

Prospective safety assessment of highly automated driving functions using stochastic traffic simulation

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Abstract (500 Words)

A number of automobile manufacturers have announced plans to bring automated driving technology to the road in the near future. In addition to economic and social benefits, potentially improved safety performance is one of the key factors motivating automated driving. With high-quality sensors working in parallel, automated driving is likely to offer safety benefits, since the system observes the environment continuously in all directions, whereas human visual perception is directly limited by the field of view and can be indirectly limited by the complexity of a scene or the cognitive burden. Humans are also subject to lapses of attention, e.g. due to fatigue.

Assessing the difference in safety performance between automated and manual driving involves a detailed analysis of this replacement. It is a more challenging task than assessment of “conventional” driver assistance systems, which usually address a more limited set of scenarios, and requires a comprehensive approach that includes the entire range of exposure of automated driving.

In general, safety assessment utilizes evidence from a variety of sources, beginning with retrospective accident analyses and including a range of prospective techniques, such as so-called naturalistic driving or field operation testing (FOT). This paper presents a technique used by BMW for assessing safety performance of highly automated driving functions using virtual experiments, including two design approaches: virtual scenario-based trials and virtual FOT.

The core technology in both designs is an agent-based Monte-Carlo simulation engine using our “stochastic cognitive model” (SCM) to describe human traffic participants, as well as sensor and functional models to describe agents with ADAS or automated driving. The paper will review key features of SCM developed to represent the behavior of virtual traffic participants (and their interactions) in real traffic. The simulation and models are parameterized base on different data sources like previous FOT-data, simulator studies, traffic data as well as accident data.

The virtual scenario-based trial design to test a virtual automated driving function (ADF) is illustrated here for two highway scenarios. Virtual “humans” drive according to a “stochastic cognitive model” developed by BMW. In an “obstacle in the lane” scenario, the virtual drivers encounter an obstacle that may appear (from their point of view) suddenly. Drivers are thus forced to decide on an action (braking, swerving, etc.) under severe time pressure, obvious collision risk, and often with inadequate time for observation of blind spots. In a “jam approach” scenario, the virtual “human” drivers enter a realistically simulated traffic jam front (e.g., position of maximum speed gradient can vary among lanes). In jam approach, typical perceptual limitations of human drivers can result in inadequate braking or counter-productive lane

changes and ultimately in collisions. Target vehicles equipped with a virtual ADF achieve improved safety in both tested scenarios.

INTRODUCTION

Based on comprehensive, sensor-based detection of vehicle surroundings, the vision of automated driving has already become reality in research vehicles (e.g., [1, 2]). Today, advanced driver assistance systems (ADAS) support the driver in demanding, complex or hazardous situations and, if necessary, can perform maneuvers automatically. Higher levels of automation could, at least temporarily, free the driver entirely from the driving task, with enormous potential for individual benefits [2]. In addition to individual mobility improvement, vehicle automation could play a central collective and socio-economic role and provide significant positive impacts on road traffic. It is widely expected that automated driving will improve traffic performance in terms of traffic flow, energy demand and traffic safety [3].

In addition to automotive manufacturers and suppliers, public decision makers, regulatory agencies, insurance companies, and consumer protection organizations are key stakeholders in the evaluation of vehicle safety. Proof of reliability and equivalent or superior safety in all operating scenarios is an important prerequisite for the introduction of ADF.

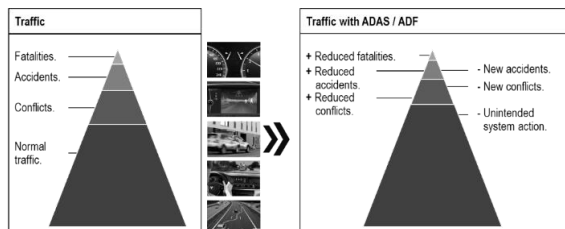


Figure 1. Changes in traffic safety due to advances in driver assistance and automation (after [4]).

Detailed safety performance assessment and optimization of ADF safety performance is a complex task. By its nature, automated driving involves long periods of relatively unchallenging, low-risk traffic flow as well as a broad spectrum of rarely occurring, but potentially complex or high-risk scenarios. Safety performance assessment in ADF is more challenging than in “conventional” driver assistance systems (ADAS), which usually address a more limited set of scenarios. ADF

assessment requires a comprehensive approach that includes the entire range of exposure.

Moreover, as in ADAS, occasional superfluous system actions or unintended consequences could theoretically arise in ADF due to the underlying uncertainties in detection and risk assessment -- not to mention the constraints imposed by the laws of physics as applied to vehicle dynamics. As a consequence, secondary risks cannot be ruled out a priori (e.g., rear-end collisions following an emergency braking maneuver).

Furthermore, the interactions between ADF and human drivers or vulnerable road users could in principle have non-obvious negative impacts on traffic safety in a particular context. For example, if there is a perception that ADF responses to potential conflicts are more defensive than human responses, human drivers could be tempted to carry out otherwise risky maneuvers, such as close lane changes in front of automated vehicles. Other forms of risk compensation by human drivers are also conceivable. As a consequence, an objective metric of traffic safety must also include possible side effects [5, 6, 7, 8], in order to quantify the ratio of desired safety improvements to unwanted side effects, and to optimize the ADF regarding this ratio.

Issues such as integrity of communication, data protection, and technical reliability are unfortunately beyond the scope of this paper. The focus here is on techniques for quantifying and optimizing the impacts of ADF on traffic safety.

SAFETY ASSESSMENT APPROACHES

Retrospective assessment and related issues

One approach for structured assessment of impacts on traffic safety of systems is retrospective analysis of accident databases linked to vehicle equipment data (if feasible [9]). Clearly, this approach can only be applied to existing systems. However, even for assessment of existing safety systems, there are several statistical constraints, particularly due to lack of statistical power (low event rates) and confounding factors. Thus, low event rates imply that large samples from accident databases and long observation times [5] are required for retrospective statistical evaluation of accident avoidance; and safety effects could be confounded because vehicles in the sample often differ in multiple aspects, but not only regarding the safety system in

question. Differences of driver population or exposure to traffic scenarios are often correlated with the availability of the system. Moreover, like-named safety systems from different manufacturers may have different functional characteristics, activation thresholds, intervention algorithms or interaction concepts with the driver.

