VALIDATION AND VERIFICATION OF THE STOCHASTIC COGNITIVE DRIVER MODEL

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Keywords: Simulation, Automated Driving, Driver Behavior Model, Validation & Verification.

ABSTRACT

For the prospective effectiveness analysis of highly automated driving functions, BMW has developed an integrated method that represents a safety assessment of these functions in the sense of proving a positive risk balance based on virtual experiments. This process is based on a stochastic approach for which the relevant scenario space is analyzed. An essential part of this is the realistic representation of driver behavior. Based on the BMW cognitive driver model (Stochastic Cognitive Model SCM) realistic driver behavior can be represented for various simulation agents in a multi-agent simulation. This is accomplished by the implementation of cognitive processes within the driver model from information acquisition via the mental representation of the environment to the assessment of the situation with the derivation of actions. The driver model is additionally parameterized by stochastic means.

Valid models are necessary for the use of the simulation-based approach to assess the safety of automated driving functions. The driver model in particular poses a major challenge. Human decisions and actions are both strongly driver-related and situation-dependent. Consequently, a considerable variation in driving behavior can be observed between different drivers in an objectively identical driving situation. This inevitably leads to the question of defining the comparison variable for validation. These challenges make it necessary to validate and verify the driving behavior with regard to different scenarios and different driver parameterizations in the simulation.

In the first part of the final presentation, the structure of the driver behavior model SCM used will be discussed and essential aspects of the stochastically parameterizable driver modeling will be highlighted. The second part deals with the process of validation and verification of this model and highlights challenges using the example of selected driving situations.

1 INTRODUCTION

1.1 Positive Risk Balance

In the last two decades numerous advanced driver assistance systems (ADAS) were introduced in the market [1]. These systems are either intended to improve the driving comfort (e.g. Adaptive Cruise Control) or to prevent collision and in case the collision is unavoidable to mitigate its consequences (e.g. autonomous emergency braking). A technology that could address both aspects is automated driving (AD) [2]. Therefore, the recent years have seen heavy research activities and developments in this area, which is documented by several research project [3][4] and demonstrations [5][6]. To differentiate the characteristics of assisted and automated driving functions (ADAS/ADS) are classified along the engagement of the driver by the SAE Level of Automation classification [7]. Up to SAE level 2, the human driver is always in charge. ADAS of up to level 2 have been introduced by different car manufactures [8]. ADS with higher levels of automation have so far only been deployed in restricted areas [9] – and in many cases combined with a safety driver. For public roads no mass production car with level 3 systems is available up to now (status autumn 2021). However, the technology is currently on the edge of entering the market [10][11].

Transferring the driving task from the human – even if it is only temporarily – to a machine raises also concerns in the society – in particular with respect to safety [13]. These concerns need to be addressed by stakeholders of automated driving (car manufacturers, suppliers, authorities, insurance companies etc.) carefully, since without public acceptance the success of AD is in jeopardy. This has been the one motivation to launch several activities on national and international level to establish ethical guidelines for automated driving. In Germany the ethic commission for automated and connected driving requests in its report a positive balance of risks with respect to the human driver in paragraph 2 and 3 [14], i.e. the ADS need to drive safer than the human driver does today. The European Ethic commission requests in its first recommendation to demonstrate that AD reduces physical harm to persons [15]. This basic principle is a driving item behind the "safety first for automated driving" white paper of an industrial consortium [16]. The ideas of this white paper have been transferred later in the ISO technical report 4804 [17] and are currently further developed in upcoming ISO specification.

Following the basic principle of achieving a positive risk balance for ADS, BMW has developed the PoRiBa (Positive Risk Balance) framework [18]. Its fundamental idea is that the positive risk balance shall not only be seen as a single number, but the idea to be safer as the human driver must be considered throughout the entire development process – ranging from the concept to the post start of production (SOP) phase (see figure). At the different stages of the process, different quantitative methods need to be applied. Here, in many aspects it is related to the approval process of pharmaceuticals. In the following it is focused on the sign-off phase, i.e. the ADS is about to be introduced in the market. Proving a positive risk balance at this stage is challenging, since there will not be any accident data available. This means that a prospective safety assessment needs to be conducted.

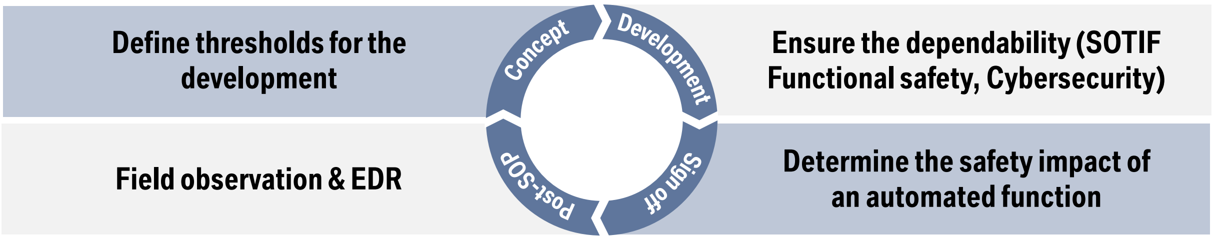


Figure 1: Overview on PoRiBa framework and the objectives at different development stage.

1.2 Prospective safety assessment by simulations

Different prospective safety assessment approaches are known today which range from rather simple approaches like the identification of the field of application by means of accident data analysis [19-21] to quite demanding approaches like field operation tests (FOT) [22][23]. Each approach has its advantages and disadvantages. The identification of the field of application allows a rather quick assessment but does not allow to analyze the safety effects in detail. The FOT approach assesses the effect of a technology under real operation conditions. However, it can only be applied at a late stage in the development, is quite resource demanding and will not provide a sufficient number of accidents to statistically analyze the safety performance of technology.

Considering the advantage and disadvantages of different approaches the conclusion is that at this stage of the development, virtual simulation-based assessment approaches are the most promising solution. They can be conducted with reasonable time effort and allow for a detailed investigation of numerous driving scenarios. For the prospective safety assessment, BMW uses the open-source simulation tool openPASS [24]. For each virtual assessment there is the question of the transferability of its conclusions to the real-world. The answer to this question highly depends on the evaluation scope and the quality of the implementation [25]. To prove the correctness of simulation validation and verification activities are essential.

