A Traffic-based Method for Safety Impact Assessment of Road Vehicle Automation

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Abstract: One of the major challenges for enabling market introduction of automated driving is to identify risks and benefits of these functions. For this purpose, a new framework for assessing the safety impact of automated driving functions has been investigated. The developed framework takes the characteristics of automated driving functions into account. Automated driving functions - in contrast to active safety systems - continuously control the behaviour of the vehicle. Thus, it is possible that automated driving functions will get involved less frequently in accident scenarios playing a major role at human driving, e.g. rear-end accident scenarios. On the other hand, it is likely that other previously irrelevant accident types will rise. Therefore, besides investigating the change of severity of an accident by using accident re-simulations, the changes of frequency of occurrence of driving scenarios induced by automated driving are considered as well. These changes in frequency of occurrence of driving scenarios are analysed by using traffic simulations. After determining the effectiveness of the automated driving function, it is projected and depicted over the whole territory of the Federal Republic of Germany. The methodology is applied on five generic automated driving functions as for example a generic "Motorway-Chauffeur" (SAE level 3) and a generic "Urban Robot-Taxi" (SAE level 4). This paper provides the results of the safety impact assessment of these automated driving functions.

Keywords: Safety impact assessment, traffic simulation, automated driving

1 Introduction

Due to technological progress in microelectronics and computing power, various automotive functions for supporting the driver have been developed during the last decade. These so-called advanced driver assistance systems (ADAS) are supporting the driver on different levels of the driving task. Driven by recent developments in algorithms for environment perception and decision making, the ultimate goal of vehicle automation seems to be a solvable task as shown by several demonstrations [1].

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However, due to an increasing complexity of decision making algorithms, identifying benefits and drawbacks will be challenging. Hence, new safety impact assessment methods have to be designed which are based on detailed accident-, FOT- and simulation data and that are assessing the automated driving functions with respect to a certain baseline. Since automated driving will not be able to avoid all accidents on roads, e.g. due to the misbehaviour of other traffic participants and physical limits, a baseline for assessment has to be defined. According to the *German Ethics Commission for Automated and Connected Driving*,

> *"[..] the licensing of automated systems is not justifiable unless it promises to produce at least a diminution in harm compared with human driving, in other words a positive balance of risks [..]"[2]*

Consequently, the reference for safety impact assessment needs to be human driver performance. In order to assess automated driving functions with respect to human driver performance, this paper introduces a method for safety impact assessment that takes the characteristics of continuous road vehicle automation according to [3] into account. Human driver performance is used as a baseline.

2 Background

For safety impact assessment of (advanced) driver assistance systems with environment perception, many different methods have been used in the past. All these methods have in common, that they compare driving situations without the system with driving situations, in which the system is activated. One valid approach for determining the effectiveness of ADAS is the accident re-simulation on basis of in-depth accident data, e.g. as applied in [4]. In this case, reconstructed accident scenarios from detailed accident data, such as the German-in-depth accident database (GIDAS) [5], are simulated with and without the considered function. The difference in performance in the situation, e.g. probability of severe injuries, is considered as the benefit of the function. A disadvantage of this approach is that new induced driving scenarios by automated driving cannot be considered, because these are not represented in the accident data. Another approach for safety impact assessment based on recorded data is the field operational test (FOT) as presented in [6]. Here, huge amounts of driving data without function (*control condition*) and with activated function (*experimental condition*) are collected. The safety impact of the considered function is analysed by investigating the change in frequency of occurrence of incidents and near-crashes compared to the baseline. For safety impact assessment of a function in defined situations, driving simulator studies can be used as well. This approach allows a detailed investigation of human driver performance with and without the considered function as demonstrated in [7], but requires a selection of situation parameters to be presented to the drivers. As described previously, automated driving functions need to be assessed in the whole entity of possible driving situations in their operational design domain. Hence, simulations of these functions in the whole traffic are a promising approach as presented in [8]. However, validation of these simulations remains challenging because of the variety and complexity of models necessary for safety impact assessment.