Such properties of retrospective studies make an unambiguous interpretation of results and conclusions about causality difficult or impossible; simple, comprehensive statements regarding safety performance changes (“effectiveness”) are not always valid [6, 7].

In addition, evaluation of the consequences of system actions is practically impossible based on retrospective studies alone. The same warning or system intervention could have quite different impact on traffic depending on possible action and reaction of involved road users in the situation. Taking the situation with a pedestrian standing on the road edge as an example, the situation contains at this moment a potential risk, since in most cases the pedestrian would wait until the vehicles pass. A warning would be in that case unnecessary and interpreted as “false alarm” by the driver. However, it cannot be completely excluded that – contrary to expectation – the pedestrian makes a sudden move towards the road, albeit with very low probability. In this case, the same early warning could have increased the driver’s attention and facilitated a proper reaction.

This discussion does not imply that the impact of system warnings or interventions are totally unpredictable, but it does imply that stochastic variations, particularly in human factors, need to be taken into account in a holistic system design and engineering approach. A thorough analysis of human factors can help to achieve the desired safety effects: The holistic approach includes choosing the right warning modality, directing it to the right place, modeling an intervention with the right gradient – and most importantly delivering the warning and intervention at the right moment.

However, traffic dynamical processes beyond the control of the engineer will always play a strong role and influence the performance of a safety measure. System optimization, in particular, optimizing the sensitivity-specificity-trade-off, could contribute to minimizing the negative side effects, and to maximizing the safety benefits, which requires microscopic view of numerous individual cases to quantify the system impact in a particular class of traffic situations (**Figure 1**). This

process cannot be achieved by purely retrospective assessment.

Summarizing, retrospective studies can enable ex-post evaluations, but can hardly be used for any optimization of ADF, due to the long feedback loop of development, retrospective evaluation, and redesign. There is an urgent need for reliable and valid predictions of traffic safety for design and optimization of ADAS and especially for ADF. However, truly prospective, controlled, and representative studies are not feasible on public roads due to ethical and practical considerations. This dilemma could be resolved using virtual, simulation-based traffic safety predictions of ADAS and ADF.

Prospective safety assessment

The concept of a virtual experiment or “trial” is expected to play a central role in comprehensive safety assessment of ADF (**Figure 2**).

Here, real traffic is replaced by simulated traffic and other “real” components by models. Validity is the central requirement in this paradigm.

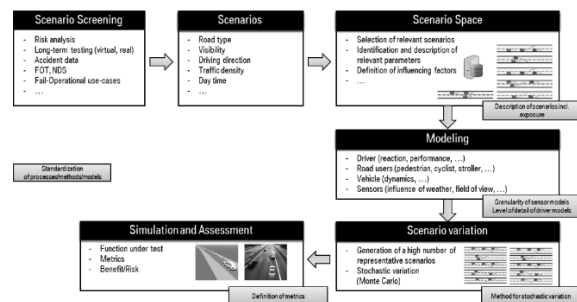


Figure 2. Process of virtual assessment of ADF.

The basic experimental design paradigm is the randomized controlled trial, comparing a “treatment group” to a control group (referred to as “baseline”). In place of real vehicles in real traffic, the subjects of the trial are virtual vehicles in virtual traffic.

One virtual design approach, similar to Advance Driver assistance systems’ assessment, involves preliminary identification of specific (rare but important) scenarios that are potentially complex or high-risk.

Typically, safety performance of automated vehicles is then tested by repeated virtual experimental units (simulations). These simulations usually have a short temporal and spatial focus and involve relatively few interactions.

In each experimental unit or trial, characteristics of agents and traffic environments are randomly drawn from appropriate model distributions. Target agents are assigned to treatment (system active) or baseline (system not present or inactive). Traffic safety indicators are captured as dependent variables, analogous to empirical tests. Effectiveness of a system can be quantified based on comparison to the baseline regarding these indicators, using appropriate statistical tests.

A second design approach is a “virtual FOT” simulation, involving generic initial conditions, a longer road section and many interactions. The virtual FOT can reveal scenarios whose risks are not evident a priori, but which emerge in the course of simulation.

An obvious advantage of prospective virtual assessment is the ability to perform controlled experiments in high-risk traffic environments. Another key advantage is generation of adequate sample sizes: quantification and statistical testing of safety effects requires an adequately large and representative sample of events. The number of events needed is typically related to the square of the relative safety effect size, just as in a randomized, controlled trial. However, since events (i.e., accidents) are inherently rare events, generally a very large sample of scenarios or very long observation periods are required. In contrast to empirical studies or test driving, virtual samples can be produced fast and with minimal cost. Finally, virtual testing can capture any data desired for evaluation, including virtual human factor data.

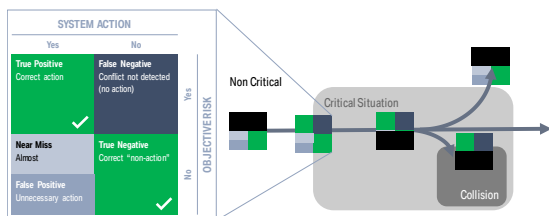


Figure 3. Categorization of possible system response in temporal sequence (following [10]).

Due to the high complexity of possible safety effects of an ADF, an appropriate metric for characterization of these effects is required. An ideal metric includes effectiveness quantification at two levels. The first level quantifies the relative frequencies of all possible fields in the situation-system-response-matrix (Figure 3). A key characteristic, adopted from medicine, is the NNT (“number needed to treat”). NNT can be defined as the ratio between all system actions and true

positives, i.e., desired system actions [11, 12, 13]. NNT can be calculated separately for each type of system action (warnings, interventions).

The second level quantifies the primary effects including both avoided accidents and mitigation (reduced injury severity or fatalities in the remaining unavoidable accidents), but also secondary effects including possible “new” accidents and their injury severity.