Each simulation represents the environment, the vehicle including technologies as well as the driver by means of models. Depending on the assessment scope and the applied simulation approach, requirements regarding model fidelity of these models vary. The international initiative to harmonize Prospective Effectiveness Assessment for Road Safety defines four simulation approaches [25]:

- A: Direct usage of real-world cases (i.e. reconstructed accidents data or field data) without any changes).
- B: Usage of real-world cases plus varying the initial values by means of distribution.

- C1: Deriving scenario mechanism and distribution from real world case and selecting a low number of representative cases.
- C2: Deriving scenario mechanisms and distributions from real world cases and applying a sampling in order to get multiple cases.

When assessing an ADS's safety performance, its fundamental mechanism must be taken into account. In contrast to a safety oriented ADAS, the ADS is constantly operating and not only in critical scenarios. Therefore, the effects of the ADS in a situation, i.e. entering the scenario with a different velocity or distance to the predecessor, must be reflected in the assessment. Hence, the simulation approach must be able to cover a large time frame and not only a couple of seconds as it is typically the case for the approaches A and B if accident data is used. The usage of FOT data would overcome this issue, but typically non or only a very limited number of accidents is recorded during an FOT. Thus, in this case, any safety performance statement would be based only on a few cases. The issue holds also true for the approach C1.

For these reasons the authors see a clear advantage in the simulation approach C2 when assessing the safety performance of ADS. This approach does not use real-world cases directly but establishes the link to them via distributions, which can be derived from accident data as well as field data depending on the scenario in question. From these distributions the starting conditions of the traffic participants are sampled [26][27]. The challenge of this approach is that in contrast to approach A and B no predefined trajectories are available. The movement of the traffic participants resulting from the starting conditions needs to be derived during the simulation by the driver behavior model. Thus, the driver behavior model is key model in this approach. Therefore, in the following sections driver behavior models in general and BMW's driver behavior model "Stochastic Cognitive Modell (SCM)" in particular as well as the related validation and verification activities are explained in more detail.

2 DRIVER BEHAVIOR MODELS IN SIMULATION

Simulation approach C2 necessarily leads to the question of how to model behavior of traffic participants in the simulation. The model itself must represent realistic traffic behavior which means that it needs to cover the entire range from "everyday driving" in uncritical situations to human reactions in critical situations.

Widely known microscopic driver models that cover driving behavior in non-critical traffic situations are for instance the Wiedemann model [28], the intelligent driver model [29], the car-following model by Gipps [30] or the driver model by Krauss [31]. These or adapted versions of them are used in traffic simulation frameworks like SUMO [32] and VISSIM [33] which are primarily applied to assess traffic flow. For this research area they are a suitable framework. Although these models are able to model realistic traffic flow with car following behavior, they lack the capability in modeling driver behavior especially in critical situations or even accidents in a realistic manner. A common aspect of these models is that the driver perceives the information of the environment and surrounding traffic as ground truth information, i.e. the information is always correct and does not consider any failures. Driver reactions are consequently not influenced by any human error. These driver behavior models do not cover any variation in the situation as well meaning that the agent's reactions are always the same for the same inputs. Thus, these models are not able to represent differences in individual driver behavior appropriately for the intended field of use described above.

Other driver models exist, that cover the behavior in critical situation. They consider the fact that human behavior is highly dependent on both physiological limitations, psychological processes and the underlying situation. Examples are the tau-theory model by Lee [34], the cognitive model by Salvucci [35] the Japanese driver model in the UN ECE ALKS regulation [36] or the driver model described by Rösener [37]. These models have in common that they model perceptional accepts of driver behavior. This means that drivers' reactions are derived from the information the driver perceives in the environment which leads to more realistic driving behavior. Adversely, these models are often tailored to certain specialized scenarios and therefore not suitable as well for the intended use within the PoRiBa framework.

An appropriate model for simulation approach C2 needs to cover both types of uncritical and critical situations to represent realistic driving behavior in all possible situations. This eventually ensures a correct baseline for the prospective assessment of automated driving function. For that reason, BMW has developed an own driver behavior model named “Stochastic Cognitive Model” (SCM).

3 BMW STOCHASTIC COGNITIVE MODEL

BMW’s driver behavior model SCM has been developed since 2014 and is used in the simulation framework openPASS for modelling the behavior of traffic participants. SCM consists of six different modules: Information Acquisition, Mental Model, Situation Manager, Action Manager, Action Implementation and finally the Driver Characteristics. These modules and their interaction are explained in more detail in this section. Figure 2 provides an overview of the information flow for one agent in a passive cut-in maneuver.