Based on the available methods presented previously, a suitable method for assessing the safety impact of road vehicle automation is defined. Although accident re-simulation based on detailed accident data is a valid approach, it will not be suitable for assessing automated driving functions since this approach is based on previously recorded detailed accident data from human driving. In order to identify new driving situations induced by automated driving functions, a FOT would be suitable. However, considering the necessary resources difficult to realize. Thus, a holistic approach including several data sources and in particular traffic simulation as proposed in [8] is realized for safety impact assessment of automated driving functions.

3 Approach for safety impact assessment

While in the past active safety systems were assessed on a set of recorded accident scenarios obtained from human driving [4], this approach will not be sufficient concerning automated driving functions. Automated driving functions – in contrast to active safety systems – are continuously controlling the behaviour of the vehicle. Due to this reason, it is possible that automated driving functions do not get involved in previously important accident scenarios any longer while other, at human driving less relevant accident scenarios, will become more important. Hence, future assessment approaches have to take the change in frequency of occurrence of driving scenarios induced by automated driving functions into account. Therefore, besides re-simulation of detailed accident scenarios for identifying the changes in severity due to automated driving, the changes in frequency of occurrence of relevant driving scenarios have to be modelled and identified as well. The overall approach for safety impact assessment incorporating the prediction of frequencies of driving scenarios is presented in Figure 1.

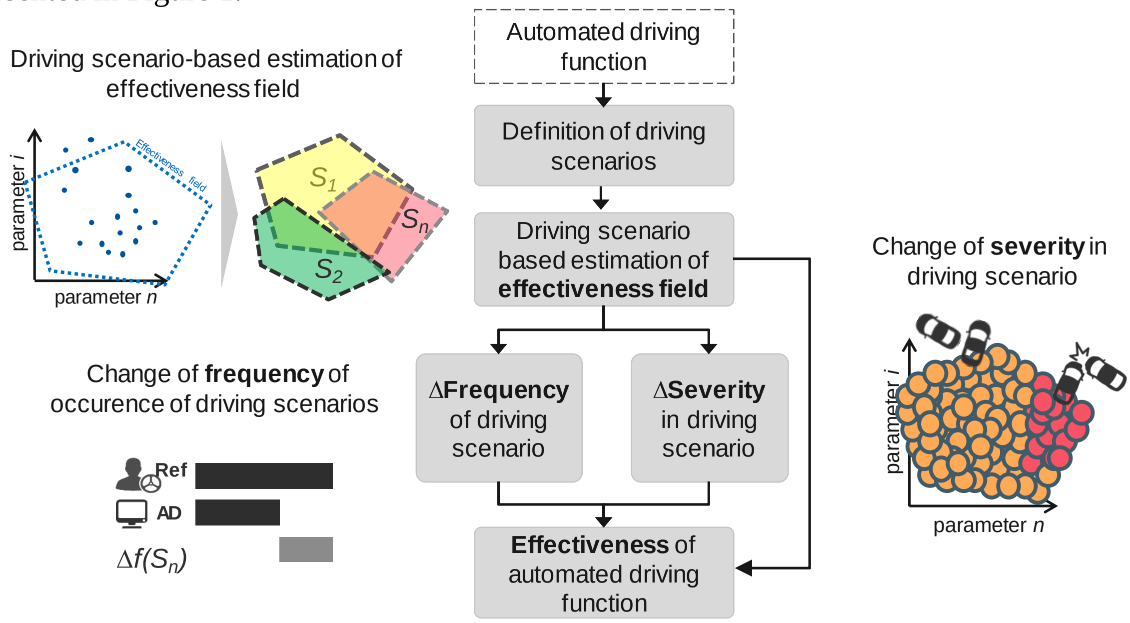


Figure 1: Methodological approach for safety impact assessment of automated driving

Based on a definition of the automated driving functions and the addressed driving scenarios the effectiveness field – all addressed accidents and safety relevant driving situations – in the considered accident data are identified. Afterwards, the changes in frequencies of occurrence of the defined driving scenarios are assessed by using traffic simulation. Of course, these changes of frequencies of driving scenarios can be derived as well from FOT-data. For identifying the changes in severity in the defined driving scenarios they are simulated with and without the automated driving function while the reference performance is modelled by human driver performance models.