Probability models can be used to derive injury severity based on detailed accident characteristics in the target scenario. To calculate the metric, two steps are required: first, calculating the impact of the system on accident characteristics in the target scenario; second, applying a conditional probability model of injury severity depending on these characteristics.

To model injury severity – quantified as MAIS (Maximum Abbreviated Injury Scale), for example – depending on accident characteristics, there are several complementary approaches. A commonly used method is the construction of statistical models (e.g., regression models) from existing accident databases (e.g., [12, 14, 15, 16]). Another approach is “co-simulation”. Here, a representative sample of time series from accident simulations is generated and analyzed using a high-resolution crash simulation, which is capable of rapidly calculating injury indicators [17, 18].

Modelling safety-relevant processes in virtual traffic

The safety performance of ADF depends on a number of interacting processes, beginning with exposure variables and related to traffic flow, dynamics of the driver-vehicle unit including human factors, technical systems, and the environment. In the context of safety assessment, the goal of simulation models is to achieve a simulation fidelity (quality) capable of capturing the effects of ADF on all safety-relevant processes. This objective is far more challenging than those of typical traffic simulation applications in the past, which were concerned with understanding traffic instability, optimization of macroscopic flow characteristics, or incident detection by traffic reconstruction. The simulation model should be capable of capturing the real-world performance of a system by considering the stochastic properties of all relevant technical and human processes in traffic, including responses to the safety system under assessment.

There are many possible interactions within a driver-vehicle unit and between traffic participants

and their surroundings. For ADF, the interaction between driver and vehicle may possibly be very limited (Figure 4). Traffic safety is a result of all elements of the driver-vehicle control loop [19], together with other factors, such as infrastructure or regulations.

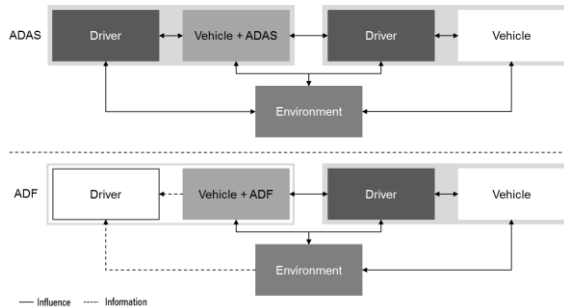


Figure 4. Possible interactions of driver-vehicle-surroundings including ADAS or ADF; each including possible interactions with another human driver (after [20]).

In principle, all relevant dynamic and human processes are represented as time series of states within the simulation. The simulated changes of those states can have both “deterministic” and “stochastic” characteristics, and it is often the stochastic variations that are important in accident processes. Simulation models must therefore be capable of representing not only deterministic processes but also stochastic properties. For example, the duration from a collision warning to braking by the driver will vary widely within a population of drivers and therefore must be regarded as stochastic [21]. The yaw rate of a vehicle on a dry surface is primarily deterministically dependent on steering wheel angle and speed, but slippage introduces an effectively stochastic component that could be important in extreme situations.

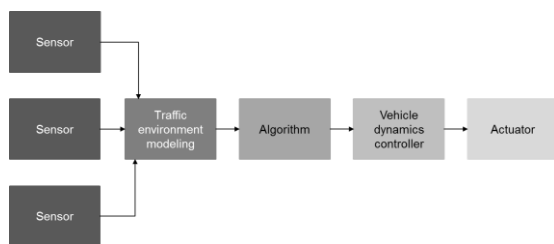


Figure 5. Generic process chain of ADF (without interaction with the driver) [22].

For technical systems, the entire process chain must be represented. The process chain generally consists of sensors, traffic environment modeling, algorithms (logic), vehicle dynamics controllers and actuators (Figure 5). Additionally, the system

impacts and feedback loops on driver, vehicle, and traffic are modeled.

By far the most important stochastic processes are related to human factors. It is known for instance that the reaction times of human drivers vary considerably [21] in response to even a controlled stimulus. Most accident processes involve at least some aspect of human factors, and the impact of ADAS or ADF cannot be evaluated virtually without taking human factors into account.

To this end, the integrated Stochastic Cognitive Model (SCM) for highway driving has been developed within BMW and applied to safety impact assessment. A core aspect of the SCM driver behavioral model is the application of stochastic methods in order to represent the behavior of different drivers (Figure 6).

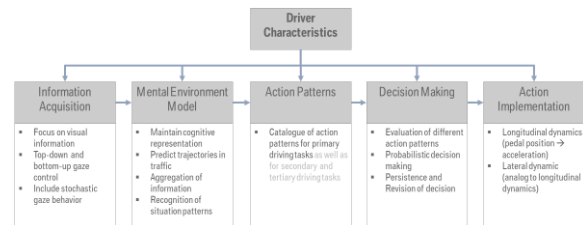


Figure 6. Overview on the used driver model for the safety impact assessment.

The SCM consists of five different sub-models that are briefly described in the following:

Information acquisition. This sub-model considers in principle auditory, haptic and visual perception of the driver. In particular in the information acquisition sub-model is focused on the visual perception, which considers the peripheral and foveal field of view of the driver as well as the gaze distribution.

Mental environment. This sub-model describes recognition of situation patterns. This sub-model considers the current information of the information acquisition sub-models as well as information from memory respectively previous time steps. All gathered information are aggregated to describe the microscopic traffic properties and extract features of the environment that are needed in the next model.

Decision making. In this sub-model the current situation is assessed according to the information derived in the previous step. Based on the outcome of the assessment a decision is taken about the next. For the selection of the taken action also statistical variations are considered.

Action Patterns. This sub-model divides the taken action base on an action pattern catalogue into primary (acceleration, deceleration, steering and constant driving), secondary (indicator use, light activation, use of the horn etc.) and tertiary driving actions (e.g. telephone or navigation use).

Action Implementation. Finally, the information of the previous sub-models are used in order to determine the pedal position – accelerator as well as braking pedal – and steering wheel angle that result in the longitudinal and lateral acceleration of the vehicle. By this the movement of the vehicle for the next time step can be determined.