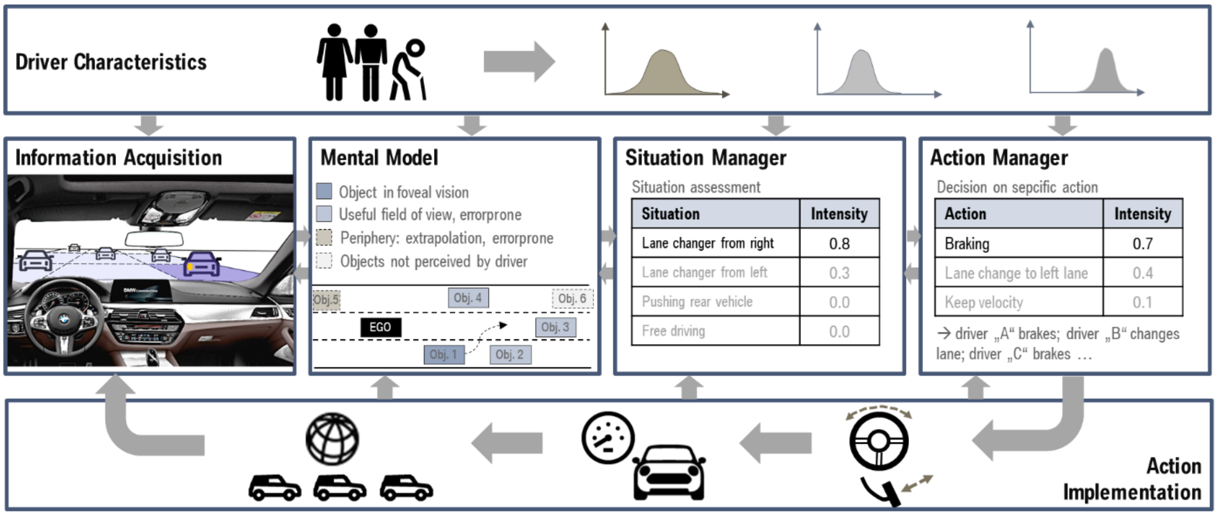


Figure 2: Overview of the information flow within SCM

Detailed modelling of the driver’s visual perception is a key input for cognitive processes which are based on the information that the driver perceives from their environment. Hence, in the submodule Information Acquisition the visual perception of the driver is modelled in a high level of detail. The gaze allocation and fixation duration to a specific area of interest is considered as a stochastic process and are therefore sampled from specific distributions. The visual perception during a specific gaze fixation considers both foveal and peripheral vision and takes the concept of the useful field of view into account. Data derived from several driving simulator studies and FOT has been used to parametrize the overall gaze behavior of SCM [38][39]. In addition, the driver’s gaze behavior can be influenced by bottom-up and top-down processes. Stimuli in the peripheral vision lead to a gaze allocation to the source of this stimulus (bottom-up) or certain actions of the driver require visual attention to a specific area (top-down).

The Mental Model represents the driver’s perceived environment. All information which is gathered through the information acquisition module is stored and updated in each timestep in this module. The stored information can be of different type: microscopic information considers data that describes the microscopic traffic around the driver, e.g. velocities and positions of surrounding vehicles. Mesoscopic information describes data that is aggregated over several other vehicles, such as the mean velocity in a specific lane. The third type of information is infrastructure information, like number of lanes of the current road, road markings or traffic signs. Due to the gaze behavior of the driver and the inherent error-proneness of perception, the information stored in the mental model might be, compared to ground truth data of the environment, incomplete and error-prone. The mental model is not only used to store information but also calculates relevant data for decisions on required actions. For instance, if the driver prepares for a merging maneuver the mental model evaluates from the position of the surrounding vehicles if there is enough space for the own vehicle to merge into a specific gap with the perceived data of the other vehicles like velocities and accelerations.

From the information that is processed in the mental model the driver recognizes and evaluates the currently given situation in the Situation Manager module. Within this process, specific features are extracted which characterizes certain situations. This means, that the driver recognizes certain characteristics of specific situations, e.g. a switched-on indicator is one of several features for the perceived situation of another vehicle changing lanes. The relationship and existence of several features leads to situation intensities which describe the degree to which the situation matches predefined situations. Examples for these predefined situations are “lane changer from left” or “following driving”.

The driver then identifies a situation-specific action to react to the given situation. This phase takes place in the Action Manager. Depending on the situation itself, the relevant features identified for this situation and additional data from the Mental Model, the driver decides for an action which could be braking, accelerating, or steering. Eventually the Action Implementation module is responsible for transferring the selected action into a driver reaction by defining pedal positions and steering wheel angles. This eventually changes the vehicle’s longitudinal and lateral movement. Other drivers in the simulation will vice versa react to the actions of this specific driver. These actions and reactions result in overall traffic behavior in the simulation.

The module Driver Characteristics influences all other modules by providing specific distributions for driver related parameters. These parameters can influence e.g. the driver’s perception and cognition, compliance to traffic rules or car-following related actions. The distributions are based on different data sources like FOTs, driving simulator studies and traffic data. For each driver in the multi-agent simulation the parameters are drawn at the beginning of the simulation from these specific distributions with the objective of getting a representative driver population. It ensures realistic driving behavior in the way that drivers with different driver characteristics may ultimately react in a different way in the objectively same situation. For the example of the cut-in maneuver in figure 2 this means that one agent in the simulation decides to brake because of the cut-in vehicle and another agent with different driver characteristics but being in the same situation chooses to change lanes.

4 VALIDATION AND VERIFICATION

A comprehensive validation and verification (V&V) of the simulative framework as well as its simulation models, particularly the driver model, is essential to ensure trustworthy and reliable results for the simulation-based approach of the positive risk balance. BMW has developed an integrated validation and verification approach for the simulation framework openPASS ranging from software tests via the models to the overall method, see figure 3.

The V&V approach is based on different system integration levels. The process is integrated into the software development cycles of the simulation framework and the single models themselves. It must be noted that the software development process uses a Scrum approach with frequently new software releases. The verification process of the actual software uses unit-tests, integration-tests and end-to-end-tests to ensure software functionality with each new software release. These represent the three bottom layers in the V&V pyramid. On top of the end-to-end-tests the models are individually validated and verified within the simulation framework (fourth layer). This is based on model-specific defined scenarios with defined outcomes for each scenario. Simulation of these scenarios takes place within an automated toolchain. This simplifies V&V activities within the short development cycles of openPASS and ensures that efforts for the overall validation and verification process are kept at reasonable level.

On top of these activities the correctness of the overall method needs to be proven. This is a challenging task since the overall method aims to investigate future traffic safety effects of a technology. The intuitive approach is to compare the derived safety impact of the simulation bases assessment with the results derived based on accident statistic. The analysis of accident statistic is only feasible in retrospective manner, i.e. after the technology has reached a certain market penetration rate and sufficient accident have been detected which can take years. Thus, either the validation is of the overall method is done by waiting until real accident data is available, or the validation is done by means of technology for which the safety impact is already known today, like e.g. AEB systems. In this case the prospective assessment method is applied in contrast to its normal use case for a technology which is already on the market. The authors have used this approach to prove the general correctness of the simulation method. However, correctness of the overall method does not guarantee correctness of all single modules. That is why the single modules need to be checked as well. In the following, a closer look is taken into this step of the V&V approach. The chosen example module is the SCM driver behavior model.

