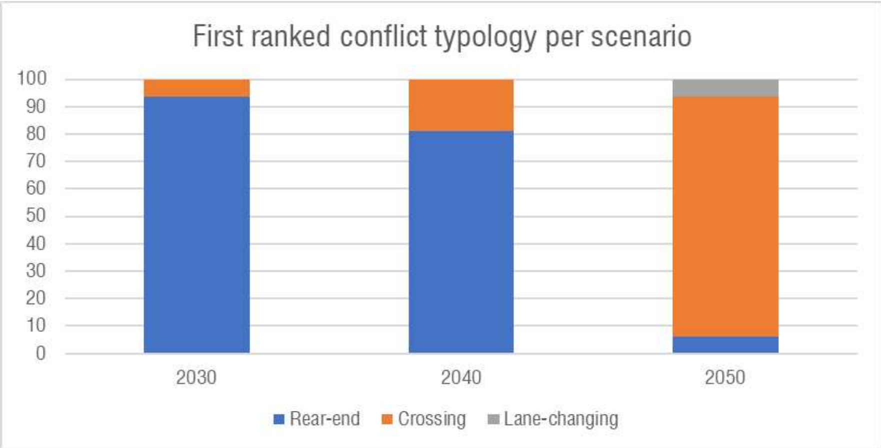

Figure 29: First ranked conflict typology per scenario in percentage over the simulated sites.

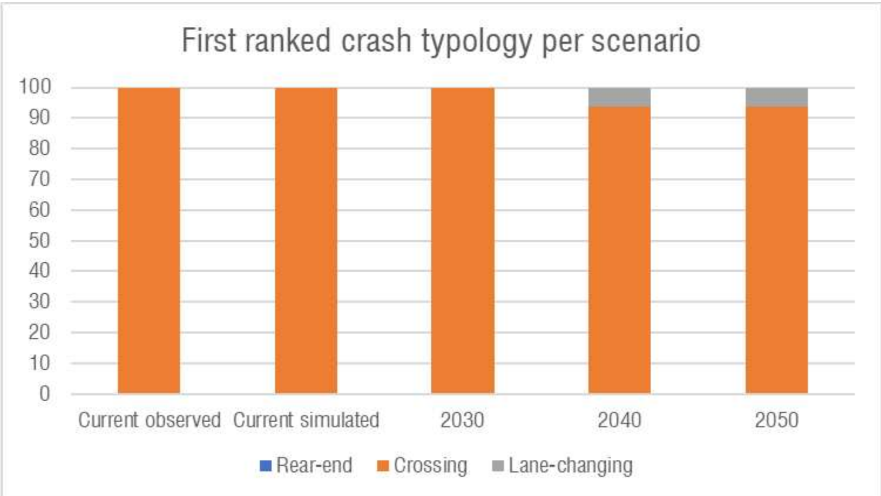

Figure 30: First ranked crash typology per scenario, in percentage for all the simulated sites. The conflict-crash conversion was made applying the procedure suggested by Tarko, 2018, dividing in crash type only to have a qualitiative idea of the crash type frequency, even if the procedure was not validated for crash typologies. Crossing are the most common for Fatal and severe crashes, and simulations still assess this.

The number of crashes recorded for each site was compared to the current scenario to understand the safety impact of automated vehicles on traffic, with the same geometrical and traffic conditions. This assumption was made since it is impossible to foresee how traffic will change because of several boundary conditions. Moreover, changing traffic volumes would have modified the simulation conditions, providing not comparable results to the current one. Since the research goal is to understand the impact on road safety of the AVs, it was necessary to work on the same starting conditions and change the vehicle types traveling at each site.

The results are summarized in the table and graph below.

Table 25: Crash variation (Cv) frequency referred to one year from the current scenario, for the three different further scenarios (2030, 2040, 2050) and for all the selected sites.

SP	Cv, Variation from current scenario		
	2030	2040	2050
SP2	-0.15	-0.06	-0.44
SP27	0.02	0.00	-0.56
SP61	0.23	0.25	-0.12
SP88	0.49	0.13	-0.08
SP111	0.19	0.70	-0.56
SP112	-0.52	-0.51	-0.75
SP124	-0.14	0.15	-0.45
SP145	0.34	0.85	-0.05
SP206	-0.45	-0.37	-0.61
SP230	0.38	0.89	-0.02
SP235_169	-0.51	-0.19	-0.73
SP235_177	-0.17	-0.21	-0.76
SP236	0.07	0.18	-0.80
SP238	-0.25	-0.73	-0.92
SP240_32	0.51	0.55	-0.17
SP240_66	0.70	0.67	-0.14

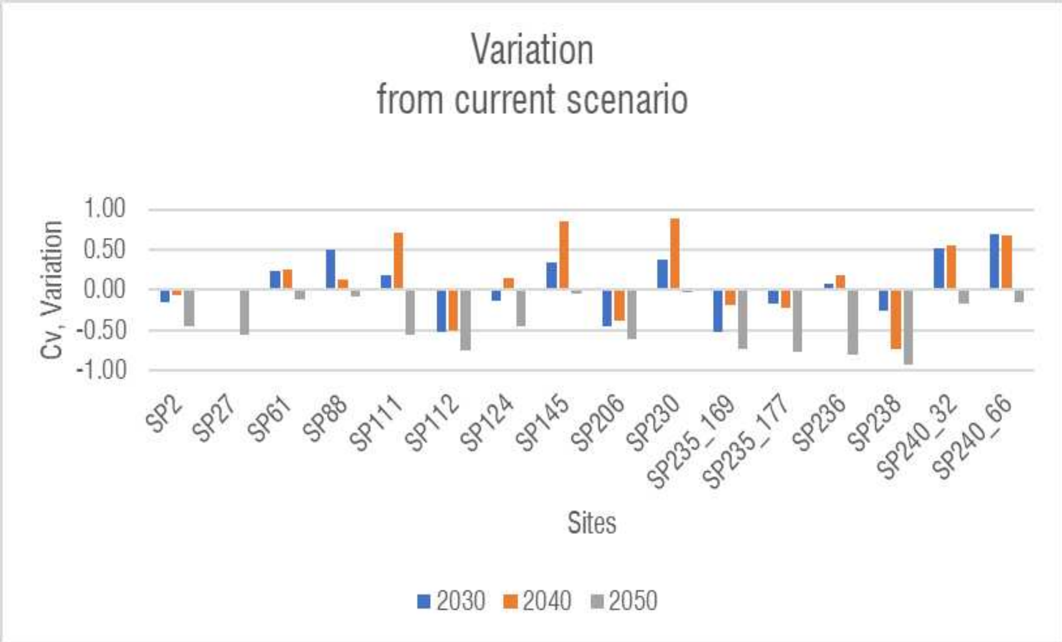

Figure 31: Crash variation for all the investigated sites for the three further scenarios (2030, 2040, 2050).