CHALLENGES FOR VIRTUAL ASSESSMENT OF AUTOMATED DRIVING FUNCTIONS

Safety related ADAS act by means of warning or intervention in sporadic events shortly before imminent collision would occur. Automated driving functions in contrast operate and intervene continuously in the driving behavior. Consequently, safety related effects of the functions – positive as well as negative – in traffic flow as a whole, not only in certain target scenarios, must be considered in the assessment of AFD (Figure 7).

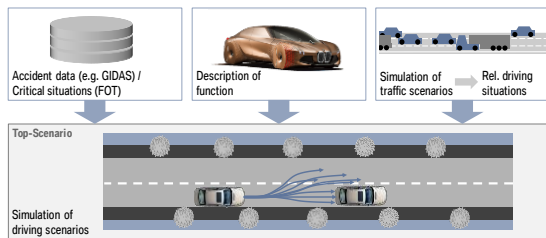


Figure 7. Identification of top scenarios for the assessment of AFD based on relevant situations as well as on continuous traffic simulation.

In general, automation has not only a potential for selective accident prevention from the perspective of the ADF-vehicle, but could, given sufficient penetration, increase overall traffic safety due to collective effects such as harmonization of traffic flow (see, for example, [25]). For example, traffic literature shows (e.g., [26]) that inappropriate speed is not only limited to individual drivers, but may be a collective phenomenon of the traffic stream. A high penetration of traffic with ADF-vehicles could thus also avoid accidents for non-equipped vehicles (due to the collective effects of early speed adjustment).

On the other hand, due to the continuous action of ADF in traffic, the situation space will be substantially larger than for current ADAS, and

prediction of all relevant situations will be difficult. This causes fundamentally new issues and methodological challenges arise for the virtual safety assessment of ADF. These issues complicate the assessment. A possible approach is an integrated and agile development and assessment process using a comprehensive tool chain.

Any methodology for continuous safety assessment during development requires a comprehensive understanding of various existing methods and their specific role and contribution in such a complex process. Figure 8 provides an abstract overview of the roles of different testing instances within an integrated development and assessment process.

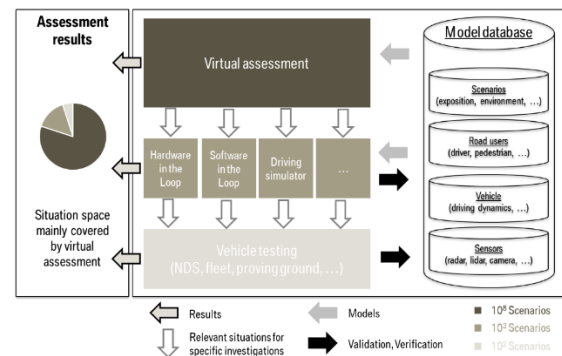


Figure 8. Development and assessment process including exemplary testing instances.

Referring to Figure 8, the scenario database as well as other models play a key role for all development and test tools. The scenarios and their frequency (in terms of an exposure model) can be stored in a scenario database and reused for different test instances.

Summarizing, the key of virtual assessment of ADF can be broken down in following aspects: modeling all relevant processes representatively and realistically, covering the large and partially unknown test space, and managing and utilizing both empirical and synthetic data. The following sections will briefly address these aspects without claiming to be exhaustive.

Process of assessing automated driving in virtual continuous simulation

In addition to traditional research methods (e.g., theoretical risk assessments, testing on the road, etc.), virtual continuous simulation offers new opportunities for “discovery” of relevant scenarios; especially, when it comes to combinations of factors which are rare and difficult to derive from theory.

One approach to discovery of “unknown” scenarios is observing longer durations or distances by long-running continuous simulation: safety-critical scenarios are not explicitly generated (e.g., by certain given constraints), but arise spontaneously from a stochastic comprehensive model of traffic flow.

In general, traffic has a very high complexity – due to the numerous direct interactions between traffic participants and indirect interactions between individuals and the collective traffic flow.

Nevertheless, traffic flow has several collective or “macroscopic” characteristics. Examples are “fundamental diagram” (empirical relationship between traffic flow and average speed on a freeway section) or “capacity” (characteristic traffic demand above which traffic flow tends to become unstable). Changes in macroscopic characteristics of traffic flow, in this context, due to ADAS or ADF, may in turn have effects on traffic safety.

Automated vehicles can affect direct interaction between vehicles, interaction between individual vehicles and traffic flow as well as collective characteristics of traffic flow. Since all of these changes can affect conflict and accident probability, they must be included in traffic safety assessment.

To this end, many processes in normal, non-assisted and non-automated traffic will need to be re-assessed by considering high context sensitivity and other skills or typical strengths of human drivers (see also [27, 28, 29, 7, 30, 19]).

An open question and subject of research and development is, to what extent automated vehicles will have capabilities comparable to those of human drivers. Some safety-relevant characteristics, such as anticipation and defensive driving, could be even more pronounced with ADF than with human drivers.

Thus, the approach of assessing ADF by means of virtual continuous simulation implies challenging requirements for comprehensive modeling. These include reproduction of all relevant processes (also error processes) in traffic flow, with their respective frequencies. Modeling the frequencies of all relevant processes and scenarios, essentially constitutes an advanced exposure model.

An initial set of scenarios can be specified using expert knowledge, field operational tests, and virtual test runs. Virtual testing generates many representations of stochastic processes in traffic based on models of traffic contexts, sensors, drivers, vehicles, and traffic dynamics. The objective is to provide a representative sample of

the overall situation space taking into account the large number of potential scenarios including low-probability events [31].

In a virtual test operation, these scenarios could be checked automatically representing a kind of safety cycle. The frequency of scenarios could depend on different factors, for example, countries or environmental conditions. Virtual testing would fulfill the requirements of a safety assessment in this construct, as described above.

Process description for assessing highly automated driving in top scenarios

A portion of possible positive contributions of ADF comes from consideration of relevant and potentially hazardous scenarios where the advantages of ADF help avoid potential accidents or mitigate their consequences. “Scenario” in this context refers to all potentially hazardous traffic situations that can lead to a certain type of conflict. Virtual testing by simulation of a single scenario results in quantification of effectiveness of an automated system in this particular scenario. The safety performance of automation then can be estimated from scenario specific effectiveness weighted by respective frequencies, i.e. “exposure” of the scenarios. The scenarios of particular interest for an ADF are referred to in the following as “top scenarios”.