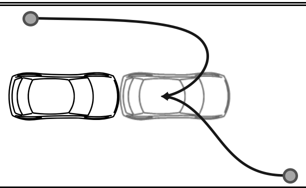
Thus, the overall effectiveness E of an automated driving function in terms of safety can be calculated by multiplication of the change of severity respectively injury risk ΔI per relevant driving scenario S_i with the change of frequency Δf of the considered driving scenario S_i for all driving scenarios n in the effectiveness field of all addressed accidents.

$$E = \sum_{i=1}^{n} \Delta I(S_i) \cdot \Delta f_i(S_i) \tag{1}$$

3.1 Definition of driving scenarios based on accident type

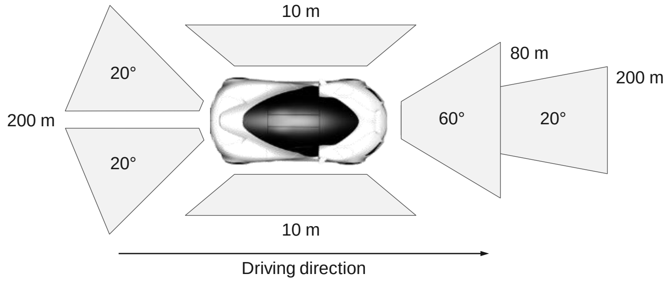
For prospective assessment of the safety impact of automated driving functions on traffic, a *scenario-based* approach is used. First, the automated driving functions and the addressed driving scenarios are described, e.g. a “Motorway-Chauffeur” is addressing amongst others the driving scenario “passive cut-in”. In total, 13 driving scenarios have been derived based on a systematic analysis of potential collision positions of two vehicles. These 13 driving scenarios are validated by checking if all three digit accident types $UTYP3$ are covered by the defined scenarios. In Table 1, an exemplary definition of a driving scenario is given.

Table 1: Definition of an exemplary driving scenario for safety impact assessment of automated driving. In the illustration, the relative movement of the cutting-in vehicle is displayed.

Driving scenario	**Description**	**Illustration of driving scenario**	**Covered three digit accident types**
Passive cut-in	An object changes (or initiates a lane change) to the lane of another vehicle resulting in a potential collision in longitudinal direction.		204, 233, 631, 632, 634, 635,641, 642, 644, 645, 646

Afterwards the driving scenarios are linked with the accident feature “three digit accident type” $UTYP3$ to the (detailed-) accident data. By using this link, the detailed accident scenarios can be extracted from *GIDAS* (German in-depth accident study) accident data [5] as well as from the national accident statistics *DESTATIS* [9]. Next to the addressed driving scenarios, the sensor view range, addressed road types and the speed range of the automated driving function are included in the definition. Furthermore, limitations of the automated driving function are considered as well. Concerning these functional limitations, it is distinguished between environmental conditions, e.g. heavy precipitation, fog and road conditions, icy roads, construction sites, limiting the automated driving function. In Table 2 an exemplary definition of an SAE level 3 “Motorway-Chauffeur” is given.

Table 2: Definition of automated driving functions for safety impact assessment on the example of the “Motorway-Chauffeur”

Parameter	**Value**
Name	Motorway-Chauffeur
Level of automation according to [SAE16]	3
Sensor view range	
Adressed driving scenarios	• Driving without influence from leading vehicle • Approaching static object • Approaching leading vehicle • Approaching traffic jam • Passive cut-in • Lane change
Road types and speed range	• Motorways: 0 - 130 km/h
Functional limitations	• Environmental conditions: all, except heavy precipitation (rain and snow) and fog • Road conditions: no icy road, no construction sites

3.2 Identification of effectiveness fields

After defining the assessed automated driving functions including the driving scenarios they are addressing, the accidents in which the automated driving functions have a potential impact are identified. These so-called *effectiveness fields* are estimated in the in-depth accident data and national accident statistics by using the three digit accident type $UTYP3$. Besides, the effectiveness fields are limited based on the addressed road types and limitations defined for the automated driving functions. For example, from all accidents with personal injuries $A(P)$ occurring on Motorways in Germany (6 % of all accidents), a Motorway-Chauffeur is addressing 53 %. The other accidents in the domain cannot be addressed due to the reason that driving scenarios are not covered by the functional scope of the automated driving function (12 %), driver and vehicle related limits such as technical failures or alcohol use (9 %), functional limitations (14 %) and no car involvement in the accident (12 %), see Figure 3.