From the results, the safety benefits of traffic made almost exclusively by AVs (fully and partially automated) are remarkable. All the investigated sites, accordingly to the traffic conditions, the extension, and the current dangerousness of the site itself, show that in 2050 the crashes will be reduced. The scenarios in 2030 and 2040 are less safe than in 2050. The 2040 scenario is always more dangerous than the 2030 one since the traffic is promiscuous, and vehicles can face dangerous situations. Many PAVs, which still rely on human drivers, RVs, and few FAVs, which can be misinterpreted, lead to a crash increase in almost all investigated situations. The only sites where the promiscuous traffic is safer than the one in 2030 are characterized by a free flow regime or congested flow regime. Two conditions during which the interactions are controlled (or almost null) and the vehicles must follow a certain path. Hence, the behavior of vehicles scarcely affects the surrounding ones. In this context, having more technologically advanced vehicles make the interactions safer. It is interesting to note that every time the site shows observed crashes lower than 5 crashes/year and risky situations, like a 4-leg intersection, congested roundabout, or multiple consecutive 3-leg intersections with few vehicles (where the speeds become high), the potential benefit of having some technological help by the vehicles reduces the recorded crash number. In these situations, all three scenarios, even with promiscuous traffic, show remarkable benefits in road safety.

All the other sites show that the potential benefits of technologies in traffic are negligible when boundary conditions severely impact safety, such as multiple 4-leg intersections, free flowing conditions, different geometry conditions in the same site (combinations of intersections typologies, for example), and high traffic density.

The combination of more controlled behaviors due to the set parameters for AVs leads to safer conditions, but not in all cases. This is justifiable because not all vehicles (e.g., RVs) follow a rule-based and safe behavior; thus, during the simulations, trajectories followed by this kind of vehicle dangerously intersect the AV ones. In addition, the AVs, starting from the assumption of more intelligent communication and understanding of the surrounding environment, might cross the intersections faster (as highlighted in 3.2), and the great promiscuity of traveling vehicles increases the dangerousness of the intersection itself due to different conflicting behaviors. That is why the 2050 scenario, which consists of 95% AVs is the safest. Almost all the vehicles follow the same behaviors, and the presence of RVs is negligible in the interaction with other vehicles. Moreover, it might be considered something that the simulation cannot represent, i.e., the fact that in 2050, RVs should be more used to the presence of AVs, so their behavior might be different from the current one and more AV-friendly. This other aspect can be considered by applying a factor to the crash recording of the 2050 scenario.

The possible improvement of safety might involve FAVs exclusively on roads. This might ensure the highest rate of safe-driving behavior on rural roads since the human factor could be discharged. This analysis concludes that AVs are not always safe because a human can badly interact with them, especially in the early stages (2040) and when the automation is not full (2030) since the driver must be aware of a greater number of variables than in the current scenario, understanding and mitigating also the technological issues. In this sense, ad-hoc lanes for AVs and different road geometry, especially at intersections, enabling more cautious behavior, might be a great solution for waiting for fully automated vehicles to be deployed massively.

Moreover, these results can be useful for the AV manufacturer to be aware of the potential in terms of the safety of the vehicles so long as they are fully automated and ready to minimize dangerous situations and interactions with RVs. It also seems that the manufacturers should focus more on precise and efficient fully automated vehicles than semi-automated ones. In this sense, literature agrees with these findings (Kalra and Groves, 2017; Sparrow and Howard, 2017). Another possible countermeasure can be to deploy fully AVs with the cautious driving parameters of PAVs, in order to have vehicles completely automated but with more cautious behaviors that can be more easily understood by human drivers. This solution can enable human drivers to get used to automated vehicles and AVs to be safe in traffic interaction in promiscuous scenarios.

3.5 HAZARD INDEX (HI)

The results obtained from the scenarios made it possible to calculate a Hazard Index associated with each kind of vehicle. To reach this goal, more information about the crash occurrence in case of traffic made of 100% FAVs and 100% PAVs were required. This simulation was made for all the scenarios, following the same procedure and methodology used for all the others.

In this case, it was hypothesized that all the vehicles in one case were fully automated and in the other partially automated. The conflicts extracted from the 1-year-simulation were converted into crashes by applying the methodology suggested by Tarko, 2018. The obtained results are summarized in the table below.

Table 26: Crash recording and comparison among all the simulated scenarios, for all the investigated sites.

SP	Crash frequency					
	100 FAVs	100 PAVs	Current Scenario (100 RVs)	2030	2040	2050
2	5.53	8.11	15.94	13.62	14.91	8.88
27	0.14	0.25	0.61	0.62	0.61	0.27
61	7.22	9.78	13.78	16.96	17.18	12.09
88	1.57	2.74	3.86	5.76	4.36	3.54
111	0.75	1.34	3.39	4.03	5.77	1.51
112	8.76	10.30	48.92	23.55	24.06	12.21
124	0.32	0.42	1.61	1.39	1.84	0.89
145	3.38	4.46	6.02	8.08	11.11	5.72
206	9.83	11.06	44.59	24.41	28.04	17.52
230	0.75	0.89	1.13	1.56	2.14	1.10
235_169	0.36	0.42	1.77	0.86	1.43	0.47
235_177	16.28	18.02	89.58	74.36	70.44	21.72
236	0.20	0.23	1.19	1.28	1.41	0.24
238	0.03	0.04	0.60	0.45	0.16	0.05
240_32	2.56	3.82	5.52	8.34	8.57	4.59
240_66	11.88	15.39	20.00	33.97	33.48	17.13

The results showed how the presence of only FAVs drastically reduces the number of crashes for all the scenarios. The scenario 100%PAVs also remarks a crash reduction. The absence of RVs improved the safety of a site. Under this light, it is possible to associate each type of vehicle (relying on three scenarios made of 100% of one category of vehicles) with a coefficient of equivalence to represent the safety related to that specific category. The PAVs were used as the benchmark to calculate the coefficient of crash reduction, related to the other vehicles.

