Road safety related impacts within the Levitate project

Road Safety Working Group, working paper

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Executive summary

LEVITATE (Societal level impacts of connected and automated vehicles) is a Horizon 2020 project that aims to forecast impacts of developments related to Cooperative, Connected and Automated Mobility (CCAM). Impacts are estimated for different so-called 'sub use cases' (SUCs) that reflect applications or interventions which can be implemented by policy makers. The impacts for the sub use cases are estimated by comparing the situation with intervention to the situation without intervention, i.e., the baseline scenario. The baseline scenario reflects the starting point for which increasing penetration levels of first cautious and later more ambitious automated vehicles (CAVs) are estimated over time (table 1).

Table 1 CAV Deployment scenarios in Levitate

CAV Deployment Scenarios								
Type of Vehicle	A	B	C	D	E	F	G	H
Human-Driven Vehicle - passenger vehicle	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation (Cautious) CAV - passenger vehicle	0%	20%	40%	40%	40%	40%	20%	0%
2nd Generation (ambitious) CAV -- passenger vehicle	0%	0%	0%	20%	40%	60%	80%	100%
Human-driven - Freight vehicle	100%	80%	40%	0%	0%	0%	0%	0%
Freight CAV	0%	20%	60%	100%	100%	100%	100%	100%

One of the relevant impact areas of CCAM is road safety. This Working Document 1) discusses in which way road safety is impacted by increasing penetration levels of connected and automated vehicles (CAVs) and 2) quantifies the road safety impacts of increasing penetration levels of CAVs as far as possible.

Identified road safety impacts

First of all, it was investigated in which ways road safety is impacted by increasing penetration levels of CAVs. The impact diagram that was constructed in Deliverable 3.1 was used as a basis for this investigation and was further elaborated with a review of literature and expert knowledge. To check whether all relevant impacts were included, we discussed the identified impacts with experts outside Levitate and asked for additional input.

Deliverable 3.1 makes a distinction between primary or direct impacts and secondary or indirect impacts. Road safety is expected to be influenced both directly and indirectly by increasing penetration levels of CAVs.

Primary road safety impacts of CAVs
Many risks related to human drivers are expected to be prevented or decreased by CAVs. CAVs are assumed to obey traffic rules and are expected to be able to prevent most human driver errors. Moreover, they are expected to have lower reaction times and less variability in driving behaviour. Therefore, CAVs will likely have a lower risk of being involved in a crash than human driven vehicles.

On the other hand, some new potential risks might be introduced by CAVs. These potential new risks include:
- Risks related to system failures or system degraded performance; problems related to sensors, software or other components of the system
- Risk related to cyber-security; hacking, cyber attacks
- Risks related to transition of control to human drivers or mode-confusion

Secondary road safety impacts of CAVs
In addition, some rebound/indirect effects can be expected, caused by changes in broader factors that in turn affect road safety. Indirect impacts include changes in modal split, total distance traveled and route choice, as well as changes in traffic behaviour of other road users and infrastructural changes due to the introduction and increasing penetration levels of CAVs.

Development of impacts over time
The impact of CAVs on road safety is not a static figure, but will likely evolve over time as CAVs are expected to become progressively safer, drivers and other road users will become more experienced in dealing with CAVs, and the penetration level of different types of CAVs is expected to increase over time. To account for developments in performance of CAVs over time, two types of CAVs are distinguished within Levitate; first generation, comprising more cautious CAVs, and second generation, comprising more ambitious/aggressive CAVs.

Quantification of road safety impacts
Concerning the quantification of road safety impacts, the available literature was first studied looking for quantitative information on road safety impacts. Second, road safety impacts were estimated by combining three approaches:
1. Impacts of decreased reaction times and driver variability on crash rates between motorized vehicles are estimated by means of microsimulation.
2. The impact of improved driving behaviour on crash rates between motorized vehicles and vulnerable road users is estimated by using crash data and assumptions concerning types of crashes that can be prevented by CAVs and reduced reaction times.
3. The estimated impacts on crash rates are combined with estimated impacts on distance travelled that are determined via other methods within LEVITATE to estimate the overall impact on the number of crashes.

Information from literature
Available literature provides some quantitative information on road safety impacts of increasing penetration levels of CAVs. Previous microsimulation studies estimated impacts of lower reaction times and less variations in driving behaviour and report reductions of safety critical events up to 99% at a 100% penetration rate of CAVs. By combining different studies it is possible to determine dose-response curves that provide

estimated impacts for increasing penetration rates. Quantitative information on the size of potential new risks of CAVs was not found in literature.

Other types of studies that were considered in the literature review are studies combining crash data from human driven vehicles and CAVs, studies looking at disengagement reports, studies that use data from tests with CAVs and studies that apply naturalistic driving data. These studies however are not suitable for estimating future impacts of CAVs that are not fully developed yet. Driving simulator studies can be used for obtaining more information on specific impacts like transition of control or impacts of CAVs on human drivers.

Microsimulation approach

Impacts on crashes between motorized vehicles are estimated by means of a microsimulation model (AIMSUN) that is also used to estimate impacts on, for example, travel times and emissions within Levitate. Output from the AIMSUN microsimulation model is postprocessed using the software application SSAM (Surrogate Safety Assessment Model) to estimate changes in conflicts per distance travelled. A probabilistic method proposed by Tarko (2018) is then applied to estimate the change in crash rate based on the change in conflicts and their Time to Collision (TTC) values. Impacts on conflict and crash rates are estimated for three calibrated and validated networks: Manchester (UK), Leicester (UK), and Athens (GR). As light and heavy good vehicles appeared to have an unrealistically high share in the number of conflicts and may not be reasonably modelled in the test networks, it was decided to remove these vehicles from the analysis. Moreover, as there seemed to be a peak in conflicts with TTC ≤ 0.1 sec that is likely caused by limitations in the microsimulation and/or SSAM software, it was decided to exclude these conflicts from the analysis as well.

At 100% market penetration rate of CAVs, conflicts per 1000 vehicle-kilometer are estimated to be reduced by almost 90%. Results are comparable for the three networks. The expected change in crash rate differs between the three networks: at 100% penetration of CAVs, crash rates are estimated to decrease by 87% in the Manchester network, 92% in Leicester, and 68% in the Athens network, all in comparison to present values with 0% CAV market penetration rate.

Impacts on vulnerable road users

Unmotorized vulnerable road users (VRUs), comprised of pedestrians and cyclists, are not included in the microsimulation model and therefore, crashes involving VRUs are not taken into account in the impacts discussed above. As developments related to CCAM are expected to impact road safety of VRUs as well, another approach based on crash statistics was taken to estimate the impacts on crashes with VRUs.

This approach is based on three main assumptions:

1. It is assumed that all crashes that were caused by human-driven vehicles (car is 'at fault') can be prevented by CAVs
2. As CAVS are expected to have lower reaction times than human-driven vehicles, it is assumed that the remaining crashes (VRU is 'at fault') are less severe when CAVs are involved instead of human-driven vehicles
3. The CAV systems are highly developed and reliably operational across all relevant real-world scenarios.

The share of crashes for which the pedestrian or cyclist is registered to be 'at fault' differs between cities and countries. Based on crash statistics from a number of countries, we assume that about 70% of the crashes is caused by human-driven vehicles. In that case, 70% of the VRU-car crashes can be prevented in case of a 100% penetration level of CAVs. Taking into account the extra reduction in (severe) crashes due to the reduced impact speed, it is estimated that 91% of all fatal crashes between VRUs and cars can be prevented in the case that all cars are fully automated.

Overall impact taking into account changes in modal split

To estimate the overall impact of increasing penetration levels of CAVs on road safety, the impacts on crash rates that are estimated above, are combined with estimated impacts on distance traveled with various transport modes. The impacts on distances traveled are estimated by means of System Dynamics/Mesosimulation and are discussed in more detail in Deliverable 5.3 (Roussou, Müller, et al., 2021) and Deliverable 6.3 (Sha et al., 2021).

The impacts on modal split for the baseline scenario are only available for the Athens network. In Athens, the distance traveled by car is expected to increase by around 8%, due to a decrease in active travel of 2% and a decrease in travel by public transport of 6%. An increase in travel by private car transport is expected to have a slight negative effect on road safety. Overall, this results in an expected decrease in crashes of 74% in comparison to present values with 0% CAV market penetration rate.

Discussion and limitations

It should be stressed that the quantification of impacts in this report is based on many assumptions. The results based on microsimulation for example depend on the parameter settings for the behaviour of human-driven and automated vehicles. Moreover, freight vehicles and TTC values ≤ 0.1 sec were removed from the analysis. The impact on VRU-car crashes is also based on assumptions concerning the share of crashes that can be prevented by CAVs and the expected reaction time of CAVs. Furthermore, for both impacts described above, it is assumed that CAVs function perfectly and that the human drivers don't need to and are not able to take over control. In addition, issues related to hacking or cyber-attacks are not taken into account.

The impacts on vehicle kilometers travelled are used as fixed input for the estimation of the overall road safety impacts and are outside the scope of this report, yet also these estimations are based on assumptions. Further indirect impacts are not taken into account when estimating the overall road safety impacts.

Furthermore, the results are based on estimations for a limited number of cities. Impacts or crashes between cars are estimated for three networks and the proportion of remaining crashes appear to differ between the three networks. The estimated impacts on VRU is based on crash data from a limited number of countries and model split impacts were only available for Athens. Therefore it is not possible to determine to which extent the estimated total impacts are transferable to other networks.

Because of these limitations, the quantified impacts discussed in this report should be seen as a rough estimate of the potential road safety impacts of increasing penetration levels of CAVs. Unavailability of real-world data makes it impossible to validate the results.

In general, it should be noted that it is very difficult to quantify expected road safety impacts of increasing penetration levels of CAVs as CAVs will continue to develop over time and future vehicle specifications are not yet known. Moreover, policy makers can influence the road safety impacts of CAVs, for example by regulating the conditions that must be met by CAVs to be allowed on the public roads. Moreover, measures like urban shuttles, provision of dedicated lanes or automated freight consolidation have additional impacts on road safety. These impacts are also identified in LEVITATE and are discussed in Deliverables 5.4, 6.4 and 7.4 of the Levitate project.

Although the exact impacts are not known yet, CAVs are expected to improve road safety. They would not be accepted by road users and policy makers if they would not improve road safety. However, it should be stressed that CAVs cannot be expected to solve all road safety problems. First of all, even systems that are very well designed can fail, and cyber-attacks and manipulation of the software cannot be fully prevented. Secondly, it should also be noted that only crashes involving vehicles which can be replaced by AVs can be prevented. A significant amount of crashes do not involve motorized vehicles and these crashes -for example single bicycle crashes- cannot be prevented by CAVs.

1 Introduction

This document discusses and quantifies road safety impacts of increasing penetration levels of connected and automated vehicles.

Levitate aims to forecast the impacts of Cooperative, Connected and Automated Mobility (CCAM). One of the relevant impact areas of CCAM is road safety. This Working Document discusses and quantifies the road safety impacts of increasing penetration levels of Connected and Automated Vehicles (CAVs).

1.1 Levitate

LEVITATE (Societal level impacts of connected and automated vehicles) is a Horizon 2020 project which has the following main objectives:

1. To develop a range of **forecasting and backcasting scenarios** and baseline conditions relating to the deployment of one or more mobility technologies that will be used as the basis of impact assessments and forecasts. These will cover three primary use cases – automated urban transport, passenger cars and freight services.
2. To establish a **multi-disciplinary methodology** to assess the short, medium and long-term impacts of Cooperative, Connected and Automated Mobility, (CCAM) on wide range of impact area's among which mobility, safety environment, and society. Several quantitative indicators will be identified for each impact type.
3. To apply the methods and **forecast the impact of CCAM** over the short, medium and long term for a range of use cases, operational design domains and environments and an extensive range of mobility, environmental, safety, economic and societal indicators. A series of case studies will be conducted to validate the methodologies and to demonstrate the system.
4. To develop a **new web-based policy support tool (PST)** in which above methods are incorporated to enable city and other authorities to forecast impacts of CCAM on urban areas. The methods developed within Levitate will be available within a toolbox allowing the impact of measures to be assessed individually. A Decision Support System will enable users to apply backcasting methods to identify the sequences of CCAM measures that will result in their desired policy objectives.

Within the Levitate project, many different impact areas are investigated for different sub use cases. Deliverable 3.1 discusses the potential impacts of CCAM as well as indicators that can be applied to measure the different types of impact. The sub use cases reflect interventions that can be implemented by policy makers. The impacts for the sub use cases are estimated by comparing the situation with intervention to the situation without intervention, i.e., the baseline scenario. The baseline scenario reflects the starting point from which increasing penetration levels of first cautious and later more ambitious automated vehicles are estimated over time (table 1.1).

Table 1.1 CAV Deployment scenarios in Levitate

CAV Deployment Scenarios								
Type of Vehicle	A	B	C	D	E	F	G	H
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2nd Generation (Ambitious) CAV -- passenger vehicle	0%	0%	0%	20%	40%	60%	80%	100%
Human-driven - Freight vehicle	100%	80%	40%	0%	0%	0%	0%	0%
Freight CAV	0%	20%	60%	100%	100%	100%	100%	100%

1.2 This document

Road safety is one of the relevant impact areas of CCAM. Therefore, Levitate aims to forecast road safety impacts of various sub-use cases as well. As a first step, it is important to estimate road safety impacts of increasing penetration levels of CAVs (the baseline scenario). Subsequently, the impacts for various sub use cases can be estimated and compared to the road safety impacts of the baseline scenario.

This document focusses on the impacts of increasing penetration levels of CAVs on road safety. Chapter 2 discusses in which way road safety is affected by increasing penetration levels of CAVs. Chapter 3 subsequently provides an overview of quantitative information that is available in literature on different types of road safety impacts. Chapter 4 discusses the quantification of impacts within Levitate and presents the results of this quantification. Chapter 5 finally, presents the conclusions from this report.

2 Identifying road safety impacts

This chapter discusses in which ways road safety is affected by increasing levels of Connected and Automated Vehicles (CAVs).

Deliverable 3.1 (Elvik et al., 2019) discusses the (different types of) impacts of Cooperative, Connected and Automated Mobility (CCAM). A distinction is made between direct impacts, systemic impacts and wider impacts. Direct impacts are changes that are noticed by each road user on each trip, like travel time and vehicle operating costs. Systemic impacts are system-wide impacts within the transport system. Wider impacts are changes occurring outside the transport system, such as changes in land use and employment. Road safety is one of the systemic impacts of CCAM.

Deliverable 3.1 makes a further distinction between primary impacts and secondary impacts. A primary impact is an impact that directly emanates from the automation technology, whereas a secondary impact (rebound impact; behavioral adaptation) is generated by the introduction or change of a primary impact and indirectly affects, for example, road safety.

Automated vehicles (AVs) affect road safety directly (primary impact) as they are expected to have a lower risk of being involved in a crash than human driven vehicles. Especially in the case of vehicles that are able to communicate with each other, i.e. if they are connected (CAVs), the risk of a crash will probably be reduced. In addition, some rebound effects can be expected. It is for example likely that modal split and total distance traveled are affected by increasing levels of (C)AVs and it is known that modal split and distance traveled have an impact on the number of crashes. Sections 2.1 and 2.2 further discuss the primary and secondary impacts.

The general impact diagram that was constructed in Deliverable 3.1 was used as a basis for identifying the ways in which road safety is impacted by CAVs. The different ways in which road safety is impacted are further elaborated in this report by means of a review of literature discussing road safety impacts of developments related to vehicle automation (also see Chapter 3 in which quantitative information from the literature is discussed) and consultation of experts within Levitate. The identified impacts were also discussed with experts outside Levitate at a Webinar discussing road safety impacts.

The impacts of CAVs on road safety are not static figures, but are expected to develop over time, for example related to different levels of automation. The development of road safety impacts over time is discussed in Section 2.3.

2.1 Primary impacts

The essence of AVs is that the driving task is transferred from the human driver to the vehicle itself. Most crashes involve some form of human (driver) error, although it should be noted that this does not necessarily mean that the driver is accountable for the crash. Implementation of automated vehicles is expected to reduce the effect that human driver errors play in crashes. Potentially, automated vehicles should be able to prevent most human driver errors.

On the other hand, some new potential risks might be introduced by automated vehicles. First of all, the system might fail due to for example broken detectors, software malfunctioning or cyber security problems. Moreover, systems have their technical limits: CAVs might have difficulties with detecting (actually recognizing) other road users, especially in case of poor visibility due to for example bad weather conditions. Another issue might be that traffic signs are not clearly visible or readable for CAVs or that road alignment is not understandable for CAVs, for example because they are not clearly visible or temporary markings are applied in combination with normal markings in case of road works. In general, human drivers are probably better in dealing with unexpected or new situations. Finally, as CAVs are not fully automated yet and drivers may need to take over the driving task in specific conditions or in case of system failure, there is an increased risk due to transition of control.

The primary impacts are discussed in more detail below. It should be noted that only crashes that involve vehicles that can be replaced by CAVs can be prevented. A significant amount of crashes do not involved motorized vehicles. In the Netherlands for example, more than half of the seriously injured road users are injured in a road crash in which no motorized vehicle was involved (SWOV, 2020). These are single bicycle crashes, crashes between cyclists and crashes between cyclists and pedestrians and these crashes are not expected to be affected by the introduction of Connected and Automated vehicles[1].

Human (driver) errors

Human drivers make (unintentional) mistakes and in some cases disobey traffic rules. These mistakes and violations increase the risk of a traffic crash. Fully automated vehicles completely take over the driving task of the human driver and therefore eliminate the risk due to human driver errors (of the human driver in the vehicle that is automated).

More specifically, automated vehicles are assumed to respect traffic rules and therefore all crashes that result from disobeying of traffic rules are expected to be prevented by automated vehicles. Moreover, errors due to human shortcomings such as reduced attention, drowsiness, and lack of situational awareness will mostly cease to exist when the vehicle is driving fully automatically. Furthermore, automated vehicles are expected to have lower reaction times and are expected to be better at detecting other road users as they can be equipped with multiple cameras/sensors. When vehicles are connected, they are able to communicate with each other, which could even further reduce reaction times and hence increase safety.

Operator responsibility

During the introductory period of automated vehicles there is the potential for decreased safety due to human error or unfamiliarity with the new systems. This is most notable in moments that the human driver has to take over control from the automated vehicle or assumes the vehicle is capable of self-driving when it is in fact not.

1. We should note that in some of these crashes, a motorized vehicle might be indirectly involved, e.g. when a cyclist makes a manoeuvre to prevent a crash with a motorized vehicle and falls. These crashes might be prevented by CAVs.

Mode confusion indicates that the human driver is unsure about the current capabilities of the vehicle. This is most dangerous when it is assumed that the vehicle will drive automatically when it is not currently capable of doing so. Several studies show that drivers think the vehicle is in self-driving mode, even when the interface indicates otherwise (Banks et al., 2020).

In addition to human errors there are also indications of drivers purposefully sabotaging car systems related to self-driving. This is especially relevant for current systems that are unable to fully take over the driving task and rely on the human driver being in the loop. Studies show that the systems designed to check if the driver is engaged such as hands-on-wheel detection are being circumvented (Wilson et al., 2020).

System failure
In any vehicular system, failure of the system can occur due to failure in mechanical, electrical, electronic components and sometimes even software errors. Typically, for a vehicular system, there are multiple modes of failures and to ensure safe operation of CAVs, the design and testing must go through rigorous testing to ensure reliable operation. Section 3.3 discusses in more detail how to deal with system failures.

Cyber risks
With the introduction of computer-controlled vehicles also comes the introduction of cyber risks. This type of risk becomes even more prominent when AVs become connected. Therefore, the potential risk of an outside attack on the control systems of a vehicle or related infrastructure should be taken into account. Additionally, users might also make changes to the software so that their vehicles for example exceed speed limits or accept lower safety thresholds.