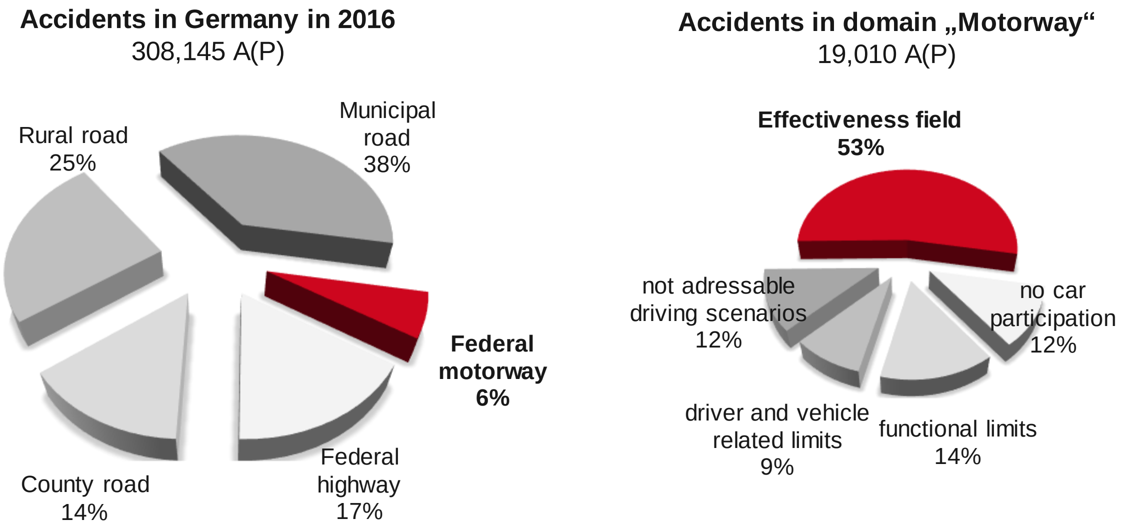


Figure 3: Analysis of accidents with personal injuries $A(P)$ in DESTATIS data with regard to road class (left) and with regard to functional limits, driver- and vehicle related limits, type of participation and addressed driving scenarios (right) on the example of the "Motorway-Chauffeur"

Finally, resulting from the analysis are the number of accidents per driving scenario in the effectiveness field and the distributions of situational variables (e.g. velocities of all participants) necessary for simulation per driving scenario, see Figure 4.

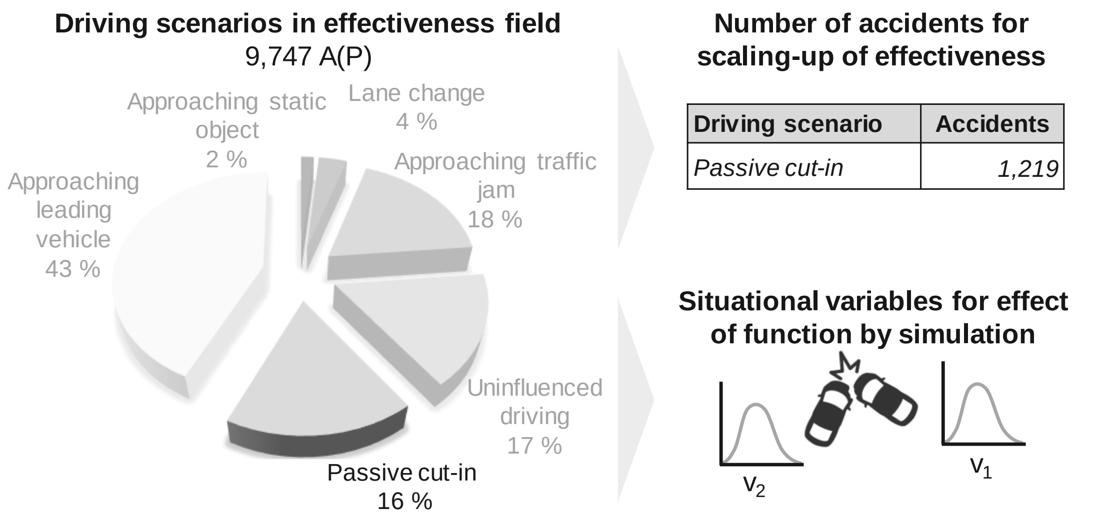
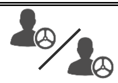
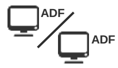