The FAVs have a HI, Hazard Index, equal to 0.76 if compared to the PAVs. The RVs have an HI of 3.59 if compared to the PAVs. In this optic, the market penetration rates of the vehicles for the scenarios 2030, 2040, and 2050 were calculated considering these HIs, as it is shown in the following.

Table 27: Calculated equivalent market penetration rates by multiplying the used market penetration rates of vehicles by the HIs, for each type of vehicle (3.59 for RVs, and 0.76 for FAVs).

	Market Penetration Rates			**Equivalent Market Penetration Rates**			
	FAVs	**PAVs**	**RVs**	**FAVs eq**	**PAVs eq**	**RVs eq**	**TOT**
Current scenario (2022)	0	0	100	0	0	359	359
2030	0	75	25	0	75	90	165
2040	20	67.5	12.5	15	68	45	146
2050	60	35	5	45	27	18	90
100% FAVs	100	0	0	76	0	0	76
100% PAVs	0	100	0	0	100	0	100

The results of these new market penetration rates are in line with the crash occurrence simulated for the scenarios 2030, 2040, and 2050. Hence, the HIs adequately represent each vehicle category's safety adequately. Moreover, it is possible to assess that the scenario with 100% FAVs could happen as a further step than the 2050 scenario. The scenario of 100% PAVs seems unrealistic since once the FAVs become a reality in everyday traffic, it is not probable that they will disappear. For this reason, it was assumed an indicative date for the scenario 100% FAVs, 2060, and no date for the scenario 100% PAVs. A correlation between years and average crash frequency for all the sites (crash/year) was found as well as one for the equivalent market penetration rate and years. In this way, the trend of crashes varying the traffic composition was investigated.

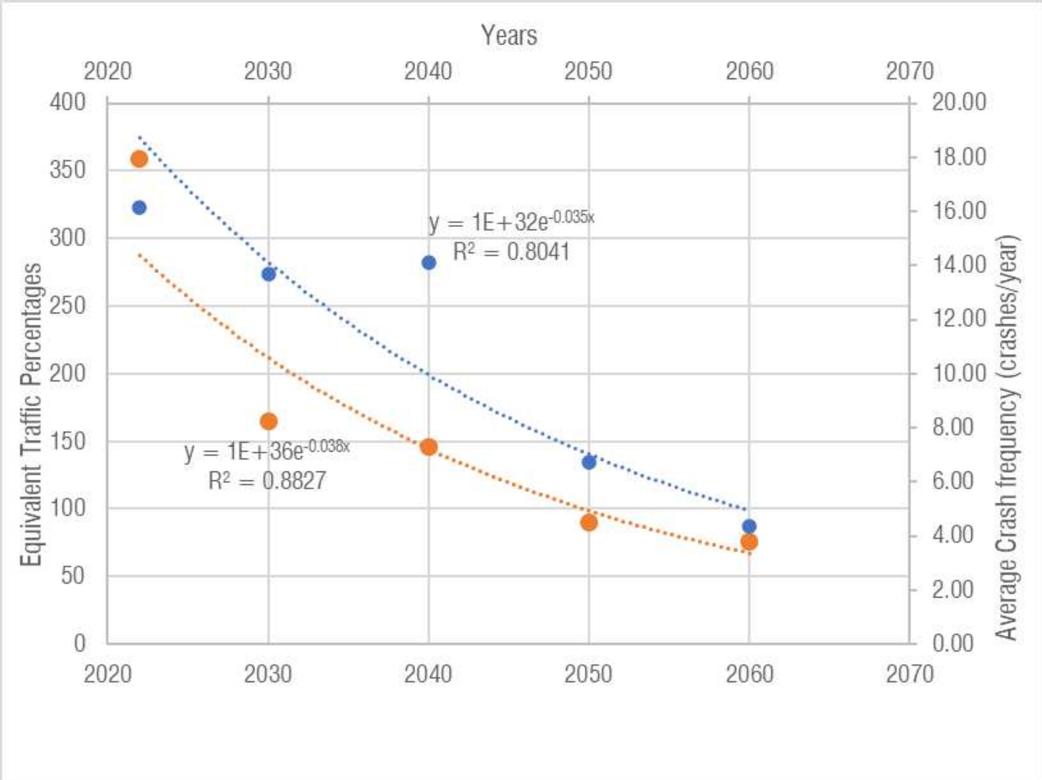

Figure 32: Relationship Years-Average Crash Frequency (blue dots); Years-Equivalent Traffic Percentage (orange dots). Both the relationships were interpolated by an exponential curve. Each curve has the equation and the related goodness of fit (R^2).

The graph in Figure 32 clearly shows how the equivalent market penetration rate and the crash frequency follow the same law, with almost the same trend. Both relationships can be simplified using an exponential curve. For the crash occurrence, the goodness of fit is lower than for the equivalent market penetration since there is a greater variability for the crash frequency than for the equivalent market penetration. The correlations found and the goodness of fit of both curves enable using the HIs to convert the AADT into an equivalent AADT. This equivalent AADT could be used as an independent variable valid to represent the market penetration and the safety of the three vehicle categories in the development of the ad hoc SPF for AVs.

$$AADT_{equivalent} = HI_{FAV} \times FAVs_{AADT} + 1PAVs_{AADT} + HI_{RV} \times RVs_{AADT}$$

$$= 0.76 \times FAVs_{AADT} + 1 \times PAVs_{AADT} + 3.59 \times RVs_{AADT}$$

(Eq.18)

3.6 SAFETY PERFORMANCE FUNCTION (SPF) FOR AUTOMATED VEHICLES

The attempts at recreating a safety performance function, SPF, starting from the available calculated data by simulations, were intensive. The first issue was whether the negative binomial distribution or the linear one was more suitable for representing the crash phenomenon. The independent variables tested were Tr1+Com2.

The negative binomial distribution has resulted to be more suitable for the scenario to simulate. The coefficients of the function variables were considered to be significant for the model in reproducing the phenomenon, if the p-value was lower than 5% for both. Then it was necessary to calculate the goodness of fit of the model by using Nagelkerke R^2.

The combination Tr1+Com2 showed a promising statistical significance of the two coefficients (Table 30). The tables below (Table 28 and 29) summarize the values of the dependent and independent variables, as well the results of the analysis (coefficient values and statistical significance, in Table 30).

Table 28: Calculated equivalent AADT by multiplying the AADT by the HIs, for each type of vehicle (3.59 for RVs, and 0.76 for FAVs).