Due to the inherent vulnerabilities in connected and/or automated vehicles it will be difficult to prevent all hacking attempts and cyber-attacks. Despite that, Deliverable 3.2 concludes that the potential cyber risks of AVs are no reason not to implement them. The introduction of AVs will still result in a reduction of fatalities and seriously injured road users, even with potential attacks.

2.2 Secondary impacts

CAVs also affect road safety in a more indirect manner, through changes in other factors that in their turn affect road safety. Other road users could for example change their traffic behavior due to automated vehicles. Moreover, CAVs could lead to a change in vehicle kms traveled, modal split and route choice. Finally, also the road design might change due to CAVs.

Behavioral adaptation
Other road users, i.e. human drivers and other types of road users like cyclists and pedestrians, might adapt their driving behavior when close to automated vehicles. Human drivers might adopt smaller time-headways when they are surrounded by automated vehicles. This can already occur when driving next to a platoon of freight vehicles (Gouy, Wiedemann, Stevens, Brunett, & Reed, 2014). Differences in rule adherence between automated vehicles and human driven vehicles can also result in unwanted behavior. Due to the strict adherence of AVs to the speed limit drivers in a vehicle behind the AV are forced to either adjust their speed or to overtake the vehicle. A large scale study done in the Netherlands shows that 2 out of 3 test drivers with

mandatory speed assist experienced negative interactions with other drivers (AVV, 2001). A driving simulator study within the LEVITATE project explores the extent of behavioral adaptation of human car drivers when surrounded by automated vehicles. The results of this simulation study will be published at a later moment.

Moreover, cyclists and pedestrians might change their crossing behavior when confronted with AVs. Research shows that pedestrians are not confident in the capabilities of AVs to stop when approaching a pedestrian (Rodríguez Palmeiro et al., 2018). Nevertheless, no observable difference in pedestrian crossing behavior was found between situations in which vehicles explicitly identified as self-driving and those situations in which this was not the case (Rodríguez Palmeiro et al., 2018). A similar experiment design for cyclists also shows no difference in crossing behavior (Vlakveld, van der Kint, & Hagenzieker, 2020). An overview of the knowledge gaps related to pedestrian and cyclist interactions with AVs can be found in Schagen, Kint, and Hagenzieker (2017).

Changes in km travelled
Changes in distances travelled are likely to appear with the introduction of (more advanced) AVs. These changes might be due to a modal split change but they might also be due to the fact that one is able to make more kilometers (e.g. freight transport without the need for resting periods for the driver) or one has a lower cost valuation of travel time as one can engage in other activities when the car is driving itself. Moreover, there is the potential for vehicles to drive around empty in order to avoid parking fees, resulting in increased travel. Also interventions concerning restricting access for AVs or non-AVs to certain areas might influence the amount of travel directly.

In general, the number of km traveled is positively related to the number of crashes. As crash rates differ between different types of roads, it is also relevant to know on which types of roads the extra km of travel occur.

Changes in modal split
The introduction of AV based transport has the potential to change the modal split drastically. Removed need for a driver license, easier access to public transport, the ability to do work while travelling and automated delivery all influence the modal split allocations. A change in modal split will naturally result in a change of kilometers travelled in a certain type of vehicle and it might also affect the share of active travel modes. Crash rates differ between different travel modes and therefore, changes in modal split also have an impact on road safety.

Changes in route choice
When automated vehicles are also connected, they are able to share information concerning congestion with each other. If this information is shared with the drivers, it enables drivers to adopt their route choice to select the fastest route or the route with the least congestion. As the safety level differs between routes, changes in route choice can also affect road safety.

Infrastructural measures
To be able to deal with CAVs, the infrastructure needs to meet certain requirements (Farah, Erkens, Alkim, & van Arem, 2018). Road alignment for example should be clearly visible and non-interrupted and also road signs should be clearly visible so they can be read by the AV cameras. This might also help other road users to prevent errors due to for example missing of traffic signs or misinterpretation of road alignment. Moreover,

also on a more network level, CAVs might lead to infrastructural changes. On street parking might for example not be needed anymore within residential areas or city centres, as level 5 CAVs should be able to drive around empty and park somewhere out of the residential area. As on street parking poses a potential safety risk for vulnerable road users as well as crossing vehicles, the banning of on street parking probably has a positive impact on road safety. Moreover, dedicated lanes might be introduced for CAVs, which might also influence the number of available lanes for non-automated vehicles and traffic circulation. This is one of the sub-use cases that is studied within Levitate.

2.3 Development of impacts over time

The impacts of CAVs on road safety are not static , but are expected to develop over time. First of all, CAVs themselves are expected to develop over time as the development work in autonomous vehicles field progresses with increased reliability in hardware (e.g., sensors, actuators) and operating software. Secondly, the penetration level of different types of CAVs is expected to increase over time. Third, also the behaviour of other road users related to CAVs could develop over time as road users (as well as drivers of partly automated vehicles) are getting used to CAVs.

For any product, typically, hazard rate can be described by a bathtub curve as shown in figure 2.1 (Dhillon, 2004). Infant mortality relates to product (or system failures) due to poor workmanship, manufacturing process, poor packaging, start-up human error, inadequate debugging, etc. During useful-life phase, the hazard rate is constant, and failures occur randomly which is usually due to undetectable defects, abuse, human errors and higher stresses than expected, etc. During the wear-out phase, hazard rate increases due to poor maintenance, components failure due to end of life, wear due to friction and corrosion, etc.

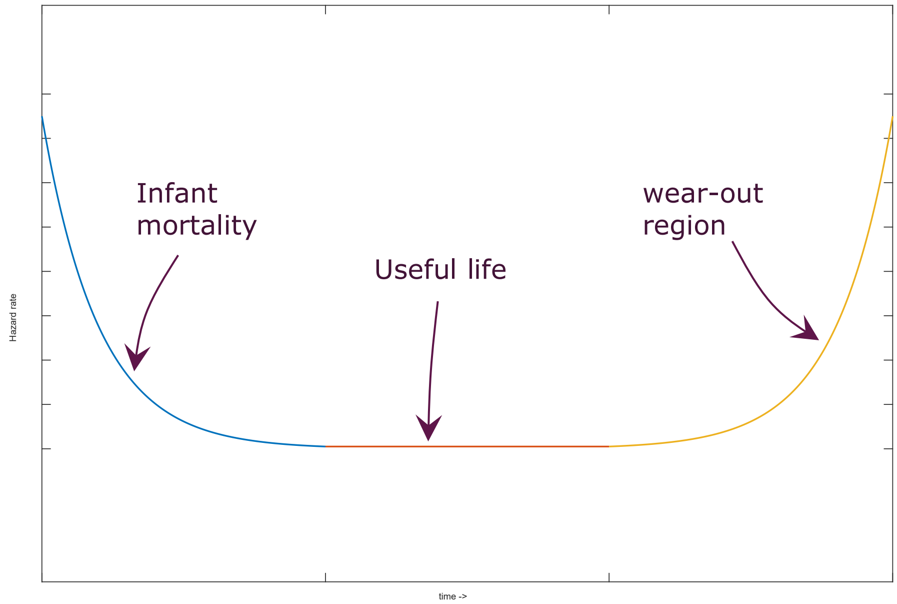


Figure 2.1: ‘Bathtub’ curve for hazard rate (failure rate) for a product

Moreover, the development of CAVs also affect implementation of CAVs in the traffic system. Deliverable 3.1 stated that the implementation of CAVs can be viewed as a process developing along the following four dimensions:

1. Levels of automation (SAE levels 1 to 5)
2. Domains of operation
3. Involvement of traffic management
4. Market penetration

Levels of automation

Concerning the levels of automation, SAE level 1 refers to a fully manual vehicle with no automation, level 2 refers toadvanced driver assistance systems (ADAS) that support the driver and do not take over control. Real automation starts at SAE level 3, in which the vehicle can drive without the driver control, but only in case it is actively turned on and within clearly defined operational domains. The driver will be asked to take over control when needed. Level 4 vehicles are fully automated, but still restricted to defined operational domains. Level 5 vehicles are fully automated in all parts of the road systems. Safety impacts depend on the level of automation. Safety impacts of ADAS (SAE level 2 systems) are discussed in Deliverables 5.1, 6.1 and 7.1 (Boghani et al., 2019; Hu et al., 2019; Roussou et al., 2019). In case of SAE level 3 vehicles, Transition of Control is a relevant issue. Level 3 is widely regarded as a hazardous solution (Banks et al., 2018), and FERSI, for example, calls for avoiding it altogether (Anund, Lindström, Schagen, & Linder, 2020). In case of Level 4 and Level 5 automation, driving will be fully automated, either in part of the traffic system or everywhere.

Domains of operation

Concerning the domains of operation (also known as Operational Design Domain - ODD), three levels of implementation where distinguished in Deliverable 3.1:

1. Automated vehicles can only operate on designated areas where other traffic is not permitted.
2. Automated vehicles are allowed to operate on some public roads where non-automated traffic is also found.
3. Automated vehicles are allowed to operate on all parts of the road system.

In level 1, there will be no interaction between automated vehicles and other road users (human drivers, cyclists and pedestrians), whereas in level 2 there are some interactions and in level 3 there are more interactions. Moreover, the technical requirements of CAVS will be higher in case of level 2 and 3 and primary safety impacts might be most easily obtained in level 1 and most difficult to obtain in level 3.

Involvement of traffic management

The third dimension refers to whether traffic is being monitored and regulated by a traffic management center or not. It does not seem altogether unlikely that the operation of automated vehicles in large cities will, at least initially, be controlled by a traffic management center. This could be seen as an extra measure to prevent errors by automated vehicles and could result in a higher safety impact.

Market penetration

The fourth dimension of implementation concerns how fast vehicles at different levels of automation will penetrate the market. Maximum safety benefits are expected to occur when all vehicles will be fully automated (100% penetration rate of SAE level 5 vehicles).

However, this is expected to take quite some time. If the development of automation technology follows the “evolutionary” model of proceeding from SAE level 2 to 3, and further on to 4 and 5, there will be a long period of time when traffic will consist of a mixture of vehicles at all these levels of automation. During this transition period, that could well take 30 to 35 years (Elvik et al., 2019), road safety will be affected by interactions between human drivers and different levels of automated vehicles.

Also secondary impacts on road safety are probably influenced by the different implementation dimensions of CAVs. Modal split changes might for example increase with increasing penetration levels of CAVs and mileage of CAVs might increase when they become fully automated and can drive around without a driver.

2.4 Summary

Automated vehicles (AVs) are expected to affect road safety in several ways, both directly and indirectly. First of all, AVs are expected to have a lower risk of being involved in a crash than human driven vehicles, especially when vehicles are able to communicate with each other, i.e., if they are connected (CAVs). This is based on the expectation that (C)AVs are able to prevent most human driver errors and don’t violate the traffic rules. On the other hand, some new potential risks, like system failures and cyber security issues, might be introduced by automated vehicles. Moreover, when CAVs are not fully automated yet and drivers may need to take over the driving task in specific conditions or in case of system failure, there is an increased risk due to transition of control.

In addition, some rebound/indirect effects can be expected, caused by changes in broader factors that in turn affect road safety. It is for example likely that modal split and total distance traveled are affected by increasing levels of (C)AVs and it is known that modal split and distance traveled have an impact on the number of crashes. Other rebound effects are other road users changing their traffic behaviour when confronted with AVs,changes in route choice and infrastructural changes related to the introduction of AVs.

The impacts of CAVs on road safety are not static, but are expected to develop over time. Firstly, CAVs are expected to become safer over time as the development work in the autonomous vehicles field progresses with increased reliability in hardware (e.g., sensors, actuators) and operating software. Secondly, the penetration level of different types of CAVs is expected to increase over time.

3 Current knowledge

This chapter explores the current literature on the different types and size of road safety impacts of CAVs that were identified in the previous Chapter and summarizes the relevant results. The focus is on primary impacts.

3.1 Introduction

This chapter explores the current literature about road safety impacts with regard to CAVs. Only the primary impacts are discussed here as they reflect direct relationships between automation and road safety. A number of indirect impacts will be quantified within Levitate, but they are outside the scope of this literature review.

Before we examine the impacts that are discussed in literature, we briefly explain how the literature search was conducted and which safety assessment methods are available for the estimation of road safety impacts of CAVs.

3.1.1 Literature search method

A literature search on currently known road safety impacts of CAVs was performed. For this search a combination of the following search terms was used, searching in Google Scholar: automated/self-driving vehicles/driving cars, road safety, traffic/micro simulation, platooning. Only literature including information relevant to the road safety assessment of automated vehicles for the passenger car use case was used in this literature review. The literature search mainly focused on mitigated risks and the resulting literature did not provide information on degraded performance and cyber security. The information on these issues is based on expert knowledge from a systems engineer and Deliverable 3.2.

3.1.2 Safety assessment methods

Expected impacts of future CAVs can be obtained in various ways. In Deliverable 3.2 different methods for impact assessment are discussed and compared (Elvik et al., 2020). Deliverable 3.2 makes a distinction between historical or retrospective methods and future oriented methods. In this section we consider a subset of these methods, i.e. those relevant for safety related impacts. While none of the methods will provide a perfect impact assessment, it is expected that combining results from different methods will increase validity and scope.

Real world data

Real world data consist of crash and disengagement reports of conventional vehicles and (C)AVs. For (C)AVs, this can encompass data on currently deployed ADAS systems (SAE level 1 and 2) or test vehicles (SAE levels 3-5). Caveats when comparing real world crash data between CAVs and conventional vehicles have been identified:

- There are about 1 million times more km driven with conventional vehicles than with CAVs (Schoettle & Sivak, 2015).
- Current CAV technology can only be used in limited (generally less demanding) conditions than conventional vehicles. (Schoettle & Sivak, 2015). More in general,

CAV technology is still being developed and improved, so current crash rates are probably not representative for future CAVs.
- Conventional vehicle crash rates are incomplete due to underreporting of minor crashes, while CAVs are subject to stricter regulations with regard to crash reporting. These regulations also differ between states/countries. (Blanco et al., 2016)
- Crash data from CAVs only includes a few drivers, which are likely not a representative sample of the drivers present in the conventional vehicle crash data.

Driving simulator experiments

Driving simulator experiments place a participant in a simulated vehicle. This allows researchers to present situations that would not be safe on public roads. Studies focus for example on transition of control in different situations and the impact of AVs on human driver behavior. Impacts related to driver behavior such as time headway, reaction times and workload are often used as indicators of road safety within simulator experiments. Caveats of driving simulator research that have been identified:
- Uncertain generalizability to other situations
- Driving simulator driving dissimilar to real world driving

Traffic simulation

Traffic microsimulation models simulate the behavior of individual vehicles within a predefined road network and are used to predict the likely impact of changes in traffic patterns resulting from changes to traffic flow, vehicle behavior or from changes to the environment (Wikipedia). The assumptions for simulating vehicular manoeuvres are based on a variety of quantitative models. The minimum headways (car-following) and minimum gap acceptance (crossing at intersections) are mostly fixed values (based on findings from literature). The road user in microsimulation is modelled according to general characteristics. These characteristics can be changed. However, the producers of the simulation framework warn the user for output that is not calibrated in any way for these alternative characteristics. Note, all road users obey the traffic rules.

These models were not designed to analyze traffic safety and cannot simulate actual crashes. However, the surrogate safety measures derived from such methods can possibly be used to develop estimates of safety impacts. Young, Sobhani, Lenné, and Sarvi (2014) have reviewed a large number of publications about simulations related to road safety. They conclude that "these models have potential in measuring the level of conflict on parts of the network and the measure of conflict correlated well with crash statistics".

Several caveats have been identified when using microscopic traffic simulations to assess the safety impacts of CAVS:
- Usability of surrogate safety measures (Guo, Klauer, Hankey, & Dingus, 2010)
- Simulation of human driving behavior for safety assessment
- Simulation of CCAM for safety assessment

Other

In addition to the methods mentioned above there are several other methods used in quantifying safety impacts of AV systems. The three more common methods will be discussed shortly.

Naturalistic driving (including field operational tests)
Naturalistic driving studies (including field operational tests) utilize vehicles equipped with different cameras and sensors to record vehicle and driver behavior while the vehicle is in normal everyday use. Naturalistic driving studies allow for analysis of relations between driver, vehicle, road, and other external factors. Advantages are usage of real-word vehicle and driver behavior, often over longer periods. However, not all new technology can be tested on public roads. In addition to this there is no guarantee that all situations of interest will be common. Since there is no control of the situations that will be encountered there is no guarantee that all variations of a situation are covered in the dataset. Infrequent situations such as emergency braking could never occur at all.

Current studies are only able to use the technology that is available today, which means that the driving systems used are likely not as advanced as those yet to come. The results of naturalistic driving studies are therefore not directly able to forecast future impacts of AVs.

Test track
Test Track studies utilize a private track to test situations that might not occur or be unsafe on public roads. The vehicles used in these studies are equipped with sensors to gather the data in question. Advantages are strict control over the situations, which allows for testing of very specific parts of a system. In addition it is possible to utilize a vehicle that is designed to emulate not fully completed or available technology and see how it behaves outside the lab. These studies are however limited in their generalizability due to the low number of vehicles and situations used and are thus not suitable for estimation of future AV impacts.

Literature deduction
Literature deduction studies utilize known data to make an estimation of future effects. The effectiveness of a new system is determined based on information of other studies or on assumptions. By then applying this effectiveness on a historic crash data it can be determined which part of crashes could possibly be prevented with the new system. This type of study is dependent on accurate and detailed crash data and relies on assumptions about systems to determine when they are effective.

3.2 Mitigated risks

3.2.1 Reduction of reaction times and driver variability
Automated vehicles are expected to have lower reaction times than human drivers. When a vehicle can react more promptly to a situation, it can be assumed that safety is improved. (Kusano & Gabler, 2012) estimated that perfectly working systems could prevent up to 50% of the moderately to fatally injured casualties by applying assumed system effectiveness to historic crash data.

Most available studies use microsimulation models to estimate impacts of reduced reaction times and reduced driver variability related to increasing penetration levels of automated vehicles. Bahram et al. (2014) for example report a reduction of safety critical events of 49.9% at 50% penetration rate of AVs, and a reduction of 98.9% at 100% penetration rate. According to Bahram et al (2014) the improvements are due to smaller variations in speed and reduced reaction times. Other microsimulation studies report comparable results (Morando, Tian, Truong, & Vu, 2018); Papadoulis, Quddus, and Imprialou (2019).

By combining different studies it is possible to determine dose-response curves for the penetration rate of AVs and the impacts on road safety. More information about this method and several dose-response curves can be found in deliverable 3.2 (Elvik et al., 2020).

Please note that most microsimulation studies report reductions in safety critical events. These cannot just be translated directly into reductions in crashes. Chapter 4 proposes an approach to estimate reductions in crashes using microsimulation output concerning the number of conflicts.

3.2.2 Elimination of traffic violations and driver degraded performance

The microsimulation studies discussed above focus on the operational level of driving. Automated vehicles also affect driving behavior at a strategical and tactical level. In case automated vehicles are programmed in such a way that traffic violations are not possible, potential unsafe situations due to traffic violations are prevented.

Vaa, Assum, and Elvik (2014) performed a safety analysis of several in-vehicle systems that reduce traffic violations. Please note that these are not fully automated (SAE level 5) vehicles, but rather ADAS systems (SAE level 2). A combination of estimated risk contribution due to speeding and an estimate on the effectiveness of an intelligent speed adaptation (ISA) system is used to determine the potential impact on road safety. Together with results from a field trial this shows a potential reduction in fatalities between 9% and 20%. Alcolock is assumed to prevent 98% of all alcohol related crashes when installed in all vehicles, which is estimated at 16% of all fatalities in Norway.