Figure 4: Analysis of accidents with personal injuries $A(P)$ in effectiveness field with respect to driving scenarios on the example of the "Motorway-Chauffeur"

3.3 Change of frequencies of occurrence of relevant driving scenarios

In the identified effectiveness fields, the potential impact of the automated driving functions in terms of safety is estimated. Automated driving functions are operating continuously and consequently may get involved with a higher frequency in certain driving scenarios while the frequency of other driving scenarios may decrease compared to human driving. Hence, the changes of frequencies of occurrence $\Delta f_i(S_i)$ of the addressed driving scenarios are assessed by using traffic simulations. For considering the effects within mixed traffic conditions of human driven and automated vehicles, it is distinguished whether a human driven or an automated vehicle has induced or “caused” a certain driving scenario. For example, a human driver cutting-in in front of the automated vehicle can cause a “passive cut-in” driving situation. In this case, the human driver induced the driving situation while the automated vehicle was involved in it. Based on this principle, a classification scheme for driving situations is introduced, see Table 3.

Table 3: Types of interactions in mixed traffic conditions

Type of interaction	Type of vehicle driving scenario **induced** by	Type of vehicle **involved:**	Illustration
HUM-HUM	Human driver	Human driver	
HUM-ADF	Human driver	Automated driving function	
ADF-HUM	Automated driving function	Human driver	
ADF-ADF	Automated driving function	Automated driving function	

The changes of frequencies for all four defined “types of interactions” are analysed by using traffic simulation data of human driven and automated vehicles for several market penetration rates of automated vehicles. For traffic simulation, a 26 km long section of the German motorway A2 around Hanover is used. In Figure 5 an exemplary section of the considered traffic scenario (left) and the change of frequency of the driving scenario “approaching leading vehicle” is presented (right).

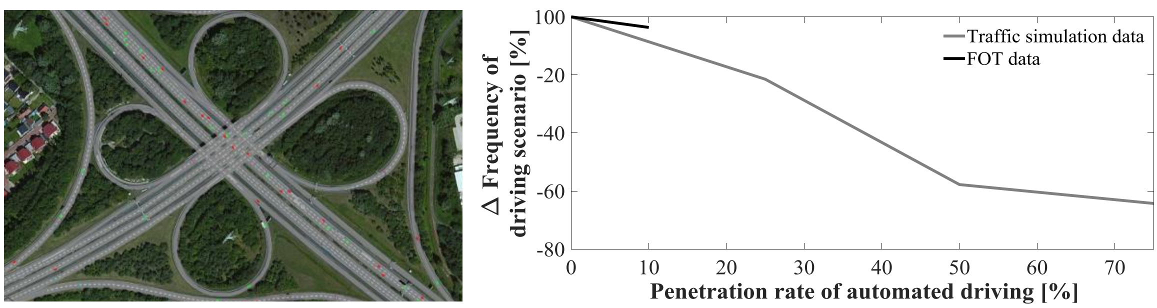


Figure 5: Traffic scenario for estimation of changes in frequencies of driving scenarios (left) and change of frequency of “approaching leading vehicle” driving scenario

3.4 Change of severity in relevant driving scenarios

The changes of severity ΔI in the considered driving scenarios are estimated by re-simulation of the addressed accidents in the effectiveness fields with and without the considered automated driving function, see Figure 6. For this purpose, the situational variables resulting from the effectiveness field analysis of the GIDAS data are used. For reference performance, driver models parameterized from driving simulator studies such as [7] are used. Resulting is the change in severity per driving scenario. For example, in the driving scenario “passive cut-in” the probability for a severe injury can be reduced by 42.3 % by the “Motorway-Chauffeur”.