Using virtual experimental design (as for ADAS), an appropriate reference sample of relevant scenarios can be defined and considered. For scenario-based assessment, representative scenarios are needed. The contribution to effectiveness due to ADF can be quantified using a sample of virtual experiments, once the scenarios and their frequencies are known: From the set of relevant scenarios, individual situations are “sampled”, i.e., created virtually. The values of all stochastic variables are drawn from appropriate distributions. Sampling may be repeated or independent. In repeated sampling, each randomly generated scenario is simulated multiple times (e.g., with / without ADF), whereas in independent sampling, new samples are drawn for each run.

The effectiveness of ADF is, among other things, determined by the system limits. These can theoretically depend on the traffic context (such as vehicle speed or road class given by a digital map), environmental conditions (light conditions, weather) or on conditions for automatic system activation or deactivation. Furthermore, system activation by the driver or other human factors can influence effectiveness.

Detection systems in traffic are subject to system limits and to various uncertainties and latencies. As a consequence, in practice, detection systems themselves often show stochastic characteristics. For example, the time for stable object recognition by means of a camera can depend on partial occlusion of the object or complexity of the traffic scene. The algorithms for situation detection and action usually rely on measurements from the detection systems; the derived characteristics (such as estimated “time to collision” for a detected object) are therefore also subject to corresponding latencies and uncertainties that require appropriate, mostly stochastic, modeling. Also, system actions often act indirectly by stimulating a driver reaction (e.g., warnings) or interact with (stochastic) driver actions (e.g., by lowering the threshold for brake assist). Overall, stochastic characteristics have a major impact on the overall safety assessment of ADF.

With increasing complexity of the systems, an abstract representation of the functionality of an automatic driving system may require considerable effort. Also, verifying that an abstract system model actually behaves like the real technical system poses a challenge with increasing system complexity. To meet this challenge, alternative approaches are possible:

Instead of abstract models, real components can be directly connected to the simulation using an appropriate test facility (e.g., Hardware-in-the-loop) [28]. In addition, findings from such test benches can be used for calibration and validation of relevant models in the simulation even without a direct connection. The actual code may be used in the simulation instead of an abstract model of the system logic. This results new challenges for the simulation and the models used due to the technical interfaces used.

Philosophy and procedural approaches for validation and verification

A key issue concerns the validation of process models and, by extension, plausibility of simulation results. Validation of models involves utilization of appropriate testing procedures for each particular method in the development chain. Each method, for instance test driving or a driving simulator, is used for validating the vehicle model or for MMI concepts. A validated model database is the prerequisite for the reliability of virtual testing; the quality of the models is of key importance for the development chain and the validity of the assessment result.

Verification of simulated system actions represents another important element of the inspection process, by drawing samples from all simulations and testing these in recognized test institutes.

APPLICATION OF THE ASSESSMENT METHOD

The virtual scenario-based trial design to test a *virtual ADF* is illustrated here for two “top” highway scenarios. In an “obstacle in the lane” scenario, the virtual drivers encounter an obstacle that may appear (from their point of view) suddenly. In a “jam approach” scenario, the virtual “human” drivers enter a realistically simulated traffic jam front (e.g., position of maximum speed gradient can vary among lanes). The two scenarios illustrate the approach of **Figure 7** for either a technically challenging scenario (obstacle in the lane) or a statistically frequent scenario (rear-end collision while approaching the end of a traffic jam). Both scenarios are described in more detail in the following.

Obstacle in the lane scenario

In this scenario the safety potential of a hypothetical automated driving function is investigated for an “obstacle-in-the-lane” scenario. The virtual experimental design for this scenario is illustrated in **Figure 9**.

The obstacle is located in the middle lane of a three-lane motorway, so that vehicles can attempt to either brake or maneuver to the left or right to avoid collision with the obstacle.

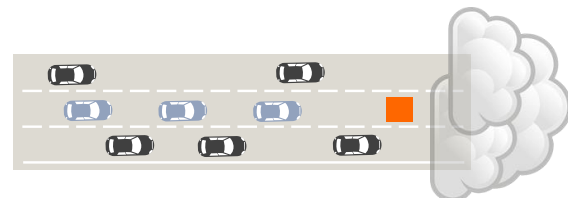


Figure 9. Scenario “obstacle in the lane” with the three target vehicles (light blue) and the obstacle (orange).

For the analysis, impact assessment focusses on the first three vehicles that approach the obstacle. The three target vehicles are either driven by the SCM driver model (human driver) or by the automated driving function. The vehicles of the surrounding traffic are all controlled according to the SCM driver model.

This scenario presents a rather complex challenge for human drivers. It requires several timely and generally irrevocable decisions that depend on the currently perceived state of surrounding traffic. The

main options include (1) braking in lane; (2a,b) swerving (left or right) just enough to avoid the obstacle, but returning to the original lane; (3a,b) changing lanes (left or right), a combination of braking with swerving (4a,b) or lane changing (5a,b), both limited however by controllability (friction ellipse). Drivers are thus forced to decide on an action (braking, swerving, etc.) under severe time pressure, obvious collision risk, and often with inadequate time for observation of blind spots.

The default option (0) is to wait too long and crash into the obstacle. Since the time required for a human driver to choose among n alternatives (here $n=9$) tends to increase with $\ln n$ [32], option (0) is unfortunately quite common in practice, even if the driver has good perception of surrounding traffic.

In simulations of the obstacle-in-the-lane scenario with SCM drivers, two main types of collisions were observed:

Collision with the obstacle by one of the three target vehicles. A typical chain of events leading to collision is that a preceding vehicle that blocks the target driver's view of the obstacle executes its lane change rather late. In this case, even if the target driver begins one of the response options (1) – (5) discussed above, it will often be too late to avoid the obstacle -- due to the laws of physics. These phenomena depend of course on the individual (stochastically modelled) response characteristics.