Moreover, automated driving does not experience drowsiness or distraction. Research done by Vaa et al. (2014) shows that with a sleep/fatigue warning system the number of fatalities could be reduced by 14%. Because this impact is estimated using a different approach than those mentioned above it is not possible to simply add all the impacts together.

3.3 Potential new risks

The introduction of automated vehicles brings not only a reduction in certain risks, it also introduces new potential risks. For example, even when crashes due to human factors are reduced, there is always a potential for system failures and degraded performance of the (automated) vehicle. In addition, connected and/or automated vehicles may add new vulnerabilities to hacking, data privacy and cyber-attacks. Another risk is expected in only partially-automated vehicles during transitions between automated driving and human driving modes, especially regarding the reaction time needed for the driver to reengage in the driving task. This section discusses these risks and, where possible, their potential mitigation in more detail.

3.3.1 Degraded performance

Just as human drivers can experience degraded performance, so can automation. The probability of a crash due to system degradation or failures is very difficult to forecast, as it depends on the failure levels of all components and the design and implementation of the system. Moreover, it likely differs between different manufacturers and is not a static figure as individual components as well as the system as a whole develops over time. Nevertheless, measures can be taken during the design and engineering phases to account for expected component degradation/failures. This section deals with measures that can be taken during the design and implementation stages. First, it is explained in more detail how the control system changes due to automation.

Failure in the control systems of the vehicle or potential issues with the programming of the vehicle could result in a compromise in road safety. Automated vehicles will rely on navigation logics and maps stored within its computers, to navigate through the road network and its traffic. When a situation occurs that is unfamiliar to its database, it is possible that the vehicle no longer has an approach/strategy for that situation and may revert to a safer alternative. This can potentially lead to a decrease in road safety due to unexpected behavior of the vehicle.

Once a 'higher-level' decision is made, say, 'follow this road', the vehicle will need to accelerate and cruise at its allowable speed. At this point, 'lower-level' control systems responsible for setting the acceleration will aim to match the speed of the vehicle close to the speed limit of the road that it is driving on. Typically, a human driver will also follow the same principle. This results in a closed loop system as shown in Figure 3.1 below. Here, the input demand is represented by a block with step signal which shows change of speed from one level to another level. This serves as a reference for the control system to follow. Please note that the demand could also be in any other form than step. The comparator block simply compares the current speed with the demand speed and produces the difference. The controller will calculate an appropriate amount of effort that is needed to reduce the difference between current speed and demanded speed of the vehicle. This effort is then executed by the actuator which causes an input into the process which then results into new speed. This new speed is noted by the sensor and it is fedback to the comparator to compare the new speed with the demanded speed. This continues forever unless otherwise interrupted by a 'higher-level' command that changes the demand, for example step change from current speed to 0 in case of braking decision. Typically, an aggressive or gentle controller is decided by the controller parameters chosen in the control law (in our example, PID).

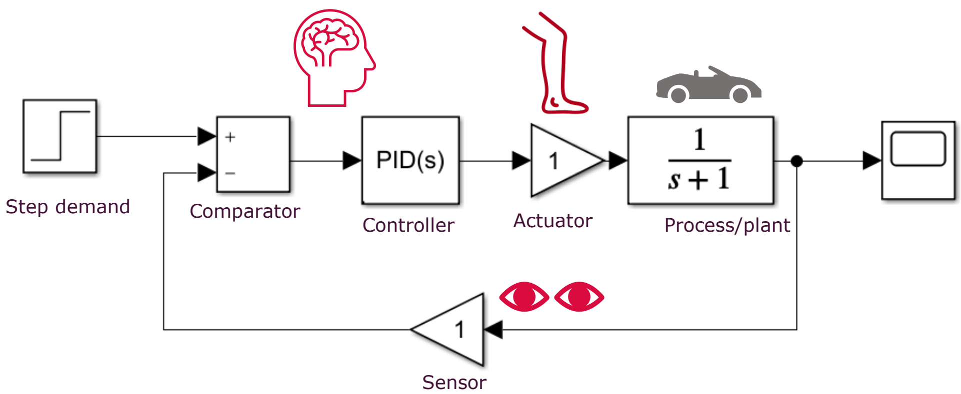


Figure 3.1 A typical control system representation for manual control of car's speed.

For the system described above, its simulated output will look like that shown in the Figure 3.2 below. Two different curves relate to two different settings (controller gains) in the controller which in turn relates to different driving style. Blue curve relates to someone driving gently to reach the maximum allowable speed whilst the orange curve relates to someone driving harshly to reach the maximum allowable speed.

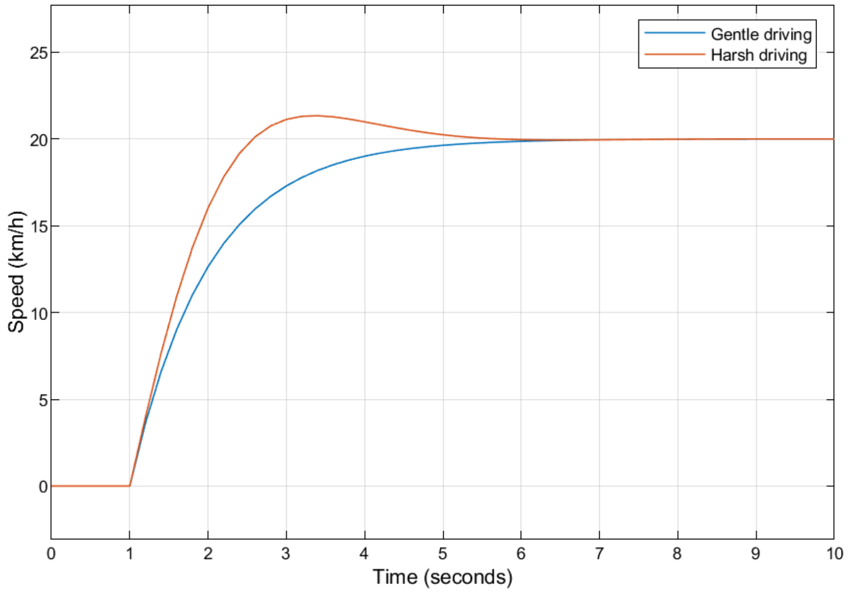


Figure 3.2 Comparison of different controller settings (representing different driving styles) and resulting response from it to a step demand in speed.

In both of these responses, sensor delay is considered to be zero, i.e. change in speed is noticed by the controller straightaway. In physical systems, degraded components can cause offset, delays, backlashes, etc. and affects the system output. To simulate the effect from delay, the above system is introduced with a unit delay as shown below in Figure 3.3.

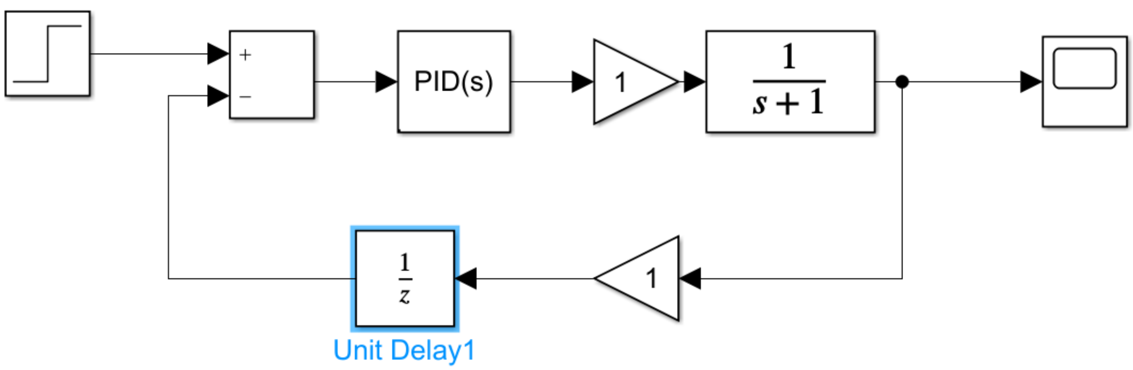


Figure 3.1 A control scheme showing delay in sensing.

As seen from the results in Figure 3.4 below, it is apparent that the system response becomes aggressive because the feedback is delayed and appropriate action is also delayed; causing the system to become more aggressive in its response. Please note that both gentle and harsh driving styles are shown here to show the effect of delay in sensing. Usually, systems are designed to handle the delays in sensing but the point of showing this effect was to illustrate the importance of addressing the changes within the system and accommodate those changes to provide satisfactory output from the system.

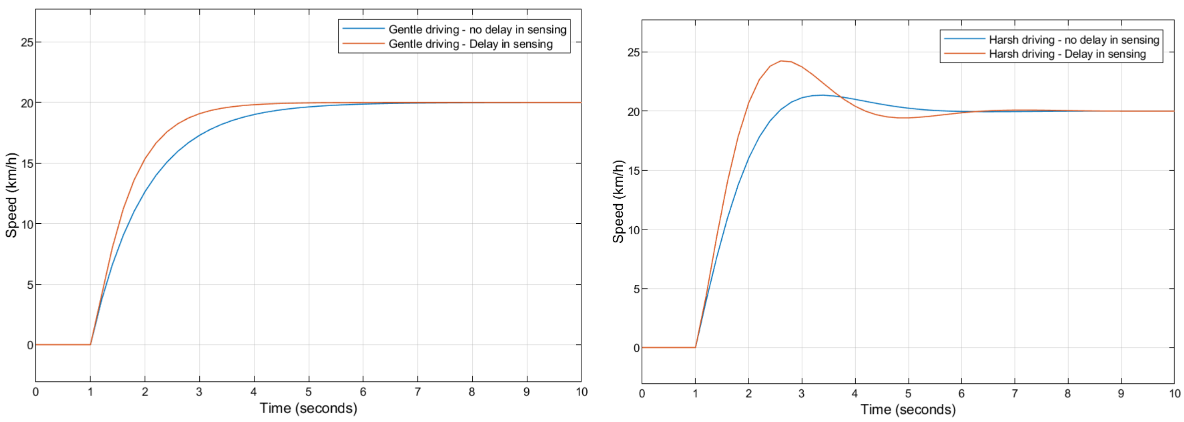


Figure 3.2 Systems response due to delay in sensing.

A well-engineered system includes robust controller or adaptive controller to account for the uncertainty and changes within the system over time, within the specified bounds. For example, over time, wear in brake discs mean that same amount of force is not available given the angular position of brake pedal. In our routine driving, our brain recalibrates itself to provide optimum braking force by pressing the brake pedal slightly more to account for the wear that has occurred. This essentially means that we are adapting to changes within the system. Controllers can also be designed to adapt to changes within the system such that it always meets the demand (in our example, braking force). It is expected that AVs will also have the level of adaptation to changes in system behaviour due to wear. However, there are times when the components may fail completely when they are at the end of their lives. And it is important to account for those failures.

Failure of components

In a human-driven vehicle, the system components that carry out the driving related functions are shown in Figure 3.1. It could be argued that the failure of human body parts is unheard of but can happen. For example, a person would not go blind suddenly in the middle of a driving task. Eyes and other body parts can degrade gradually and are usually checked for their health over the long term. Similarly, physical components in a vehicle also degrade. Additionally, safety critical systems will need to be designed to tolerate faults to either continue to function properly or safely shutdown the operation. For this, many approaches are used but most common is use of redundancies, either in hardware, software or both.

Handling of failures: design stage
Due to multiple factors (user, environment, functions) that affect a CAV throughout its lifecycle, failure of components or subsystems is inevitable. However, it is possible to mitigate the consequences of those failures by designing the system and its functionalities accordingly. There are many methods within broad systems engineering and more specifically 'reliability engineering' that are used to design the product to improve its robustness and reliability up to a sufficient level that the product requires. These methods include Fault Tree Analysis (FTA), Cause and Effect Diagram (CAED), Failure Modes and Effect Analysis (FMEA), Markov methods, and Hazard and Operability Analysis (HAZOP). Most of these methods enable designers to work out problems and failures within the system to be produced (i.e., during the design stage) and some are also able to provide statistical analysis for indicators such as Failure rates, Mean Time to Failure (MTTF), Mean Time Between Failures (MTBF), reliability, availability, etc. These methods mostly focus on system failures but do not include user errors to sufficient detail. Systems Theoretic Process Analysis (STPA). The reader is directed to further reading materials (Dhillon, 2004; Leveson, 2012) into this field of study to gain further knowledge and understanding of these methods and how they may be useful to design safe and reliable systems.

Handling of failures: implementation stage
A physical system without failures is impossible to achieve as stated earlier. However, it is possible to design mitigation strategies to handle those failures to result in continued operation either with full performance or degraded but safe performance. These strategies include mainly redundancy-based approaches in designing a fault tolerant system. There are many types of redundancies that can be developed in a system but broadly speaking, they can include hardware as well as software redundancies. These approaches implement mathematical ways of working out whether a component of part of the system is faulty and choose the appropriate action based on that. A simplest implementation could be done by voting system where for example for hardware redundancy in sensors, voting of 2 out of 3 is taken as majority and conflicting sensor value (1 out of 3) is ignored. One such implementation is shown in figure below.

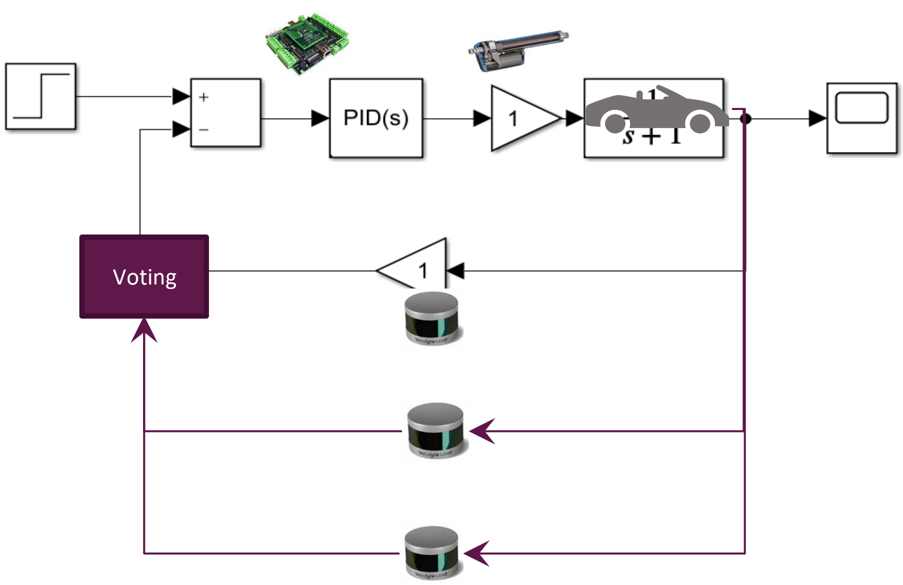


Figure 3.3 An exemplary scheme showing redundancy in sensor.

A further classification of faults can be developed by implementing strategies in fault detection, isolation and recovery that could also be used in health monitoring of the system. Again, the reader is directed to reading material (Koren & Krishna, 2010; Meskin & Khorasani, 2015) to enhance understanding and user knowledge of such techniques.

Regulating risks of system failure

In order to address safety risks at an early stage, government bodies can set requirements for minimum levels of safety testing by manufacturers before a new vehicle is allowed on the road. Within the EU, technologies such as automated vehicles which do not comply with the existing EU type-approval for new vehicles can still apply for provisional approval through an Exemption Procedure published in 2019 (European Commission, 2019). This Exemption Procedure lays out a series of safety requirements for which the manufacturer must provide sufficient proof of compliance before the vehicle is approved for the European market. Manufacturers must demonstrate through sufficient testing that, for example, the vehicle obeys all traffic rules, does not cause preventable crashes and interacts safely with other road users such that "at least an equivalent level of safety and environmental protection is ensured" compared with the requirements in the existing EU type-approval (European Commission, 2019).

In particular with regard to object recognition and sensor performance, the outputs of the EU project ENABLE-S3 (European Initiative to Enable Validation for Highly Automated Safe and Secure Systems) are relevant for vehicle developers and policy makers, as it provides information on whether the available technologies are road ready. The testing tools developed in ENABLE-S3 could be utilized to define baseline metrics/fundamental scenarios and (under varying weather and daylight conditions) that the algorithms of AVs would have to prove their performance in, before being allowed on the road or more specifically in the cities or other environments.

Even still, as with any new CCAM-related technology, it is important to keep in mind that rare crash events which are not detected during manufacturer testing and only appear once such vehicles are used on a large scale and over a longer time period are possible. This can for example also been seen in flight safety; also in airplanes, many measures are taken to minimize the impact of system failures, but crashes still occur. Continuous monitoring, testing and phased approval (e.g. pilots) can be used to learn from and mitigate potential safety deficiencies.

Summary

In summary, by removing human factors from the loop, human errors may be eliminated. However, human operator also serves as a health monitoring system in the sense that we notice changes in braking, unusual systems response and take action accordingly to carry out safe manoeuvres, do necessary repairs, etc. By removing the human operator we can expect effects from failures that may go unnoticed if the system is not well engineered to monitor the changes and failures accordingly. A well-engineered system would improve safety of the system and the users, and we should expect the design of AVs to have gone through such a rigorous process during the design considering its entire lifecycle to avoid unsafe mishaps. However, it cannot be expected that the system is 100% safe; also airplanes still crash despite of all the measures that are taken to prevent crashes. There is no information on the probability of crashes due to system failures related to CAVs.

3.3.2 Cyber-attacks

Due to the inherent vulnerabilities in connected and/or automated vehicles it will be difficult to prevent all cyber-attacks. It is not possible to quantify risks of cyber-attacks (Elvik et al., 2020), it is however possible to describe potential scenarios. Deliverable 3.2 (Elvik et al., 2020) conducts a security risk assessment of AVs as described by the Norwegian Standard for Security Risk Assessment.

In this analysis, 5 scenarios are included to determine potential risks and the effects they could have on the transport system as a whole. These scenarios are based on different motivations for hacking – for the fun/challenge, financial gain, emotions, political/religious- and different actor capacities: lone actor, ad hoc group, organized group, state. The five scenarios included in Deliverable 3.2 (Elvik et al., 2020) are:

- Playful teenagers
- Kidnapping for ransom
- Domestic abuse
- Autopilot manipulation
- Paralyzing the transport system

From the discussion of the scenarios it was concluded that it might be difficult to stop all illegal takeovers of autonomous vehicles, that it is uncertain whether it will be possible to remove all possibilities of autopilot manipulation and that, although paralysis of the transport system requires high-capacity attackers and attempts of such attacks will therefore probably be rare, it will probably be impossible to prevent all such attacks.

However, despite these risks, according to Deliverable 3.2, it seems improbable that any of the discussed scenarios would result in more fatalities and seriously injured road users than currently occur annually in traffic.

3.3.3 Transition of control

As long as vehicles are not fully automated and fully capable of handling all circumstances, take-over requests to human drivers are likely to occur. When a take-over request occurs, the human driver is prompted to resume manual control of the vehicle, which can be a demanding task. The amount of time needed for take-overs reported in literature varies greatly, with studies reporting take-over times below 1 second and others reporting 20 seconds. Results from a meta-analysis suggest that the available time to take over control, the engagement in non-driving related tasks, the level of automation, prior experience with take-overs and the type of take-over request (auditory, visual, tactile) affect take-over time (Zhang, de Winter, Varotto, Happee, & Martens, 2019). Although take-over time by itself is probably not a good indicator of road safety, some simulator and test-track studies have shown increased reaction times to automation failures when the level of automation increased (Strand, Nilsson, Karlsson, & Nilsson, 2014), and reduced reaction times to a braking lead-vehicle when ACC was active compared to manual driving (Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014; Rudin-Brown & Parker, 2004). These results suggest that take-overs decrease road safety. However, due to the complexity of take-overs and the scarcity of knowledge about real-life scenarios we are unable to quantify the related road safety effects in Levitate.