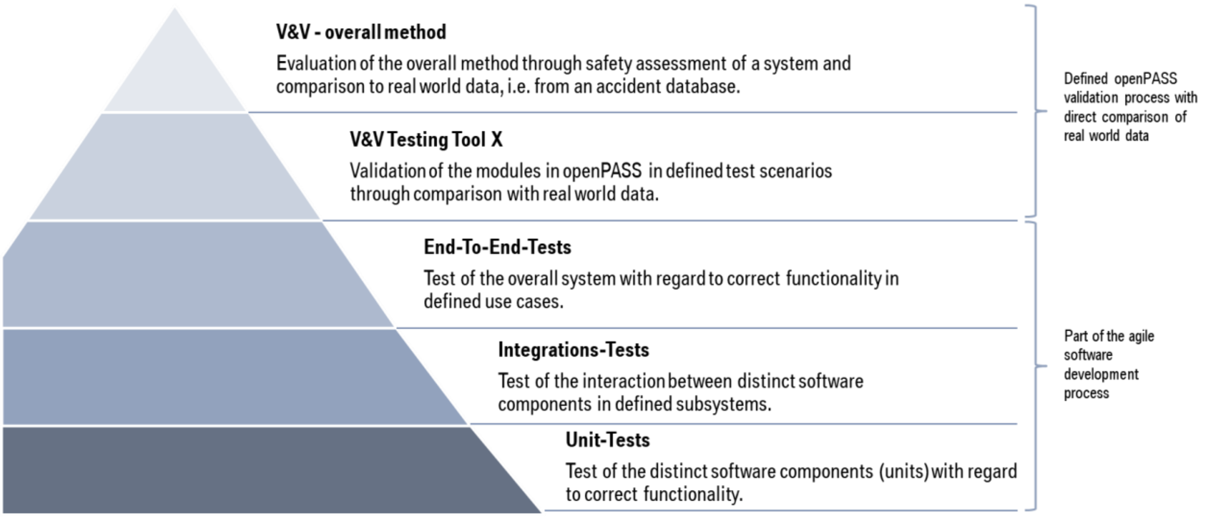


Figure 3: Validation and Verification levels

The validation of SCM combines two aspects: traffic behavior and individual driver behavior. Traffic behavior focuses on the analysis of all drivers in a traffic simulation and should answer the question if the overall traffic in simulation correctly represents real world traffic. Therefore, endurance simulations with varying inputs like traffic volume, number of lanes and existence of any speed limit are performed and specified parameters, e.g. velocities, accelerations and time headways (THW), are compared to real-world data from FOTs or drone data sets. Figure 4 shows the exemplary parameter distribution of THW for the SCM release May 2021. Exemplary results from endurance runs in openPASS are compared to BMW FOT data and drone data from the HighD dataset [40][41]. The THW distribution shows that the overall following behavior in simulations correspond to real-world following behavior of drivers. Especially for higher THWs there seems to be some differences in data and for openPASS. This is mainly due to limitations of the different data recording methods. For FOT data the recorded THWs are limited to the sensor range of the vehicle and therefore there are rarely THWs above 4 s. Similarly, for the HighD data the THWs are limited to the observed length of the highway section which is around 400 meters.

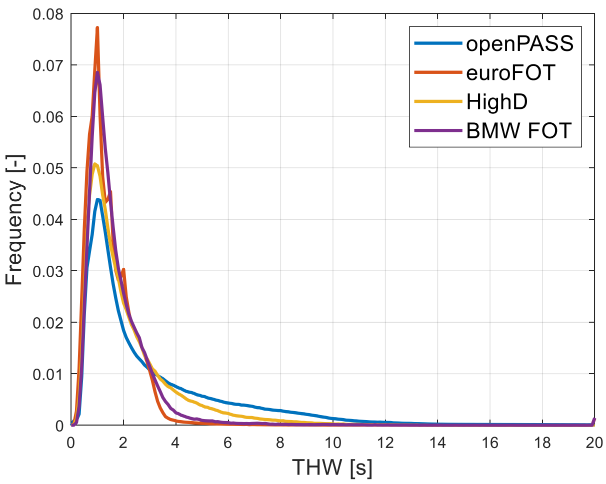


Figure 4: time headway (THW) distribution of openPASS and real-world data.

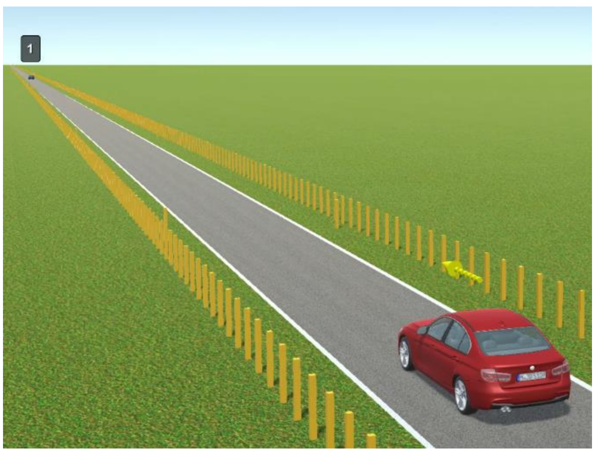
The aspect of individual driver behavior should answer the question if the driver behavior model in the simulation correctly replicates the range of real-world driving behavior in different situations.

Therefore, basic driving situations like free driving, approaching a slower vehicle, response to a speed limit sign or reaction in a defined critical scenario are analyzed with only one agent simulated. Predefined parameters, e.g. velocity, acceleration or reaction time are compared to criteria derived from real world data, e.g. FOTs or driving studies. It must be noted that a significant challenge within the validation of driver behavior is, that there is not any generally “wrong” driving behavior. The following example illustrates this statement. In the situation of a speed limit in a given highway section, there might be real-world drivers that comply to traffic rules and adjust their velocity to the speed limit. Conversely, there might also be drivers that ignore the traffic rules and still choose to drive faster than the present speed limit. Both behaviors must be shown in the simulation to have a realistic representation of real-world traffic. Therefore, the validation of the individual driver behavior is not validated by a single simulation run but with a high number of simulation runs. This enables the examination of the parameter distributions of a set of agents with different driver characteristics which take the range of driving behavior into account.

This paper focuses on the V&V activities concerning critical situations. For the validation of SCM behavior in these situations artificial critical scenarios are generated in openPASS. The criticality in the analyzed scenario is induced by a standing vehicle in the middle of the ego lane and a reduced SCM’s visibility range of 100 m. Normally, the view range of the SCM agent is larger. However, this would lead to a relatively comfortable braking maneuver and not to a critical situation as intended here. The view range of 100 m is comparable to bad weather conditions such as heavy rain or fog in real world driving situations. For having a closer look solely at SCM’s perception and reaction in this situation no other traffic is allowed besides the obstacle, which is a standing vehicle. The road is one single lane to limit possible actions of SCM to longitudinal maneuvers. With more than one lane SCM may try to evade the standing vehicle in some cases which in this case is not the required outcome.