Collision between a target vehicle and another vehicle. A second typical accident sequence occurs when a target driver decides to change lanes (or swerve) urgently, without sufficient safety check on the intended adjacent lane. Here, the known threat from an obstacle ahead could outweigh the uncertain threat of possible adjacent conflicts. This thoroughly rational risk-minimization strategy will not always succeed. For example, another vehicle could have recently entered the conflict zone due to a relatively fast approach. Moreover, the perceptual data available to a driver confronted with an urgent threat is uncertain, and his intuitive decision process can have irrational (reflexive, emotional) components.

In target vehicles equipped with a virtual ADF, several main differences compared to the human SCM models are assumed: first, instead of data acquisition (perception) from an area of interest (AOI) only after gaze fixation on that area of interest, the ADF sensor is assumed to perceive all visible AOI continuously and simultaneously. Second, the ADF algorithm is assumed to compute

a braking reserve time to the preceding vehicle using sensors that are assumed to accurately detect speed differences. (The estimated braking reserve time in the ADF is of course still somewhat uncertain due to uncertain dynamics of the preceding (human driven) vehicle.) Third, the decision to brake, swerve, or change lanes was programmed deterministically based on the most likely safe outcome if one exists, otherwise, the default here is braking. Finally, the modelled response time for action implementation (**Figure 6**) is only slightly stochastic and on the average faster for an ADF-equipped target vehicle than the mean of the statistical distribution for human drivers.

For each of the 40,000 experimental units (simulation runs) considered here, we record whether (and if so, when) a collision has occurred, and whether one of the three target vehicles was involved. The data is "censored" at the time of simulation termination, i.e., it is unknown what might have occurred after the simulation termination, and accident risk is quite dynamic as discussed below. Moreover, the simulation run terminates after any accident, including accidents not involving a target vehicle. An appropriate representation of safety performance in this virtual experiment is to compute "survival" probability curves (**Figure 10**) by the well-known Kaplan-Meier or product-limit method. The relative safety performance of the ADF and SCM driver models can then be tested using the log-rank statistic.

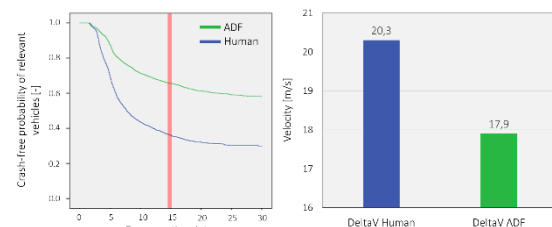


Figure 10. Overall results of the simulation of the "obstacle in the lane"-scenario.

The overall simulation results of the simulation show a safety benefit of the ADF target vehicles over "human" (SCM-model driven) vehicles. Overall the probability of "survival" (target not having an accident) in this scenario was 28.3% higher with automated driving (+94% relatively speaking). In addition, in case of collisions, the mean velocity difference between the involved vehicles is 15% lower for the automated driving vehicles.

Incidentally, the Kaplan-Meier curves illustrate the dynamics of risk exposure for the target vehicles in

this simulation scenario, which can be thought of in two phases. The first phase includes the approach and possible avoidance of the obstacle by the target vehicles. The phase takes about 17 s (for the 3 target vehicles) on the average and includes the main potential benefits of the automated driving function. The second phase describes the time after the target vehicles have passed the obstacle. During this phase, driving challenges are less severe for the target vehicles, although secondary accidents could still occur, for example, due to human drivers returning to their original lane after braking and swerving. However, the impact of automated driving appears lower than during the first phase.

The dependence of ADF safety performance on environmental factors in this scenario (traffic volume and range of visibility) is summarized in **Table 1**.

Table 1: Environmental factors and their influence on ADF safety performance in the obstacle-in-the-lane scenario

Scenario		Probability of remaining crash-free [-]			
Parameter	Value	SCM Driver	ADF	Delta (absolute)	Delta (relative)
Overall	-	29.9%	58.2%	-28.3%	-48.6%
Traffic volume	900 veh./h	30.9%	61.6%	-30.5%	-49.8%
	1200 veh./h	28.9%	54.8%	-25.9%	-47.3%
Range of view	250 m	30.4%	56.5%	-26.1%	-46.2%
	125 m	29.5%	59.9%	-30.4%	-50.8%

The absolute accident risk decrease with the automated driving function was between 25% and 30%. If the traffic flow is reduced, the probability of survival for automated and manual driving is increased. The same applies for an increased range of view.

Traffic-jam-approach scenario

Figure 11 illustrates the scenario “traffic jam approach” by a target vehicle (simulated as the fourth vehicle in the right lane).

Here, a rear-end conflict occurs while the target vehicle is approaching the end of the traffic jam. The main challenge in this driving scenario is the higher speed difference between the target vehicle and the rear end of the traffic jam, which is either standing still or slowly moving (approx. 30 km/h).

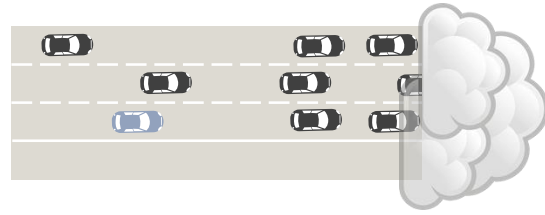


Figure 11. Scenario “approaching traffic jam” with the target vehicle (light blue) and the surrounding vehicles (black)

The existence of a large speed gradient in traffic flow presents severe challenges to a human driver. To avoid causing a collision, a driver must perceive the situation correctly (and in time) and respond appropriately. Whereas late perception or inadequate braking response are likely to lead to a rear-end collision, incorrect perception (with inappropriate response) could lead to misguided swerving or lane changes, causing possible secondary conflicts with approaching vehicles in adjacent lanes.

Accidents caused by a simulated “human” target vehicle occur most frequently when the target vehicle is not capable of slowing down in time to prevent a rear-end collision. However, accidents with the target vehicle can also occur if the driver performs a lane change while approaching the traffic jam and fails to perceive a potential conflict in surrounding traffic in this demanding situation.

As above, target vehicles equipped with a virtual ADF have continuous, simultaneous data acquisition from all AOI. They will decide deterministically how to respond, and respond faster on the average.