3.4 Conclusion

Available literature provides some quantitative information on road safety impacts of increasing penetration levels of CAVs. Some microsimulation studies have been carried out that estimate impacts of lower reaction times and less variations in driving behavior on safety critical events. These studies report reductions of safety critical events up to 99% in case of a 100% penetration rate. By combining different studies it is possible to determine dose-response curves that provide estimated impacts for increasing penetration rates.

A different approach is presented by Vaa et al. (2014). They estimate crash reductions of systems that prevent violations or driver degraded performance by combining available crash data with information or assumptions concerning effectiveness of the systems. Estimates based on current systems range from 14% reduction in fatalities due to fatigue detection to up to 20% decrease in fatalities with ISA (Vaa et al., 2014).

As was discussed in the previous chapter, potential new risks of CAVs related to software and hardware are centered around degraded performance of the automation system, errors in operator responsibility, and cyber risks. No quantitative information on the size of these risks was found in literature.

Other types of studies that were considered in this literature review are studies combining crash data from human driven vehicles and CAVs, studies looking at disengagement reports, studies that use data from tests with CAVs and studies that apply naturalistic driving data. These studies however have a number of caveats and are not suitable for estimating future impacts of CAVs that are not fully developed yet. Driving simulator studies can be used for obtaining more information on specific impacts like transition of control or impacts of CAVs on human drivers.

In summary, although the available literature provides some quantitative information on road safety impacts of increasing penetration levels of CAVs, it does not provide a complete picture and overall estimate of impacts on road safety.

4 Quantification of impacts within Levitate

This chapter discusses the quantification of road safety impacts of increasing penetration levels of CAVs done within Levitate. A major part is played by microsimulation. One important limitation of the microsimulations done in Levitate is that vulnerable road users are not included in the applied microsimulation model. As CAVs are expected to affect crashes between cars as well as vulnerable road users, it was decided to estimate the latter based on crash statistics. This is discussed in Section 4.2. Section 4.3 subsequently discusses secondary impacts of CAVs.

Within LEVITATE, the pragmatic choice has been made to model impacts of CAVS as a function of the market penetration rate of (cautious and ambitious) level 5 automated vehicles, whenever possible. Therefore, impacts related to Transition of Control will not be taken into account in this Chapter.

4.1 Microsimulation

Within Levitate, the microsimulation environment AIMSUN is used to estimate impacts on traffic (speeds, volumes, congestion) of increasing penetration levels of CAVs as well as impacts of different sub-use cases. Microsimulation models can be used to estimate road safety impacts as well.

At the beginning, microscopic simulation was mostly employed for transportation efficiency analysis in signalised intersections, arterial networks and freeway corridors. The developments in human behaviour modelling and real-time vehicle data acquisition have made it possible to use microscopic simulation in traffic safety and traffic conflict analysis (Guido et al., 2019). The potential to use microsimulation for traffic safety and traffic conflict analyses was firstly recognized by Darzentas, Cooper, Storr, and McDowell (1980).

In microscopic simulation models, traffic is described at the level of individual vehicles interacting with each other and the road infrastructure. This behaviour is captured in different sets of rules which determine when a vehicle accelerates, decelerates, changes lane, and how and when vehicles choose and change their routes to their destinations (Burghout, Koutsopoulos, & Andréasson, 2005).

The appropriateness of microscopic simulation for assessing safety depends on the ability of these microsimulation models to capture complex behavioural relationships that could lead to crashes and to establish a link between simulated surrogate safety measures and crash risk (Cunto, 2008). It is essential to ensure that the model inputs represent accurately the safety performance at a given location over time, that they have been determined according to observational data and that can be validated using real world observations (Cunto, 2008). In order to evaluate the safety impacts of CAVs within Levitate, the surrogate safety analysis and Surrogate Safety Assessment Model (SSAM) is applied. This is explained in more detail in Section 4.1.2. First, we discuss the use of conflicts based on surrogate safety measures.

4.1.1 Surrogate safety analysis – conflicts

Traditionally, road traffic safety analysis has relied mostly on crash statistics as the main data source. This method has several shortcomings including poor collision data quality and availability (Essa, 2015; Fyfe, 2016; Ismail, 2010; Imprialou & Quddus, 2019). Over the years, numerous problems associated with crash data have been discussed. The most important aspects are that not all crashes are reported and information for the pre-crash traffic conditions, as well as information on the behavioral aspects of road users is rarely available (Papazikou, 2019). Due to these limitations associated with using historical collision data, alternative traffic safety research methods, such as the use of surrogate safety measures, have been developed in order to assess the safety of traffic facilities more effectively. The measures can help to assess the safety of a given location without waiting for crashes to actually occur as these methods use events that occur at a much greater frequency than crash rates (Ariza, 2011; Bachmann, 2009). Therefore, there is a need to use some kind of surrogate measures to complement crashes, i.e., traffic safety indicators (Laureshyn, Svensson, & Hydén, 2010).

Literature has suggested a number of indicators which can be used as surrogate safety measures (Tarko, 2018a); however, traffic conflicts have been the most predominant one found in the literature (Gettman et al., 2008).

In more detail, as discussed in Papazikou (2019), driving can entail a number of microscopic critical events which do not need to evolve into actual crashes. The interaction between the road users can be seen as a continuum of safety related events that constitute different levels of a pyramid (Hydén, 1987). "Undisturbed passages" are situated at the bottom while crashes are found at the very top rendering the pyramid as a severity scale. Between crashes and undisturbed passages, there are different types of traffic conflicts. Amundsen and Hydén (1977) provided the most prevalent definition of traffic conflict as "an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movement remain unchanged".

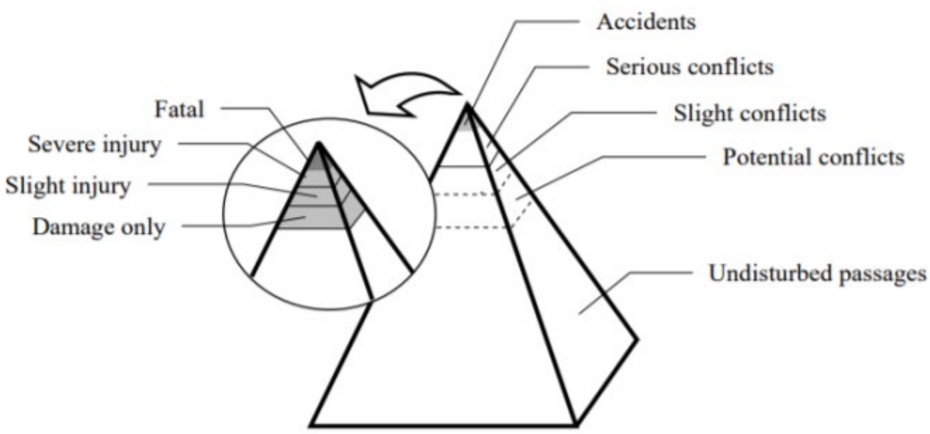


Figure 4.1 Hyden's safety pyramid according to the Traffic Conflict Technique (Hyden, 1987)

One dimension of severity is the proximity to a crash and the other refers to the potential consequences in case a crash had occurred. The Swedish Traffic Conflict Technique (TCT) assumes that near-crashes or traffic conflicts share the same underlying causes and therefore, they can act as a tool to evaluate and reduce hazardous situations. By observing near-crashes that take place in a greater frequency than crashes, one can assess traffic safety within a shorter period of time. However, according to Shinar (1984) the usefulness of TCT as a surrogate measure has been validated through studies that provide mixed results. For instance, Williams (1981) concluded in his review that TCT is not as useful as a predictor of crashes as the relationship between the conflicts and the crashes is not established and the way "conflicts reflect hazard in the road system" has not been demonstrated. On the other hand, there are researchers that argue the validity of crash data and claim that some safety indicators can better describe unsafe situations and predict crashes (Archer, 2005; Migletz, Glauz, & Bauer, 1985; Svensson, 1992).

In this context, a recent report by the InDeV (Polders & Brijs, 2018) project summarized key advantages and disadvantages involved in traffic conflict techniques. The advantages have been reported to include: collection of data over a relative short time period, more detailed information due to observing the conflicts in field than can be obtained through crash reports and aproactive approach for identifying and resolving safety issues. On the other hand, the disadvantages include: required adequacy in data collection, extensive field work and subsequent data processing involved, and difficulty in determining the relation between conflicts and crashes resulting in difficulties translating conflicts to expected number of crashes.

With technological advancements, conflict based safety evaluation can be realized through microsimulation modelling providing increased objectivity and reliability in this surrogate approach (Mahmud, Ferreira, Hoque, & Tavassoli, 2019). In 2003, the Federal Highway Administration (FHWA) released a report called 'Surrogate Safety Measures from Traffic Simulation Model', which established a start of a concerted effort to extract surrogate safety measures from microsimulation models (Gettman & Head, 2003). Since then, many studies have been undertaken to evaluate the ability of microscopic traffic simulation models to obtain conflicts (Cunto, 2008; Essa, 2015; Fyfe, 2016; Gettman & Head, 2003). In our study, a software application called Surrogate Safety Assessment Model (SSAM) is utilized to detect traffic conflicts employing safety indicators such as Time to Collision (TTC), Post-Encroachment Time (PET), Deceleration Rate (DR), Maximum of the speeds of the two vehicles (MaxS) and Maximum relative speed (DeltaS). The details of using the Surrogate Safety Assessment Model (SSAM) in this project are presented in section 4.1.2.

The whole approach of micro-simulation and safety assessment, however, is an accumulation of assumptions made about different influencing factors. Microsimulation is not meant to provide an absolutely faithful representation of reality, and it is not used towards that purpose. Rather, microsimulation is mostly used to compare different situations with each other, e.g. comparing an existing situation with a few alternative new situations. In that case situations are compared with the assumptions for both situations being the same. In case the assumptions have the same influence on both the existing situation and the various alternative scenarios, it is less of a problem that microsimulations do not accurately reflect the real world.

4.1.2 SSAM

Description and capabilities

The Surrogate Safety Assessment Model (SSAM) is a software application designed to perform statistical analysis of vehicle trajectory data output from microscopic traffic simulation models. SSAM analyses interactions between vehicles and calculates several surrogate safety measures for each interaction in order to identify conflict events. The software provides a number of surrogate safety measures for each conflict that is detected in the trajectory data and then generates summaries (mean, max, etc.) of each surrogate measure. SSAM calculates several surrogate safety measures calculated by SSAM for each conflict event, such as the following:

- Minimum time-to-collision (TTC).
- Minimum post-encroachment time (PET).
- Initial deceleration rate (DR).
- Maximum deceleration rate (MaxD).
- Maximum speed (MaxS).
- Maximum speed differential (DeltaS).
- Classification as lane-change, rear-end, or path-crossing event type.
- Vehicle velocity change had the event proceeded to a crash (DeltaV).

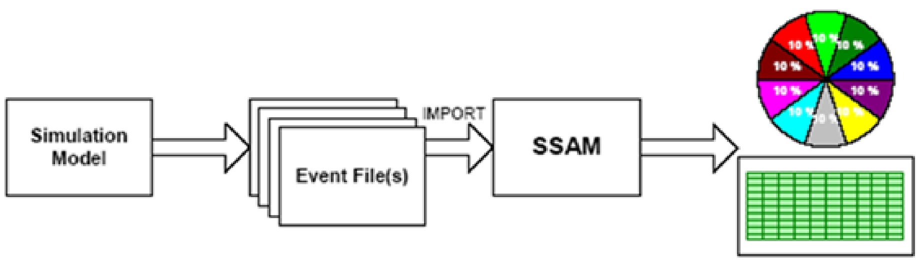


Figure 4.2 SSAM operational concept (Gettman et al., 2008)

In SSAM, conflicts are identified based on the specific thresholds for TTC and PET and the conflict angle. The default value for TTC and PET are 1.5 seconds and 5.0 seconds respectively, which are suggested by previous research studies (Gettman & Head, 2003; Gettman et al., 2008). The conflict severity is defined according to the TTC values, low values of TTC and PET indicate high severity levels of expected crashes (Habtemichael and Santos, 2014), and the lower the TTC value, the more severe the conflict. If TTC=0 and/or PET=0, then SSAM marks the event as a crash; if 0<TTC≤1.5s, and 0<PET⩽5s, then SSAM identifies this event as a conflict.

Based on the conflict angle, conflicts are classified into four maneuver types: rear-end, lane-change, crossing conflicts and unclassified. It should be noted that the threshold values of TTC, PET and conflict angles for different conflict types have been calibrated by the United States Federal Highway Administration (FHWA) (Gettman et al., 2008). Moreover, the location of the conflicts in terms of the link and the lane where they occurred are provided by the SSAM software.

Within the LEVITATE project, SSAM identifies conflicts between Human-driven Vehicles (HV), between CAVs or between CAVs and human-driven vehicles (HVs). The conflict type is available and defined by the conflict angle that can be adjusted in the software. It should be mentioned that TTC values equal to zero should be removed from the relevant datasets for more robust results. This is because they are considered as simulation errors and therefore invalid events.

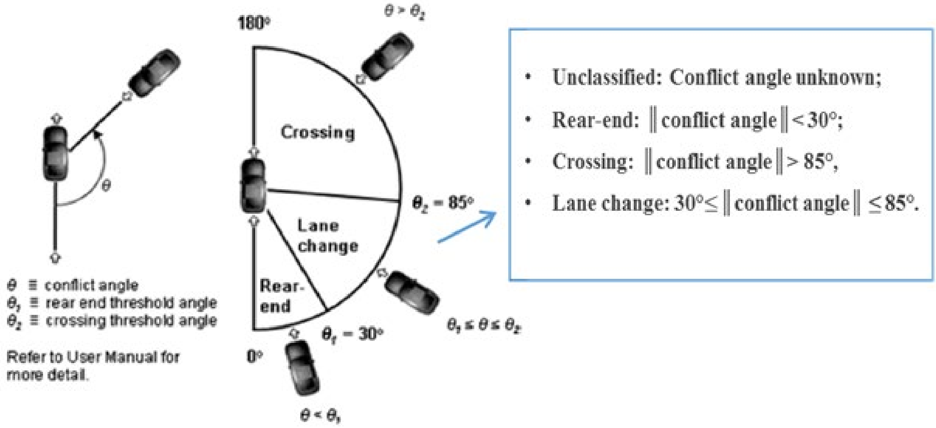


Figure 4.3 Conflicts types by angle (Pu and Joshi, 2008)

TTC and PET thresholds for conflict identification can be set according to the conditions. In the literature, a TTC value of less than 1.5s for human driven vehicles denotes a hazardous situation, while this threshold decreases to 1s or 0.75 for CAVs (Morando et al., 2018; Sinha, Chand, Wijayaratna, Virdi, & Dixit, 2020; Virdi, Grzybowska, Waller, & Dixit, 2019). Respectively a PET threshold of 5s is usually used for identification of dangerous conditions (Morando et al., 2018; Morando, Truong, & Vu, 2017). There is also a study by Ukkusuri, Sagir, Mahajan, Bowman, and Sharma (2019) that assigns different TTC thresholds by levels of autonomy, where threshold used for SAE level 5 is 0.6s.

<u>Limitations and required assumptions</u>

In spite of the fact that SSAM is a very useful tool, there are limitations that should be taken into account regarding the road safety assessment. These limitations have led to relevant assumptions in the frame of LEVITATE project approach, which are explained in the subsequent paragraphs.

Within LEVITATE, CAV deployment scenarios are investigated, in other words, how the increasing CAV penetration rate affects the society with respect to traffic safety. In this context, it is possible to have interactions between HVs, between CAVs and between HVs and CAVs. TTC thresholds should be different in different interactions, but as this is a not easy endeavour, the following assumption was made based on the literature (Morando et al., 2018; Sinha et al., 2020; Virdi et al., 2019):

TTC thresholds were set for the following/second vehicle and were set to 1.5s for HVs, 1.0s for Cautious CAVs and 0.5s for Aggressive CAVs.

It is important to note that some controversies still remain regarding using simulated conflicts for safety assessment. One of the major concerns is that the vehicle trajectory files generated by microsimulation models cannot reflect complicated drivers' behaviour in the real world (Huang, Liu, Yu, & Wang, 2013).

A recent review by Wang et al. (2021) on surrogate safety measures and their applicability in safety performance evaluation of CAVs highlighted that even though most of the previous CAV safety studies assume the conventional surrogate safety measures to be reasonable and transferable to the traffic environment with CAVs, the validation of surrogate safety measures has to be examined and compared when field data become available. The authors further emphasized the need of exclusive surrogate safety measures for CAVs, based on real data or driving simulator studies, particularly due to differences in characteristics and behaviors between HDVs and CAVs (with different levels of automation/connectivity).

Another limitation of SSAM is that only conflicts between vehicles can be detected, and not those involving pedestrians or cyclists. The vulnerable road users' safety is an extremely significant parameter for the introduction of CAVs, their public acceptance and the societal impacts that they are assumed to offer. As SSAM does not take into account VRUs, their safety will be investigated in an alternative way within LEVITATE. Details can be found in Section 4.2.

4.1.3 Converting the number of conflicts to the number of crashes

Despite conflicts as a surrogate safety measure having a number of practical advantages from a research standpoint, in order to draw conclusions about the resulting traffic safety implications it is nevertheless of interest to link conflicts to crash rates. Within LEVITATE, we are thus interested in road safety impacts in terms of crashes or crash rates and not directly in terms of conflicts. Therefore, it was decided to convert the number of conflicts to numbers of crashes. In the literature, this is done both empirically based on crash data or with theoretical, probabilistic models of the relationship between conflicts and crashes. An empirical relationship between crashes and conflicts based on the crash-conflict ratio was proposed by previous studies (Hauer, 1982; Hydén, 1987; Migletz et al., 1985) based on the observed number of crashes and conflicts. Past studies on the crash-conflict relationship estimated the association between the crash and conflict counts with a simple ratio of crashes to conflicts or with more elaborated regression techniques, often confirming a relationship but limited by the availability and generalizability of empirical data.

However, due to the unavailability of suitable crash data for future scenarios involving highly-automated vehicles, it is not possible to calibrate an empirical model using observed data. Therefore, in translating conflict output from SSAM to crash predictions, a theoretical model is of particular interest due to its generalizability (e.g., not specific to one location) and the absence of scenario-specific crash data. The method proposed by Tarko (2018b, 2020) instead considers a crash as one potential outcome of an observable conflict, such that the probability of collision depends on the time to collision (TTC) between vehicles involved in a conflict. This method thus relies on TTC distributions and does not require crash data in order to estimate the expected number of crashes. In the method of Tarko (2018b), a crash is avoided if the evasive manoeuvre necessary to avoid collision is predicted to be performed quickly enough. The response delay of the evasive manoeuvre is shown to follow a Lomax distribution in initial validation efforts (Tarko, 2021; Tarko, 2020; Tarko & Lizarazo, 2021). In this way, a Lomax distribution can be used to estimate the probability of crashes based on claimed traffic conflicts during the traffic conflicts observation period. The Lomax distributions used in the Tarko (2018b) method are based on the properties of the traffic conflict phenomenon.

Mathematically, the Lomax distribution of exceedance x for the value of k (corresponding to traffic conflict) can be expressed by the following equation:

$$F(x) = \begin{cases} 1-(1+\theta x)^{-k} \; if \; \theta > 0 \\ 1-e^{-rx} \; if \; \theta = 0 \end{cases}$$

Where, r=response rate (1/unit separation), k and θ are the shape and scale parameter of the distribution, respectively.