The agent under investigation is spawned a few hundred meters behind the standing vehicle, see left side of figure 4. This at one hand ensures that there is enough time at the beginning of the simulation for obtaining an equilibrium state, which in this case means arriving at the agent’s desired velocity after being spawned with a defined initial velocity. On the other hand, it guarantees that the standing vehicle is not yet in the visibility distance of the driver, as the moment when the standing vehicle will become visible for the driver as well as the following timesteps are essential for the analysis. The simulation was performed with 200 runs which means 200 different agent configurations when it comes to the individual driver characteristics.

The simulation results show that after being spawned, the drivers start to adjust their speed to their desired velocity, see right plot of figure 5. The desired velocity of each agent is one the driver characteristics that are sampled at the beginning of the simulation. The mean (desired) velocity of these 200 runs is approximately 115 km/h. Within a distance of 100 m to the standing vehicle, the driver is able to see the obstacle. All simulated agents try to avoid the collision and start to brake after having recognized the standing vehicle. 31 of the 200 simulation runs result in a collision, whereas the agents in the other 169 runs are able to resolve the critical situation and come to a standstill before they reach the standing vehicle.



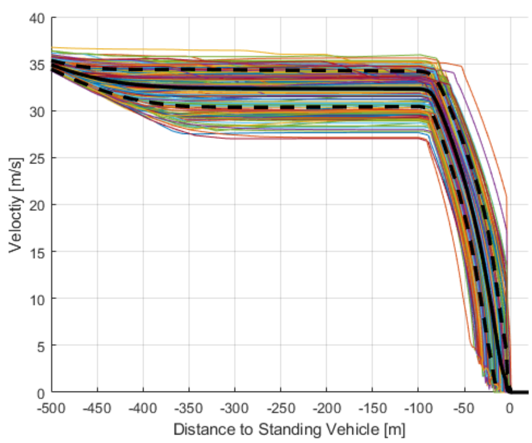


Figure 5: critical situation of a standing vehicle, visualization (left) and velocity plot (right)

Two points in time are particularly relevant when it comes to the analysis of driver reaction in a critical situation: the moment when the standing vehicle is seen by the driver and the moment when the driver reacts to the standing vehicle. For both moments the distributions of TTCs are shown in figure 6. The TTC at the first detection is the first time when the agent is looking in the front area. This happens not until the driver is within the visibility range of 100 m. If the driver is distracted by the time when the standing vehicle becomes visible it's the first point of time when the driver is looking in the front areas. The TTC distribution lies in a range from 2 to 3.8 s. The TTC at time of reaction is depicted on the right side in figure 6. It is calculated for the moment when the driver's deceleration is more than 2 m/s². The distribution lies within the range from 1.4 to 3.4 s. Several studies by van der Horst and Hogema [42] examined drivers braking due to a stationary object. For hard braking the average TTC at the time when braking starts in the latest possible moment, for which the drivers thought of being able to stop the vehicle without a collision, is approximately 1.6 s at 50 km/h 1.9 s at 70 km/h and increases with velocity. So, for the TTC at time of reaction the simulated cases lie in a range which also in real world situations lead to hard braking maneuvers. This shows that the parameters for the scenario are in a range that lead to critical situations for the driver which was the original objective of the scenario. Occurrence of collisions in 31 runs of total 200 runs is a consequence of these rather critical situations.

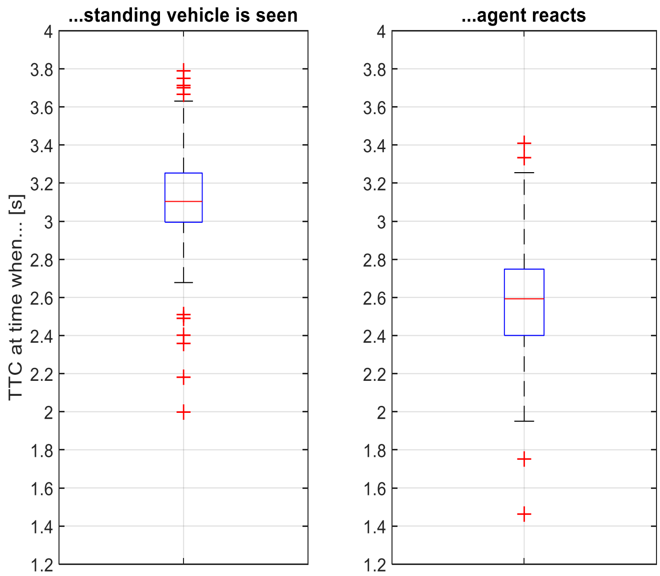


Figure 6: TTC when the standing vehicle was seen (left) and at the time of reaction (right), all runs

Further investigation of the collision cases in contrast to the cases where the agents can prevent a collision shows a difference in reaction times, see figure 7. The reaction time in this case is defined as the time interval from the point of time at which the driver sees the standing vehicle to the point of time when the driver starts braking. This time interval is commonly referred to as brake reaction time in literature. The overall observed reaction times of SCM largely correspond to several studies, e.g. [43-48]. However, it must be noted that literature provides a large range for reasonable reaction times because of highly influential factors like study designs and analyzed situations [48-50]. Comparing reaction times to the meta-analysis of Green [49] who investigated the results 40 publications to brake reaction times, it rather seems that SCM drivers tend to react faster than the reaction times of drivers in situations with low uncertainty (0.70 s to 0.75 s) or surprise intrusion (around 1.5 s). In contrast to that the results from Meehmood and Esea [48] show that surprising situations lead to lower reaction times with values ranging from 0.58 to 1.00 s compared to normal driving situations. Also, Summala [50] arguments in his commentary to Green [49] that brake reaction times in surprising and more critical situations rather tend to be between 1.0 s and 1.3 s. The results and discussion show that a more detailed analysis of real-world driver reactions to a stationary vehicle under different conditions is necessary in order to get an even better understanding of driver reaction in this particular situation as the situation itself seems to have considerable influence on the outcome of reaction times.