As above, for each of the 8000 experimental units (simulation runs) considered here, we record whether (and if so, when) a collision has occurred, and whether the target vehicle was involved. Due to censoring, the results are shown in terms of “survival” probability curves (**Figure 12**).

It is important in this design to note that many accidents involving the target vehicle and included in the statistics are caused by another driver, for example, the driver to the rear. Hence, many of the accidents are not addressed by the ADF.

Figure 12. Probability of remaining crash free for SCM vs. ADF by traffic variance (high vs. low) and jam speed (30 km/h vs. 0 km/h) in jam approach scenario.

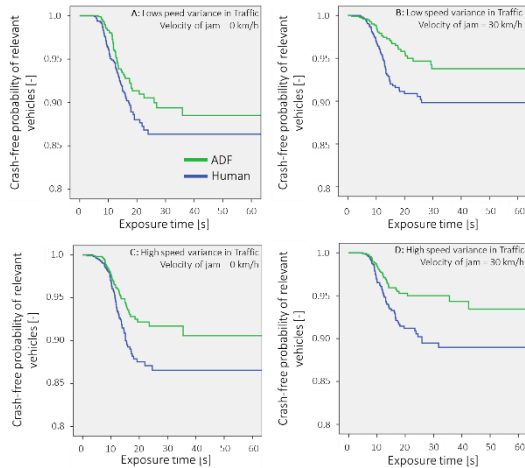


Figure 13. Probability of remaining crash free for SCM vs. ADF by traffic variance (high vs. low) and jam speed (30 km/h vs. 0 km/h) in jam approach scenario.

The accident reduction for target vehicle due to ADF was considered for low and high traffic variance and for jam speed 30 vs. 0 km/h at the jam front. The system was effective in all cases. **Table 1** shows a moderately greater effectiveness of the ADF in the case of the 30 km/h jam and a rather small difference depending on traffic variance, which might have affected the probability of last-minute lane changes.

Table 2. Accident reduction of target vehicles due to ADF in different experimental conditions.

	Traffic jam speed 0 km/h	Traffic jam speed 30 km/h
Traffic variance low	27.9%	48.7%
Traffic variance high	37.6%	46.2%

CONCLUSION AND OUTLOOK

The task of safety assessment and optimization of automated functions raises new issues. In contrast to ADAS assessment, quality measures of traffic safety are principally related to all traffic scenarios in which a function is active. Since automation may change collective traffic characteristics, safety analysis must go beyond isolated human errors in currently occurring traffic processes and the impact of automation on these. Newly emerging, automation-related, scenarios have to be considered for a comprehensive safety assessment.

Validation and safety assessment of automated functions have to be understood as continuous and iterative tasks during development, not as singular activities at the end of the development phase. Due

to the variety of possible influences, the necessary assessment of automation approaches during development would be extremely problematic based, for example, solely on fleet testing, since detection of rare effects requires correspondingly long observation periods. In addition, testing would have to be repeated, in principle, after every single change of the function.

The approach of simulation-based virtual experiments can be interpreted as knowledge synthesis. Still, some challenges for the assessment of automated systems arise. Relevant scenarios for automation are a priori unknown and can only partially be identified using existing methods. Due to the generally larger situation space involved in automation, modeling results in considerably more complexity as for the assessment of ADAS.

Quality requirements for traffic simulation are correspondingly higher, especially in terms of process models used. Traffic simulation will need to consider error processes and their resolution in normal traffic in more depth. The challenges include improved modeling of psychological processes, e.g., attention or activation (Yerkes-Dodson) [33]. An important aspect of the safety potential of ADF arises from avoidance of errors resulting from lack of driver activation and resulting attention lapses.

Despite sophisticated technology, systems will still be subject to system limits within the near future. Virtual experiments could make an important contribution to design and optimization of take-over requests to human drivers, in addition to safety assessment.

Critical traffic situations can require a decision among several unfavorable alternatives for action. Here again, virtual assessment can support the development of transparent decision algorithms, including possible ethical considerations. A general discussion of such alternatives has already begun in public [34]. Potentially, all stakeholders can achieve consensus on best-practice guidelines for the prioritization of alternative actions, prior to market introduction.

Many (novel) projects, initiatives, organizations, and research activities are focusing on the effects of ADAS regarding traffic safety. So far, however, an international consensus on methodological issues in the context of an overall safety assessment of ADAS and ADF is still lacking.

Consequently, the objective is an international consensus and implementation of scenarios,

models, and the overall assessment approach by all relevant stakeholders in an international context.

Considering the importance and complexity of decisions and challenges, the initiative “Prospective Effectiveness Assessment for Road Safety” (P.E.A.R.S.) has the objective of developing a standardized and harmonized method for the overall effectiveness assessment of new systems, such as ADAS or ADF, which is accepted by all stakeholders. Both benefits and potential risks should be quantified as part of the assessment. The objectives are, among others, a higher degree of legal predictability, and adequate and objective consideration of individual and societal interests. This open platform provides important prerequisites for a global harmonization and standardization.

Other important influences on safety such as integrity of communication, data protection, and technical reliability were beyond the scope of this paper, but could be addressed by stochastic simulation methods as well.