Relationship between average response rate r, k, and θ can be expressed as r = kθ *("at the limit where θ reaches 0 while k reaches infinity)"*.

Exceedance x, used as response delay, is measured as the difference between threshold separation s_c (such as TTC) and observed smallest separation (s_m) i.e. $x=s_c-s_m$

Exceedance x has the mean value and variance for only certain ranges of k. The k can be obtained from the following equation:

$$\hat{k} = \frac{-\sum_{i=1}^{n} log\left(1-\frac{i-0.5}{n}\right) log(1+\frac{x_i}{s_c})}{\sum_{i=1}^{n}[log(1+x_i/s_c)]^2}$$

Where, s_c=threshold separation, x_i = ith exceedance ordered from the lowest value x_1 to the largest value x_n.

To estimate the expected number of crashes during the observation period (Q_C), following formulation is used.

$Q_C = Q_N \cdot P\,(C\ N) = n \cdot 2^{-K}$,

$\hat{k}$ from the above equation, and Q_N = n is the number of observed traffic conflicts and crashes during the observation period. More details of Andrew Tarko's method can be found in Tarko (2018b). In initial validation efforts conducted by the author (Tarko, 2021; Tarko, 2020; Tarko & Lizarazo, 2021), the response delay of the evasive manoeuvre is shown to follow a Lomax distribution.

Due to the adequacy of the proposed method by Tarko (2018b) to estimate the probability of crashes from identified conflicts, this approach was selected for translating number of conflicts to number of crashes.

4.2 Impacts related to vulnerable road users

The topic of vulnerable road users' safety is crucial to the assumed benefits of automated vehicles, with safety as one of the main arguments for their adoption. However, the interactions of automated vehicles with other road users are complex and require carefully chosen safeguards, in order not to endanger vulnerable road users, for whom the collision with an automated vehicle would be even more dangerous than in car to car collisions.

Unmotorized vulnerable road users (VRUs), in this context referring to pedestrians and cyclists, are not included in the microsimulation models that are used in Levitate to forecast the impacts of CAVs. As VRUs are very relevant for road safety, we tried to include VRUs in another way when estimating road safety impacts. With regards to the aims and needs of the Levitate project, we decided to estimate the impact of automated vehicles on vulnerable road users by means of crash statistics, based on data from Austria and Vienna in particular.

4.2.1 Approach

Our approach is built upon 2 fundamental assumptions:

1. Based on an analysis of current crash causes, we can make a projection of which causes of crashes between cars and vulnerable road users could be mitigated by CAVs and which not. An important limitation of this approach is that the statistics of initially assumed crash causes are hard to validate and the final determined causes may not always be recorded or publicly available. Moreover, it could be debated which causes of crashes can be prevented by perfectly functioning CAVs and which groups of crashes cannot.
2. For the crashes in which cyclists or pedestrians are at fault, we still assume a potential reduction of crash severity, based on the reaction time of an automated vehicle, compared to the reaction time of a human driver. The reaction time and braking capabilities have been defined for the microsimulations already. We add a means to estimate the effects of these capabilities on collisions with VRUs below, based on braking distance formulae.

The second assumption is based on a formula of braking distance:

$$\mathrm{d} = v\ RT + \frac{v^2}{2a}$$

Here d is the braking distance, v is the driven speed, RT is the reaction time and a is the maximum deceleration. We used the maximum deceleration in this case, to represent a best case braking effort.

This formula above is utilized to, given RT (human reaction time and CAV reaction time), v (the actual driving speed of a human and a CAV vehicle) and decelerations a (for human driving vehicles and CAVs) calculate an "equivalent speed" that reflects how much more efficient a vehicle driven by a system with lower reaction time can perform a braking manoeuvre. We achieve this by asking what the driving speed of a human would have to be, to achieve the same braking distance as an AV driving at speed v:

$$v_{Human}\ RT_{AV} + \frac{v_{Human}^2}{2a_{AV}} = v_{AV} RT_{Human} + \frac{v_{AV}^2}{2a_{Human}}$$

Here RT_{human} is the old reaction time (human reaction time), RT_{AV} is the new reaction time (AV reaction time), v_{human} is (crucially) the physically driven speed **of both vehicles**, a_{human} is the human capacity to decelerate, a_{AV} is the AV's capacity to decelerate and v_{AV} is the "equivalent speed" that a human would have to drive in order to have the same braking distance as the CAV. This lower speed estimates the AVs capabilities for faster braking (i.e., an AV *driving at* v_{Human} can brake at least as efficiently as a human driving at the speed v_{AV}, but having reaction time RT_{human}). The formula assumes $RT_{human}>RT_{AV}$.

As a source for the to-be-assumed reaction times, we use the values implemented in the AIMSUN simulation models, employed for the microsimulation studies described above. The reaction times and maximum decelerations are shown in Table 4.1.

Table 4.1: max deceleration and reaction time values for different types of vehicles used in simulation.

	Max Deceleration	Reaction time
Human	5 m/s^2	1.5 s
1st Generation AV	7 m/s^2	1.0 s
2nd Generation AV	9 m/s^2	0.5 s

The reasoning for our estimate is, that a CAV with superior braking capabilities (higher deceleration) and better reaction times can brake at least as well for a suddenly appearing VRU as a human driver driving at a lower speed. In other words, the AV driving at the higher v_{human} can brake as well as a human driving who would have to drive at the lower v_{AV}.

Combined with a mapping of the relation between physically driven speed v_{human} and equivalent braking speed v_{AV} (when comparing superior reaction time and maximum deceleration to a human), an estimate of the reduction in crash numbers and fatalities can be derived. Several formulae connecting driven speed and crash numbers and crash severity exist for human drivers. We chose an approach from the literature that is based directly on driven speeds (for humans) and provides special cases for estimating how crash numbers and crashes of diverse severity types change, if the driven speed is changed, which allows us to directly use our "speed equivalency" outlined above: A relation between driven speeds and number of crashes known as the "power model" due to the exponential form of the relationship has been proposed in several works (for instance Elvik, Christensen et al, 2004, Cameron & Elvik, 2010). This model stipulates that the number of crashes in a traffic system will change approximately according to:

$$N_{new} = N_{old} * \left(\frac{v_{new}}{v_{old}}\right)^{model\_exponent}$$

Where N_{new} is the resulting number of crashes and N_{old} is the previous number of crashes (before v_{old} was replaced by v_{new}). The model exponent can be adjusted to the precise type of crashes and road (urban/rural, fatalities, injury crashes, serious injury).

As mentioned in the beginning of this section, some crashes might be prevented by CAVs. The share of crashes that might be prevented is estimated using crash statistics that provide information on the causes of crashes, such as the Viennese crash data that is available from the public statistics organisation Statistik Austria. Using the 2016 Vienna crash data, which contains an indicator on whether a road user was suspected to be "primarily at fault", the respective numbers for this in Vienna 2016 are 20% for pedestrians and 18% for cyclists. Other cities and countries provide different levels of pedestrian and cyclist at fault crashes, for instance:

- Hungary: Pedestrians at Fault 33%, Cyclists at Fault 30%, see Glász and Juhász (2017)
- Vienna: Pedestrians at Fault 20%, Cyclists at Fault 18%, see Statistik Austria 2016
- San Francisco: Pedestrian at Fault 30%, Cyclist at Fault 44%, see Salon and McIntyre (2018)
- Hawaii: Pedestrians at Fault 7%, see Kim, Brunner, and Yamashita (2008)
- North Carolina: Pedestrians at Fault 59%, see Ulfarsson, Kim, and Booth (2010)
- Israel: Pedestrians at Fault in car-pedestrian crashes on "urban roads" 30%, see Gitelman, Balasha, Carmel, Hendel, and Pesahov (2012)

If we assume that all crashes in which the motorized vehicle is registered to be 'at fault' and none of the crashes in which the pedestrian/cyclist is registered to be 'at fault' can be prevented by perfectly functioning CAVs, these data can be used to estimate the percentage of crashes that can be prevented by CAVs.

The numbers presented above are based on published studies or crash data and demonstrate substantial differences in the percentage of at-fault VRUs. A possible approach to increase transferability of impacts of CAVs on VRU crash numbers might be to use some cities/countries as reference cases that a user selects. Unless specified otherwise, we will assume a default level of 30% for pedestrians and cyclists at fault, since this would appear to be a common, not overly optimistic or pessimistic, value within the observed range. We will provide the user with the opportunity to change the value.

If 30% of VRUs were at fault (and hence potentially unmitigated by CAVs) in car-pedestrian crashes, with humans driving an assumed speed of v_{old} and CAVs being able to react like a human driving at speed v_{new}, then we can apply the above formulae to generate a first impact estimate/dose response curve. The discussion in Cameron and Elvik (2010), suggests an exponent to be used for the effect of speed on the number of injury crashes would be 2.0, giving us (for the remaining share of injury crashes) a final estimation formula of the form:

$$prop_{new} = 0.7 * prop_{human} + 0.3 * (prop_{human} + prop_{1stGen} * \left(\frac{v_{1stGen}}{v_{Human}}\right)^2 + prop_{2ndGen} * \left(\frac{v_{2ndGen}}{v_{Human}}\right)^2)$$

In this formula $prop_{new}$ denotes the remaining share of crashes, while $prop_{human}$ denotes the share of human driven vehicles, $prop_{1stGen}$ denotes the current penetration rate (between 0 and 1) of 1st generation AVs and $prop_{2ndGen}$ denotes the penetration rate (between 0 and 1) of 2nd generation AVs. Naturally, the sum of these three rates equals 100% at all times. An estimate of resulting crash numbers N_{est} can then be obtained by multiplying this formula with a starting number of crashes $N_{initial}$, resulting in $N_{est} = prop_{new} * N_{initial}$.

Accounting for the additional effect of the power model, we obtain the following dose-response curve (for an assumed driven speed of 40 km/h, a human reaction time of 1.5 seconds and new reactions times of 1 second and 0.5 seconds for 1st and 2nd generation AVs).

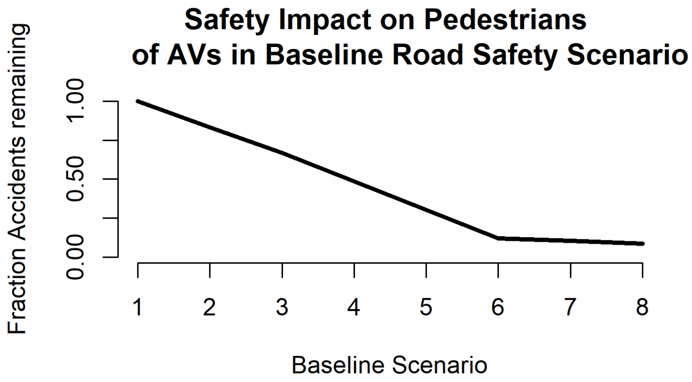


Figure 4.4: Changes in the proportion of crashes remaining according the VRU impact model of CAVs based on the penetration levels suggested by the LEVITATE baseline scenario (see table below).

Baseline Step	1	2	3	4	5	6	7	8
Human	100%	80%	60%	40%	20%	0%	0%	0%
1st Gen AV	0%	20%	40%	40%	40%	40%	20%	0%
2nd Gen AV	0%	0%	0%	20%	40%	60%	80%	100%

Table 4.2: Changes in penetration level of the different generation CAVs according to the baseline scenario steps in LEVITATE.

4.2.2 Required assumptions

- Automated vehicles function perfectly in their intended domain (sensor failure, control algorithm failure and use restrictions (weather, light) are separate discussion points).
- All crashes for which the motorized vehicle is registered to be ‘at fault’ can be prevented in case of perfectly functioning CAVs whereas none of the crashes for which the pedestrian or cyclist is registered to be ‘at fault’ can be prevented.
- Changes in the amount of kms traveled with different transport modes are not taken into account in this estimation. These impacts are further discussed in Section 4.3.

4.3 Secondary impacts

The secondary impacts of CAVs on safety result from, for example, changes in mobility and driving behavior of human drivers when surrounded by AVs. To more accurately present the safety effect it is important to include these secondary impacts.

By combining the output of the microsimulations with impacts on kilometers driven with different transport modes that are estimated in another part of the LEVITATE project, it is possible to estimate the impact of changes in kilometers driven with different transport modes on road safety. Other secondary impacts cannot be quantified, due to a lack of information.

4.3.1 Required assumptions

Similar to the primary impacts, in order to quantify the effects of indirect impacts on road safety within LEVITATE some assumptions have been made:

- The impact calculations use crash risks based on the previously described methods of microsimulation and the VRU approach. This is done for the different modes of transport (Human driver, first generation AV, second generation AV, VRUs).
- Impacts of modal split change are limited to human driven cars, CAVs, VRUs and buses/automated shuttles. Changes in travel by powered two wheelers and other modes of transport are not included in this analysis because they are not included in the modal split analyses that are carried out within Levitate.

Within the PST the user is able to supply starting values for the current modal split to better approach the area and scenario they wish to consider. Initial values are available that are applied when no knowledge of suitable starting values is available. For values about the future modal split the data obtained by the system dynamics group is used.

4.3.2 Safety impacts of modal split changes

As risk rates (casualties per km traveled) differ between different transport modes, changes in modal split affect the total number of crashes. The introduction and increasing market penetration of CAVs is likely to influence modal split and thus have an indirect impact on road safety as well.

Changes in modal split are estimated using System Dynamics and mesoscopic simulation and are discussed in more detail in Roussou, Müller, et al. (2021), and Sha et al. (2021). The estimated impacts on modal split are applied in this report to estimate the indirect road safety impacts related to the estimated changes in modal split.

A complicating factor is that not only the modal split is affected by increasing penetration levels of CAVs, but also the risk rates of the various transport modes. These impacts therefore have to be considered simultaneously. Multiplying the change in risk rate of a certain mode of transport by its change in share of the modal split gives an estimate of the change in the expected number of crashes. When this is done for all modes of transport a new total impact on the number of crashes can be determined. We distinguish five different modes of transport within this approach: Human driven cars, first and second generation CAVs, VRUs, and other vehicles which describe buses and public transport.

A two-step approach is taken which consists of a VRU specific determination which is then combined with a step determining the motorized transport impacts.

Modal split impacts formula:

$$Number\ of\ victims\ (VRU) = V_h \times V_v \times R_{hv} + V_a \times V_v \times R_{av} + V_v \times V_v \times R_{vv} + V_o \times V_v \times R_{ov}$$

$$Number\ of\ victims\ (total) = V_h \times R_h + V_a \times R_a + V_o \times R_o + Number\ of\ victims\ (VRU)$$

Descriptions of the variables are given in table 4.3.

Transport mode	Transport volume	Risk for user	Risk for VRU
Human driven car	V_h	R_h	R_{hv}
CAV	V_a	R_a	R_{av}
VRU	V_v	R_v	R_{vv}
Other transport	V_o	R_o	R_{ov}

Table 4.3: Description of symbols used in modal split impacts formula

Using this equation, it is assumed that a doubling of CAVs will yield in a doubling of the CAV transport volume (V_a).
As a result of using this equation, it is assumed that doubling the traffic volume of CAVs will double the component $V_a \times V_v \times R_{av}$ so this will not result in double the number of total victims unless the other contributions become zero. An increase in traffic volume (a positive value of dV_a) of CAVs will result in an increase of $dV_a \times V_v \times R_{av}$ victims. If the increase of dV_a is the result of a change in modal split it may reflect a similar *decrease* of traffic volume (a negative value of dV_h) of conventional cars due to human driven cars being traded in for CAVs, resulting in:

$$dV_a \times V_v \times R_{av} - dV_h \times V_v \times R_{hv}$$

Thus, depending on whether the risk of CAVs is lower than that of human driven vehicles $R_{av} < R_{hv}$ this could yield a reduction in the number of victims. The equation also allows calculations concerning the effect of traffic volume and different vehicle types.

The changes in transport volume for the different transport modes are estimated using system dynamics and mesoscopic simulation as mentioned earlier. The risks for the different modes are a result of the microsimulation and vulnerable road user methods described earlier in chapter 4.1 and 4.2. Based on the expected changes in risk and changes in exposure of the different transport modes, the expected change in the number of crashes (% decrease or increase) can be calculated using the formulas discussed above. This calculation can be made for different penetration levels of CAVs and for different interventions/Sub-use cases. In order to translate the relative number of crashes to an actual number, it is necessary that a starting value is supplied for the number of crashes of the different modes. Because the formula utilizes relative changes it is independent of starting traffic volume and risks. These starting values can vary significantly between different countries.

4.4 Results: quantified impacts for increasing penetration levels of CAVs

Quantified impacts concern comparisons between the baseline scenario where traffic comprises only human-driven vehicles, and CAVs market penetration rate (MPR) ranging from 0% to 100%. No Sub-use case (or intervention) specific effects are discussed here, those are presented in Deliverables 5.4 (Roussou et al., 2021), 6.4 (Chaudhry et al., 2021) and 7.4 (Hu et al., 2021).

4.4.1 Impacts quantified using microsimulation

The safety assessment approach using micro-simulation technique and Surrogate Safety Assessment Model (SSAM), as explained under Section 4.1, was tested on three calibrated and validated networks, being Manchester (UK), Leicester (UK), and the city of Athens (GR). In general, the model development and calibration involved details of the road network in the study area, peak hour traffic demand, vehicle types, signal timing data, vehicular behaviour and lane usage, journey times, bus routes, stations, and timetable information. A comprehensive set of traffic counts was used to compare and validate the modelled flows with observed traffic counts. Modelled journey times were also compared and validated against observed journey times during the peak hours.

Two types of CAVs were considered in this study: 1st Generation CAVs and 2nd Generation CAVs. Both types are assumed to be fully automated vehicles with level 5 automation. The main idea behind modelling these two types is based on the assumption that technology will advance with time. Therefore, 2nd Gen CAVs will have improved sensing and cognitive capabilities, decision making, driver characteristics, and anticipation of incidents etc. The two main driving profiles of CAVs are presented below (also see Table 4.1):

- 1st Generation: limited sensing and cognitive ability, long gaps, early anticipation of lane changes than human-driven vehicles and longer time in give way situations.
- 2nd Generation: advanced sensing and cognitive ability, data fusion usage, confident in taking decisions, small gaps, early anticipation of lane changes than human-driven vehicles and less time in give way situations.

Key parameters for human-driven vehicles (HDVs), 1st Generation CAVs and 2nd Generation CAVs were adjusted for defining the vehicular behaviours. These included time gap, acceleration and deceleration characteristics, over-taking behaviour and lane changing behaviour, give way behaviour at unsignalized intersection, behaviour approaching a signalized intersection and several others. The parametric assumptions and values on the key variables were based on findings of a comprehensive review of literature on modelling CAVs behaviours. The details on each variable assumptions as well as the references can be found in Levitate CAV behavioural modelling guide (Chaudhry et al., 2022).

The networks' characteristics are presented in Figure 4.5. Traffic was simulated for the peak hours of 1700 – 1800, 1200 – 1300, and 0800 – 0900 for Manchester, Leicester and Athens, respectively. In general, the three test networks reasonably represent the configuration of an urban area in the European region. However, there are differences among the networks in terms of scale, type of area, number of intersections, traffic flow, fleet composition (particularly percentage of freight and public transport vehicles), etc.