Nevertheless, having a driver model in the simulation with better reaction capabilities than real-world drivers is not harmful for the results of the PoRiBa for the reason that the effect of an ADS on traffic safety is rather underestimated and therefore more conservative.

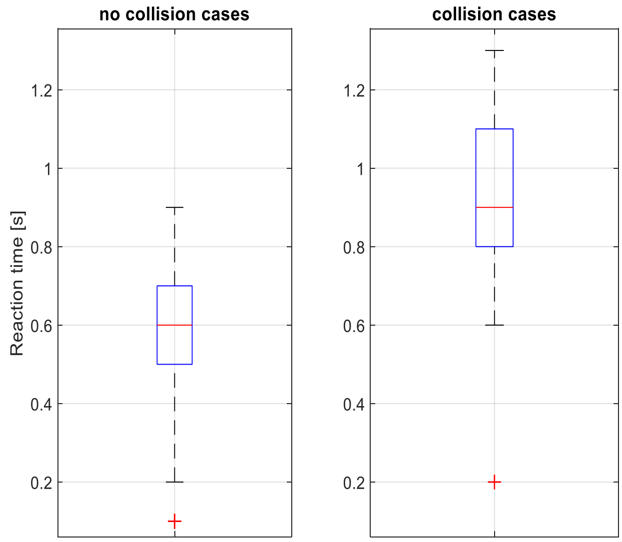


Figure 7: Reaction times for the 169 runs without a collision (left) and the 31 collision cases (right)

The reaction times of SCM agents preventing a collision (n=169) are considerably lower than the reaction times of the agents in the runs with a collision. However, reaction times between 0.6 s and 0.9 s occur both in collision cases and no collision cases so there must be additional influencing factors for collision events. Figure 8 shows TTC at time of reaction and minimal acceleration for collision and no collision cases. Especially the area of TTCs between 2.2 s and 2.5 s seems interesting because in this area, some SCM agents are able to prevent a collision whereas other agents cannot avoid a collision. A reason might be different minimal accelerations which is an additional driver characteristics parameter in the simulation. Within the runs with no collisions for a TTC at reaction between 2.2 s and 2.5 s the drivers seem to apply higher decelerations whereas lower decelerations lead to a higher collision rate. This behavior is as well observed in real traffic, in which drivers react differently to a critical situation based on their attention and driving capabilities [50][51].

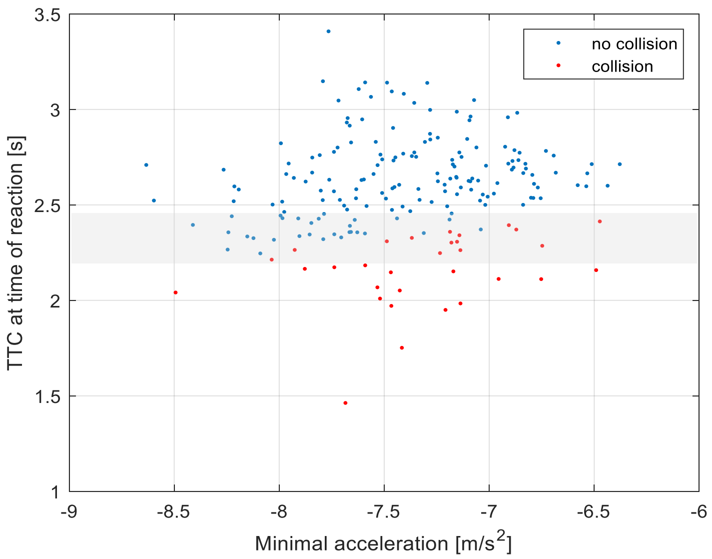


Figure 8: TTC at time of reaction and minimal acceleration for collision and no collision cases

Summarizing the observations, SCM behavior in simulation shows that the overall cognitive processes regarding information acquisition to decision for an action can largely represent real world driver behavior. In the case of critical situations single driver behavior is analyzed in the situation of a sudden obstacle within poor visibility conditions. SCM shows that in the same situation regarding starting parameters, different behavior for different agents concerning recognition and reaction is observed which is caused by the various driver characteristics like reaction times and acceleration behavior. This shows that the overall objective of representing a range of drivers rather than one single driver is reached with the driver characteristics and their impact on the cognitive process. When it comes to TTC at reaction the observed values in simulation lies within a range that also real-world drivers would evaluate as a rather critical situation. The analysis shows that reaction times and braking performance of SCM agents in this specific critical situation largely correspond to real world driver behavior.

6 CONCLUSIONS

This paper presented an approach for the validation and verification for the BMW stochastic cognitive driver model SCM. For the prospective safety assessment approach for automated driving functions within the presented PoRiBa framework a valid driver behavior model is conclusively necessary for the representation of realistic driver behavior in simulations. A comprehensive validation and verification of the method as well as the simulation tool including all models is essential for obtaining reliable results. The overall V&V process at BMW which focuses on all levels, from the overall method to the single modules, and which is embedded in the agile software development process was shown.

Especially the validation of the driver model poses the challenge of defining the range of correct realistic driving behavior as this is both driver-related and situation-dependent and therefore may vary within the objectively same situation over different drivers. The validation and verification of driving behavior combines the two aspects of analyzing traffic behavior and individual driving behavior. The traffic behavior analysis focuses on the complete driver population in simulation and focuses on parameter distributions of the overall traffic. The distribution of the time headway in comparison to real-world data was given as an example. Macroscopic traffic behavior in endurance simulations generally shows good results in comparison to distributions from real-world data.

Nevertheless, it is also necessary to investigate individual driving behavior. Therefore, simple situations are analyzed and evaluated over a range of simulated agents. The paper showed the example of a critical scenario defined by an obstacle on a one-lane road in difficult weather conditions, which is characterized by a low visibility range. Driver behavior with regard to reaction times and braking accelerations and their relationship with the occurrence of a collision in the situation. The results show that the scenario and its conditions lead to critical events and collision cases. Reaction times of SCM are considerably lower in simulations without a collision compared to collision cases. For drivers with similar reaction times to the critical situation the braking acceleration is lower for those drivers which runs resulted in a collision. Compared to several studies with real-world drivers the SCM results are observable in real-world critical situations as well. However, real-world studies show a wide range of possible brake reaction times and therefore further investigation of specific critical scenarios is necessary for better understanding of the influencing factors in these situations. So further scenarios need to be investigated in the future in order to validate SCM behavior in the complete range of real-world driving. Depending on the scenario specification the investigation of different driver parameters and their effects is necessary.