		AADT				AADT equivalent			
	SITES SP	FAVs	PAVs	RVs	Tot	FAVs eq	PAVs eq	RVs eq	Tot eq (Tr1)
2030	2	0	7256	2419	9675	0	7256	8676	15932
	27	0	1364	455	1819	0	1364	1632	2996

	61	0	4953	1651	6604	0	4953	5921	10874
	88	0	7907	2636	10543	0	7907	9454	17361
	111	0	5983	1994	7977	0	5983	7152	13135
	112	0	11034	3678	14712	0	11034	13192	24226
	124	0	4309	1436	5745	0	4309	5150	9459
	145	0	4810	1603	6413	0	4810	5749	10559
	206	0	9078	3026	12104	0	9078	10853	19931
	230	0	2357	786	3143	0	2357	2819	5176
	235_169	0	4163	1388	5551	0	4163	4978	9141
	235_177	0	7160	2387	9547	0	7160	8561	15721
	236	0	6030	2010	8040	0	6030	7209	13239
	238	0	1109	370	1479	0	1109	1327	2436
	240_32	0	5573	1858	7431	0	5573	6664	12237
	240_66	0	13754	4585	18339	0	13754	16445	30199
2040	**2**	1935	6530	1209	9674	1466	6530	4336	12332
	27	364	1227	227	1818	276	1227	814	2317
	61	1321	4458	826	6605	1001	4458	2963	8421
	88	2109	7117	1318	10544	1598	7117	4727	13442
	111	1595	5384	997	7976	1208	5384	3576	10168
	112	2942	9931	1839	14712	2229	9931	6596	18756
	124	1149	3878	718	5745	870	3878	2575	7324
	145	1283	4329	802	6414	972	4329	2876	8177
	206	2421	8170	1513	12104	1834	8170	5427	15431
	230	628	2121	393	3142	476	2121	1410	4006
	235_169	1110	3746	694	5550	841	3746	2489	7076
	235_17	1909	6444	119	9546	1446	6444	4279	12169

	7			3					
	236	1608	5427	1005	8040	1218	5427	3605	10250
	238	296	998	185	1479	224	998	664	1886
	240_32	1486	5015	929	7430	1126	5015	3332	9473
	240_66	3668	12378	2292	18338	2779	12378	8221	23377
2050	**2**	5804	3386	484	9674	4397	3386	1736	9519
	27	1091	636	91	1818	827	636	326	1789
	61	3962	2311	330	6603	3002	2311	1184	6496
	88	6326	3690	527	10543	4792	3690	1890	10373
	111	4786	2792	399	7977	3626	2792	1431	7849
	112	8827	5149	736	14712	6687	5149	2640	14476
	124	3447	2011	287	5745	2611	2011	1029	5652
	145	3848	2245	321	6414	2915	2245	1151	6311
	206	7262	4236	605	12103	5502	4236	2170	11907
	230	1885	1100	157	3142	1428	1100	563	3091
	235_169	3330	1943	278	5551	2523	1943	997	5463
	235_177	5728	3341	477	9546	4339	3341	1711	9391
	236	4824	2814	402	8040	3655	2814	1442	7910
	238	887	517	74	1478	672	517	265	1454
	240_32	4458	2601	372	7431	3377	2601	1334	7313
	240_66	11003	6418	917	18338	8336	6418	3289	18043

Table 29: Calculated Com2 by multiplying the intersection density by the CMFs, for each type of intersection (0.243 for Roundabout, and 1.872 for 4-leg intersections).

SP	**Intersection number**			**Length (Km)**	**Intersection density (Int/Km)**			**Com2**
	3-Leg	**4-Leg**	**Roundabout**		**3-Leg**	**4-Leg**	**Roundabout**	
2	5		1	6.35	0.787	0.000	0.157	0.826
27	3			15.39	0.195	0.000	0.000	0.195
61	3	1		35.03	0.086	0.029	0.000	0.139
88		1	1	4.47	0.000	0.224	0.224	0.473
111			1	11.6	0.000	0.000	0.086	0.021

112		1		6.66	0.000	0.150	0.000	0.281
124	1			6.96	0.144	0.000	0.000	0.144
145	2		1	27.3	0.073	0.000	0.037	0.082
206	1	1	3	7.98	0.125	0.125	0.376	0.451
230	3			17.71	0.169	0.000	0.000	0.169
235_169	1		1	11.74	0.085	0.000	0.085	0.106
235_177	2	1		14.62	0.137	0.068	0.000	0.265
236		1		10.58	0.000	0.095	0.000	0.177
238	2			28.96	0.069	0.000	0.000	0.069
240_32		1	1	22.28	0.000	0.045	0.045	0.095
240_66	1	1	1	11.87	0.084	0.084	0.084	0.262

Table 30: Summary of results of the tested model with general linear model negative binomial distribution.

	Coefficient estimates (standard errors in parenthesis)
	Total crashes
(Intercept)	-3.143e+00*** (2.898e-01)
Tr1	1.897e-04*** (2.253e-05)
Com2	2.328e+00*** (6.831e-01)
Goodness of fit measures	
Nagelkerke R^2	0.743

***Means that the p-value is lower than 0.05

Hence, the two independent variables chosen to depict the three different scenarios and the relative difference in crash occurrence are Tr1 and Com2. They are linked according to the following equation:

$$N_{SPF\_AVs} = L \times e^{-3.143+1.897 \times 10^{-4} \times Tr1+2.328\ Com_2} \quad \text{(Eq.19)}$$

The Nagelkerke R^2 has been calculated for this combination, and it can be considered acceptable because greater than 0.25. Thus, considering the probabilistic nature of crashes, this developed function seems to be able to reproduce what happens with the different market penetration rates of technology. The form of the equation could be adapted to several possible different scenarios since the main variables have been formulated, as well as their nature. It will also be possible to calibrate this function to other contexts and scenarios, simply varying the input data and the expected outcome. This consideration is because the investigated sites are limited and related to the Province of Bari for two-way two-lane rural roads. Varying one of these three starting points, the calibration can be different, and the values of the parameters may vary, but the function will still have the same equation.

Physically speaking, the values obtained for the function show how increasing the intersections per km makes the site more dangerous; moreover, decreasing the percentage of RVs in the traffic has the opposite effect. Hence the function represents what is supposed to happen in traffic: an increase in vehicle interactions in the presence of RVs or, at least, of humans completing driving tasks leads to a rise in dangerous situations and potential crashes. The risk link to the intersections can be mitigated by the presence of fully AVs rather than RVs or partially AVs. By reducing both, the number of intersections and the number of human-driven vehicles, the sites seem to be safer.