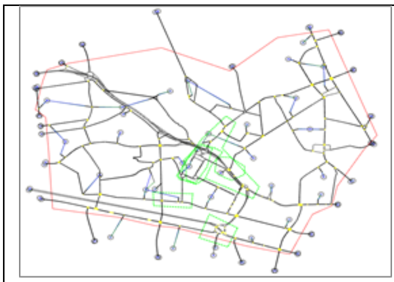
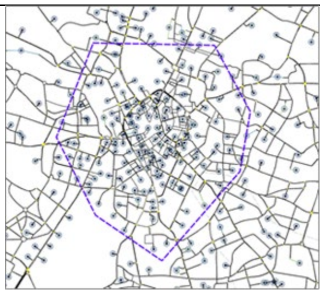
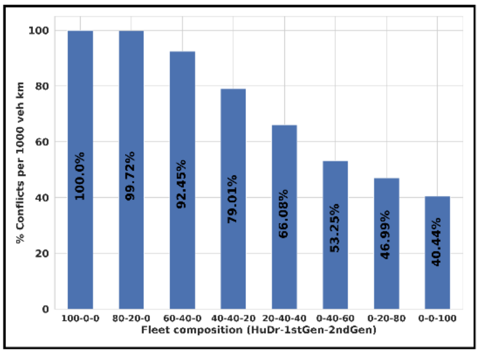
		
Manchester Area: 13km^2 Nodes: 308 Sections:732 Traffic Characteristics: • Car: 23226 trips • LGV: 1867 trips • HGV: 763 trips	Leicester Area: 10.2km^2 Nodes: 788 Sections:1988 Traffic Characteristics: • Car:23391 trips • LGV: 3141 trips • HGV:16 trips	Athens Area: 20km^2 Nodes: 1137 Sections:2580 Traffic Characteristics: • Car: 82270 trips • Truck:3110 trips

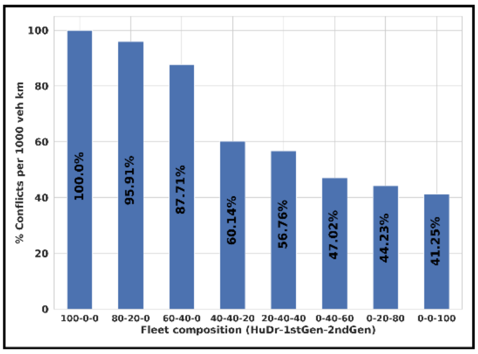
Figure 4.5. Test Networks for Microsimulation Analysis

The deployment of 1st and 2nd generation CAVs in the network was tested for different market penetration rates (MPR), from 0% to 100% in 20% increments. The fleet composition included passenger, freight, and public transport vehicles as presented in Table 1.1 under section 1.1, and automation was considered for both passenger and freight vehicles.

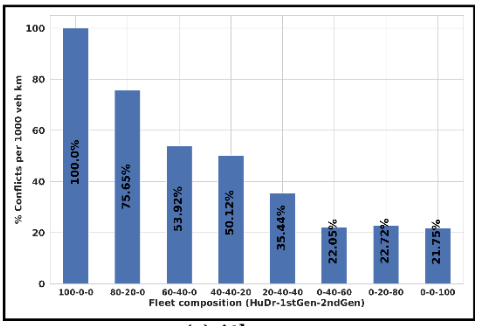
The results from the surrogate safety assessment are presented below in Figure 4.6, showing the percentage conflicts (normalized per 1000 veh-km) against varying fleet composition for the three study networks. For each scenario, 10 simulation runs were performed. The conflicts are further disaggregated by vehicle type in Figure 4.7.



(a) Manchester

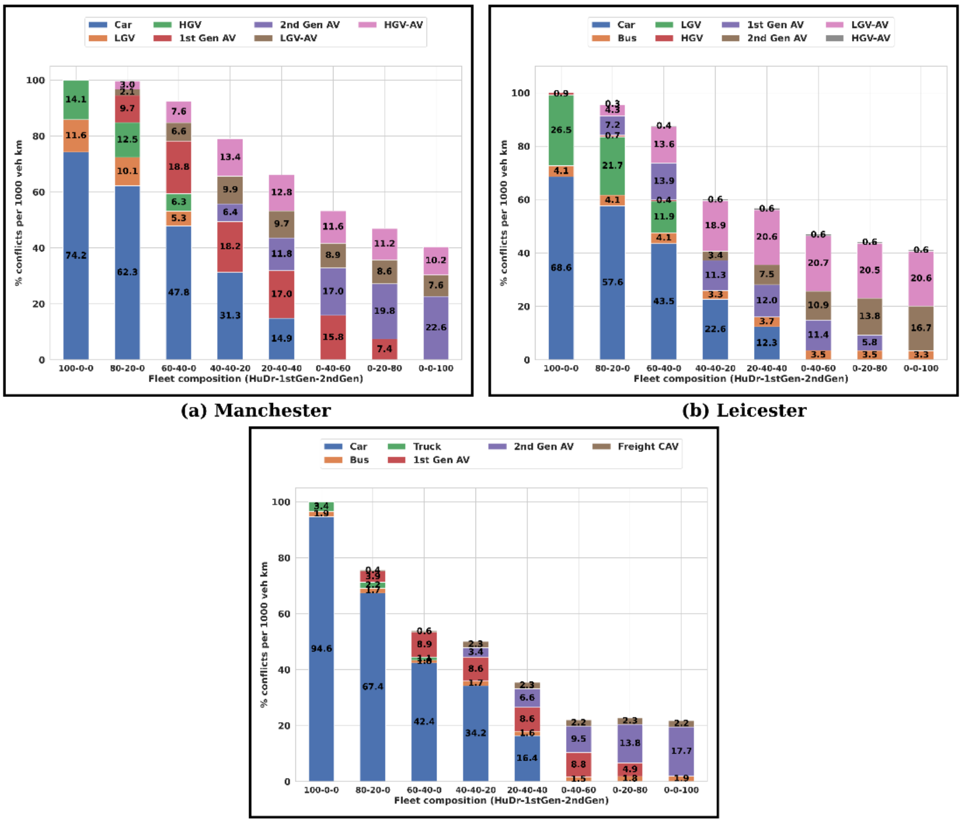


(b) Leicester



(c) Athens

Figure 4.6: Percentage change in conflicts per 1000 veh-km travelled based on varying MPR (including freight and public transport vehicles): (a) Manchester, (b) Leicester, (c) Athens



(c) Athens

Figure 4.7: Percentage change in conflicts per 1000 veh-km travelled with following vehicle type based on varying MPR (including freight and public transport vehicles): (a) Manchester, (b) Leicester, (c) Athens

Overall, in all three networks, a decreasing trend in conflicts with higher penetration rates of CAVs can be observed, which agrees with expectations based on the previous literature. However, the reduction rate varies between the networks. The variation in reduction of conflicts can be attributed to the differences in network characteristics and vehicular composition. Also, it is important to note that if we compare number of conflicts per vehicle type, CAV conflicts are less than human-driven vehicles (HDVs).

There is marginal decrease in conflicts at low MPRs which can likely be explained by the fact that due to differences in driving behaviour of CAVs, HDVs may have difficulties interacting with CAVs. Moreover, since the predominant mode is still HDV at low MPR scenarios, the interactions involving HDVs are much more than those involving only CAVs. Findings from some previous studies have rather a small increase in conflicts at low MPRs. Two microsimulation-based studies indicated that the introduction of automated vehicles/vehicles with ADAS in mixed traffic conditions may be more dangerous (Shi, Li, Cai, Zhang, & Wu, 2020), especially when the market penetration of these vehicles is lower than 40% compared to traffic flow consisting of human drivers only (Yu, Tak, Park, & Yeo, 2019). This is believed to be due to inhomogeneous traffic arising due to differences in driving behaviour. Results from initial empirical studies of CAV crashes at low penetration rates suggest a similar dynamic, with rear-end crashes where an HDV collides into a CAV accounting for a much larger share of crashes than is typical for rear-end crashes amongst HDVs alone (Favaro, 2017; Petrovic, 2020).

At full market penetration, the modelling results indicate a significant reduction in conflicts; however, the reduction is not as much as reported by other microsimulation-based studies i.e., above 80% (Papadoulis et al., 2019; Virdi et al., 2019).

Further investigation of the patterns of conflicts revealed that a considerable percentage of conflicts are caused by freight vehicles, especially in the Leicester network which has a comparatively higher percentage of freight vehicles (approximately 12% of total demand) than other networks. In the Leicester network, more than 20% of conflicts in all MPR scenarios were generated by LGVs (human-driven and/or automated), as shown by the heat maps in Figure 4.8. This finding is explainable as due to having limited knowledge on the automation of freight vehicles, they may not be realistically modelled in the test networks.

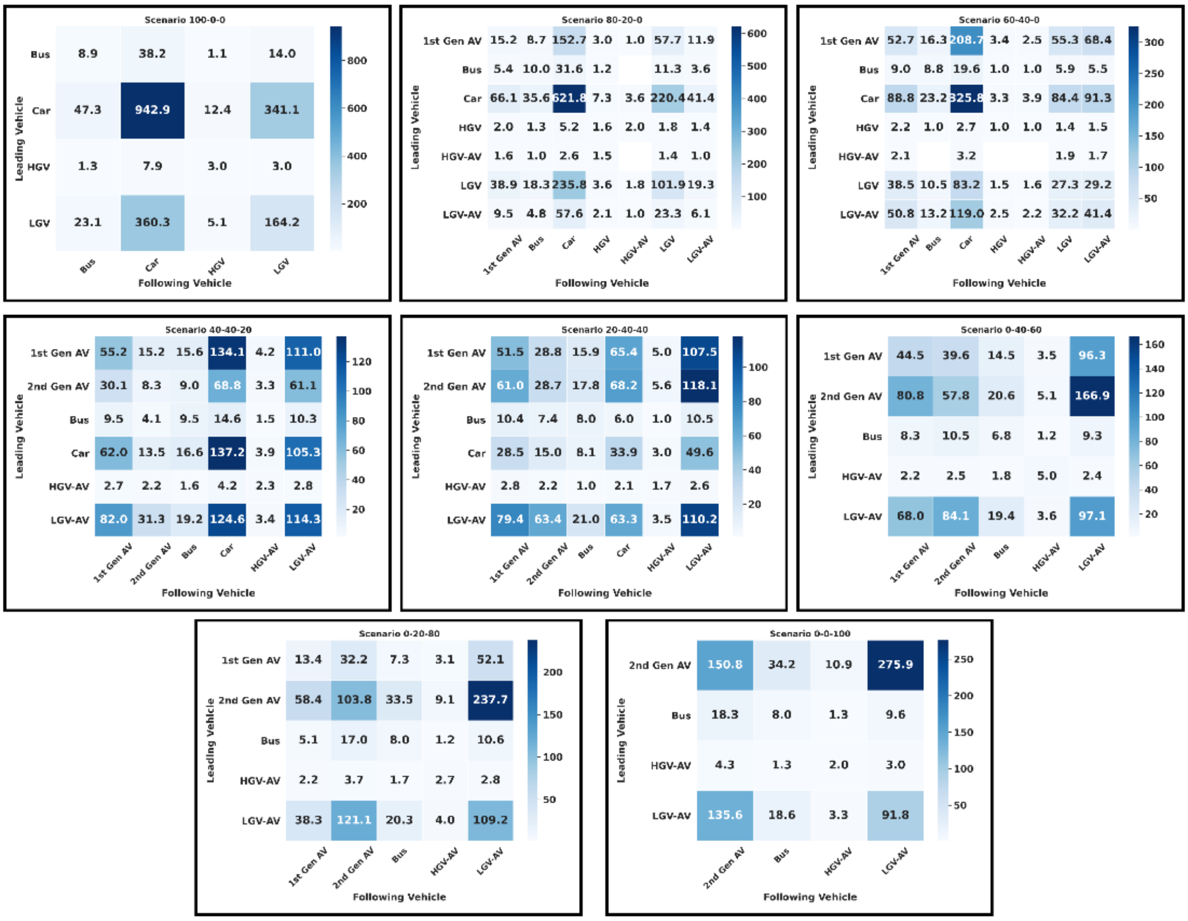


Figure 4.8. Heat Maps of Results from Leicester Network showing conflicts by leading and following vehicle type

In order to examine the trends based on only passenger vehicles which were explicitly modelled, the conflicts results were generated by removing the conflicts involving freight and public transport vehicles (Figure 4.9), which clearly show a further and more consistent reduction in the total number of conflicts. The conflicts plots per vehicle type in Figure 4.10 provide further details about the vehicle types involved. Since the results showed a large number of conflicts arising due to interactions involving freight vehicles, most probably primarily due to the lack of explicit modelling of these vehicles, a pragmatic choice was made to exclude them from further analyses.

From the plots presented in Figures 4.9 and 4.10, it can be observed that even though there is a substantial reduction after removing the freight vehicles, the percentage reduction across the scenarios and particularly at 100% MPR of CAVs is still not as expected, based on other studies (Papadoulis et al., 2019; Virdi et al., 2019), and indicates the need for further investigation.

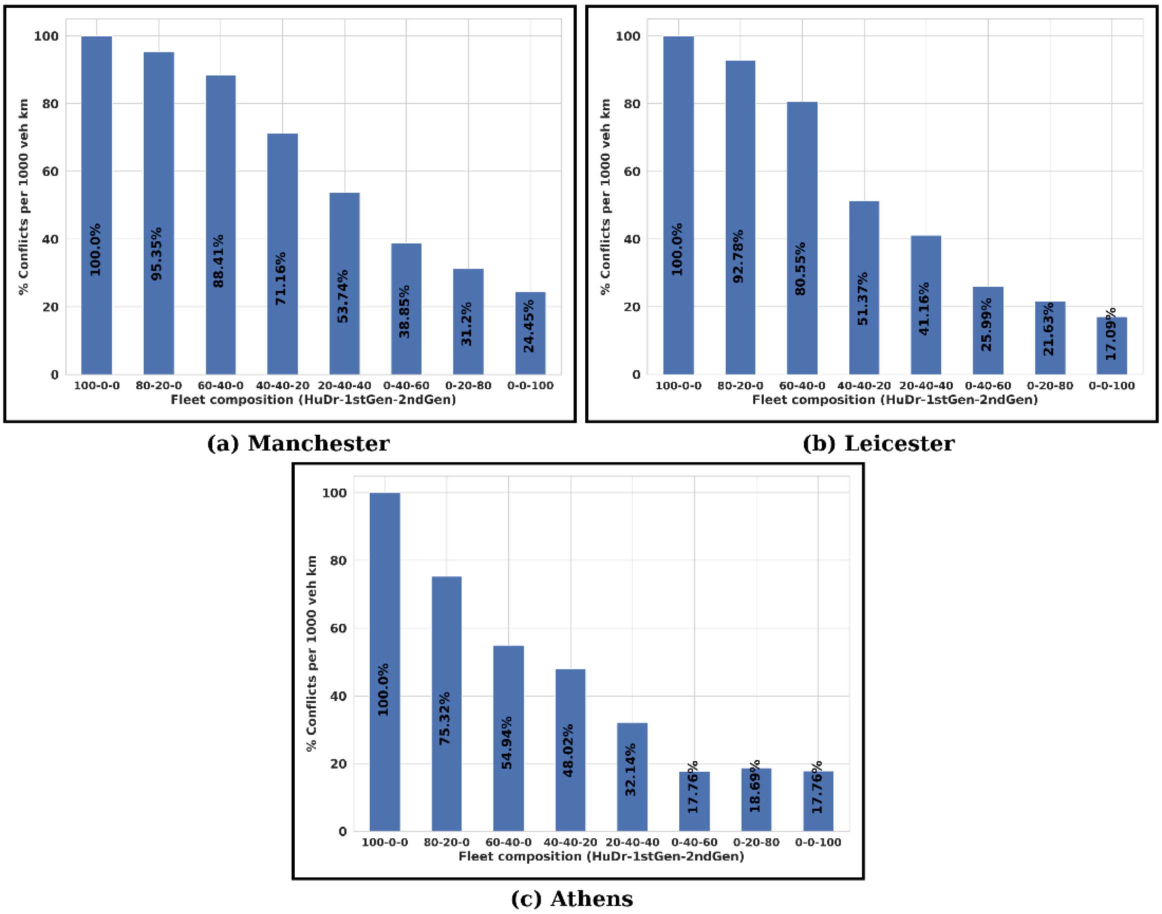
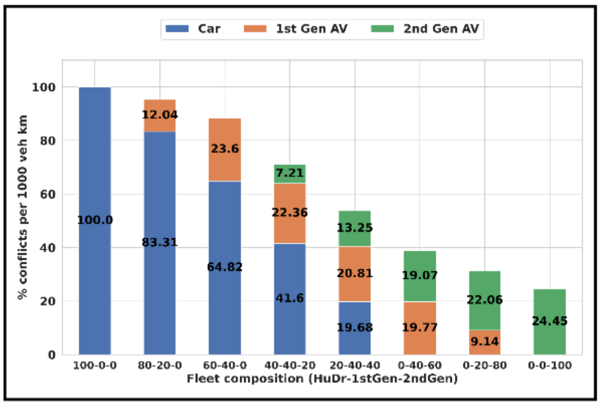
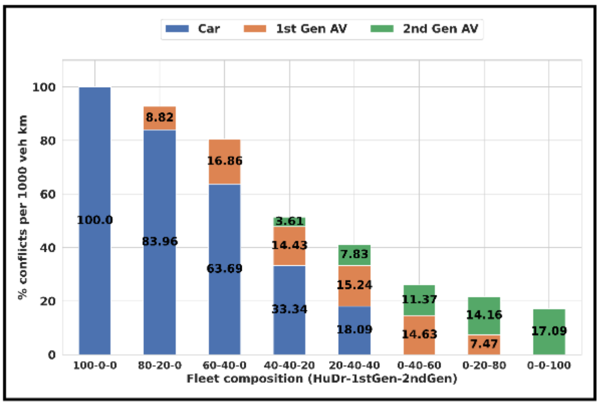


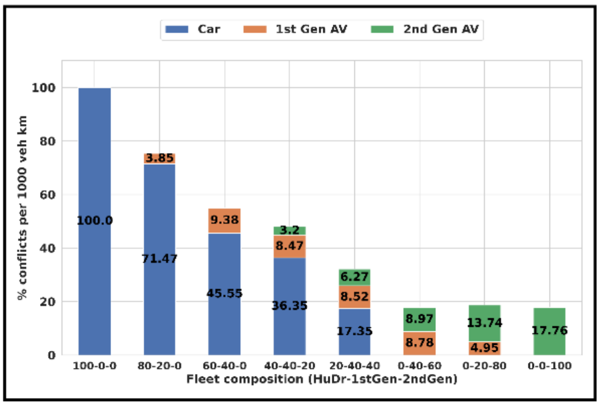
Figure 4.9: Percentage change in conflicts per 1000 veh-km travelled based on varying MPR (excluding freight and public transport vehicles): (a) Manchester, (b) Leicester, (c) Athens.



(a) Manchester



(b) Leicester



(c) Athens

Figure 4.10 Percentage change in conflicts per 1000 veh-km travelled with vehicle type based on varying MPR (excluding freight and public transport vehicles): (a) Manchester, (b) Leicester, (c) Athens.

To gain more insight into the conflict results, the distributions of TTC values for all conflict events at a given market penetration rate were examined. Figure 4.11 illustrates a series of TTC distributions for the Manchester network based on the fleet market penetration rate. The TTC thresholds below which an interaction is regarded as a conflict were set to 1.5s for human-driven vehicles, 1.0s for 1st Gen CAVs and 0.5s for 2nd Gen CAVs, as discussed in Section 4.1.2. It can be clearly observed that a significant number of events are falling at very low TTC values, i.e. at 0.1s.