REFERENCES

[1] Martinez von Robert, R., Raisch, F., Fahrerassistenz / Hochautomatisiertes Fahren - Akzeptanz und Kundennutzen, VDA Technischer Kongress, 2018.

[2] ACEA, Automated driving - Roadmap for the deployment of automated driving in the European Union, https://www.acea.auto/files/ACEA_Automated_Driving_Roadmap.pdf, 2019.

[3] Etemad, A., Piloting Automated Driving on European Roads, L3Pilot Summer School, https://l3pilot.eu/fileadmin/user_upload/Downloads/L3Pilot_SummerSchool_Presentations/L3Pilot_SummerSchool_presentation_Aria_Etemad_20200909.pdf, 2020.

[4] AdaptIVe project, Final project results, deliverable 1.0, https://www.adaptive-ip.eu/files/adaptive/content/downloads/AdaptIVe-SP1-v1-0-DL-D1-0-Final_Report.pdf, 2017.

[5] Ziegler, J., Dang, T., Franke, U., Lategahn, H., et al., Making Bertha Drive — An Autonomous Journey on a Historic Route, IEEE Intelligent Transport Magazine, vol 6, no. 2, pp 8-20, 2014.

[6] Waymo, Waymo Safety Report September 2020, 2020-09-waymo-safety-report.pdf, 2020.

[7] SAE, Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles, 2016.

[8] Ulrich, L., BMW's Autonomous "Extended Traffic Jam Assistant" Needs Supervision, IEEE Spektrum, https://spectrum.ieee.org/cars-that-think/transportation/self-driving/bmws-autonomous-extended-traffic-jam-assistant-needs-supervision, 2019.

[9] City Mobil 2, Final Report, https://cordis.europa.eu/docs/results/314/314190/final1-final-publishable-report.pdf, 2016.

[10] Honda, Honda Launches next generation Honda sensing elite safety system with level 3 automated driving features, presse release, https://hondanews.eu/eu/en/cars/media/pressreleases/329456/honda-launches-next-generation-honda-sensing-elite-safety-system-with-level-3-automated-driving-feat, 2021.

[11] Daimler, Introducing Drive Pilot: An Automated Driving System for the Highway, https://www.daimler.com/documents/innovation/other/2019-02-20-vssa-mercedes-benz-drive-pilot-a.pdf, 2019.

[12] Walker, A., Are self-driving cars safe for our cities?, https://archive.curbed.com/2016/9/21/12991696/driverless-cars-safety-pros-cons, 2020.

[13] Othman, K., Public acceptance and perception of autonomous vehicles: a comprehensive review, AI Ethics, https://doi.org/10.1007/s43681-021-00041-8, 2021.

[14] Di Fabio, U., Broy, M., Brüngger, R., Eichhorn, U., Grunwald, A., Heckmann, D., Hilgendorf, E., Kagermann, H., Losinger, A., Lutz-Bachmann, M., Lütge, C., Markl, A., Müller, K., Nehm, K., Ethic commission: automated and connected driving, Report of ethics commission appointed by the federal minister of transport and digital infrastructure. https://www.bmvi.de/SharedDocs/EN/publications/report-ethics-commission.pdf?__blob=publicationFile, 2017.

[15] Bonnefon, J.-F., Cerny, D., Danaher, J., Deviller, N., Johansson, V., Kovacikova, T., Martens, M., Mladenovic, M. N., Palade, P., Reed, N., Santoni de Sio, F., Tsinorema, S., Wachter, S., Zawieska, K., Ethics of Connected and Automated Vehicles: recommendations on road safety, privacy, fairness, explainability and responsibility. Horizon 2020 Commission Expert Group to advise on specific ethical issues raised by driverless mobility (E03659). Publication Office of the European Union: Luxembourg. https://ec.europa.eu/info/sites/info/files/research_and_innovation/ethics_of_connected_and_automated_vehicles_report.pdf, 2020.

[16] Wood, M., Knobel, C., Garbacik, N., Robbel, P., Boymanns, D., Smerza, D., Maass, M., Löhning, M., Dalong, L., Radboud, D. T., Dehlink, B., Timmons, A., Meijs, M., Kaule, D., Bellotti, Harb, M., Krüger, R., O'Brien, M. et al., Safety first for automated driving. White paper of different car manufacutres and suppliers. https://www.press.bmwgroup.com/global/article/attachment/T0298103EN/434404, 2019.

[17] ISO 4804 (2020) Road vehicles — Safety and cybersecurity for automated driving systems — Design, verification and validation. ISO Technical report 4804:2020

[18] Kauffmann, N., Positive Risikobilanz als Maxime für die Entwicklung des automatisierten Fahrens, safe.tech Konferenz, 2021.

[19] Kocherscheidt, H., Wege zur Effizienzbetrachtung von Fahrerassistenzsystemen, 1. Tagung Aktive Sicherheit durch Fahrerassistenz, München, Germany, https://mediatum.ub.tum.de/doc/1145552/1145552.pdf, 2004.

[20] Dryselius, B., Pro-Gen Safety group summary report: Estimation of the potential safety effects of different possible PROMETHEUS-Functions, Prometheus (Program). PRO-GEN Safety Group, Published By: Prometheus Office Stuttgart, Germany, 1990.

[21] Sternlund, S., The safety potential of lane departure warning systems—A descriptive real-world study of fatal lane departure passenger car crashes in Sweden. Traffic Injury Prevention, 18(sup1), S18–S23. https://doi.org/10.1080/15389588.2017.1313413, 2017.

[22] Kessler, C., Etemad, A., Alessandretti, G., Heinig, K., Selpi, Brouwer, R., Cserpinszky, A., Hagleitner, W., Benmimoun, M., Final Report, euroFOT project deliverable D11.3., https://www.eurofot-ip.eu/download/library/deliverables/eurofotsp120121212v11dld113_final_report.pdf, 2012.