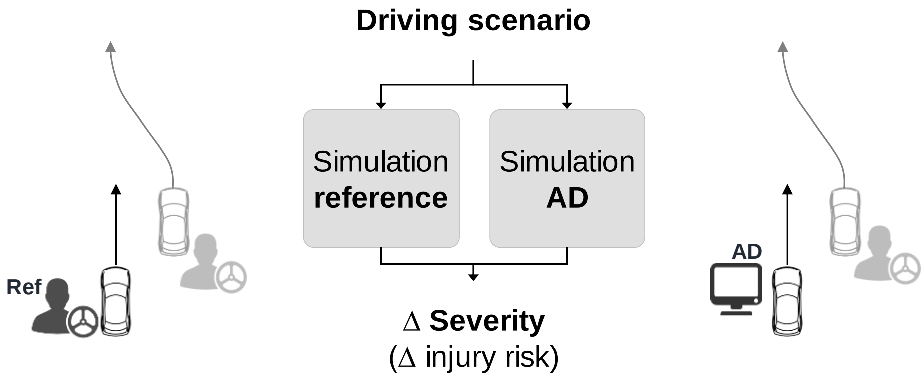


Figure 6: Re-simulation of accident situations for changes in severity in driving scenarios

3.5 Effectiveness of automated driving function

Finally, the effectiveness of the automated driving function in the effectiveness field is derived based on the changes in frequencies of all driving scenarios and the changes in severity in all driving scenarios. This process is illustrated on the example of the “passive cut-in” driving scenario at 50 % market penetration of the Motorway-Chauffeur, see Figure 7. Afterwards, the calculated effects are applied to the target population of accidents in the effectiveness fields.

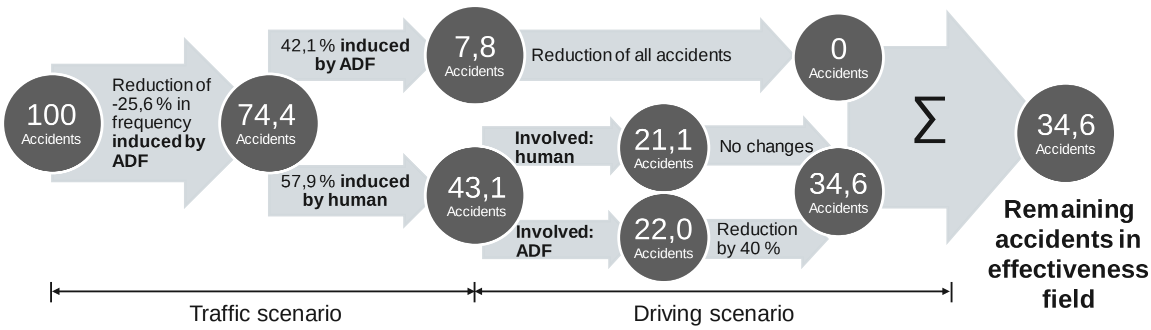


Figure 7: Method for deriving the effectiveness of an automated driving function on traffic scenario and driving scenario level on the example of a “passive cut-in” driving scenario and a market penetration of 50 %.

3.6 Projection of effectiveness on national level in Germany

The simulation-based estimated effectiveness for the different automated driving functions is scaled-up on national level for the Federal Republic of Germany. Since the effectiveness of the automated driving function is determined based on detailed GIDAS accident data that is only available for a limited geographical region in Germany the effects have to be corrected and projected by using the national accident statistics. For this purpose, the correction factors per driving scenario are derived based on the frequency of occurrence of the defined driving scenarios in GIDAS detailed accident and national accident statistics by using the three-digit accident type.On basis of the Urban Robot-Taxi the results presented in Figure 8 will be explained. In the operation domain of the Urban Robot-Taxi 205,321 accidents with personal injuries occurred in 2016. Since only automated driving functions of passenger cars are considered, just those accidents can be addressed where at least one passenger car is among the first two participants of the accidents. These 36,486 accident cannot be addressed (see light gray area). Furthermore, 47,487 accidents per year are outside the functional limits of the Urban Robot-Taxi (see dark gray area) due to not addressed driving scenarios, alcohol and drug use, technical failures and limitations of the Urban Robot-Taxi (rain, fog, ice, construction sites).