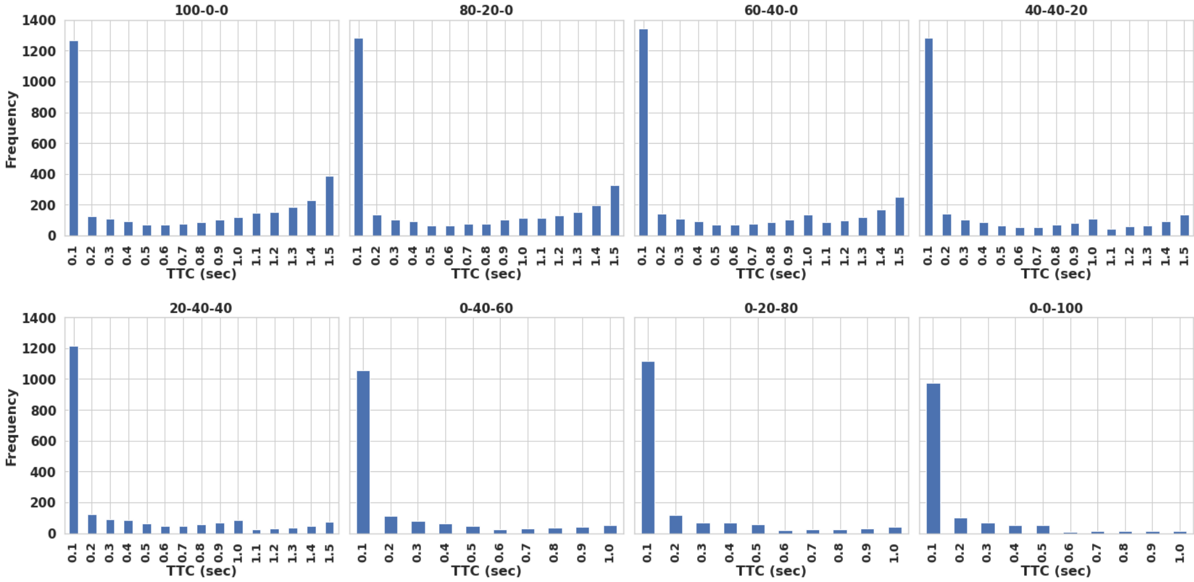


Figure 4.11: TTC distribution based on Fleet Market Penetration of CAVs

However, very low values of TTC (0.1s) represent a crash/near-crash situation, which clearly shows noise/systematic bias (could be either from Aimsun or/and SSAM) in the data as simulation models are not designed for crash events. This is also one of the limitations of traffic micro-simulation and SSAM software for estimating vehicular conflicts. As identified by Virdi et al. (2019), SSAM is likely to mark even safe interactions involving CAVs as conflicts due to having a smaller gap. Another situation identified by Virdi et al. (2019), is shown in the figure below where SSAM can potentially incorrectly assign an event as conflict. This occurs when a vehicle has initiated lane change; however, is unable to complete this manoeuvre due to a congested environment as demonstrated in Figure 4.12. Due to these reasons, it is reasonably justified to remove the noise in the conflicts data due to very low TTC values (0.1s).

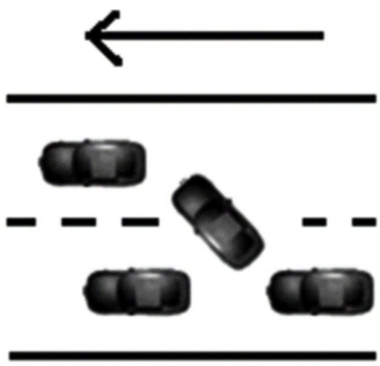
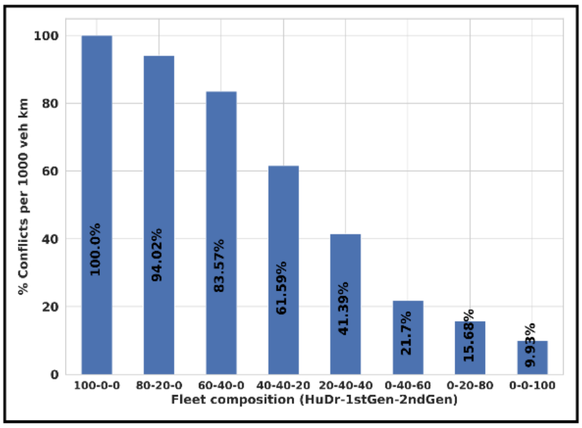
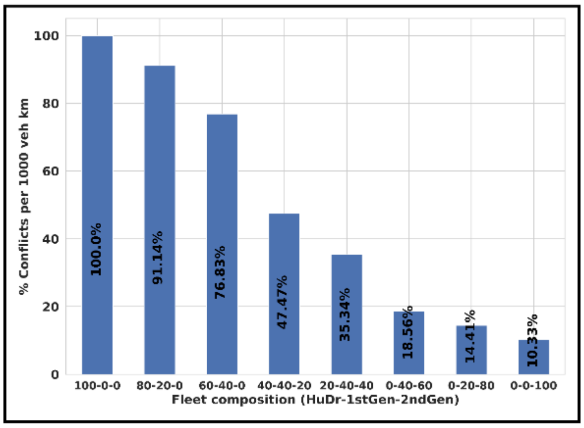


Figure 4.12: Example of an incorrectly identified conflict event in SSAM (Virdi et al, 2019)

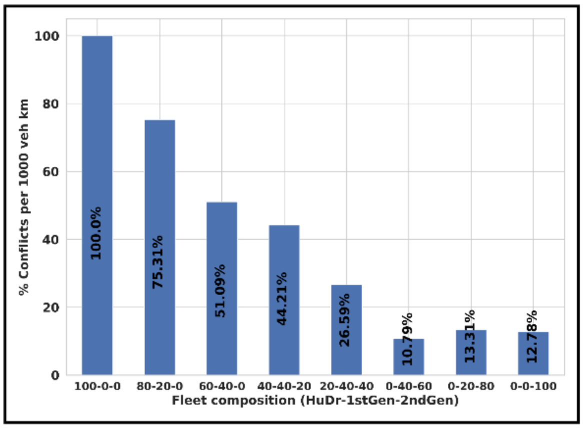
The events corresponding to TTC=0 were already removed from the plots presented earlier (Figure 4.8 – 4.12). The following plots are generated after removing TTC values of 0.1, which provide percent reduction in conflicts per 1000 veh-km.



(a) Manchester



(b) Leicester



(c) Athens

Figure 4.13. Percentage change in conflicts after removing noise in the data (0.1s TTC events): (a) Manchester, (b) Leicester, (c) Athens

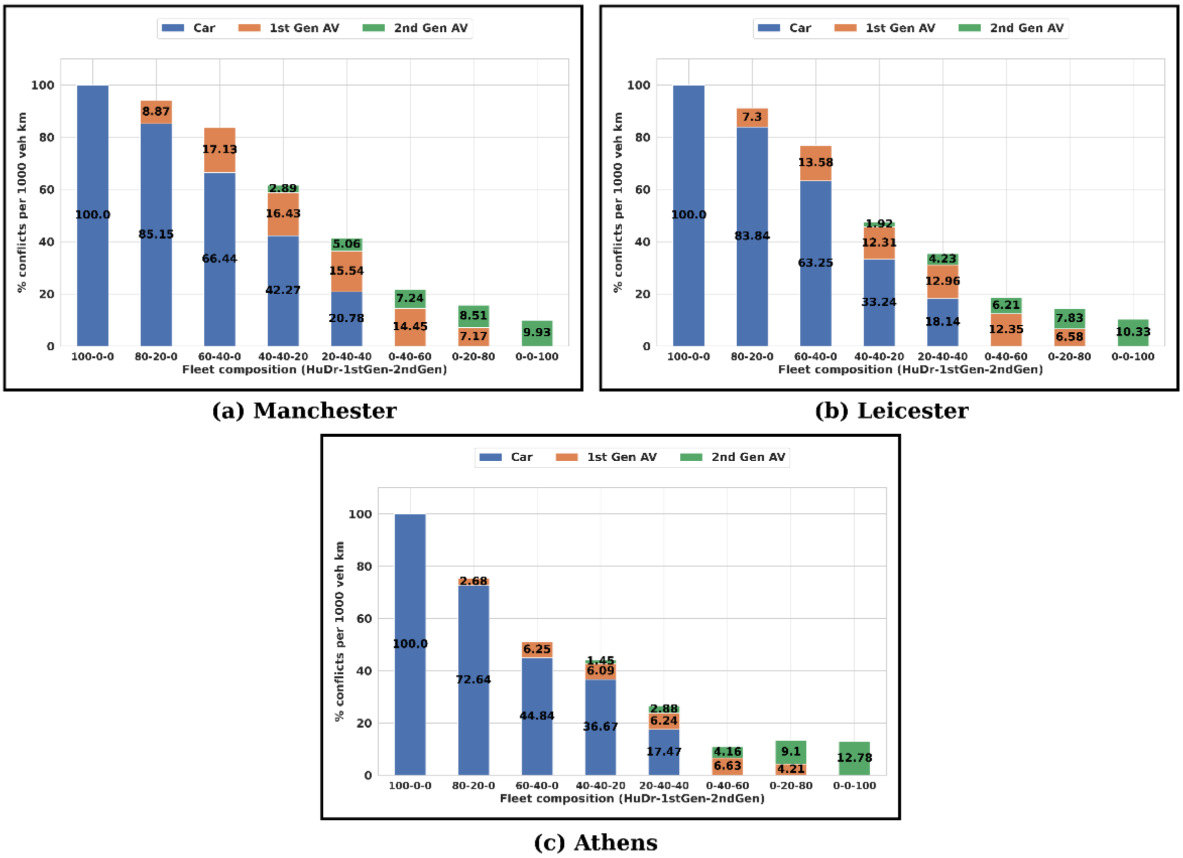


Figure 4.14. Percentage change in conflicts per vehicle type after removing noise in the data (0.1s TTC events): (a) Manchester, (b) Leicester, (c) Athens

The percentage reduction in conflicts per 1000 veh-km at 100% MPR of CAVs is found to be 90.07% in Manchester network, 89.67% in Leicester network, and 87.22% in Athens network.

Estimation of Crashes from Conflicts

The simulation experiments in the previous section explored the results for conflicts. As mentioned in Section 4.1.3, within Levitate, we are interested in road safety impacts in terms of crashes or crash rates, not in terms of conflicts. Therefore, the estimated numbers of conflicts are converted into numbers of crashes using a probabilistic method proposed by Tarko (2018b) as explained in section 4.1.3. Figures 4.15 and 4.16 show the total number of crashes and crashes per vehicle type respectively, calculated based on the above-mentioned approach for varying MPR of CAVs.

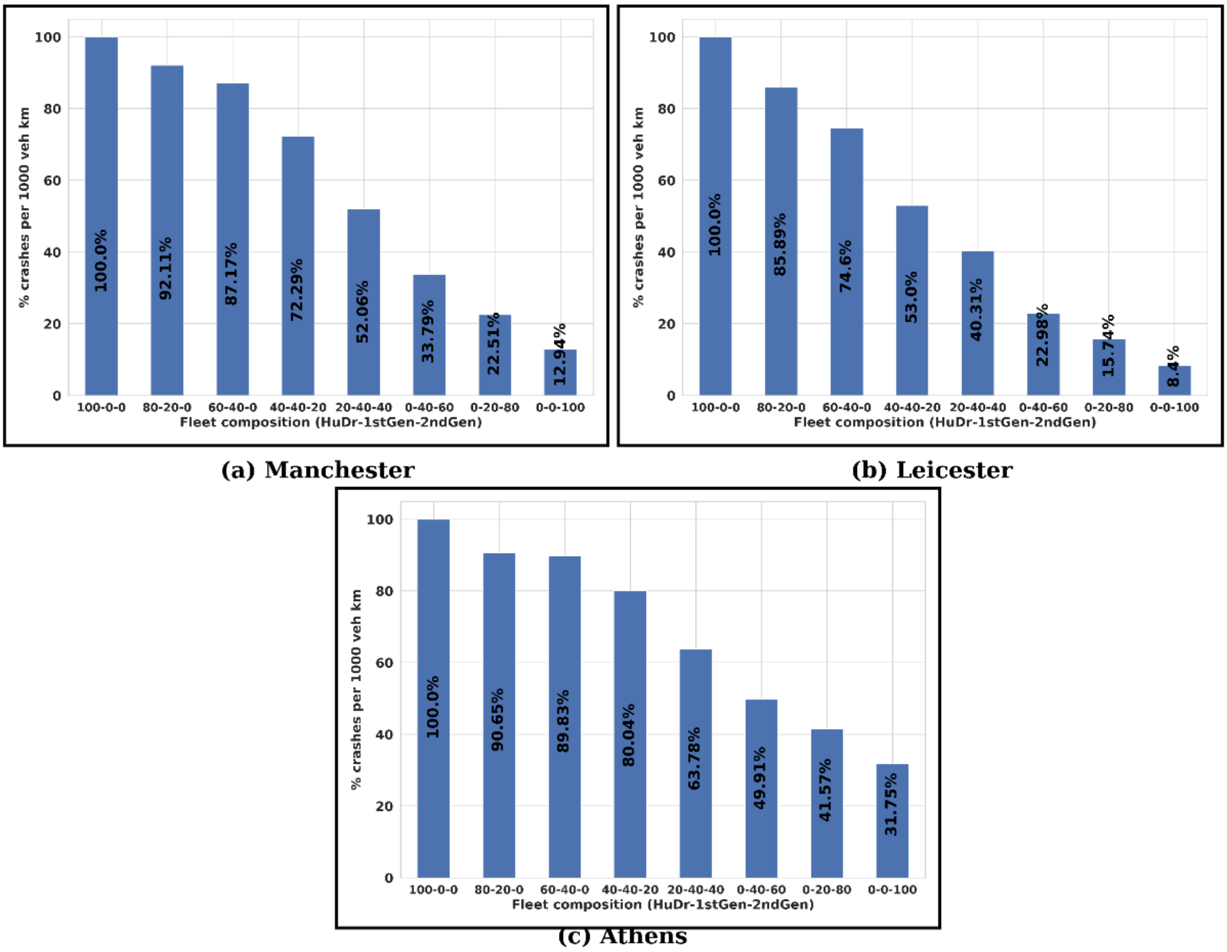


Figure 4.15 Percentage change in crashes per 1000 veh-km travelled based on varying MPR: (a) Manchester, (b) Leicester, (c) Athens

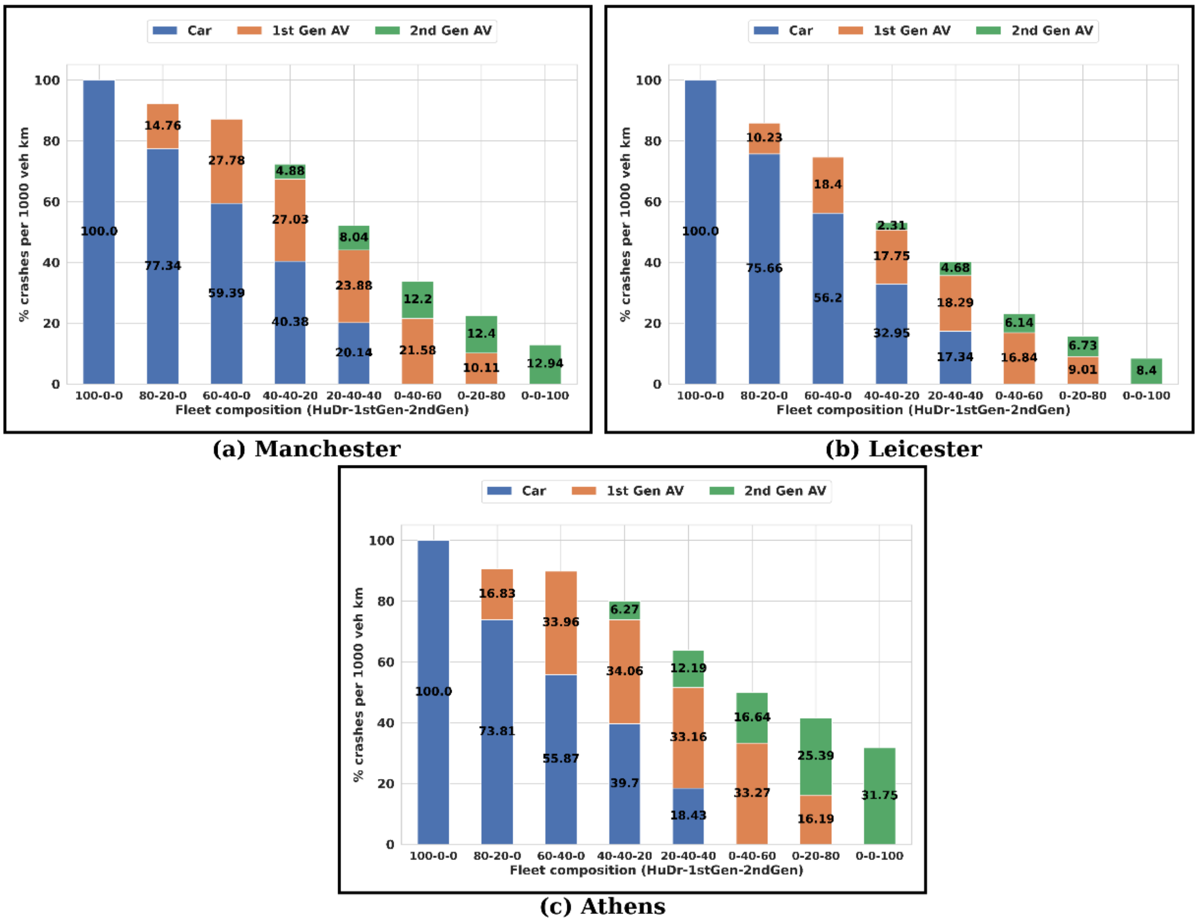


Figure 4.16 Percentage change in crashes per 1000 veh-km travelled with vehicle type based on varying MPR: (a) Manchester, (b) Leicester, (c) Athens

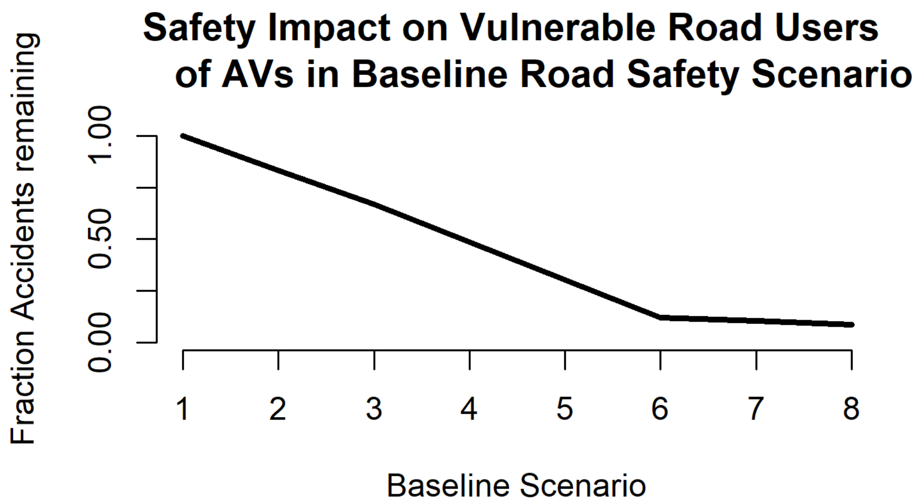
The percentage reduction in crashes at full MPR of CAVs is estimated to be almost 87% in the Manchester network, almost 91.6% in Leicester, and 68.25% in the Athens network.

It is important to note that the unavailability of real-world data limits calibration of the simulation and SSAM models with respect to identifying interactions involving CAVs as real conflicts, making it impossible to fully validate the results. The definition and estimation of conflicts is imperative and consequently impacts the estimation of crashes through the applied probabilistic method (Tarko, 2018b). The Lomax distribution used in the method is based on properties of the traffic conflict phenomenon. If conflicts are not adequately identified or, in other words, non-conflicts are not separated, application of this method on all events claimed as conflicts can potentially over-estimate the expected number of crashes. Therefore, it is extremely important to reasonably define and identify conflicts between different vehicle types. Additionally, more knowledge is needed on understanding the relation between surrogate safety measures and actual crashes.