REFERENCES

- [1] M. Aeberhard *et al.*, “Experience, Results and Lessons Learned from Automated Driving on Germany’s Highways” in *Intelligent Transportation Systems Magazine*, IEEE, 2015, 7(1):42–57.
- [2] M. Bahram *et al.*, “Microscopic Traffic Simulation Based Evaluation of Highly Automated Driving on Highways”, in *17th International IEEE Conference on Intelligent Transportation Systems - ITSC 2014*, IEEE, 2014.
- [3] A. Etemad and A. Bartels, “A Stepwise Market Introduction of Automated Driving” in *21st ITS World Congress*, Detroit, 2014.
- [4] C. Hydén, “The development of a method for traffic safety evaluation: The Swedish Traffic Conflicts Technique”, in *Bulletin 70*, Department of Traffic Planning and Engineering, Lund University, Sweden, 1987.
- [5] F. Fahrenkrog *et al.*, “Bewertung Aktiver Sicherheit: Vom Test zur Wirksamkeitsanalyse“, in *ATZ*, 2014, 1(116):34–39.
- [6] T. Helmer *et al.*, chapter “Requirements and methods to ensure a representative analysis of active safety systems”, in *11th International Symposium and Exhibition on Sophisticated Car Occupant Safety Systems*, Fraunhofer-Institut für Chemische Technologie ICT, ISSN 0722-4087, 2012, pages 6.1–6.18
- [7] K. Kompass *et al.*, “Der Beitrag von Fahrerassistenzsystemen zur Aktiven und Passiven Sicherheit - die Integrale Sicherheit als Antwort auf die wachsenden Anforderungen an die Fahrzeugsicherheit“, in *4. Tagung Sicherheit durch Fahrerassistenz*, 2010.
- [8] A. Weitzel *et al.*, “Absicherungsstrategien für Fahrerassistenzsysteme mit Umfeldwahrnehmung“, in *BASt-Bericht F98*, Bundesanstalt für Straßenwesen, 2014.
- [9] T. Zangmeister *et al.*, “Simultaneous evaluation of multiple safety functions in passenger vehicles“, in *International Technical Conference on the Enhanced Safety of Vehicles*, 20th ESV, 2007, pages 07-0174.
- [10] D. G. Kleinbaum and M. Klein, *Logistic Regression. A Self Learning Text. Statistics for Biology and Health*, Springer, 2010.
- [11] R. J. Cook and D. L. Sackett, “The number needed to treat: a clinically useful measure of treatment effect”, in *British Medical Journal*, 1995, 18:452–454.
- [12] T. Helmer, *Development of a Methodology for the Evaluation of Active Safety using the Example of Preventive Pedestrian Protection*. ISBN 978-3-319-12888-7, Springer Theses, Springer, 2015.
- [13] E. Schechtman, “Odds Ratio, Relative Risk, Absolute Risk Reduction, and the Number Needed to Treat – Which of These Should We Use?” in *Value in Health*, 2002, 5(5):431–436.
- [14] T. Helmer *et al.*, “Injury risk to specific body regions of pedestrians in frontal car crashes modeled by empirical, in-depth accident data”, in *Proceedings of the 54th Stapp Car Crash Conference*, 2010.
- [15] T. Helmer *et al.*, “Kinematical, physiological, and vehicle-related influences on pedestrian injury severity in frontal car crashes: multivariate analysis and cross-validation”, in *Proceedings of the International Research Council On Biomechanics of Injury (IRCOBI)*, 2010, pages 181–198.
- [16] T. Helmer *et al.*, “Predicting the Injury Severity of Pedestrians in Frontal Vehicle Crashes based on Empirical, In-depth Accident Data”, In *International Journal of Intelligent Transportation Systems Research*, 2011, 9(3):139–151.
- [17] I. Ferenczi *et al.*, chapter “Effectiveness analysis and virtual design of integrated safety systems illustrated using the example of integrated

- pedestrian and occupant protection”, in *12th International Symposium and Exhibition on Sophisticated Car Occupant Safety Systems*, Fraunhofer-Institut für Chemische Technologie ICT, 2014.
- [18] P. Wimmer *et al.*, “A Simulation Method for Virtual Design and Evaluation of Integrated Safety Systems”, in *NAFEMS World Congress*, 2013.
- [19] K. Kompass *et al.* “Safety and Comfort Systems: Introduction and Overview”, in *Handbook of Intelligent Vehicles*, Editor: A. Eskandarian, Springer, 2012.
- [20] R. Bernotat, “Anthropotechnik in der Fahrzeugführung“ in *Ergonomics*, 1970, 13(3):353–377.
- [21] *NHTSA Driver Performance Data Book*, USDOT, 1987.
- [24] K. Kompass *et al.*, chapter “Gesamthafte Bewertung der Sicherheitsveränderung durch FAS / HAF im Verkehrssystem: Der Beitrag von Simulation“, in *Fahrerassistenz und Aktive Sicherheit. Wirksamkeit – Beherrschbarkeit – Absicherung*, expert verlag, Renningen, 2015, pages 45–66.
- [25] C. Steinhoff *et al.*, “Problematik präventiver Schaltungen von Streckenbeeinflussungsanlagen“, in *BMVBW Forschung Straßenbau 853*, Bundesanstalt für Straßenwesen, 2001.
- [26] T. Connolly and L. Åberg, “Some contagion models of speeding”, in *Accident Analysis and Prevention*, 1993, 25(1):57–66.
- [27] C. Domsch and W. Huber, “Integrale Sicherheit - ein ganzheitlicher Ansatz für die Fahrzeugsicherheit“, in *17. Aachener Kolloquium Fahrzeug- und Motorentchnik*, 2008.
- [28] T. Helmer *et al.*, “Development of an integrated test bed and virtual laboratory for safety performance prediction in active safety systems (F2012-F05-005)”, in *FISITA 2012 World Automotive Congress - Proceedings and Abstracts*, ISBN 978-7-5640-6987-2, 2012.
- [29] W. Huber *et al.*, “Der Fahrer steht im Mittelpunkt - Fahrerassistenz und Aktive Sicherheit bei der BMW Group“, in *24. VDI / VW-Gemeinschaftstagung - Integrierte Sicherheit und Fahrerassistenzsysteme*, volume 2048 of VDI-Berichte, Düsseldorf, 2008, pages 123–137.
- [30] K. Kompass and W. Huber, “Integrale Sicherheit – Effektive Wertsteigerung in der Fahrzeugsicherheit“, in *Technischer Kongress*, VDA, 2009.
- [31] A. Zlocki *et al.*, “Evaluation and sign-off methodology for automated vehicle systems based on relevant driving situations”, in *94th Annual Meeting*, Transportation Research Board (TRB), Washington D.C., USA, 2015.
- [32] W. E. Hick, “On the rate of gain of information”, in *Quarterly Journal of Experimental Psychology*, 1952.
- [33] R. M. Yerkes and J. D. Dodson, “The relation of strength of stimulus to rapidity of habit-formation”, in *Journal of Comparative Neurology and Psychology*, 1908, 18:459–482.
- [34] H. Prantl, “Error“, in *Süddeutsche Zeitung*, 2015, 37:13.