As mentioned in paragraph 3.3, the SPF has been developed on the basis of simulated crashes and not on the basis of real-world crashes (dividing the simulated one by 9) because of the absence of validation of this correlation 9:1 for further scenarios. In this optic, scaling the obtained results from the simulation by 9 because it could have added more uncertainties to the model. It was found that for each observed crash, 9 were simulated for the current scenario. For further scenarios, this correlation cannot be adopted since other crashes could occur, such as the ones due to technological failures or misunderstanding of automated behavior by human drivers.

Another attempt was made with the development of the SPF. Since the scenario 100 FAVs was calculated and hypothesized to happen in 2060, for the determination of the HI, this scenario (2060) was included in the model. It was added to the already existent variable values, also the ones for 2060, as it is shown in table.

Table 31: Integrated values for 2060 scenario to develop the SPF.

Scenario	SP	Probable crash/year	Com2	Tr1	L (Km)	N
2060	**2**	5.53	0.83	7329	6.35	6
	27	0.14	0.19	1377	15.39	0
	61	7.22	0.14	5002	35.03	7
	88	1.57	0.47	7987	4.47	2
	111	0.75	0.02	6043	11.60	1
	112	8.76	0.28	11146	6.66	9
	124	0.32	0.14	4352	6.96	0
	145	3.38	0.08	4859	27.30	3
	206	9.83	0.45	9169	7.98	10
	230	0.75	0.17	2380	17.71	1
	235_169	0.36	0.11	4205	11.74	0
	235_177	16.28	0.26	7232	14.62	16
	236	0.20	0.18	6091	10.58	0
	238	0.03	0.07	1120	28.96	0
	240_32	2.56	0.09	5630	22.28	3
	240_66	11.88	0.26	13893	11.87	12

Tr1 was calculated by multiplying the entire AADT for the HI related to FAVs, i.e., 0.76. Com2, as well as the L (Km), are unchanged from the other scenarios (2030, 2040, 2050). The crash frequency is the crash frequency calculated by converting conflicts extracted by the simulations into crashes, thanks to the extreme value approach proposed by Tarko, 2018.

The results of this SPF are summarized below.

Table 32: Summary of results of the tested model with general linear model negative binomial distribution, including 2060 scenario.

	Coefficient estimates (standard errors in parenthesis)
	Total crashes
(Intercept)	-3.295e+00*** (2.471e-01)
Tr1	2.012e-04*** (2.004e-05)
Com2	2.465e+00*** (5.861e-01)
Goodness of fit measures	
Nagelkerke R^2	0.78

***Means that the p-value is lower than 0.05

The model including more data fits the variables better. This means that the proposed SPF can potentially explain the crash phenomenon with AVs in future scenarios. Moreover, by amplifying the dataset about the crash from future scenarios, the model converges to 1, providing evermore reliable predictions.

The obtained equation is the following.

$$N_{SPF\_AVs} = L \times e^{-3.295+2.012 \times 10^{-4} \times Tr1+2.465\ Com_2} \quad \text{(Eq,20)}$$

The presented SPFs are valuable for depicting an ongoing scenario with different and changing penetration rates of AVs. When AVs will be deployed 100% in traffic, there could be another SPF, which represents a more static condition, on the penetration side and can represent other variables strictly related to crash occurrence. In this sense, the prediction will also be corrected by the observed crash, as it is shown by Eq.4. There will be predicted data and observed data that combined will provide the expected crash frequency.

Moreover, the results of this SPF can be corrected by more data and calibrated for all other scenarios. The presented values for the coefficients are extracted for the specific investigated context. Apart from this consideration about the value of the coefficients used to develop the SPF, the methodology and the presented variables are a solid base to rely on while considering safety assessment in the presence of AVs.

CHAPTER 4

SUMMARY, CONCLUSIONS AND LIMITATIONS

The present work aims at providing a methodological framework for road safety assessment with the introduction of automated vehicles (AVs). Future considerations about safety must consider the chance that new types of vehicles can be integrated in traffic. Hence both planning procedure and road design requires safety assessment for further scenarios, but currently these assessments are done considering the traffic not affected by any technological introduction but made of RVs. Hence this work aims at filling this gap and to provide a procedure to follow when doing future safety assessments considering AVs in traffic. In this work the proposed methodological framework was tested in the context of the PUMS of the Province of Bari to show its applicability. It is blatant how this work cannot find a unique response to this huge issue, but it can significantly contribute to the question by providing some crucial outcomes useful for further research and implementation. One of the first concerns related to the field of AVs is the lack of existing observed crash datasets because they are still in their infancy and because international regulations limit their use for safety purposes. Introducing such vehicles in traffic can be dangerous, and the occurrence of fatalities can drastically reduce their use and make people less confident with technologies in traffic. Hence, it is possible to rely on limited datasets or simulate them. The most feasible way to simulate traffic and create a strong and wide crash dataset is to work with traffic simulations.

On the other hand, traffic simulators are calibrated for human vehicles. Some car-following and lane-changing models aim at reproducing the human mental workload. The main concern was to find a reliable model to depict AVs in their different forms (fully automated, also known as Assertive, and partially automated, also called Cautious). A comparison among all the available models was run, and it was found that there is not a better model in general, but that the boundary conditions and external input deeply affect the most suitable model for the designed situations. In the case of this research, the area under investigation was the one of the Province of Bari, particularly speaking two-way, two-lane rural roads. This choice was supported by the availability of a precisely observed crash dataset for Regular vehicles (RVs) and for the great number of crashes that occurred on this type of road. The Gipps model was found to be the most suitable model for the description of the sites, characterized by variable traffic and speeds and low percentage of fatalities; and for describing the behavior of AVs, in the mentioned conditions since it relies on the safety distance model, i.e., on physical parameters describing the kinematic of the vehicles.