[23] Sayer, J. R., Bogard, S. E., Funkhouser, D., LeBlanc, D.J., Bao, S., Blankespoor, A.D., Buonarosa, M. L., Winkler, C. B. , Integrated Vehicle-Based Safety Systems Heavy-Truck Field Operational Test Key Findings Report, The University of Michigan Transportation Research Institute, Report No. DOT HS 811 362, https://deepblue.lib.umich.edu/bitstream/handle/2027.42/77988/102672.pdf?sequence=1&isAllowed=y, 2010.

[24] openPASS (2021).*OpenPASS Working Group*. https://openpass.eclipse.org/

[25] P.E.A.R.S. Consortium (2021) Prospective effectiveness assessment for road safety – overview, UNECE VMAD Sub Group 2 Virtual Testing, Meeting 24th Feb. 2021,

[26] Helmer T., Development of a Methodology for the Evaluation of Active Safety using the Example of Preventive Pedestrian Protection (doctoral thesis, TU Berlin). https://depositonce.tu-berlin.de.https://depositonce.tu-berlin.de/bitstream/11303/4270/2/helmer_thomas.pdf, 2014.

[27] Fahrenkrog, F., Wang, L., Platzer, T., Fries, A., Raisch, F., Kompaß, K., Prospective safety effectiveness assessment of automated driving function – from the method to the results. Enhanced Safety of Vehicles, Eindhoven, Netherlands https://www-esv.nhtsa.dot.gov/Proceedings/26/26ESV-000166.pdf, 2019.

[28] Wiedemann R., Simulation des Straßenverkehrsflusses, Schriftenreihe des Instituts für Verkehrswesen, Universität Karlsruhe, 1974.

[29] Treiber M., Hennecke A., Helbing D., Congested traffic states in empirical observations and microscopic simulations, *Physical review*, ***62* (2)**, 2000, pp. 1805-1824.

[30] Gipps P. G., A behavioural car following model for computer simulation, *Transportation Research Part B: Methodological*, 15 (2), 1981, pp. 105-111.

[31] Krauß S., Microscopic Modeling of Traffic Flow: Investigation of Collision Free Vehicle Dynamics, Dissertation, DLR-Forschungsbericht 98-08, 1998.

[32] Lopez, P. A., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y. P., Hilbrich, R., Lücken, L., Rummel, J., Wagner, P. and Wießner, E., Microscopic Traffic Simulation using SUMO, *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 2575-2582.

[33] Fellendorf, M., Vortisch, P., Validation of the Microscopic Traffic Flow Model VISSIM in Different Real-World Situations, *Transportation Research Board (TRB), 80th Annual Meeting, Washington DC*, 2001.

[34] Lee, D. N., A theory of visual control of braking based on information about time-to-collision, *Perception*, 5 (4), 1976, pp. 437-459.

[35] Salvucci, D. D., Modeling driver behavior in a cognitive architecture, Human Factors, 48, 2006, pp. 263-380.

[36] UN Regulation No. 157 - Automated Lane Keeping Systems (ALKS), 2021.

[37] Rösener, C., A Traffic-based Method for Safety Impact Assessment of Road Vehicle Automation, Dissertation, RWTH Aachen University, 2020.

[38] Witt M., Ring P., Wang L., Kompaß K., Prokop G., Modelling stochastic gaze distribution for multi-agent traffic simulation – Impact of driver characteristics and situational traffic circumstances on the driver's gaze behaviour, 7. Interdisziplinärer Workshop Kognitive Systeme: Mensch, Teams, Systeme und Automaten, Braunschweig, 2018.

[39] Witt, M., Wang, L., Prokop, G., Kompaß, K., Kognitive Fahrerverhaltensmodellierung in der virtuellen Bewertung von Fahrerassistenzsystemen unter Berücksichtigung der Ausprägungen menschlichen Fahrens, 8. Tagung Fahrerassistenz, München, 2017.

[40] N.N., https://www.highd-dataset.com/, RWTH Aachen University, 2021.

[41] Krajewski, R., Bock, J., Kloeker, L. and Eckstein, L., The highD Dataset: A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems, *2018 21st International Conference on Intelligent Transportation Systems (ITSC),* 2018, pp.2118-2125.

[42] Horst, A.R.A. van der, Hogema, J., Time-To-Collision and Collision Avoidance Systems, Vision in Vehicles III, Gale et al. (Eds.), Elsevier, pp. 19-26.

[43] Bäumler, H.: Reaktionszeiten im Straßenverkehr; VKU (Verkehrsunfall und Fahrzeugtechnik), Vieweg Verlag, 2008.

[44] Burckhardt, M.: Reaktionszeiten bei Notbremsvorgängen, Verlag TÜV Rheinland, 1985.

[45] Burckhardt, M. Burg, H., Gnadler, R., Näumann, E., Schiemann, G.: Die Brems-Reaktionsdauer von Pkw-Fahrern. *Der Verkehrsunfall*, 1981.

[46] Johannson, G., Ruman, K., Driver's Brake Reaction Times, *Human Factors*, 13(1), 1971, pp. 23-27.

[47] Boren, N.L., Chiang, D., Braking Response Times for 100 Drivers in the Avoidance of an Unexpected Obstacle as Measured in a Driving Simulator, *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 40 (18), 1996, pp. 900–904.

[48] Mehmood, A., Easa S., Modeling Reaction Time in Car-Following Behaviour Based on Human Factors, International Journal of Engineering and Applied Sciences, 5(2), 2009, pp. 93-101.

[49] Green, M., "How Long Does It Take to Stop?" Methodological Analysis of Driver Perception-Brake Times, *Transportation Human Factors*, 2(3), 2000, pp. 195-216.

[50] Summala H., Brake Reaction Times and Driver Behavior Analysis, *Transportation Human Factors,* 2(3), 2000, pp. 217-226.

[51] Markkula, G., Engström, J., Lodin, J., Bärgman, J., Trent, V., A farewell to brake reaction times? Kinematics-dependent brake response in naturalistic rear-end emergencies, *Accident Analysis and Prevention*, 95 (Part A), 2016, pp. 209-226.

[52] Engström, J., Aust, M. L., Viström, M. Effects of Working Memory Load and Repeated Scenario Exposure on Emergency Braking Performance. Human Factors, 2010, 52(5), pp. 551-559.