Nonetheless, the results in terms of percentage change between scenarios and the impact of different network characteristics and fleet composition provide useful insights into the safety impacts of CAVs. Future research should be directed on addressing the existing methodological limitations and biases, as well as calibration of models to adequately incorporate conflict characteristics of CAVs. The implementation of CAVs should ideally lead to prevention of all crashes involving human errors, particularly at higher to full penetration rate; however, as indicated by our analysis results and also reported by several other studies (Shi, Li, Cai, Zhang, & Wu, 2020, Yu, Tak, Park, & Yeo, 2019, Favaro, 2017; Petrovic, 2020), the early and interim phases of implementation could be challenging for improvement in safety and therefore require substantial research and testing for safe operations.

4.4.2 Quantified impacts on VRUs

For an assumed speed of 40 km/h, a human reaction time of 1.5 seconds and new reactions times of 1 second and 0.5 seconds for 1st and 2nd generation AVs, and changes in the proportions of human driven vehicles, 1st and 2nd generation AVs as below (Baseline Scenario), we have the following change in crash proportions:



Baseline Step	1	2	3	4	5	6	7	8
Human	100%	80%	60%	40%	20%	0%	0%	0%
1st Gen AV	0%	20%	40%	40%	40%	40%	20%	0%
2nd Gen AV	0%	0%	0%	20%	40%	60%	80%	100%
Proportion crashes remaining	1.0	0.84	0.67	0.49	0.3	0.12	0.1	0.09

Table 4.4: The proportion of crashes remaining is combined with a so called starting value to estimate the absolute number of remaining crashes. These starting values reflect the current number of crashes in a city.

4.4.3 Quantified impacts of changes in modal split and total impacts

In order to quantify the indirect impacts on road safety the changes in modal split are combined with the quantifications obtained from the microsimulation. Because expected changes in modal split are only available for the Athens network, quantification of the indirect impacts are only reported for that case. The changes in modal split are shown in Figure 4.17. An increase of private car travel of about 8% is expected in the final step where all human vehicles are replaced by 2nd generation AVs. This increase stems from a decrease in public transport of 6% and a decrease in active travel of 2%.

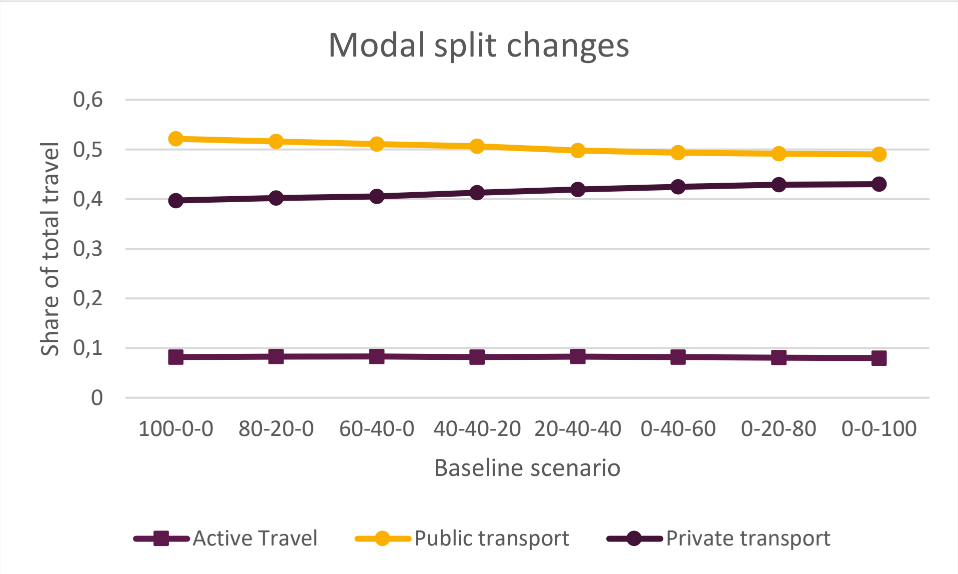


Figure 4.17: Modal split changes

When the changes in modal split are combined with the quantification from the microsimulation, the impact on road safety can be shown. Figure 4.18 shows these results.

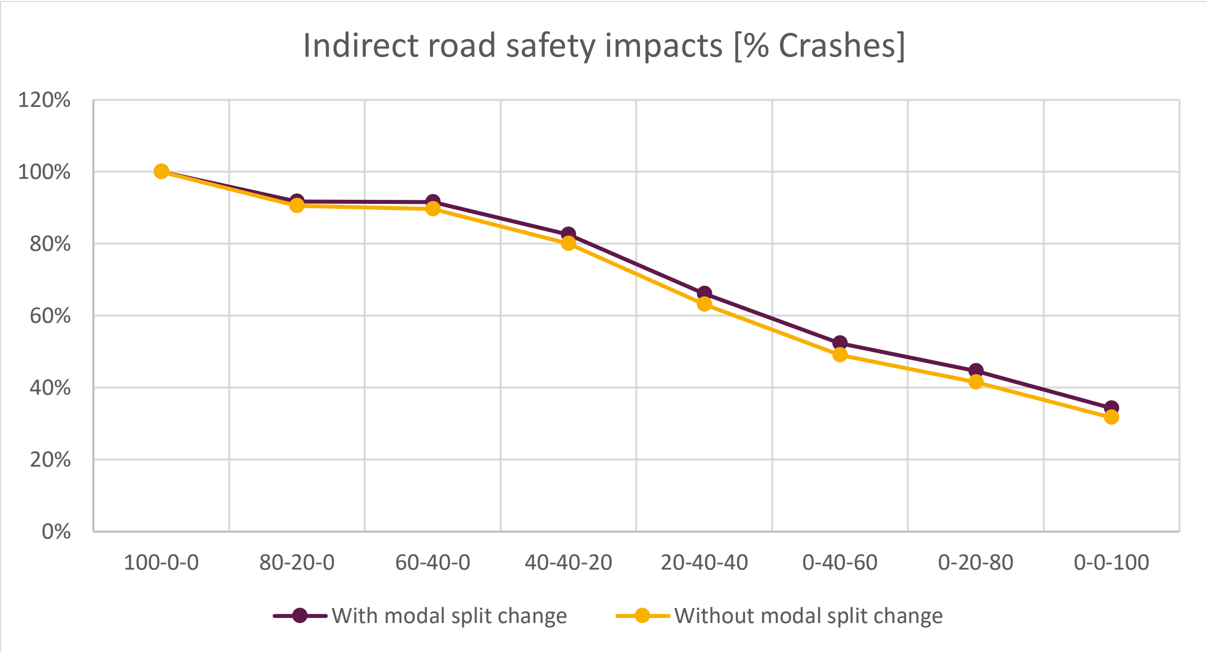


Figure 4.18: Indirect impact on road safety

The total impact on road safety is calculated by combining the quantification of the VRU impact together with the indirect impact. The results are displayed in Figure 4.19. Because the indirect impact is limited to the Athens network, the total impacts are also limited to this network. It is important to note that these results do not directly translate to other cities.

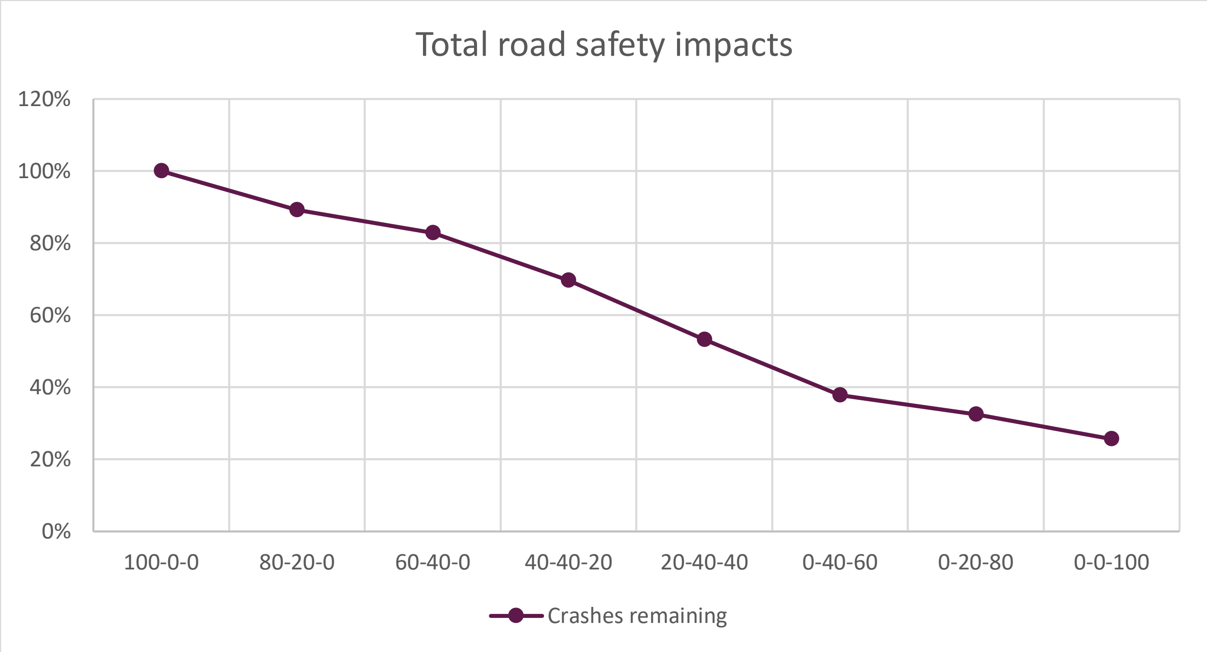


Figure 4.19: Total impact on road safety

4.5 Discussion

This chapter discusses the quantification of road safety impacts of increasing penetration levels of Connected and Automated Vehicles (CAVs) within Levitate. Crash rates between cars are expected to decrease by between 67% to 90% depending on the network at 100% penetration level of CAVs SAE level 5. Crash rates between cars and VRUs are expected to decrease by about 90%. Changes in modal split are expected to increase the share of private car transport at the cost of active and public transport. This has a slight negative effect on road safety compared to the scenario that disregards modal split.

It is important to note that the quantification in this chapter is based on many assumptions and has some limitations. First of all, quantification of impacts within Levitate is limited to the following types of impacts:

- Impacts on car-car crashes due to improved driving behaviour
- Impacts on care to pedestrian/cycling crashes due to prevention of violations, driving errors and improved reaction time
- Indirect impact due to a change in modal split

Impacts related to for example system failures, cyber-attacks and impacts of CAVs on behaviour of other road users are not taken into account.

Moreover, the following assumptions are made according to the behaviour of CAVs:

- AVs are expected to be fully automated, human drivers are not asked to take over control of the vehicle, and
- AVs are assumed to respect all traffic rules and are assumed to adapt their behaviour to the specific conditions in order to prevent crashes as much as possible.

Finally, the different estimations have their own limitations which are discussed in more detail in the different sections.

5 Conclusions

Levitate aims to forecast the impacts of Cooperative, Connected and Automated Mobility (CCAM). One of the relevant impact areas of CCAM is road safety. This Working Document discusses and quantifies the road safety impacts of increasing penetration levels of Connected and Automated Vehicles (CAVs). This chapter summarizes the main conclusions.

5.1 Expected impacts of CAVs

Connected and automated vehicles (CAVs) affect road safety in several ways, both directly and indirectly. First of all, CAVs are assumed to obey traffic rules and are expected to be able to prevent most human driver errors. Moreover, they are expected to have lower reaction times and less variability in driving behaviour. Therefore, CAVs will likely have a lower risk of being involved in a crash than human-driven vehicles. On the other hand, some new potential risks, like system failures, cyber security issues, and issues related to transition of control or mode confusion might be introduced by automated vehicles.

In addition, some rebound/indirect effects can be expected, caused by changes in broader factors that in turn affect road safety. Indirect impacts include changes in modal split, total distance traveled and route choice, as well as changes in traffic behaviour of other road users and infrastructural changes due to the introduction and increasing penetration levels of CAVs.

The impact of CAVs on road safety is not a static figure, but is expected to develop over time as CAVs are expected to become progressively safer and the penetration rate of different types of CAVs is expected to increase over time.

5.2 Quantification of impacts

It is very difficult to quantify expected road safety impacts of increasing penetration levels of CAVs as CAVs will continue to develop over time and future vehicle specifications are not yet known. Moreover, it should be noted that policy makers can influence the road safety impacts of CAVs, for example by regulating the conditions that must be met by CAVs to be allowed on public roads. Furthermore, measures such as automated urban shuttles, provision of dedicated lanes or automated freight consolidation have additional impacts on road safety. These impacts are also identified in Levitate and are discussed in Deliverables 5.4, 6.4 and 7.4 (Chaudhry et al., 2019; Hu et al., 2021; Roussou, Oikonomou, et al., 2021).

Available literature provides some quantitative information on road safety impacts of increasing penetration levels of CAVs. Previous microsimulation studies estimated impacts of lower reaction times and less variations in driving behavior and report reductions of safety critical events up to 99% in case of a 100% penetration rate of CAVs. By combining different studies it is possible to determine dose-response curves of the estimated impacts for increasing penetration rates. Quantitative information on the size of potential new risks of CAVs was not found in the literature.

Within Levitate, road safety impacts are quantified by combining three different approaches:

- By means of postprocessing output from a microsimulation model (AIMSUN), impacts of decreased reaction times and driver variability on crash rates between motorized vehicles are estimated.
- The impact of improved driving behaviour on crash rates between motorized vehicles and vulnerable road users is estimated by using crash data and assumptions concerning types of crashes that can be prevented by CAVs and reduced reaction times.
- The estimated impacts on crash rates are combined with estimated impacts on distance travelled that are determined via other methods within LEVITATE to estimate the overall impact on the number of crashes.

Microsimulation approach

Concerning the microsimulation approach, impacts on conflict and crash rates are estimated for three calibrated and validated networks: Manchester (UK), Leicester (UK), and Athens (GR). Output from the AIMSUN microsimulation model is postprocessed using the software application SSAM (Surrogate Safety Assessment Model) to estimate the change in conflicts. A probabilistic method proposed by Tarko (2018b) is applied to estimate the change in crash rate based on the change in conflicts. It should be noted that goods vehicles and conflicts with TTC ≤ 0.1 sec could not be adequately modeled and are thus removed from the analysis.

At 100% market penetration rate of CAVs, conflicts per 1000 vehicle-kilometer are estimated to be reduced by almost 90%. Results are comparable for the three networks. Because the types of conflicts (TTC value distributions) differ between the cities, the resulting change in crash rate differs between the three networks: at 100% penetration of CAVs, crash rates are estimated to decrease by 87% in the Manchester network, 92% in Leicester, and 68% in the Athens network.

Impacts on vulnerable road users

Unmotorized vulnerable road users (VRUs), comprised of pedestrians and cyclists, are not included in the microsimulation model and therefore, crashes involving VRUs are not taken into account in the impacts discussed above. As developments related to CCAM are expected to impact road safety of VRUs as well, another approach based on crash statistics was taken to estimate the impacts on crashes with VRUs. This approach is based on two main assumptions:

1. It is assumed that all crashes that were caused by human-driven vehicles (car is 'at fault') can be prevented by CAVs
2. As CAVS are expected to have lower reaction times than human-driven vehicles, it is assumed that the remaining crashes (VRU is 'at fault') are less severe when CAVs are involved instead of human-driven vehicles

The share of crashes for which the pedestrian or cyclist is registered to be 'at fault' differs between cities and countries. Based on crash statistics from a number of countries, we assume that about 70% of the crashes is caused by human-driven vehicles. In that case, 70% of the VRU-car crashes can be prevented in case of a 100% penetration level of CAVs. Taking into account the extra reduction in (severe) crashes due to the reduced impact speed, it is estimated that 91% of all fatal crashes between VRUs and cars can be prevented in the case that all cars are fully automated.

Overall impact taking into account changes in modal split
To estimate the overall impact of increasing penetration levels of CAVs on road safety, the impacts on crash rates that are estimated above are combined with estimated impacts on distance traveled with various transport modes. The impacts on distances traveled are estimated by means of System Dynamics/Mesosimulation and are discussed in more detail in Deliverable 5.3 (Roussou et al., 2021) and Deliverable 6.3 (Sha et al., 2021).

According to the estimations from Deliverable 5.3 (Roussou et al., 2021) and Deliverable 6.3 (Sha et al., 2021) the distance traveled by car will increase by around 8%. This is due to a decrease in active travel of 2% and a decrease in travel by public transport of 6%. An increase in travel by private car transport is expected to have a slight negative effect on road safety.

Combined with the decreases in crash rates of car-car crashes of 68% in the Athens network, the expected impact on the number of car-car crashes in Athens is a reduction of 66%. The distance traveled by active transport modes (walking and cycling) is expected to decrease by 2%. Combined with the decreases in crash rates of VRU-car crashes of 91% the total number of all combined crashes is estimated to decrease by 75% in Athens.

Limitations
It should be stressed that the impacts discussed above are based on many assumptions. The results based on microsimulation for example depend on the parameter settings for the behaviour of human-driven and automated vehicles. Moreover, freight vehicles and TTC values ≤ 0.1 sec were removed from the analysis. Also, the translation of conflicts to crashes is based on certain critical assumptions. The impact on VRU-car crashes is based on assumptions concerning the share of crashes that can be prevented by CAVs and the expected reaction time of CAVs. Moreover, for both impacts described above, it is assumed that CAVs function perfectly and that the human drivers don't need to and are not able to take over control. In addition, issues related to hacking or cyber-attacks are not taken into account.

The impacts on vehicle kilometers travelled are used as fixed input for the estimation of the overall road safety impacts and are outside the scope of this report, yet also these estimations are based on assumptions. Further indirect impacts are not taken into account when estimating the overall road safety impacts.

Furthermore, the results are based on estimations for a limited number of cities. Impacts or crashes between cars are estimated for three networks and the proportion of remaining crashes appear to differ between the three networks. The estimated impacts on VRU is based on crash data from a limited number of countries and model split impacts were only available for Athens. Therefore it is not possible to determine to which extent the estimated total impacts are transferable to other networks.

Because of these limitations, the quantified impacts discussed in this report should be seen as a rough estimate of the potential road safety impacts of increasing penetration levels of CAVs. Unavailability of real-world data makes it impossible to validate the results and the calculated impacts cannot just be applied to other cities.

5.3 Final comments

As automated vehicles develop over time, it is very difficult to predict their impacts. The future vehicle specifications are not known yet and impacts are also influenced by policy related to connected and automated vehicles. The quantified impacts that are discussed in this report are based on many assumptions and do not include all potential impacts; impacts related to system failures and cyber-attacks are for example not included. Therefore, the road safety impacts discussed in this report, should be seen as a first global estimate of potential road safety impacts of CAVs. The Policy Support Tool (PST) that is being developed within Levitate can be used to estimate impacts of additional measures related to Cooperative, Connected and Automated Mobility (CCAM) and to further explore potential impacts.

Although the exact impacts are not known yet, CAVs are expected to improve road safety. It can be expected that they won't be accepted by road users and policy makers if they would not improve road safety. However, it should be stressed that CAVs cannot be expected to solve all road safety problems. First of all, even systems that are very well-designed can fail, and cyber-attacks and manipulation of the software cannot be fully prevented. Secondly, it should also be noted that only crashes involving vehicles which can be replaced by AVs can be prevented. A significant amount of crashes do not involved motorized vehicles. In the Netherlands, for example, more than half of the serious road injuries occur in a road crash in which no motorized vehicle was involved (SWOV, 2020). Most of these crashes won't be affected by the introduction of Connected and Automated vehicles.

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