After selecting the model, it was useful also to describe the safety. It was possible to work on the Surrogate Safety Measures (SSM) used by the SSAM algorithm. Recording the trajectories coming from the simulations, it was possible to assess the safety of a site, counting the conflicts. The conflicts were assumed to occur by selecting the Time To Collision equal to 1.5 as a threshold. The choice of this metric was supported by literature and several studies in this field. The conflict recordings were useful for the safety assessment. Starting from the conflict count, it was possible to predict the number of simulated crashes. This procedure can be made in several ways, but the Extreme Value approach was chosen, as suggested by Tarko, 2018. Starting from the number of conflicts (not divided by type), it was possible to obtain the number of crashes for each site. This procedure was applied to the 23 selected sites to validate the current scenario. However, it was found that the trajectories did not lead to conflicts in the case of only segments because the models at the base of simulations try to keep safe behavior as long as possible, even if the parameters are set to reproduce aggressive drivers. Hence, the segments were discharged by the validation, and only 16 sites were analyzed, characterized by the presence of at least one intersection. This choice was justified by the importance constituted by the intersections in the safety assessment. Intersections represent the most dangerous road element, also in rural environment, where 41% of all crashes occurred. Hence, analyzing just the intersections, discharging the segments, gave a representative portrait for the safety assessment, indeed (Berloco et al., 2022).

The validation of the current scenario led to finding out that simulated crashes and observed crash are related by means of a constant scale factor, equal to 9. The relationship between simulated and observed crashes was linear and it had an acceptable goodness of fit (0.518).

This calculation was made before analyzing the AV scenarios. A distinction among different levels of AVs was made, considering the SAE level classification as a reference. SAE level vehicles 2-3 were partially automated (PAVs), or called Cautious AVs, while SAE level vehicles 4-5 were fully automated (FAVs) or called Assertive AVs. This distinction was supported by the replacement of some parameters in the calculation. The replace of the parameters was made after having studied the most significant one in the model. The sensitivity analysis was run using 5 different values (minimum, maximum, mean, 5th percentile, and 95th percentile) to attribute to each parameter to test their effect on conflict recording. The most significant parameters were found to be Clearance and Sensitivity Factor for Rear-end and Lane-changing, with a huge increase of conflicts for the second one (up to three times the average value) and a huge decrease in conflicts for the first one (up to one-third of the average). The same parameters have dangerous effects in the case of PAVs or FAVs, leading to a remarkable increase in conflicts (up to twice the conflicts recorded by using RV values). The sensitivity analysis also tried to depict different scenarios to assess safety in several traffic conditions. The most promising scenarios in conflict reduction were the ones with FAVs and PAVs (both in mixed traffic, 50% FAVs and 50% PAVs; 50% RVs and 50% PAVs, 50% FAVs and 50% RVs, and single-type-vehicle traffic, 100% PAVs or FAVs). This consideration was promising for the testing of scenarios in terms of crashes. It was blatant that increasing the interaction among vehicles with the same behavior and approach to traffic situations would decrease the number of conflicts for all the conflict typologies (rear-end, crossing, and lane-changing).

The AV scenarios were tested following the average prediction made by Austroads about the AV market penetration. Three different scenarios were tested: short-term (2030), mid-term (2040), and long-term (2050). The percentage of FAVs increases from 0% to 60%, while the one of PAVs goes from 75% to 35% in the period 2030-2050. This implies that RVs decreased. The sites used for validating the current scenario were used for calculating the safety performance of further scenarios.

The first consideration is that the 2050 scenario always showed a decrease in crashes (conflicts were converted into crashes using the Extreme Value approach but considering a TTC equal to 0.5 s rather than 1.5 s, only in the long-term scenario, since the number of FAVs was greater than 50%, as suggested by literature). The 2040 scenario showed the most dangerous circumstances almost for all the sites, this is due to the great promiscuity of vehicles circulating on roads. Having different vehicle types, following different behaviors negatively impacts on road safety. This condition of extreme danger for 2040 is confirmed, except for those sites with isolated vehicles or congested traffic, i.e., those situations that force the vehicles to assume a constrained behavior or without interactions among vehicles. In these two cases, even if there is a great promiscuity of vehicles in traffic, dangerous situations seem to decrease. In these cases, the 2030 scenario was more dangerous since it was mostly populated by human-driven vehicles. For all the other cases the 2030 scenario is safer than 2040, which is considered to be the worst one in terms of road safety. In any case, the 2030 scenario and the 2040 scenario were more dangerous than the current one and the 2050 scenario.

There are few cases, representing the exceptions to the highlighted trend by both the short-term scenario (2030) and the mid-term one (2040), that showed a crash decrease from the current scenario for the 2030 and the 2040. This condition is observed for those sites where the of observed crash frequency (current scenario) is lower than 5 crash/year and there are risky situations, like a 4-leg intersection, congested roundabout, or multiple consecutive 3-leg intersections with few vehicles (where the speeds can be high). In such situations, the potential benefit of having technological help from vehicles reduces the potential risky interactions among vehicles and so the recorded crash number.

Starting from the number of predicted crashes obtained by simulations, it was possible to define the Hazard Index (HI) propaedeutic for the assessment of safety. The HI provides an indication about the safety of each kind of vehicle. This calculation was possible because of the simulation of three scenarios made just of one category of vehicle for all the investigated sites: the scenario 100% PAVs, the scenario 100% FAVs, the scenario 100% RVs (which is the current scenario). Thanks to these simulations, the mean crash frequency associated to each specific type of vehicle was calculated. Setting a benchmark, that in this specific case was the PAV, the HI was calculated as the ratio between the j-esim vehicle type crash frequency and the PAV crash frequency. Two different HIs were obtained, one for the FAVs (0.76) and one for the RVs (3.59). They meant that one FAV is less dangerous than a PAV, 0.76 times; and one RV is 3.59 more dangerous than a PAV. Thanks to the HI, the available AADT for all the sites and scenarios was converted into an equivalent AADT, which was calculated by multiplying each vehicle type by its HI and then the sum was made, as explained in Eq.18.

This equivalent AADT was used as one of the two independent variables selected to predict the mean crash frequency (dependent variable) with the ad hoc SPF for AVs. The equivalent AADT was useful because it provides a piece of information about traffic, vehicle type, and so the simulated scenario, accounting for the safety of the different types of vehicles. The ad hoc SPF for AVs has been estimated by statistical analysis (thanks to R software), using, as already mentioned, just two variables (since the number of sites was 16, the number of significant independent variables was limited to 2). The first variable takes into account the intersection density (the number of intersections divided by the total length of the site in Km) and the combination of intersections (thanks to the CMFs for each type of intersection), and it was called Com2. The second one, called Tr1, is the equivalent AADT calculated by means of the HIs.

These two variables were linked through a general linear model and assuming a negative binomial distribution of the errors, with a statistical significance of the coefficients linked to the main variables calculated by the p-value. The p-value was lower than 0.05 for both coefficients, assessing their statistical significance. The goodness of fit was then calculated by the Nagelkerke R^2 greater than 0.25 (0.742). The meaning of the two variables in crash prediction is that by increasing the intersection density or decreasing the FAVs percentage, the crash frequency increases.