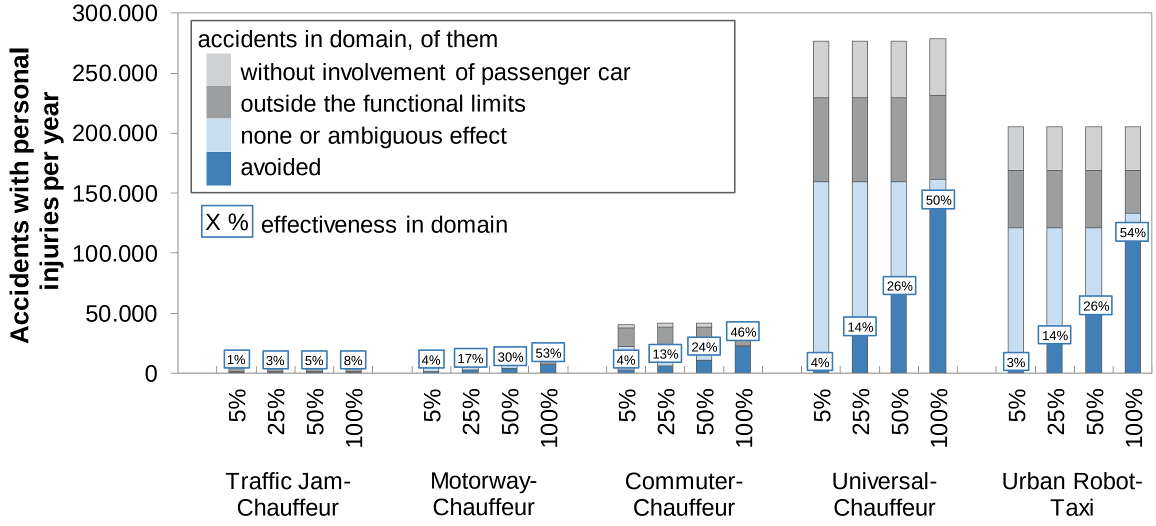


Figure 8: Effectiveness of the considered automated driving functions

The light blue area represents the number of accidents that are potentially addressable, but cannot be avoided according to the simulation results. These are for example accidents that cannot be avoided due to physical constraints. However, the severity of these accidents possibly can be reduced by a reduction of the collision speed. The dark blue area represents the number of avoided accidents. Hence, the Urban Robot-Taxi can avoid 52,517 accidents at a market penetration of 50 %. This equals an effectiveness of 26.5 % of all accidents in the operation domain.

4 Conclusion

According to the statements in [1], automated driving functions need to show a positive risk-balance compared to human driving in terms of traffic safety. Therefore, a framework for safety impact assessment of road vehicle automation has been introduced in this work. In contrast to already existing methods for safety impact assessment of active safety, this framework is considering the changes in frequency of occurrence of driving scenarios due to the continuous operation principle of automated driving functions. Traffic simulations with automated driving functions have investigated the changes in frequency of occurrence. For determination of the change in severity in relevant driving scenarios, accident re-simulations were used. After determining the effectiveness of the automated driving functions, they are projected and depicted over the whole territory of the Federal Republic of Germany. The results indicate that, e.g. a Motorway-Chauffeur at a market penetration of 50 % has a potential for reducing about 30 % of all accidents on German motorways resulting in personal injury. This equals 2 % of all accidents on German roads. The Urban Robot-Taxi can avoid 26.5 % of all accidents with personal injury within city-limits at a market penetration of 50 %. This equals 17 % of all accidents on German roads.

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