This function is suitable for this scenario, but the variables can be calibrated for other penetration rates, technology involved in the study, contexts, and road types.

The obtained SPF represents a fundamental result for practitioners and stakeholders involved in developing and implementing AVs in daily traffic. Knowing the impact of AVs on road safety before implementing them can prevent AVs from being dangerous and not appreciated by the community. This work confirms something already stated by previous studies, i.e., the idea that promiscuous traffic can lead to more complex situations and be hard to handle by both human and non-human drivers. Thus, planning the introduction of AVs can be made carefully to prevent dangerous situations. The most suitable countermeasures to prevent the dangerous implementation of AVs in traffic thought after the obtained results in this work are the following:

- Designing separated/dedicated lanes for AVs of any type (fully or partially) in case of new roads; for the existing ones allowing AVs to circulate on reserved lanes for Bus and Taxi, that have low traffic volume characterized by highly specialized drivers. There will be reserved lanes for Buses, Taxis, and AVs.

- Setting all the parameters of fully AVs as cautious, in order to avoid differences among the AVs and let human drivers become more comfortable with these technologies and used to a homogenous behavior.

Despite the mentioned contributions brought by this research to state of the art about AVs, the project has some limitations that further analyses would improve. The first issue is that this work was developed only for two-way, two-lane rural roads of the Province of Bari; thus, the results cannot be generalized without accurate calibration and validation in other contexts. The results are just a part of a wider research idea, also pursued by Horizon Europe, of predicting the safety impact of AVs. In this context, this specific work significantly contributes to the analysis. This work can be improved considering rural roads with pedestrians and cyclists, two active components of traffic that are endangered by the interactions with all the circulating vehicles. The overall safety analysis after the introduction of AVs can be run considering also freeways and urban roads, which show different characteristics and types of vehicle interactions.

Moreover, the analysis can be extended to those sites without intersections characterized by single segments where few dangerous interactions happening, difficultly repeatable through a simulation due to their irrational nature. However, further analysis can go deeper and analyzing them in detail. The use of simulations for assessing road safety is the current only way to deal with AV introduction in traffic since there is still no acceptance to test them on roads freely. Under this consideration, it might be analyzed and overcome the problem related to segments and the safe and rule-based behavior that each model imposes on the vehicles. It is debatable that even by setting parameters in the models to force aggressive behaviors, the traffic models try to minimize the dangerousness. This aspect is reflected in the trajectories and the Surrogate Safety Measures. A possible way is to code the scripts of the models differently, forcing at the beginning aggressive behaviors or creating some categories of vehicles not subject to the strict rules of the models. These are alternatives that might be tested. Taking traffic models into account, it is always important considering that simulated vehicles follow the rules and mathematical algorithms based on vehicle physics. It becomes useless to analyze the model results by assessing some mental behaviors or more complex reactions by drivers.

Another consideration is related to the crash analysis. The introduction of AVs may bring new types of crashes, still unknown. They could be due to different human reactions to AV traffic decisions or technological failures. For this reason, the obtained simulated crashes have not been scaled by 9, attempting at reproducing the "real" crashes, exploiting the linear relationship found for simulated-observed in the current scenario.

Other considerations about crashes can be done by looking at the boundary conditions of roads. In the current and future scenarios, possible issues can be aroused by inadequate pavement conditions in terms of signals and friction. Moreover, the intersection geometry deeply affects how vehicles interact. Hence, new layouts suitable for AVs can modify the safety of the sites for AVs and RVs (maybe the latter can be affected negatively).

When considering the aggregate crash prediction by simulations, after the conversion from conflicts, it is possible to assess that the considered crashes are just the fatal and severe ones (F+I). Hence, the percentage of F+I crashes coming from the different conflict types might be deeply analyzed. Not considering the aggregate number of conflicts but differentiating it by types is still not suggested by literature in the conversion conflicts-crashes. This is because the results are still unreliable; thus, attempting to find the number of crashes by type (Rear-end, crossing, lane-changing) by the extreme value approach can provide unreliable results. Despite this consideration, practically speaking, the ranking provided in Table 24 highlights realistic outcomes, i.e., crossing crashes are the most frequent among the F+I ones; it is rare have lane-changing conflicts become F+I crashes, as well as Rear-end.

Under this light, it is possible to understand the solid base that this work aims at providing for the future of analyses in the field of road safety assessment in the presence of new technologies, but also the fact that it is a small contribute and several works need to be done to obtain an overall vision about the safe introduction of AVs in traffic.

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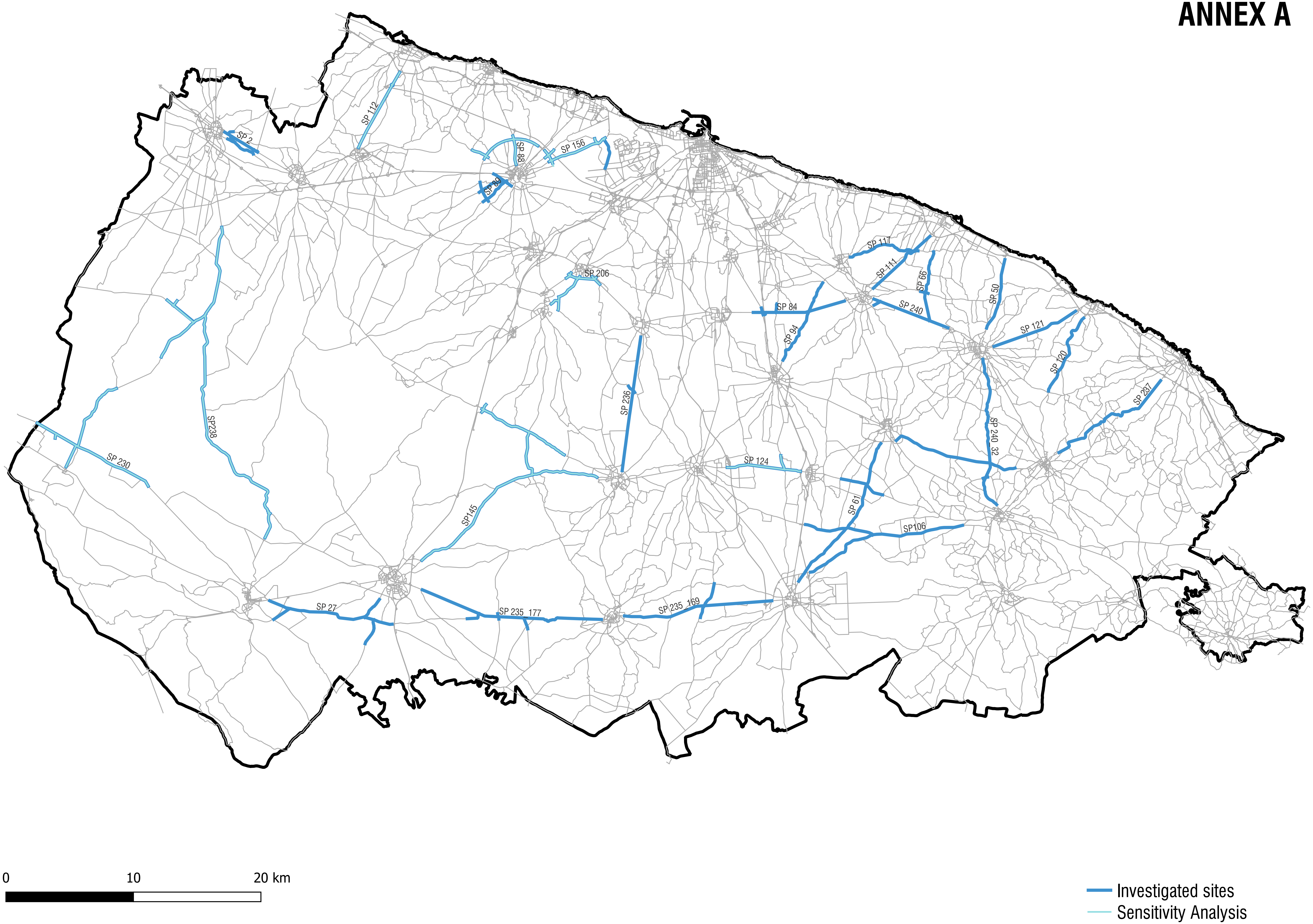
ANNEXES

ANNEX A



SP 2
SP 112
SP 88
SP 156
SP 89
SP 206
SP 117
SP 111
SP 66
SP 50
SP 84
SP 240
SP 94
SP 121
SP 120
SP 236
SP 237
SP238
SP 230
SP 240_32
SP 124
SP145
SP 61
SP106
SP 27
SP 235_177
SP 235_169
0
10
20 km
Investigated sites
Sensitivity Analysis

ANNEX B

SP	GEH							
	Weekdays				Weekend-Vacation			
	Fall	Summer	Winter	Spring	Fall	Summer	Winter	Spring
2	0.12	0.01	0.00	0.03	0.09	0.09	0.04	0.05
27	0.17	0.46	0.03	0.03	0.30	0.05	0.10	0.09
50	0.16	0.00	0.06	0.05	0.04	0.00	0.02	0.06
61	0.05	0.43	0.06	0.34	0.14	0.09	0.96	0.14
84	0.07	0.02	0.06	0.00	0.12	2.38	0.15	0.05
88	0.14	0.01	0.02	0.02	0.02	0.05	0.02	0.07
89	0.74	0.16	0.01	0.07	0.02	0.06	0.06	0.03
111	0.10	0.02	0.03	0.00	0.58	0.66	0.50	0.08
112	0.13	0.02	0.05	0.12	0.99	1.21	0.94	0.91
120	0.07	0.01	2.11	0.03	0.52	0.66	0.53	0.48
121	0.08	0.01	0.05	0.03	0.62	0.68	0.51	0.60
124	0.12	0.02	0.01	0.02	0.68	0.77	0.76	0.95
145	0.08	0.06	0.03	0.07	0.72	0.99	0.04	0.78
156	0.29	0.03	0.02	0.00	0.02	1.99	0.04	1.78
206	0.10	0.02	0.01	0.02	1.40	1.00	0.85	0.89
230	0.13	0.03	0.07	0.12	1.14	1.12	0.95	1.05
235_177	0.15	0.00	0.07	0.02	1.07	1.34	0.96	1.19
235_169	0.03	0.05	1.02	0.08	0.89	1.00	0.24	0.91
236	0.05	0.02	0.02	0.00	0.76	0.90	0.76	0.82
237	0.06	0.01	0.05	0.03	0.64	0.65	0.55	0.62
238	0.04	0.07	0.04	0.02	0.49	0.54	0.51	0.67
240_32	0.20	0.02	0.00	0.01	1.00	1.03	1.01	0.67
240_66	0.29	0.05	0.02	0.01	0.01	0.29	0.37	0.98

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SHORT CURRICULUM

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Ph.D. candidate in “Risk and environmental, territorial and building development Ph.D. Course”

DICATECh – Politecnico di Bari

Born in Bari (Italy) on July 23rd, 1996. The author obtained a bachelor’s degree in Civil and Environmental Engineering with full marks in 2017 from the Politecnico di Bari, developing a thesis about mortars with PFU. In 2019, from the same university, he obtained a master's degree in Civil Engineering (roads and transports) with full marks, defending a thesis entitled " Hydraulic and Filtration behavior of the porous asphalt system for stormwater treatment at the Adriatic Bridge in Bari " partly developed at the University of Florida as visiting student. The same year, he started the Ph.D. course in "Risk, Environmental, Territorial and Building Development” (XXXV cycle). During the three years of the doctorate school, the author deepened his knowledge concerning road safety, learning how to use traffic models and simulators and algorithms for safety analysis thanks to Surrogate Measures. Part of the Ph.D. research was developed abroad at the Norwegian University of Science and Technology, supervised by prof. Aakre and prof. Ryeng, who gave profound insights into human factors and transportation analyses. During his Ph.D., he was also involved in many other research activities, concerning pavement analysis, planning (he worked on the Sustainable Urban Mobility Plan of the Province of Bari), and traffic calming. He was the author of some journal and conference papers and co-author of two books about Road Safety (published by Francoangeli editore).
He supported the didactic activities for the “Road Safety” course (Master’s Degree in Civil Engineering, 2020/2021 chair: prof. P. Colonna) and for the “Construction of

Roads, Railways and Airports” course (Bachelor and master’s degree in Civil Engineering, 2020/2021/2022 chair: prof. V. Ranieri). The author is part of the research team POLIROADTECH ICAR/04, of the AIIT and SIIV or-ganization.